

Three Essays in Health Economics

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Abstract

Chapter 1: Born With The Blues? Effects of Prenatal Nutritional Deficiency on Depression in Adulthood

It is well established that maternal behaviour during pregnancy has a lasting effect on the child for years to come. Studies show that in utero nutritional shocks can have prolonged effects on health and labour market outcomes later in life of the offspring. In this paper I investigate whether such nutritional deficiencies during gestation can have an extended impact on mental health in adulthood. Using the fourth wave of Indonesian Family Life Survey (IFLS), I find that Muslim individuals who were potentially exposed to Ramadan in the first and third trimester have significantly higher scores on the depression scale than those who were not exposed. This effect is particularly significant among Muslim males who were exposed in the first trimester and Muslim females who were exposed in the third trimester. Similar effects of exposure are also found on the probability of being depressed in the Muslim population. The absence of such impact of exposure in the non-Muslim population suggests that nutritional deficiencies during the gestation period can have lasting effects on mental health and may increase the possibility of developing depression later in life.

Chapter 2: Should We Use Rank or Income in Socioeconomic Health Inequality Measurement?

The literature on socioeconomic health inequality uses individuals' socioeconomic rank (p) to develop the concentration index. In this paper I construct an alternative framework by directly using individuals' income level (y) to rank them and develop stochastic dominance conditions to investigate whether this method leads to the same conclusion as using the socioeconomic ranks (p). Using World Health Survey data for five South Asian countries, I conclude that using the socioeconomic ranks (p) and income levels (y) to rank individuals lead to different results in dominance tests adjusted for different equivalence scales.

Chapter 3: Economic Evaluations of Public Health Awareness Campaigns

To address the *arbitrariness* problem of the health concentration index's value caused by assuming the existence of a ratio-scaled variable, Makdissi and Yazbeck [2014] adopted a counting approach to measure health inequality. In this paper, I apply this counting approach in a two-fold way. Firstly, I estimate the values of population health status and health inequality in United States using the National Health Interview Survey (2010) data. Then, assuming increased government expenditure on health awareness, I simulate the effects such policy interventions and see what improvements in the public health can be achieved. Also, I propose the *count-approach incremental cost effectiveness ratio (C-ICER)* which is a simple measure to assess the cost effectiveness of public health awareness campaigns.

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Table of Contents

General Introduction	1
1 Born With The Blues? Effects of Prenatal Nutritional Deficiency on Depression in Adulthood	4
1.1 Introduction	5
1.2 Literature Review	7
1.3 Data	10
1.4 Results	17
1.4.1 Identification of the Effects of Exposure on Depression Scale Scores . . .	17
1.4.2 Identification of the Effects of Exposure on the Probability of Being Depressed	32
1.4.3 Religiosity	36
1.4.4 Implied Fasting Rate	41
1.5 Conclusion	42
Appendix 1: Tables	44
2 Should We Use Rank or Income in Socioeconomic Health Inequality Measurement?	60
2.1 Introduction	61

2.2	Theoretical Framework	63
2.2.1	Measuring Population Health	63
2.2.2	Rank dependent ethical principles	66
2.2.3	Stochastic Dominance Conditions	71
2.3	Empirical Illustration	80
2.3.1	The Data	80
2.3.2	Stochastic dominance among countries	89
2.4	Conclusion	101
	Appendix 2.B: Pairwise comparison of Lorenz and Generalized Lorenz curves	105
	Appendix 2.C: Pairwise comparison of Population Health Dominance curves	109
	Appendix 2.D: Pairwise comparison of Population Health Dominance curves Using World Bank PPP	140
	Appendix 2.E: Pairwise comparison of Socioeconomic Health Inequality Dominance curves	151
	Appendix 2.F: Pairwise comparison of Socioeconomic Health Inequality Dominance curves Using World Bank PPP	182
3	Economic Evaluations of Public Health Awareness Campaigns	193
3.1	Introduction	194
3.2	Theoretical Framework	198
3.3	Cost Effectiveness of Public Health Campaigns: Introducing the <i>C-ICER</i> . . .	201
3.4	Empirical Illustration	206
3.4.1	Simulation of improvement in diseases related to smoking	209
3.4.2	Simulation of improvement in diseases related to obesity	213

3.4.3	Calculating the <i>C-ICERs</i> of health awareness campaigns against Smok-	
	ing and Obesity	217
3.5	Conclusion	219
	Bibliography	221

General Introduction

This doctoral dissertation consists of three different chapters, with topics ranging from mental health to developing a theoretical framework in socioeconomic health inequality measurement to evaluating the cost effectiveness of public health campaigns. The first chapter investigates whether in utero shocks, measured by potential exposure to nutritional deficiencies, can have an extended impact on mental health in adulthood. It is well established that maternal behaviour during pregnancy has a lasting effect on the child, and individuals who were exposed to nutritional shocks during gestation have worse general health and higher probabilities of developing symptoms of coronary heart disease and type-2 diabetes later in life (Van Ewijk [2011]). Such nutritional deficiencies suffered while in utero may have effects on cognitive abilities in early childhood as well, Almond et al. [2015] found that children aged 7 who were possibly exposed to nutritional shocks in utero score lower in math and reading tests. I extend this research by investigating whether such nutritional deficiencies experienced while in utero have any impact on depression later in life. Using the fourth wave of the Indonesian Family life Survey (IFLS), I find that the individuals who were potentially exposed to nutritional shocks while in utero during the first and third trimesters have higher scores on the depression scale than those who were not exposed. This effect is significant for males who were exposed in the first trimester and for females who were exposed in the third trimester. I also find that those who were exposed to such nutritional shocks at any period during gestation have a higher probability of being depressed later in life than those who were not exposed.

Some researchers argue that the existing rank-dependent indices employed in the literature, which are used to measure the socioeconomic inequality of health, reflect a relationship between socioeconomic ranks and health levels, because these indices measure the socioeconomic status by *ranks* and the health status by the *level* of the health variable under

consideration. In the second chapter, I present a theoretical framework of testing stochastic dominance in socioeconomic health inequality measurement by directly using individuals' income level (y) to rank them and then proceed to develop the required stochastic dominance conditions to investigate whether this method leads to the same conclusion as using the socioeconomic ranks (p), which has been widely used in the literature. Using the World Health Survey (2002) data for five South Asian countries (i.e., Bangladesh, India, Nepal, Pakistan, Sri Lanka), I find that using the income approach leads to different results than using the socioeconomic positions approach for both population health and socioeconomic health inequality dominance tests; for example, India dominates Bangladesh in the second order when socioeconomic status p is used, but there is non-dominance (i.e., the two curves cross each other) when income y is used. The reverse case was also found; there is non-dominance in the second order between India and Sri Lanka when socioeconomic status p is used, but Sri Lanka dominates India when income y is used.

Health care is one of the top-most priorities of governments around the world currently. One important aspect of public health policies is the prevention of diseases and promotion of health among residents in a jurisdiction. Because such importance is given to health care, it is of the utmost interest to the government to measure and monitor health status among the population in the most efficient, cost effective, and accurate way possible. Governments want to raise awareness among residents to adopt healthy lifestyles and abstain from harmful habits that are detrimental to health, because in the long run, such preventive measures would put less strain on the health care system. Health awareness campaigns are a useful way to raise awareness about a particular health issue in the population. In the last chapter of this thesis, I use a two-fold approach to evaluate the cost effectiveness of such public health awareness campaigns. First by using the National Health Interview Survey (NHIS) data from the United States for the year 2010, I measure the population health achievement and socioeconomic

health inequality by following Makdissi and Yazbeck [2014], who redefine the health status variable so that it captures the socioeconomic inequality in the health attainments. Following this method gets rid of the arbitrariness problem of the concentration index, which is a widely accepted measure to evaluate socioeconomic health inequality. I then use simple simulation techniques to demonstrate the effects of policy changes on not just a particular health problem, but on the comprehensive *public health* status in the population which is channelled through a number of health problems at the same time. This way, I am able to demonstrate what the expected effect will be because of a single change in the government policy, in the form of a health awareness campaign, on a number of health problems and the following translated effects on socioeconomic health inequality.

Chapter 1

Born With The Blues? Effects of Prenatal Nutritional Deficiency on Depression in Adulthood

1.1 Introduction

The idea that prenatal exposure to adverse conditions in utero may have lasting effects on the health and well-being of an individual has been an interesting topic for researchers for some time now. The ‘Fetal Origins Hypothesis’ proposed by Barker [1995] postulates that in utero nutritional factors (and not the genetic factors) are the dominant cause of heart disease, type-2 diabetes, and other degenerative conditions in adult health. Such nutritional deficiencies in the gestation period among a large number of individuals can be caused by some sort of severities like war, famine, or endemic diseases. However, finding reliable and required data in such rare events can be difficult. Researchers are thus particularly attracted to using Ramadan, which lasts for a month every year, as a natural experiment to investigate the effects of systematic fasting of pregnant mothers on their child.

Ramadan, the ninth month in the Islamic calendar year (Hijri), is the holiest time of the year for Muslims all around the world. Fasting, along with refraining from bad behaviour and increased religious observance, make Ramadan a month of self-purification. Fasting from pre-dawn until sunset during Ramadan is the third pillar in Islam and mandatory for all adult Muslims, except for those who are sick, travelling, and women who are menstruating. Pregnant women are also allowed to opt out of fasting. Those who are unable to fast during Ramadan, need to make up for the missing days later or by giving donation to charity. Although it is not required by the religion, many pregnant women choose to fast during Ramadan (Makki [2002], Joosop et al. [2004]). Researchers have been using Ramadan fasting during pregnancy to evaluate the impact of exposure to nutritional shortfalls that the child in utero may be subject to for some time now. Almond and Mazumder [2011] was the first study to use Ramadan fasting to estimate the short and long-term effects of exposure on the child. Using data for Muslims in Michigan, they found that in utero exposure to Ramadan is

associated with lower birth weights (which may have prolonged effects over the life period of the child) and a lower share of male births. Using census data from Uganda and Iraq, they also showed that adults who were exposed to Ramadan in utero have higher probabilities of having mental or learning disabilities and less wealth. Van Ewijk [2011] used data from Indonesia and found that people who were possibly exposed to Ramadan during gestation have worse general health and higher probabilities of developing symptoms of coronary heart disease and type-2 diabetes later in life. Almond et al. [2015] looked into the mathematics and reading test scores of children aged 7 in England and found that the score are 0.05-0.08 standard deviations lower for those who were possibly exposed to Ramadan in early pregnancy. Majid [2015] estimated the effects of Ramadan exposure on cognitive skills and labour supply behaviour and found that the exposed score lower on cognitive and mathematics tests, and are more likely to work fewer hours and to be self employed. Although these papers look into the effects of exposure on physical health and cognitive development in the long run, there seems to be a gap in the literature that investigates the possible effects of prenatal exposure to Ramadan and mental health. This paper fills that gap by investigating the effects of in utero nutritional deficiencies, identified by maternal fasting during Ramadan (which is assumed and not reported by survey data), on mental health in the long run as measured by individuals' scores in the depression scale.

The rest of the paper is organized as follows. In the next section, I provide a brief review of relevant literature. Section 3 discusses the data I have used for analyses. Section 4 outlines the results of my estimations and section 5 concludes the paper.

1.2 Literature Review

Many of the studies that try to find a relationship between in utero nutritional shocks and their effects later in life use uncommon and severe historical events like famine and infectious diseases for identification purposes (Almond [2006], Chen and Zhou [2007]). There is also evidence of seasonal variations in health at birth; in other words, the month of birth can have effect on health (Doblhammer and Vaupel [2001], Costa and Lahey [2005]). A number of researchers use the Muslim holy fasting month of Ramadan as a natural experiment in maternal fasting. Ramadan fasting during pregnancy can lead to sharp decline in maternal glucose levels along with other biochemical changes in the fetal environment, a phenomenon known as ‘accelerated starvation’ (Prentice et al. [1983], Malhotra et al. [1989]). These altered metabolic profiles associated with fasting have been associated with diminished cognitive function during childhood, and experimental animal studies suggest that these alterations may hamper neurological development. Cunha and Heckman [2007] found that prenatal development can impact health capital and skill formation. However, while analyzing the relationship between outcomes in adulthood and in utero Ramadan exposure, Azizi et al. [2004] found no significant difference in the IQ’s of school-age children by maternal fasting behaviour. The growing literature on the development origins of adult health and disease has emphasized that the supply of glucose and oxygen are the two key signals of the maternal environment during early embryonic development (Gluckman and Hanson [2004]). One proposed mechanism is that restricted nutrition leads to a reprogramming of the neuroendocrine system. Consistent with this, Dikensoy et al. [2009] documented heightened levels of the hormone cortisol among pregnant women fasting during Ramadan. Of those individuals who are clinically depressed, about one-half will have an excess of a hormone in their blood called cortisol. This hormone is believed to be related to clinical depression since the high levels usually reduce to a normal

level once the depression disappears.

There is also evidence that fetal environment may be important in the development of the central nervous system and in the etiology of poor mental health. A number of studies have found that low birth weight can be a risk factor for schizophrenia. Many studies have found an inverse relation between birth weight adjusted for gestational age and depression (Nilsson et al. [2001], Cheung [2002], Cheung et al. [2002], Gale and Martyn [2004], Wiles et al. [2005]). It is possible that maternal factors are driving the association between birth weight and depression. Paarlberg et al. [1999] found that in the first trimester of pregnancy maternal depression is associated with an increased risk of low birth weight. Orr and Miller [1995] and Hirshfeld-Becker et al. [2004] found association between maternal depression during pregnancy and future depression in her child. Timonen et al. [2004] found that insulin resistance and diabetes may be related to depression, but the direction and nature of the association are unclear.

Among other studies, Alati et al. [2007] examined the relationship between birth weight and adult depression measured at the age of 21, and they found a weak inverse relation between birth weight and symptoms of depression and for females using Australian birth cohort data, while no relationship was found for male samples. The study provides some support for a fetal origin of adult depression. The gender difference should also be taken into consideration by researchers, since male and female fetuses have different growth patterns and organ development timing; females grow faster than males (Lampl and Jeanty [2003]). There is evidence of skewed sex ratios at birth because of maternal nutritional shocks, especially around the time of conception. Mathews et al. [2008] found that expecting mothers who had skipped breakfast around the time of conception skewed sex ratios in favour of girls among the newborns, most likely through selective attrition of male conceptuses. Cameron [2004] showed that maternal nutrition around the time of conception is positively associated with the

likelihood of male child among mammals. Using natality data from Michigan, Almond and Mazumder [2011] found that among children of Arab mothers who were potentially exposed to Ramadan in utero during the first month of gestation, there is a significantly negative effect on the likelihood of a male birth, whereas no such effect was found for non-Arabs. These studies show that male and female fetuses respond differently to nutritional shocks during gestation and therefore the estimations presented in this paper include results for males and females separately.

Using Ramadan fasting as a natural experiment, Almond and Mazumder [2011] also found that those who were prenatally exposed to Ramadan are more likely to have a mental or learning disability when Ramadan occurred during the first month of pregnancy. Majid [2015] estimated the effects of in utero nutrition shocks over the life cycle, and they found that exposed children score lower on cognitive and mathematics tests. Adhvaryu et al. [2014] looked into the effects of economic shocks early in life and its effect on mental health that continues to persist in the long run. Using real producer prices of cocoa in Ghana, it was found that low cocoa prices drove the income of cocoa farmers down, which in turn decreased their ability to afford sufficient amount of food, which implies that some children suffered nutritional deficiency while in utero. Consequently, low cocoa prices at the time of birth of these individuals substantially increased the incidence of severe mental illness as measured by the Kessler Psychological Distress Scale (K10).

The objective of this paper is to investigate whether nutritional shocks in utero have any lasting effects on depression in adulthood by using Ramadan as a natural experiment, and contribute to the growing literature that investigates prenatal exposure to adverse conditions (i.e., nutritional shocks) and mental health.

1.3 Data

I use data from the fourth wave of the Indonesian Family Life Survey (IFLS) provided by Rand Corporation. IFLS is an on-going longitudinal survey that collects extensive socioeconomic and health information and is representative of about 83% of the entire Indonesian population collected from 13 provinces (Strauss et al. [2009]). The first wave of the survey (IFLS-1) was carried out in 1993-94. The fourth wave which I use in this paper was conducted in 2007-08. Household interviews were carried out by teams of 6–8 interviewers and 2 health workers, who were selected based on an appropriate mix of language abilities and trained in two phases. A proxy book was used for collecting limited information from other household members about those who could not be interviewed in person. The survey gathered detailed information on household expenditures, knowledge of health facilities, housing characteristics, socioeconomic information (educational, marital, work, migration histories, asset ownership etc.), health information (smoking habits, insurance coverage, food intake, use of inpatient and outpatient care, mental health etc.), information on children (educational history, morbidity, inpatient and outpatient visits etc.), physical health assessments, and cognitive assessments. A total of 13,535 households and 44,103 individuals (21,652 males and 22,451 females) were interviewed in the process. Everyone over age 11 was interviewed (for children below the age 11, a parent or caretaker was interviewed). The dataset also contains information on each person's exact date of birth and religion, which are required for this study. Some people in the survey did not know their exact date of birth, which made them unusable for the analysis and they were discarded.

A new section was added in the IFLS-4 survey questionnaire to assess the presence of depression in the respondents. In order to make IFLS-4 more comparable to international surveys, respondents aged 15 and over were asked a series of 10 questions from the short

version of Centre for Epidemiologic Studies Depression Scale (CES-D). Andresen et al. [1994] tested the short form CES-D scale for reliability and validity by screening for depression among a sample of well older adults and found that the short form CES-D questionnaire with 10 questions showed good predictive accuracy compared to the full length version of the CES-D with 20 questions. Zhang et al. [2012] found the 10-item CES-D to be a comparable tool to measure depressive symptoms among HIV-positive research participants in British Columbia.

I follow Van Ewijk [2011] to determine whether a person was in utero during Ramadan using his/her exact date of birth. Using January 1st, 1900 as a reference point in time, I calculated the distance of each person's date of birth from that day. The same is done for the historic dates of Ramadan from year 1900 onwards.¹ Then I matched each person's birth date to see if there is an overlap between Ramadan dates and the length of pregnancy which is 266 days on average from the day of conception. Those individuals who were conceived within the interval commencing right after Ramadan in one year and 266 days before the starting date of Ramadan next year (i.e., within 59-60 days per Islamic Hijri year) were certainly not in utero during Ramadan, and they were identified as 'not exposed'. This is the reference group in all analyses, all of the results presented in the next section are relative to this group. I also exclude those who were calculated to be conceived fewer than 21 days after the end of Ramadan from the 'not exposed' group because if the pregnancies had lasted more than the average of 266 days, then this would create a misspecification by labelling the exposed as not exposed. Kieler et al. [1995] showed that pregnancies lasting for three weeks or more beyond the average term are rare, and so this ensures that no one is deemed to be 'not exposed' while in fact he/she might have been exposed to Ramadan. To assess the effects of exposure to

¹The historic dates of Ramadan and the conversion of Hijri calendar to Gregorian calendar are retrieved from <http://www.staff.science.uu.nl/~gent0113/islam/ummalkura>, accessed on June 21st, 2016.

Ramadan while in utero, I divided the total length of pregnancy into four groups for those who were exposed: those who were exposed to Ramadan in utero (including everyone who were exposed for a single day to those who were exposed for a full month), those who were conceived during Ramadan (i.e., day of conception was during Ramadan), those who were exposed to a full month of Ramadan in trimester 1, those who were exposed to a full month of Ramadan in trimester 2, and those who those who were exposed to a full month of Ramadan in trimester 3. For all regression estimates presented in this study, the control group consists of individuals who were definitely not exposed while in utero during Ramadan. To calculate the exposure during first, second and third trimester, I primarily consider a full month's exposure to Ramadan, which is consistent with the literature. However, it should be noted that there are individuals who were partially exposed to Ramadan while in utero. To account for them, I use a weighted dummy to capture the effects of partial exposure on depression scale scores and run the same regression; the results are consistent with the ones found with full month's exposure. This is discussed in section-1.4.1 in detail.

One additional benefit of using the IFLS-4 survey is that the study is carried out in Indonesia, a constitutionally secular country with the largest Muslim population (202.9 million in 2011) in the world (Miller [2009]), and also with a tropical climate located right on the equator. It means that the daylight hours and temperatures are almost constant in Indonesia throughout the year. This advantage obliterates the need to account for the number of daylight hours during Ramadan each year, which would otherwise be required in order to analyze this question (most other countries which do not have constant number of daylight hours). Indonesia, however, has a monsoon season which lasts from November to March. The Islamic calendar moves about 11 days forward relative to the Gregorian calendar, which means that in every 33 years Ramadan covers the whole Gregorian calendar year and both seasons. Since the age of the individuals in my sample ranges from 15 – 100 years, seasonality

is presumably not a concern in this study.

There are a number of covariates which are known to be associated with depression; for example, body mass index (BMI), health status, age, gender, socioeconomic status, smoking status, physical activity, iodine deficiency etc. These variables are used in the regression presented in the results section in the following.

Table 1.1 below shows the summary statistics for the treatment group (i.e., those who were potentially exposed to Ramadan in utero) and the control group (i.e., those who were not exposed to Ramadan in utero). There is no way to be sure from the survey data about which mothers actually fasted in Ramadan during pregnancy from the information provided in the survey, but those who did are in the treatment group. In that sense this is an Intent-to-Treat (ITT) case. It can be seen from the summary statistics that on average Muslims are slightly younger, a little less religious (religiosity is measured on a scale of 1 to 4, where 1 corresponds to being very religious and 4 corresponds to being not religious), on average score lower on the depression scale, and have worse health status (health status is measured on a scale of 1 to 9, with 1 being much worse and 9 being very good) than their non-Muslim counterparts on average in the sample. The share of depressed people is also less among Muslims than non-Muslims. The proportion of tobacco users and the usage of iodized household salt are also higher among Muslims on average. The share of females is higher than males in the sample for both Muslims and non-Muslims. For both Muslims and non-Muslims, the difference in mean scores between exposed and not exposed groups are tested for each of the covariates and the associated p -values are reported. Also, none of the covariates used in the regression are significantly different for Muslims and non-Muslims. The correlation among the explanatory variables used in this study are given in Table 1.25 in Appendix-1.

Table 1.1: Summary statistics by exposure and religion:

	Muslims			Non-Muslims		
	Exposed	Not Exposed	$p(\text{difference})$	Exposed	Not Exposed	$p(\text{difference})$
<i>Panel A:</i>						
Age	36.798 (15.502)	36.483 (15.692)	0.310	38.069 (16.255)	38.903 (17.725)	0.372
Male	0.473 (0.499)	0.493 (0.500)	0.054*	0.482 (0.500)	0.477 (0.500)	0.854
Household size	2.877 (1.386)	2.880 (1.369)	0.913	2.796 (1.389)	2.786 (1.368)	0.893
No. of observations	22868	2821		2695	350	
<i>Panel B:</i>						
Religiosity	2.195 (0.563)	2.194 (0.540)	0.919	2.014 (0.534)	2.012 (0.566)	0.945
No. of Observations	21745	2683		2485	325	
<i>Panel C:</i>						
Depression scores	4.024 (3.531)	3.946 (3.344)	0.279	4.485 (3.655)	4.255 (3.661)	0.284
Depressed	0.069 (0.254)	0.061 (0.239)	0.104	0.095 (0.293)	0.077 (0.267)	0.289
BMI	22.332 (4.399)	22.290 (4.501)	0.644	22.839 (4.256)	22.657 (3.605)	0.461
Health status	5.840 (0.844)	5.836 (0.858)	0.831	5.959 (0.836)	6.034 (0.839)	0.132
Tobacco usage	0.332 0.471	0.344 0.475	0.236	0.307 0.461	0.334 0.472	0.322
Vigorous activity	0.302 (0.459)	0.298 (0.458)	0.725	0.301 (0.459)	0.347 (0.477)	0.095*

Continued on next page

Table 1.1 – continued from previous page

	Muslims			Non-Muslims		
	Exposed	Not Exposed	$p(\text{difference})$	Exposed	Not Exposed	$p(\text{difference})$
Moderate activity	0.804 (0.397)	0.791 (0.407)	0.095*	0.737 (0.440)	0.724 (0.448)	0.691
Walking	0.860 (0.347)	0.855 (0.352)	0.476	0.845 (0.362)	0.837 (0.370)	0.726
Log of food expenditure per capita	10.664 (0.743)	10.658 (0.711)	0.651	10.845 (0.787)	10.798 (0.803)	0.310
Log of food production per capita	8.624 (1.400)	8.587 (1.407)	0.263	8.842 (1.464)	8.915 (1.506)	0.465
Log of non-food expenditure per capita (type-1)	11.279 (1.258)	11.257 (1.244)	0.398	11.588 (1.504)	11.559 (1.629)	0.751
Log of non-food expenditure per capita (type-2)	12.760 (1.352)	12.711 (1.343)	0.075*	13.230 (1.657)	13.306 (1.691)	0.442
Household iodized salt	0.871 (0.335)	0.863 (0.344)	0.226	0.739 (0.439)	0.718 (0.451)	0.417
No. of Observations	21793	2691		2489	326	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Means of each variable presented with standard deviation in parentheses. Type-1 non-food items include electricity, water, fuel, telephone, personal toiletries, recreation and entertainment, transportation etc. Type-2 non-food items include clothing, household supplies and furniture, medical costs, ritual ceremonies, charities, gifts, taxes, and other expenditures not mentioned.

The summary statistics in Table 1.1 are presented in three panels with different sample sizes, as the data availability from the survey was different for different variables. Panel A consists of 28,734 samples, which are used in the simple regressions presented in section-1.4.1. Data on religiosity was available for 27,238 individuals as shown in Panel B, which are used in the regressions presented in section-1.4.3. Lastly, Panel C consists of 27,299 individuals, which are used in the regressions with additional explanatory variables presented in section-1.4.1.

In the IFLS-4 survey, the depression scale scores (i.e., the dependent variable in the regressions used in this study) were available for a total of 29,025 individuals. Of these, 66 individuals did not know their exact date of birth, which made them unusable. Furthermore, information on the religion for another 225 individuals were also missing. This yielded the sample size used for the simple regressions (i.e., without additional explanatory variables) to 28,734. When the additional variables were added to the samples, some individuals had missing information on height, weight, household expenditures, physical activities, tobacco usage, or measured health status. Discarding them reduced the sample size by 1,435—bringing the total sample size with additional explanatory variables to 27,299. Because the dropped samples were so few relative to the overall sample size, it would be unlikely that the dropped individuals would create any systematic difference in the observed characteristics in the observations that were used in the regressions and have any impact on the results. Table 1.22 in Appendix-1 shows a comparison of the observed characteristics between the dropped observations and the ones used in the study. It can be seen that there is no systematic difference between the two groups. Also, as there is less consensus in the literature on using survey weights in multivariate models, such as regression (Gelman [2007], Kott [2007], Winship and Radbill [1994]); no survey weights are used in the estimations.

1.4 Results

1.4.1 Identification of the Effects of Exposure on Depression Scale Scores

Simple Regression

Van Ewijk [2011] investigates the effects on in utero exposure to Ramadan on general health, type 2 diabetes, and coronary heart problems by regressing health status on exposure, age, age^2 , age^3 , age^4 , and calendar month of birth fixed effects. To identify the effects of in utero exposure to Ramadan on cognitive skills, child labour incidence, and labour supply behaviour later in life, Majid [2015] regressed the outcomes of interest on exposure to Ramadan, age, age squared, and calendar month of birth fixed effects, and dropped the family and community level time-invariant covariates by differencing across two time periods t_1 and t_2 . To identify the effects of exposure to Ramadan on depression while in utero, I start by following the same aforementioned basic specification:

$$DepressionScore_i = \beta_0 + \beta_1 exposure_i + \beta_2 age + \beta_3 age^2 + \lambda_m + \epsilon_i \quad (1.1)$$

The depression score for each individual is regressed on the exposure dummies, age of the individual, age squared, and birth-month fixed effects (λ_m). The ‘exposure’ measure consists of dummies which indicate an overlap between Ramadan dates and gestation dates. Separate regressions are run for different ‘exposure’ categories, namely exposure at any stage during pregnancy, conception during Ramadan, full-month exposure in trimester 1, full-month exposure in trimester 2, and full month exposure in trimester 3 for males and females separately. Results from OLS regressions for Muslims and non-Muslims are given in Table 1.2 below. It

should be noted that all regressions presented in this paper used an intercept in the model. ²

Table 1.2: Effects of being exposed to Ramadan in utero on depression scale scores- OLS Estimates:

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.087 (0.067)	0.064 (0.094)	0.111 (0.097)	0.243 (0.211)	0.111 (0.292)	0.407 (0.312)
Conceived during Ramadan	0.085 (0.098)	0.003 (0.139)	0.151 (0.141)	0.368 (0.314)	0.202 (0.409)	0.422 (0.470)
Exposed in trimester 1	0.154* (0.084)	0.220* (0.115)	0.083 (0.125)	0.102 (0.268)	0.123 (0.399)	0.073 (0.386)
Exposed in trimester 2	0.067 (0.085)	-0.090 (0.118)	0.207 (0.126)	0.212 (0.259)	0.187 (0.383)	0.111 (0.373)
Exposed in trimester 3	0.159* (0.086)	0.052 (0.121)	0.268** (0.124)	0.382 (0.265)	0.310 (0.370)	0.545 (0.375)
No. of observations	25689	12211	13478	3045	1467	1578
Mean scores	4.037	3.974	4.095	4.500	4.319	4.669

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, and month-of-birth. Robust standard errors are clustered by households.

It can be seen that Muslims who were potentially exposed to Ramadan fasting while in utero during the first and third trimesters have positive effects on their scores in the depression scale, which are significant at the 10% level. These individuals have 15.4% higher scores in the depression scale compared to those who were not exposed. Among these, males have a higher and significant score than females. Also, the individuals who were exposed in their

²Using the difference-in-difference modelling technique would be another way to check the effects of exposure on the depression scale scores. Almost all studies that look into the effects of Ramadan exposure on various outcomes use OLS and fixed/random effects modelling, and this study is consistent with that approach. Also, none of the covariates used in the regression are significantly different for Muslims and non-Muslims.

third trimester have 15.9% higher score than those who were not exposed. Of these, the females have a higher and significant score than males. No such effect of exposure is found for the non-Muslims, which implies that exposure to Ramadan in utero has no relevance to their scores in the depression scale. This is the result I anticipated, since the non-Muslims are not expected to fast during Ramadan and there should be no systematic nutritional deficiency in utero for them during the month of Ramadan.

There is a possibility that the adverse impacts on depression scale scores might be caused by some other family level unobservable variables that are not being captured by the model. These family level unobservable variables are those which might have an effect on the responses used to calculate the depression scores at the time of the interviews. Using fixed effects or random effects models are two ways to account for this. The underlying assumption for using fixed effects model is that the unobserved individual-specific characteristics are correlated with the control variables, whereas for the random effects model it is assumed that the unobserved individual-specific characteristics are uncorrelated with the control variables. In this paper, I assume that the family-specific characteristics are uncorrelated with the control variables and thus the random effects model will be more appropriate. This is because the family level unobservable variables that might have an impact on the depression scores (e.g., emotional and/or financial shocks, loss of family members, loss of family pets etc.) are unlikely to have a correlation with the control variables used. Both fixed effects and random effects models remove the omitted variable bias (created by the unobserved variables) by measuring changes within a group. In order to ensure that the time-invariant family level unobservable variables are not driving these results, Van Ewijk [2011] used biological siblings fixed effects for children and found similar results comparable to OLS estimates. Majid [2015] used household fixed effects for adults to test the robustness of the OLS estimates. Fixed effects models are used when there is a possibility of something within the individuals

(i.e., individual characteristics) that might affect the estimator and create bias. On the other hand, random effects models should be used when there are reasons to believe that the differences across entities (e.g., households in my case) have some influence on the dependent variable. Random effects models are particularly useful for analyzing the impacts of variables that do not vary over time. The Hausman specification test (Hausman [1978]) is a well known method to determine the appropriateness of a fixed effects versus a random effects model. In this test, the fixed effects estimator is assumed to be consistent, and the random effects estimator is assumed to be consistent and efficient under the null hypothesis. Under the alternative hypothesis, the fixed effects estimator is consistent and the random effects estimator is inconsistent. The test compares the difference between the fixed effects and random effects coefficients. A p-value lower than a set significance level (1%, 5% etc.) is suggestive of rejecting the null hypothesis and choosing a fixed effects model. Otherwise, a random effects model would be more appropriate. To determine whether a household fixed effects model or a household random effects model is appropriate for my regression model, I carry out the Hausman test for each regression. The p-values from the Hausman tests are given in Table 1.12 (for households with two or more members including household head, spouse and other members) and in Table 1.13 (for all samples) in Appendix-1. Separate tests are reported to check whether there is any significant differences in estimates due to the composition of households (i.e., for households where both the household head and the spouse are present versus households with no such restrictions. It can be seen from Table 1.12 that none of the p-values are significant at 1% level, and most of them are not significant at 5% level. For all samples, it can be seen in Table 1.13 that most of the p-values are non-significant. Therefore, it appears that a household random effects model would be more appropriate in my case. Table 1.3 below shows the estimates of household random effects for the sample of households with two or more members, including the household head, his/her

spouse, and other members living in the household. It can be seen that with the household random effects, there is a small significant effect on the depression scale scores for the exposed Muslim females. More significant effects of exposure are evident for Muslim females who were exposed to Ramadan in trimester 2.

Table 1.3: Effects of being exposed to Ramadan in utero on depression scale scores - household Random Effects estimates for restricted sample:

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.062 (0.075)	0.003 (0.107)	0.216* (0.115)	0.410* (0.215)	0.316 (0.301)	0.486 (0.330)
Conceived during Ramadan	0.146 (0.116)	-0.020 (0.159)	0.335* (0.172)	0.365 (0.338)	0.264 (0.244)	0.425 (0.557)
Exposed in trimester 1	0.176* (0.095)	0.176 (0.130)	0.190 (0.146)	0.166 (0.280)	0.121 (0.418)	-0.107 (0.401)
Exposed in trimester 2	0.090 (0.097)	-0.167 (0.133)	0.375** (0.149)	0.413 (0.261)	0.299 (0.381)	0.496 (0.378)
Exposed in trimester 3	0.113 (0.098)	-0.001 (0.137)	0.251* (0.145)	0.527* (0.292)	0.634 (0.405)	0.509 (0.425)
No. of observations	18455	9321	9134	2147	1085	1062
Mean scores	3.924	3.888	3.961	4.328	4.238	4.420

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, and month-of-birth for the sample of households with two or more members, containing the household head, his/her spouse, and other members living at the household during the time of the survey. Robust standard errors are clustered by households.

In order to obtain a better comparison between the OLS estimates and the household random effects estimate, I also estimate the household random effects model for all households in the sample (i.e., not restricted to households with the household head and his/her spouse

present). Results are shown along with the OLS estimates that are given in Table 1.2 for a easier comparison between Muslims and non-Muslims in separate tables (Table 1.4 and Table 1.5) below.

Table 1.4: Effects of being exposed to Ramadan in utero on Depression scale scores - OLS estimates vs. household Random Effects estimates for Muslims:

Muslims						
	All		Male		Female	
	OLS	Random Effects	OLS	Random Effects	OLS	Random Effects
Exposed	0.087 (0.067)	0.052 (0.065)	0.064 (0.094)	0.054 (0.094)	0.111 (0.097)	0.108 (0.097)
Conceived during Ramadan	0.085 (0.098)	0.085 (0.098)	0.003 (0.139)	0.002 (0.139)	0.151 (0.141)	0.151 (0.141)
Exposed in trimester 1	0.154* (0.084)	0.148* (0.083)	0.220* (0.115)	0.195* (0.115)	0.083 (0.125)	0.083 (0.125)
Exposed in trimester 2	0.067 (0.085)	0.063 (0.084)	-0.090 (0.118)	-0.095 (0.118)	0.207 (0.126)	0.206 (0.126)
Exposed in trimester 3	0.159* (0.086)	0.156* (0.085)	0.052 (0.121)	0.046 (0.121)	0.268** (0.124)	0.264** (0.123)
No. of observations	25689	25689	12211	12211	13478	13478
Mean scores	4.037	4.037	3.974	3.974	4.095	4.095

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, and month-of-birth. Robust standard errors are clustered by households.

Table 1.5: Effects of being exposed to Ramadan in utero on depression scale scores - OLS estimates vs. household Random Effects estimates for non-Muslims:

Non-Muslims						
	All		Male		Female	
	OLS	Random Effects	OLS	Random Effects	OLS	Random Effects
Exposed	0.243 (0.211)	0.271 (0.208)	0.111 (0.292)	0.092 (0.288)	0.407 (0.312)	0.385 (0.308)
Conceived during Ramadan	0.368 (0.314)	0.372 (0.317)	0.202 (0.409)	0.257 (0.410)	0.422 (0.470)	0.422 (0.470)
Exposed in trimester 1	0.102 (0.268)	0.080 (0.267)	0.123 (0.399)	-0.013 (0.398)	0.073 (0.386)	-0.073 (0.368)
Exposed in trimester 2	0.212 (0.259)	0.084 (0.255)	0.187 (0.383)	0.189 (0.374)	0.111 (0.373)	0.048 (0.371)
Exposed in trimester 3	0.382 (0.265)	0.488* (0.269)	0.310 (0.370)	0.322 (0.369)	0.545 (0.375)	0.590 (0.377)
No. of observations	3045	3045	1467	1467	1578	1578
Mean scores	4.500	4.500	4.319	4.319	4.669	4.669

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, and month-of-birth. Robust standard errors are clustered by households.

It can be seen that the household random effects estimates are a little lower than the OLS estimates in magnitude for Muslims. The standard errors of the random effects estimates are little smaller than the standard errors of the OLS estimates in some instances. In random effects models, it is assumed that the explanatory variables do not vary over time, and the family level unobservable variables (as in this case) are uncorrelated with the control variables. The little variability within the explanatory variables often causes the random effects model estimates to have smaller standard errors. For other estimates, both the OLS estimates and random effects estimates have similar standard errors. This gives me the assurance about the

robustness of the OLS estimates. The significant results are also similar in both models. The most profound impact of exposure can be seen for the females who were exposed during their third trimester in utero to Ramadan, their scores on the depression scale is 26.8% higher in the OLS model and 26.4% higher with the household random effects, compared to those who were not exposed. On the other hand, the household random effects estimates are higher in some cases and lower in other cases than the OLS estimates for the non-Muslims. However, the standard errors for both models do not change much. As expected, there are no significant results of exposure to Ramadan found on the depression scale score for the non-Muslims (except for those who were exposed in the third trimester, low level of significance is found with household random effects).

Regression with Additional Explanatory Variables

Results using the basic specification in equation (1.1) indicate that there is indeed a positive effect on the scores in the depression scale for those who were exposed to Ramadan during their first and third trimesters in utero. Now I add additional explanatory variables in my regression to estimate the true and more comprehensive underlying relationship between depression scores and in utero exposure to Ramadan, provided that the previous regression model omitted relevant explanatory variables; and estimate the following equation:

$$DepressionScore_i = \beta_0 + \beta_1 exposure_i + \beta_2 age + \beta_3 age^2 + \beta_4 X_i + \lambda_m + \epsilon_i \quad (1.2)$$

Where X_i includes body mass index, measured health status, socioeconomic status, smoking status, physical activity status, and indicator for iodine deficiency. A brief explanation of

these covariates are given below.³

The body mass index (BMI) can have an influence on the mental state of a person, although the exact mechanism that can explain the relationship between depression and obesity is not clear. Studies that look into the relationship between depression and BMI report conflicting results. So far three hypotheses have been suggested regarding this matter: a positive association, which postulates that higher depression is associated with greater obesity (Becker et al. [2001], Richardson et al. [2006], Baumeister and Härter [2007]), a negative association, which suggests higher depression is associated with lower obesity (Crisp and McGuiness [1976], Crisp et al. [1980]), and studies that find no association between depression and obesity (John et al. [2005]). However, it is not the case that only overweight status has a link with depression; the opposite also holds, as being underweight can also be associated with depression. IFLS-4 includes height and weight measures for each observations which I use to calculate the BMI.⁴

The overall physical health status and wellness of an individual can have an impact on his/her mental health as well. Chapman et al. [2005] found that mental illnesses– depressive disorders to be specific–are associated with increased incidence of chronic diseases. Koster et al. [2006] found that in older adults low socioeconomic status predicted the incidence of depression, and part of this association was explained by physical health status. Using a cross-sectional cohort study, Nachtegaal et al. [2009] found that hearing status is negatively correlated with higher stress, depression, and loneliness in young and middle-aged adults. In the IFLS-4 survey, trained nurses took measurements of a set of health variables (e.g., height, weight, blood pressure, lung capacity, pulse, hemoglobin level etc.) and rated the health of each individual compared against the health status of other people of same age and sex using

³Cross terms (i.e., product between the explanatory variables) could be used to improve the estimation of the regression; however, this is not done here because of possible multi-collinearity.

⁴BMI is calculated as: $weight(kg)/[height(meter)]^2$.

a nine-point scale (in which 1 referred to much worse and 9 referred to much better).

Age, gender, and socioeconomic status can also influence the incidence of depression in a population. Several researchers have found depression to be the most frequent cause of emotional stress later in life, which significantly decreases quality of life in older adults (Berkman et al. [1986], Blazer et al. [1987], Blazer et al. [1991], Blazer [2003]). Using the National Epidemiologic Survey of Alcoholism and Related Conditions (NESARC), which consists of face-to-face interviews of more than 43,000 adults aged 18 years and older in the United States, Hasin et al. [2005] found that being female, Native American, middle aged, widowed, separated, or divorced, and having low income increased the risk of having major depressive disorder (MDD). IFLS-4 includes the age and gender of all participants in the survey. The survey also includes information on household food production, food expenditures, and expenditure on non-food items (for example, electricity, water, fuel, telephone, recreation and entertainment etc.). I include the log of per capita food expenditure, food production, and non-food expenditure in the regression. Education is not used as a predictor of depression because the relationship between the level of education and depression is limited and inconclusive in the literature (Miech et al. [1999], Sargeant et al. [1990]). Although education may have an impact on income, which in turn may affect depression, there is no clear indication that education can have a direct impact on depression.

Numerous studies have found a relationship between smoking and depression, which holds for different age groups. Using data from the National Comorbidity Survey conducted from 1991 to 1992 in the United States on individuals aged 15-54 years, Lasser et al. [2000] found that persons with mental illness are about twice as likely to smoke as other persons. Fergusson et al. [1996], Goodman and Capitman [2000], and Fergusson et al. [2003] have found smoking to be a powerful determinant of developing depressive symptoms among adolescents. This holds true for adults as well; Breslau et al. [1991] found young adults in Detroit with nicotine

dependence had higher rates of major depression and anxiety disorders. Breslau et al. [1993] also found that young adults with a history of nicotine dependence had a higher rate of first-incidence Major Depressive Disorder (MDD) in the follow-up period in the survey than persons with no history of nicotine dependence. Jorm et al. [1999] found that adult smokers had more depression and anxiety symptoms compared to non-smokers from a community survey conducted in Canberra, Australia in 1997. Lastly, this relationship between smoking and depression is evident among the elderly; Lam et al. [2004] examined the association between smoking and depressive symptoms among the elderly (aged 65 or over) in Hong Kong and found that current and former smokers were more likely to have depressive symptoms than those who never smoked. In the IFLS-4 survey, respondents are asked about their smoking habits: whether they currently smoke, and if so, how much, and those who had quit smoking are asked when they quit and how much they had smoked before quitting. Those who chewed tobacco, smoked a pipe, smoked self-rolled cigarettes, or smoked cigarettes/cigars at the time of the survey are identified as smokers in my regression.

An abundance of research has proved that physical activities provide not only a range of health benefits, but also prevent the development of mental disorders and reduce depressive symptoms (Farmer et al. [1988], Bhui and Fletcher [2000], Lampinen et al. [2000], Dunn et al. [2001], Goodwin [2003], Motl et al. [2004]). The IFLS-4 survey asks respondents regarding vigorous physical activities (efforts that make breathing much harder than normal and may include heavy lifting, digging, plowing, aerobics, fast cycling, cycling with loads etc.), moderate physical efforts (activities that make breathing somewhat harder than normal and may include carrying light loads, bicycling at a regular pace, or mopping the floor), and walking in the last seven days from the time of the survey.

Lastly, a very useful feature of the IFLS-4 survey that can be used in this study is the inclusion of measures of iodine content in household salts of the individuals who participated

in the survey. Iodine is an important mineral that the body needs to make thyroid hormones. These hormones control the body's metabolism and allow for proper bone and brain development during pregnancy and infancy.⁵ Hypothyroidism, a condition in which the body lacks sufficient quantities of the thyroid hormone, has long been known to cause depression (Asher [1949]). Whybrow et al. [1969] tested persons with hypothyroidism and hyperthyroidism and found that almost 100% of the patients with hypothyroidism had severe depression. Delange [1994] estimated that at least one billion people are at the risk of iodine deficiency disorders (IDD), which causes mental deficiencies. During the IFLS-4 survey, salt from every household was tested for iodine content and 13.80% of the households had non-iodized salt.

Table 1.6 and Table 1.7 below outline the results from the regression estimated with the aforementioned additional explanatory variables on depression scale scores for Muslims and non-Muslims, respectively.⁶ The household random effects estimates are given alongside the OLS estimates for a easier comparison. Muslims who were exposed to Ramadan at any period while in utero have 15.5% higher scores than those who were not exposed. The estimates are even higher for those Muslims who were exposed during their first and third trimesters in utero (28.8% and 24.6% higher scores than the non-exposed, respectively). In particular, males are more affected among those who were exposed in the first trimesters while females are more affected among those exposed in their third trimesters. All of these estimates are highly significant. However, there are no such effects of exposure on the non-Muslims. This pattern is what I expected because non-Muslims are not subject to fasting during the Ramadan period, and if there is such an adverse effect of fasting on scores in the depression scale, it should not have any effect on the non-Muslim population.

⁵Source: National Institute of Health: Office of Dietary Supplements.

⁶I also estimate the OLS regression *excluding* pregnant mothers since their BMI change significantly during pregnancy. The results are given in Table 1.14 in Appendix-1 and they are similar to the results presented here.

Table 1.6: Effects of being exposed to Ramadan in utero on depression scale scores - OLS vs. Household Random Effects estimates with additional explanatory variables for Muslims

Muslims						
	All		Male		Female	
	OLS	Random Effects	OLS	Random Effects	OLS	Random Effects
Exposed	0.155** (0.078)	0.092 (0.075)	0.132 (0.110)	0.112 (0.110)	0.167 (0.112)	0.164 (0.111)
Conceived during Ramadan	0.135 (0.114)	0.129 (0.113)	0.096 (0.161)	0.084 (0.160)	0.147 (0.162)	0.147 (0.162)
Exposed in trimester 1	0.288*** (0.100)	0.276*** (0.099)	0.390*** (0.136)	0.338** (0.137)	0.181 (0.146)	0.184 (0.146)
Exposed in trimester 2	0.095 (0.099)	0.098 (0.098)	-0.056 (0.139)	-0.063 (0.140)	0.248* (0.147)	0.244* (0.147)
Exposed in trimester 3	0.246** (0.102)	0.239** (0.101)	0.137 (0.144)	0.123 (0.145)	0.312** (0.145)	0.316** (0.144)
No. of observations	24484	24484	11264	11264	13220	13220
Mean scores	4.016	4.016	3.939	3.939	4.081	4.081

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households.

Table 1.7: Effects of being exposed to Ramadan in utero on depression scale scores - OLS vs. Household Random Effects estimates with additional explanatory variables for non-Muslims

Non-Muslims						
	All		Male		Female	
	OLS Random Effects		OLS Random Effects		OLS Random Effects	
Exposed	0.361 (0.251)	0.360 (0.244)	0.223 (0.381)	0.240 (0.374)	0.508 (0.345)	0.352 (0.340)
Conceived during Ramadan	0.457 (0.404)	0.452 (0.411)	0.221 (0.561)	0.923 (0.668)	0.401 (0.569)	0.548 (0.514)
Exposed in trimester 1	0.328 (0.319)	0.355 (0.320)	0.265 (0.530)	0.081 (0.414)	0.342 (0.442)	0.227 (0.428)
Exposed in trimester 2	0.419 (0.302)	0.304 (0.297)	0.269 (0.477)	0.269 (0.477)	0.268 (0.412)	0.121 (0.416)
Exposed in trimester 3	0.525 (0.324)	0.570* (0.317)	0.501 (0.470)	0.647 (0.462)	0.632 (0.436)	0.544 (0.435)
No. of observations	2815	2815	1300	1300	1515	1515
Mean scores	4.459	4.459	4.267	4.267	4.623	4.623

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households.

It can be seen that coefficients become larger and statistically significant at higher confidence levels when additional explanatory variables are added to the regression model. One possible explanation for this is these additional explanatory variables have a strong effect, so without adding them the unexplained variability is large and the significance is weak, while after adjusting these additional variables the unexplained variability is not large any more and the coefficients become statistically significant at a higher confidence levels. Because the

simple regression estimates presented in Table 1.4 and Table 1.5 are smaller than the estimates found with additional explanatory variables, the simple regression estimates are subject to omitted variable bias. Omitting an explanatory variable in the regression means estimating a misspecified model, where omitted variable is correlated with the error term. To illustrate, assume the correct specification of a model is: $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \epsilon_i$, and we omit the variable X_2 and estimate the misspecified model instead: $Y_i = \beta_0 + \beta_1 X_{i1} + \epsilon_i^*$. Then, in the misspecified model, the error term is: $\epsilon_i^* = \beta_2 X_{i2} + \epsilon_i$. As in this case the estimates from the simple regressions are smaller than the those from the regressions with additional variables, the simple regression estimates are subject to downward omitted variable bias.

By construction, the estimates presented in Table 1.2 to Table 1.7 only consider individuals with a full month's exposure to Ramadan during the first, second and third trimesters in utero. To account for those who experienced a partial exposure to Ramadan during their first, second or third trimester, I use a partial dummy to capture the effects of this on their depression scale scores. To calculate the partial weights of such exposures, the number of days that the person was exposed to Ramadan in utero was divided by the length of total days of Ramadan during that year. For example, if a person was exposed to Ramadan in utero for 3 days during her first, second or third trimester and the length of Ramadan in which the exposure occurred was 29 days, then the weight of this exposure was calculated to be $3 \div 29$ or 0.10344. The effects of being exposed to Ramadan in utero on depression scale scores including those who were partially exposed are given in Table 1.18 (for Muslims) and Table 1.19 (for non-Muslims) in Appendix-1. Once again, it can be seen that for Muslims who were exposed during first, second and third trimesters have significant effects of exposure on their depression scale scores, whereas no significant effects are found for non-Muslims. As a robustness check, I also estimate the effects of being exposed to Ramadan on depression scale scores by using a 50% threshold rule (i.e., if someone was exposed for 15 days or more in

a trimester, then this was counted as a full exposure in that trimester, as a Ramadan month is usually 29 or 30 days). These regression estimates are given in Table 1.20 (for Muslims) and Table 1.21 (for non-Muslims) in Appendix-1. It can be seen that the results are similar to what I find with partial exposure dummies. Also, none of the estimates were significant for non-Muslims, which re-confirms that there is no effect of exposure on the depression scale scores for non-Muslims, as expected. In addition to this, I also used the partial dummies to identify exposure to all three trimesters in a single regression; the estimation results are given in Table 1.23 (for Muslims) and Table 1.24 (for non-Muslims) in Appendix-1.

1.4.2 Identification of the Effects of Exposure on the Probability of Being Depressed

Simple Regression

Next I estimate the simple regression to check if exposure to Ramadan has any significant impact on the probability of being depressed. The range of possible scores in the short-version of the CES-D scale (CES-D-10) is between 0 (i.e., for those who are not depressed at all) and 30 (i.e., the highest score possible with depression), and individuals with score equal to or above 10 are considered depressed. I grouped all individuals as depressed (with score equal to or above 10) and non-depressed (with score below 10) categories and used it as the dependent variable in my regression. Although the LPM is subject to some shortcomings that need to be addressed, there is a preference for using the linear probability model (LPM) in the literature, and is seen as a suitable alternative to the probit or logit models. The results tables shown in this section use the LPM for estimating the effects on exposure on the probability of being depressed, and as a robustness check I also estimate the probit model, which is presented in Appendix-1. The comparison between LPM and probit estimates is

also done in the literature (Friedman and Schady [2013]). One such shortcoming of using the LPM is that the estimates are not constrained to the unit interval and thus they can be biased and inconsistent. Horrace and Oaxaca [2006] show that the potential bias of the LPM increases as the relative proportion of the predicted probabilities that fall outside the unit interval increases. To address this issue, Wooldridge [2002] mentions that if the main purpose of the estimate the partial effect of the independent variable on the response probability, then having some predicted values outside the unit interval may not be very important. In my estimations, none of the estimates in my LPM model goes outside of the unit interval, which gives me confidence that these estimates are unbiased and consistent. Another limitation of using the LPM is that the ordinary least squares estimation imposes heteroskedasticity in the case of a binary response variable (as in my case). To address this, I use robust standard errors clustered by households. The results of this estimation is given in Table 1.8 below.^{7,8}

⁷I also estimate a probit model as a robustness check. While the estimates from the probit model cannot directly be compared to the OLS estimates, they are similar in significance. Results are included in Table 1.15 in Appendix-1.

⁸I could also estimate a bivariate probit model; however, in order to apply bivariate Probit, a higher correlation between the two outcomes (i.e., depressed or not, and Muslims or not) is needed. Here, the correlation between these two outcomes is -0.03, implying there is almost no correlation.

Table 1.8: Effects of being exposed to Ramadan in utero on the probability of being depressed
- OLS estimates:

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.011** (0.005)	0.014** (0.006)	0.007 (0.007)	0.012 (0.016)	-0.002 (0.023)	0.027 (0.024)
Conceived during Ramadan	0.008 (0.007)	0.009 (0.010)	0.007 (0.010)	0.016 (0.026)	-0.022 (0.032)	0.054 (0.040)
Exposed in trimester 1	0.014** (0.006)	0.017** (0.008)	0.009 (0.009)	0.009 (0.021)	0.013 (0.031)	0.009 (0.030)
Exposed in trimester 2	0.010* (0.006)	0.004 (0.008)	0.015 (0.009)	0.001 (0.021)	-0.012 (0.029)	0.003 (0.031)
Exposed in trimester 3	0.011* (0.006)	0.011 (0.008)	0.011 (0.009)	0.019 (0.020)	0.006 (0.029)	0.030 (0.029)
No. of observations	25689	12211	13478	3045	1467	1578
No. of depressed	1801	776	1025	285	117	168
Mean depressed	0.070	0.064	0.076	0.094	0.080	0.106

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probability of being depressed regressed on Ramadan exposure, age, age squared, and month-of-birth. Robust standard errors are clustered by households.

The results show that the share of depressed Muslim individuals who were exposed to Ramadan while in utero and those who were exposed during their third trimester is 1.1% more likely to be depressed than those who were not exposed. This probability is 1.4% among the males who were exposed. Among those who were exposed in trimester 1, significant impacts are found for all Muslims (1.4% more likely to be depressed) and Muslim males (1.7% more likely to be depressed) than those who were not exposed at all. These results are consistent with the estimations presented thus far. Once again, none of the estimates for the non-Muslims are found to be significant as expected.

Regression with Additional Explanatory Variables

Next I group the individuals between depressed and non-depressed categories based on their scores in the depression scale and estimate the regression to see the probability of being depressed with additional explanatory variables. The results are shown in Table 1.9 below.⁹

Table 1.9: Effects of being exposed to Ramadan in utero on the probability of being depressed
- OLS estimates with additional explanatory variables:

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.014** (0.006)	0.015** (0.007)	0.012 (0.008)	0.024 (0.019)	0.010 (0.027)	0.039 (0.027)
Conceived during Ramadan	0.011 (0.008)	0.009 (0.011)	0.012 (0.012)	0.028 (0.033)	0.004 (0.044)	0.045 (0.048)
Exposed in trimester 1	0.021*** (0.007)	0.023** (0.009)	0.018* (0.011)	0.028 (0.024)	0.023 (0.041)	0.033 (0.034)
Exposed in trimester 2	0.012* (0.007)	0.003 (0.009)	0.020* (0.011)	0.012 (0.023)	0.001 (0.035)	0.008 (0.033)
Exposed in trimester 3	0.015** (0.007)	0.011 (0.010)	0.014 (0.011)	0.034 (0.025)	0.024 (0.035)	0.041 (0.034)
No. of observations	24484	11264	13220	2815	1300	1515
No. of depressed	1675	682	993	261	103	158
Mean depressed	0.068	0.061	0.075	0.093	0.079	0.104

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households.

⁹The same OLS regression is estimated *excluding* pregnant mothers which yields similar estimates. The results are shown in Table 1.16 in Appendix-1.

The results are similar to the ones presented in Table 1.8. It can be seen that the Muslims who were exposed in utero to Ramadan are 1.4% more likely to be depressed than the non-exposed group. The effect is similar and also significant among males. There is suggestive evidence that Muslims who were exposed during the first trimester are 2.1% more like to be depressed than those who were not exposed, while this probability is 2.3% for males and 1.8% for females. Exposure in the third trimester also has significant effect on the likelihood of being depressed (1.5%). Once again, no such effects of exposure are evident for the non-Muslims; none of the estimates are significant as expected. I also estimate a probit regression of this model, and the significance levels of the estimates are similar to those found here. This gives me the confidence that the estimates from the linear probability models are robust and free of the usual concerns regarding bias and inconsistency of the estimates. Results of the probit estimations are given in Table 1.17 in Appendix-1.

There are some limitations of these results which require to interpret the estimates with caution. First of all, I do not observe in the data set which mothers had actually fasted during Ramadan while they were pregnant.

1.4.3 Religiosity

A new feature of the IFLS-4 survey is the inclusion of individual religiosity measures. Muslim respondents were asked questions such as how many times a person prays and whether they eat only halal food. Other similar questions were asked to Christians and Hindus (e.g., how often do you pray/read the bible, do you practice puja/mantra; do you actively participate in religious activities etc.). Respondents self-rated their own religiosity on a scale of 1 to 4, where 1 corresponds to being very religious, and 4 to being not religious. Gaduh [2011] has shown that this subjective measure is correlated with more objective measures (frequency

of prayers, participation in religious activities etc.) of religiosity. The average score in the religiosity measure in my sample is 2.177 (the average score for Muslims is 2.195 and the average score for non-Muslims is 2.014). Following Majid [2015], I group Muslim individuals into ‘religious’ (i.e., those with religiosity scores of 1 and 2) and ‘less religious’ (i.e., those with religiosity scores of 3 and 4) categories. For the estimations presented in this section, a dummy variable was used for the ‘religious’ and ‘less religious’ Muslims.

As mentioned before, I only observe the religious identities of the individuals who participated in the survey, however, there is no way to know if a person was truly exposed to Ramadan fasting while in utero (i.e., I do not know if his/her mother observed fasting during the month of Ramadan). I assume that the majority of Muslim mothers fast during Ramadan and thus the regression estimates of those who were exposed in utero should differ significantly than non-Muslims who were in utero during the same period. By the same assumption, it is expected that the impact of exposure to Ramadan will be more significant for religious Muslims and to a smaller extent for the less religious Muslims, since the fraction of fasting mothers is expected to be lower in the latter group.

Table 1.10 below shows the estimates of prenatal Ramadan exposure on the depression scale scores for religious and less religious Muslims. As expected, it can be seen that the effect of exposure is positive and very significant for the religious group who were exposed in trimesters 1 and 3. Males who were exposed during the first trimester are affected, while the impact is significant on the females who were exposed during the third trimester. None of the estimates are significant for the less religious Muslims.

Table 1.10: Effects of being exposed to Ramadan in utero on depression scale scores - OLS estimates with religiosity:

	Religious Muslims			Less Religious Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.131 (0.087)	0.094 (0.126)	0.162 (0.120)	0.205 (0.181)	0.189 (0.226)	0.168 (0.300)
Conceived during Ramadan	0.088 (0.125)	-0.029 (0.178)	0.153 (0.178)	0.162 (0.279)	0.231 (0.369)	-0.112 (0.419)
Exposed in trimester 1	0.294*** (0.109)	0.378** (0.156)	0.213 (0.155)	0.152 (0.244)	0.289 (0.293)	-0.180 (0.429)
Exposed in trimester 2	0.069 (0.110)	-0.092 (0.156)	0.223 (0.157)	0.077 (0.249)	-0.049 (0.316)	0.242 (0.422)
Exposed in trimester 3	0.246** (0.112)	0.048 (0.159)	0.362** (0.155)	0.310 (0.249)	0.477 (0.334)	0.099 (0.371)
No. of observations	19066	8172	10894	5362	3061	2301
Mean depressed	3.858	3.724	3.959	4.561	4.498	4.644

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households.

Table 1.11 below outlines the probability estimates of being depressed for religious and less religious Muslims at different stages of exposure. The difference in estimates that were apparent in Table 1.5 between two groups of Muslims now become less apparent. Among those who were exposed at any time during gestation, the probability of being depressed is now higher for the less religious group, especially for the males. However, when people who were exposed in first and third trimesters, the probability of being depressed is significant among the religious Muslims and not for the other group.

Table 1.11: Effects of being exposed to Ramadan in utero on the probability of being depressed
- OLS estimates with religiosity:

	Religious Muslims			Less religious Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.010* (0.006)	0.009 (0.008)	0.011 (0.009)	0.024* (0.014)	0.030** (0.015)	0.011 (0.025)
Conceived during Ramadan	0.009 (0.009)	-0.003 (0.012)	0.018 (0.013)	0.009 (0.021)	0.034 (0.027)	-0.028 (0.034)
Exposed in trimester 1	0.018** (0.008)	0.018* (0.011)	0.018 (0.011)	0.020 (0.018)	0.031 (0.020)	-0.004 (0.035)
Exposed in trimester 2	0.007 (0.008)	-0.004 (0.010)	0.016 (0.011)	0.025 (0.019)	0.018 (0.021)	0.029 (0.036)
Exposed in trimester 3	0.015* (0.008)	0.004 (0.011)	0.020* (0.011)	0.013 (0.017)	0.030 (0.021)	-0.018 (0.029)
No. of observations	19066	8172	10894	5362	3061	2301
No. of depressed	1148	408	740	517	269	248
Mean depressed	0.060	0.050	0.068	0.096	0.088	0.108

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households.

The results discussed here are subject to some limitations that need to be addressed. Firstly, I only observe the religion of the person who participated in the survey, and not of his/her mother's religion during pregnancy. If there are people who converted to Islam later in life, and their mothers were not Muslims while pregnant (and therefore did not fast during Ramadan), there is a chance of misclassification. Secondly, I used the average length of human pregnancy (266 days) to calculate the date of conception from the given date of birth

of the individuals. Those who were born prematurely might have been classified as *exposed*, but in fact they should have been put in the non-exposed group. Thirdly, there is no way to be sure of which Muslim mothers had actually fasted in Ramadan while they were pregnant. Since fasting is not mandatory for the pregnant mothers, some might have chosen not to fast at all. These three reasons imply that the regression results presented here are possibly a mitigated form of the true effects of exposure. In that sense, all the regression estimates presented here are ITT (intent-to-treat) effects. These three limitations imply that the true effects of exposure to Ramadan fasting may have an even larger effect on depression than the results presented here suggest. Fourthly, in this paper I assume that Muslim mothers did not choose selective timing of pregnancy to avoid overlap of gestation period with Ramadan. While sexual intercourse is forbidden during fasting in the daytime, there is restriction after breaking the fast after sunset. Van Ewijk [2011] used an earlier version of the IFLS survey and interviewed obstetricians and midwives about selective timing of pregnancy and found that this is not an issue at all, because it is quite difficult to plan a pregnancy in such a way that exposure to Ramadan is completely avoided, since the window to get pregnant is relatively small. This paper essentially uses the same survey data. Majid [2015] also show evidence against any selective timing of births in Indonesia. Lastly, the survey data may contain some mistakes regarding the dates of births, measures of socio-economics indicators, and depression scale scores for the individuals. There might also be concerns of whether in utero exposure to Ramadan fasting is really driving the results. There can be numerous factors that can impact the score of any individual on the depression scale measure. However, using a large enough sample size and finding significant effects on the Muslims and no effect on the non-Muslims give me confidence that there is in fact systematic differences between the treatment and the control group and exposure has a role on individual scores in the depression scale later in life.

1.4.4 Implied Fasting Rate

The inclusion of religiosity measures in the IFLS-4 survey enables to perform back of the envelope calculation of the implied fasting rate, as shown by Majid [2015]. Assuming that there is a correlation between religiosity and fasting during pregnancy, and the fasting rate during Ramadan is 100% among religious Muslims, estimates of the religious Muslims in Table 1.10 can be interpreted as a proxy for average treatment effects on the children of those mothers who observed fasting during pregnancy (ATT). The implied fasting rate then can then be calculated as the ratio of ITT to ATT. Using the significant OLS estimates from Table 1.6 and Table 1.10 for all Muslims who were exposed in trimester-1, the implied fasting rate is calculated to be 97.95%. The rate is calculated to be 86.18% using estimates for females who were exposed in trimester-3. Majid [2015] used the same IFLS-4 survey but a different sample and found this rate to be between the range 68% and 82%. Pew Research Centre's Forum on Religion and Public Life conducted a worldwide survey on Muslims in 2012 and found that the median percent who fast during Ramadan in Southeast Asia (region where Indonesia is located) to be 99%.¹⁰ However, as mention previously, I do not observe which mothers had actually fasted in Ramadan during their pregnancy, so there might be some religious mother who chose not to fast while pregnant, and there might be some less religious mothers who chose to fast anyway. This implied fasting rate is thus largely based on assumption and should be interpreted carefully.

¹⁰Source:<http://www.pewforum.org/2012/08/09/the-worlds-muslims-unity-and-diversity-executive-summary/unifying-rituals>.

1.5 Conclusion

There is much evidence in the literature about the adverse effects of in utero nutritional deficiencies on physical health and labour market outcomes later in life, however, not much work has been done to explore the possibilities of extending these adversities to mental health. Using the Muslim holy month of Ramadan as a natural experiment for maternal fasting in pregnancy, I look at the effects of exposure of the unborn child on his/her mental health later in life, measured by the CES-D scale, a widely accepted screening test for depression and depressive disorder. Using the fourth wave of the Indonesian Family life Survey (IFLS), I find that the Muslims who were potentially exposed to Ramadan fasting while in utero during first and third trimesters have higher scores on the depression scale than those who were not exposed. This effect is significant for males who were exposed in the first trimester and for females who were exposed in the third trimester. The CES-D scale identifies those individuals as *depressed* who have a score of 10 or more out of a possible maximum score of 30. Based on this, I categorize every person in my sample as in depressed and non-depressed groups and estimate whether exposure to Ramadan has any effect on the probability of being depressed. The results show that Muslims who were exposed to Ramadan at any period during gestation have a higher probability of being depressed later in life than those who were not exposed. These effects were found to be significant for Muslim males as well. Muslim individuals, especially males who were exposed during the first trimester also showed a higher probability of being depressed than the non-exposed people, whereas the effect on Muslim females were found to be less significant. Estimates were less significant (at 10% level) for the Muslims who were exposed in the second and third trimesters. These results corroborate that there is indeed some adverse effects of in utero exposure to nutritional deficiencies (which are channelled through Ramadan fasting in this case) on mental health, which may contribute to

a higher probability of developing depression later in life.

To my knowledge, this is the first ever study that uses Ramadan fasting as a natural experiment to look into the possible adversities of nutritional disruption and deficiencies during gestation period on mental health states of individuals in the long run. Ramadan is observed each year by millions of Muslims all around the world, and although it is not required to fast for pregnant mothers, many continue to do so. Negative effects of such maternal fasting on the offspring's physical health and labour outcomes later in life have already been established in the literature, and this paper finds evidence that these effects may apply to mental health as well. Future studies may want to look at other regions around the world to see whether the link between in utero nutritional deficiency and depression later in life holds true and establish a more profound implication of maternal fasting on the child's mental health in years to come.

Appendix 1

Table 1.12: Hausman test statistics (χ^2 values) for sample households with two or more members; includes household head, spouse, and other members.

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	25.56**	17.42	11.13	23.52**	7.06	14.26
Conceived during Ramadan	23.55**	11.95	15.07	15.22	11.98	24.75**
Exposed in trimester 1	25.81**	23.11**	13.72	15.17	16.73*	21.68*
Exposed in trimester 2	15.59	20.16*	18.58	14.53	16.27	17.80
Exposed in trimester 3	10.73	21.16*	9.88	16.51	12.69	13.51
No. of observations	18455	9321	9134	2147	1085	1062

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.13: Hausman test statistics (χ^2 values) for all sample households.

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	22.11*	12.66	8.72	29.08***	8.77	19.61
Conceived during Ramadan	19.79	15.53	15.78	13.74	9.13	18.67
Exposed in trimester 1	31.08***	1.67*	13.07	15.31	37.90***	21.59*
Exposed in trimester 2	18.84	18.18	27.91***	18.72	13.83	17.81
Exposed in trimester 3	4.83	15.75	6.13	24.16**	11.43	15.73
No. of observations	25689	12211	13478	3045	1467	1578

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.14: Effects of being exposed to Ramadan in utero on depression - OLS estimates with explanatory variables excluding mothers who answered 'yes' to the question 'are you pregnant?':

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.158** (0.079)	0.132 (0.110)	0.174 (0.115)	0.321 (0.255)	0.223 (0.381)	0.448 (0.355)
Conceived during Ramadan	0.141 (0.115)	0.096 (0.161)	0.163 (0.167)	0.403 (0.406)	0.221 (0.561)	0.337 (0.576)
Exposed in trimester 1	0.295*** (0.101)	0.390*** (0.136)	0.187 (0.149)	0.277 (0.321)	0.265 (0.530)	0.262 (0.449)
Exposed in trimester 2	0.087 (0.101)	-0.056 (0.139)	0.237 (0.150)	0.384 (0.304)	0.269 (0.477)	0.203 (0.418)
Exposed in trimester 3	0.231** (0.103)	0.137 (0.144)	0.281* (0.147)	0.545 (0.328)	0.501 (0.470)	0.675 (0.445)
No. of observations	23977	11263	12714	2761	1300	1461
Mean scores	4.018	3.939	4.089	4.465	4.267	4.641

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, and month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households.

Table 1.15: Effects of being exposed to Ramadan in utero on the probability of being depressed
- simple model Probit estimates:

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.082** (0.040)	0.120* (0.060)	0.052 (0.054)	0.070 (0.102)	0.008 (0.152)	0.123 (0.144)
Conceived during Ramadan	0.061 (0.055)	0.080 (0.086)	0.043 (0.074)	0.077 (0.152)	-0.196 (0.269)	0.254 (0.194)
Exposed in trimester 1	0.101** (0.049)	0.141* (0.072)	0.063 (0.068)	0.055 (0.129)	0.090 (0.204)	0.037 (0.178)
Exposed in trimester 2	0.076 (0.049)	0.034 (0.075)	0.103 (0.066)	0.014 (0.129)	-0.050 (0.182)	0.012 (0.188)
Exposed in trimester 3	0.089* (0.049)	0.092 (0.072)	0.082 (0.066)	0.109 (0.120)	0.081 (0.188)	0.144 (0.162)
No. of observations	25689	12211	13478	3045	1467	1578
No. of depressed	1801	776	1025	285	117	168
Mean depressed	0.070	0.064	0.076	0.094	0.080	0.106

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probability of being depressed regressed on Ramadan exposure, age, age squared, and month-of-birth. Standard errors are clustered by households.

Table 1.16: Effects of being exposed to Ramadan in utero on the probability of being depressed
- OLS estimates with explanatory variables excluding mothers who answered 'yes' to the question 'are you pregnant?':

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.013** (0.006)	0.015** (0.007)	0.011 (0.008)	0.021 (0.019)	0.010 (0.027)	0.034 (0.028)
Conceived during Ramadan	0.011 (0.008)	0.009 (0.011)	0.012 (0.012)	0.022 (0.033)	0.004 (0.044)	0.036 (0.048)
Exposed in trimester 1	0.020*** (0.007)	0.023** (0.009)	0.017 (0.011)	0.023 (0.024)	0.023 (0.041)	0.025 (0.034)
Exposed in trimester 2	0.011 (0.007)	0.003 (0.009)	0.018 (0.011)	0.010 (0.023)	0.001 (0.035)	0.003 (0.033)
Exposed in trimester 3	0.014* (0.007)	0.011 (0.010)	0.012 (0.011)	0.035 (0.025)	0.024 (0.035)	0.045 (0.035)
No. of observations	23977	11263	12714	2761	1300	1461
No. of depressed	1642	682	960	252	103	149
Mean depressed	0.068	0.061	0.076	0.091	0.079	0.102

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, and month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households.

Table 1.17: Effects of being exposed to Ramadan in utero on the probability of being depressed
- Probit estimates with additional explanatory variables:

	Muslims			Non-Muslims		
	All	Male	Female	All	Male	Female
Exposed	0.109** (0.049)	0.147* (0.076)	0.087 (0.066)	0.158 (0.127)	0.080 (0.202)	0.230 (0.169)
Conceived during Ramadan	0.084 (0.068)	0.096 (0.109)	0.078 (0.091)	0.186 (0.200)	−0.082 (0.398)	0.323 (0.251)
Exposed in trimester 1	0.155*** (0.060)	0.216** (0.089)	0.122 (0.081)	0.171 (0.154)	0.131 (0.283)	0.211 (0.223)
Exposed in trimester 2	0.094 (0.061)	0.035 (0.097)	0.142* (0.081)	0.105 (0.171)	−0.037 (0.283)	0.041 (0.239)
Exposed in trimester 3	0.121** (0.060)	0.123 (0.092)	0.111 (0.079)	0.269 (0.153)	0.241 (0.233)	0.388 (0.214)
No. of observations	24484	11264	13220	2815	1300	1515
No. of depressed	1675	682	993	261	103	158
Mean depressed	0.068	0.061	0.075	0.093	0.079	0.104

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, and month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households. Standard errors are clustered by households.

Table 1.18: Effects of being exposed (including partial exposure) to Ramadan in utero on depression scale scores - OLS vs. household Random Effects estimates with additional explanatory variables for Muslims

Muslims						
	All		Male		Female	
	OLS	Random Effects	OLS	Random Effects	OLS	Random Effects
Exposed	0.175** (0.083)	0.123** (0.081)	0.330 (0.116)	0.298 (0.115)	0.030 (0.118)	0.029 (0.117)
Exposed in trimester-1	0.217** (0.090)	0.189** (0.089)	0.339*** (0.125)	0.287** (0.125)	0.098 (0.129)	0.099 (0.129)
Exposed in trimester-2	0.251*** (0.090)	0.209** (0.088)	0.339*** (0.124)	0.288** (0.124)	0.176 (0.128)	0.185 (0.128)
Exposed in trimester-3	0.237*** (0.090)	0.206** (0.089)	0.366*** (0.125)	0.344*** (0.124)	0.117** (0.129)	0.124** (0.129)
No. of observations	24484	24484	11264	11264	13220	13220
Mean scores	4.016	4.016	3.939	3.939	4.081	4.081

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households. Results for “Conceived” are not presented because by definition individuals in the “Conceived” category were exposed for one day.

Table 1.19: Effects of being exposed (including partial exposure) to Ramadan in utero on depression scale scores - OLS vs. household Random Effects estimates with additional explanatory variables for non-Muslims

Non-Muslims						
	All		Male		Female	
	OLS	Random Effects	OLS	Random Effects	OLS	Random Effects
Exposed	0.401 (0.262)	0.435 (0.258)	0.143 (0.399)	0.141 (0.399)	0.591 (0.353)	0.522 (0.348)
Exposed in trimester-1	0.171 (0.288)	0.194 (0.285)	-0.060 (0.447)	-0.061 (0.447)	0.301 (0.395)	0.303 (0.395)
Exposed in trimester-2	0.106 (0.280)	0.075 (0.280)	0.235 (0.452)	0.190 (0.442)	0.094 (0.394)	0.095 (0.384)
Exposed in trimester-3	0.485 (0.280)	0.494 (0.276)	0.286 (0.454)	0.240 (0.444)	0.583 (0.380)	0.477 (0.362)
No. of observations	2815	2815	1300	1300	1515	1515
Mean scores	4.459	4.459	4.267	4.267	4.623	4.623

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households. Results for “Conceived” are not presented because by definition individuals in the “Conceived” category were exposed for one day.

Table 1.20: Effects of being exposed (including partial exposures of 15 or more days counted as full exposure) to Ramadan in utero on depression scale scores - OLS vs. household Random Effects estimates with additional explanatory variables for Muslims

Muslims						
	All		Male		Female	
	OLS	Random Effects	OLS	Random Effects	OLS	Random Effects
Exposed	0.170* (0.089)	0.148* (0.087)	0.283** (0.124)	0.248** (0.123)	0.050 (0.126)	0.049 (0.126)
Exposed in trimester-1	0.224** (0.095)	0.212** (0.094)	0.314** (0.131)	0.288** (0.131)	0.120 (0.137)	0.120 (0.137)
Exposed in trimester-2	0.095 (0.095)	0.088 (0.094)	0.012 (0.134)	0.006 (0.134)	0.184 (0.138)	0.177 (0.138)
Exposed in trimester-3	0.228** (0.094)	0.212** (0.093)	0.346*** (0.131)	0.303** (0.131)	0.107** (0.136)	0.114* (0.136)
No. of observations	24484	24484	11264	11264	13220	13220
Mean scores	4.016	4.016	3.939	3.939	4.081	4.081

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households. Results for “Conceived” are not presented because by definition individuals in the “Conceived” category were exposed for one day.

Table 1.21: Effects of being exposed (including partial exposures of 15 or more days counted as full exposure) to Ramadan in utero on depression scale scores - OLS vs. household Random Effects estimates with additional explanatory variables for non-Muslims

Non-Muslims						
	All		Male		Female	
	OLS	Ramdon Effects	OLS	Random Effects	OLS	Random Effects
Exposed	0.349 (0.295)	0.371 (0.297)	0.170 (0.464)	0.137 (0.460)	0.451 (0.413)	0.431 (0.413)
Exposed in trimester-1	0.310 (0.313)	0.337 (0.316)	0.134 (0.500)	0.131 (0.499)	0.431 (0.436)	0.418 (0.446)
Exposed in trimester-2	0.419 (0.293)	0.372 (0.287)	0.260 (0.451)	0.392 (0.447)	0.435 (0.409)	0.231 (0.419)
Exposed in trimester-3	0.375 (0.304)	0.381 (0.304)	0.237 (0.511)	0.248 (0.424)	0.388 (0.426)	0.203 (0.407)
No. of observations	2815	2815	1300	1300	1515	1515
Mean scores	4.459	4.459	4.267	4.267	4.623	4.623

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households. Results for “Conceived” are not presented because by definition individuals in the “Conceived” category were exposed for one day.

Table 1.22: Summary statistics for dropped and used observations:

	Dropped observations	Used observations	$p(\text{difference})$
Age	36.905 (15.618)	36.912 (15.627)	0.898
Male	0.474 (0.489)	0.476 (0.499)	0.944
Household size	2.862 (1.365)	2.868 (1.366)	0.758
Religiosity	2.188 (0.606)	2.187 (0.603)	0.619
Depression scores	4.135 (3.512)	4.061 (3.528)	0.724
BMI	22.412 (4.388)	22.378 (4.390)	0.439
Health status	5.823 (0.814)	5.853 (0.845)	0.144
Tobacco usage	0.313 (0.544)	0.331 (0.471)	0.988
Vigorous activity	0.315 (0.455)	0.304 (0.455)	0.896
Moderate activity	0.832 (0.521)	0.796 (0.403)	0.945
Walking	0.814 (0.311)	0.858 (0.350)	0.898
Log of food expenditure per capita	10.728 (0.722)	10.682 (0.747)	0.465
Log of food production per capita	8.429 (1.240)	8.645 (1.410)	0.888
Log of non-food expenditure per capita (type-1)	11.311 (1.289)	11.309 (1.291)	0.726

Continued on next page

Table 1.22 – continued from previous page

	Dropped observations	Used observations	$p(\text{difference})$
Log of non-food expenditure per capita (type-2)	12.618 (1.692)	12.805 (1.394)	0.622
Household iodized salt	0.858 (0.350)	0.857 (0.350)	0.945

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Means of each group presented with standard deviation in parentheses. Type-1 non-food items include electricity, water, fuel, telephone, personal toiletries, recreation and entertainment, transportation etc. Type-2 non-food items include clothing, household supplies and furniture, medical costs, ritual ceremonies, charities, gifts, taxes, and other expenditures not mentioned.

Table 1.23: Effects of being exposed (including partial exposure) to Ramadan in utero on depression scale scores - OLS vs. household Random Effects estimates with additional explanatory variables and exposure dummies for Muslims

	OLS			Random Effects		
	All	Male	Female	All	Male	Female
Trimester 1 exposure	0.011* (0.101)	-0.017 (0.150)	0.030 (0.138)	0.002 (0.100)	-0.033 (0.150)	0.030* (0.138)
Trimester 2 exposure	0.078 (0.108)	0.100 (0.153)	0.051* (0.151)	0.061 (0.107)	0.106 (0.152)	0.055 (0.151)
Trimester 3 exposure	0.122 (0.099)	0.252 (0.149)	0.016* (0.133)	0.101 (0.098)	0.227 (0.149)	0.019* (0.133)
No. of observations	24484	24484	11264	11264	13220	13220
Mean scores	4.016	4.016	3.939	3.939	4.081	4.081

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, and month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households.

Table 1.24: Effects of being exposed (including partial exposure) to Ramadan in utero on depression scale scores - OLS vs. household Random Effects estimates with additional explanatory variables and exposure dummies for non-Muslims

	OLS			Random Effects		
	All	Male	Female	All	Male	Female
Trimester 1 exposure	0.073 (0.323)	-0.222 (0.467)	0.171 (0.457)	0.069 (0.323)	-0.222 (0.467)	0.201 (0.455)
Trimester 2 exposure	-0.587 (0.311)	-0.038 (0.436)	-0.884 (0.446)	-0.579 (0.306)	-0.038 (0.436)	-0.898 (0.441)
Trimester 3 exposure	0.671 (0.296)	0.372 (0.449)	0.885 (0.416)	0.686 (0.290)	0.372 (0.449)	0.837 (0.409)
No. of observations	2815	2815	1300	1300	1515	1515
Mean scores	4.459	4.459	4.267	4.267	4.623	4.623

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Depression scores regressed on Ramadan exposure, age, age squared, and month-of-birth, body mass index, measured health status, log per capita food expenditure, log per capita food production, log per capita non-food expenditure, smoking status, physical activity status, and household salt iodine rate. Robust standard errors are clustered by households.

Table 1.25: Correlation among the explanatory variables:

	Exposure	Age	Age-squared	BMI	Health status	Iodine	Tobacco
Exposure	1						
Age	0.005	1					
Age-squared	0.001	0.978	1				
BMI	-0.008	0.024	0.021	1			
Health status	0.000	-0.156	-0.165	0.008	1		
Iodine	0.015	-0.028	-0.036	0.002	0.123	1	
Tobacco	-0.010	0.094	0.079	-0.007	0.031	-0.013	1
Vigorous act.	-0.003	0.006	-0.021	0.005	-0.033	-0.079	0.298
Moderate act.	0.010	-0.084	-0.111	-0.005	-0.048	-0.013	0.019
Walking	0.010	-0.008	-0.020	-0.004	-0.070	-0.048	0.033
Log food exp.	0.009	-0.020	-0.031	0.006	0.083	0.095	0.021
Log food prod.	0.007	0.060	0.067	-0.001	0.057	0.036	-0.008
Log non-food exp.(type 1)	0.012	-0.059	-0.072	0.002	0.135	0.158	-0.045
Log non-food exp.(type 2)	0.008	-0.050	-0.064	0.003	0.146	0.157	-0.040

Table : Correlation among the explanatory variables - Continued:

	Vigourous	Moderate	Walking	Food exp.	Food prod.	Non-food exp. type-1	Non-food exp. type2
Vigourous	1						
Moderate	0.206	1					
Walking	0.135	0.167	1				
Food exp.	-0.081	-0.018	-0.040	1			
Food prod	0.003	-0.004	-0.008	0.073	1		
Non-food exp. type1	-0.135	-0.055	-0.096	0.516	0.169	1	
Non-food exp. type2	-0.104	-0.053	-0.078	0.427	0.169	0.511	1

Chapter 2

Should We Use Rank or Income in Socioeconomic Health Inequality Measurement?

2.1 Introduction

Most of the literature on health inequality has been developed based on the well-established knowledge on the measurement of income inequality. The Gini coefficient, which measures inequality in the distribution of income among the residents in a country, has also been used to measure inequality in health outcomes (Le Grand [1987]). This measurement is done by plotting the cumulative proportion of the population in ascending order (starting with the sickest person) against the cumulative proportions of health outcomes and then calculating the area between the diagonal and the Lorenz curve which provides a measure of inequality. But, doing so misses the socioeconomic dimension of health inequality; any change in the distribution of health that involves a sick person getting healthier and a healthy person getting sicker while keeping the average level of health constant would translate into a reduction of health inequality, regardless of these individuals' socioeconomic status. To address this and to add the socioeconomic dimension in the measurement of health inequality, Wagstaff et al. [1991] introduced the concentration index and the associated health concentration curve, where individuals are ranked by their socioeconomic status (p), starting with the person with the lowest level and are plotted against a health variable. The concentration curve thus shows the share of health held by the cumulative proportion of the population ranked from poorest to richest. The concentration curve can be used to measure inequality in any health variable of interest. The concentration index is defined as positive when the concentration curve lies below the diagonal (i.e., health is concentrated more heavily among the least disadvantaged people) and negative when the curve lies above the diagonal (i.e., health is concentrated more heavily among the most disadvantaged people) (Wagstaff et al. [1991]). The concentration curve can also be used to assess inequality in ill-health.

Stochastic dominance is widely used in the analysis of income distributions and inequality

and it is particularly useful when comparing two or more distributions. Economists usually check for non-intersection of concentration curves to analyze the distributive effects of a tax reform (Lambert [1993]). Health concentration curves can also be used to compare socioeconomic health inequality for a pair of distributions. Makdissi and Yazbeck [2014] developed two positional stochastic dominance tests based on the comparison of transformations of the concentration curves which is similar to the well-known Lorenz ranking of income distributions. These tests are based on ranking the individuals by their socioeconomic positions (p). However, one may argue that using socioeconomic positions (p) may not fully represent the underlying wider differences in income among the individuals (for example, two persons with income levels \$1 and \$100 have wider income gap than two persons with income levels \$1 and \$2, but this wider gap is not reflected when they are ranked based on their socioeconomic positions, because in both cases the difference in their ranks is the same). The well-developed literature on socioeconomic health inequality is based on the rank-dependent indices (e.g., the health concentration index (Wagstaff et al. [1991]), the extended health concentration index (Pereira [1998], Wagstaff [2002]), the bounded variable indices (Wagstaff [2005], Erreygers [2009]), and the symmetric index (Erreygers et al. [2012])) which often finds that the inequality in socioeconomic dimension is positively related to the inequality in health achievements. However, Erreygers et al. [2015] argue that because the socioeconomic status is measured by *ranks* but the health status variable is measured by the *level* of the health variable while computing these indices, the asymmetric treatment of the socioeconomic status and the health variable reflects a causal relationship between socioeconomic ranks and health levels. To correct for this, Erreygers et al. [2015] propose a set of indices based on the *levels* which the individuals attain in both the socioeconomic and health domains. This paper is based on the same idea—if one believes that the income-health gradient is based on income (y) rather than socioeconomic status (p) in a population distribution and the underlying dif-

ferences in income levels of individuals should be taken into account, then maybe it would be more appropriate to use y instead of p to rank these individuals. Using survey data from five countries in South Asia, I test this hypothesis and find evidence that using individuals' incomes y instead of using their socioeconomic ranks p leads to different dominance results among these countries.

The rest of the paper is organized as follows. In section 2 I present the theoretical framework to develop income-dependent ethical principles and two required stochastic dominance conditions. Section 3 demonstrates the empirical illustration and testing of these dominance conditions using the World Health Survey (WHS) for five South Asian countries. Section 4 summarizes the findings and concludes the paper.

2.2 Theoretical Framework

2.2.1 Measuring Population Health

To develop the population health measures, I follow Makdissi and Yazbeck [2014] but within a framework in which individuals are ranked based on their level of income (y) and not on their socioeconomic status (p). Let $F(y)$ be the cumulative distribution function of income y . The health information of an individual with income y is categorical in nature and provides information on K health attributes. I assume that the function $H(y) = (h_1(y), h_2(y), \dots, h_k(y))$ represents this information. Also, there exists a function $\phi(H(y))$ that transforms this information on the K health attributes into a scalar and reflects the overall health status level of the individual. To avoid the arbitrary assignment of numerical values to health categories and to obtain information on the breadth of the health problems, I count the dimensions in which the individual has a health condition which is below a specified acceptable threshold. I

assume for each of the health attributes, there exists a previously defined threshold τ_k , below which the individual is considered to have a health problem with that attribute. Consider the following transformation:

$$\gamma(H(y)) = (\iota(h_1(y) < \tau_1), \iota(h_2(y) < \tau_2), \dots, \iota(h_k(y) < \tau_k)) \quad (2.1)$$

where $\iota(h_k(y) < \tau_k)$ is an indicator function which assumes a value of 1 if $h_k(y) < \tau_k$ and 0 otherwise. $\gamma(H(y))$ takes into account the total number of health attributes where the individual has a problem and gives the aggregate health status of that individual. Let $\Theta = (\theta_1, \theta_2, \dots, \theta_K)$ be a vector of weights for health attributes where the taxicab norm $\|\Theta\|_1$ is equal to K .¹ The breadth of the health problems is thus given by $s(H(y))$, where $s(H(y)) = \gamma(H(y))\Theta'$ is the weighted sum of health attributes in which the individual has a problem. Following Makdissi and Yazbeck [2014], the aggregation procedure within an individual that is invariant to any monotonic transformation applied to numerical values of health categories is:

$$\phi(H(y)) = \frac{K - s(H(y))}{K} \quad (2.2)$$

This measure is a quantification of an individual's health achievement, because it is a numerical representation of the weighted proportion of health attributes for which the individual is without problems.

Moving on to the aggregation process across individuals, Wagstaff [2002] introduced the notion of health achievement as a weighted average of health levels of individuals where the worse-off people have higher weights than those who are better-off. Makdissi and Yazbeck

¹The taxicab norm of the vector $x = (x_1, x_2, \dots, x_n)$ is defined by $\|x\|_1 := \sum_{i=1}^n |x_i|$.

[2014] write the population health achievement index in the following form:

$$A(H) = \int_0^1 v(p)h(p)dp \quad (2.3)$$

where $v(p)$ is the weight function associated with the socioeconomic status p , $v(p) \geq 0$ (i.e., the weight function is positive or equal to zero) and $v'(p) < 0$ (i.e., less weight is put on individuals as their socioeconomic rank increases); and $h(p)$ is the health status attributes of an individual at the socioeconomic rank p . I propose that the population health index can be computed in the following way using income (y):

$$\tilde{A}(H) = \int_0^{\bar{y}} \tilde{v}(y)\phi(H(y))dF(y) \quad (2.4)$$

where $\bar{y}$ is a predefined maximum income threshold (i.e., the maximum income of an individual in a distribution), $\tilde{v}(y)$ is the weight function associated with the individual's income y , and $\phi(H(y))$ is the health status attributes of an individual at the income level y . I also assume that $\tilde{v}(y) \geq 0$ and $\tilde{v}'(y) < 0$ (in other words, less weight is put on individuals with higher income, which is consistent with policies aimed at reducing inequality). The associated socioeconomic health inequality index is given by:

$$\tilde{I}(H) = \frac{1}{\mu_\phi} \int_0^{\bar{y}} [1 - \tilde{v}(y)]\phi(H(y))dF(y)$$

$$\tilde{I}(H) = 1 - \frac{1}{\mu_\phi} \int_0^{\bar{y}} \tilde{v}(y)\phi(H(y))dF(y) \quad (2.5)$$

$$\tilde{I}(H) = 1 - \frac{\text{population health index}}{\text{average health status}} \quad (2.6)$$

where μ_ϕ is the average health status.

2.2.2 Rank dependent ethical principles

In this section I describe the set of ethical principles that relate to the degree of socioeconomic health inequality aversion. The order of these ethical principles relate to the degree of socioeconomic health inequality aversion by the social planner. As the order of the ethical principles increases, the social planner becomes more and more averse to socioeconomic health inequality aversion. Following the definitions used by Makdissi and Mussard [2008] in the context of socioeconomic health inequalities, I develop two stochastic dominance tests in a way similar to the Lorenz ranking of income distributions. These tests identify the rankings of health achievement of socioeconomic health inequalities that stays the same for any index obeying a set of ethical principles. Following Makdissi and Yazbeck [2014], I start by defining classes of population health indices $\tilde{\Omega}^\sigma$, $\sigma \in \{1, 2, \dots\}$ and classes of socioeconomic health inequalities $\tilde{\Psi}^\sigma$, $\sigma \in \{2, \dots\}$, where σ represents the order of ethical principles obeyed by the indices that belong to these classes. The role of these ethical principles is to determine the mathematical properties of the weighting function $\tilde{v}(y)$. There are many orders of positional stochastic dominance, and each can be assigned an ethical interpretation when used in the context of health achievement or socioeconomic health inequality. When two transformations of the dominance curves of a given order do not intersect, all indices that obey the ethical principles associated with this order of dominance will rank the two distributions of health statuses identically. Below I define a set of positional ethical principles to describe the normative implications underlying the functional form of $\tilde{v}(\cdot)$.

First order principle

Health achievement indices in equation (2.4) that obey the first order ethical principles are such that the health achievement weakly increases when an individual's health increases. Thus, these indices follow the Pareto principle (i.e., at least one person is made better off without anyone becoming worse off), and the Anonymity principle (i.e., only the income rank matters and not the identity of the recipient). As shown by Makdissi and Yazbeck [2014], when these principles are based on the socioeconomic rank p , then only the socioeconomic rank and the associated status matters and not the identity of the recipient. This principle is directly satisfied by having the weight function positive ($\tilde{v}(y) > 0$).

Second order principle

Second order ethical judgements relate to the Pigou-Dalton principle, which introduces a greater ethical preference for the poorer than for the richer. This principle is illustrated in Figure-2.1. Suppose that all individuals are ranked based on their income (y) in a population distribution. Then, this principle states that a mean-preserving health transfer δ_h from a person with a higher income (y_2) to another person at a lower income (y_1) constitutes a social improvement. Although in practice it is impossible to transfer one unit of health from one person to another, theoretically the compliance of this principle can be seen as a health distribution that has been obtained from another distribution after performing such transfers. In this framework there is a change in the numerical value of the function $\phi(H(y))$ if and only if there is a change in at least one health attribute k at the income level y and that this change involves a movement across the threshold τ_k . In order to satisfy the second order ethical principle, the weight function should be decreasing in income y (i.e., $\tilde{v}'(y) \leq 0$ for y). All indices belonging to $\tilde{\Omega}^2$ and $\tilde{\Psi}^2$ satisfy this condition.

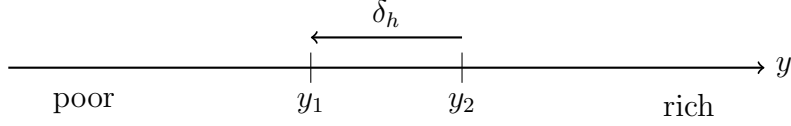


Figure 2.1: Second order ethical principle

Third order principle

The third order ethical judgement introduces the notion of transfer-sensitivity. The idea, which was introduced by Kolm [1976] in the income distribution literature, suggests that an income transfer of the value δ from an individual with higher income to another individual with lower income yields a better impact on social welfare given that the incomes are as low in the distribution as possible. So, a decision-maker following the Transfer-sensitivity principle will prefer a transfer of income from y_2 to y_1 rather than from y_4 to y_3 (where $y_4 > y_2$ and $y_3 > y_1$), given that there is no change in the variance of the distribution. Mehran [1976] and Kakwani [1980] developed a rank-dependent principle in the same framework which assumes that an income transfer from a high-income individual to a low-income individual would yield a better impact on social welfare given that the individuals' ranks are as low as possible. A decision-maker following this positional transfer-sensitivity principle will prefer a transfer of income from y_2 to y_1 rather than from y_4 to y_3 , given that the ranks of the individuals remain unchanged after the transfer and that $p_2 - p_1 = p_4 - p_3$. Makdissi and Yazbeck [2014] illustrated this principle in the context of socioeconomic health inequality, where by a transfer of health δ_h from the individual at rank p_2 to another individual at rank p_1 will more than compensate for a regressive transfer of health δ_h from an individual at the rank p_3 to another at rank p_4 because p_3 and p_4 are higher in the socioeconomic distribution. It is important to note that some researchers disagree on the desirability of this ethical principle in the context of socioeconomic health inequality measurement. Erreygers et al. [2012] argue

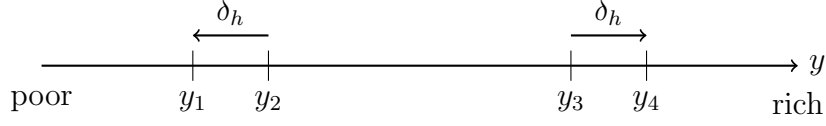


Figure 2.2: Third order ethical principle

that the asymmetric weighting scheme in the extended concentration index can conclude pro-poor bias in some instances when there is no systematic bias in favour of the rich or the poor. They propose a symmetry condition on the weight function $v(p)$ which allows to develop ethical principles that are associated to the range index of socioeconomic health inequality. While it is relevant to address this type of ethical principles, it goes beyond the scope of this paper. In this study I rank the individuals based on their income (y), and not by their socioeconomic status (p). The composite transfers in this context can be illustrated by Figure-2.2. According to the third order ethical principle, a progressive health transfer of δ_h from an individual with income y_2 to another individual with income y_1 will more than compensate for a regressive health transfer of the same magnitude (δ_h) from an individual with income y_3 to another individual with income y_4 as long as the ranks of the individuals remain unchanged after these transfers, and that $y_2 - y_1 = y_4 - y_3$. Imposing this ethical principle implies that the weighting function should be $\tilde{v}''(y) \geq 0$ for all y . This principle characterizes the sets of indices $\tilde{\Omega}^3 \subset \tilde{\Omega}^2$ and $\tilde{\Psi}^3 \subset \tilde{\Psi}^2$.

Higher order principles

Higher order indices are interpreted using the generalized transfer principle introduced by Fishburn and Willig [1984]. In the context of income distribution, these generalized transfer principles state that the weight associated with transfers at the bottom of the income distribution increases as the ethical order increases. Aaberge [2009] and Makdissi and Mussard

[2008] adjusted these principles to suit the rank dependent context. I follow Makdissi and Mussard [2008] and Makdissi and Yazbeck [2014] to adapt the principles to the context of socioeconomic health inequality. To illustrate this generalization, consider Figure-2.1, which shows a health transfer of δ_h from a higher-income (y_2) individual to a lower-income (y_1) individual. This results in an increase in health for the person with income y_1 coupled with an equivalent decrease in health for the person with income y_2 . Because monotonicity is the first order principle by definition, this health transfer can be interpreted as a combination of a positive (beneficial) first order event at the lower income level y_1 and a negative (disadvantageous) first order event at the higher income level (y_2). Similarly, a favourable composite transfer of order 3 can be interpreted as a combination of a positive second order event at the lower income level coupled with a negative second order event at the higher income level. The generalized transfer principles of higher orders continue in a similar way. For example, fourth order ethical principle is illustrated in Figure-2.3. This health transfer is a combination of two pairs of transfers, one positive pair at the lower income levels (i.e., from y_2 to y_1 and from y_3 to y_4) and one negative pair within the higher income levels (i.e., from y_5 to y_6 and from (y_8 to y_7)). Indices that obey the fourth order principle will respond favourably to this combination of composite transfers. In a similar manner, a fifth order favourable combination of transfers would be generated by a favourable fourth order combination plus an unfavourable transfer at higher income levels. This will continue for higher orders. Generalized higher order transfer principles imply that, as the ethical order increases, the weight attached to the effect of the transfers occurring at lower income levels will also increase. Blackorby and Donaldson [1978] describe these indices as becoming more Rawlsian. The positional transfer principle of order σ requires some assumptions on the weight function $\tilde{v}(y)$; the sign of the successive derivatives of $\tilde{v}(y)$ should alternate, starting with the third order derivative being negative in order to satisfy the fourth order generalized transfer principle.

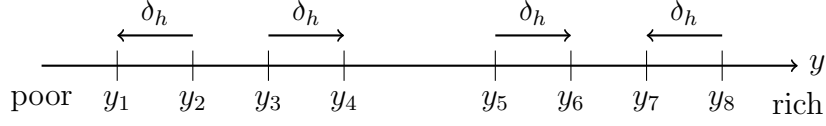


Figure 2.3: Fourth order ethical principle

It should be noted that the income transfer principles introduced here are not better than the rank dependent principles; it is a different normative approach that is worth exploring. It may be the case that two distributions having exactly the same income/health gradient would have different socioeconomic health inequality if one distribution of income has more inequality than the other.

2.2.3 Stochastic Dominance Conditions

In order to derive the dominance conditions of σ -generalized health concentration curves, I first start with the weight function. Let $\tilde{v}^i(\cdot)$ be the i th derivative of the function $\tilde{v}(\cdot) =: \tilde{v}^{(0)}(\cdot)$. I define the sets of income dependent population health measures as the following expression²:

$$\tilde{\Omega}^s := \left\{ \begin{array}{l} \tilde{A}(H) \in \Omega^1 : \tilde{v}^{(i)} \text{ is continuous and } (s-1) \text{ time differentiable} \\ \text{over } [0, 1], \quad (-1)^i \tilde{v}^{(i)}(y) > 0, \tilde{v}^{(i)}(\bar{y}) = 0, \forall y \in [0, \bar{y}], \forall i = 1, 2, \dots, s-1 \end{array} \right\} \quad (2.7)$$

and the following sets of socioeconomic health inequality measures:

²In the case of income weight functions, weights do not sum to the same values; the total value of weights depends on the density function of income. I assume vanishing marginal utilities at $\bar{y}$; this plays a similar role to allowing $y \rightarrow \infty$ in a stochastic dominance context.

$$\tilde{\Psi}^s := \left\{ \begin{array}{l} \tilde{I}(H) : \tilde{v}^{(i)} \text{ is continuous and } (s-1) \text{ time differentiable} \\ \text{over } [0, 1], \quad (-1)^i \tilde{v}^{(i)}(y) > 0, \tilde{v}^{(i)}(\bar{y}) = 0, \forall y \in [0, \bar{y}], \forall i = 1, 2, \dots, s-1 \end{array} \right\} \quad (2.8)$$

Thus, a population health measure $\tilde{A}(H) \in \tilde{\Omega}^1$ satisfies the pareto and anonymity principles; a population health measure $\tilde{A}(H) \in \tilde{\Omega}^2 \subset \tilde{\Omega}^1$ and its associated socioeconomic health inequality index $\tilde{I}(H) \in \tilde{\Psi}^2$ satisfies the second order principle of socioeconomic health inequality aversion; and $\tilde{A}(H) \in \tilde{\Omega}^3 \subset \tilde{\Omega}^2 \subset \tilde{\Omega}^1$ and $\tilde{I}(H) \in \tilde{\Psi}^3 \subset \tilde{\Psi}^2$ satisfy the principle of positional transfer sensitivity. Furthermore, $\tilde{A}(H) \in \tilde{\Omega}^s \subset \tilde{\Omega}^{s-1} \subset \dots \subset \tilde{\Omega}^2 \subset \tilde{\Omega}^1$ and $\tilde{I}(H) \in \tilde{\Psi}^s \subset \tilde{\Psi}^{s-1} \subset \dots \subset \tilde{\Psi}^3 \subset \tilde{\Psi}^2$ for all $s \in 3, 4, \dots$ satisfy the principle of sth degree positional transfer sensitivity (Aaberge [2009], Theorem 3.2A).

Now I introduce the concepts of s -generalized health concentration curves.

Definition 1. Let the distribution of health status in the population be $H^1(y) = \int_0^y \phi(H(x))dF(x)$.

The s -generalized health concentration curve, $H^s(y) = \int_0^y H^{s-1}(x)dx$ is given for all integers $s \in \{3, 4, \dots\}$.

Theorem 1. $\tilde{A}(\tilde{H}) \geq \tilde{A}(H)$ for all $\tilde{A}(\cdot) \in \tilde{\Omega}^s, s \in \{2, 3, \dots\}$ if and only if

$$\tilde{H}^s(y) - H^s(y) \geq 0, \forall y \in [0, \bar{y}] \quad (2.9)$$

Proof. By construction:

$$\begin{aligned} \Delta \tilde{A}_{\tilde{H}, H} &= \tilde{A}(\tilde{H}) - \tilde{A}(H) \\ \Delta \tilde{A}_{\tilde{H}, H} &= \int_0^{\bar{y}} \tilde{v}(y) \phi(\tilde{H}(y)) dF(y) - \int_0^{\bar{y}} \tilde{v}(y) \phi(H(y)) dF(y) \end{aligned} \quad (2.10)$$

Now, consider two income distributions y_1 and y_2 where the cumulative distributions function (CDF) of y_1 is $F(y_1)$ and the CDF of y_2 is $F(y_2)$. Then, by definition, the distribution y_1

stochastically dominates y_2 in the first order if and only if $F(y_1)$ lies nowhere above and at least somewhere below $F(y_2)$ (i.e., $F(y_1) \leq F(y_2)$). Similarly, to check for stochastic dominance in the first order between two health concentration curves, the CDFs of both distributions will have to be considered. The second order health concentration curve can be written as:

$$H^2(y) = \int_0^y \phi(H(x))dF(x)$$

And, for the third-order:

$$H^3(y) = \int_0^y H^2(x)dx$$

Similarly, for the $s + 1$ -th order:

$$H^{s+1}(y) = \int_0^y H^s(x)dy \quad (2.11)$$

Integrating equation (2.4) by parts yields:

$$\begin{aligned} \tilde{A}(H) &= \tilde{v}(y)H^1(y)\Big|_0^{\bar{y}} - \int_0^{\bar{y}} \tilde{v}'(y)H^1(y)dy \\ \tilde{A}(H) &= \tilde{v}(\bar{y})H^1(\bar{y}) - 0 - \int_0^{\bar{y}} \tilde{v}'(y)H^1(y)dy \end{aligned} \quad (2.12)$$

Now, by again integrating the last term of equation (2.12) by parts:

$$\begin{aligned} \tilde{A}(H) &= \tilde{v}(\bar{y})H^1(\bar{y}) - \int_0^{\bar{y}} \tilde{v}'(y)H^1(y)dy \\ \tilde{A}(H) &= \tilde{v}(\bar{y})H^1(\bar{y}) - [\tilde{v}'(y)H^2(y)\Big|_0^{\bar{y}} - \int_0^{\bar{y}} \tilde{v}''(y)H^2(y)dy] \end{aligned}$$

$$\tilde{A}(H) = \tilde{v}(\bar{y})H^1(\bar{y}) - \tilde{v}'(\bar{y})H^2(\bar{y}) + \int_0^{\bar{y}} \tilde{v}''(y)H^2(y)dy \quad (2.13)$$

Now, assume that for the $(s-1)$ th order:

$$\tilde{A}(H) = \tilde{v}(\bar{y})H^1(\bar{y}) + \sum_{i=1}^{s-2} (-1)^i \tilde{v}^i(\bar{y})H^{i+1}(\bar{y}) + (-1)^{s-1} \int_0^{\bar{y}} \tilde{v}^{s-1}(y)H^{s-1}(y)dy \quad (2.14)$$

Again integrating by parts :

$$\begin{aligned} \tilde{A}(H) &= \tilde{v}(\bar{y})H^1(\bar{y}) + \sum_{i=1}^{s-2} (-1)^i \tilde{v}^i(\bar{y})H^{i+1}(\bar{y}) + (-1)^{s-1} [\tilde{v}^{s-1}(y)H^s(y)]_0^{\bar{y}} - \int_0^{\bar{y}} \tilde{v}^s(y)H^s(y)dy \\ \tilde{A}(H) &= \tilde{v}(\bar{y})H^1(\bar{y}) + \sum_{i=1}^{s-2} (-1)^i \tilde{v}^i(\bar{y})H^{i+1}(\bar{y}) + (-1)^{s-1} [\tilde{v}^{s-1}(\bar{y})H^s(\bar{y}) - \int_0^{\bar{y}} \tilde{v}^s(y)H^s(y)dy] \\ \tilde{A}(H) &= \tilde{v}(\bar{y})H^1(\bar{y}) + \sum_{i=1}^{s-2} (-1)^i \tilde{v}^i(\bar{y})H^{i+1}(\bar{y}) + (-1)^{s-1} \tilde{v}^{s-1}(\bar{y})H^s(\bar{y}) + (-1)^{s-1} [- \int_0^{\bar{y}} \tilde{v}^s(y)H^s(y)dy] \\ \tilde{A}(H) &= \tilde{v}(\bar{y})H^1(\bar{y}) + \sum_{i=1}^{s-2} (-1)^i \tilde{v}^i(\bar{y})H^{i+1}(\bar{y}) + (-1)^{s-1} \tilde{v}^{s-1}(\bar{y})H^s(\bar{y}) + (-1)^s \int_0^{\bar{y}} \tilde{v}^s(y)H^s(y)dy \\ \tilde{A}(H) &= \tilde{v}(\bar{y})H^1(\bar{y}) + \sum_{i=1}^{s-1} (-1)^i \tilde{v}^i(\bar{y})H^{i+1}(\bar{y}) + (-1)^s \int_0^{\bar{y}} \tilde{v}^s(y)H^s(y)dy \quad (2.15) \end{aligned}$$

Assume $\tilde{v}(\bar{y}) = 0$ and $\tilde{v}^i(\bar{y}) = 0 \quad \forall i$ (i.e., zero weight is put on the individual with the highest income in the income distribution). Then, equation (2.15) becomes

$$\tilde{A}(H) = (-1)^s \int_0^{\bar{y}} \tilde{v}^s(y)H^s(y)dy \quad (2.16)$$

Now, I determine under which conditions $\Delta\tilde{A}_{\tilde{H},H} = \tilde{A}(\tilde{H}) - \tilde{A}(H)$ is non negative. Using

equation (2.10) and equation (2.16) I get:

$$\begin{aligned}\Delta\tilde{A}_{\tilde{H},H} &= (-1)^s \int_0^{\bar{y}} \tilde{v}^s(y) \tilde{H}^s(y) dy - (-1)^s \int_0^{\bar{y}} \tilde{v}^s(y) H^s(y) dy \\ \Delta\tilde{A}_{\tilde{H},H} &= (-1)^s \int_0^{\bar{y}} \tilde{v}^s(y) [\tilde{H}^s(y) - H^s(y)] dy\end{aligned}\tag{2.17}$$

Note that $(-1)^s \tilde{v}^s(y)$ is always positive. This implies that $\Delta\tilde{A}_{\tilde{H},H}$ is non negative only if $\tilde{H}^s(y) - H^s(y) \geq 0$. This proves for sufficiency of the condition.

To proof the necessity of the condition, I consider the $(s-1)$ derivative of the weighting function $v(y)$ (where $v^{(0)}(y) = v(y)$) has the following form:

$$v^{(s-1)}(y) = \begin{cases} (-1)^{s-1} \epsilon & y \leq y_0 \\ (-1)^{s-1} y_0 + \epsilon - y & y_0 \leq y \leq y_0 + \epsilon \\ 0 & y \geq y_0 + \epsilon \end{cases}\tag{2.18}$$

This yields:

$$v^{(s)}(y) = \begin{cases} 0 & y < y_0 \\ (-1)^s & y_0 < y < y_0 + \epsilon \\ 0 & y > y_0 + \epsilon \end{cases}\tag{2.19}$$

Now imagine that $\tilde{H}^s(y) - H^s(y) < 0$ on an interval $[y_0, y_0 + \epsilon]$ with ϵ being arbitrarily close to 0. For $v(y)$ defined as in equation (2.18), $\Delta\tilde{A}_{\tilde{H},H} < 0$. Because of the non-differentiability at y_0 and $y_0 + \epsilon$, this weight function $v(y)$ does not belong to $\tilde{\Omega}^s$. However, there is a sequence $\{v_n(y)\}$ of real-valued measurable functions belonging to $\tilde{\Omega}^s$ such that $\lim_{n \rightarrow \infty} v_n(y) = v(y)$. Applying Lebesgue's dominated convergence theorem: $\lim_{n \rightarrow \infty} \Delta\tilde{A}(\tilde{H}, H, v_n) = \Delta\tilde{A}(\tilde{H}, H, v)$. Hence it cannot be that $\tilde{H}^s(y) - H^s(y) < 0$ for some $[y_0, y_0 + \epsilon]$. This proves the necessity of

the condition. ■

Theorem 1 stipulates that a ranking between two distributions will remain unchanged for all population health indices obeying the s th order of ethical principles whenever the generalized health concentration curves of order s of these two distributions do not intersect. The distribution with the highest generalized health concentration curve will display a higher level of population health.

Definition 2. Let the distribution of ill-health status in the population be $\widehat{H}^1(y) = \int_0^y s(H(x))dF(x)$. The s -generalized ill-health concentration curve, $\widehat{H}^s(y) = \int_0^y \widehat{H}^{s-1}(x)dx$ is given for all integers $s \in \{3, 4, \dots\}$.

Corollary 1. $\tilde{A}(\tilde{H}) \geq \tilde{A}(H)$ for all $\tilde{A}(\cdot) \in \tilde{\Omega}^s, s \in \{2, 3, \dots\}$ if and only if

$$\widehat{H}^s(y) - \widehat{\tilde{H}}^s(y) \geq 0, \forall y \in [0, \bar{y}] \quad (2.20)$$

Proof. Equation (2.10) can be written as:

$$\Delta \tilde{A}_{\tilde{H}, H} = 1 - \frac{1}{K} \int_0^{\bar{y}} \tilde{v}(y)s(\tilde{H}(y))dy - 1 + \frac{1}{K} \int_0^{\bar{y}} \tilde{v}(y)s(H(y))dy \quad (2.21)$$

$$\Delta \tilde{A}_{\tilde{H}, H} = \frac{1}{K} \left[\int_0^{\bar{y}} \tilde{v}(y)s(H(y))dy - \int_0^{\bar{y}} \tilde{v}(y)s(\tilde{H}(y))dy \right] \quad (2.22)$$

From equation (2.22) I conclude that $\Delta \tilde{A}_{\tilde{H}, H} \geq 0$ if and only if:

$$\int_0^{\bar{y}} \tilde{v}(y)[s(H(y)) - s(\tilde{H}(y))]dy = \int_0^{\bar{y}} \tilde{v}(y)[\tilde{H}^1(y) - H^1(y)]dy \geq 0 \quad (2.23)$$

Equation (2.23) has the same structure as Equation (2.10) except that it has the opposite inequality sign. The sufficiency and necessity of the condition is proved by Theorem 1. ■

Corollary 1 stipulates that a ranking between two distributions remains the same for all population health indices obeying the s -th order of ethical principles whenever the generalized ill-health concentration curves of order s of these two distributions do not intersect. The distribution with the lowest generalized ill-health concentration curve will display a higher level of population health.

Now I introduce the identification of the robust ranking of socioeconomic health inequality.

Definition 3. *Let the second order health concentration curve be defined by $HC^2(y) = \int_0^y (H^1(x))/\mu_\phi dx$. The s -health concentration curve, $HC^s(y) = \int_0^y HC^{s-1}(x)dx$ is given for all integers $s \in \{3, 4, \dots\}$.*

Theorem 2. $\tilde{I}(\tilde{H}) \leq \tilde{I}(H)$ for all $I(\cdot) \in \tilde{\Psi}^s, s \in \{2, 3, \dots\}$ if and only if

$$\tilde{H}C^s(y) - HC^s(y) \geq 0, \forall y \in [0, \bar{y}] \quad (2.24)$$

Proof. Again,

$$\Delta \tilde{I}_{(\tilde{H}), H} = \tilde{I}(\tilde{H}) - \tilde{I}(H) \quad (2.25)$$

$$\Delta \tilde{I}_{(\tilde{H}), H} = 1 - \frac{\tilde{A}(\tilde{H})}{\mu_{\phi \tilde{H}}} - 1 + \frac{\tilde{A}(H)}{\mu_{\phi H}}$$

$$\Delta \tilde{I}_{(\tilde{H}), H} = \frac{\tilde{A}(H)}{\mu_{\phi H}} - \frac{\tilde{A}(\tilde{H})}{\mu_{\phi \tilde{H}}} \quad (2.26)$$

$$\Delta \tilde{I}_{(\tilde{H}), H} = \int_0^{\bar{y}} \tilde{v}(y) \frac{\phi(H(y))}{\mu_{\phi H}} dF(y) - \int_0^{\bar{y}} \tilde{v}(y) \frac{\phi(\tilde{H}(y))}{\mu_{\phi \tilde{H}}} dF(y) \quad (2.27)$$

Equation (2.27) has the same structure as Equation (2.10) except that it has the opposite inequality sign and $\phi(H(y))$ is divided by the average health status ($\mu_{\phi H}$). Sufficiency and necessity of the condition are proved by Theorem 1. ■

Theorem 2 stipulates that a ranking between two distributions remains the same for all so-

cioeconomic health inequality indices obeying the s -th order of ethical principles whenever the health concentration curves of order s of the two distributions do not intersect. The distribution with the highest health concentration curve will display a lower level of socioeconomic health inequality.

Definition 4. Let the second order modified ill-health concentration curve be defined by $\widehat{HC}^2(y) = \int_0^y (\widehat{HC}^1(x))/\mu_\phi dx$. The s -modified ill-health concentration curve, $\widehat{HC}^s(y) = \int_0^y \widehat{HC}^{s-1}(x)dx$ is given for all integers $s \in \{3, 4, \dots\}$.

Corollary 2. $\tilde{I}(\tilde{H}) \leq \tilde{I}(H)$ for all $I(\cdot) \in \Psi^s$, $s \in \{2, 3, \dots\}$ if and only if

$$\widehat{HC}^s(y) - \widehat{\tilde{H}}C^s(y) \geq 0, \forall y \in \{0, \bar{y}\} \quad (2.28)$$

Proof. From Equation (2.26):

$$\Delta \tilde{I}_{(\tilde{H}), H} = \frac{\tilde{A}(H)}{\mu_{\phi H}} - \frac{\tilde{A}(\tilde{H})}{\mu_{\phi \tilde{H}}} \quad (2.29)$$

By construction, I can write:

$$\Delta \tilde{I}_{(\tilde{H}), H} = \frac{1}{K} \int_0^{\bar{y}} \tilde{v}(y) \left[\frac{s(\tilde{H}(y))}{\mu_{\phi \tilde{H}}} - \frac{s(H(y))}{\mu_{\phi H}} \right] dy \quad (2.30)$$

Equation (2.30) has the same structure as Equation (2.22) except that it has the opposite inequality sign and that $s(H(y))$ is divided by the average health status μ_ϕ . ■

Corollary 2 stipulates that a ranking between two distributions remains the same for all socioeconomic health inequality indices obeying the s -th order of ethical principles whenever the modified ill-health concentration curves of order s of these two distributions do not intersect. The distribution with the lowest modified ill-health concentration curve will display a lower

level of socioeconomic health inequality.

In this section, I have defined the sets of income-dependent population health measures and socioeconomic health inequality measures that obey the set of ethical principles that relate to the degree of socioeconomic health inequality aversion. I have also shown that the ranking between two distributions will not change for all population health indices obeying the s th order of ethical principles as long as the generalized health concentration curves of order s of these two distributions do not cross each other; and the distribution with the highest generalized health concentration curve will display a higher level of population health. Conversely, when considering the ill-health concentration curves of two distributions, the ranking between them will not change for all population health indices obeying the s th order of ethical principles as long as the generalized ill-health concentration curves of these two distributions do not cross each other; and the distribution with the lowest generalized ill-health concentration curve will display a higher level of population health. Similarly, for the ranking of socioeconomic health inequality between two distributions, I showed that it will not change for all socioeconomic health indices obeying the s th order of ethical principles as long as the health concentration curves of order s of these two distributions do not cross each other; and the distribution with the highest health concentration curve will display a lower level of socioeconomic health inequality. Conversely, when considering the ill-health concentration curves of two distributions, the ranking between them will not change for all socioeconomic health inequality indices obeying the s th order of ethical principles as long as the generalized ill-health concentration curves of the two distributions do not cross each other; and the distribution with the lowest ill-health concentration curve will display a lower level of socioeconomic health inequality.

The following section shows how these stochastic dominance conditions can be used empirically to rank distributions based on population health and socioeconomic health inequality

measures.

2.3 Empirical Illustration

In this section I present how the framework developed in the previous section can be illustrated empirically. Most studies on income inequality and health status (Humphries and Van Doorslaer [2000], Mellor and Milyo [2002], Murthy [2006], Chatterji et al. [2011] etc.) use data from developed countries. To get a different perspective, in this study I use cross sectional data from the World Health Survey (2003) for five developing South Asian countries (Bangladesh, India, Nepal, Pakistan, and Sri Lanka) which are similar in terms of different socioeconomic indicators. The illustration is presented by looking at the population health dominance and the socioeconomic health inequality dominance among these five countries.

2.3.1 The Data

The World Health Survey was implemented by World Health Organization (WHO) in 2002-2004 in 70 countries around the world to collect information on adult health and health systems ³. Because household expenditure is more representative of permanent income, I use household expenditure as a proxy for socioeconomic status. Respondents were asked about the total household expenditure in the last 4 weeks at the time of the interview, which includes the value of all goods and services consumed or used by the household (including things produced for its own consumption). Because the data contains information on *total* household expenditure and the household compositions across countries are different, there is a need to use equivalence scales in the stochastic dominance comparisons. Equivalence scales are used to compare income and expenditures among different household sizes by dividing

³Source: World Health Organization: <http://www.who.int/healthinfo/survey/en/>.

the total household expenditure by an appropriate scale number. In the literature, various ways to specify equivalence scales have been used. Blundell et al. [1998] and Pendakur [1999] proposed semiparametric estimators of base-independent equivalence scales. Yatchew et al. [2003] embedded Pendakur [1999]’s semiparametric specification in a partial linear index model framework. In income and poverty analysis, Buhmann et al. [1988] showed the importance of the impact of different equivalence scale elasticities on poverty measurement and introduced the following parametric form to list 34 different equivalence scales:

$$W = \frac{D}{S^e} \quad (2.31)$$

where W is the economic well-being, D is the disposable income, and S is the family size. The equivalence elasticity e varies between 0 and 1; a larger e would translate into a smaller economies of scale assumed by the equivalence scale. To analyze housing deprivation orderings in Lebanon, Bibi et al. [2012] used this setting to compare among different households of varied sizes and used the following form to define the equivalence scale:

$$m(n) = n^\theta \quad (2.32)$$

where $m(n)$ is the equivalence scale and, n is the household size, and θ is the equivalence scale elasticity. In my analysis, I follow this parametric form to test stochastic dominance among the five countries using three values of the equivalence scale elasticity ($\theta = 0, 0.5, 1$). The total household expenditures is divided by the equivalence scale to get the scaled household expenditures. When $\theta = 0$, the economies of scales are the largest and when $\theta = 1$, the economies of scales are the smallest.

To develop the overall adult health status, I follow Makdissi and Yazbeck [2014] and select eight physical and three emotional attributes to define the health status of an adult. The

threshold definitions for each of these attributes are detailed in Table 2.1.

Table 2.1: Threshold Definitions for Health Attributes

Attribute	Threshold met if answer is different from <i>none</i> to each of the following questions. Overall in the last 30 days:
Vision	how much difficulty did you have in seeing and recognizing an object at an arm’s length or in reading?
Hearing	did the respondent have a hearing problem?
Ambulation	how much difficulty did you have with moving around?
Communication	how much difficulty did you have with personal relationship or participation in the community?
Cognition	how much difficulty did you have with concentrating or remembering things?
Dexterity	how much difficulty did you have with self-care, such as washing or dressing yourself?
Learning Capacity	how much difficulty did you have in learning a new task (for example, learning how to get to a new place, learning a new game, learning a new recipe etc.)?

Continued on next page

Table 2.1 – continued from previous page

Pain	how much of bodily aches or pains did you have?
Emotional Attribute	Threshold met if answer is different from <i>none</i> to the following questions
Anxiety	how much of a problem did you have with worry or anxiety?
Depression	how much of a problem did you have with feeling sad, low or depressed?
Exhaustion	have you had a period lasting several days when you have been feeling your energy decreased or that you are tired all the time?

Based on these threshold definitions, the summary of the average population health status is given in Table 2.2 below. It appears that the overall population health status is the lowest in Bangladesh and the highest in Pakistan and Sri Lanka.

Table 2.2: Summary of Health Status in South Asian Countries

	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Average value of count-health status	0.561 (0.262)	0.629 (0.291)	0.665 (0.271)	0.713 (0.290)	0.713 (0.268)
No. of observations	4728	7030	8559	6144	5577

*Standard deviations in parentheses

Next I look at the distribution of household expenditures in the population in these five

countries. All of these countries have their own currencies with a floating exchange rate with the US dollar. To have a baseline for comparing household expenditures across countries, I first use the official exchange rate to convert local currencies in US dollars and then multiply by the Purchasing Power Parity (PPP)⁴ using Penn World Table 7.1. Converting the local currencies to US dollars and then multiplying them by the PPP rate equalizes the purchasing power of the five different currencies by eliminating the differences in the price levels among these countries. Summary statistics for total household expenditure are given below in Table 2.3. It can be seen that the highest inequality exists in Bangladesh and the lowest in Sri Lanka.

Table 2.3: Summary Statistics for Total Household Expenditure (in US\$, PPP adjusted)

Country	Mean Expenditure μ	Gini Coefficient	Gini Social Welfare Function $\mu(1 - G)$	#. of Households
Bangladesh	2375.798	0.451247	1303.726	4728
India	978.505	0.441299	546.692	7030
Nepal	1685.265	0.440530	942.855	8559
Pakistan	1952.670	0.391984	1187.255	6144
Sri Lanka	2506.220	0.375625	1564.821	5577

Table 2.4 below shows the summary statistics for per capita household expenditure. In this case, it appears that the highest inequality is in India and the lowest in Sri Lanka.

⁴I understand that PPP exchange rate is subject to controversy and margin of error because it was not constructed to measure poverty. Despite the criticism, using the PPP exchange rate is an acceptable way to compare poverty and inequality across countries. The dominance rankings might change when different PPP rates are used —in that case, the relative price level changes for the countries in question would matter.

Table 2.4: Summary Statistics for Per Capita Household Expenditure (in US\$, PPP adjusted)

Country	Mean Expenditure	Gini	Gini Social Welfare Function	#. of
	μ	Coefficient	$\mu(1 - G)$	Observations
Bangladesh	484.1689	0.439254	271.496	24814
India	182.5692	0.463761	97.901	42262
Nepal	354.2902	0.444479	196.816	45247
Pakistan	295.4364	0.401657	176.772	45291
Sri Lanka	642.6777	0.383497	396.213	23860

The density curves for total and per capita household expenditures for all five countries are shown in Figure-2.4 and Figure-2.5, respectively. It can be seen that the proportion of people with lower household expenditures are more concentrated in India than other countries while Bangladesh and Pakistan have similar patterns when considering the total household expenditures. The density curves of Nepal and Pakistan have similar distributions when per capital household expenditures are considered.

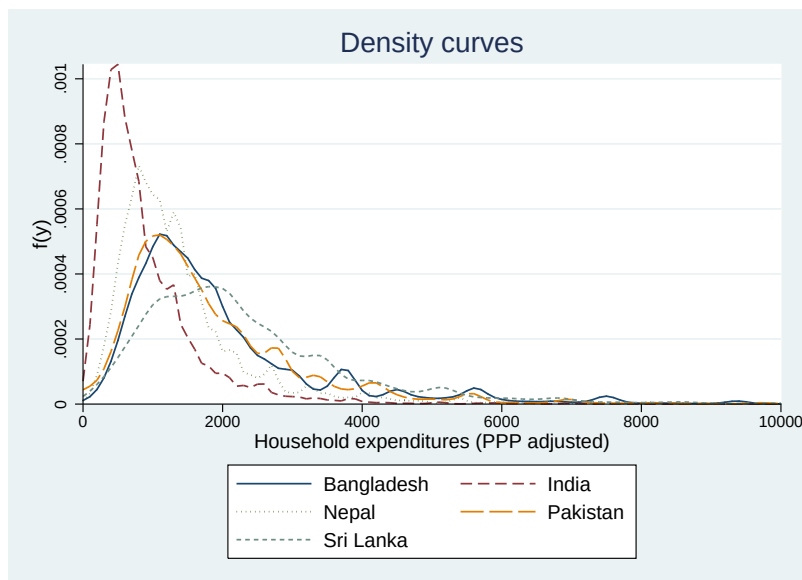


Figure 2.4: Density Curves for Total Household Expenditure: all countries

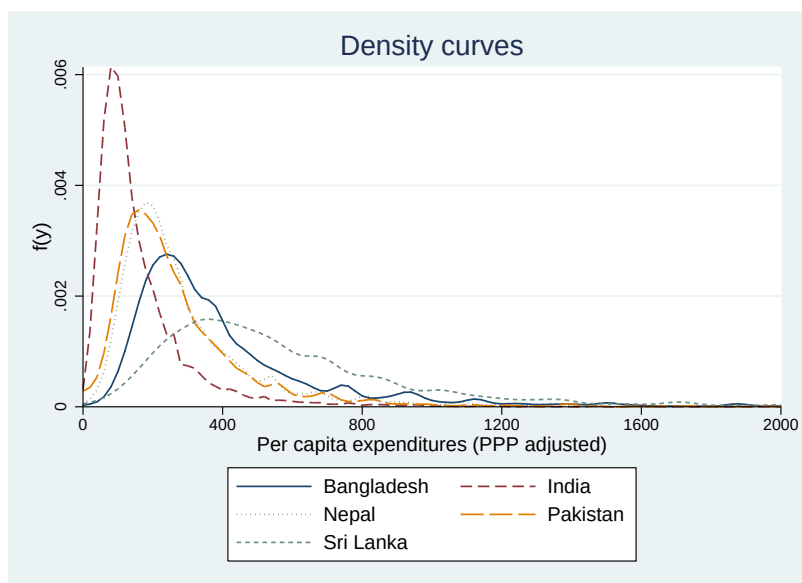


Figure 2.5: Density Curves for Per Capita Expenditure: all countries

The World Bank also provides Purchasing Power Parity (PPP) rates in the International Comparison Program (ICP) database, which are different from the PPP rates published

in the Penn World Table database. I also calculate the summary statistics and density curves for total and per capita household expenditures in Appendix-2.A. It can be seen from the summary statistics that the mean total household expenditure becomes the highest in Bangladesh, followed by Sri Lanka, Pakistan, Nepal, and India. For the mean per capita household expenditures, the highest per capital expenditure is in Bangladesh, closely followed by Sri Lanka, while the lowest per capita household expenditure is in India. There is no change in the Gini Coefficients.

Next I look at the Lorenz curves for these countries on the left panel in Figure-2.6 using total household expenditure. It appears that the curves cross each other, so it is not possible to rank the distributions. So I include the Generalized Lorenz (GL) curves in the right panel in Figure-2.6, which are used for comparing different distributions with different means. By Shorrocks' ([1983]) theorem, it is evident that the GL curve for India is dominated by the GL curves for all other countries. The GL curve for Bangladesh is dominated by the GL curve for Sri Lanka. The GL curve for Nepal is dominated GL curves for Bangladesh, Pakistan, and Sri Lanka. The GL curve for Pakistan is dominated by the GL curves for Bangladesh and Sri Lanka, while no country dominates the GL curve for Sri Lanka. The two graphs in Figure-2.7 show the Lorenz and Generalized Lorenz curves using per capita household expenditure. Once again, the Lorenz curves (shown on the left panel) cross each other so ranking the distributions is not possible. From the Generalized Lorenz curves (shown on the right panel), it can be seen that the GL curve for Pakistan is now dominated by the GL curves for Sri Lanka, Bangladesh, and Nepal. Other than this, there are no changes in the dominance orderings from those found with total household expenditure. Pairwise comparisons of Lorenz curves and Generalized Lorenz curves for all five countries are included in Appendix-2.B.

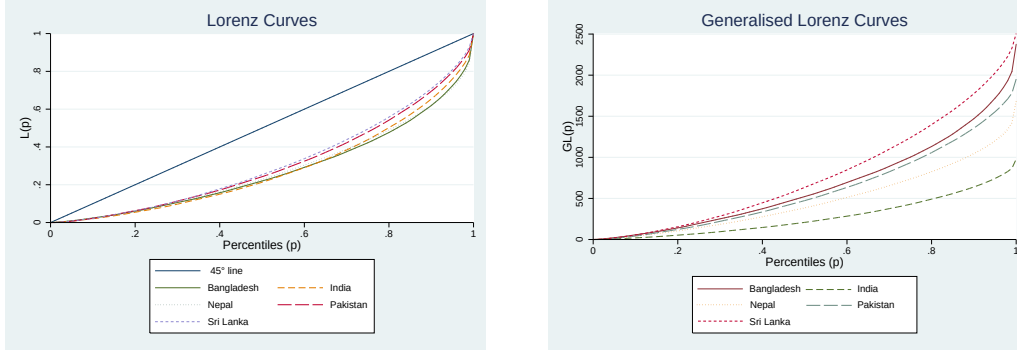


Figure 2.6: Lorenz vs. Generalized Lorenz Curves using Total Household Expenditures:All Countries

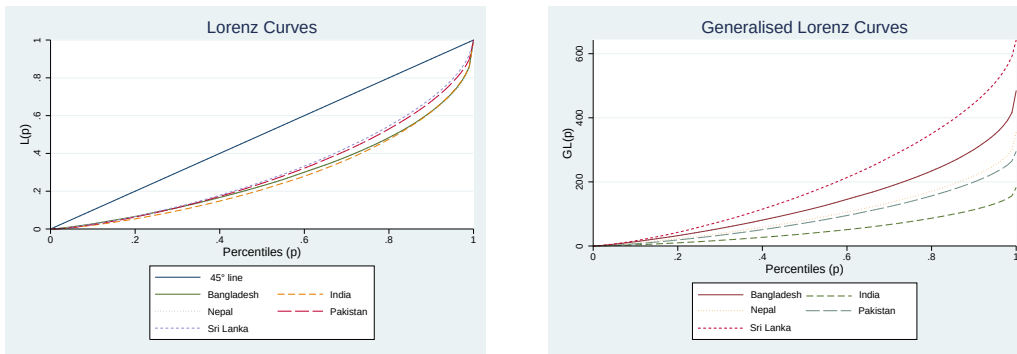


Figure 2.7: Lorenz vs. Generalized Lorenz Curves using Per Capita Expenditures:All Countries

Finally, Table 2.5 shows the population health status by quintiles of total household expenditure for each country. This provides some insight into the variation of health status across household expenditure quantiles within countries. It can be seen that the average health status grows as the total household expenditure quantiles increase for Bangladesh and Sri Lanka, which is clearly indicative of the social gradient in health. For India, the average health status decreases in the fourth and fifth quantile of the total household expenditure. The average health status decreases in the fourth quantile of the total household expenditure

but increases slightly in the fifth quantile for Nepal. For Pakistan, the average health status decreases a little in the third and fourth quantile of the total household expenditure before increasing in the fifth quantile.

Table 2.5: Summary of Health Status by Quintiles of Total Household Expenditure in South Asian Countries

	Bangladesh	India	Nepal	Pakistan	Sri Lanka
1st Quantile	0.540 (0.272)	0.616 (0.298)	0.629 (0.284)	0.705 (0.296)	0.621 (0.297)
No. of observations	971	1686	1717	1326	1116
2nd Quantile	0.553 (0.258)	0.627 (0.294)	0.664 (0.271)	0.719 (0.295)	0.708 (0.270)
No. of observations	943	1155	1718	1135	1271
3rd Quantile	0.553 (0.260)	0.644 (0.282)	0.682 (0.265)	0.718 (0.292)	0.736 (0.253)
No. of observations	1230	1419	2086	1276	960
4th Quantile	0.573 (0.263)	0.638 (0.290)	0.671 (0.263)	0.706 (0.289)	0.745 (0.253)
No. of observations	639	1514	1471	1185	1301
5th Quantile	0.594 (0.254)	0.622 (0.292)	0.677 (0.272)	0.717 (0.280)	0.760 (0.234)
No. of observations	945	1256	1567	1222	929

*Standard deviations in parentheses

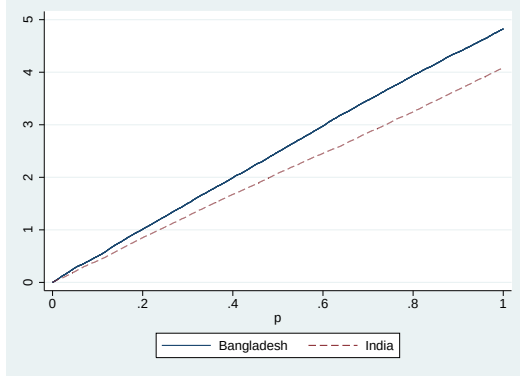
2.3.2 Stochastic dominance among countries

Using the theoretical results developed in the previous section, now I can empirically test stochastic dominance in population health and socioeconomic health inequality among the five South Asian countries. Theorem 1 specifies that the ranking between two distributions remain unchanged whenever the generalized health concentration curves of order s of these

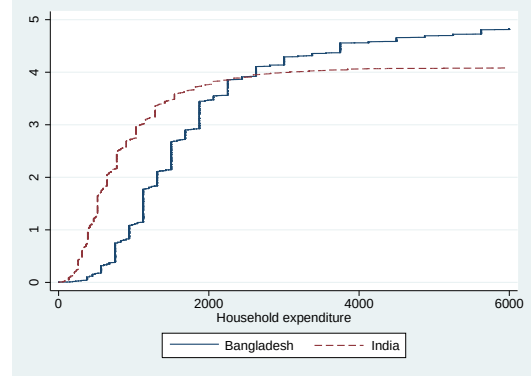
distributions do not intersect, and the distribution with the highest generalized concentration curve displays a higher level of population health. By Corollary 1, an alternative to this would be to compare the generalized ill-health concentration curves. In that case, the distribution with the lowest generalized ill-health concentration curve will display a higher level of population health as long as the generalized ill-health concentration curves of order s of the two distributions do not intersect. In this paper, I make use of Corollary 1 and use the generalized ill-health concentration curves for illustration. The objective is to investigate whether my proposed framework using household expenditure (as a proxy for income) y leads to any difference in the results in stochastic dominance tests compared with using the conventional socioeconomic rank (p). Such scenarios are presented next.

Figure-2.8 on the next page demonstrates the case where there is dominance in the second order while using socioeconomic rank (p) but non-dominance while using total household expenditure (y) for all three equivalence scale elasticities (i.e., $\theta = 0, 0.5, 1$).⁵ It can be seen that India dominates Bangladesh in the second order when p is used (as shown on the left panel diagrams in Figure-2.8) but the curves cross each other when y is used in the x-axis (as shown on the right panel diagrams in Figure-2.8). This holds for different values of the equivalence scale elasticity θ .

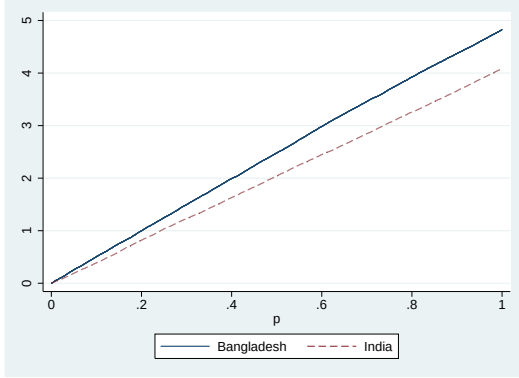
⁵There is no variation in the dominance curve positions for household expenditures greater than \$6000. This is why the dominance curves past the \$6000 level are not shown. None of the observations were dropped from the analysis.



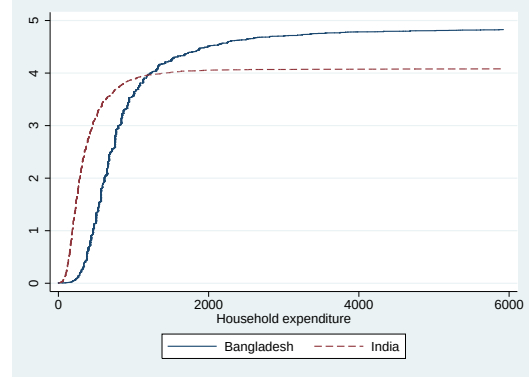
(a) using socioeconomic rank p , $\theta = 0$



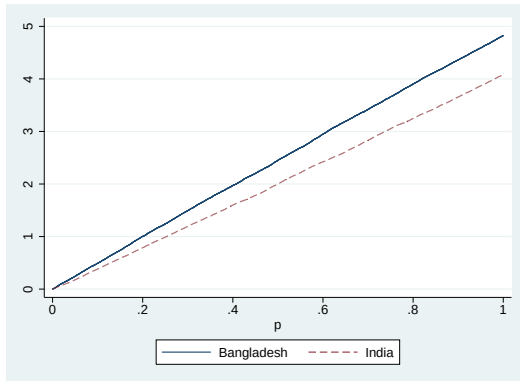
(b) using household expenditure y , $\theta = 0$



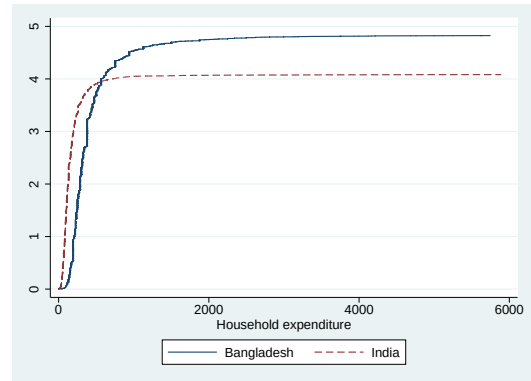
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$



(e) using socioeconomic rank p , $\theta = 1$

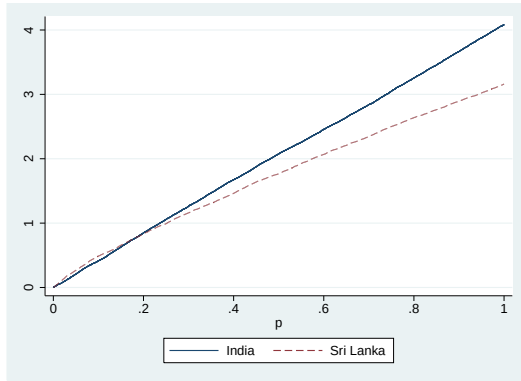


(f) using household expenditure y , $\theta = 1$

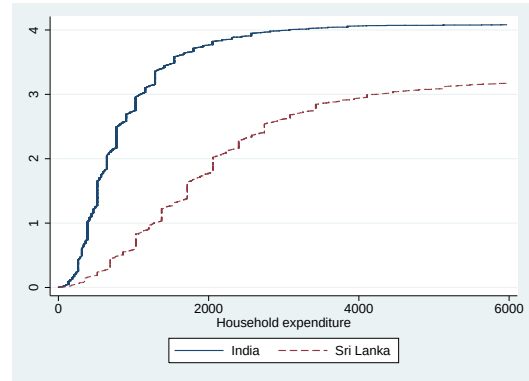
Figure 2.8: Second Order Population Health Dominance: Bangladesh & India

The reverse scenario is also found where there is non-dominance while using the socioe-

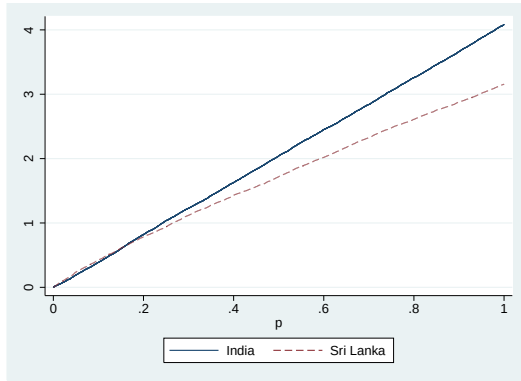
conomic ranks p but dominance while using the household expenditures y . Figure-2.9 below shows the dominance curves of India and Sri Lanka cross each other when p is used (shown on the left panel) but Sri Lanka dominates India in the second order when y is used (shown on the right panel).



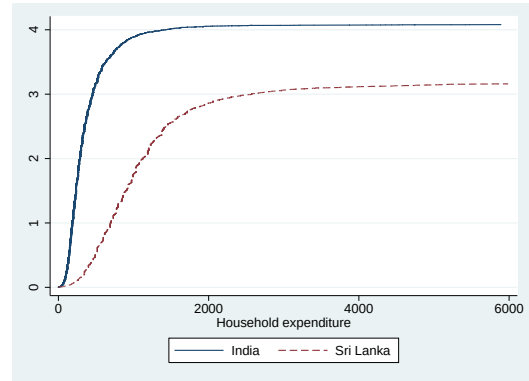
(a) using socioeconomic rank p , $\theta = 0$



(b) using household expenditure y , $\theta = 0$

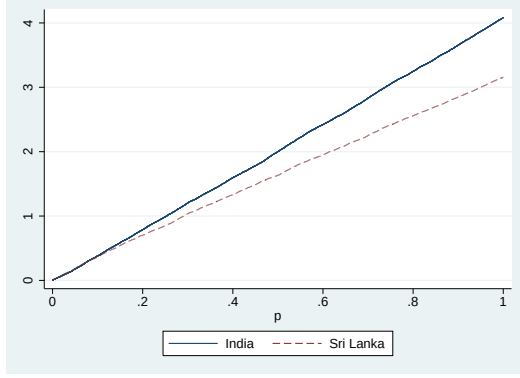


(c) using socioeconomic rank p , $\theta = 0.5$

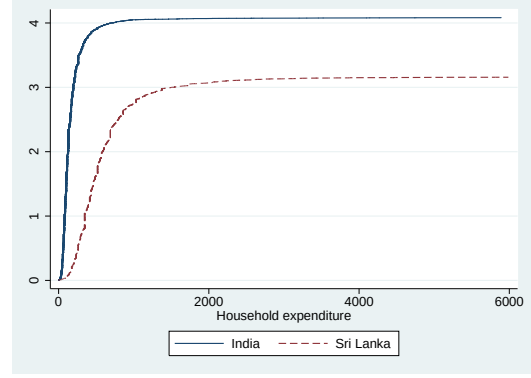


(d) using household expenditure y , $\theta = 0.5$

Figure-2.9 continued on the next page.



(e) using socioeconomic rank p , $\theta = 1$



(f) using household expenditure y , $\theta = 1$

Figure 2.9: Second Order Population Health Dominance: India & Sri Lanka

Detailed pairwise comparisons of second, third, and fourth order population health dominance among all five countries using both socioeconomic ranks (p) and household expenditures (y) can be found in Appendix 2.C.

Table 2.6 and Table 2.7 on the next page outline the results of the dominance tests in population health using total household expenditure (i.e., $\theta = 0$). I present the dominance results in a way that a country in the column dominates another country in the row, and the order of dominance is enumerated by putting 2,3, or 4 to indicate second order, third order, or fourth order dominance, respectively. ‘ND’ indicates no dominance. It is found that using household expenditures instead of socioeconomic ranks leads to different dominance results.

Table 2.6: Summary of Population Health Dominance among South Asian Countries, $\theta = 0$

Using Socioeconomic Rank p					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	2,3,4				
Nepal	2,3,4	3,4			
Pakistan	2,3,4	2,3,4	2,3,4		2,3,4
Sri Lanka	2,3,4	3,4	3,4		

*Country in the column dominates country in the row

Table 2.7: Summary of Population Health Dominance among South Asian Countries, $\theta = 0$

Using Household Expenditure y					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	ND				
Nepal	ND	2,3,4			
Pakistan	ND	2,3,4	3,4		
Sri Lanka	3,4	2,3,4	2,3,4	ND	

*Country in the column dominates country in the row

Table 2.8 and Table 2.9 next show the results of the dominance tests in population health when the equivalence scale elasticity (θ) is 0.5. It can be seen that using socioeconomic ranks and household expenditures lead to different dominance test results.

Table 2.8: Summary of Population Health Dominance among South Asian Countries, $\theta = 0.5$

Using Socioeconomic Rank p					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	2,3,4				
Nepal	2,3,4	2,3,4			
Pakistan	2,3,4	2,3,4	2,3,4		2,3,4
Sri Lanka	2,3,4	3,4	3,4		

*Country in the column dominates country in the row

Table 2.9: Summary of Population Health Dominance among South Asian Countries, $\theta = 0.5$

Using Household Expenditure y					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	ND				
Nepal	ND	2,3,4			
Pakistan	ND	2,3,4	3,4		
Sri Lanka	2,3,4	2,3,4	2,3,4	2	

*Country in the column dominates country in the row

Lastly, Table 2.10 and Table 2.11 below show the results of the dominance tests in population health when the equivalence scale elasticity (θ) is 1 (i.e., using per capita household expenditures). Once again, it can be concluded that using socioeconomic ranks leads to different dominance test results than using household expenditures.

Table 2.10: Summary of Population Health Dominance among South Asian Countries, $\theta = 1$

Using Socioeconomic Rank p					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	2,3,4				
Nepal	2,3,4	2,3,4			
Pakistan	2,3,4	2,3,4	2,3,4		2,3,4
Sri Lanka	2,3,4	2,3,4	2,3,4		

*Country in the column dominates country in the row

Table 2.11: Summary of Population Health Dominance among South Asian Countries, $\theta = 1$

Using Household Expenditure y					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	ND				
Nepal	ND	2,3,4			
Pakistan	ND	2,3,4	3,4		
Sri Lanka	2,3,4	2,3,4	2,3,4	2	

*Country in the column dominates country in the row

I also test for population health dominance among these five countries using the World Bank PPP rates, for the equivalence scale elasticity $\theta = 1$. The pairwise comparisons are given in Appendix-2.E. Also with this PPP rate, it can be seen that using socioeconomic ranks p and household expenditures y lead to different population health dominance rankings.

Next, I test for socioeconomic health inequality dominance among these countries and

find similar results. For example, India dominates Bangladesh in the second order when socioeconomic ranks (p) for individuals are used, but the curves cross each other when total household expenditure (y) is used. On the contrary, I also find a case between India and Sri Lanka where there is non-dominance when p is used but dominance in the second order when y (total household expenditure) is used. Figure-2.10 illustrates this case.

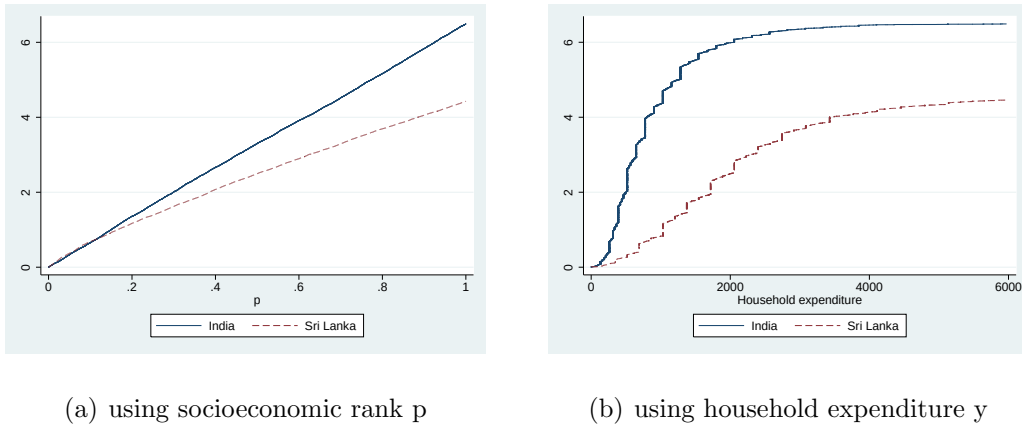


Figure 2.10: Second Order Inequality Dominance: India & Sri Lanka, $\theta = 0$

Detailed pairwise comparisons of second, third, and fourth order socioeconomic health inequality dominance among all five countries using both socioeconomic ranks (p) and household expenditures (y) can be found in Appendix-2.E.

Table 2.12 and Table 2.13 outline the results of the dominance tests in socioeconomic health inequality using total household expenditure (i.e., the equivalence scale elasticity, $\theta = 0$). Same as before, a country in the column dominates another country in the row, and the order of dominance is enumerated by putting 2,3, or 4 to indicate second order, third order, or fourth order dominance, respectively. Non-dominance, once again, is shown by ‘ND’. It is evident that using household expenditures instead of socioeconomic ranks leads to different dominance results.

Table 2.12: Summary of Socioeconomic Health Inequality Dominance among South Asian Countries, $\theta = 0$

Using Socioeconomic Rank p					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	2,3,4				
Nepal	2,3,4	2,3,4			
Pakistan	2,3,4	2,3,4	2,3,4		2,3,4
Sri Lanka	2,3,4	3,4	3,4		

*Country in the column dominates country in the row

Table 2.13: Summary of Socioeconomic Health Inequality Dominance among South Asian Countries, $\theta = 0$

Using Household Expenditure y					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	ND				
Nepal	ND	2,3,4			
Pakistan	ND	2,3,4	3,4		
Sri Lanka	3,4	2,3,4	2,3,4	ND	

*Country in the column dominates country in the row

Next I test for dominance in socioeconomic health inequality when the equivalence scale elasticity (θ) is 0.5. It can be seen that using socioeconomic ranks and household expenditures lead to different dominance test results, as shown in Table 2.14 and Table 2.15 below.

Table 2.14: Summary of Socioeconomic Health Inequality Dominance among South Asian Countries, $\theta = 0.5$

Using Socioeconomic Rank p					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	2,3,4				
Nepal	2,3,4	2,3,4			
Pakistan	2,3,4	2,3,4	2,3,4		2,3,4
Sri Lanka	2,3,4	2,3,4	3,4		

*Country in the column dominates country in the row

Table 2.15: Summary of Socioeconomic Health Inequality Dominance among South Asian Countries, $\theta = 0.5$

Using Household Expenditure y					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	ND				
Nepal	ND	2,3,4			
Pakistan	ND	2,3,4	3,4		
Sri Lanka	2,3,4	2,3,4	2,3,4	2	

*Country in the column dominates country in the row

Lastly, I test for dominance in socioeconomic health inequality among the five countries when the equivalence scale elasticity (θ) is 1 (i.e., per capita household expenditure is used). Using socioeconomic ranks (p) and per capita household expenditure (y) lead to different

dominance results, as outlined in Table 2.16 and Table 2.17 below.

Table 2.16: Summary of Socioeconomic Health Inequality Dominance among South Asian Countries, $\theta = 1$

Using Socioeconomic Rank p					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	2,3,4				
Nepal	2,3,4	2,3,4			
Pakistan	2,3,4	2,3,4	2,3,4		2,3,4
Sri Lanka	2,3,4	2,3,4	2,3,4		

*Country in the column dominates country in the row

Table 2.17: Summary of Socioeconomic Health Inequality Dominance among South Asian Countries, $\theta = 1$

Using Household Expenditure y					
	Bangladesh	India	Nepal	Pakistan	Sri Lanka
Bangladesh					
India	ND				
Nepal	ND	2,3,4			
Pakistan	ND	2,3,4	3,4		
Sri Lanka	2,3,4	2,3,4	2,3,4	2	

*Country in the column dominates country in the row

It can be seen that for both population health dominance and socioeconomic health inequality dominance, the results do not change much for different equivalence scales. This

might be because the differences in household expenditures across these countries are such that the orderings are not affected much whether the household expenditures are considered as total or on a per capita basis.

Once again, I test for socioeconomic health inequality dominance among these five countries using the World Bank PPP rates, for the equivalence scale elasticity $\theta = 1$. The pairwise comparisons are given in Appendix-2.F. Also with this PPP rate, it can be seen that using socioeconomic ranks p and household expenditures y lead to different socioeconomic health inequality dominance rankings.

2.4 Conclusion

Erreygers et al. [2015] argue that the existing rank-dependent indices in the literature which are used to measure the socioeconomic inequality of health reflect a causal relationship between socioeconomic ranks and health levels, because these indices measure the socioeconomic status by *ranks* and the health status by the *level* of the health variable under consideration. They propose a set of indices based on the *levels* which the individuals attain in both the socioeconomic and health domains, and believe that these indices which are based on socioeconomic levels rather than ranks gives a more complete picture of the socioeconomic distribution and therefore provide a more accurate measure of socioeconomic health inequality. In this paper I analyze the difference between these two approaches by investigating whether using individuals' income y instead of using their socioeconomic status p leads to different results in stochastic dominance tests. I developed the theoretical framework needed to perform the stochastic dominance tests. Using the World Health Survey (2002) data for five South Asian countries, I find that using the income approach leads to different results than using the socioeconomic positions approach for both population health and socioeco-

nomic health inequality dominance tests; for example, India dominates Bangladesh in the second order when socioeconomic status p is used, but there is non-dominance (i.e., the two curves cross each other) when income y is used. The reverse case was also found; there is non-dominance in the second order between India and Sri Lanka when socioeconomic status p is used, but Sri Lanka dominates India when income y is used. I also found an instance where there was non-dominance in the second order but dominance in the third order when household expenditure y was used. Researchers who take the Erreygers et al. [2015] analytical position can use the income based equivalent to concentration curves proposed in this paper for identifying robust rankings of health achievement and socioeconomic health inequality.

A possible extension of the paper consists of defining the weight function $\tilde{v}(y)$ and calculating the population health achievement indices for the countries, and then comparing the results with indices that are calculated using the weight function $v(p)$ in the extended concentration index in order to see if the results are significantly different.

Appendix 2.A.

Table 2.18: Summary Statistics for Total Household Expenditure (in US\$, World Bank PPP adjusted)

Country	Mean Expenditure μ	Gini Coefficient	Gini Social Welfare Function $\mu(1 - G)$	#. of Households
Bangladesh	1774.455	0.451247	973.738	4728
India	821.3106	0.441299	458.867	7030
Nepal	1167.654	0.440530	653.267	8559
Pakistan	1247.315	0.391984	758.387	6144
Sri Lanka	1381.368	0.375625	862.492	5577

Table 2.19: Summary Statistics for Per Capita Household Expenditure (in US\$, World Bank PPP adjusted)

Country	Mean Expenditure μ	Gini Coefficient	Gini Social Welfare Function $\mu(1 - G)$	#. of Observations
Bangladesh	361.620	0.439254	202.777	24814
India	153.241	0.463761	82.174	42262
Nepal	245.473	0.444479	136.365	45247
Pakistan	188.716	0.401657	112.917	45291
Sri Lanka	354.229	0.383497	218.383	23860

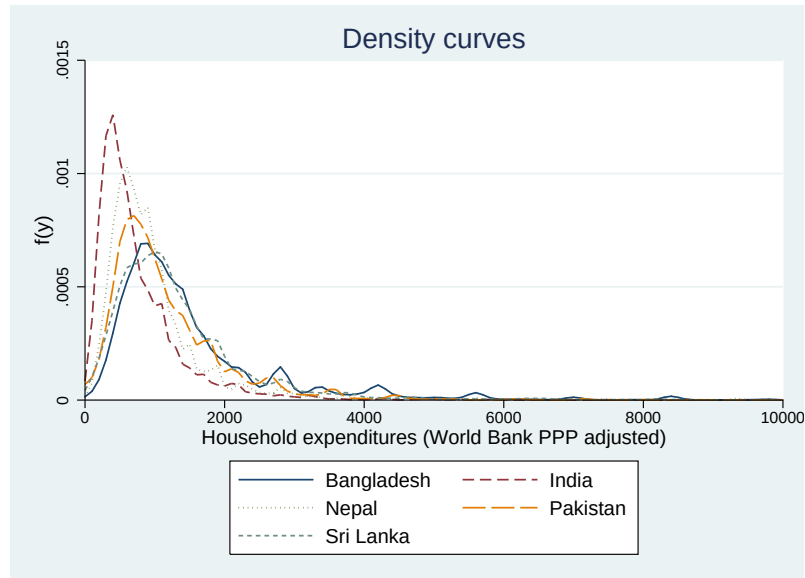


Figure 2.11: Density Curves for Total Household Expenditure: all countries - World Bank PPP adjusted

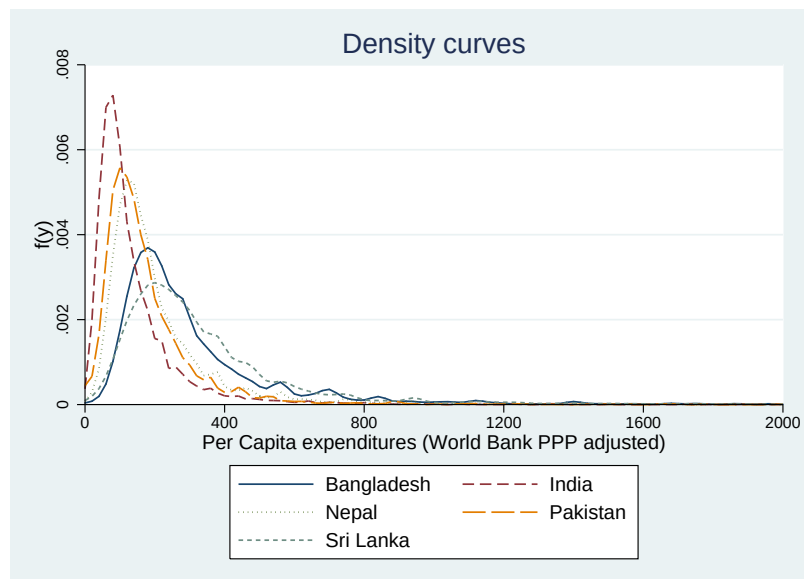


Figure 2.12: Density Curves for Per Capita Expenditure: all countries - World Bank PPP adjusted

Appendix 2.B.

2.B. Pairwise comparison of Lorenz and Generalized Lorenz curves

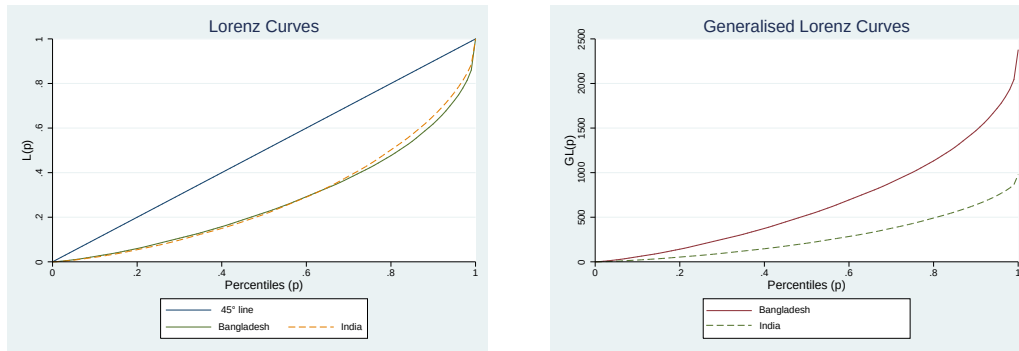


Figure 2.13: Lorenz vs. Generalized Lorenz Curve: Bangladesh & India

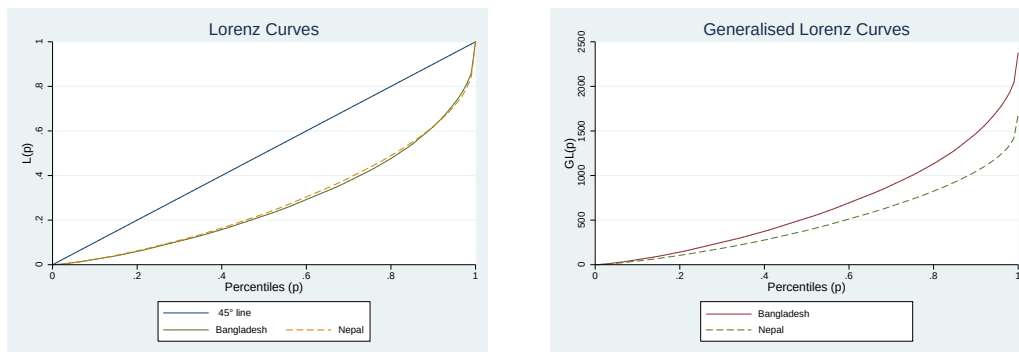


Figure 2.14: Lorenz vs. Generalized Lorenz Curve: Bangladesh & Nepal

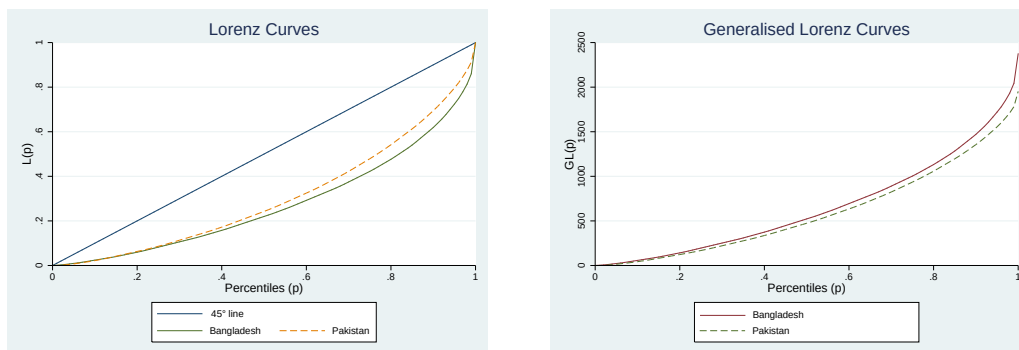


Figure 2.15: Lorenz vs. Generalized Lorenz Curve: Bangladesh & Pakistan

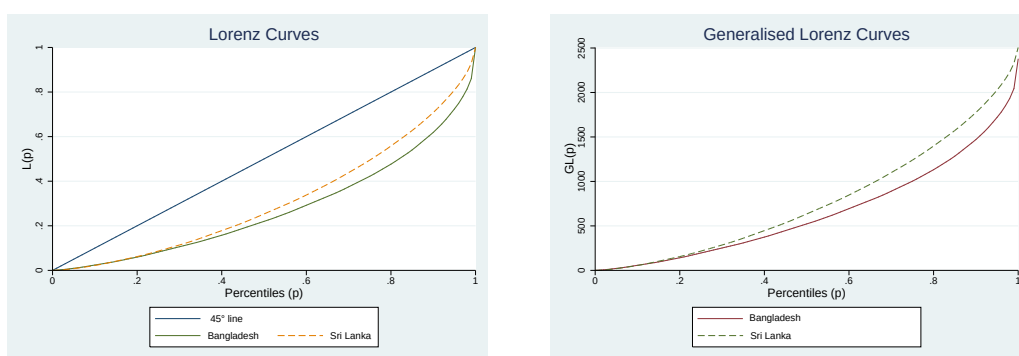


Figure 2.16: Lorenz vs. Generalized Lorenz Curve: Bangladesh & Sri Lanka

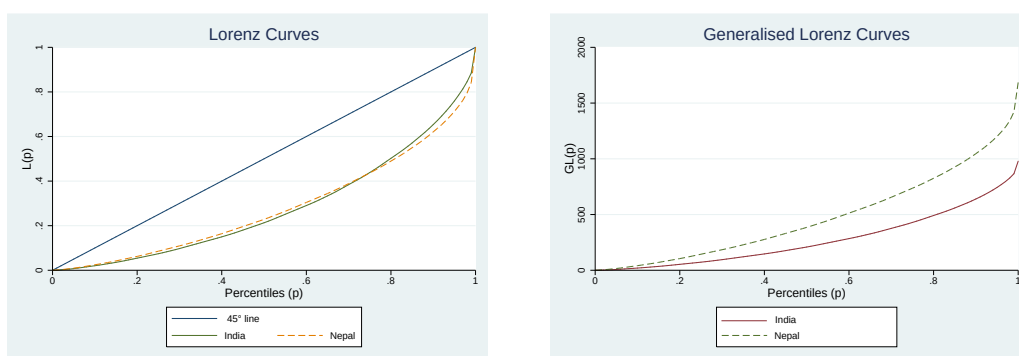


Figure 2.17: Lorenz vs. Generalized Lorenz Curve: India & Nepal

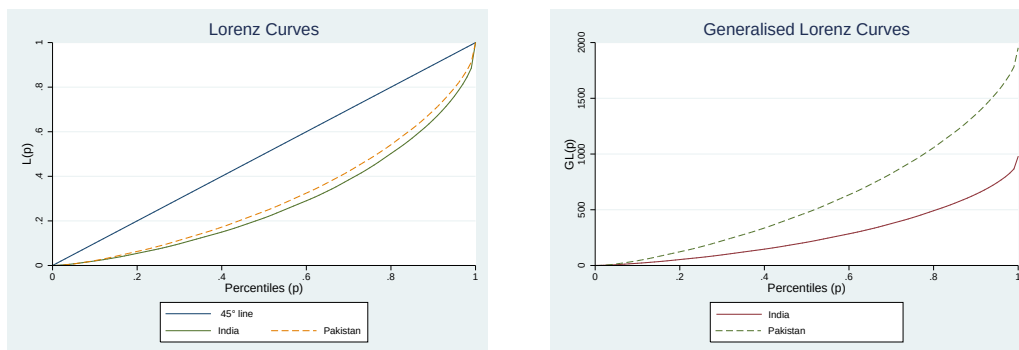


Figure 2.18: Lorenz vs. Generalized Lorenz Curve: India & Pakistan

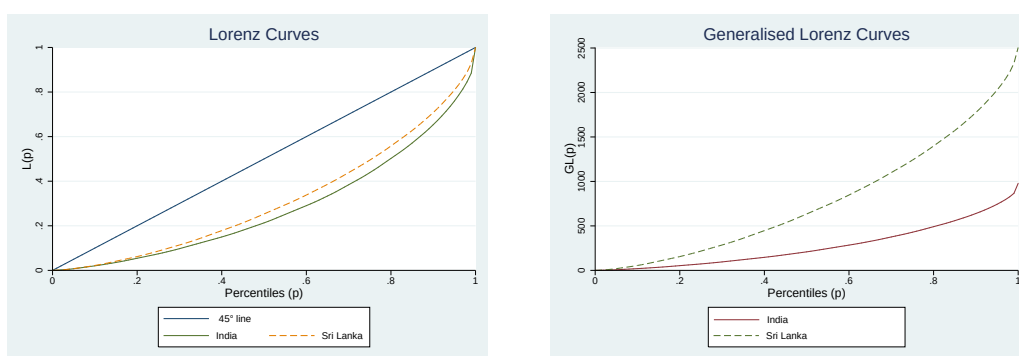


Figure 2.19: Lorenz vs. Generalized Lorenz Curve: India & Sri Lanka

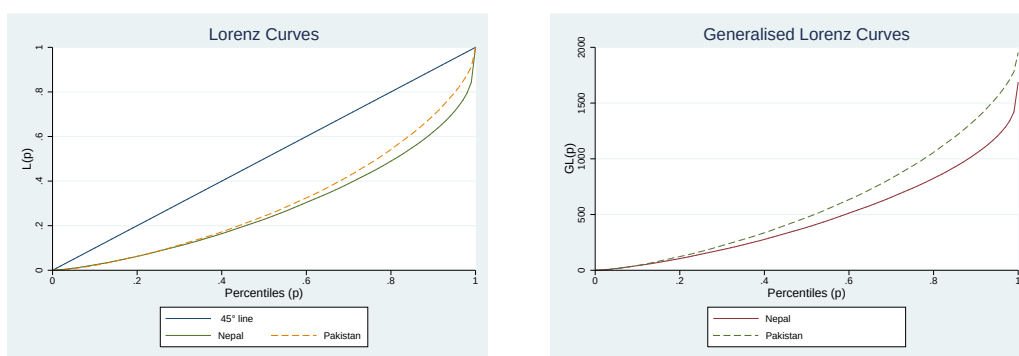


Figure 2.20: Lorenz vs. Generalized Lorenz Curve: Nepal & Pakistan

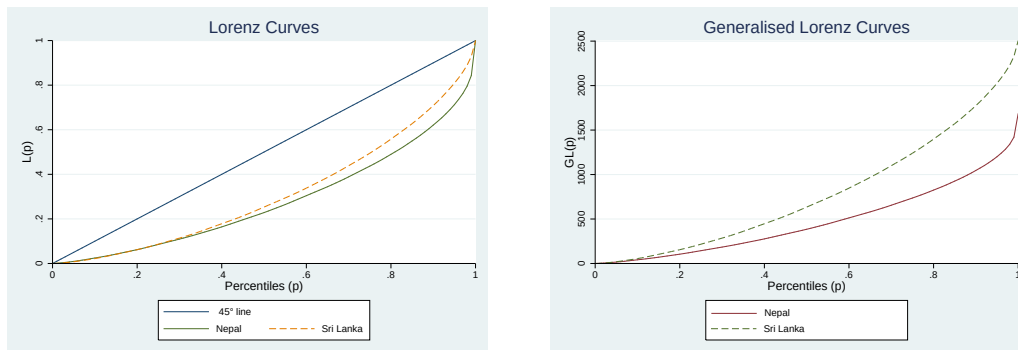


Figure 2.21: Lorenz vs. Generalized Lorenz Curve: Nepal & Sri Lanka

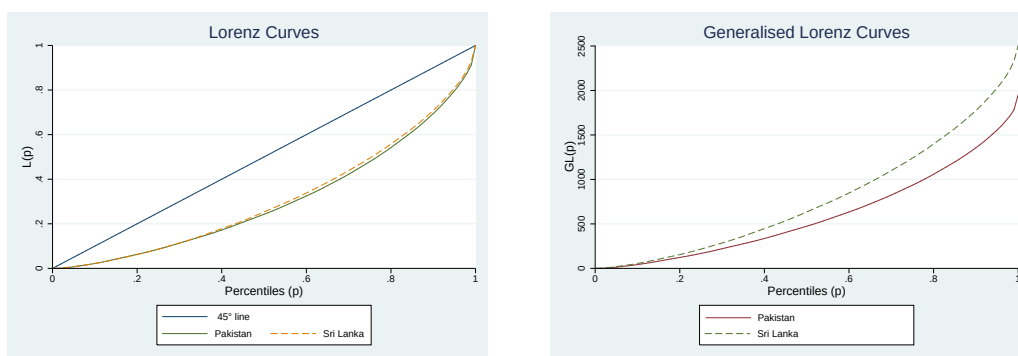
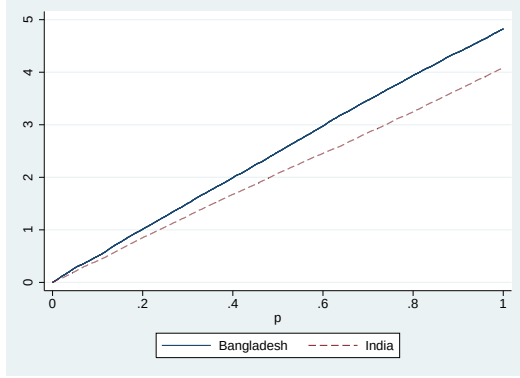


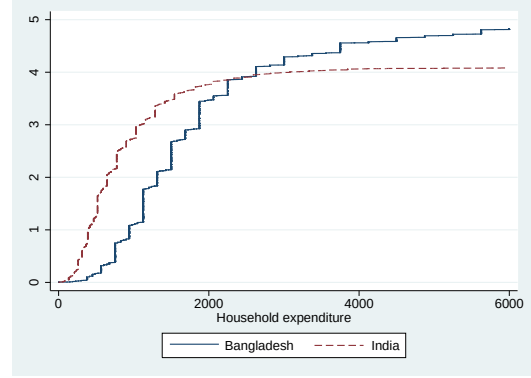
Figure 2.22: Lorenz vs. Generalized Lorenz Curve: Pakistan & Sri Lanka

Appendix 2.C.

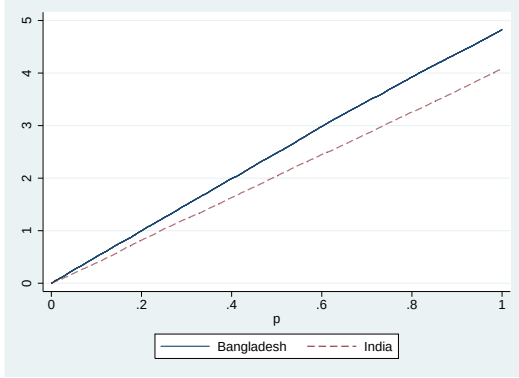
2.C. Pairwise comparison of Population Health Dominance curves



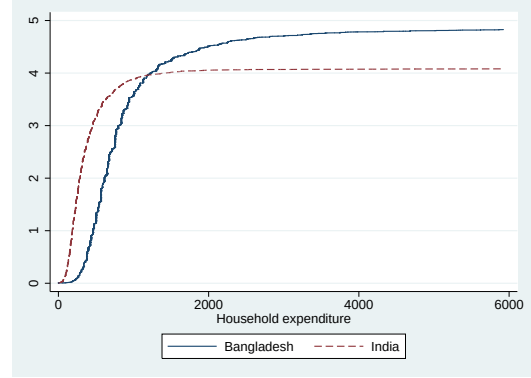
(a) using socioeconomic rank p , $\theta = 0$



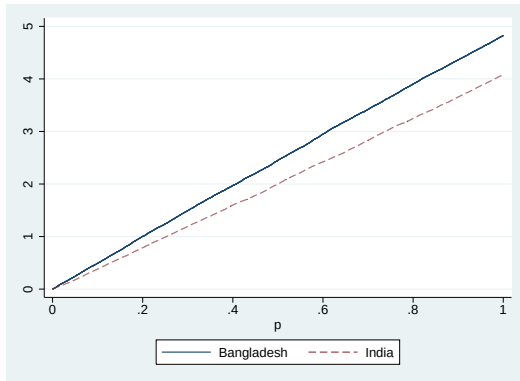
(b) using household expenditure y , $\theta = 0$



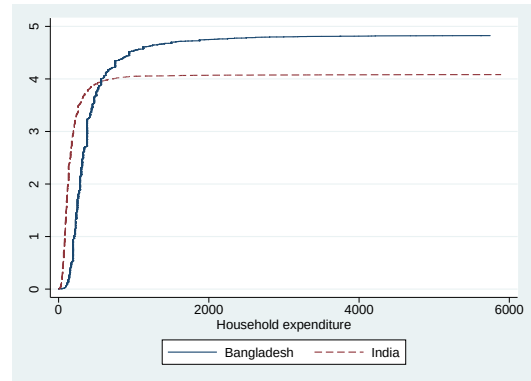
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

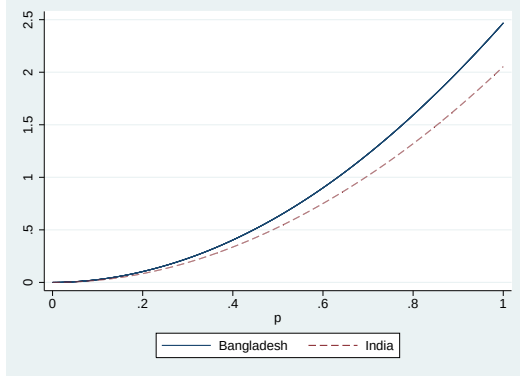


(e) using socioeconomic rank p , $\theta = 1$

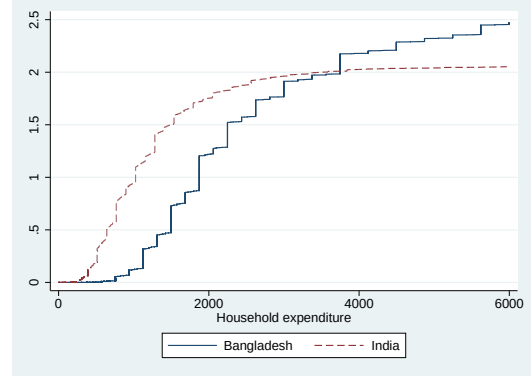


(f) using household expenditure y , $\theta = 1$

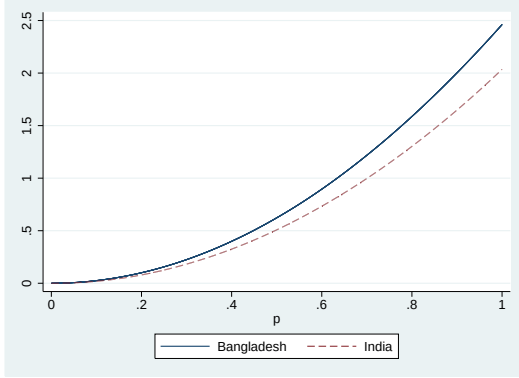
Figure 2.23: Second Order Population Health Dominance: Bangladesh & India



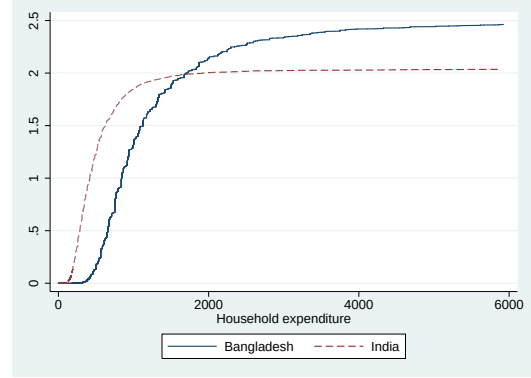
(a) using socioeconomic rank p , $\theta = 0$



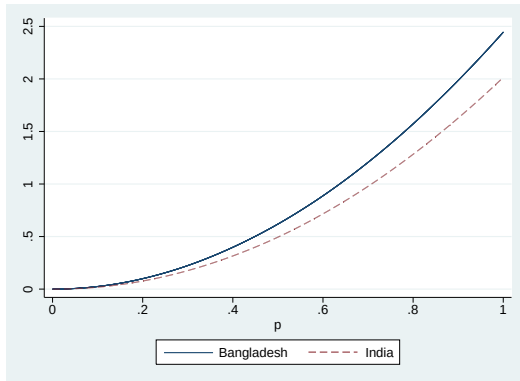
(b) using household expenditure y , $\theta = 0$



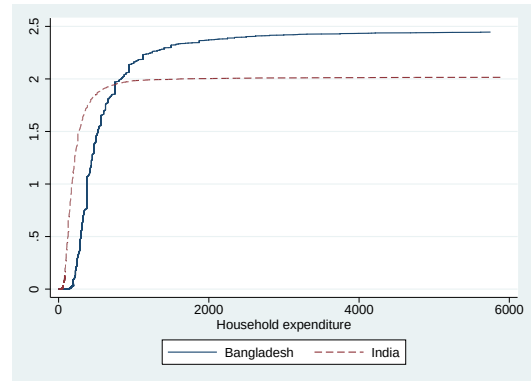
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

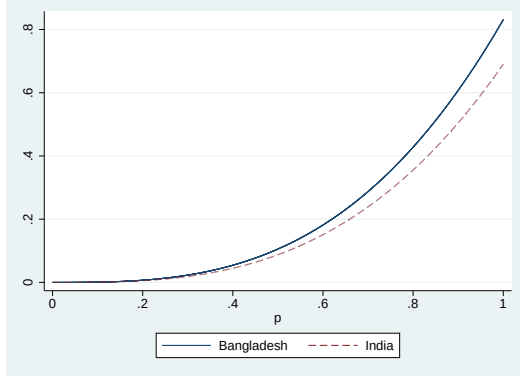


(e) using socioeconomic rank p , $\theta = 1$

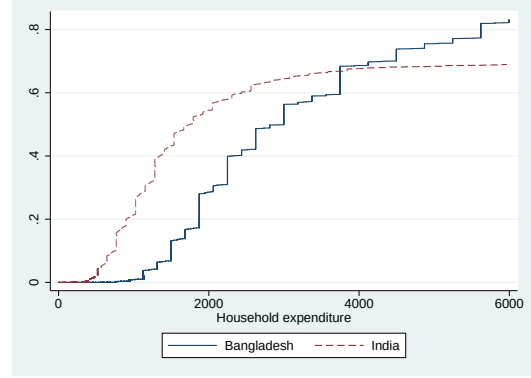


(f) using household expenditure y , $\theta = 1$

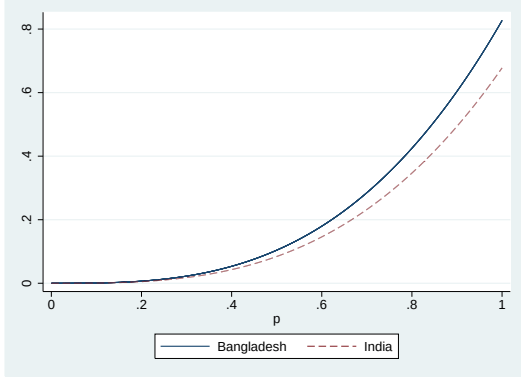
Figure 2.24: Third Order Population Health Dominance: Bangladesh & India



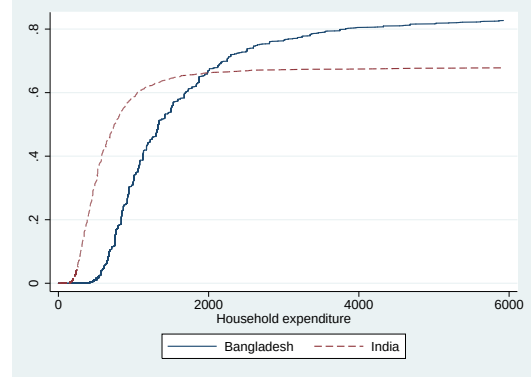
(a) using socioeconomic rank p , $\theta = 0$



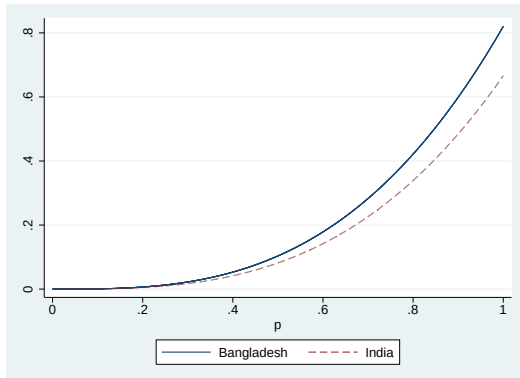
(b) using household expenditure y , $\theta = 0$



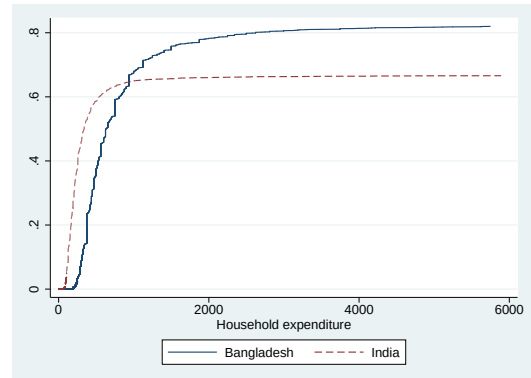
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

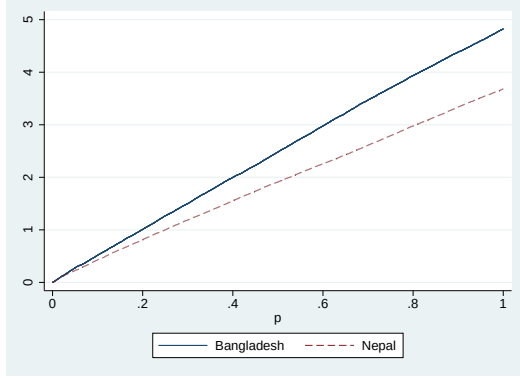


(e) using socioeconomic rank p , $\theta = 1$

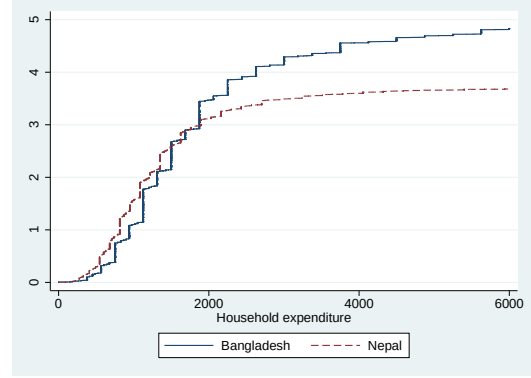


(f) using household expenditure y , $\theta = 1$

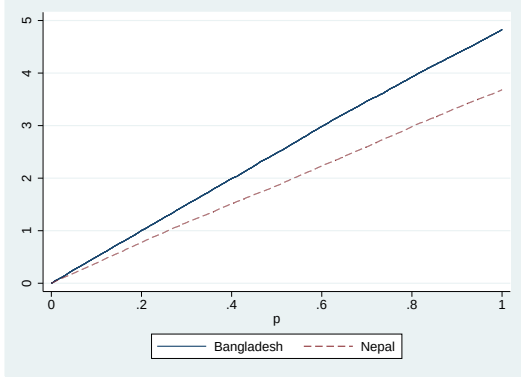
Figure 2.25: Fourth Order Population Health Dominance: Bangladesh & India



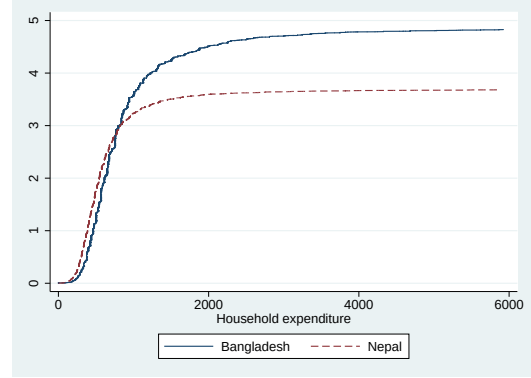
(a) using socioeconomic rank p , $\theta = 0$



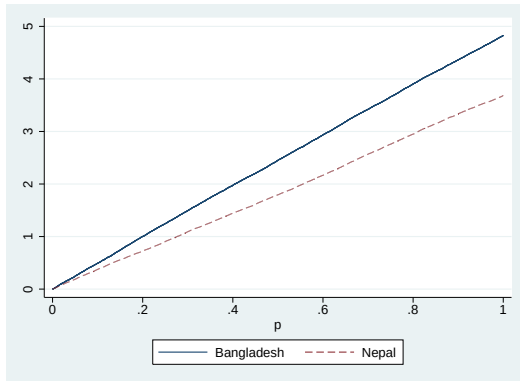
(b) using household expenditure y , $\theta = 0$



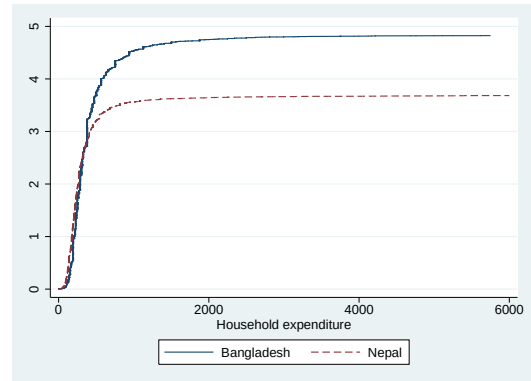
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

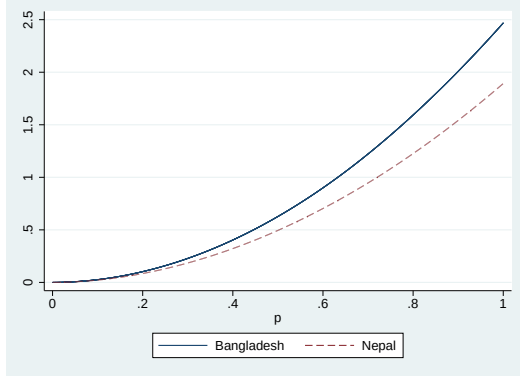


(e) using socioeconomic rank p , $\theta = 1$

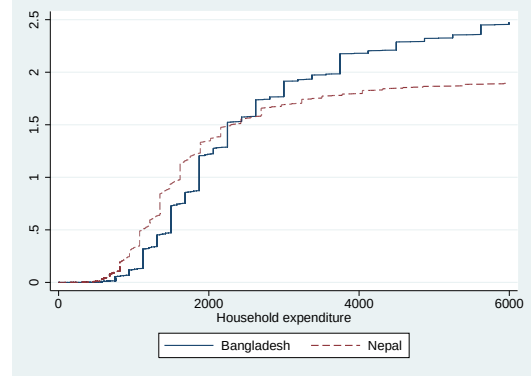


(f) using household expenditure y , $\theta = 1$

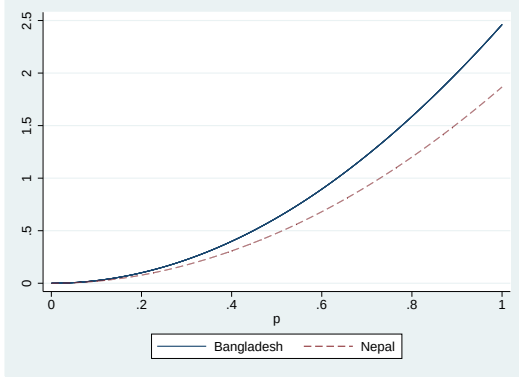
Figure 2.26: Second Order Population Health Dominance: Bangladesh & Nepal



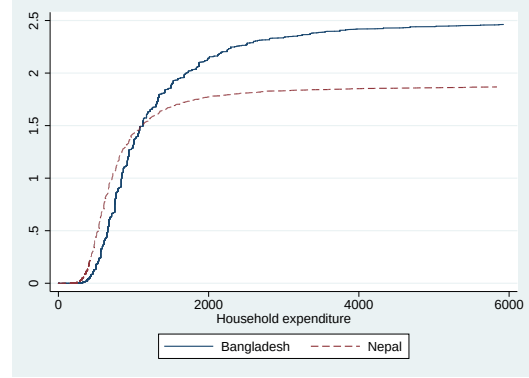
(a) using socioeconomic rank p , $\theta = 0$



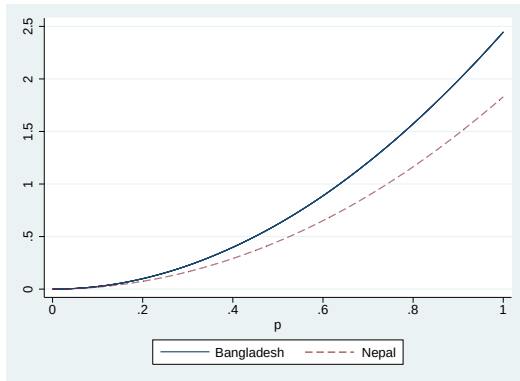
(b) using household expenditure y , $\theta = 0$



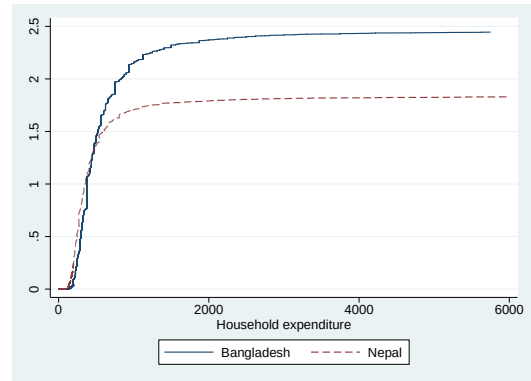
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

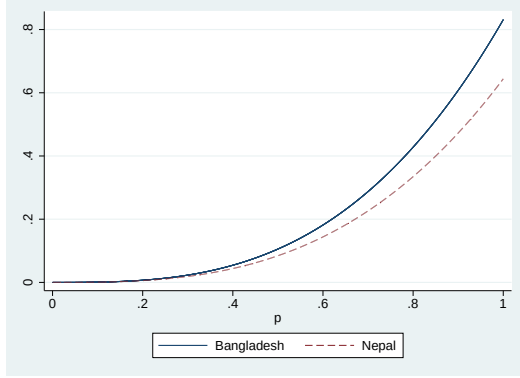


(e) using socioeconomic rank p , $\theta = 1$

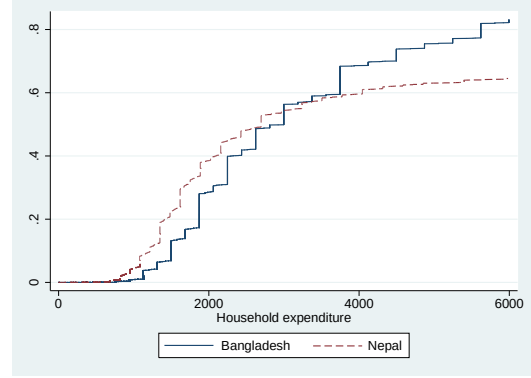


(f) using household expenditure y , $\theta = 1$

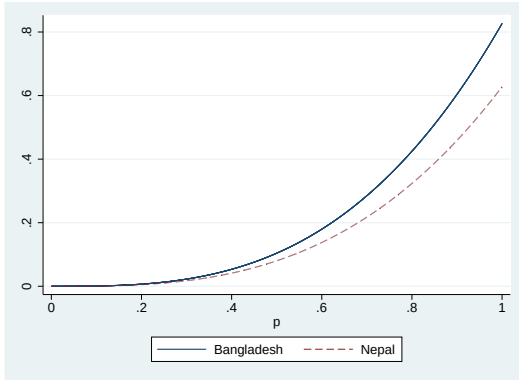
Figure 2.27: Third Order Population Health Dominance: Bangladesh & Nepal



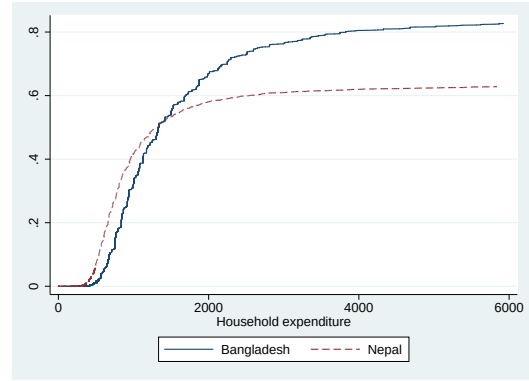
(a) using socioeconomic rank p , $\theta = 0$



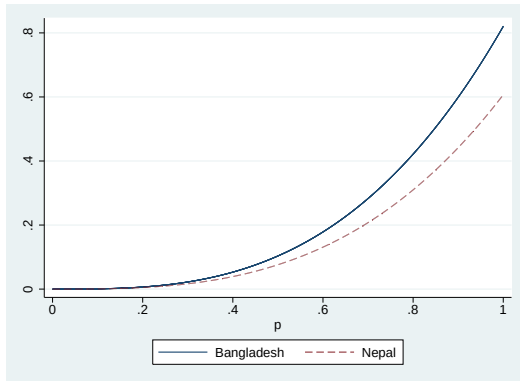
(b) using household expenditure y , $\theta = 0$



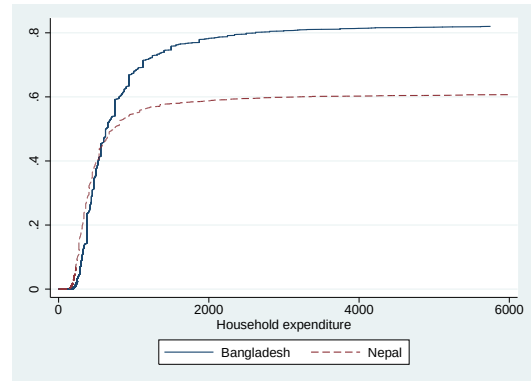
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

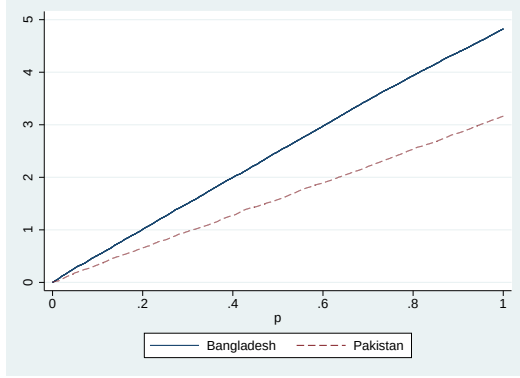


(e) using socioeconomic rank p , $\theta = 1$

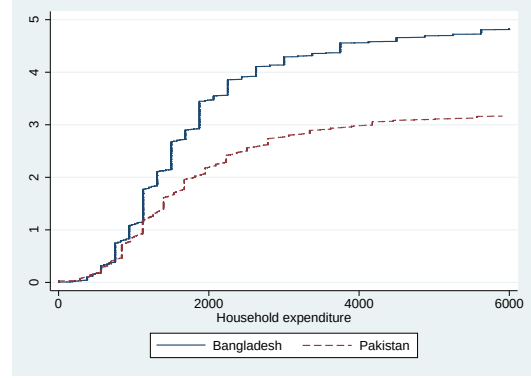


(f) using household expenditure y , $\theta = 1$

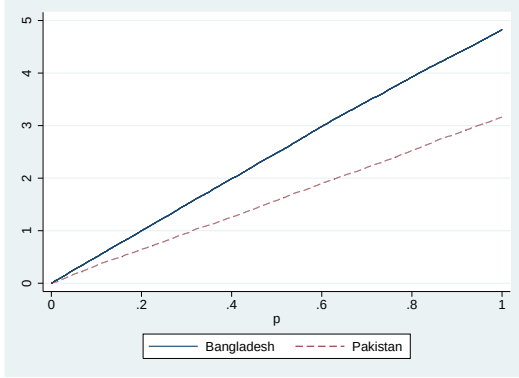
Figure 2.28: Fourth Order Population Health Dominance: Bangladesh & Nepal



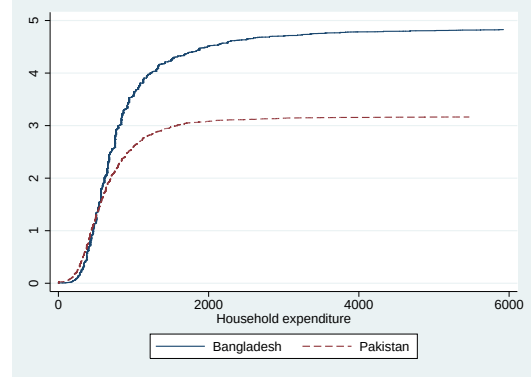
(a) using socioeconomic rank p , $\theta = 0$



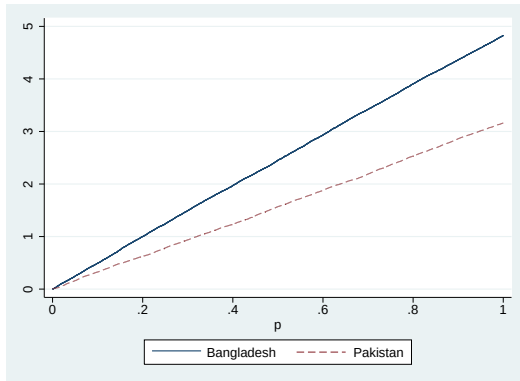
(b) using household expenditure y , $\theta = 0$



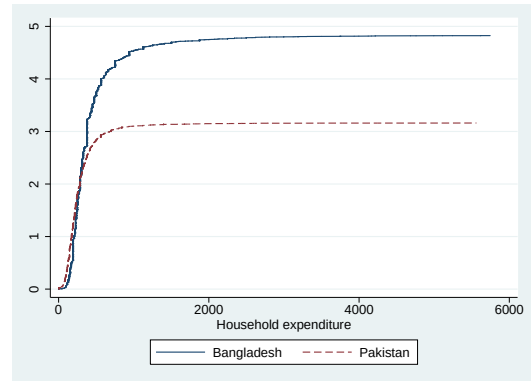
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

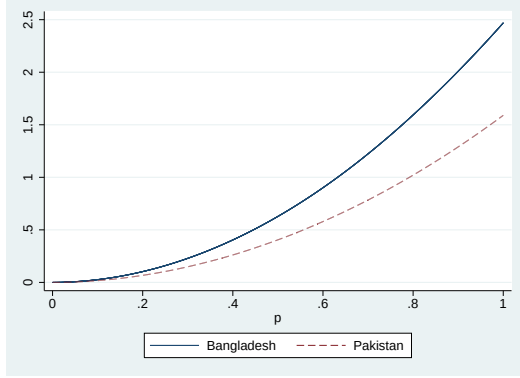


(e) using socioeconomic rank p , $\theta = 1$

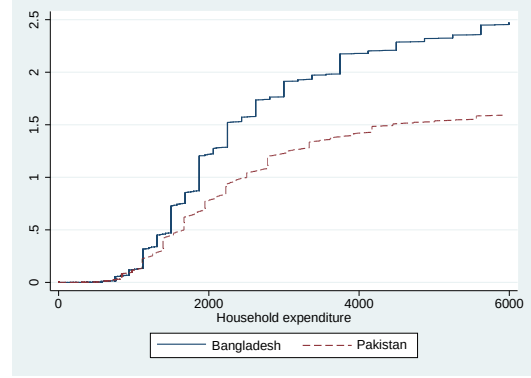


(f) using household expenditure y , $\theta = 1$

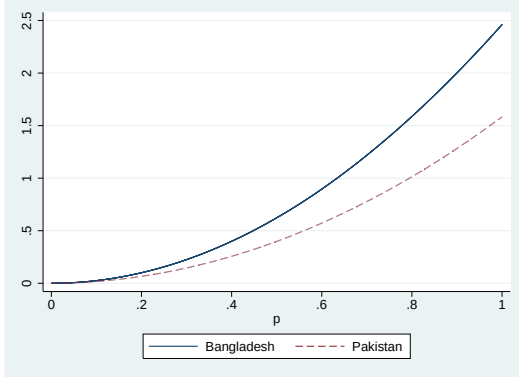
Figure 2.29: Second Order Population Health Dominance: Bangladesh & Pakistan



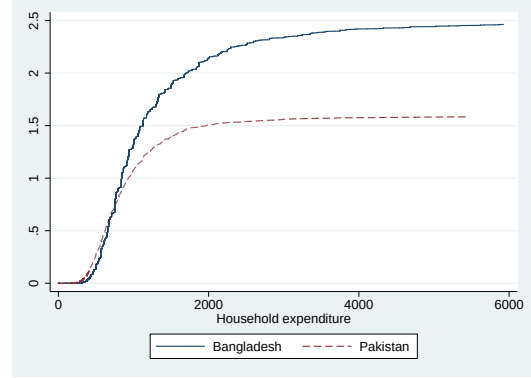
(a) using socioeconomic rank p , $\theta = 0$



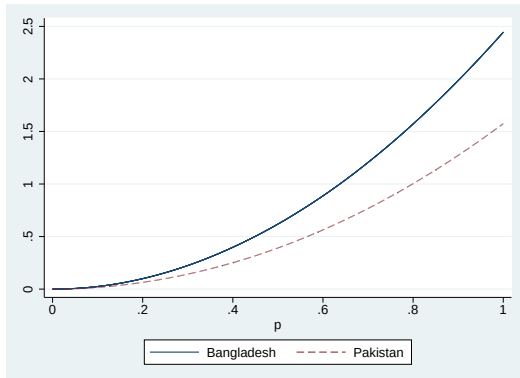
(b) using household expenditure y , $\theta = 0$



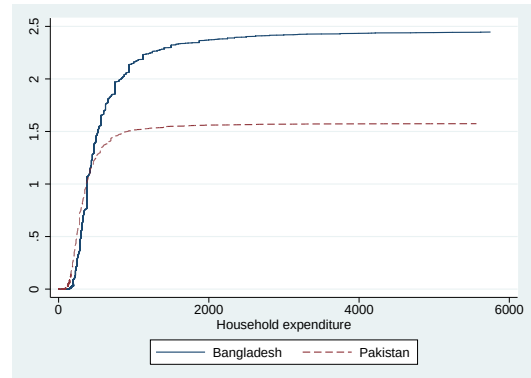
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

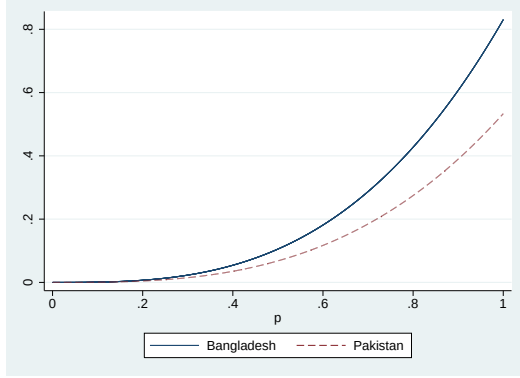


(e) using socioeconomic rank p , $\theta = 1$

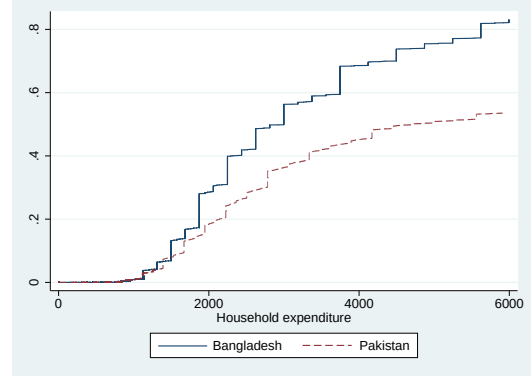


(f) using household expenditure y , $\theta = 1$

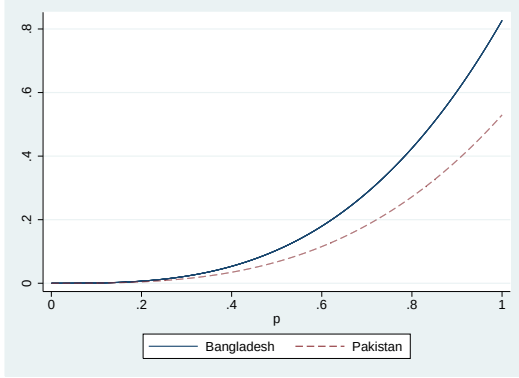
Figure 2.30: Third Order Population Health Dominance: Bangladesh & Pakistan



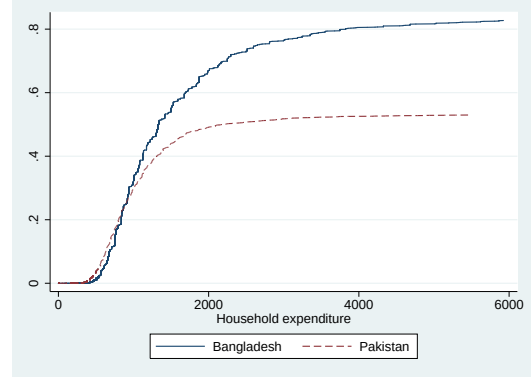
(a) using socioeconomic rank p , $\theta = 0$



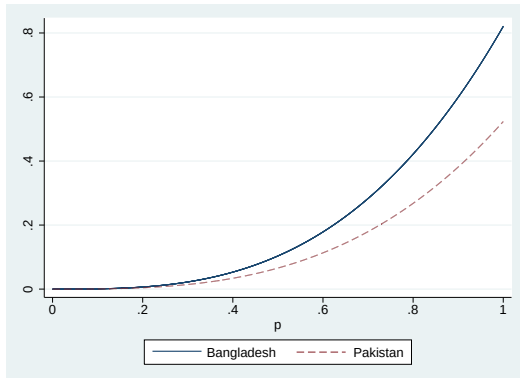
(b) using household expenditure y , $\theta = 0$



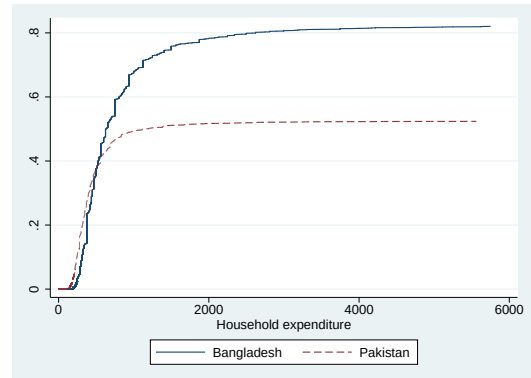
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

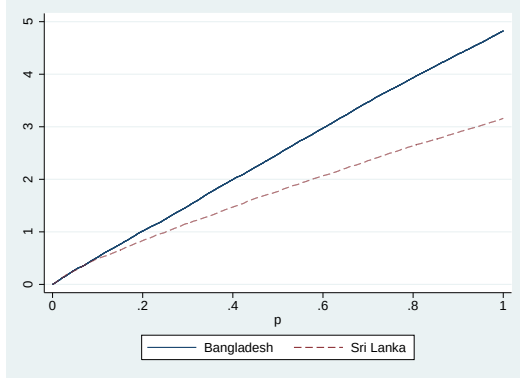


(e) using socioeconomic rank p , $\theta = 1$

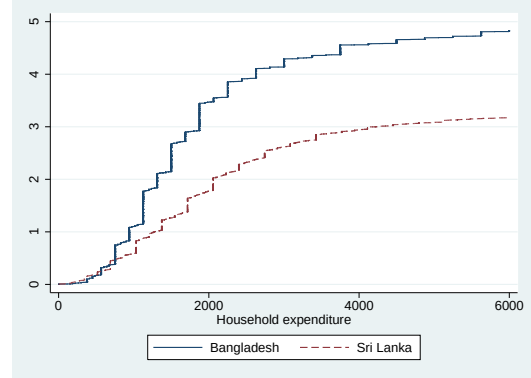


(f) using household expenditure y , $\theta = 1$

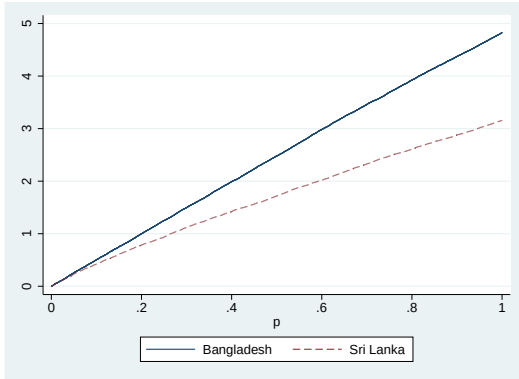
Figure 2.31: Fourth Order Population Health Dominance: Bangladesh & Pakistan



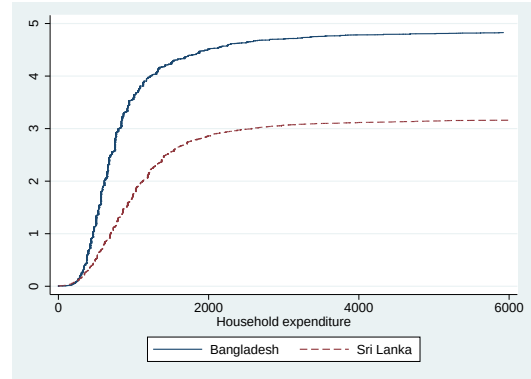
(a) using socioeconomic rank p , $\theta = 0$



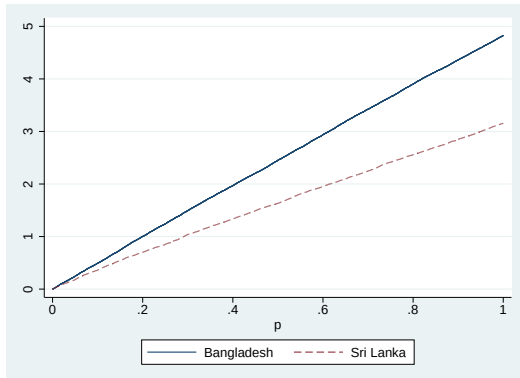
(b) using household expenditure y , $\theta = 0$



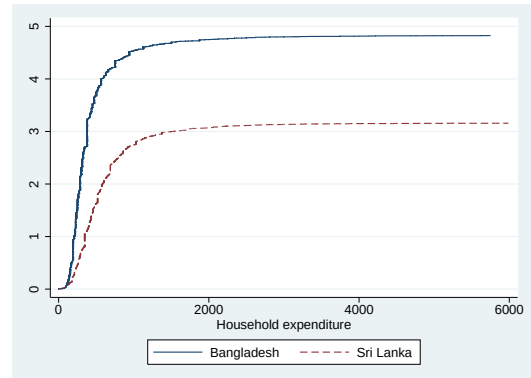
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

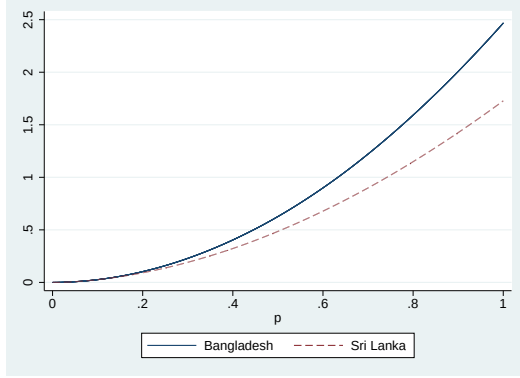


(e) using socioeconomic rank p , $\theta = 1$

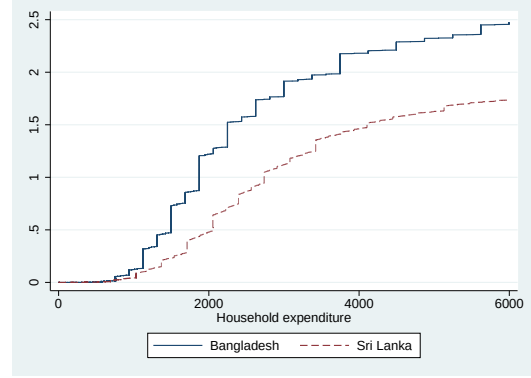


(f) using household expenditure y , $\theta = 1$

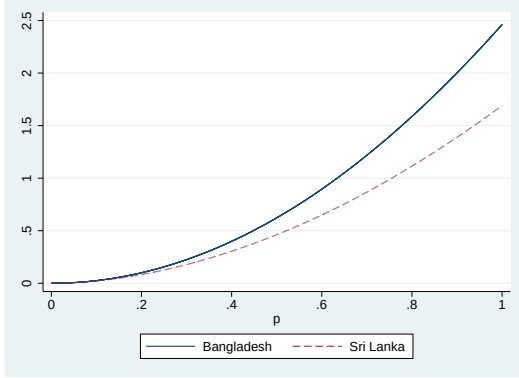
Figure 2.32: Second Order Population Health Dominance: Bangladesh & Sri Lanka



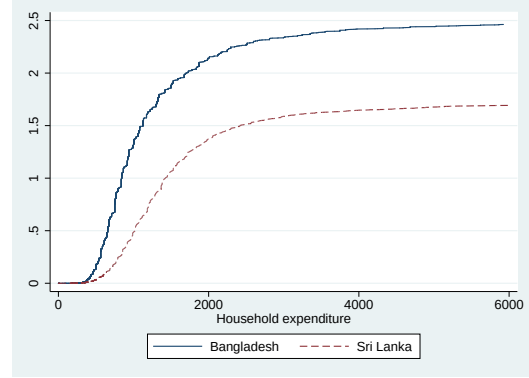
(a) using socioeconomic rank p , $\theta = 0$



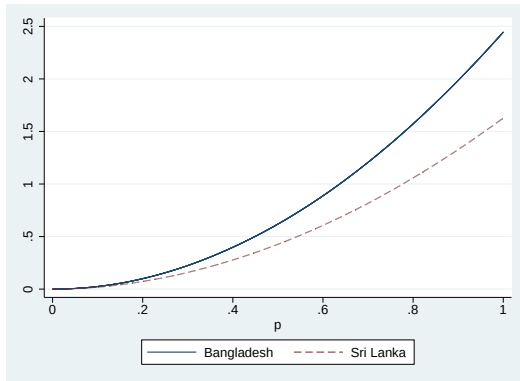
(b) using household expenditure y , $\theta = 0$



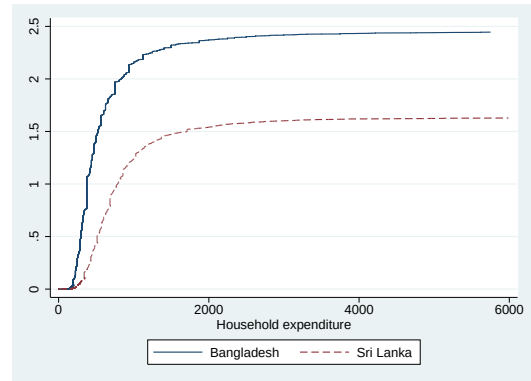
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

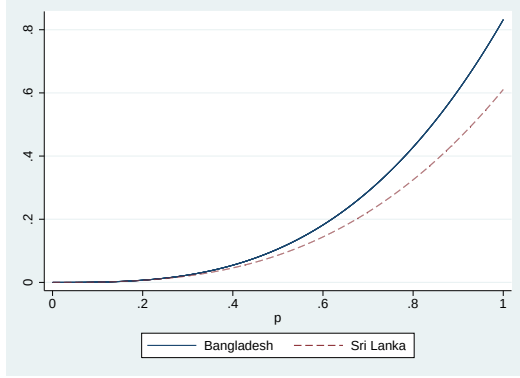


(e) using socioeconomic rank p , $\theta = 1$

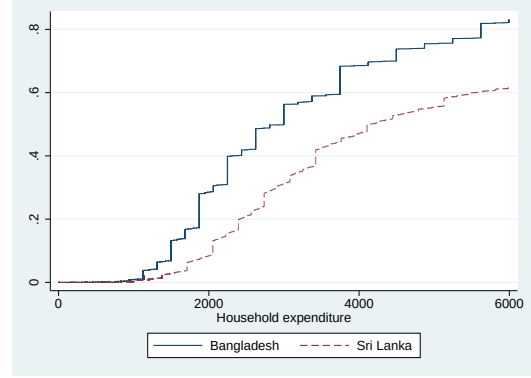


(f) using household expenditure y , $\theta = 1$

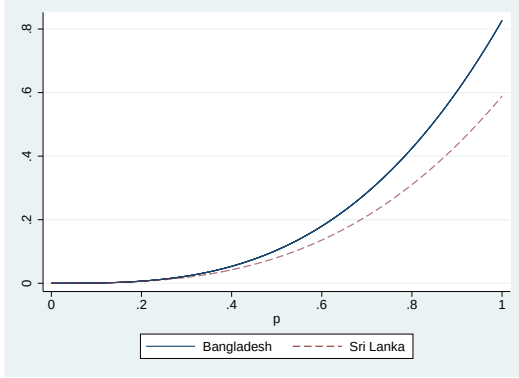
Figure 2.33: Third Order Population Health Dominance: Bangladesh & Sri Lanka



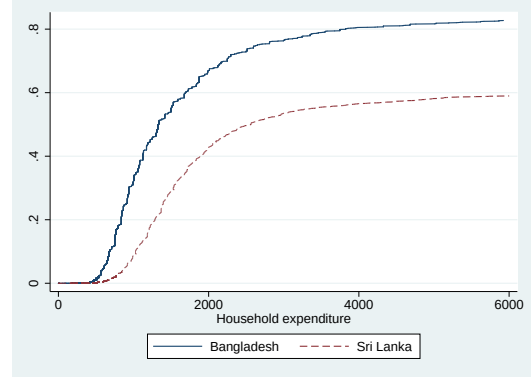
(a) using socioeconomic rank p , $\theta = 0$



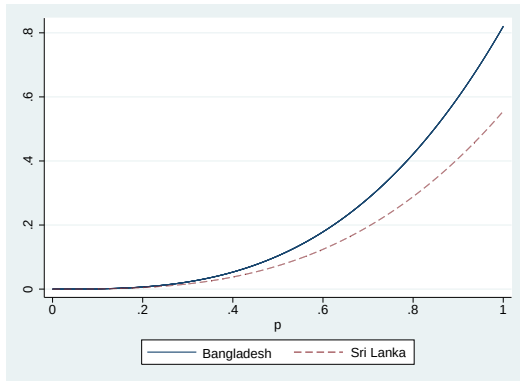
(b) using household expenditure y , $\theta = 0$



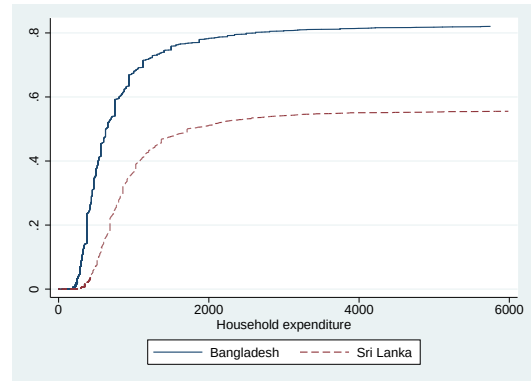
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

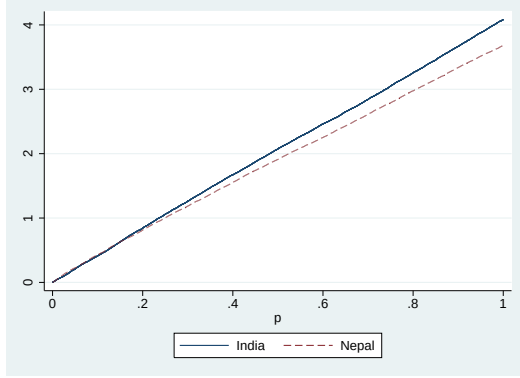


(e) using socioeconomic rank p , $\theta = 1$

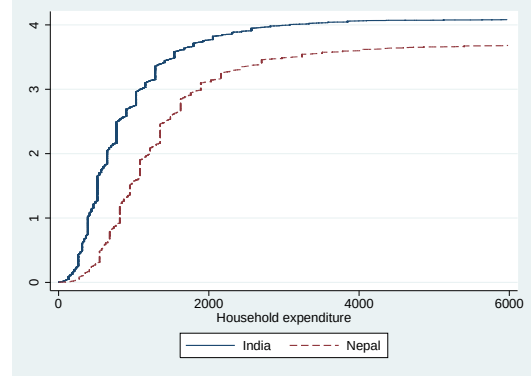


(f) using household expenditure y , $\theta = 1$

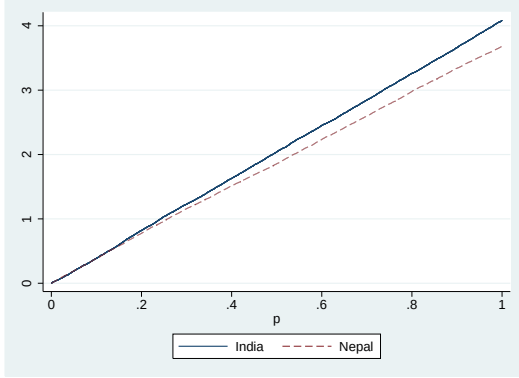
Figure 2.34: Fourth Order Population Health Dominance: Bangladesh & Sri Lanka



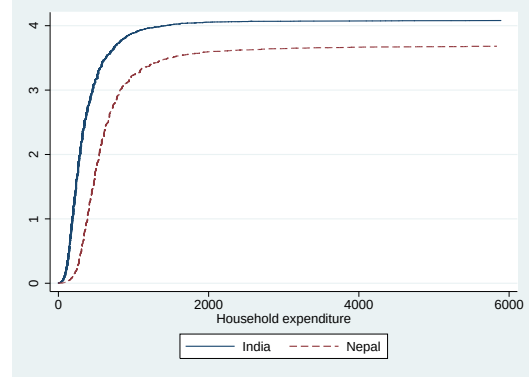
(a) using socioeconomic rank p , $\theta = 0$



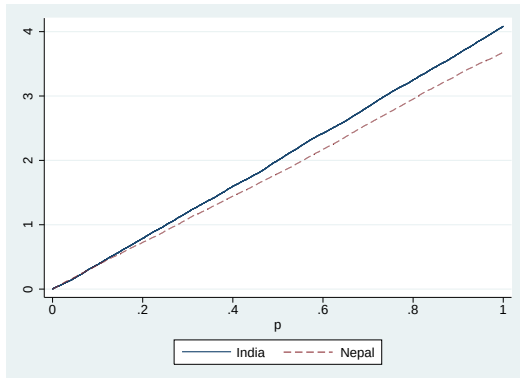
(b) using household expenditure y , $\theta = 0$



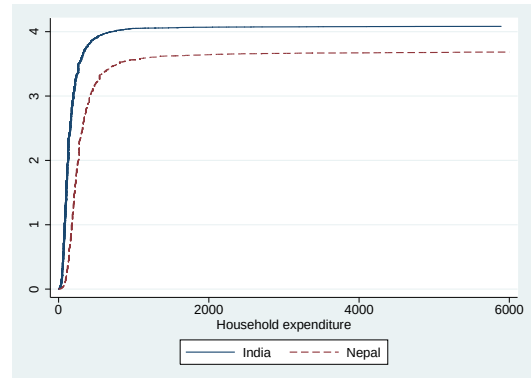
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

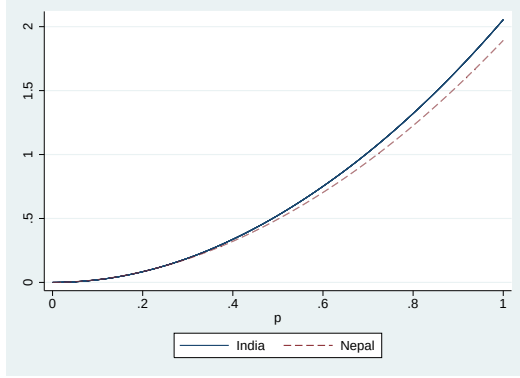


(e) using socioeconomic rank p , $\theta = 1$

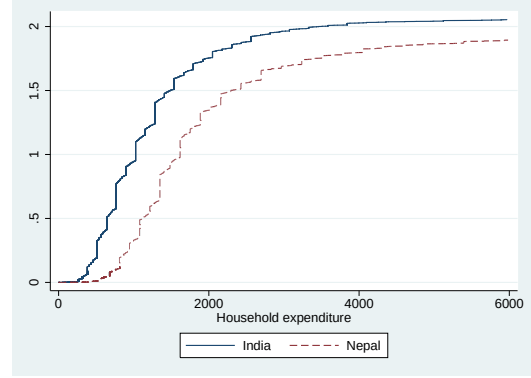


(f) using household expenditure y , $\theta = 1$

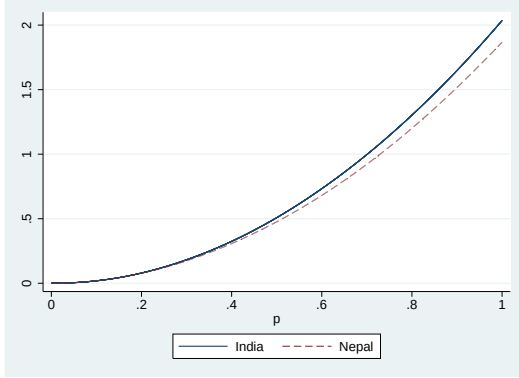
Figure 2.35: Second Order Population Health Dominance: India & Nepal



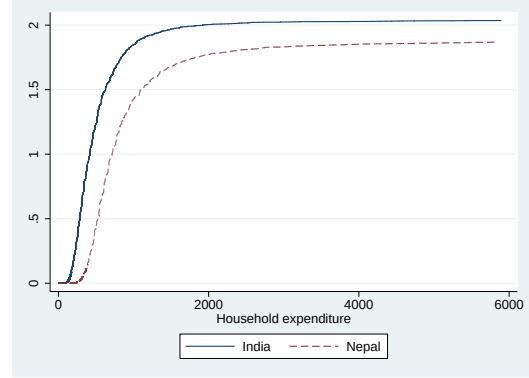
(a) using socioeconomic rank p , $\theta = 0$



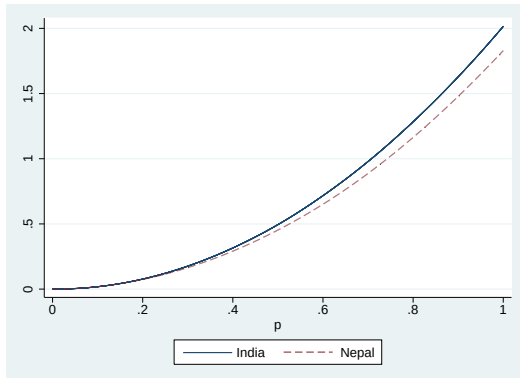
(b) using household expenditure y , $\theta = 0$



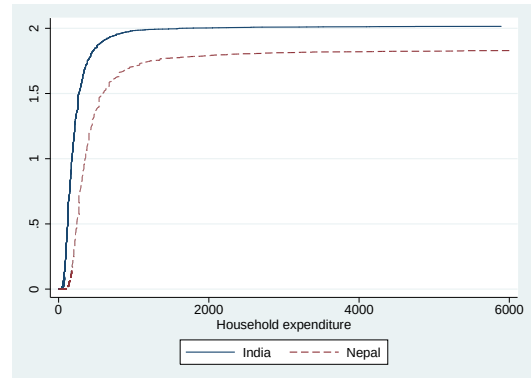
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

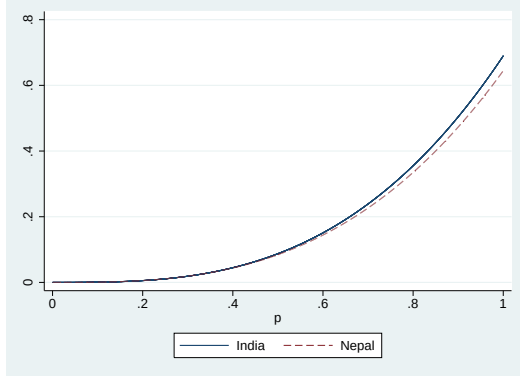


(e) using socioeconomic rank p , $\theta = 1$

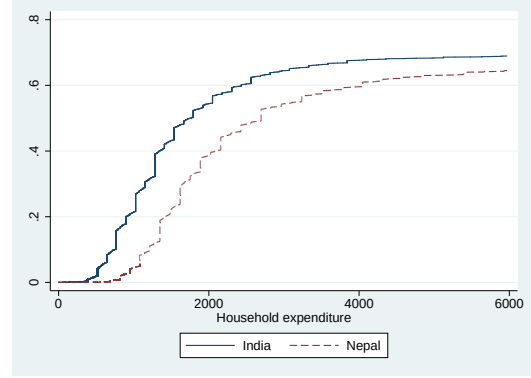


(f) using household expenditure y , $\theta = 1$

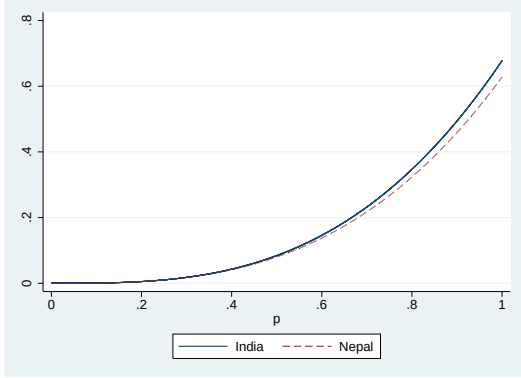
Figure 2.36: Third Order Population Health Dominance: India & Nepal



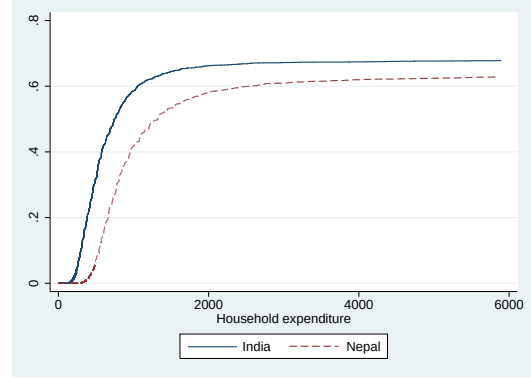
(a) using socioeconomic rank p , $\theta = 0$



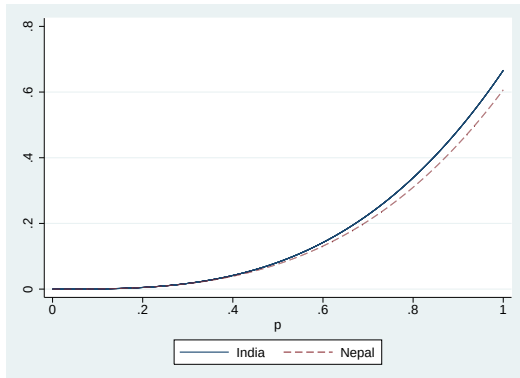
(b) using household expenditure y , $\theta = 0$



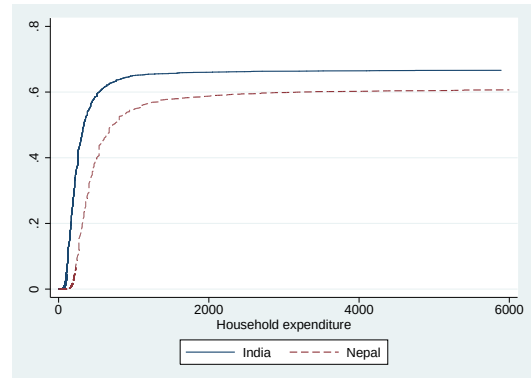
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

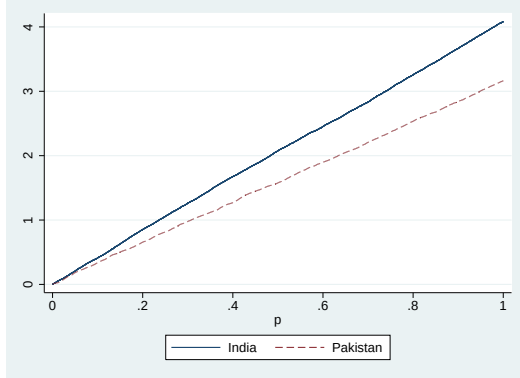


(e) using socioeconomic rank p , $\theta = 1$

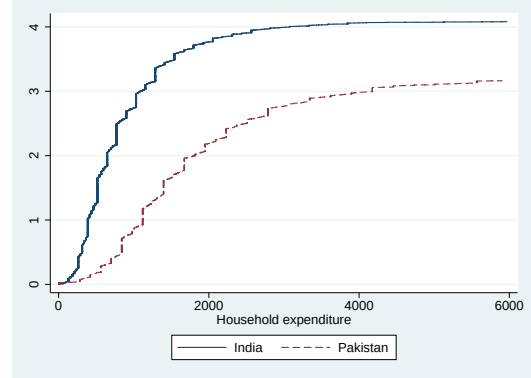


(f) using household expenditure y , $\theta = 1$

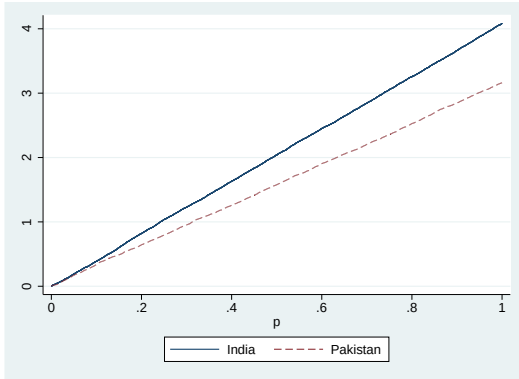
Figure 2.37: Fourth Order Population Health Dominance: India & Nepal



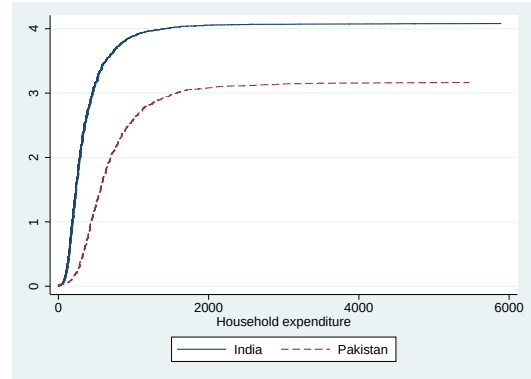
(a) using socioeconomic rank p , $\theta = 0$



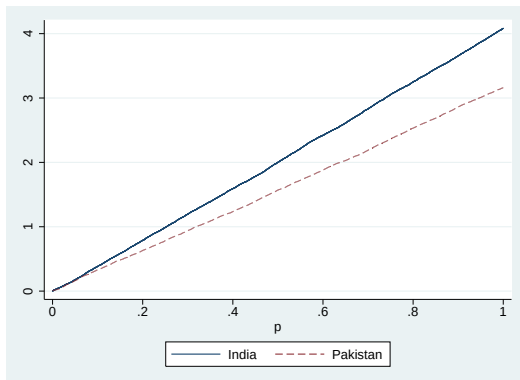
(b) using household expenditure y , $\theta = 0$



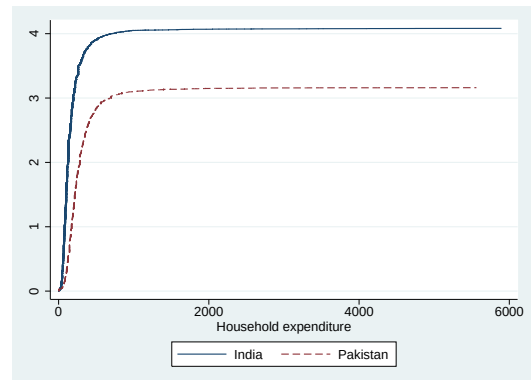
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

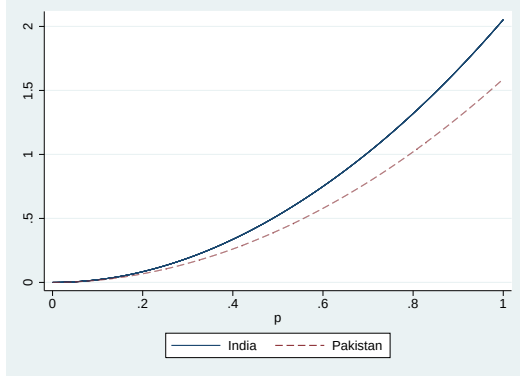


(e) using socioeconomic rank p , $\theta = 1$

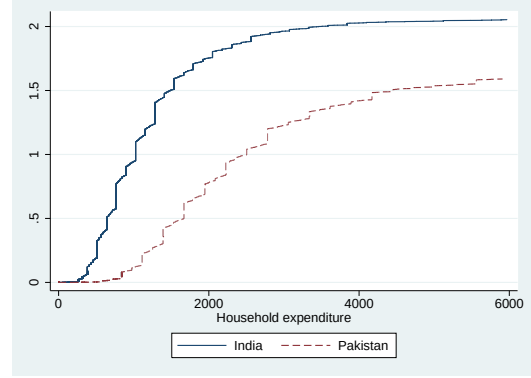


(f) using household expenditure y , $\theta = 1$

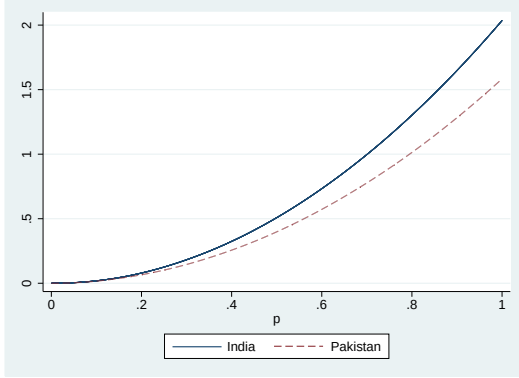
Figure 2.38: Second Order Population Health Dominance: India & Pakistan



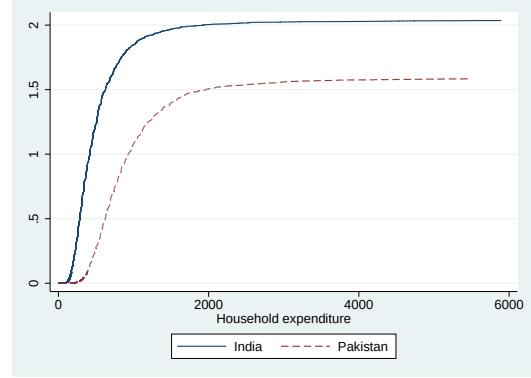
(a) using socioeconomic rank p , $\theta = 0$



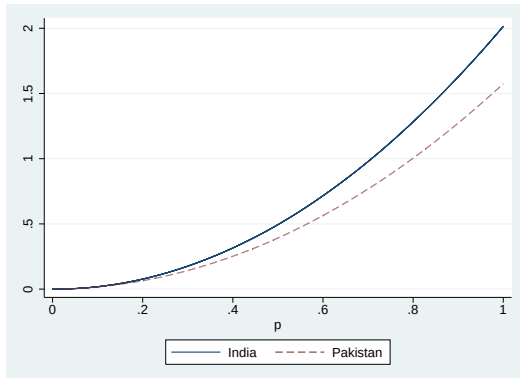
(b) using household expenditure y , $\theta = 0$



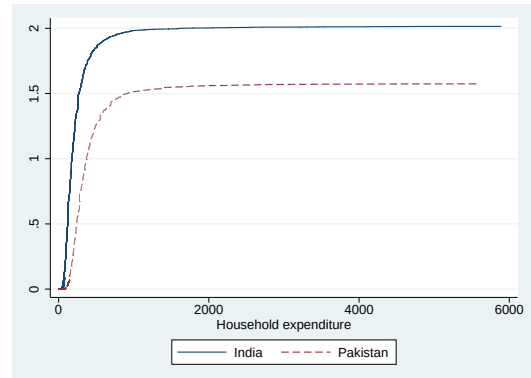
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

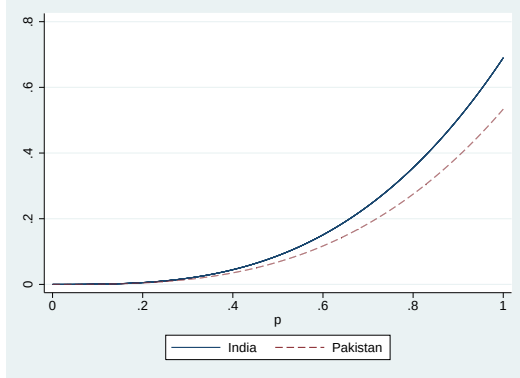


(e) using socioeconomic rank p , $\theta = 1$

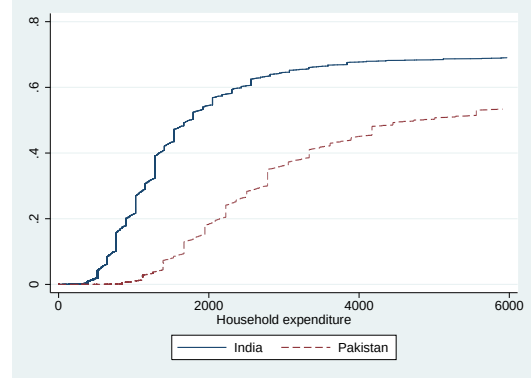


(f) using household expenditure y , $\theta = 1$

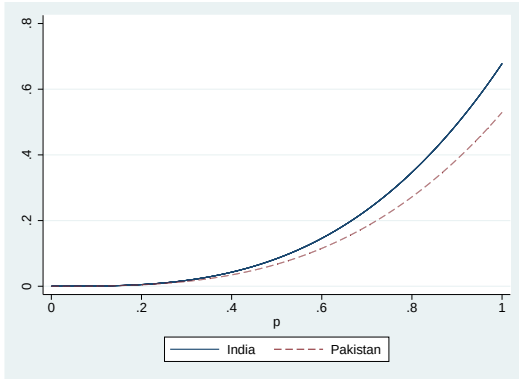
Figure 2.39: Third Order Population Health Dominance: India & Pakistan



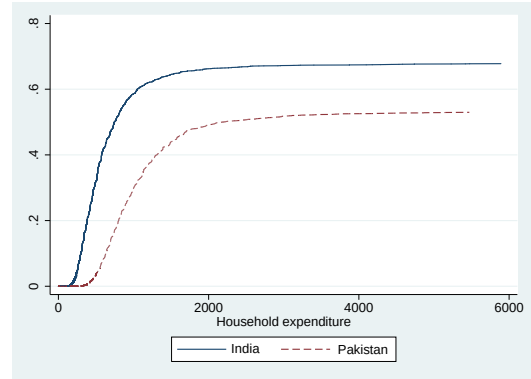
(a) using socioeconomic rank p , $\theta = 0$



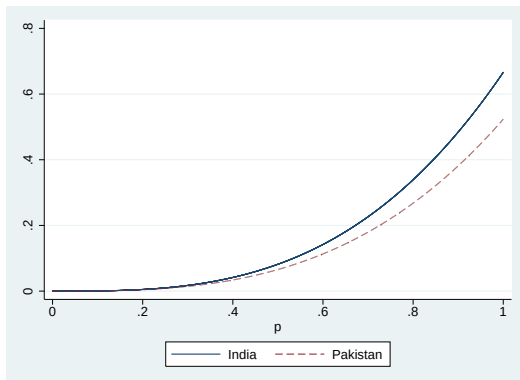
(b) using household expenditure y , $\theta = 0$



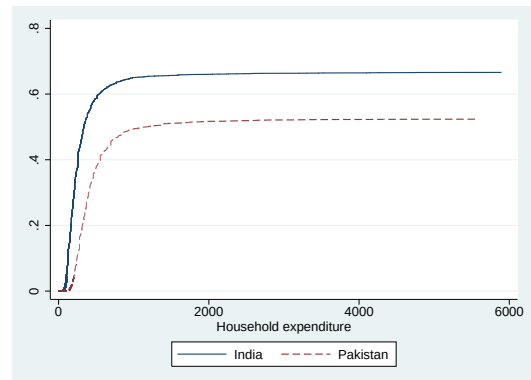
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

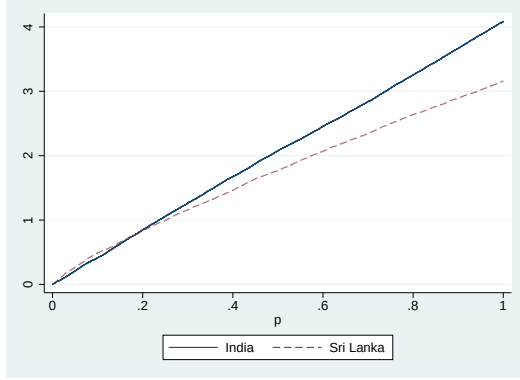


(e) using socioeconomic rank p , $\theta = 1$

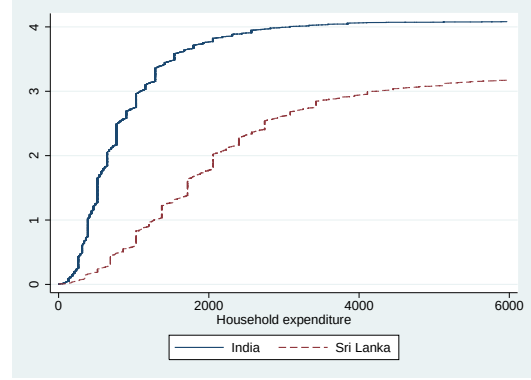


(f) using household expenditure y , $\theta = 1$

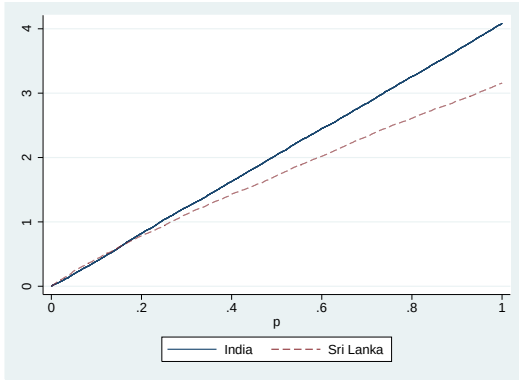
Figure 2.40: Fourth Order Population Health Dominance: India & Pakistan



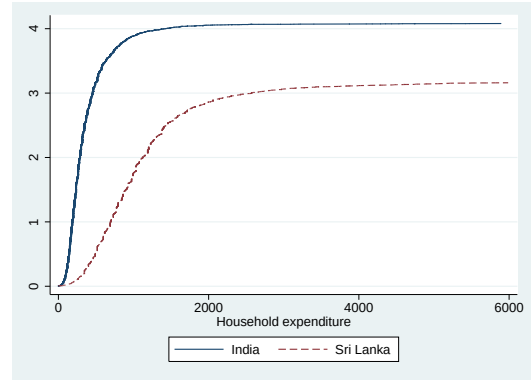
(a) using socioeconomic rank p , $\theta = 0$



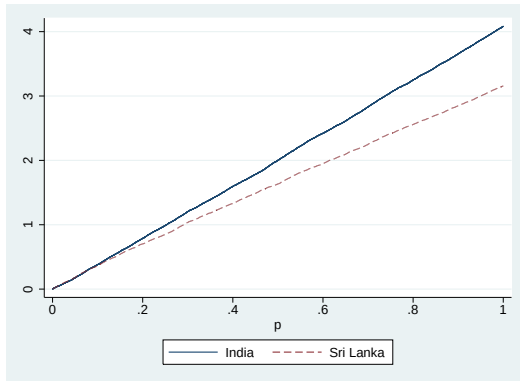
(b) using household expenditure y , $\theta = 0$



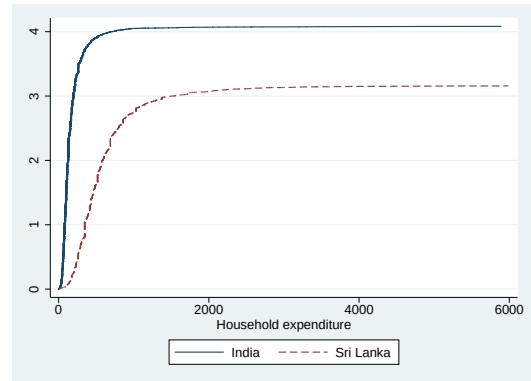
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

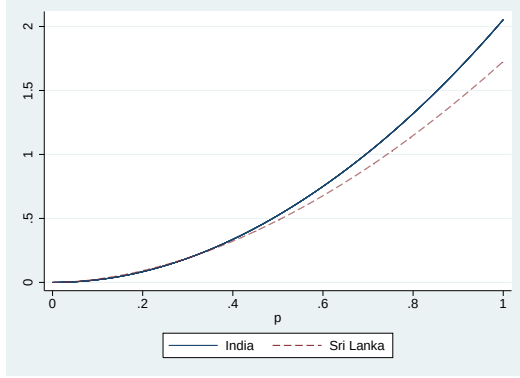


(e) using socioeconomic rank p , $\theta = 1$

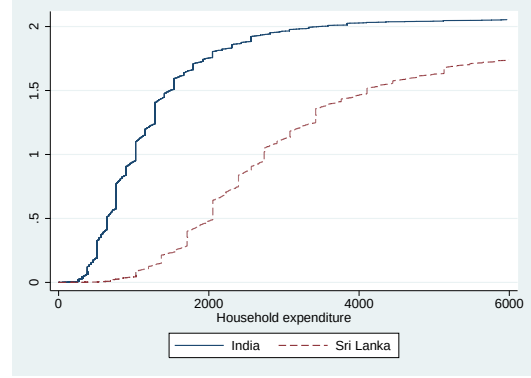


(f) using household expenditure y , $\theta = 1$

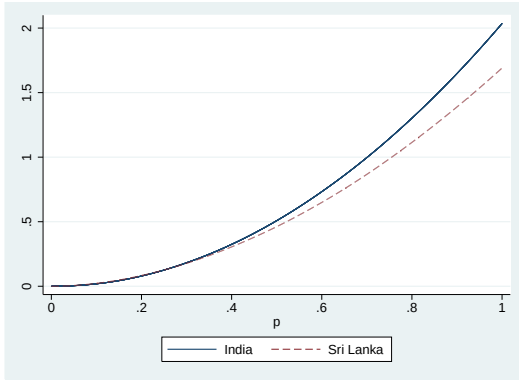
Figure 2.41: Second Order Population Health Dominance: India & Sri Lanka



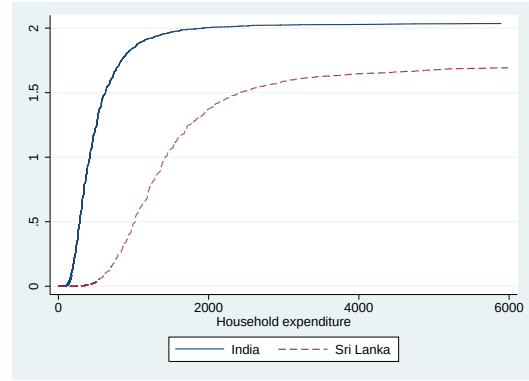
(a) using socioeconomic rank p , $\theta = 0$



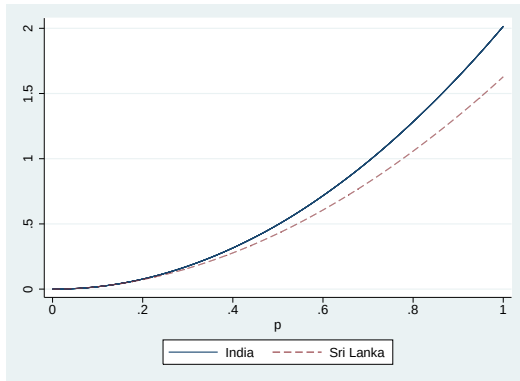
(b) using household expenditure y , $\theta = 0$



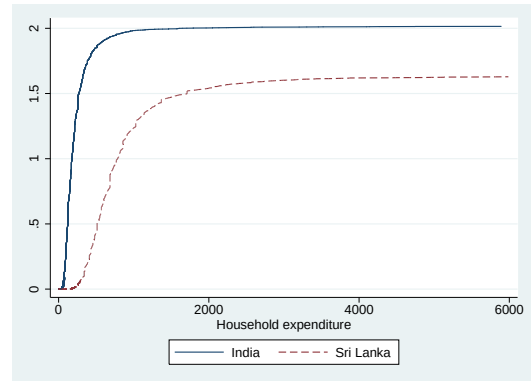
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

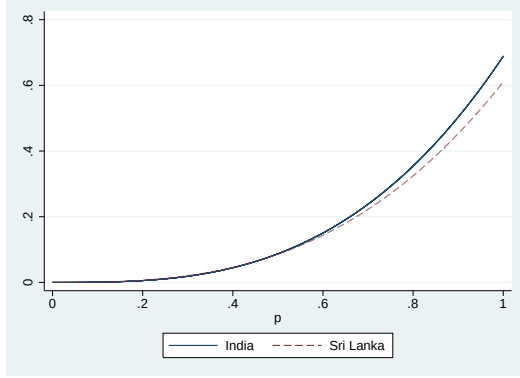


(e) using socioeconomic rank p , $\theta = 1$

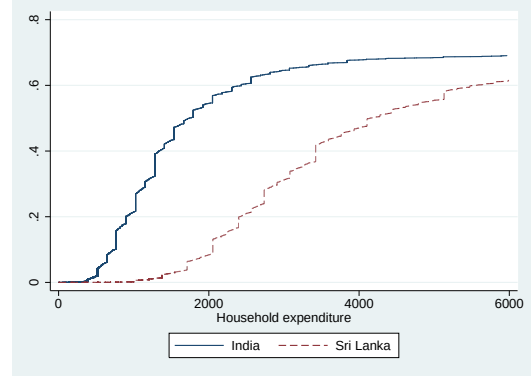


(f) using household expenditure y , $\theta = 1$

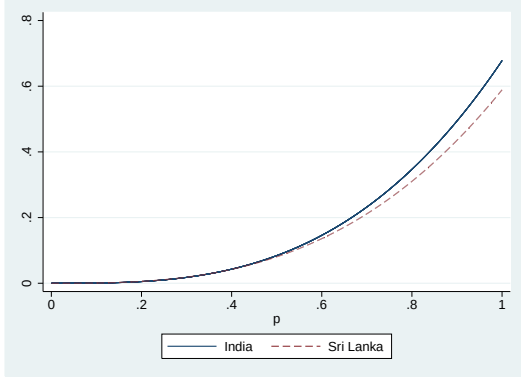
Figure 2.42: Third Order Population Health Dominance: India & Sri Lanka



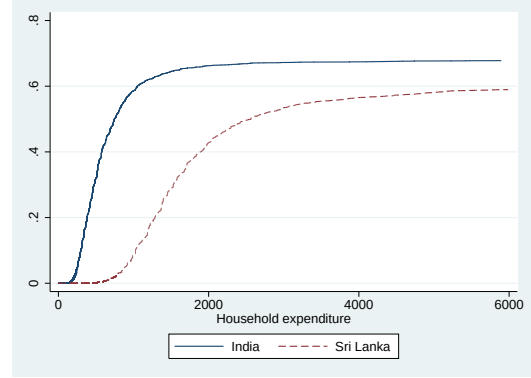
(a) using socioeconomic rank p , $\theta = 0$



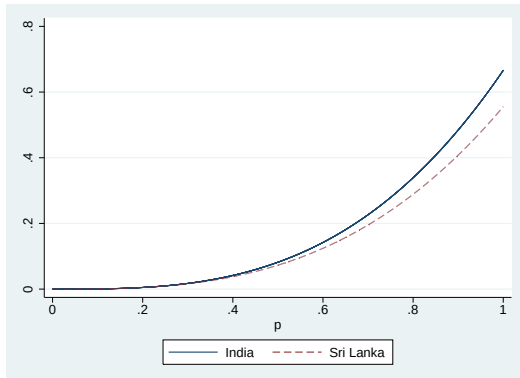
(b) using household expenditure y , $\theta = 0$



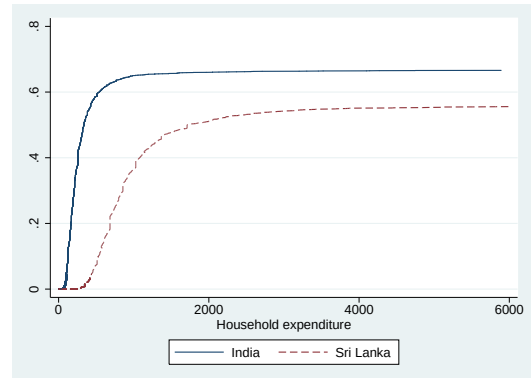
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

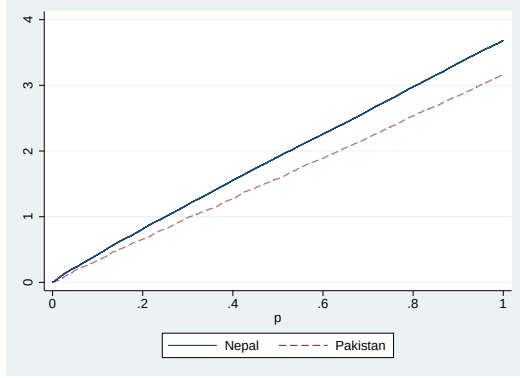


(e) using socioeconomic rank p , $\theta = 1$

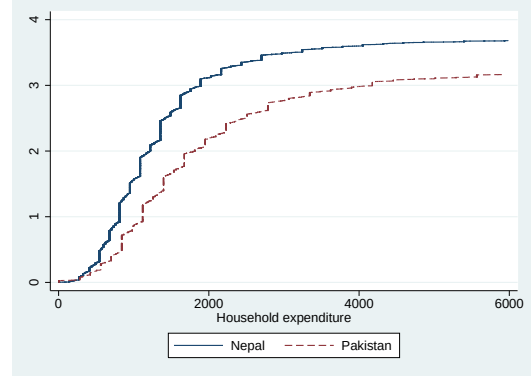


(f) using household expenditure y , $\theta = 1$

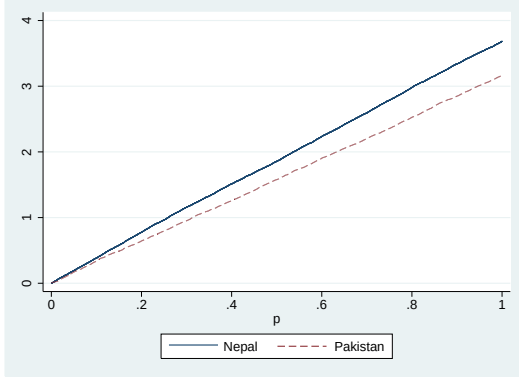
Figure 2.43: Fourth Order Population Health Dominance: India & Sri Lanka



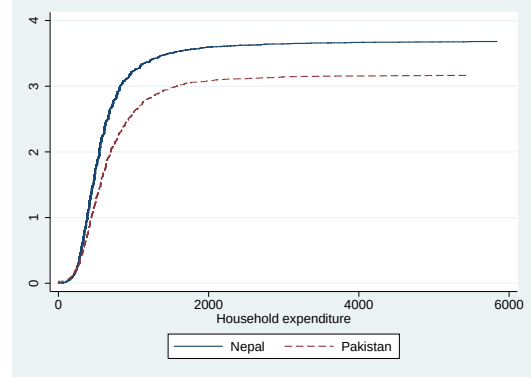
(a) using socioeconomic rank p , $\theta = 0$



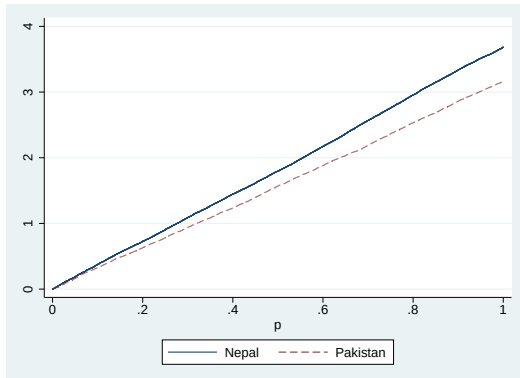
(b) using household expenditure y , $\theta = 0$



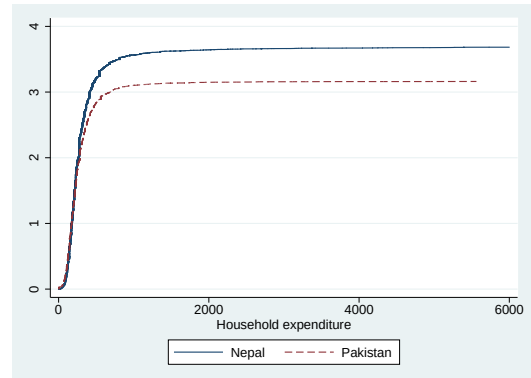
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

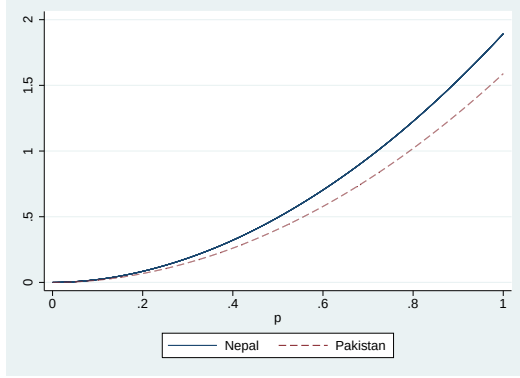


(e) using socioeconomic rank p , $\theta = 1$

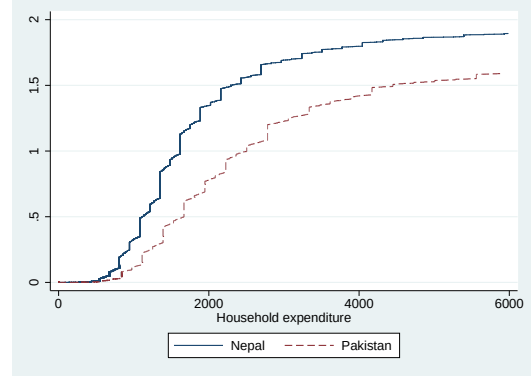


(f) using household expenditure y , $\theta = 1$

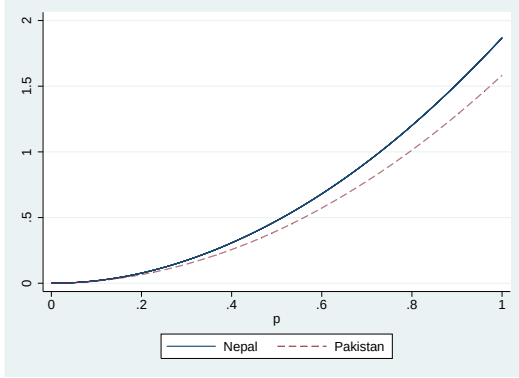
Figure 2.44: Second Order Population Health Dominance: Nepal & Pakistan



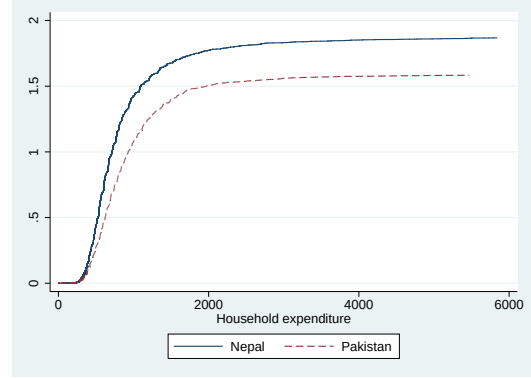
(a) using socioeconomic rank p , $\theta = 0$



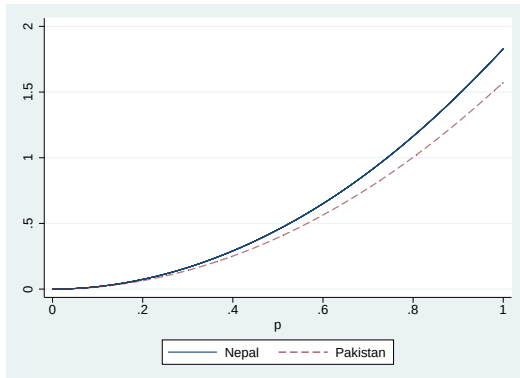
(b) using household expenditure y , $\theta = 0$



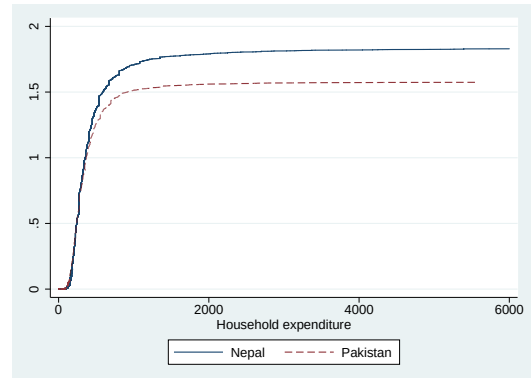
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

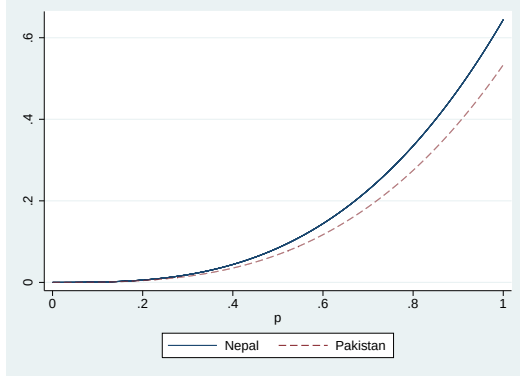


(e) using socioeconomic rank p , $\theta = 1$

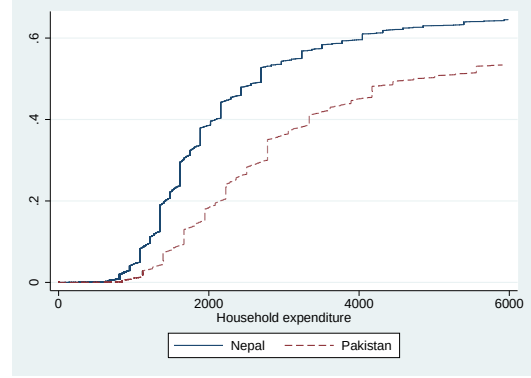


(f) using household expenditure y , $\theta = 1$

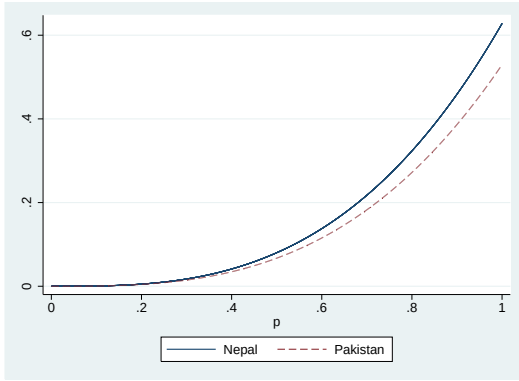
Figure 2.45: Third Order Population Health Dominance: Nepal & Pakistan



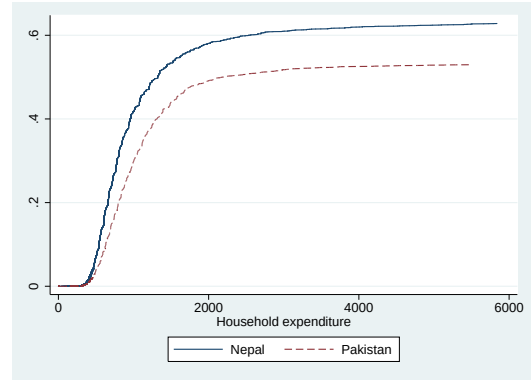
(a) using socioeconomic rank p , $\theta = 0$



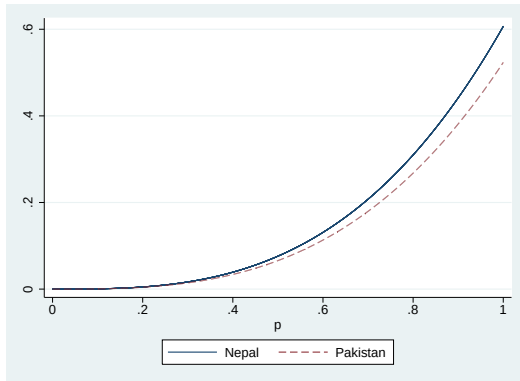
(b) using household expenditure y , $\theta = 0$



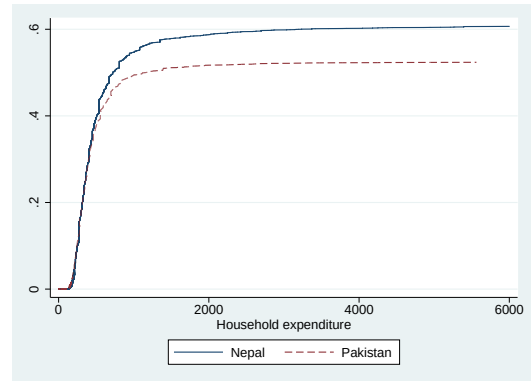
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

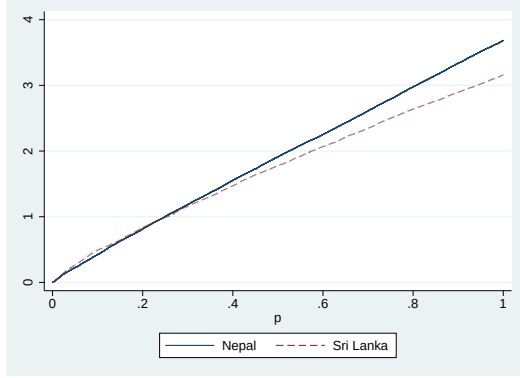


(e) using socioeconomic rank p , $\theta = 1$

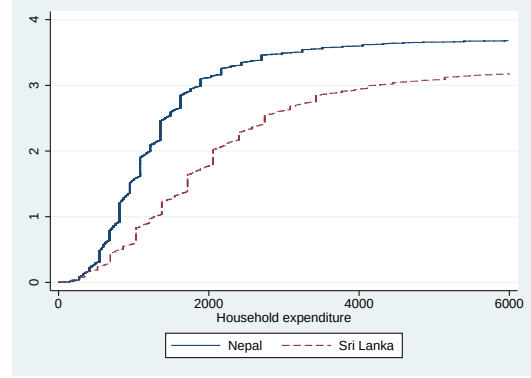


(f) using household expenditure y , $\theta = 1$

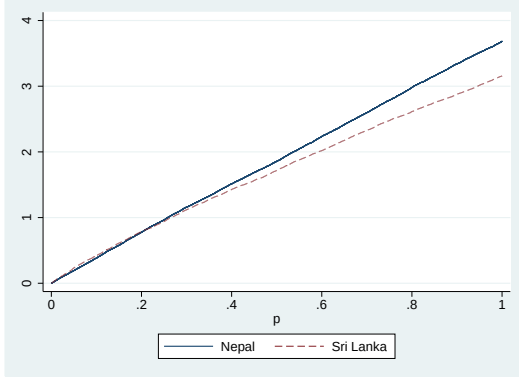
Figure 2.46: Fourth Order Population Health Dominance: Nepal & Pakistan



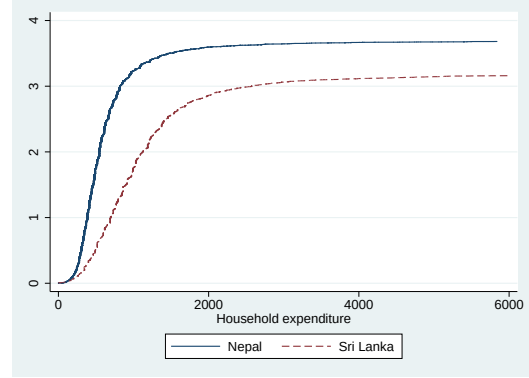
(a) using socioeconomic rank p , $\theta = 0$



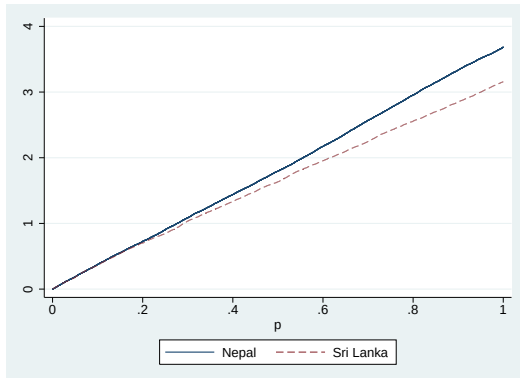
(b) using household expenditure y , $\theta = 0$



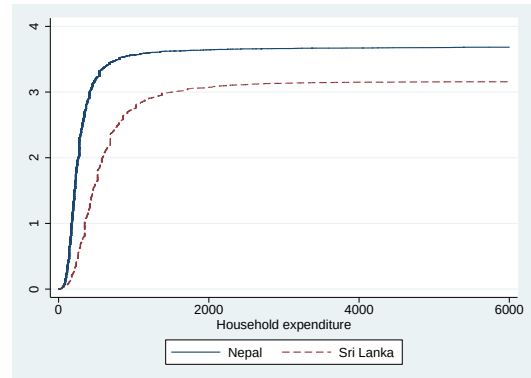
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

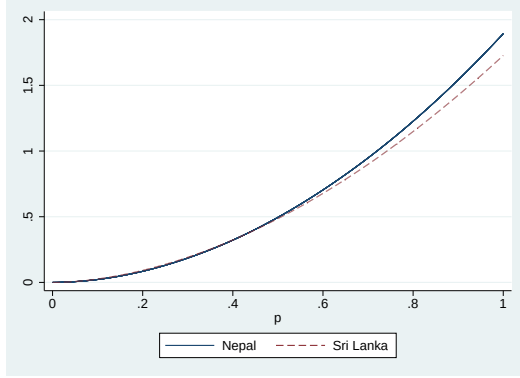


(e) using socioeconomic rank p , $\theta = 1$

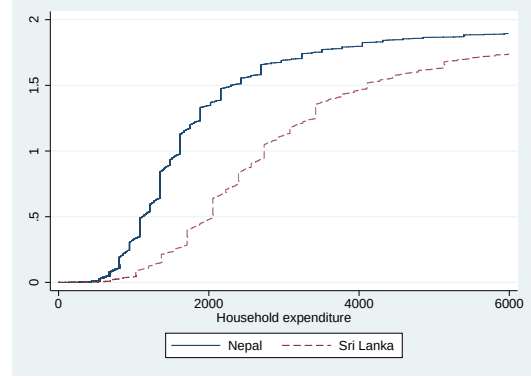


(f) using household expenditure y , $\theta = 1$

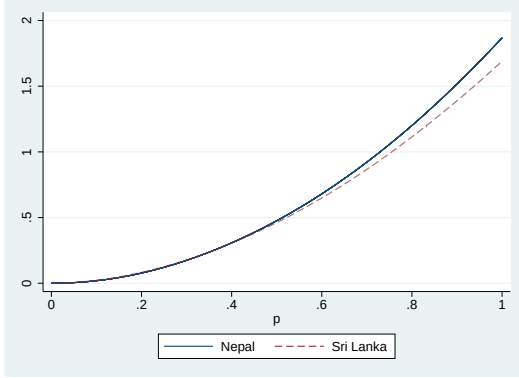
Figure 2.47: Second Order Population Health Dominance: Nepal & Sri Lanka



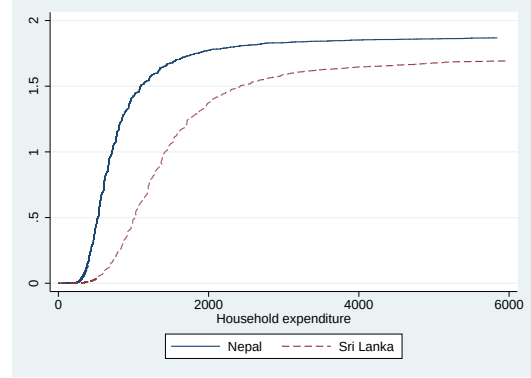
(a) using socioeconomic rank p , $\theta = 0$



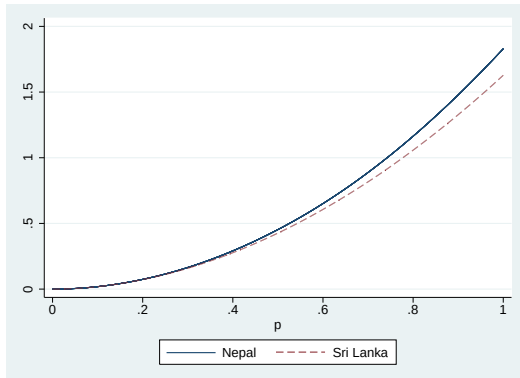
(b) using household expenditure y , $\theta = 0$



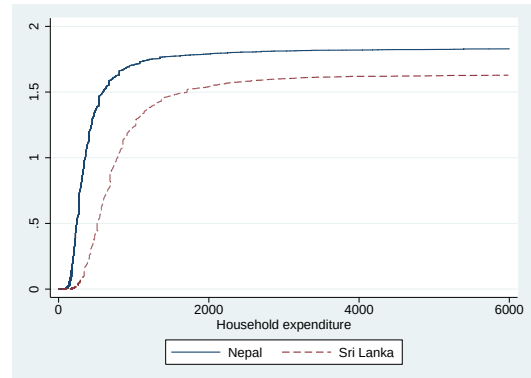
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

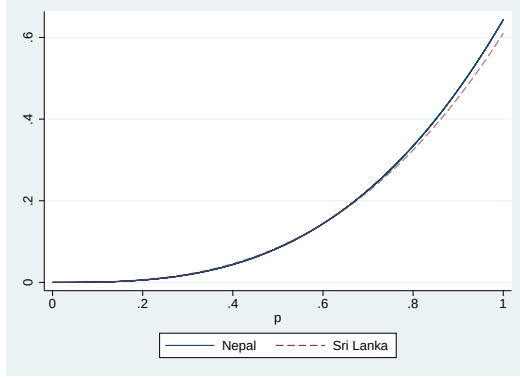


(e) using socioeconomic rank p , $\theta = 1$

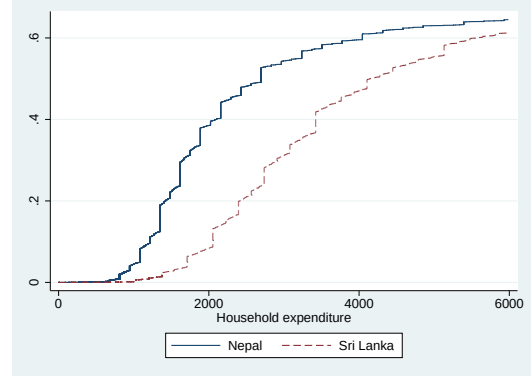


(f) using household expenditure y , $\theta = 1$

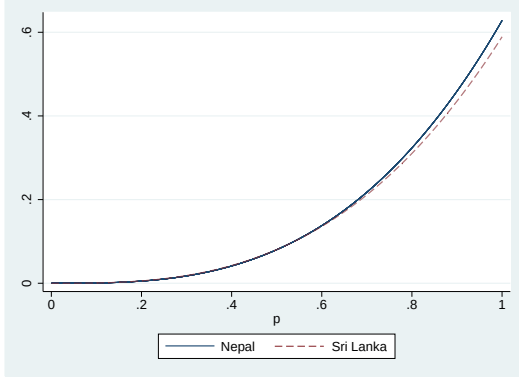
Figure 2.48: Third Order Population Health Dominance: Nepal & Sri Lanka



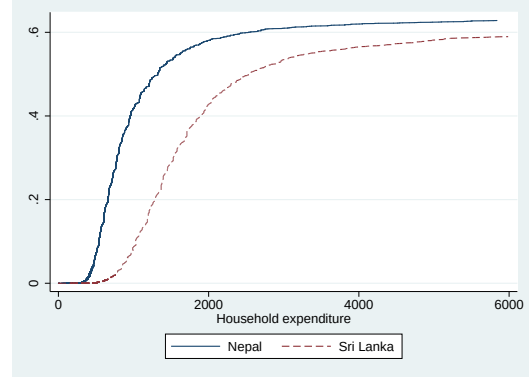
(a) using socioeconomic rank p , $\theta = 0$



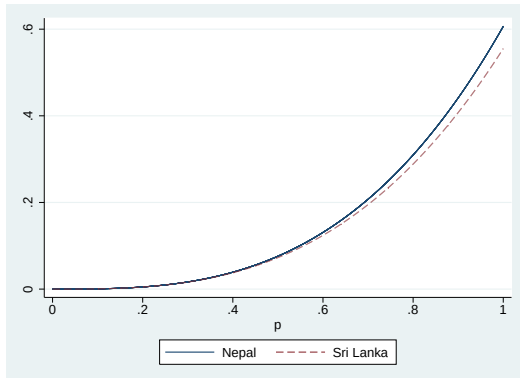
(b) using household expenditure y , $\theta = 0$



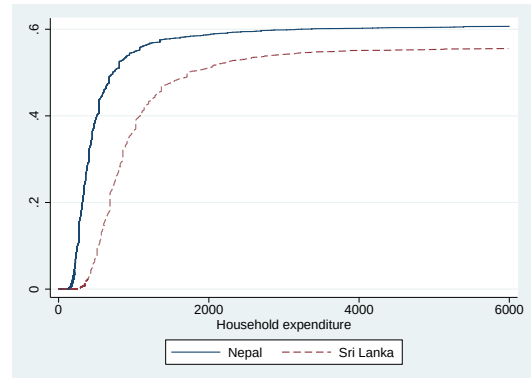
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

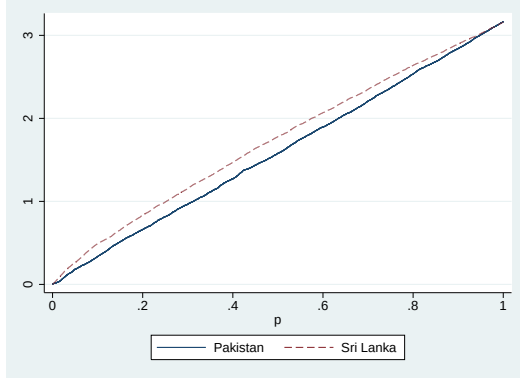


(e) using socioeconomic rank p , $\theta = 1$

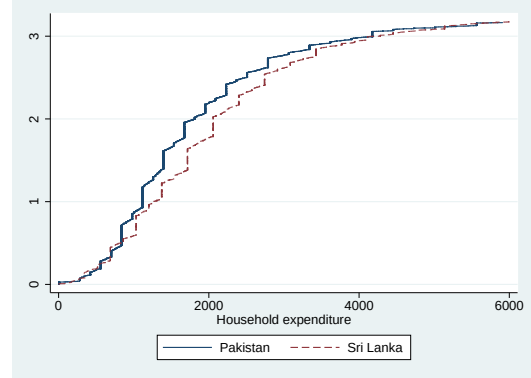


(f) using household expenditure y , $\theta = 1$

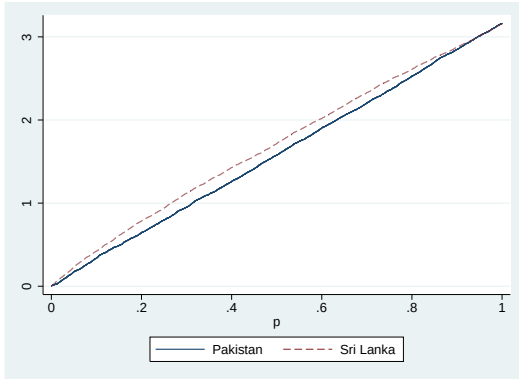
Figure 2.49: Fourth Order Population Health Dominance: Nepal & Sri Lanka



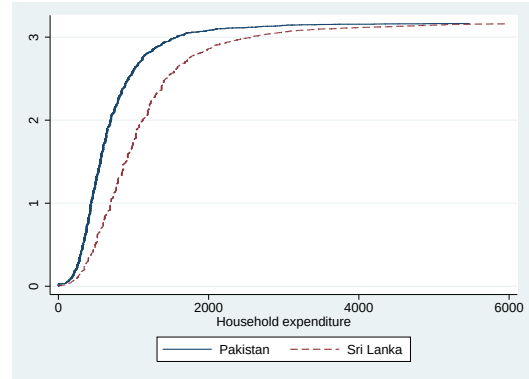
(a) using socioeconomic rank p , $\theta = 0$



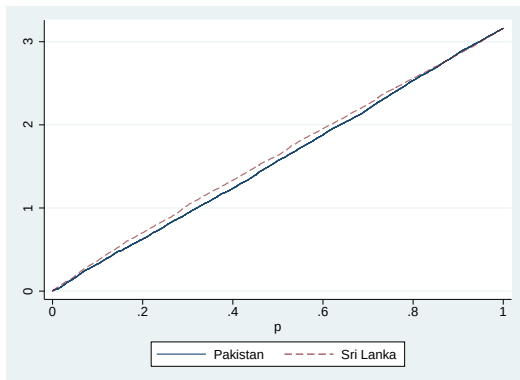
(b) using household expenditure y , $\theta = 0$



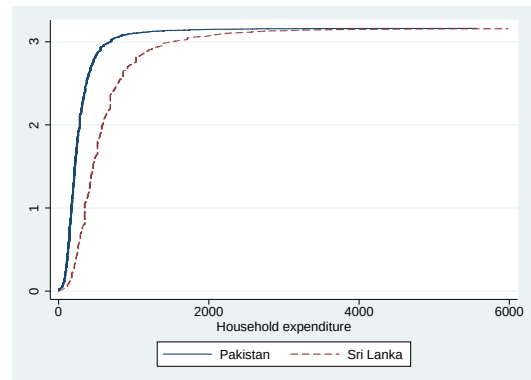
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

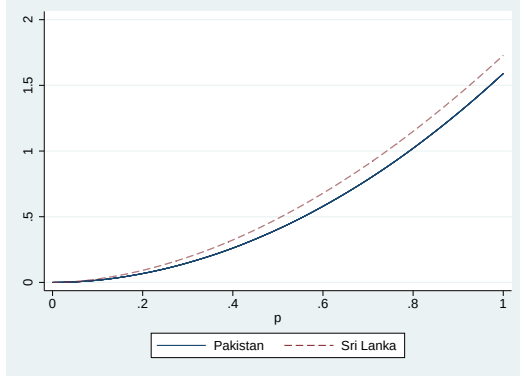


(e) using socioeconomic rank p , $\theta = 1$

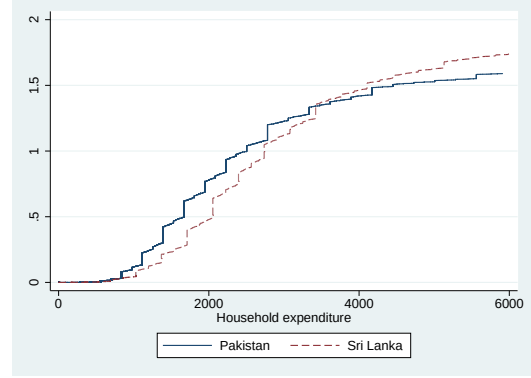


(f) using household expenditure y , $\theta = 1$

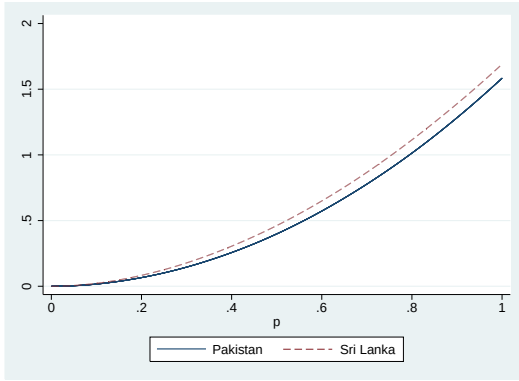
Figure 2.50: Second Order Population Health Dominance: Pakistan & Sri Lanka



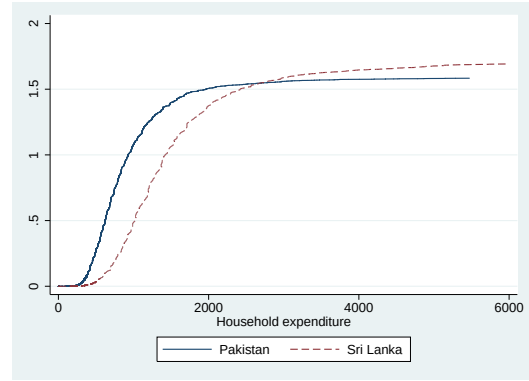
(a) using socioeconomic rank p , $\theta = 0$



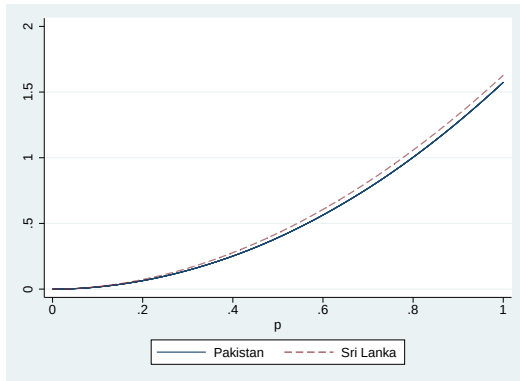
(b) using household expenditure y , $\theta = 0$



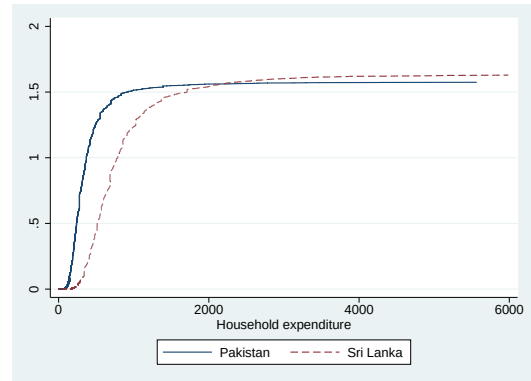
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

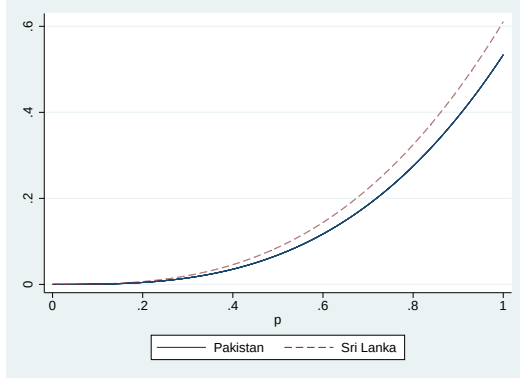


(e) using socioeconomic rank p , $\theta = 1$

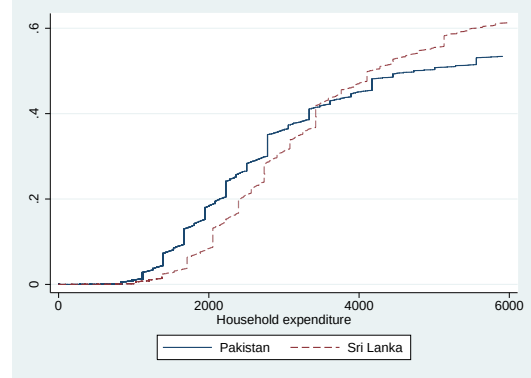


(f) using household expenditure y , $\theta = 1$

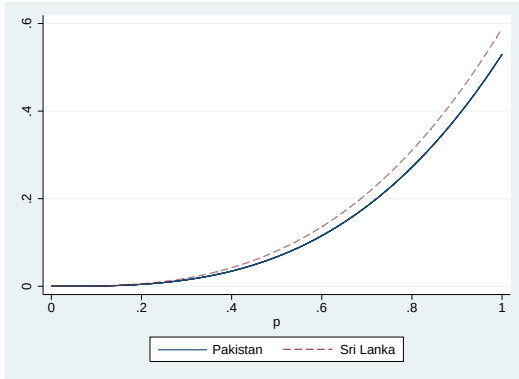
Figure 2.51: Third Order Population Health Dominance: Pakistan & Sri Lanka



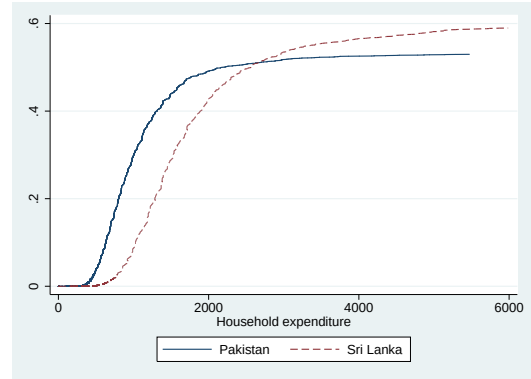
(a) using socioeconomic rank p , $\theta = 0$



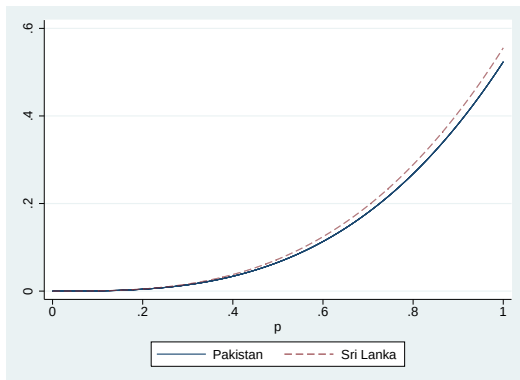
(b) using household expenditure y , $\theta = 0$



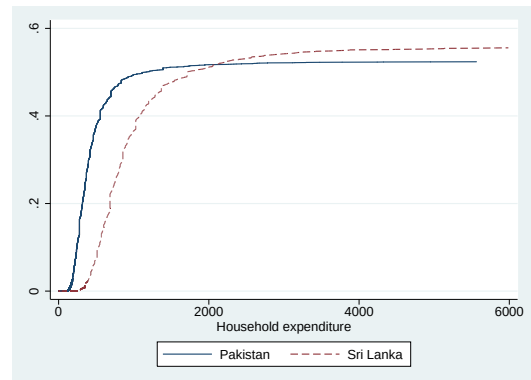
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$



(e) using socioeconomic rank p , $\theta = 1$

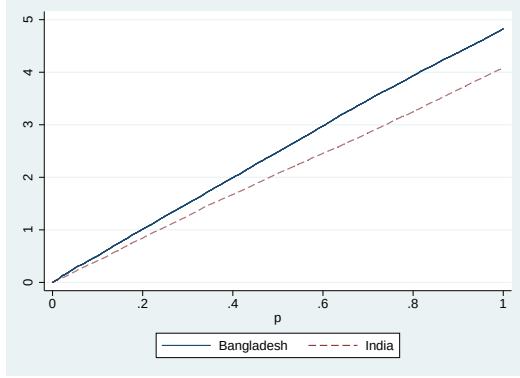


(f) using household expenditure y , $\theta = 1$

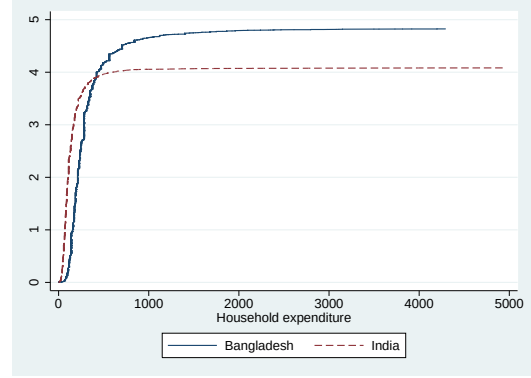
Figure 2.52: Fourth Order Population Health Dominance: Pakistan & Sri Lanka

Appendix 2.D.

2.D. Pairwise comparison of Population Health Dominance curves Using World Bank PPP

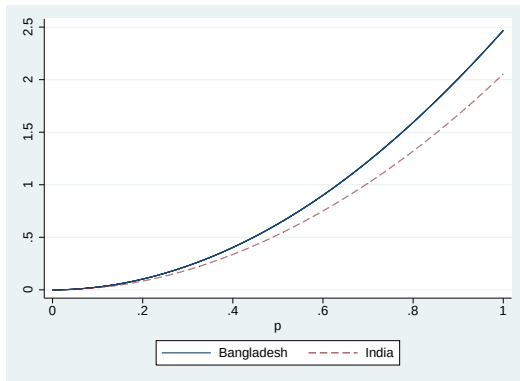


(a) using socioeconomic rank p , $\theta = 1$

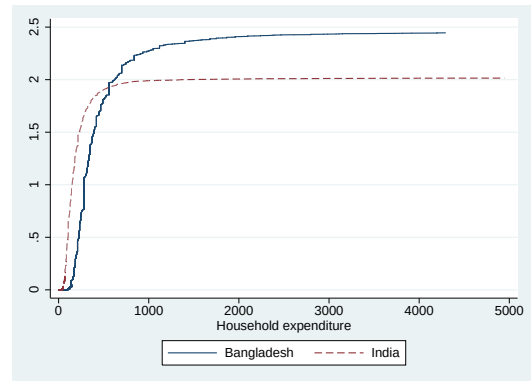


(b) using household expenditure y , $\theta = 1$

Figure 2.53: Second Order Population Health Dominance: Bangladesh & India

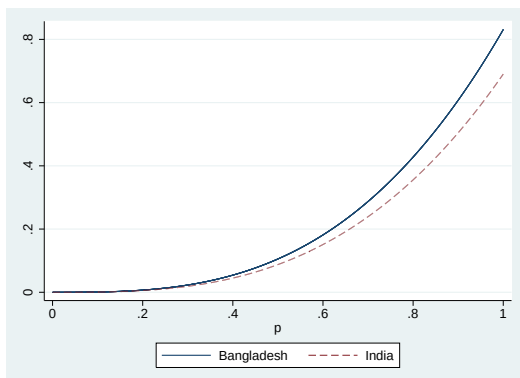


(a) using socioeconomic rank p , $\theta = 1$

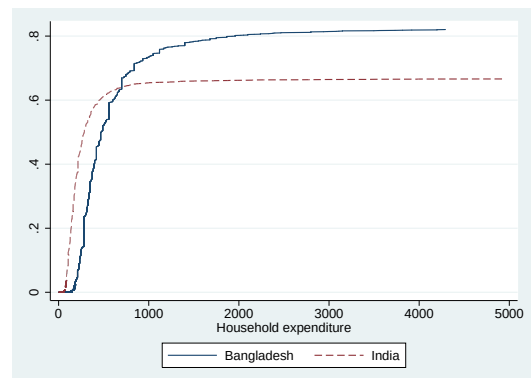


(b) using household expenditure y , $\theta = 1$

Figure 2.54: Third Order Population Health Dominance: Bangladesh & India

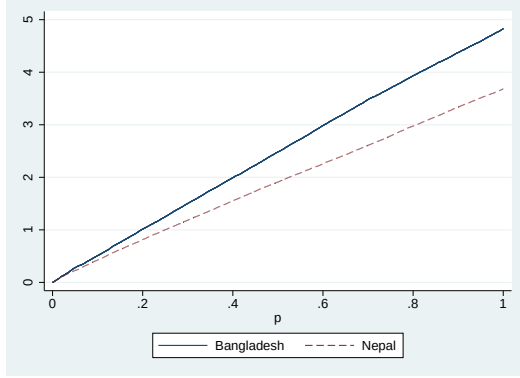


(a) using socioeconomic rank p , $\theta = 1$

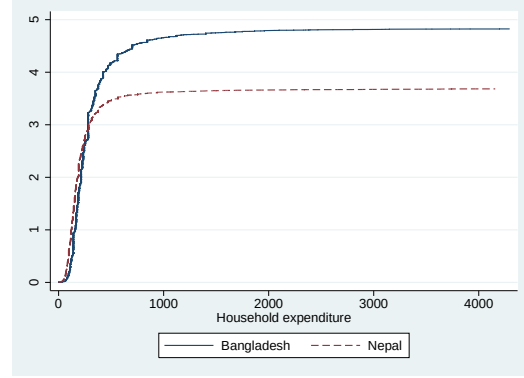


(b) using household expenditure y , $\theta = 1$

Figure 2.55: Fourth Order Population Health Dominance: Bangladesh & India

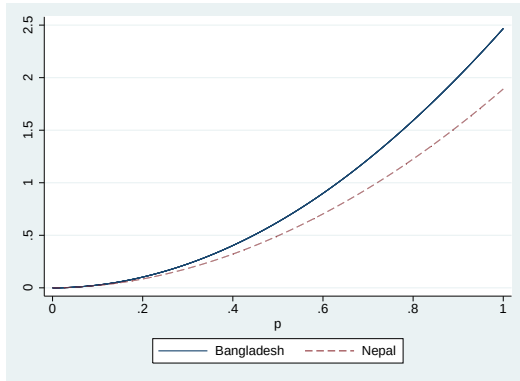


(a) using socioeconomic rank p , $\theta = 1$

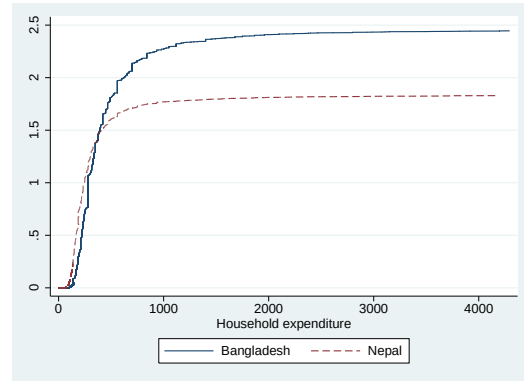


(b) using household expenditure y , $\theta = 1$

Figure 2.56: Second Order Population Health Dominance: Bangladesh & Nepal

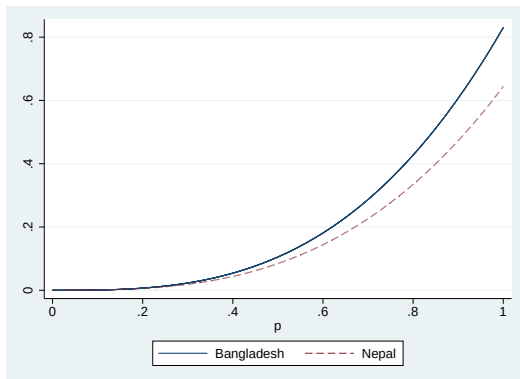


(a) using socioeconomic rank p , $\theta = 1$

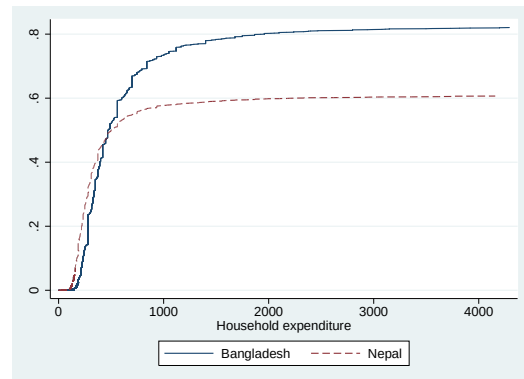


(b) using household expenditure y , $\theta = 1$

Figure 2.57: Third Order Population Health Dominance: Bangladesh & Nepal

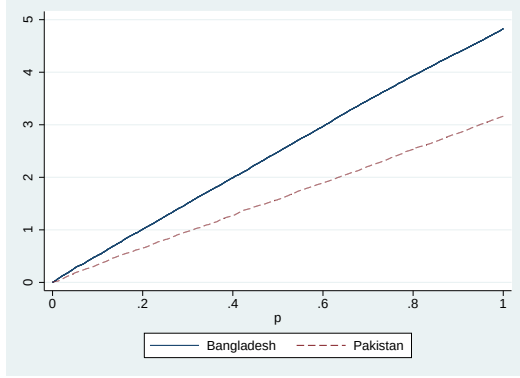


(a) using socioeconomic rank p , $\theta = 1$

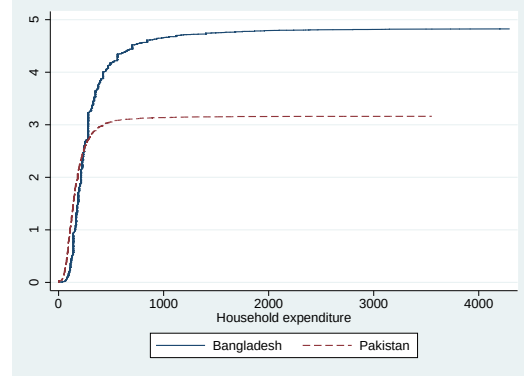


(b) using household expenditure y , $\theta = 1$

Figure 2.58: Fourth Order Population Health Dominance: Bangladesh & Nepal

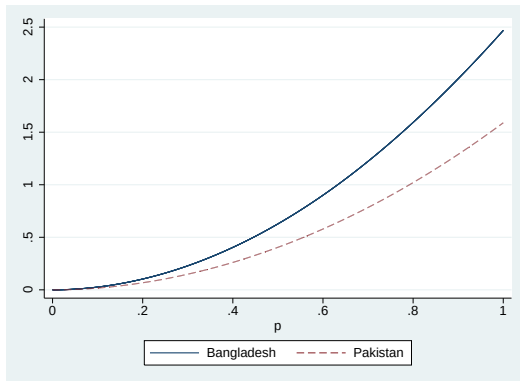


(a) using socioeconomic rank p , $\theta = 1$

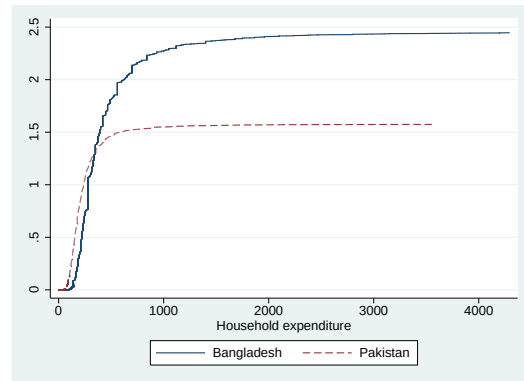


(b) using household expenditure y , $\theta = 1$

Figure 2.59: Second Order Population Health Dominance: Bangladesh & Pakistan

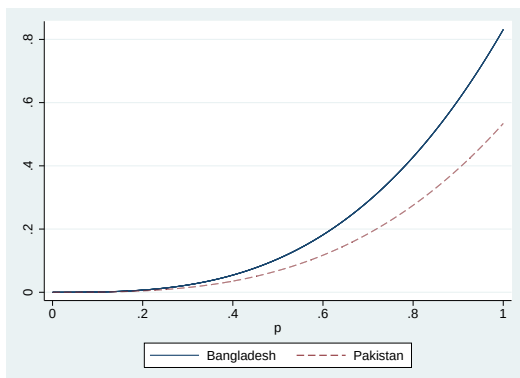


(a) using socioeconomic rank p , $\theta = 1$

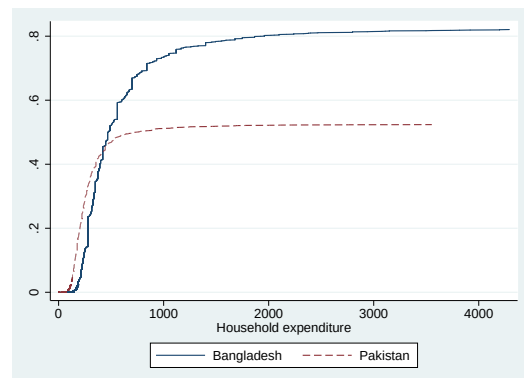


(b) using household expenditure y , $\theta = 1$

Figure 2.60: Third Order Population Health Dominance: Bangladesh & Pakistan

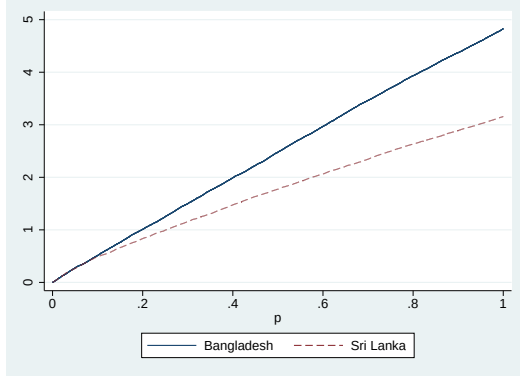


(a) using socioeconomic rank p , $\theta = 1$

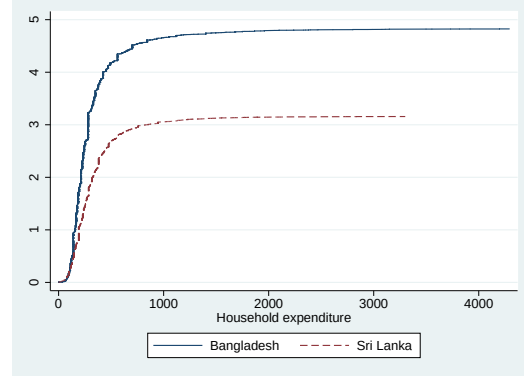


(b) using household expenditure y , $\theta = 1$

Figure 2.61: Fourth Order Population Health Dominance: Bangladesh & Pakistan

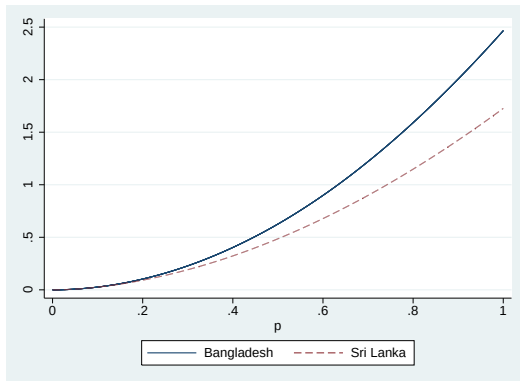


(a) using socioeconomic rank p , $\theta = 1$

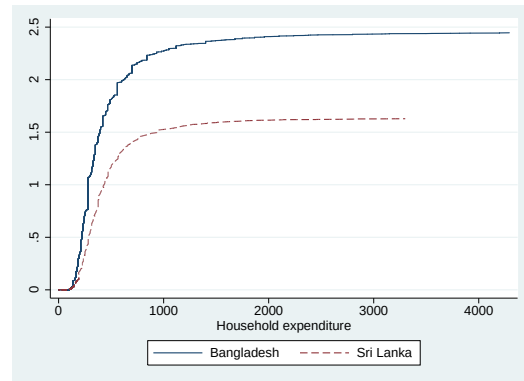


(b) using household expenditure y , $\theta = 1$

Figure 2.62: Second Order Population Health Dominance: Bangladesh & Sri Lanka

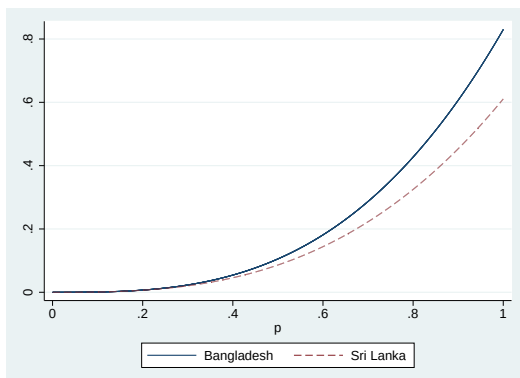


(a) using socioeconomic rank p , $\theta = 1$

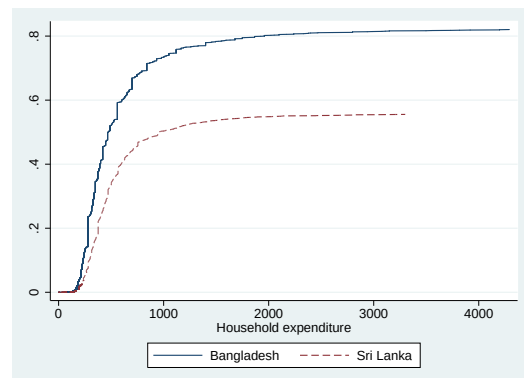


(b) using household expenditure y , $\theta = 1$

Figure 2.63: Third Order Population Health Dominance: Bangladesh & Sri Lanka

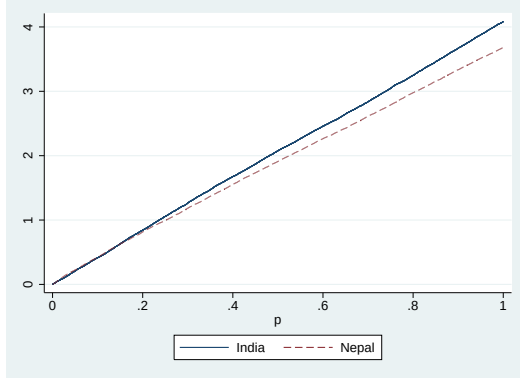


(a) using socioeconomic rank p , $\theta = 1$

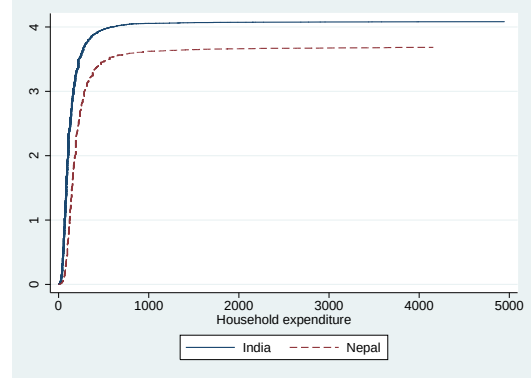


(b) using household expenditure y , $\theta = 1$

Figure 2.64: Fourth Order Population Health Dominance: Bangladesh & Sri Lanka

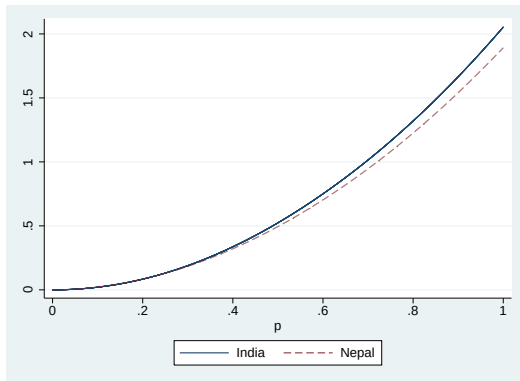


(a) using socioeconomic rank p , $\theta = 1$

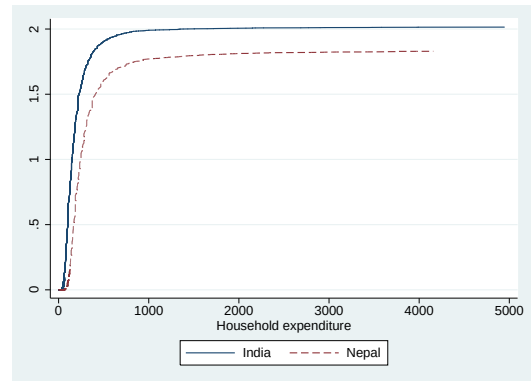


(b) using household expenditure y , $\theta = 1$

Figure 2.65: Second Order Population Health Dominance: India & Nepal

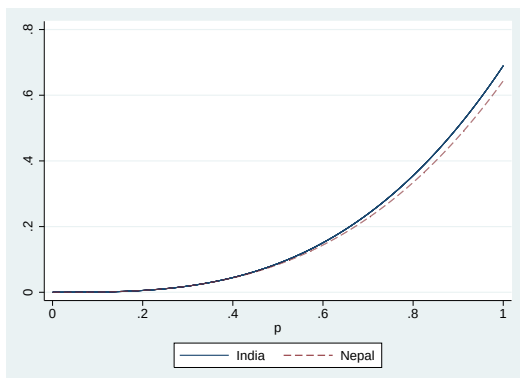


(a) using socioeconomic rank p , $\theta = 1$

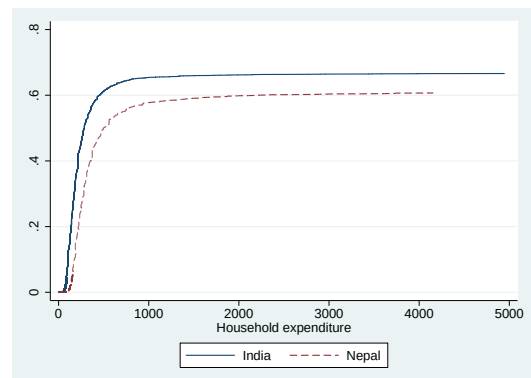


(b) using household expenditure y , $\theta = 1$

Figure 2.66: Third Order Population Health Dominance: India & Nepal

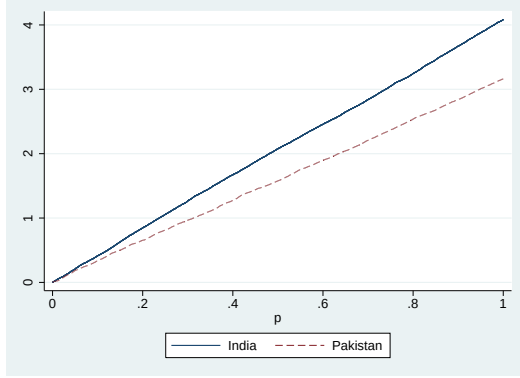


(a) using socioeconomic rank p , $\theta = 1$

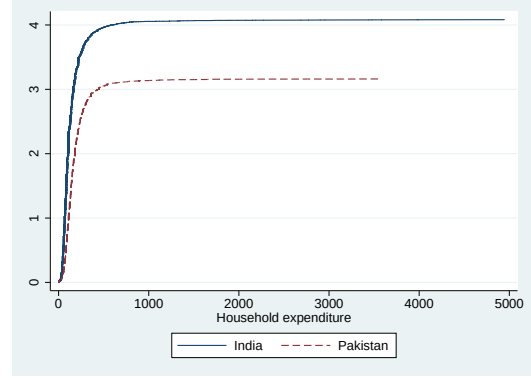


(b) using household expenditure y , $\theta = 1$

Figure 2.67: Fourth Order Population Health Dominance: India & Nepal

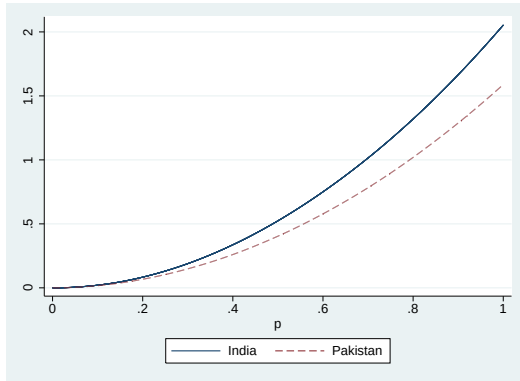


(a) using socioeconomic rank p , $\theta = 1$

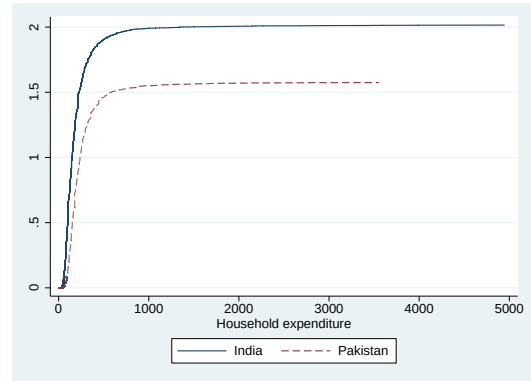


(b) using household expenditure y , $\theta = 1$

Figure 2.68: Second Order Population Health Dominance: India & Pakistan

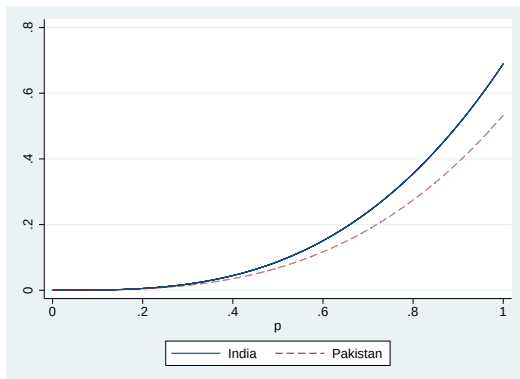


(a) using socioeconomic rank p , $\theta = 1$

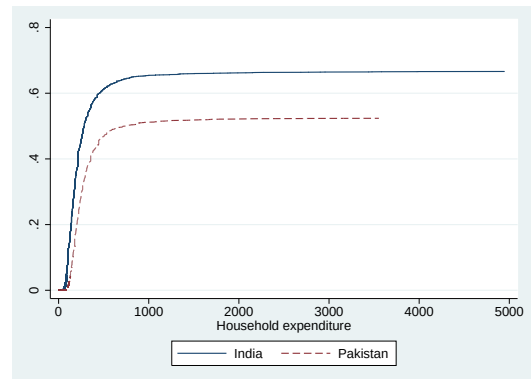


(b) using household expenditure y , $\theta = 1$

Figure 2.69: Third Order Population Health Dominance: India & Pakistan

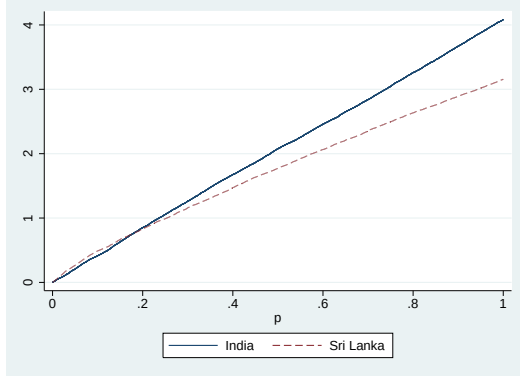


(a) using socioeconomic rank p , $\theta = 1$

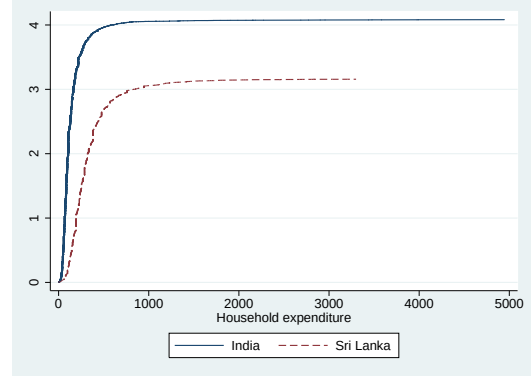


(b) using household expenditure y , $\theta = 1$

Figure 2.70: Fourth Order Population Health Dominance: India & Pakistan

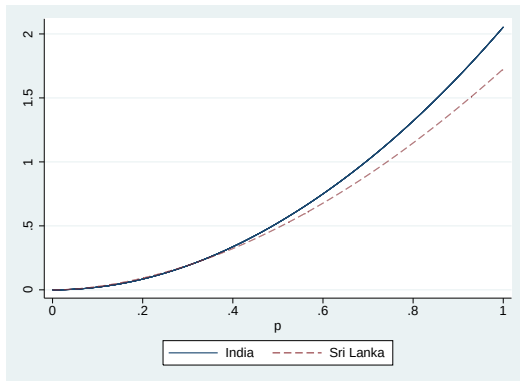


(a) using socioeconomic rank p , $\theta = 1$

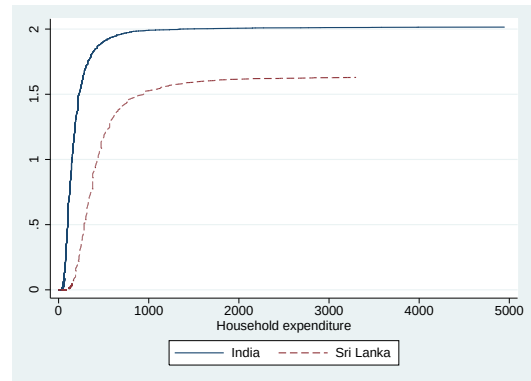


(b) using household expenditure y , $\theta = 1$

Figure 2.71: Second Order Population Health Dominance: India & Sri Lanka

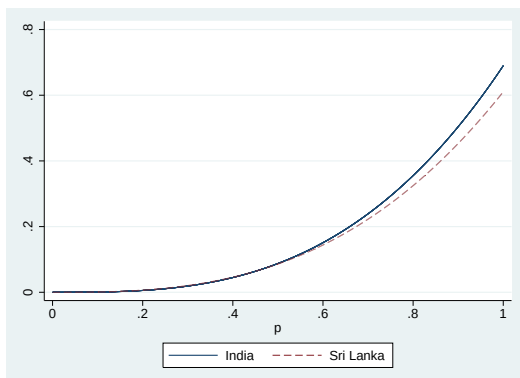


(a) using socioeconomic rank p , $\theta = 1$

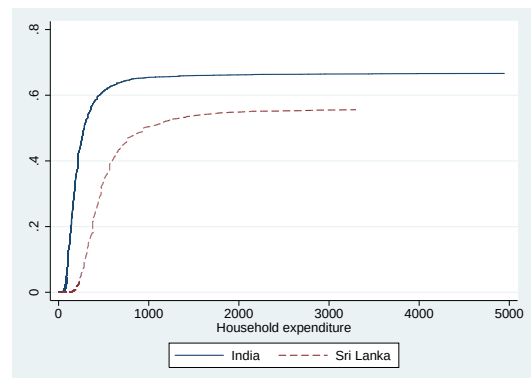


(b) using household expenditure y , $\theta = 1$

Figure 2.72: Third Order Population Health Dominance: India & Sri Lanka

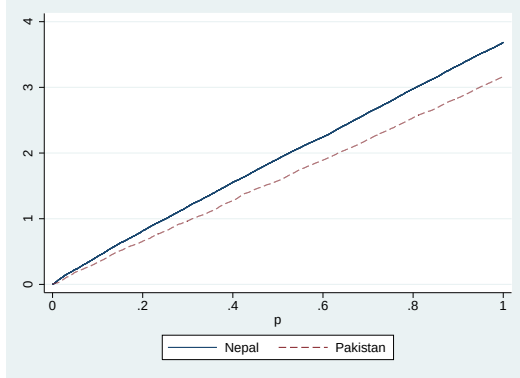


(a) using socioeconomic rank p , $\theta = 1$

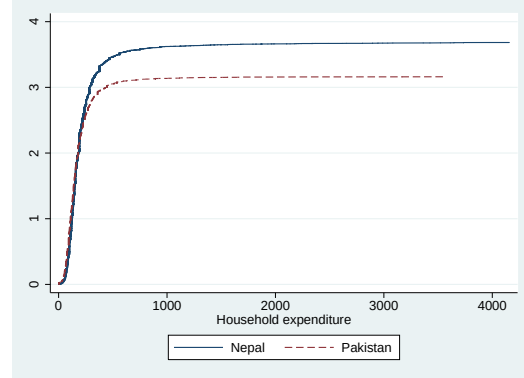


(b) using household expenditure y , $\theta = 1$

Figure 2.73: Fourth Order Population Health Dominance: India & Sri Lanka

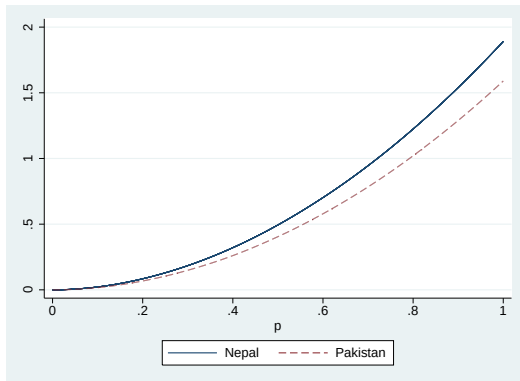


(a) using socioeconomic rank p , $\theta = 1$

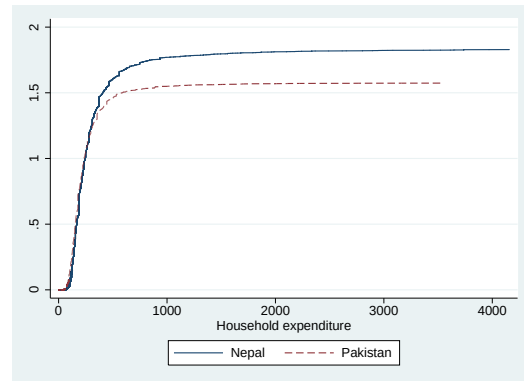


(b) using household expenditure y , $\theta = 1$

Figure 2.74: Second Order Population Health Dominance: Nepal & Pakistan

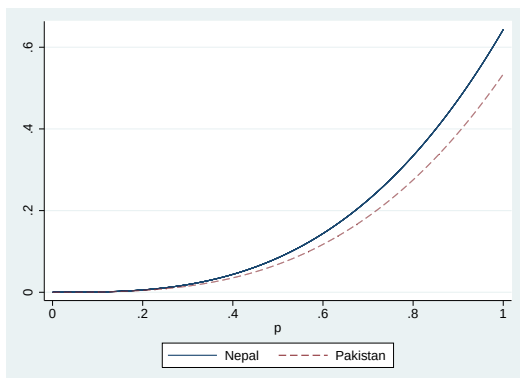


(a) using socioeconomic rank p , $\theta = 1$

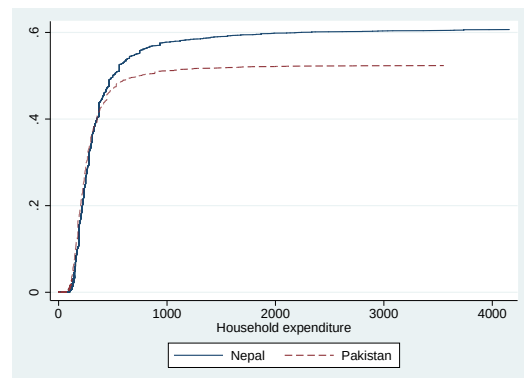


(b) using household expenditure y , $\theta = 1$

Figure 2.75: Third Order Population Health Dominance: Nepal & Pakistan

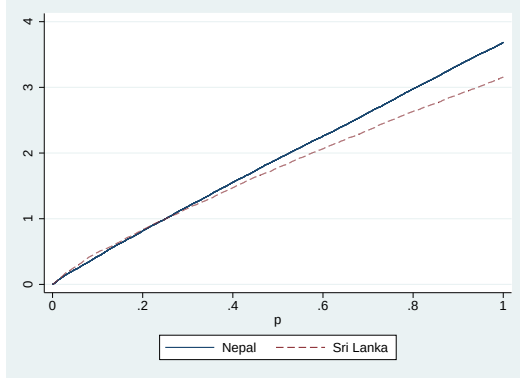


(a) using socioeconomic rank p , $\theta = 1$

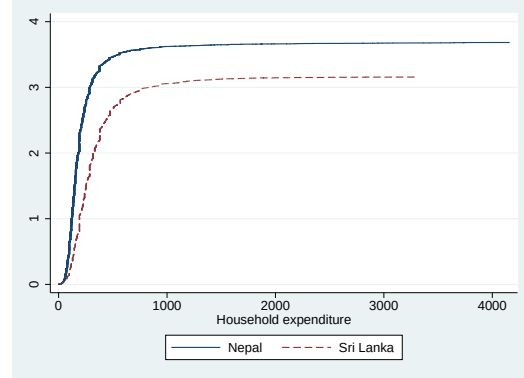


(b) using household expenditure y , $\theta = 1$

Figure 2.76: Fourth Order Population Health Dominance: Nepal & Pakistan

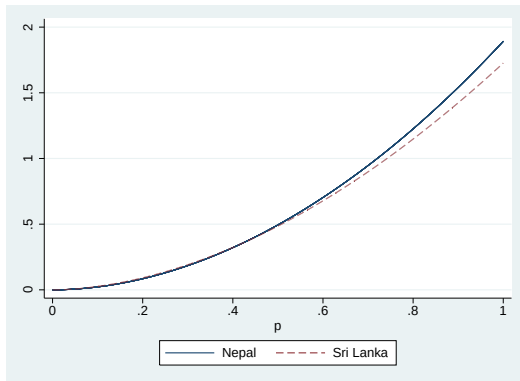


(a) using socioeconomic rank p , $\theta = 1$

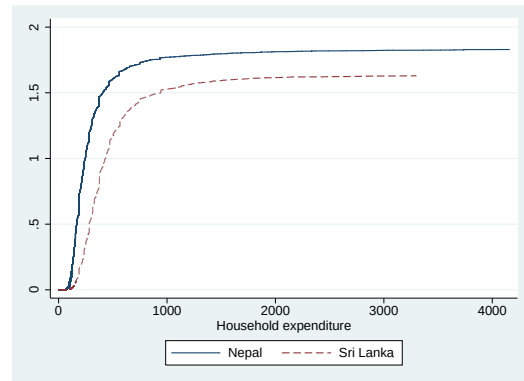


(b) using household expenditure y , $\theta = 1$

Figure 2.77: Second Order Population Health Dominance: Nepal & Sri Lanka

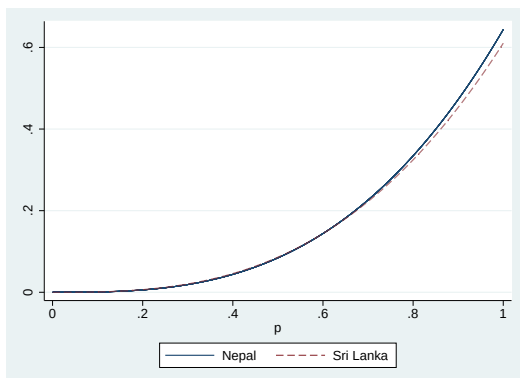


(a) using socioeconomic rank p , $\theta = 1$

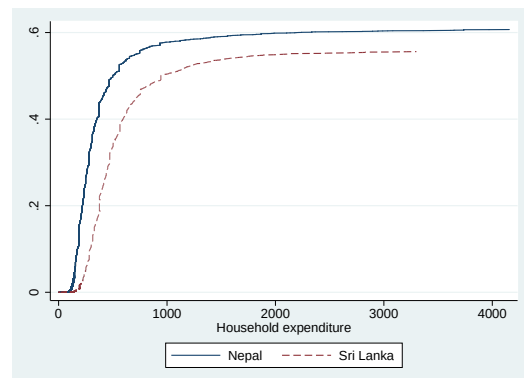


(b) using household expenditure y , $\theta = 1$

Figure 2.78: Third Order Population Health Dominance: Nepal & Sri Lanka

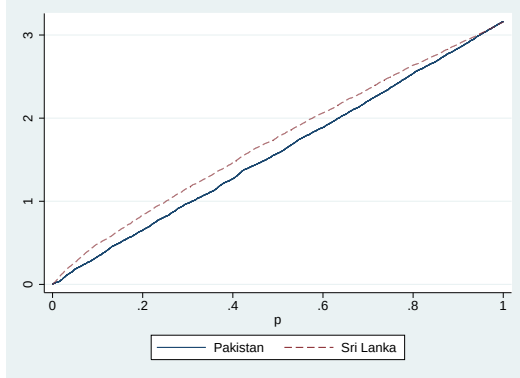


(a) using socioeconomic rank p , $\theta = 1$

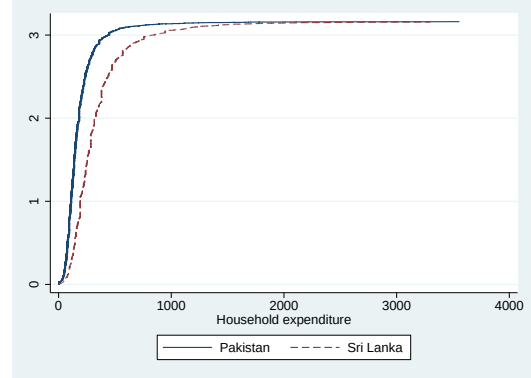


(b) using household expenditure y , $\theta = 1$

Figure 2.79: Fourth Order Population Health Dominance: Nepal & Sri Lanka

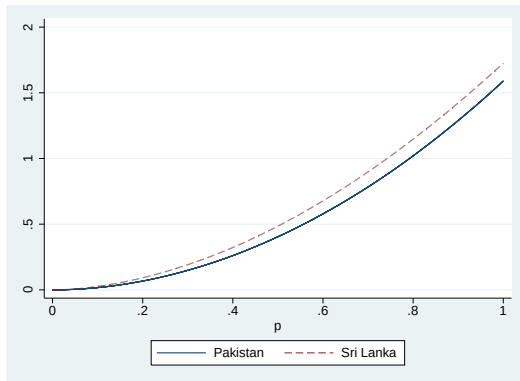


(a) using socioeconomic rank p , $\theta = 1$

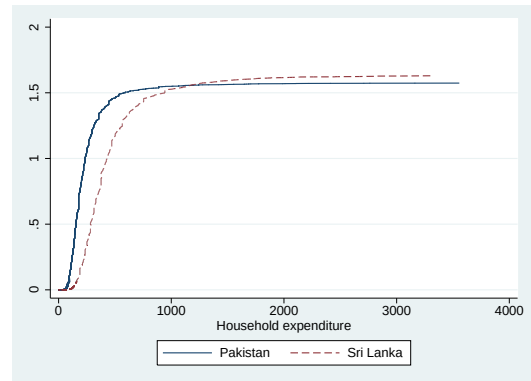


(b) using household expenditure y , $\theta = 1$

Figure 2.80: Second Order Population Health Dominance: Pakistan & Sri Lanka

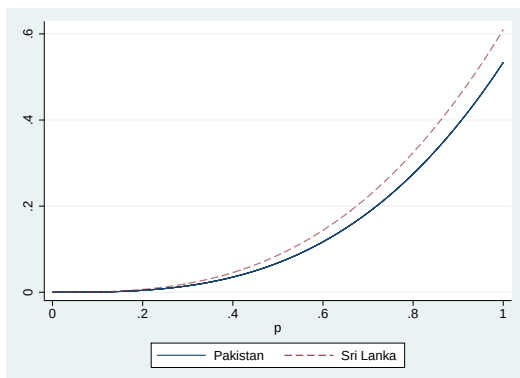


(a) using socioeconomic rank p , $\theta = 1$

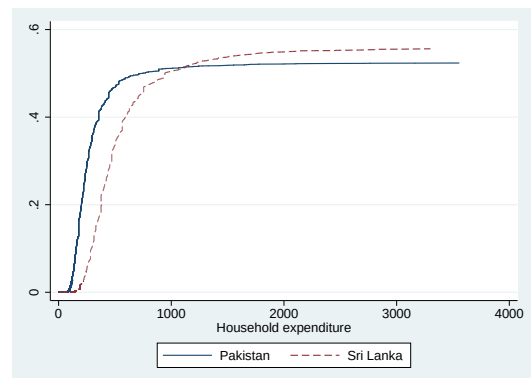


(b) using household expenditure y , $\theta = 1$

Figure 2.81: Third Order Population Health Dominance: Pakistan & Sri Lanka



(a) using socioeconomic rank p , $\theta = 1$

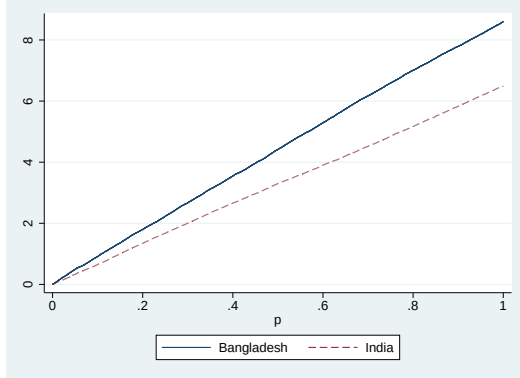


(b) using household expenditure y , $\theta = 1$

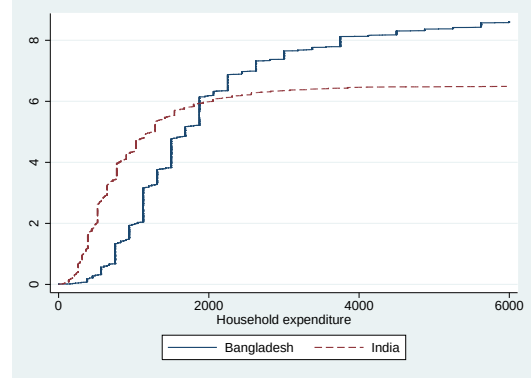
Figure 2.82: Fourth Order Population Health Dominance: Pakistan & Sri Lanka

Appendix 2.E.

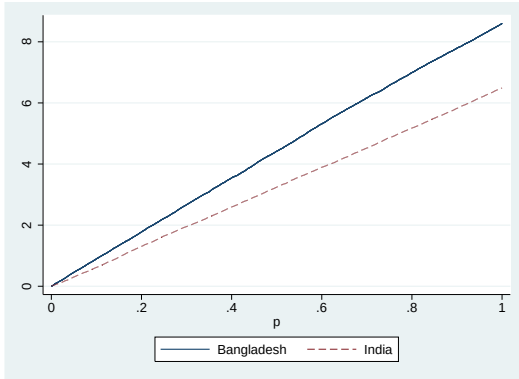
2.E. Pairwise comparison of Socioeconomic Health Inequality Dominance curves



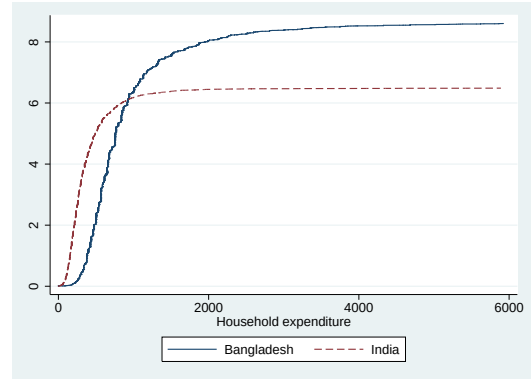
(a) using socioeconomic rank p , $\theta = 0$



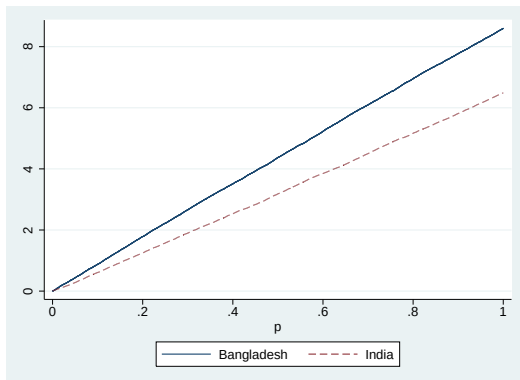
(b) using household expenditure y , $\theta = 0$



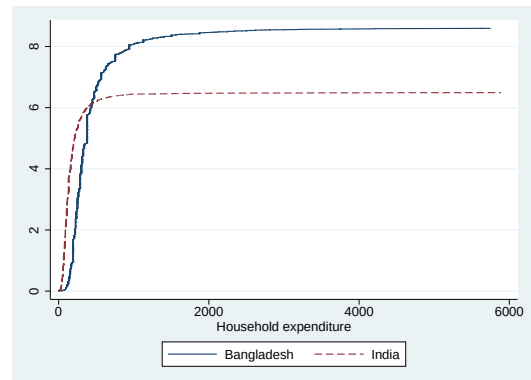
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

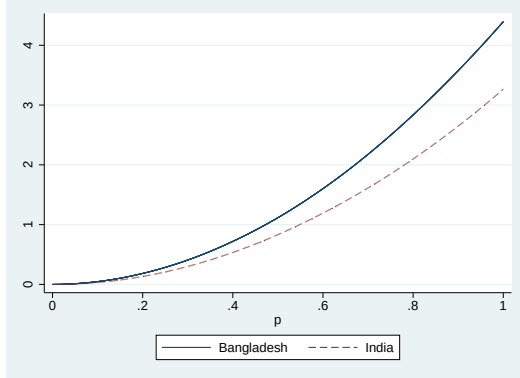


(e) using socioeconomic rank p , $\theta = 1$

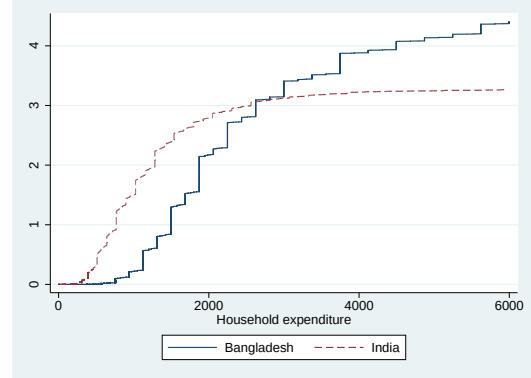


(f) using household expenditure y , $\theta = 1$

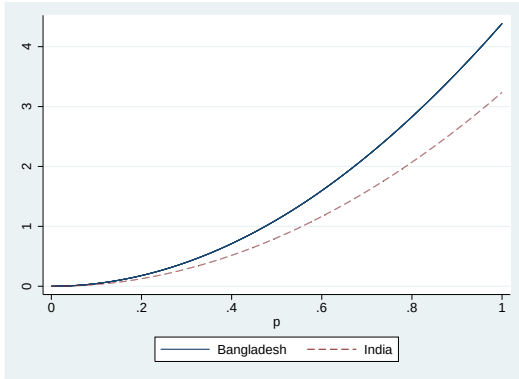
Figure 2.83: Second Order Inequality Dominance: Bangladesh & India



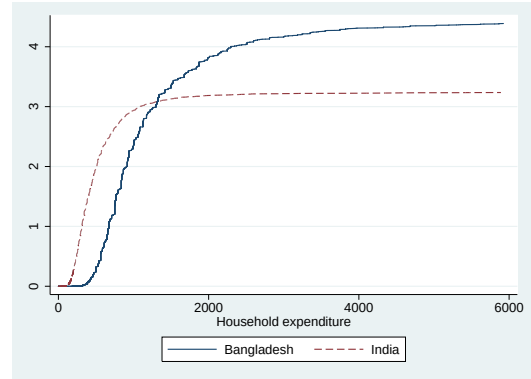
(a) using socioeconomic rank p , $\theta = 0$



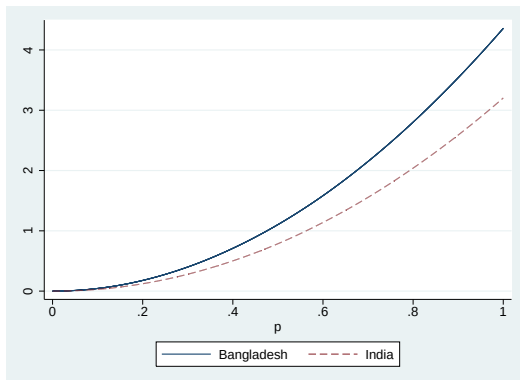
(b) using household expenditure y , $\theta = 0$



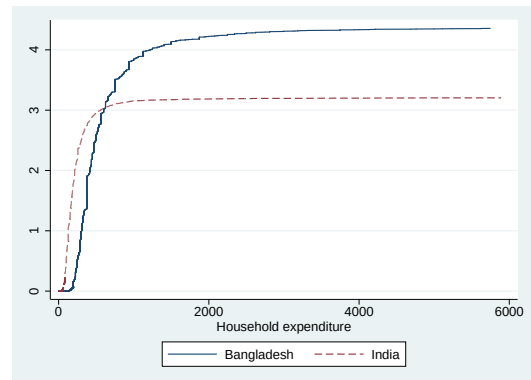
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

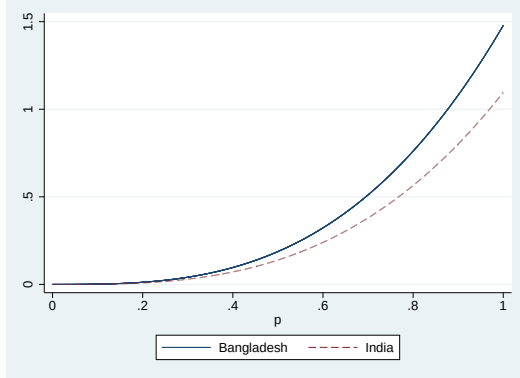


(e) using socioeconomic rank p , $\theta = 1$

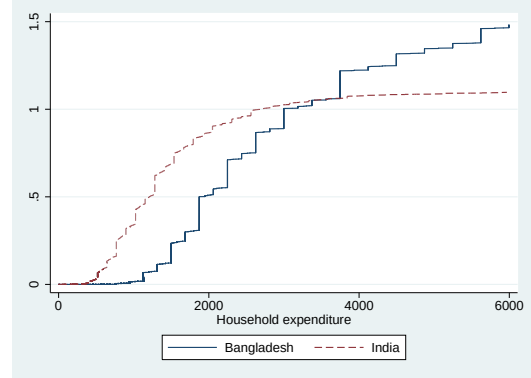


(f) using household expenditure y , $\theta = 1$

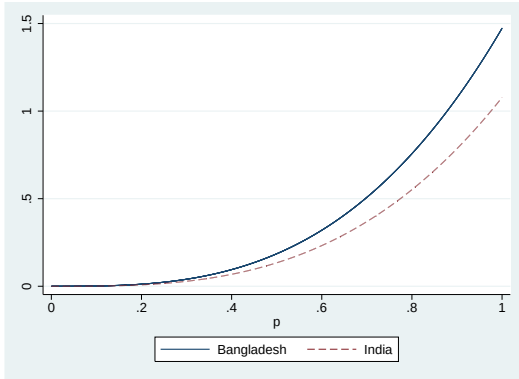
Figure 2.84: Third Order Inequality Dominance: Bangladesh & India



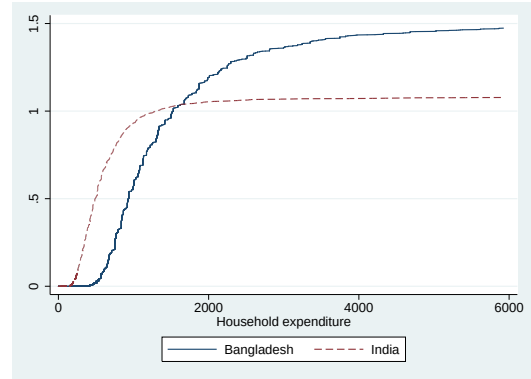
(a) using socioeconomic rank p , $\theta = 0$



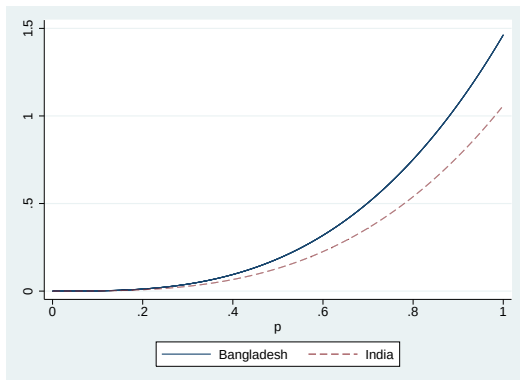
(b) using household expenditure y , $\theta = 0$



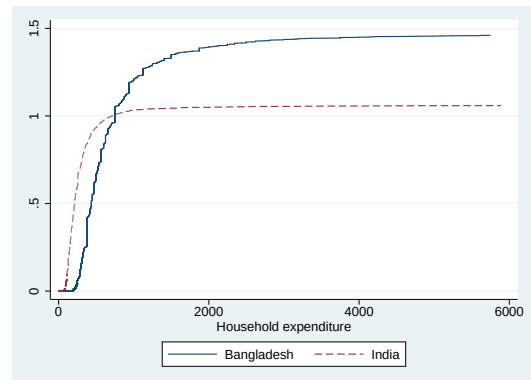
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

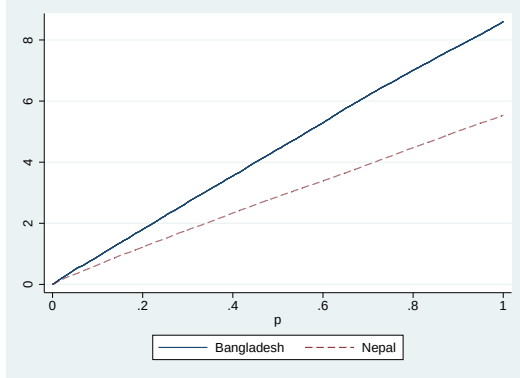


(e) using socioeconomic rank p , $\theta = 1$

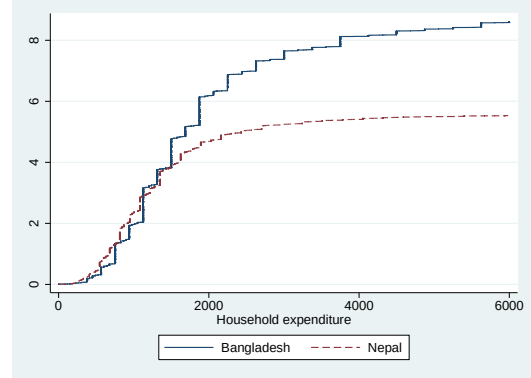


(f) using household expenditure y , $\theta = 1$

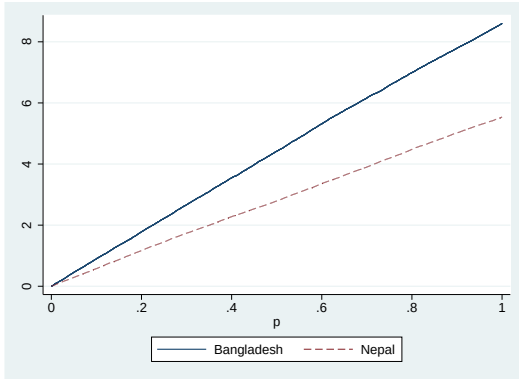
Figure 2.85: Fourth Order Inequality Dominance: Bangladesh & India



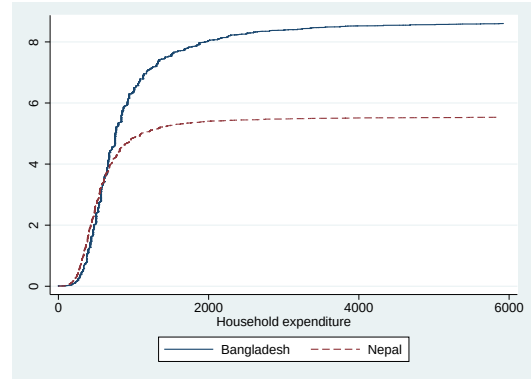
(a) using socioeconomic rank p , $\theta = 0$



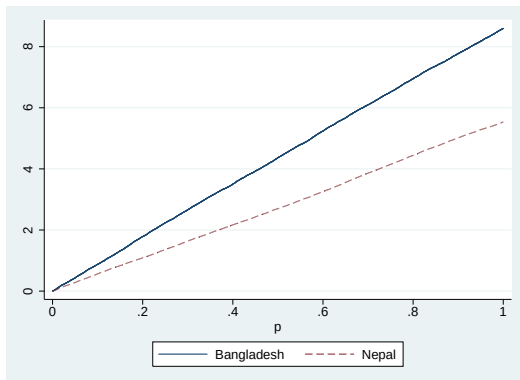
(b) using household expenditure y , $\theta = 0$



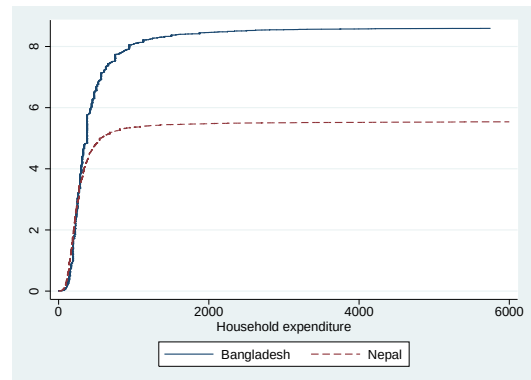
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

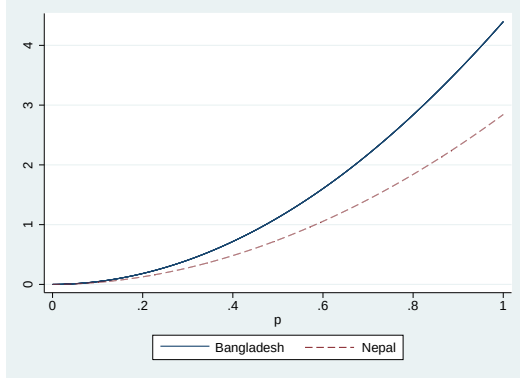


(e) using socioeconomic rank p , $\theta = 1$

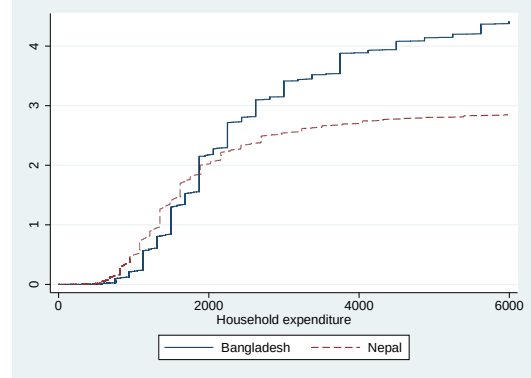


(f) using household expenditure y , $\theta = 1$

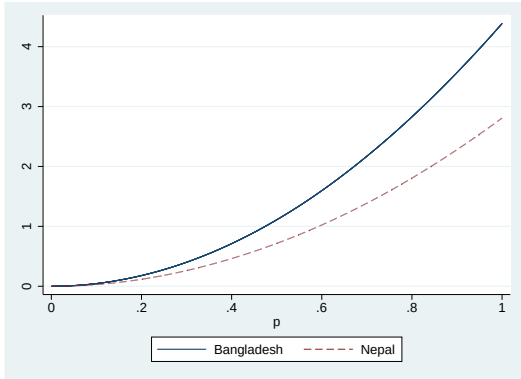
Figure 2.86: Second Order Inequality Dominance: Bangladesh & Nepal



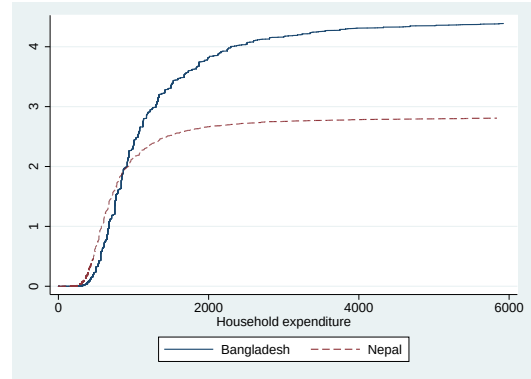
(a) using socioeconomic rank p , $\theta = 0$



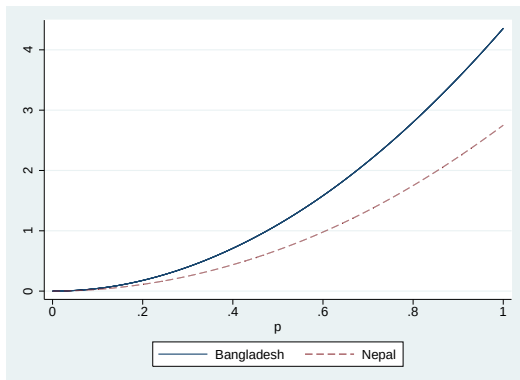
(b) using household expenditure y , $\theta = 0$



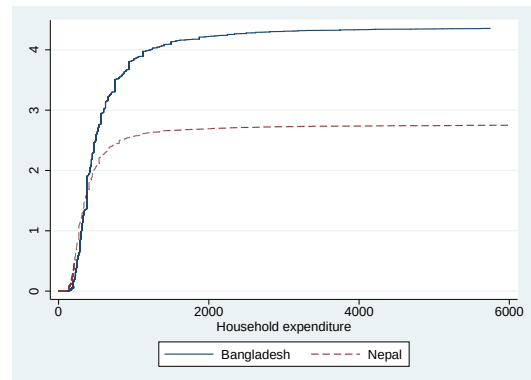
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

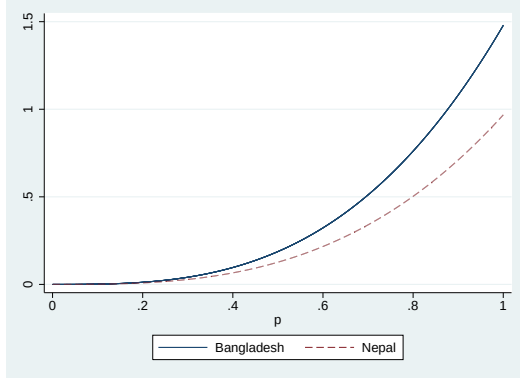


(e) using socioeconomic rank p , $\theta = 1$

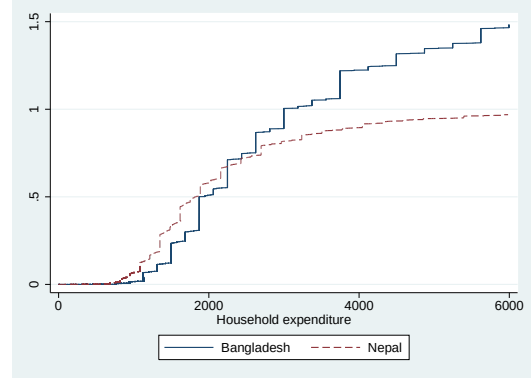


(f) using household expenditure y , $\theta = 1$

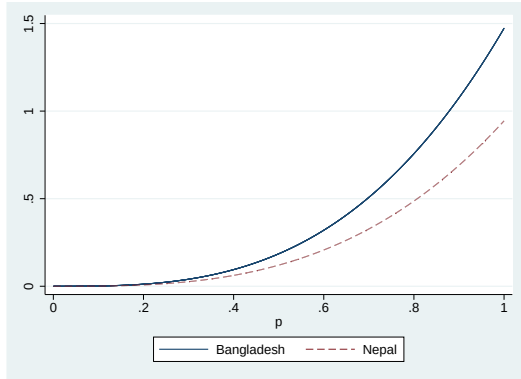
Figure 2.87: Third Order Inequality Dominance: Bangladesh & Nepal



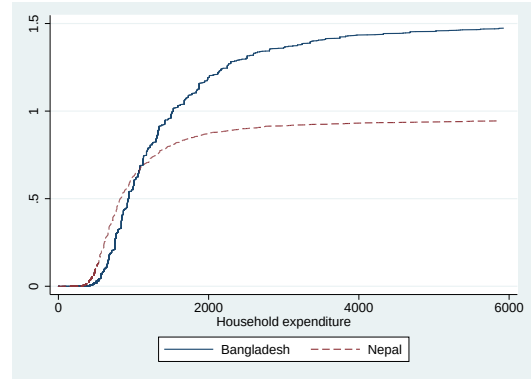
(a) using socioeconomic rank p , $\theta = 0$



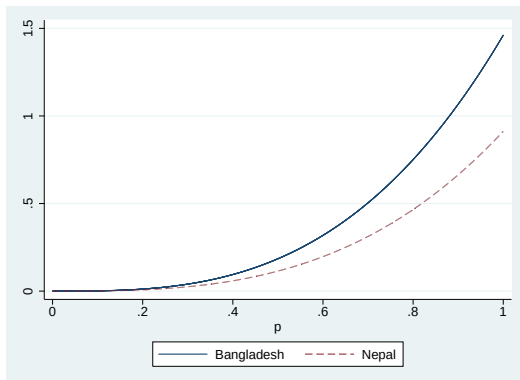
(b) using household expenditure y , $\theta = 0$



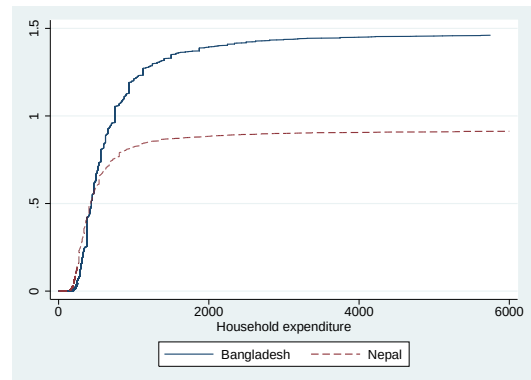
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

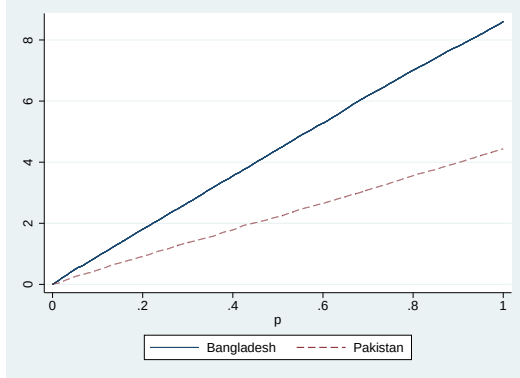


(e) using socioeconomic rank p , $\theta = 1$

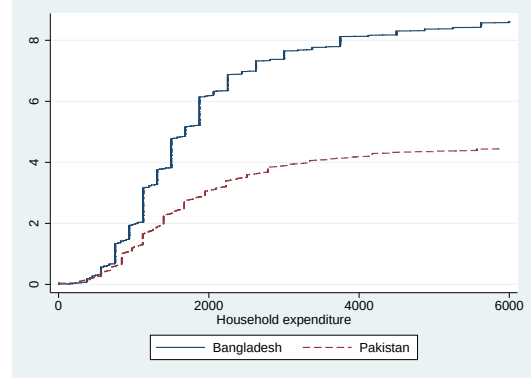


(f) using household expenditure y , $\theta = 1$

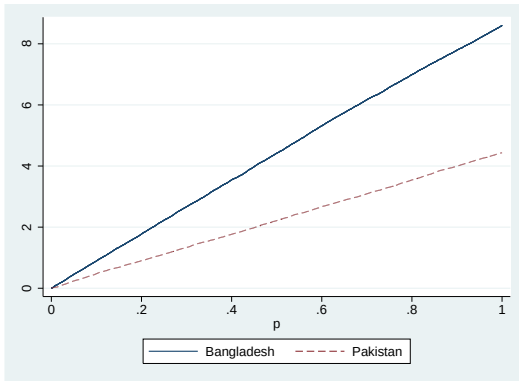
Figure 2.88: Fourth Order Inequality Dominance: Bangladesh & Nepal



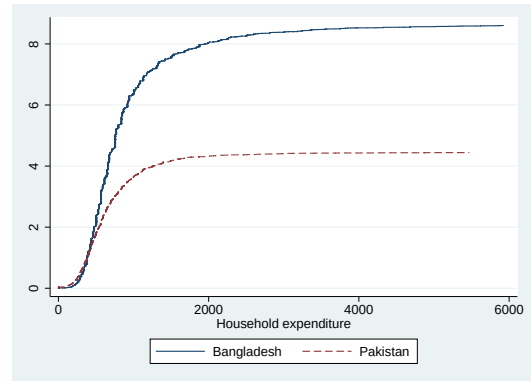
(a) using socioeconomic rank p , $\theta = 0$



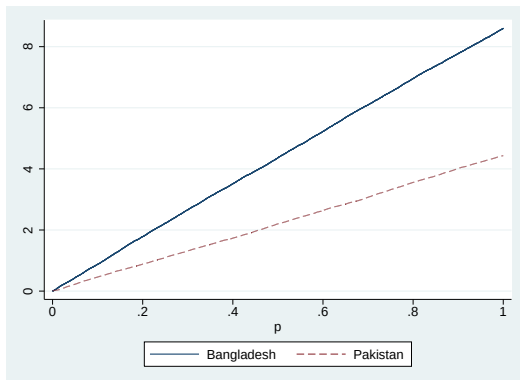
(b) using household expenditure y , $\theta = 0$



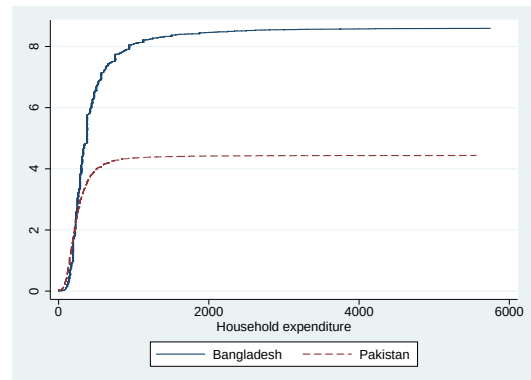
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

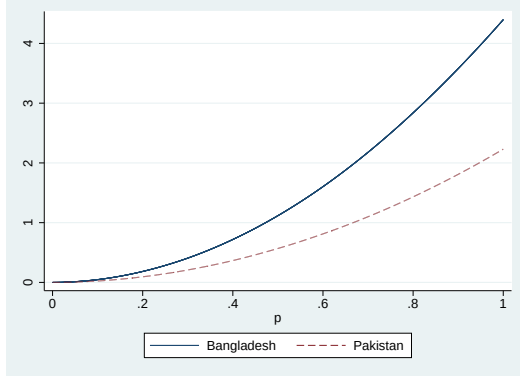


(e) using socioeconomic rank p , $\theta = 1$

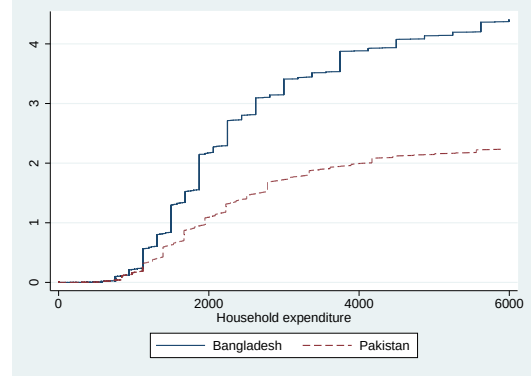


(f) using household expenditure y , $\theta = 1$

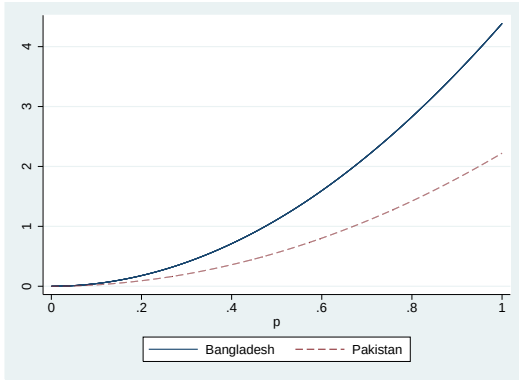
Figure 2.89: Second Order Inequality Dominance: Bangladesh & Pakistan



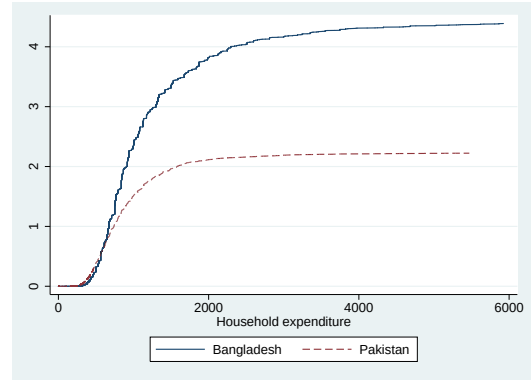
(a) using socioeconomic rank p , $\theta = 0$



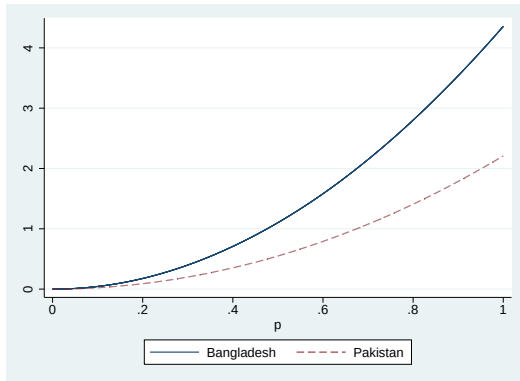
(b) using household expenditure y , $\theta = 0$



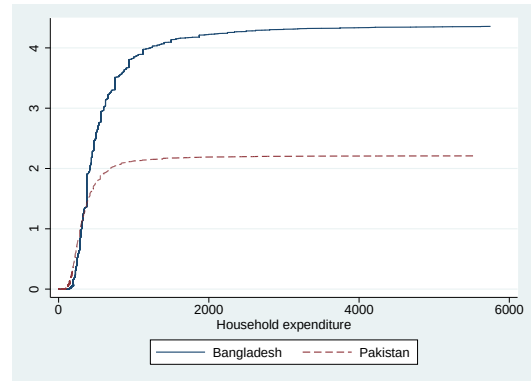
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

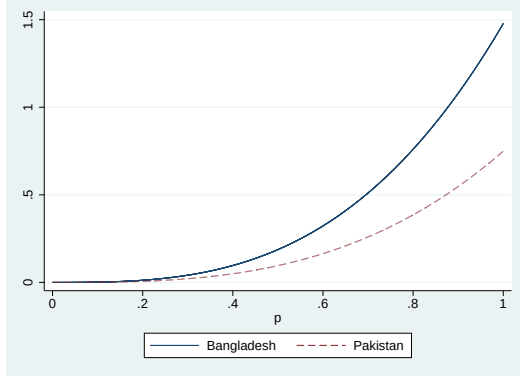


(e) using socioeconomic rank p , $\theta = 1$

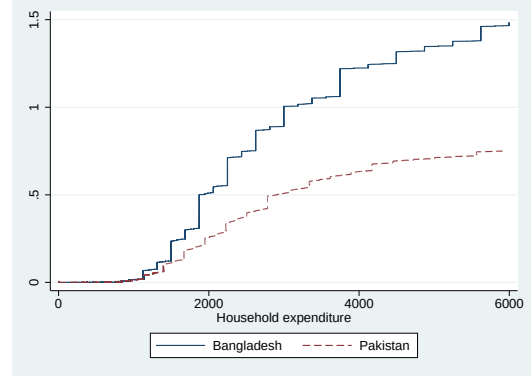


(f) using household expenditure y , $\theta = 1$

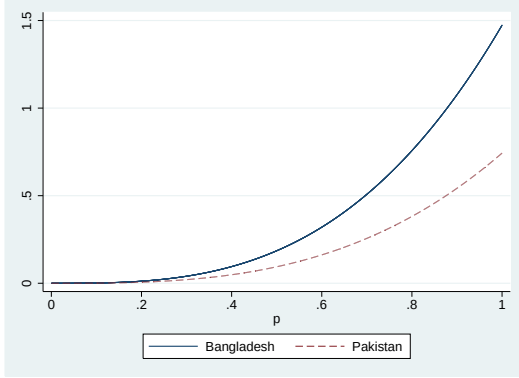
Figure 2.90: Third Order Inequality Dominance: Bangladesh & Pakistan



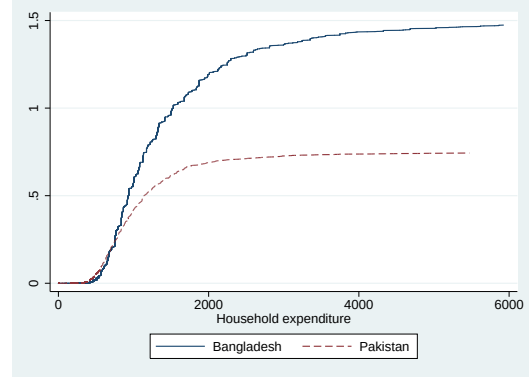
(a) using socioeconomic rank p , $\theta = 0$



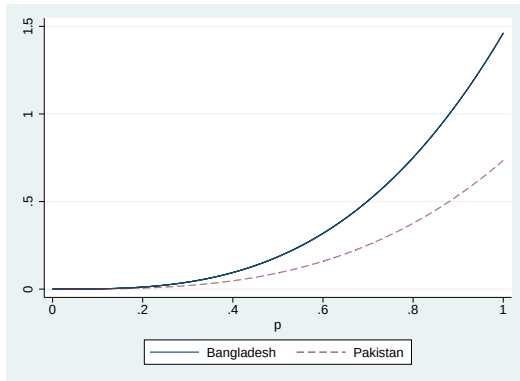
(b) using household expenditure y , $\theta = 0$



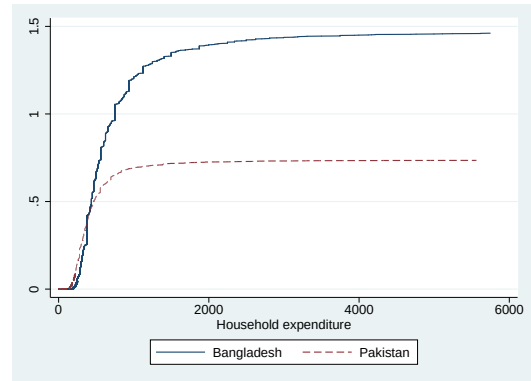
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

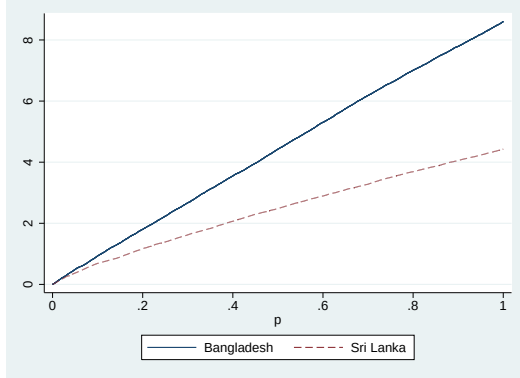


(e) using socioeconomic rank p , $\theta = 1$

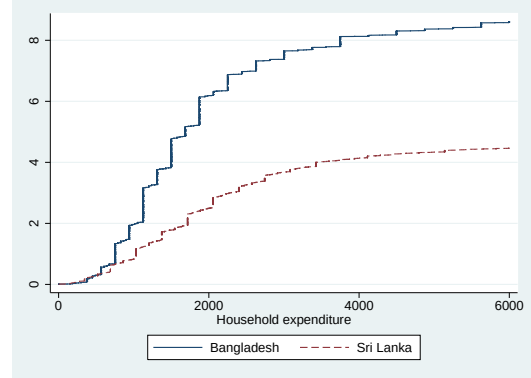


(f) using household expenditure y , $\theta = 1$

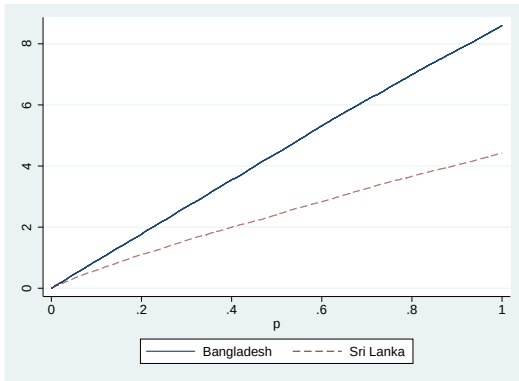
Figure 2.91: Fourth Order Inequality Dominance: Bangladesh & Pakistan



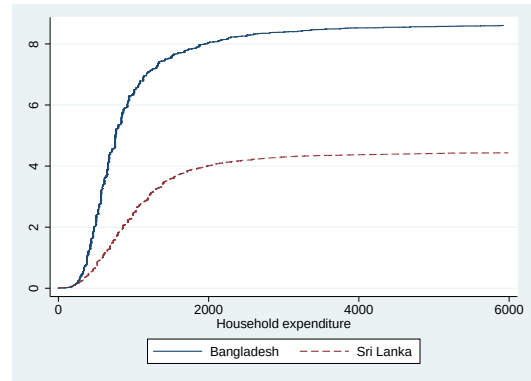
(a) using socioeconomic rank p , $\theta = 0$



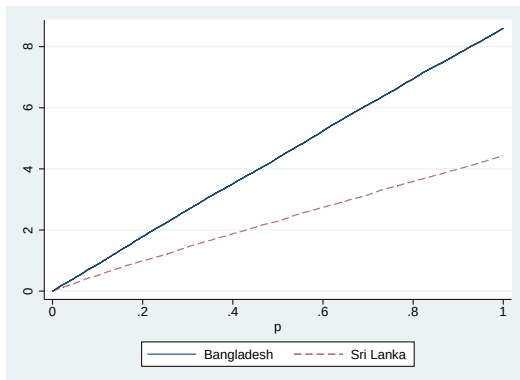
(b) using household expenditure y , $\theta = 0$



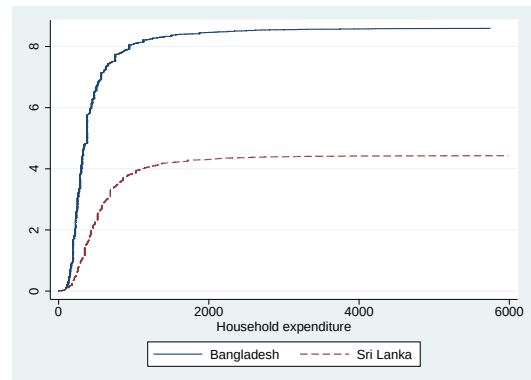
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

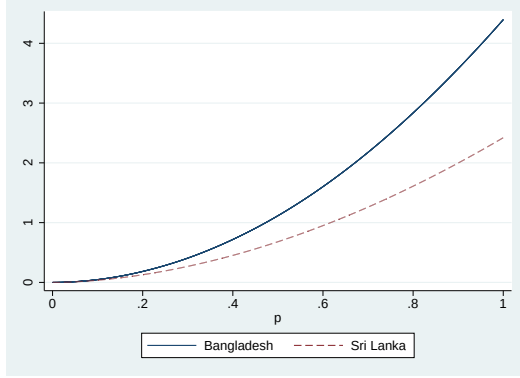


(e) using socioeconomic rank p , $\theta = 1$

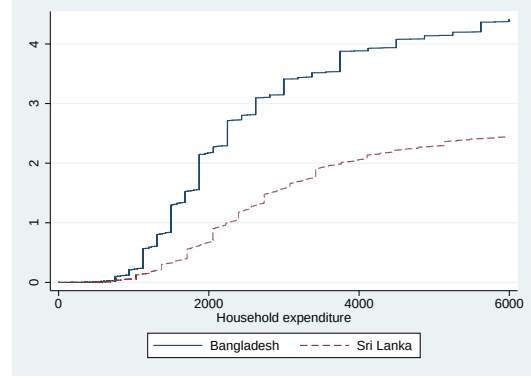


(f) using household expenditure y , $\theta = 1$

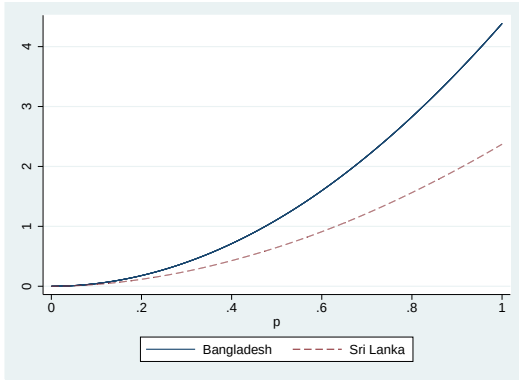
Figure 2.92: Second Order Inequality Dominance: Bangladesh & Sri Lanka



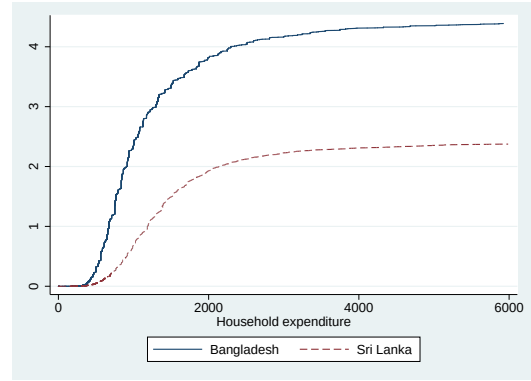
(a) using socioeconomic rank p , $\theta = 0$



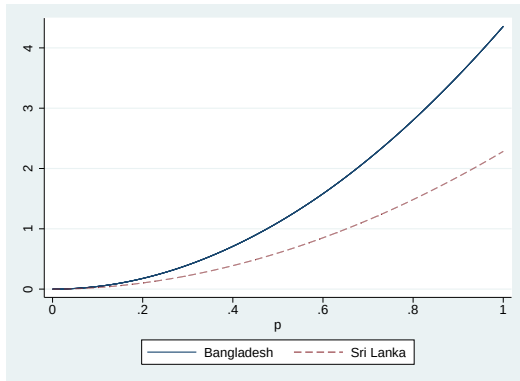
(b) using household expenditure y , $\theta = 0$



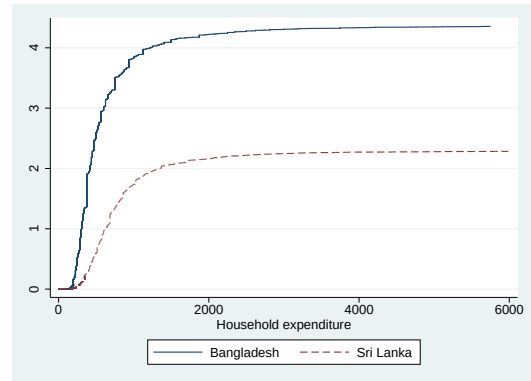
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

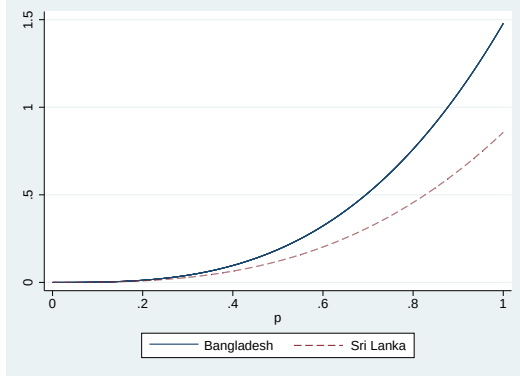


(e) using socioeconomic rank p , $\theta = 1$

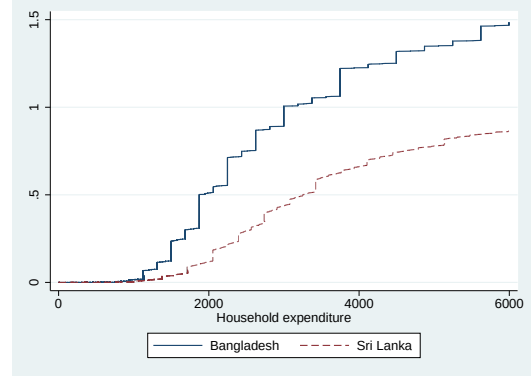


(f) using household expenditure y , $\theta = 1$

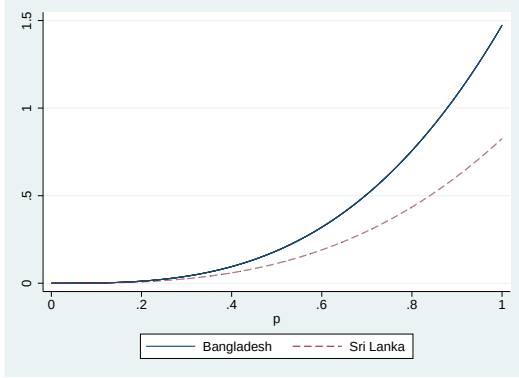
Figure 2.93: Third Order Inequality Dominance: Bangladesh & Sri Lanka



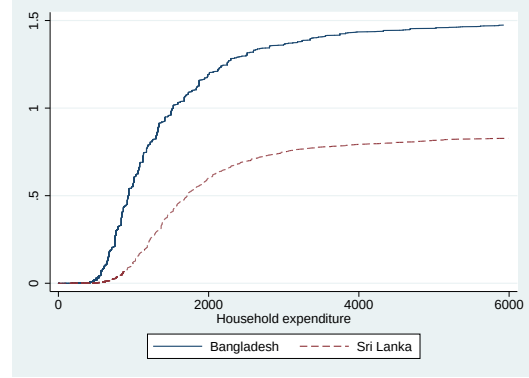
(a) using socioeconomic rank p , $\theta = 0$



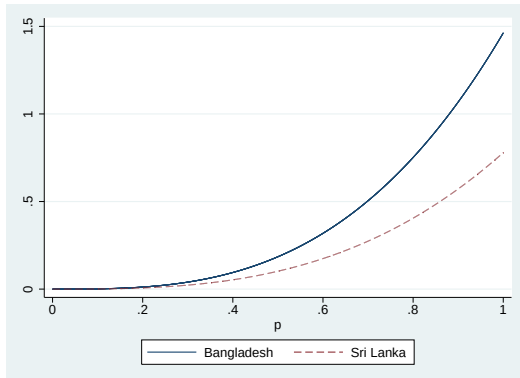
(b) using household expenditure y , $\theta = 0$



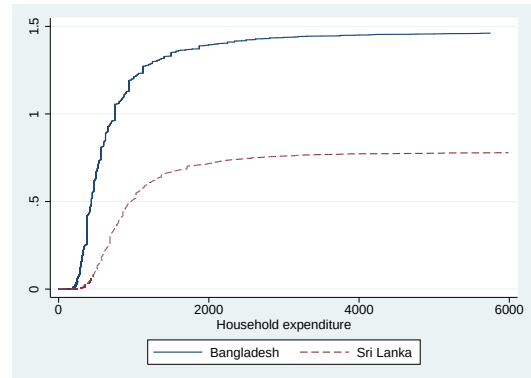
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

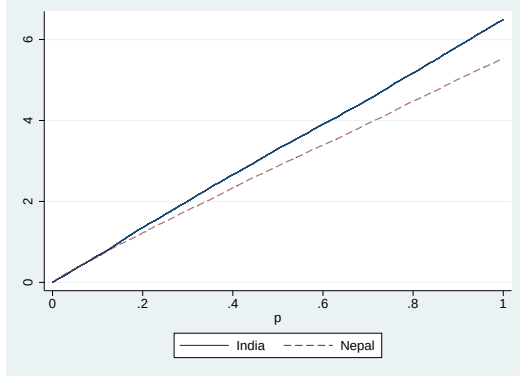


(e) using socioeconomic rank p , $\theta = 1$

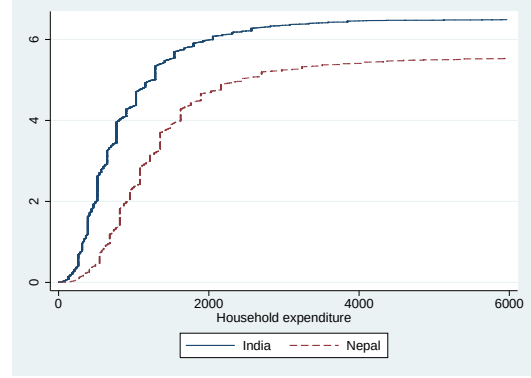


(f) using household expenditure y , $\theta = 1$

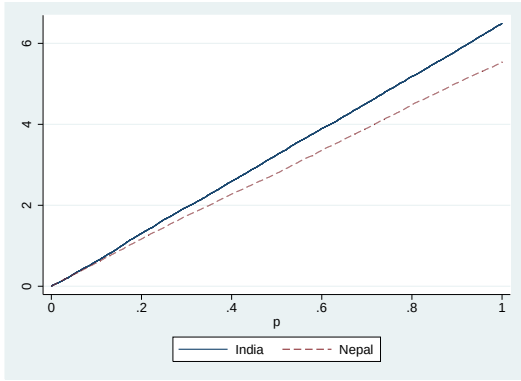
Figure 2.94: Fourth Order Inequality Dominance: Bangladesh & Sri Lanka



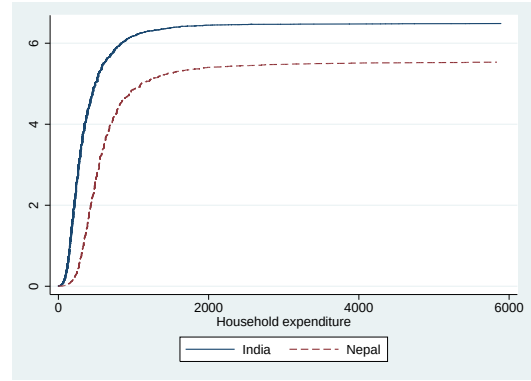
(a) using socioeconomic rank p , $\theta = 0$



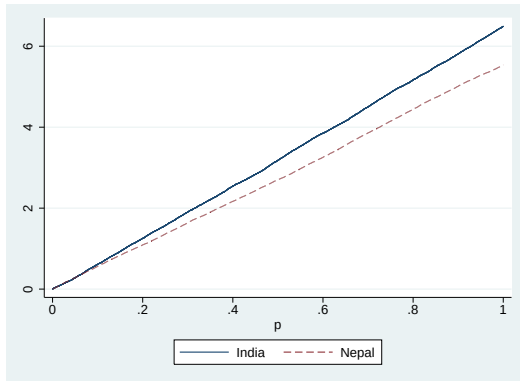
(b) using household expenditure y , $\theta = 0$



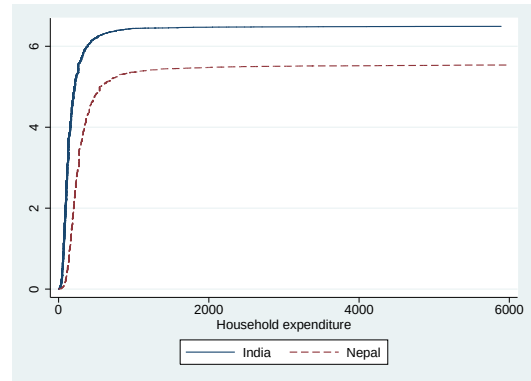
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

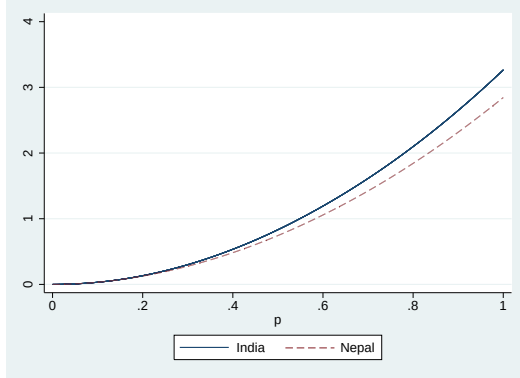


(e) using socioeconomic rank p , $\theta = 1$

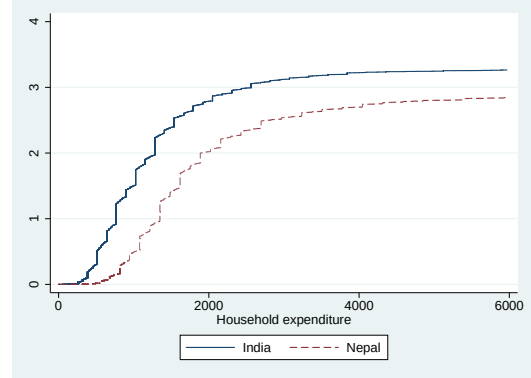


(f) using household expenditure y , $\theta = 1$

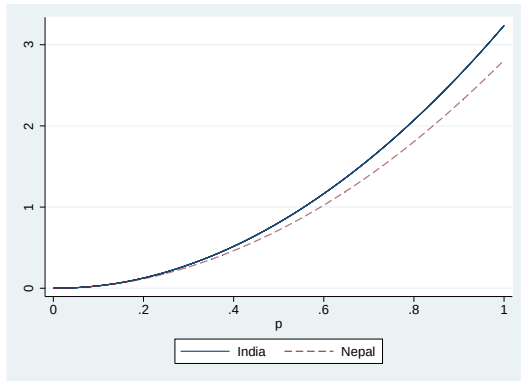
Figure 2.95: Second Order Inequality Dominance: India & Nepal



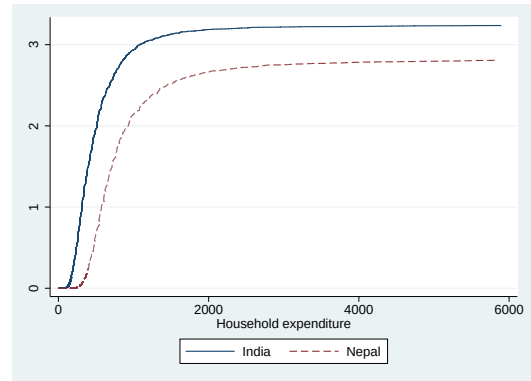
(a) using socioeconomic rank p , $\theta = 0$



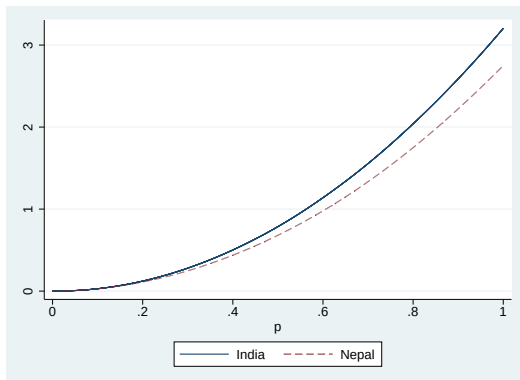
(b) using household expenditure y , $\theta = 0$



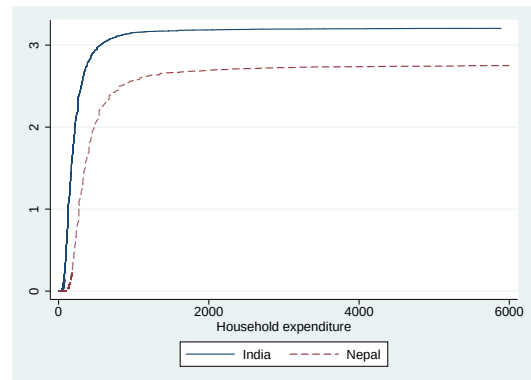
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

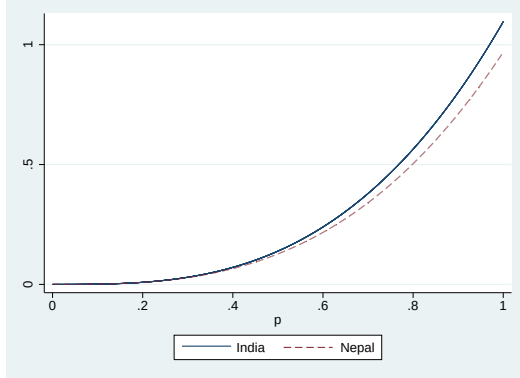


(e) using socioeconomic rank p , $\theta = 1$

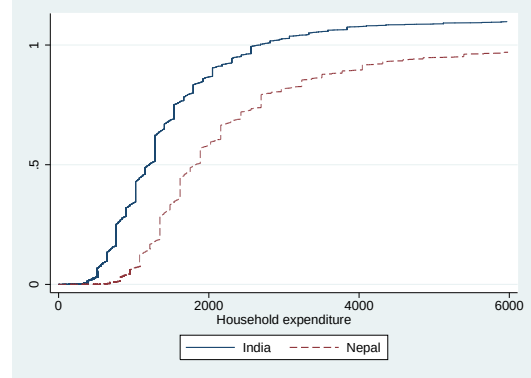


(f) using household expenditure y , $\theta = 1$

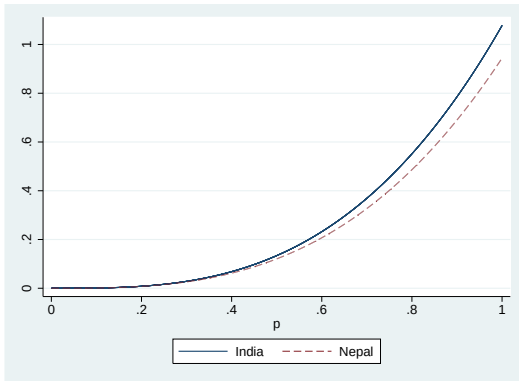
Figure 2.96: Third Order Inequality Dominance: India & Nepal



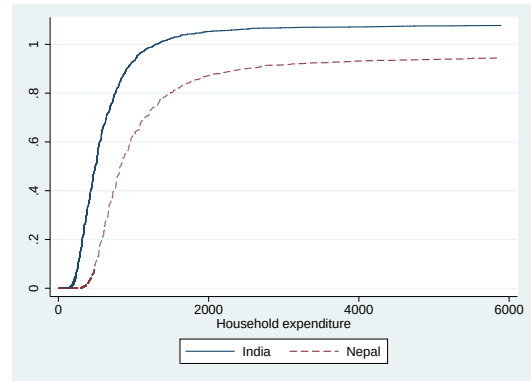
(a) using socioeconomic rank p , $\theta = 0$



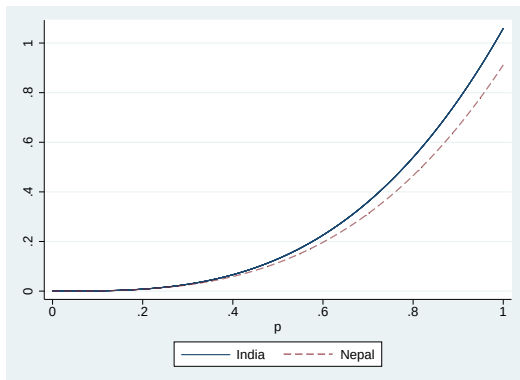
(b) using household expenditure y , $\theta = 0$



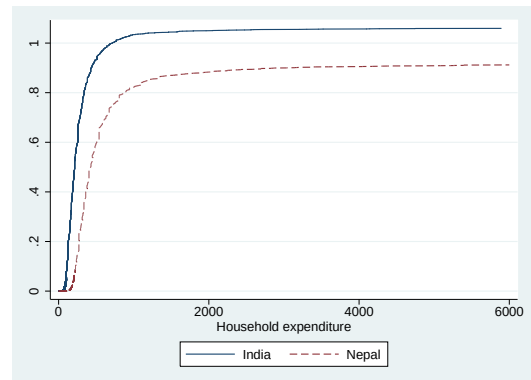
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

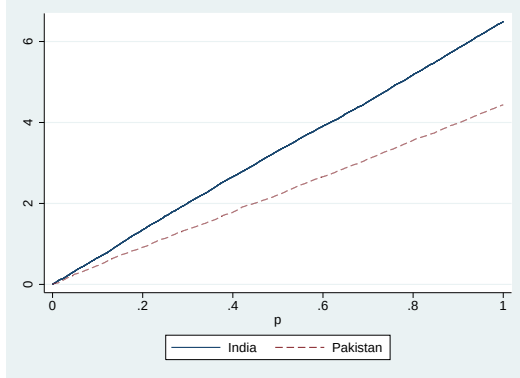


(e) using socioeconomic rank p , $\theta = 1$

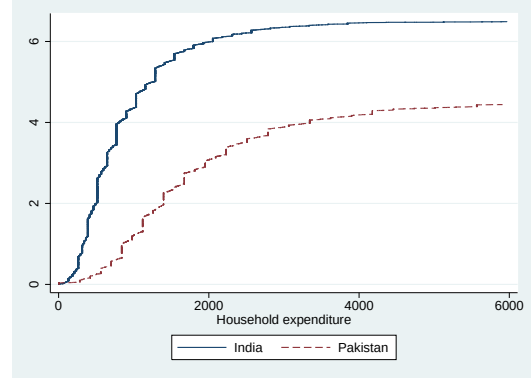


(f) using household expenditure y , $\theta = 1$

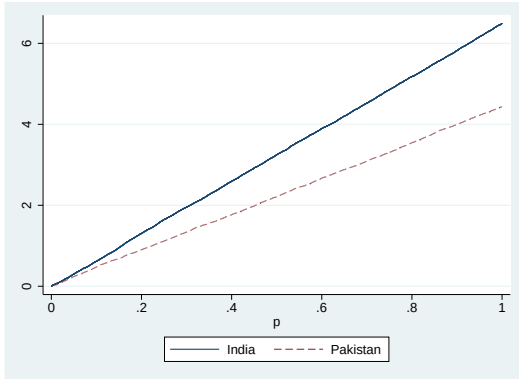
Figure 2.97: Fourth Order Inequality Dominance: India & Nepal



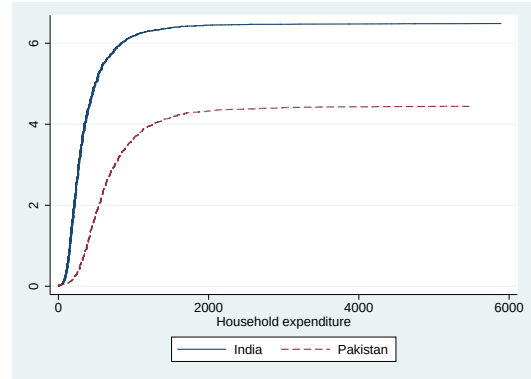
(a) using socioeconomic rank p , $\theta = 0$



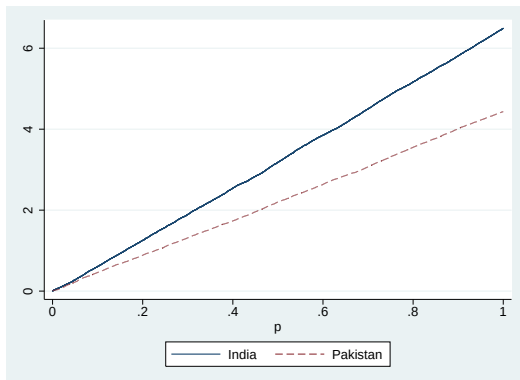
(b) using household expenditure y , $\theta = 0$



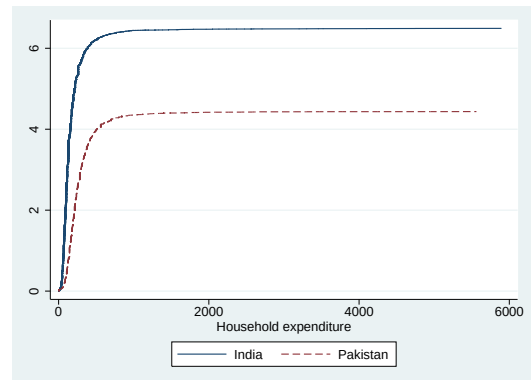
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

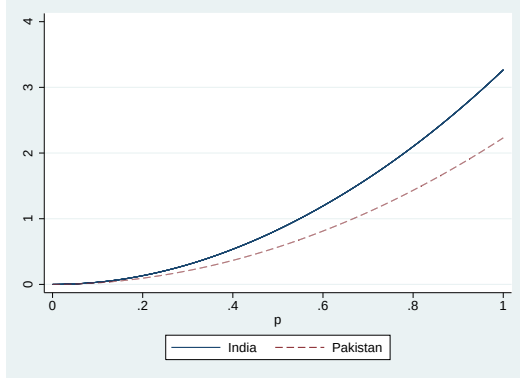


(e) using socioeconomic rank p , $\theta = 1$

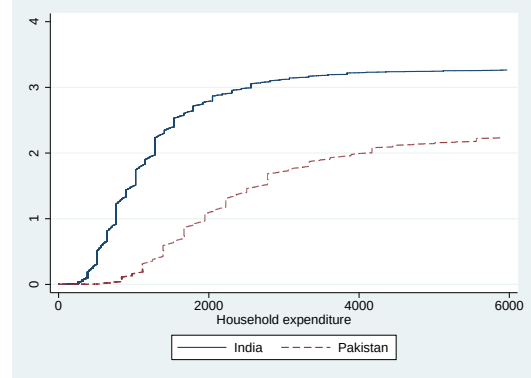


(f) using household expenditure y , $\theta = 1$

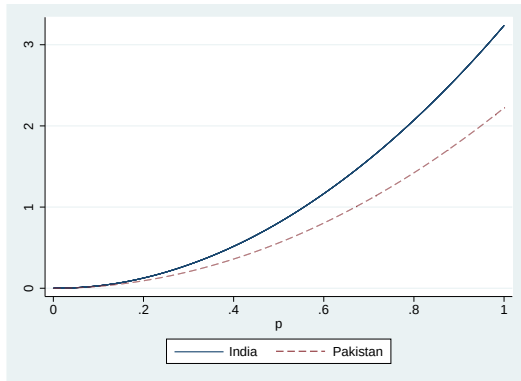
Figure 2.98: Second Order Inequality Dominance: India & Pakistan



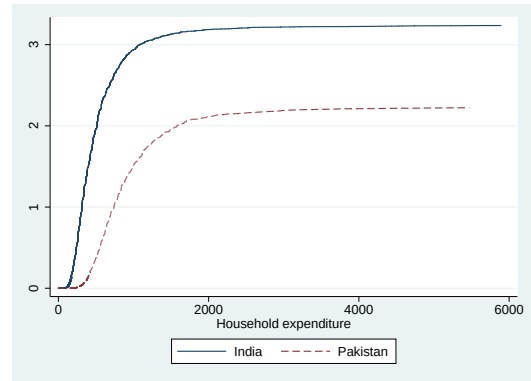
(a) using socioeconomic rank p , $\theta = 0$



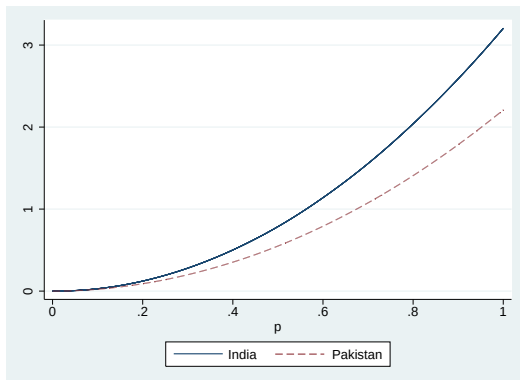
(b) using household expenditure y , $\theta = 0$



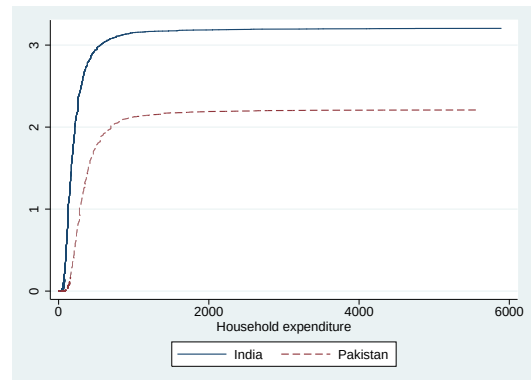
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

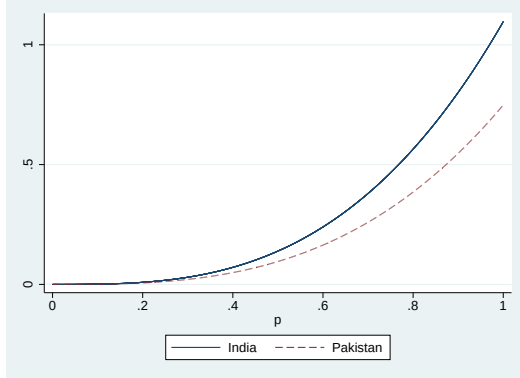


(e) using socioeconomic rank p , $\theta = 1$

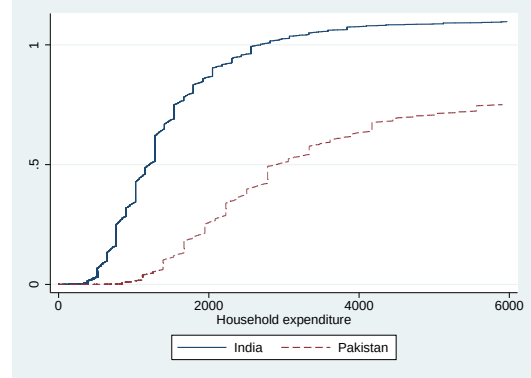


(f) using household expenditure y , $\theta = 1$

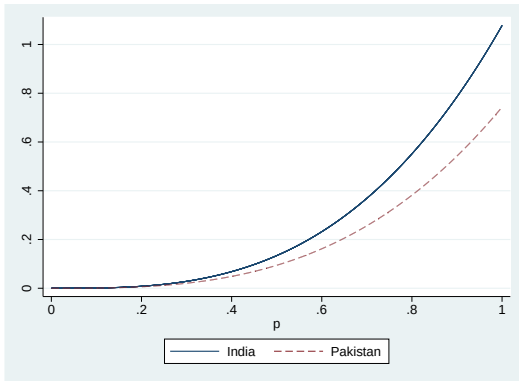
Figure 2.99: Third Order Inequality Dominance: India & Pakistan



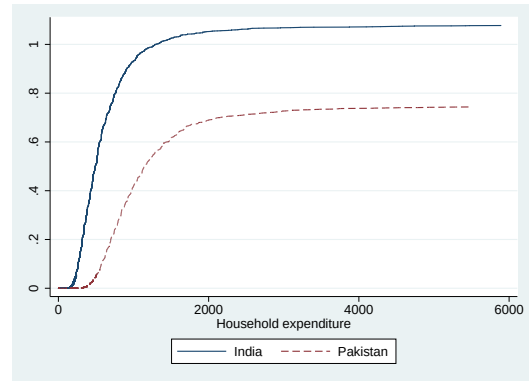
(a) using socioeconomic rank p , $\theta = 0$



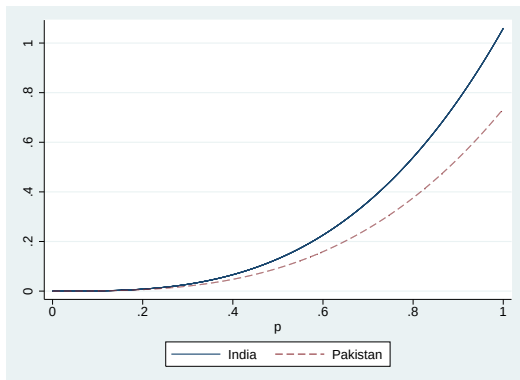
(b) using household expenditure y , $\theta = 0$



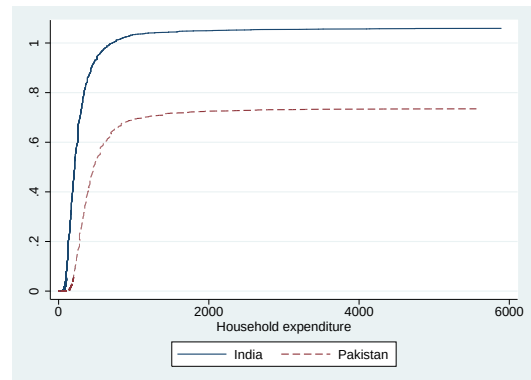
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

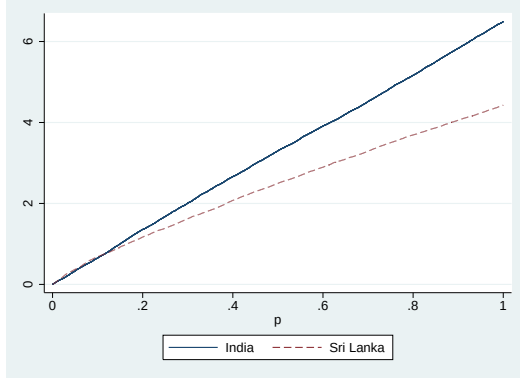


(e) using socioeconomic rank p , $\theta = 1$

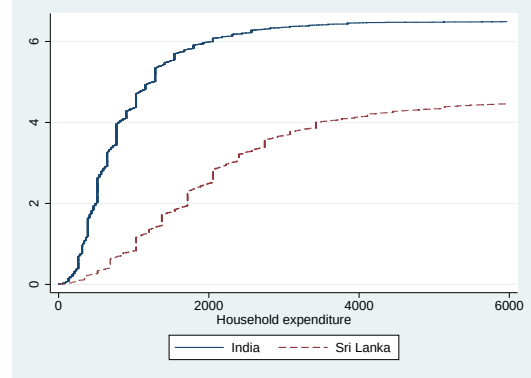


(f) using household expenditure y , $\theta = 1$

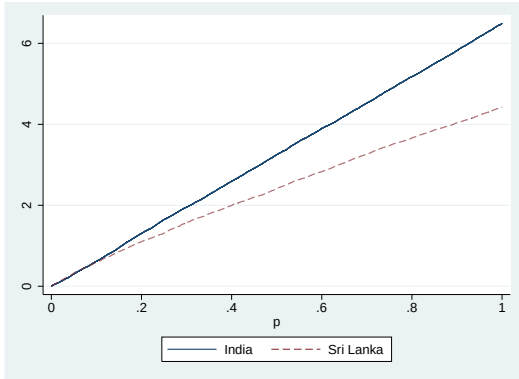
Figure 2.100: Fourth Order Inequality Dominance: India & Pakistan



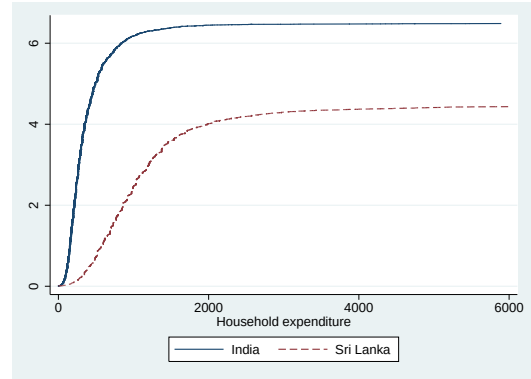
(a) using socioeconomic rank p , $\theta = 0$



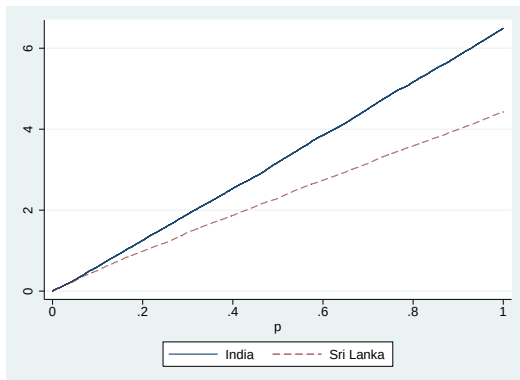
(b) using household expenditure y , $\theta = 0$



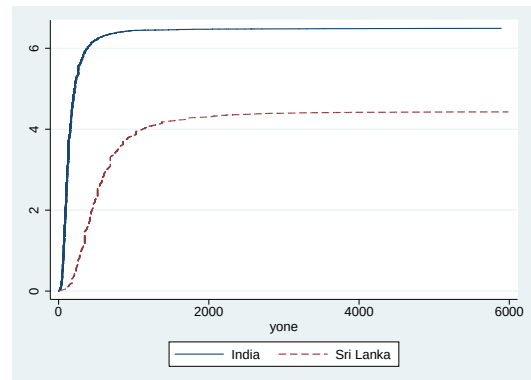
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

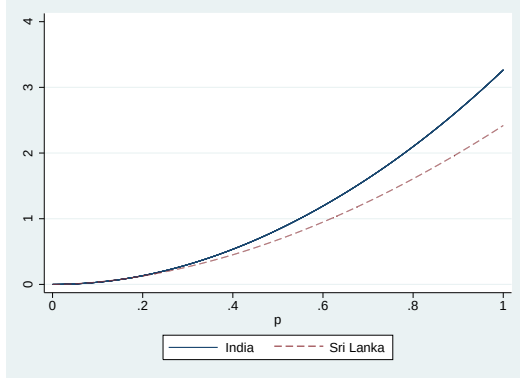


(e) using socioeconomic rank p , $\theta = 1$

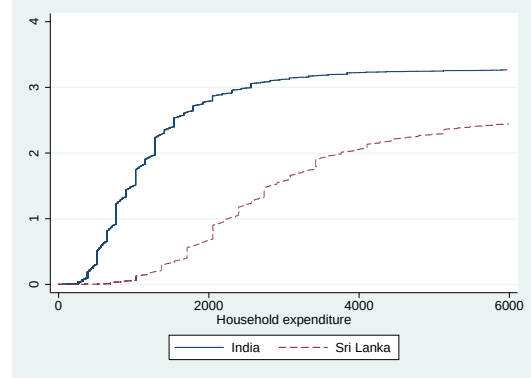


(f) using household expenditure y , $\theta = 1$

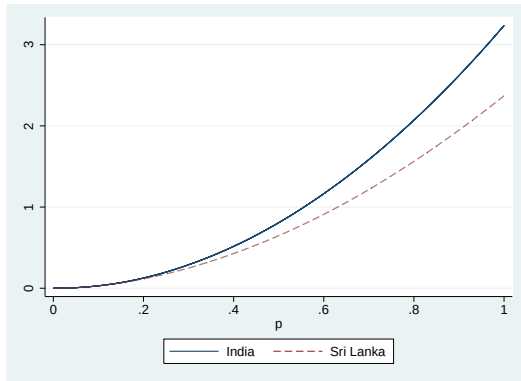
Figure 2.101: Second Order Inequality Dominance: India & Sri Lanka



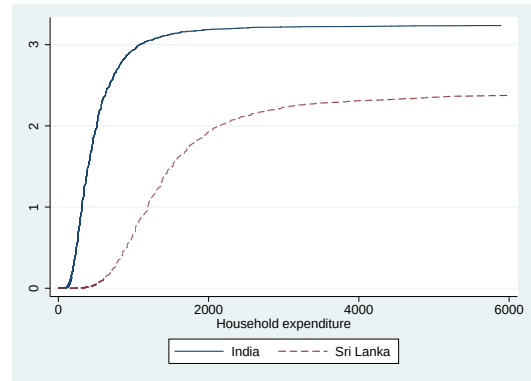
(a) using socioeconomic rank p , $\theta = 0$



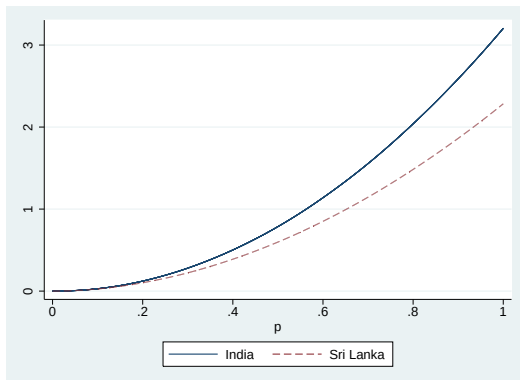
(b) using household expenditure y , $\theta = 0$



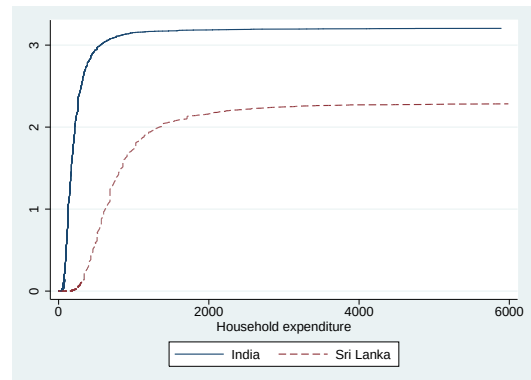
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

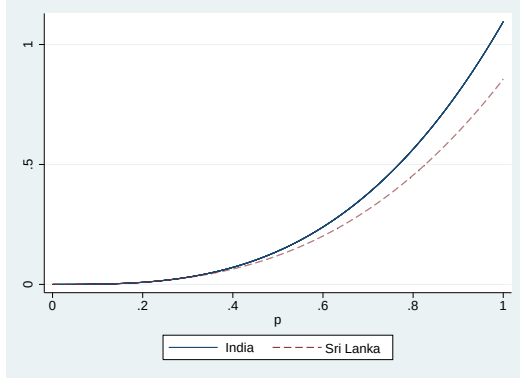


(e) using socioeconomic rank p , $\theta = 1$

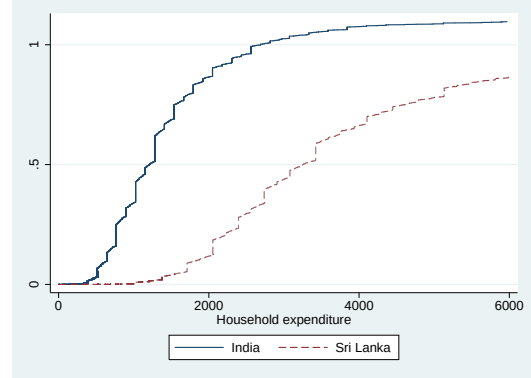


(f) using household expenditure y , $\theta = 1$

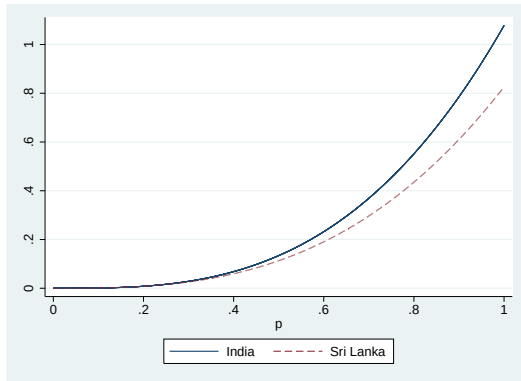
Figure 2.102: Third Order Inequality Dominance: India & Sri Lanka



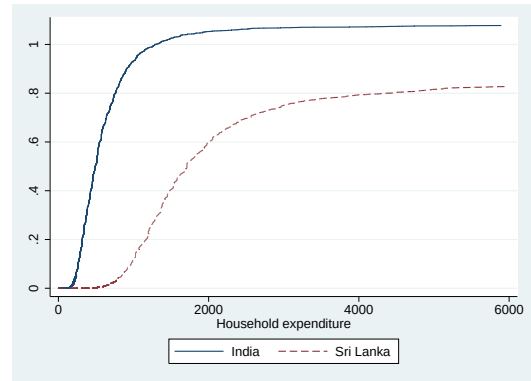
(a) using socioeconomic rank p , $\theta = 0$



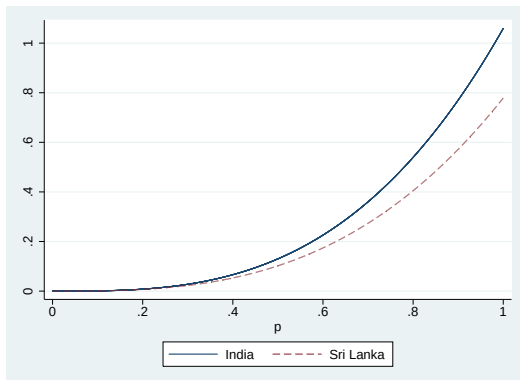
(b) using household expenditure y , $\theta = 0$



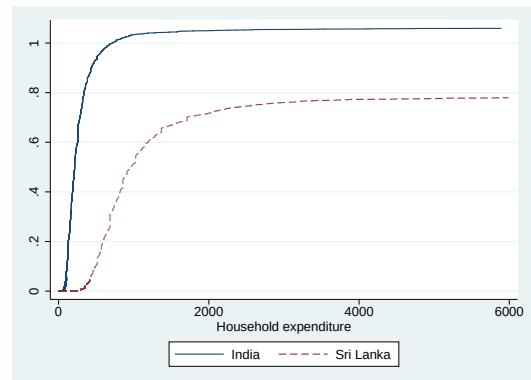
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

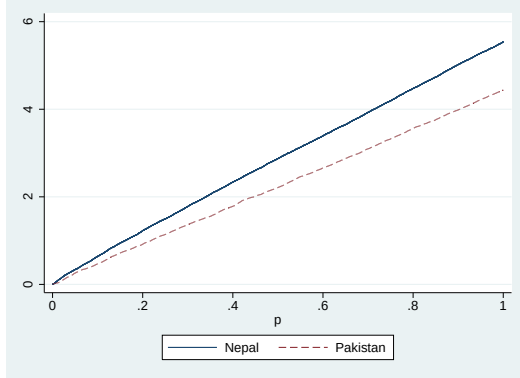


(e) using socioeconomic rank p , $\theta = 1$

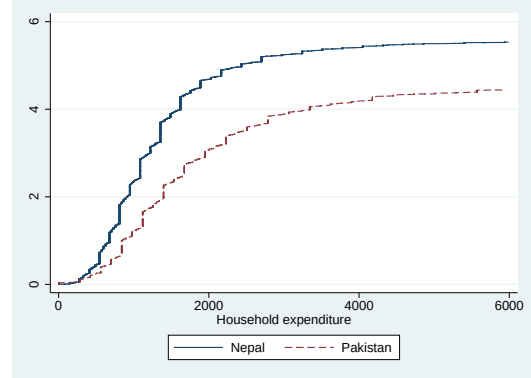


(f) using household expenditure y , $\theta = 1$

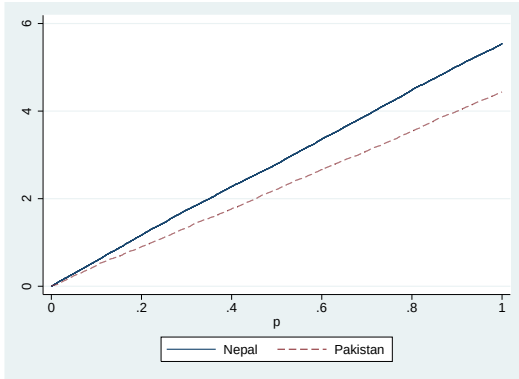
Figure 2.103: Fourth Order Inequality Dominance: India & Sri Lanka



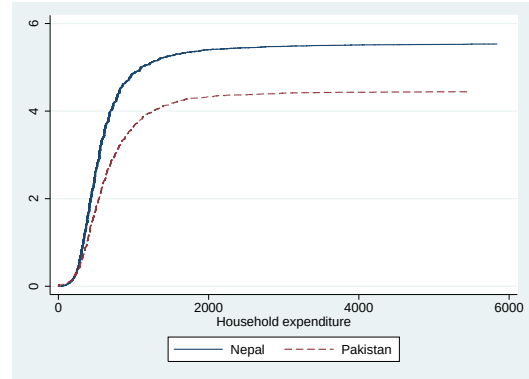
(a) using socioeconomic rank p , $\theta = 0$



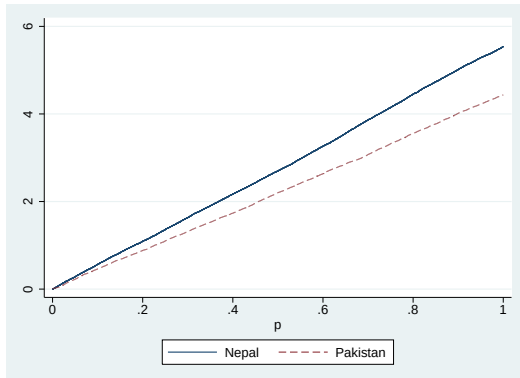
(b) using household expenditure y , $\theta = 0$



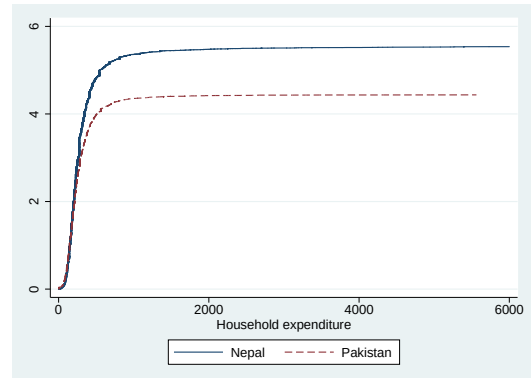
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

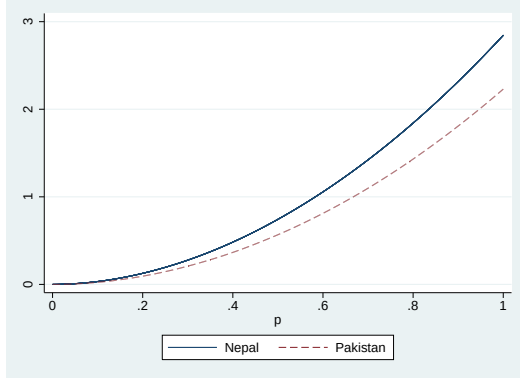


(e) using socioeconomic rank p , $\theta = 1$

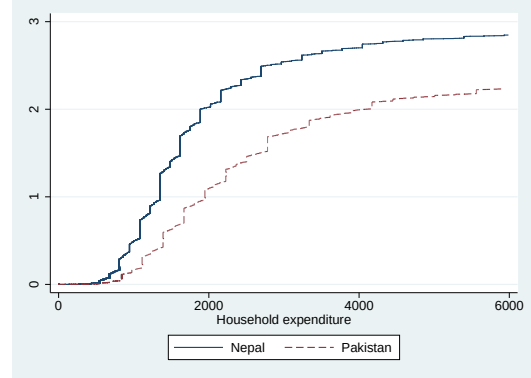


(f) using household expenditure y , $\theta = 1$

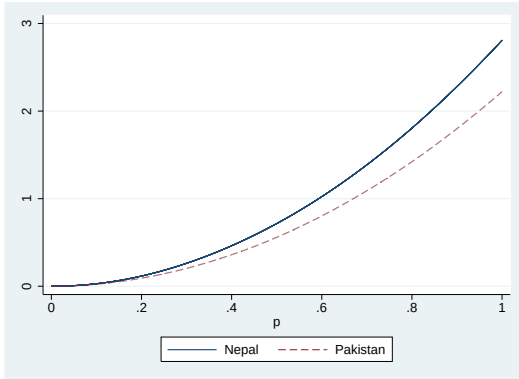
Figure 2.104: Second Order Inequality Dominance: Nepal & Pakistan



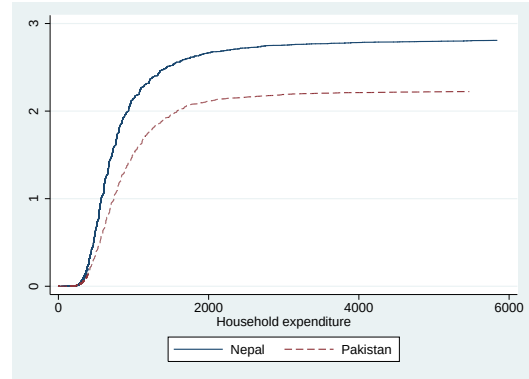
(a) using socioeconomic rank p , $\theta = 0$



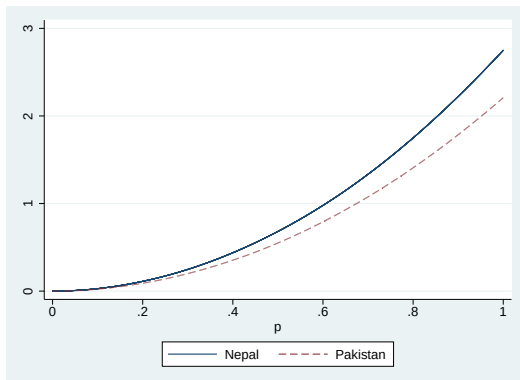
(b) using household expenditure y , $\theta = 0$



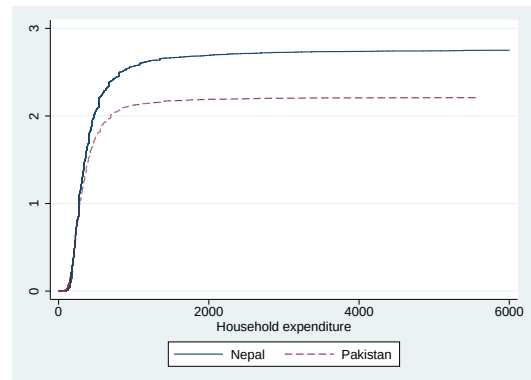
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

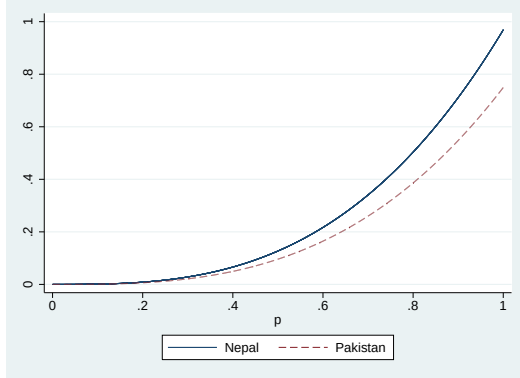


(e) using socioeconomic rank p , $\theta = 1$

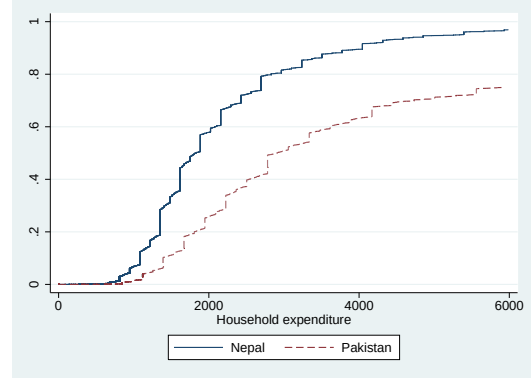


(f) using household expenditure y , $\theta = 1$

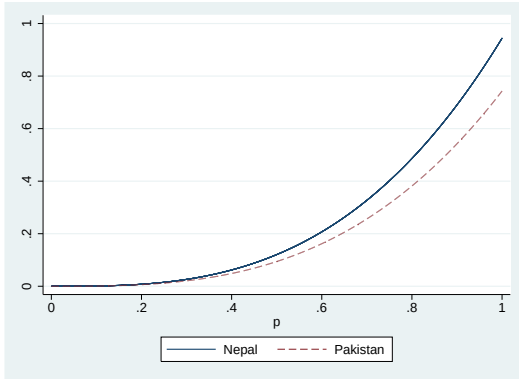
Figure 2.105: Third Order Inequality Dominance: Nepal & Pakistan



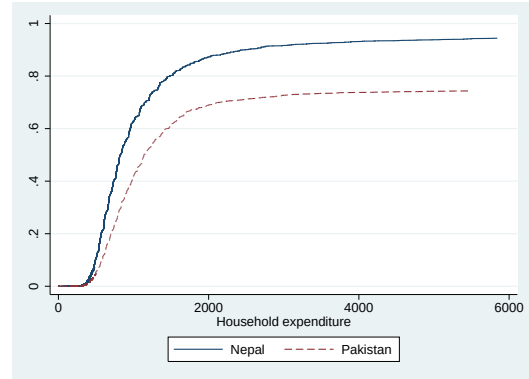
(a) using socioeconomic rank p , $\theta = 0$



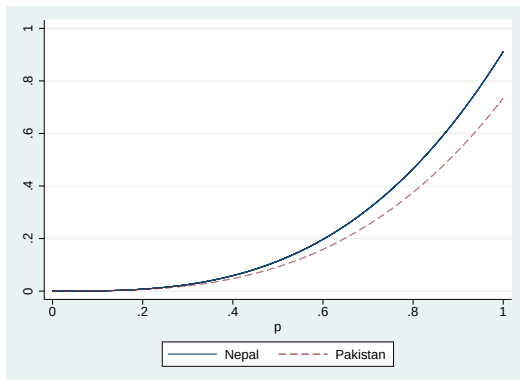
(b) using household expenditure y , $\theta = 0$



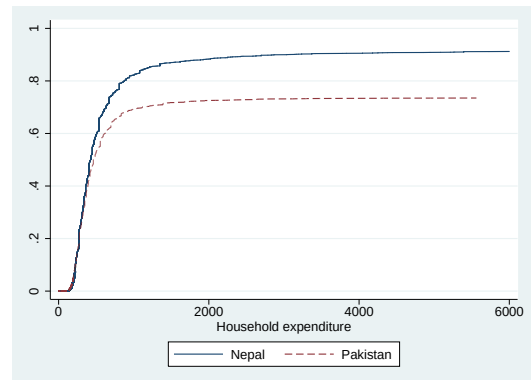
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

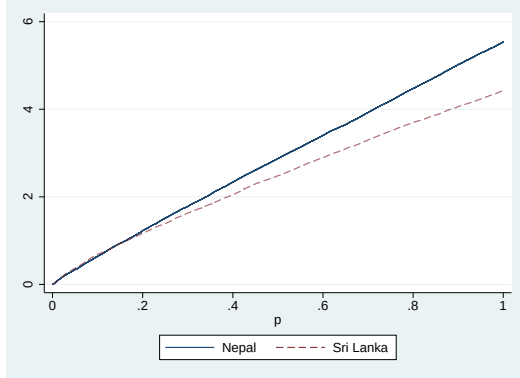


(e) using socioeconomic rank p , $\theta = 1$

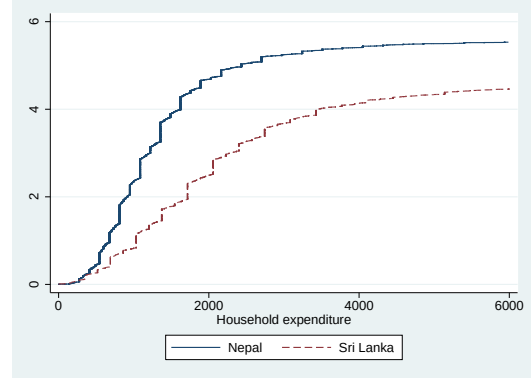


(f) using household expenditure y , $\theta = 1$

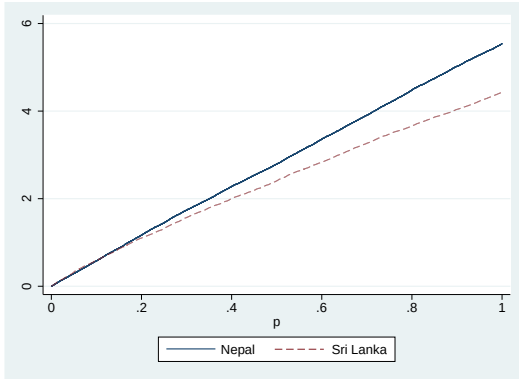
Figure 2.106: Fourth Order Inequality Dominance: Nepal & Pakistan



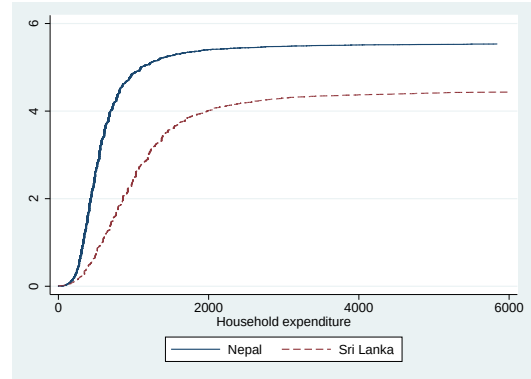
(a) using socioeconomic rank p , $\theta = 0$



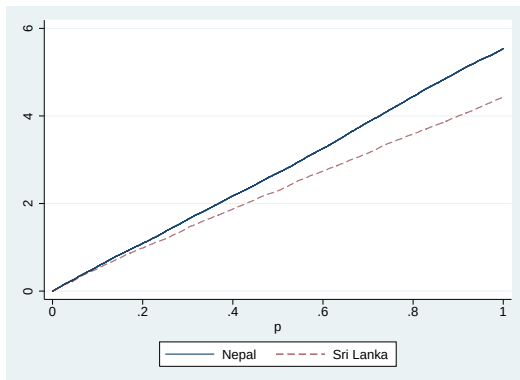
(b) using household expenditure y , $\theta = 0$



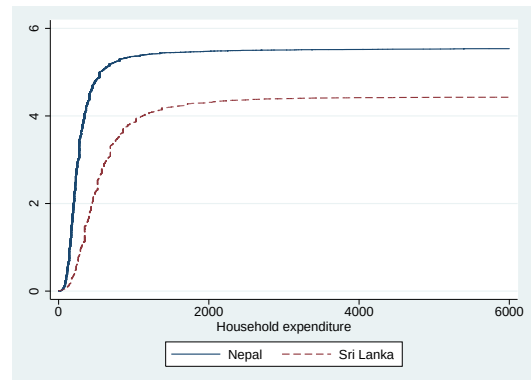
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

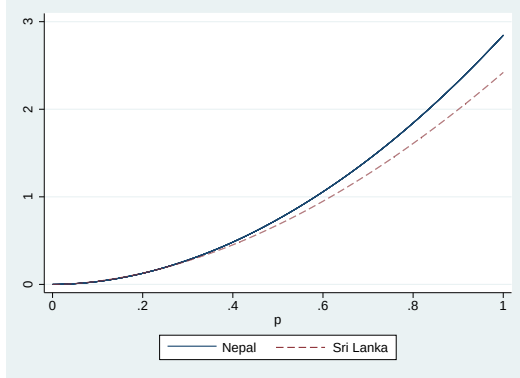


(e) using socioeconomic rank p , $\theta = 1$

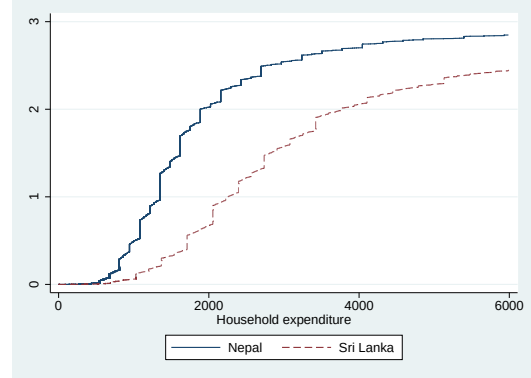


(f) using household expenditure y , $\theta = 1$

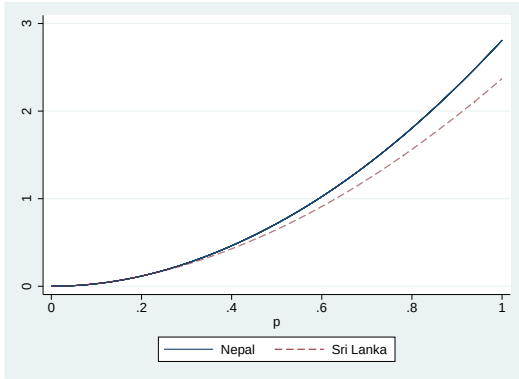
Figure 2.107: Second Order Inequality Dominance: Nepal & Sri Lanka



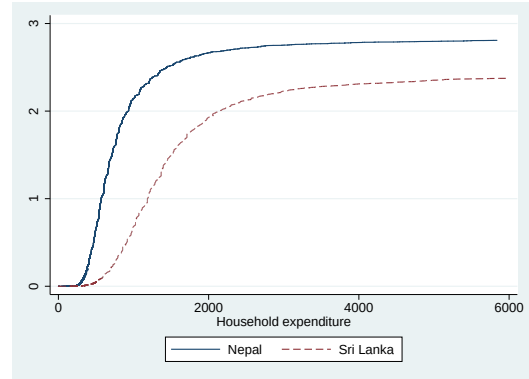
(a) using socioeconomic rank p , $\theta = 0$



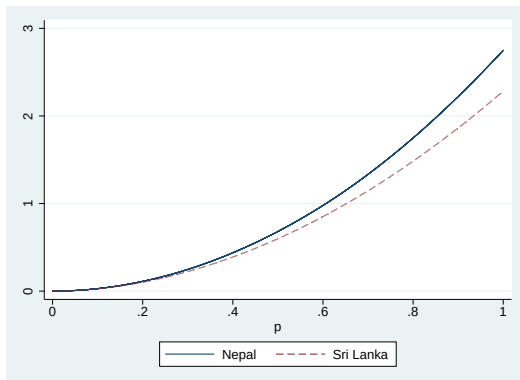
(b) using household expenditure y , $\theta = 0$



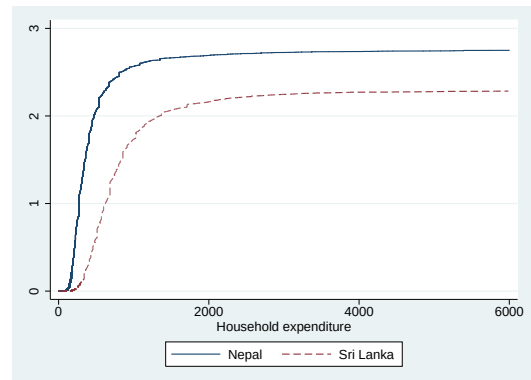
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

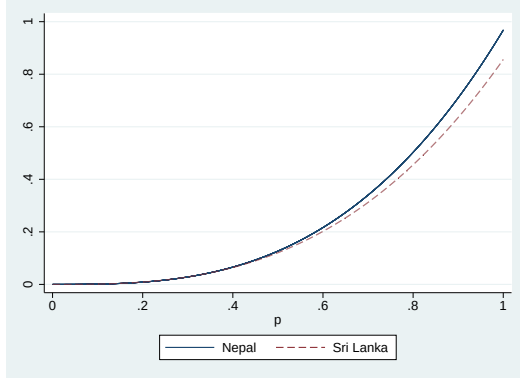


(e) using socioeconomic rank p , $\theta = 1$

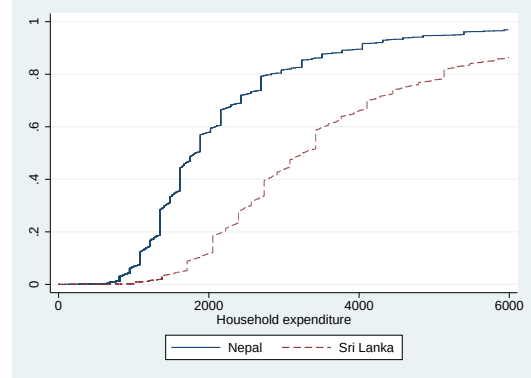


(f) using household expenditure y , $\theta = 1$

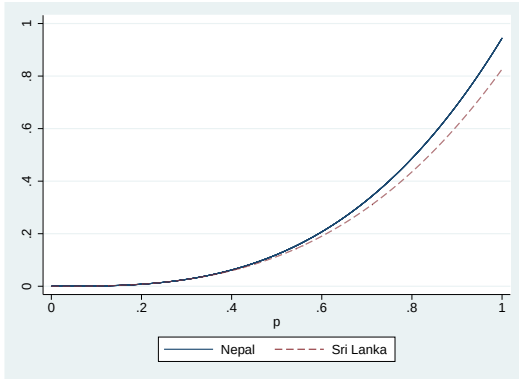
Figure 2.108: Third Order Inequality Dominance: Nepal & Sri Lanka



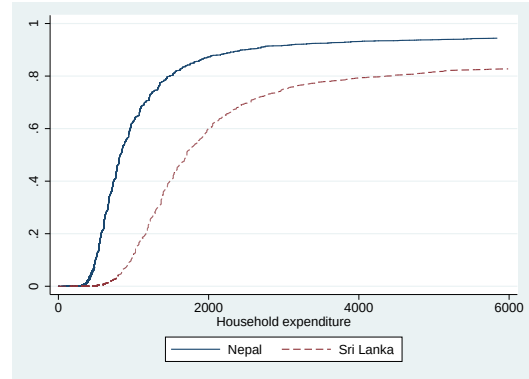
(a) using socioeconomic rank p , $\theta = 0$



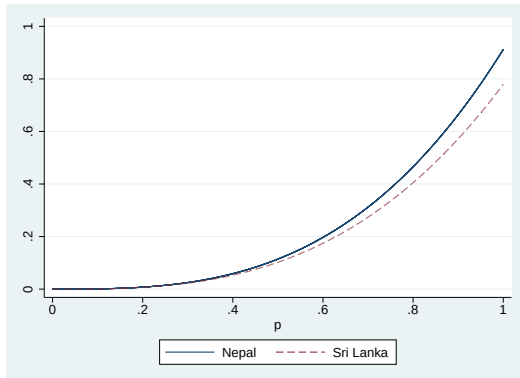
(b) using household expenditure y , $\theta = 0$



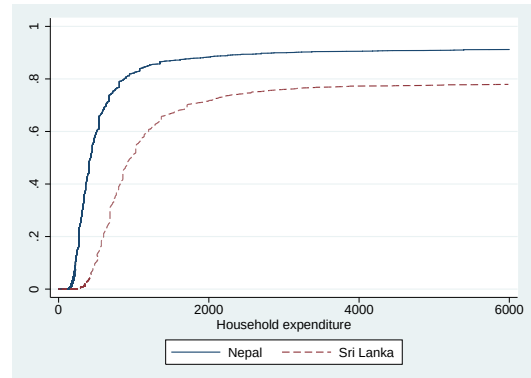
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

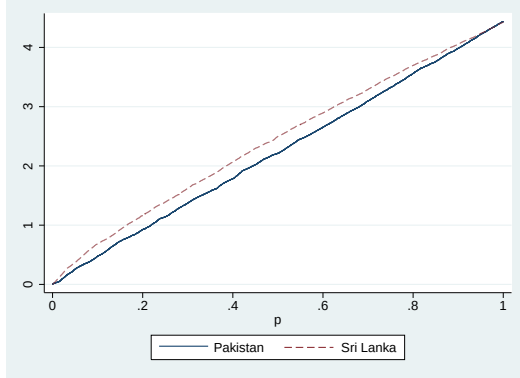


(e) using socioeconomic rank p , $\theta = 1$

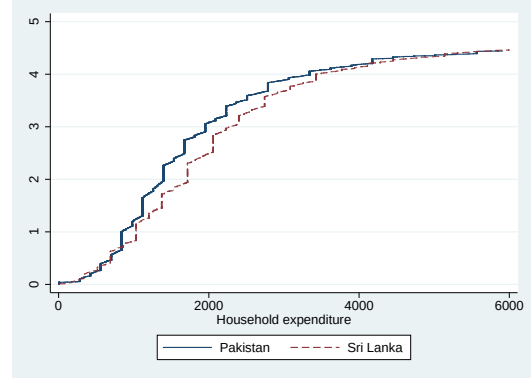


(f) using household expenditure y , $\theta = 1$

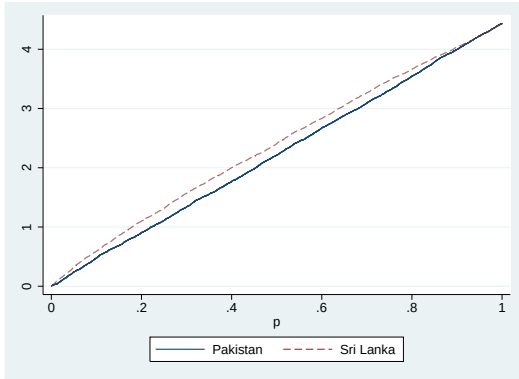
Figure 2.109: Fourth Order Inequality Dominance: Nepal & Sri Lanka



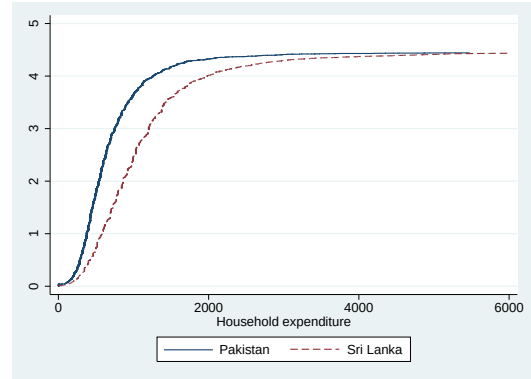
(a) using socioeconomic rank p , $\theta = 0$



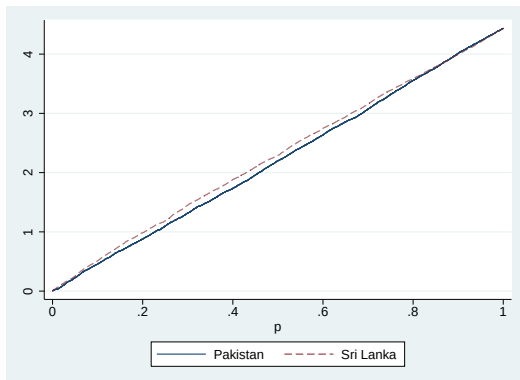
(b) using household expenditure y , $\theta = 0$



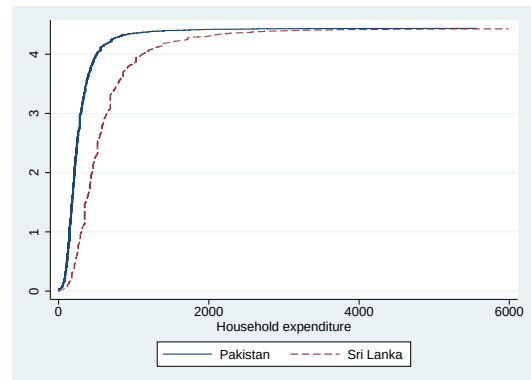
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

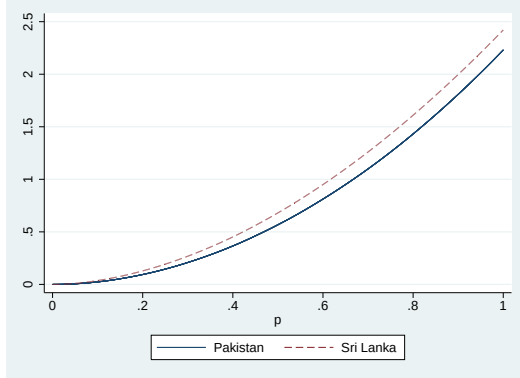


(e) using socioeconomic rank p , $\theta = 1$

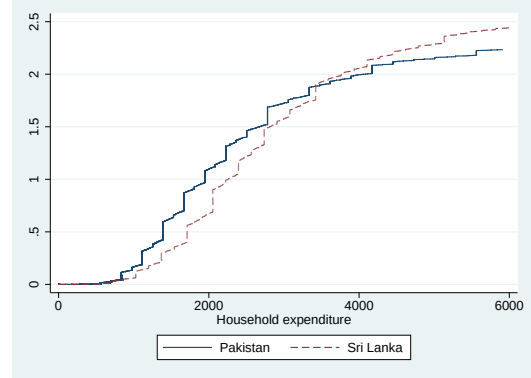


(f) using household expenditure y , $\theta = 1$

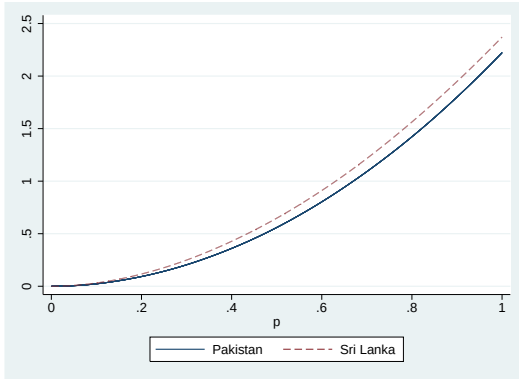
Figure 2.110: Second Order Inequality Dominance: Pakistan & Sri Lanka



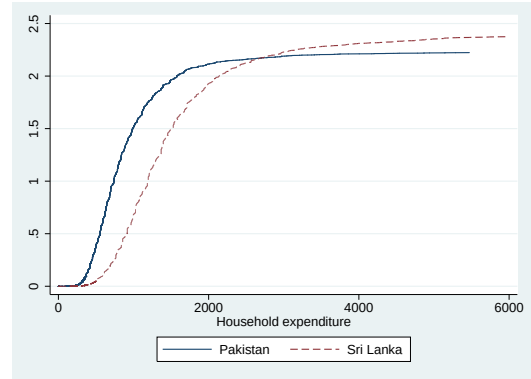
(a) using socioeconomic rank p , $\theta = 0$



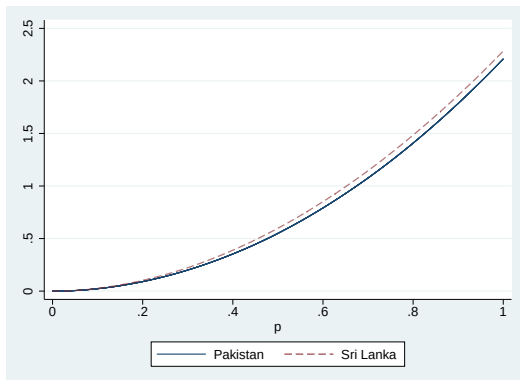
(b) using household expenditure y , $\theta = 0$



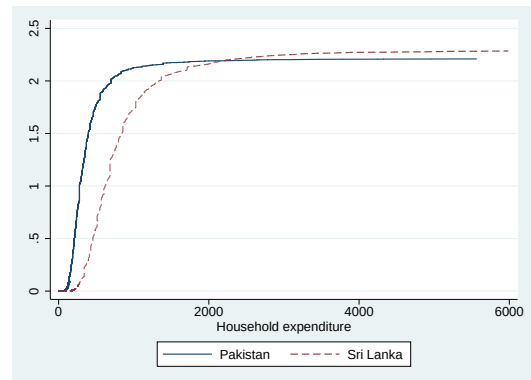
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$

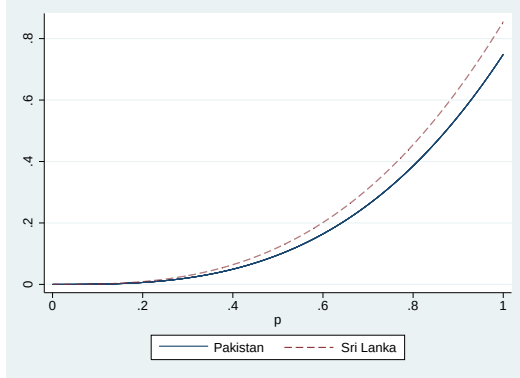


(e) using socioeconomic rank p , $\theta = 1$

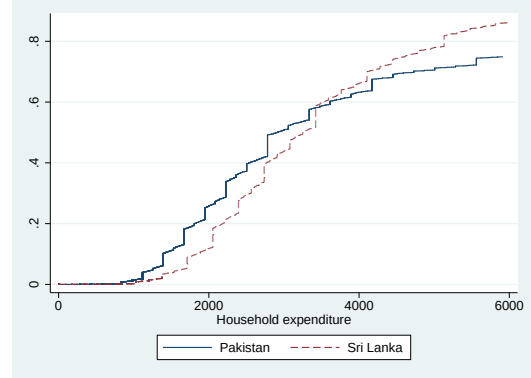


(f) using household expenditure y , $\theta = 1$

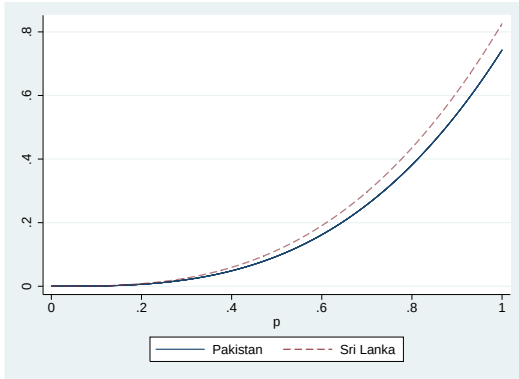
Figure 2.111: Third Order Inequality Dominance: Pakistan & Sri Lanka



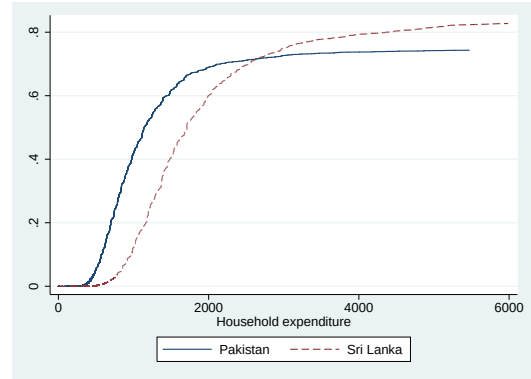
(a) using socioeconomic rank p , $\theta = 0$



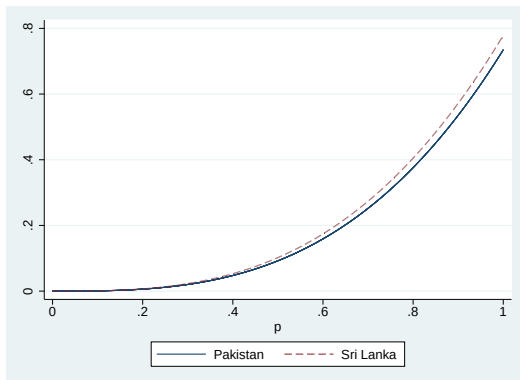
(b) using household expenditure y , $\theta = 0$



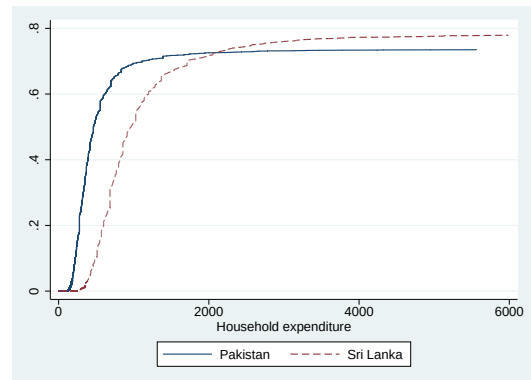
(c) using socioeconomic rank p , $\theta = 0.5$



(d) using household expenditure y , $\theta = 0.5$



(e) using socioeconomic rank p , $\theta = 1$

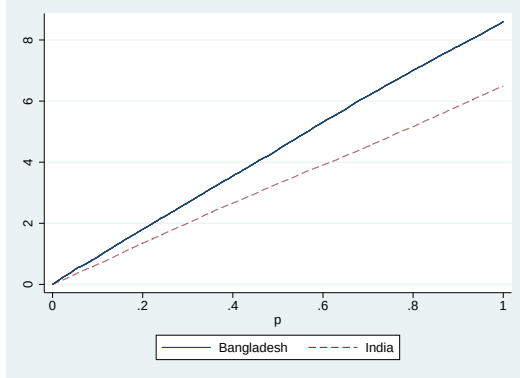


(f) using household expenditure y , $\theta = 1$

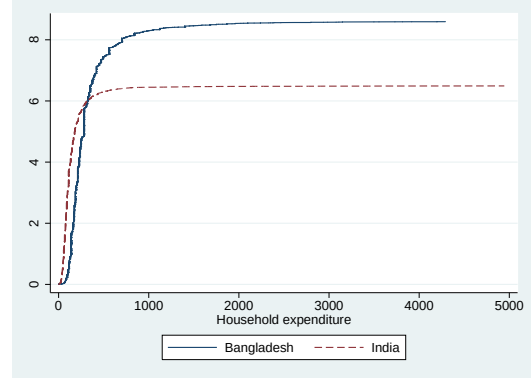
Figure 2.112: Fourth Order Inequality Dominance: Pakistan & Sri Lanka

Appendix 2.F.

2.F. Pairwise comparison of Socioeconomic Health Inequality Dominance curves Using World Bank PPP

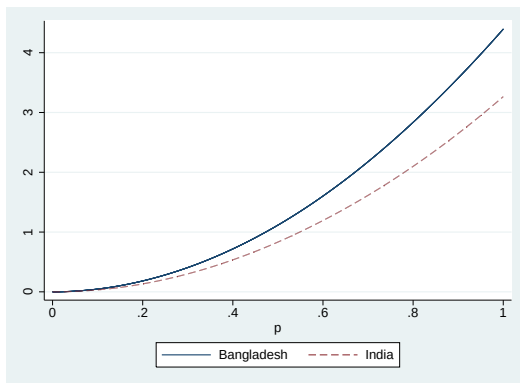


(a) using socioeconomic rank p , $\theta = 1$

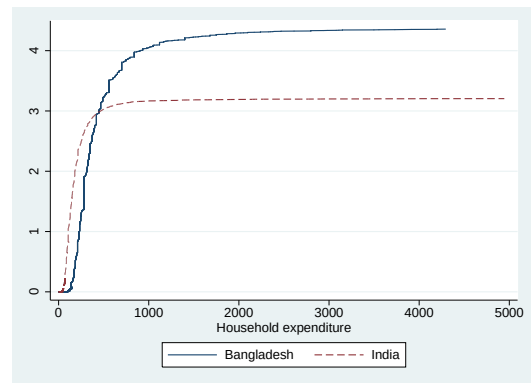


(b) using household expenditure y , $\theta = 1$

Figure 2.113: Second Order Inequality Dominance: Bangladesh & India

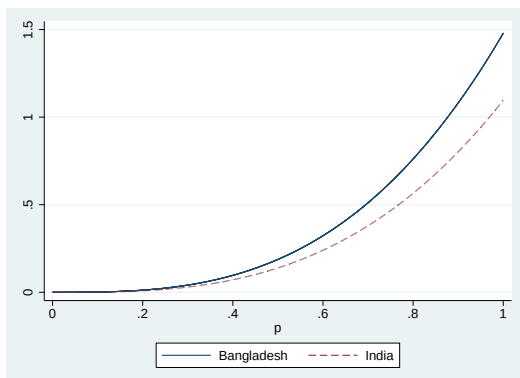


(a) using socioeconomic rank p , $\theta = 1$

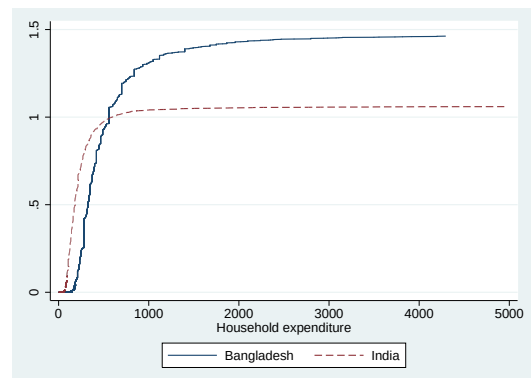


(b) using household expenditure y , $\theta = 1$

Figure 2.114: Third Order Inequality Dominance: Bangladesh & India

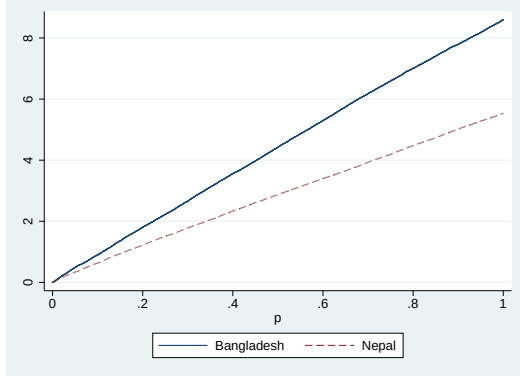


(a) using socioeconomic rank p , $\theta = 1$

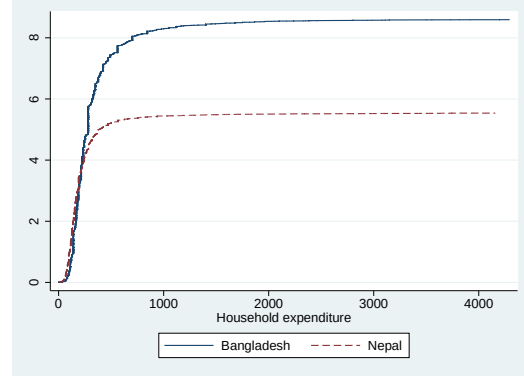


(b) using household expenditure y , $\theta = 1$

Figure 2.115: Fourth Order Inequality Dominance: Bangladesh & India

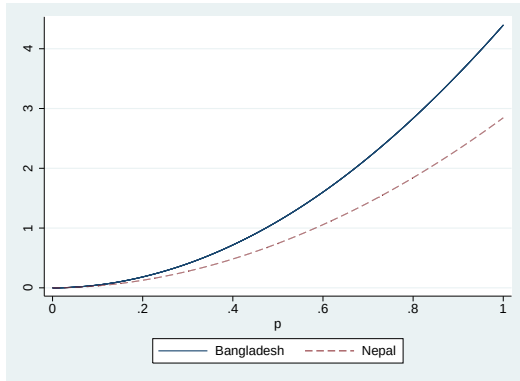


(a) using socioeconomic rank p , $\theta = 1$

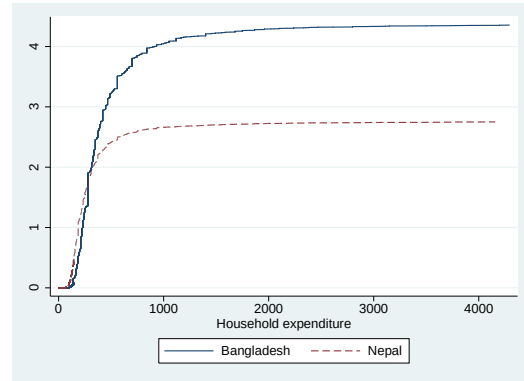


(b) using household expenditure y , $\theta = 1$

Figure 2.116: Second Order Inequality Dominance: Bangladesh & Nepal

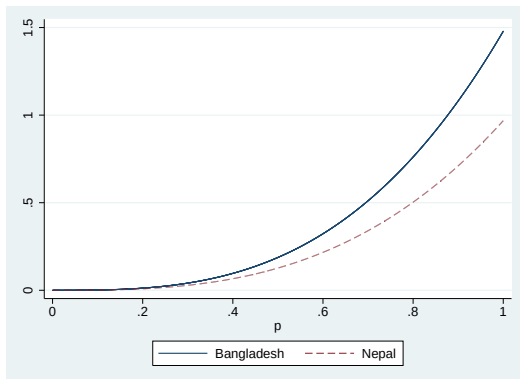


(a) using socioeconomic rank p , $\theta = 1$

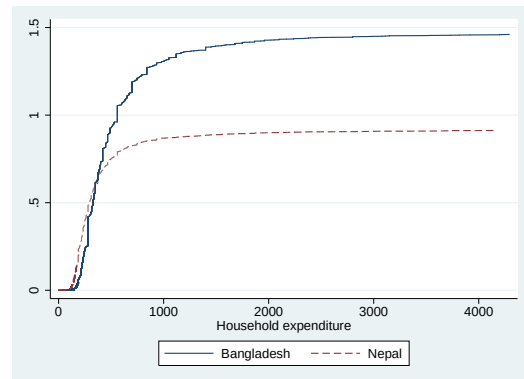


(b) using household expenditure y , $\theta = 1$

Figure 2.117: Third Order Inequality Dominance: Bangladesh & Nepal

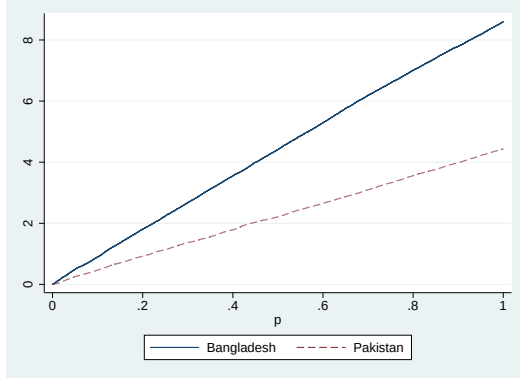


(a) using socioeconomic rank p , $\theta = 1$

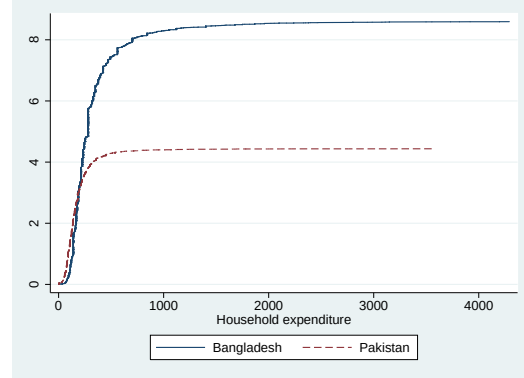


(b) using household expenditure y , $\theta = 1$

Figure 2.118: Fourth Order Inequality Dominance: Bangladesh & Nepal

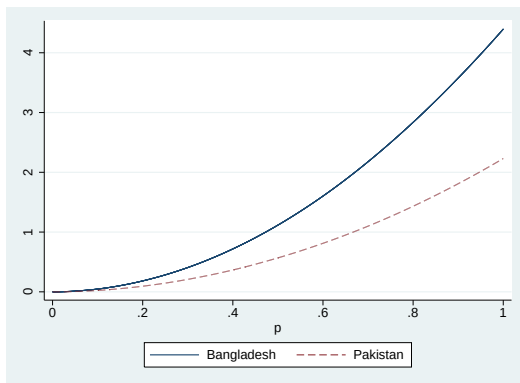


(a) using socioeconomic rank p , $\theta = 1$

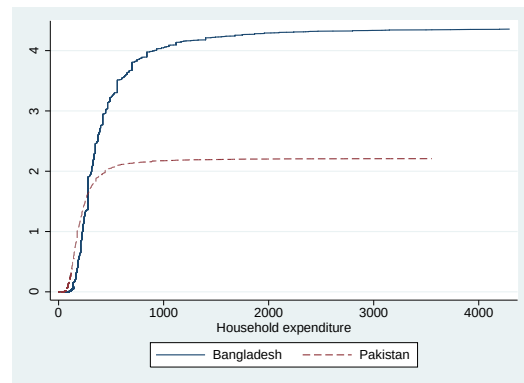


(b) using household expenditure y , $\theta = 1$

Figure 2.119: Second Order Inequality Dominance: Bangladesh & Pakistan

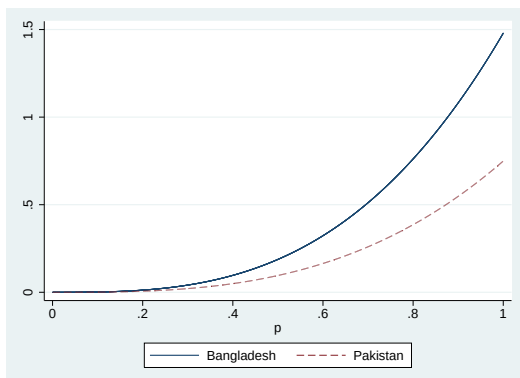


(a) using socioeconomic rank p , $\theta = 1$

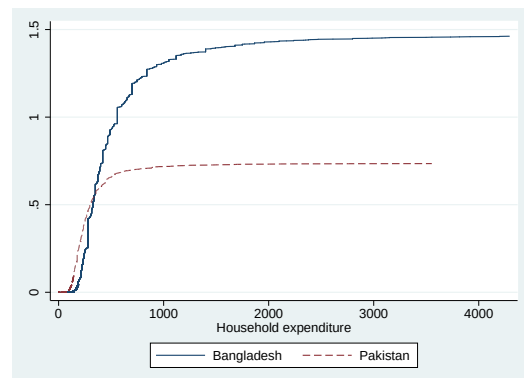


(b) using household expenditure y , $\theta = 1$

Figure 2.120: Third Order Inequality Dominance: Bangladesh & Pakistan

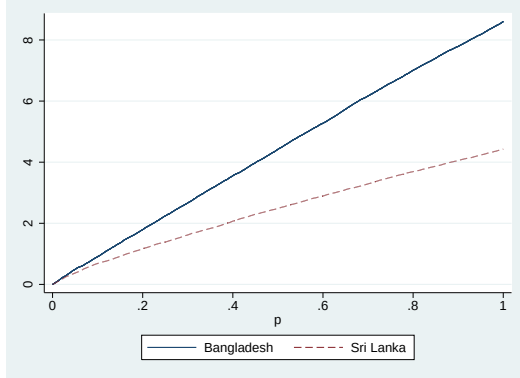


(a) using socioeconomic rank p , $\theta = 1$

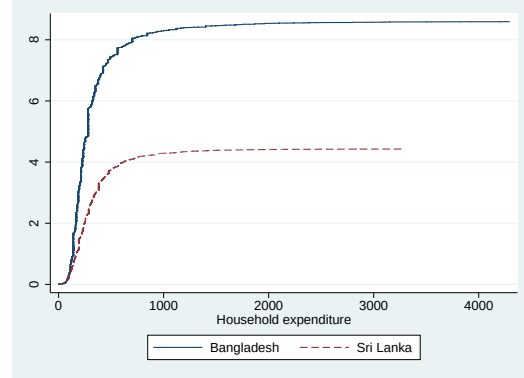


(b) using household expenditure y , $\theta = 1$

Figure 2.121: Fourth Order Inequality Dominance: Bangladesh & Pakistan

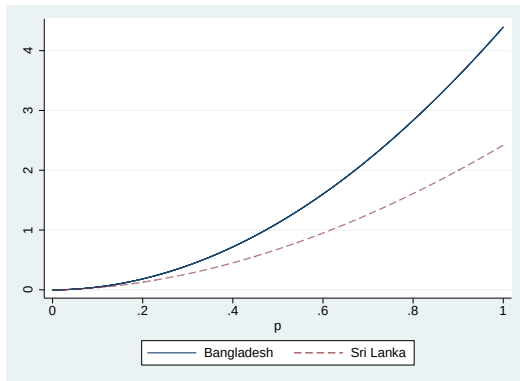


(a) using socioeconomic rank p , $\theta = 1$

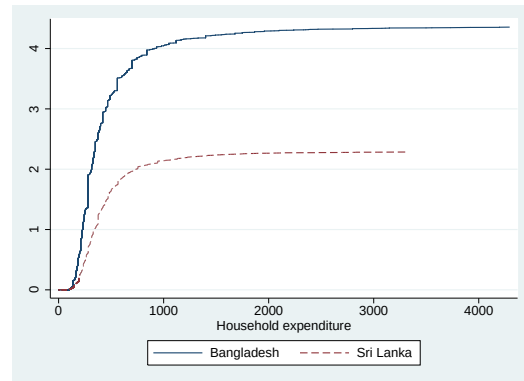


(b) using household expenditure y , $\theta = 1$

Figure 2.122: Second Order Inequality Dominance: Bangladesh & Sri Lanka

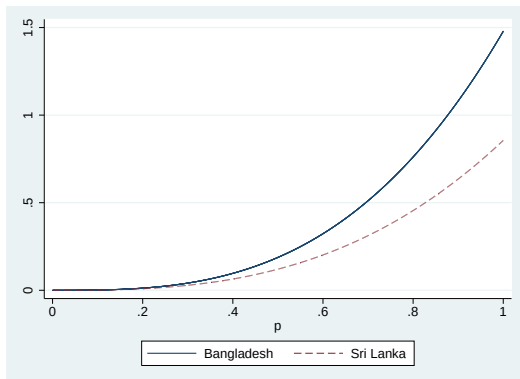


(a) using socioeconomic rank p , $\theta = 1$

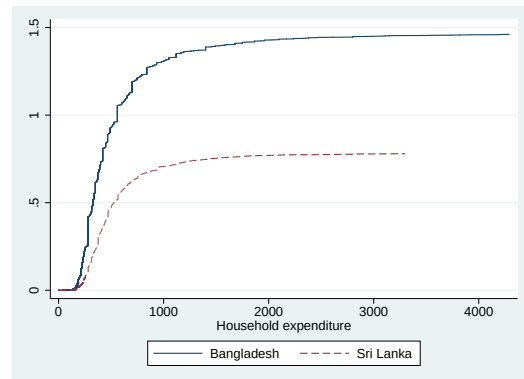


(b) using household expenditure y , $\theta = 1$

Figure 2.123: Third Order Inequality Dominance: Bangladesh & Sri Lanka

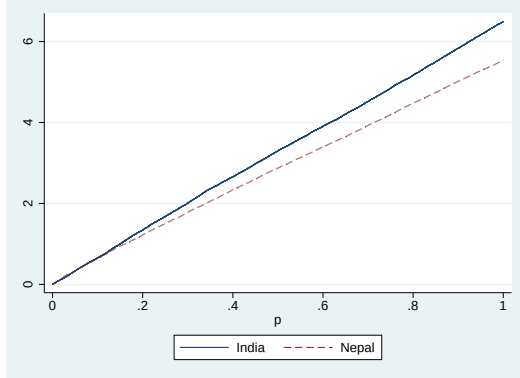


(a) using socioeconomic rank p , $\theta = 1$

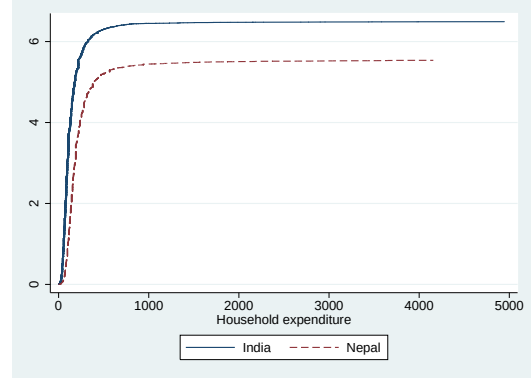


(b) using household expenditure y , $\theta = 1$

Figure 2.124: Fourth Order Inequality Dominance: Bangladesh & Sri Lanka

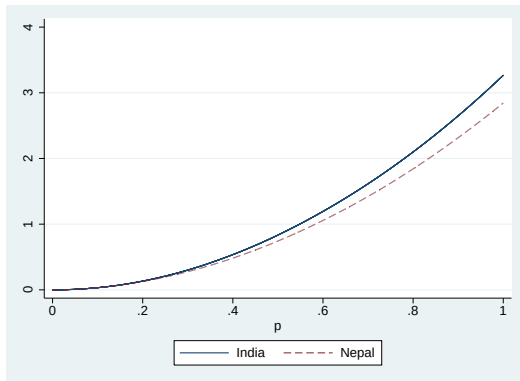


(a) using socioeconomic rank p , $\theta = 1$

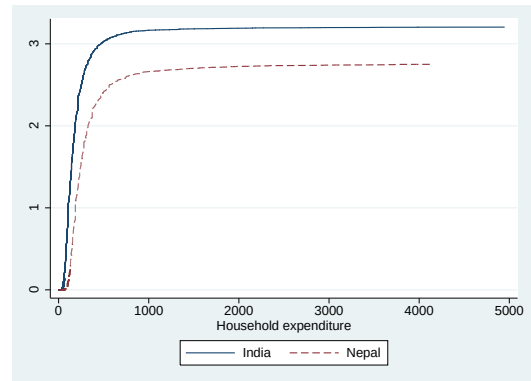


(b) using household expenditure y , $\theta = 1$

Figure 2.125: Second Order Inequality Dominance: India & Nepal

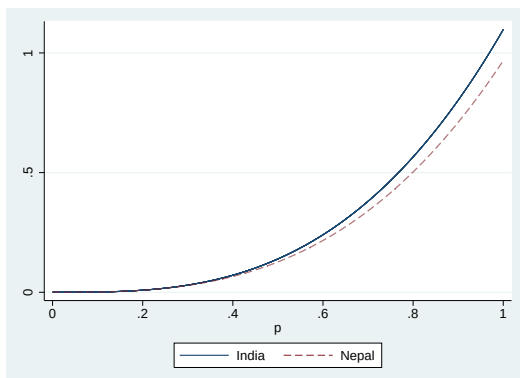


(a) using socioeconomic rank p , $\theta = 1$

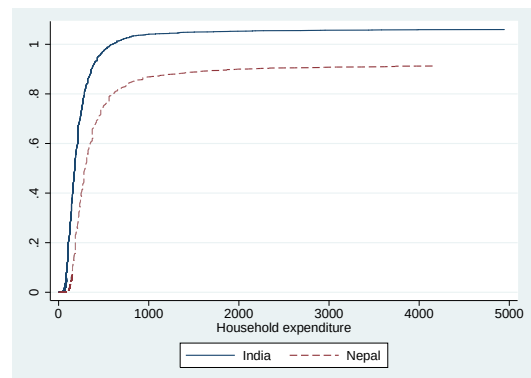


(b) using household expenditure y , $\theta = 1$

Figure 2.126: Third Order Inequality Dominance: India & Nepal

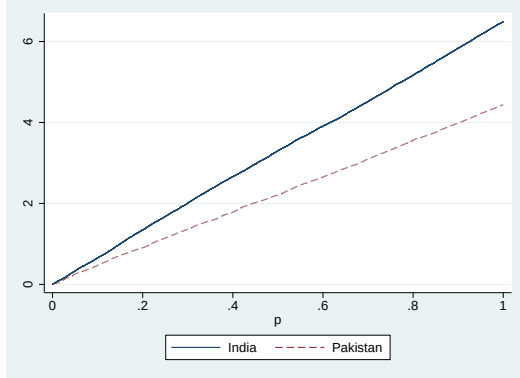


(a) using socioeconomic rank p , $\theta = 1$

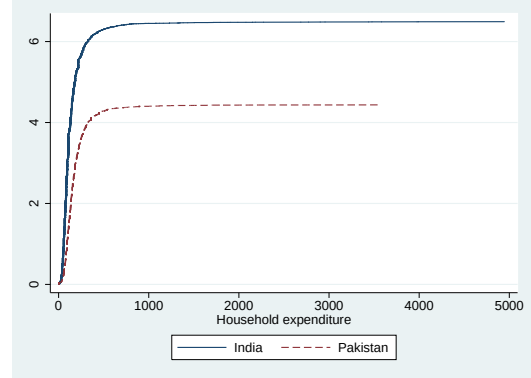


(b) using household expenditure y , $\theta = 1$

Figure 2.127: Fourth Order Inequality Dominance: India & Nepal

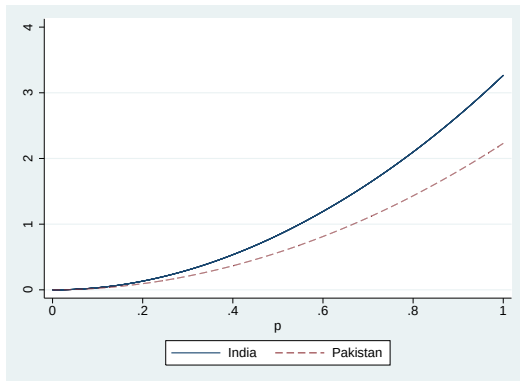


(a) using socioeconomic rank p , $\theta = 1$

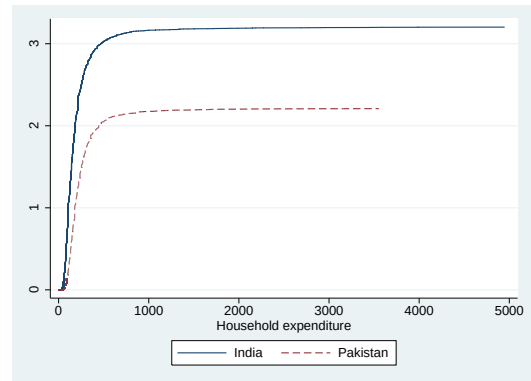


(b) using household expenditure y , $\theta = 1$

Figure 2.128: Second Order Inequality Dominance: India & Pakistan

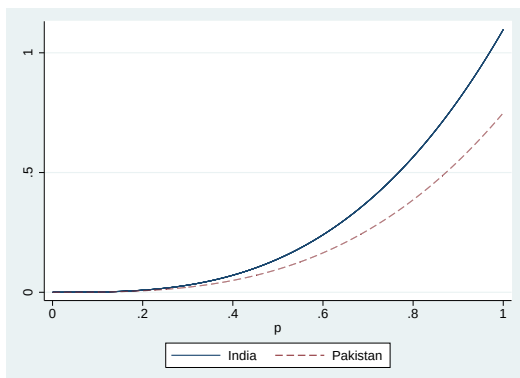


(a) using socioeconomic rank p , $\theta = 1$

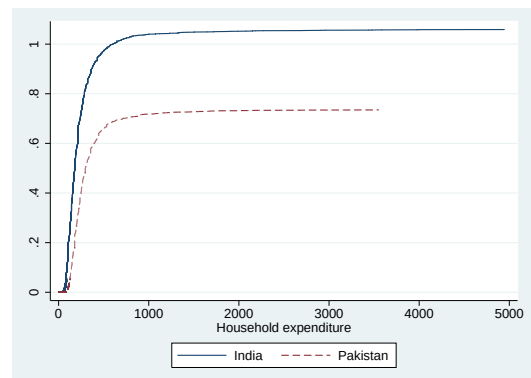


(b) using household expenditure y , $\theta = 1$

Figure 2.129: Third Order Inequality Dominance: India & Pakistan

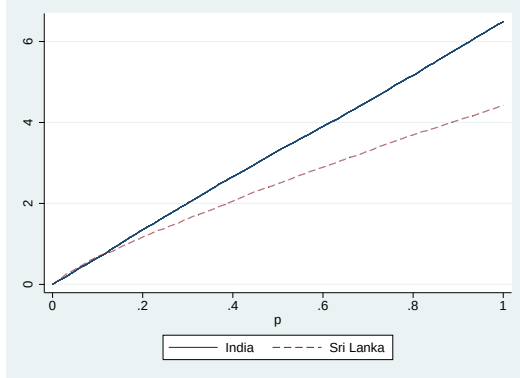


(a) using socioeconomic rank p , $\theta = 1$

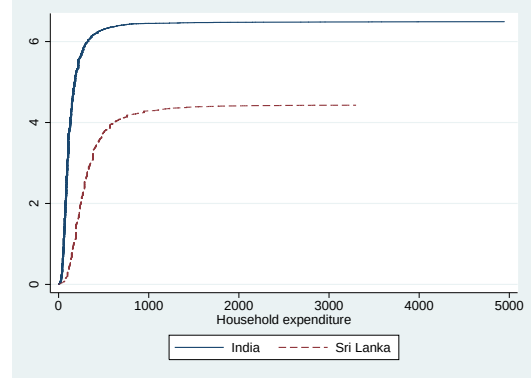


(b) using household expenditure y , $\theta = 1$

Figure 2.130: Fourth Order Inequality Dominance: India & Pakistan

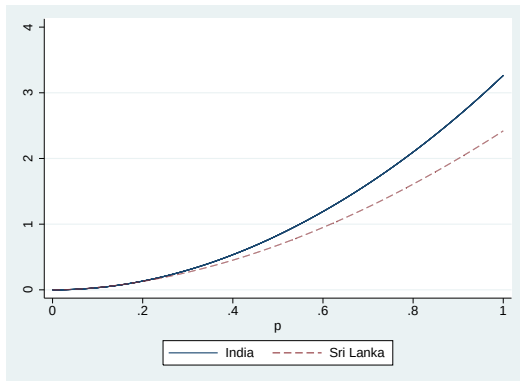


(a) using socioeconomic rank p , $\theta = 1$

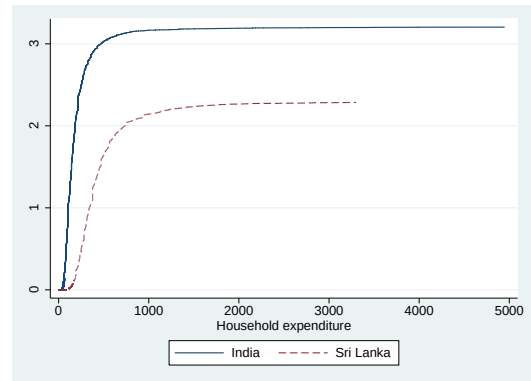


(b) using household expenditure y , $\theta = 1$

Figure 2.131: Second Order Inequality Dominance: India & Sri Lanka

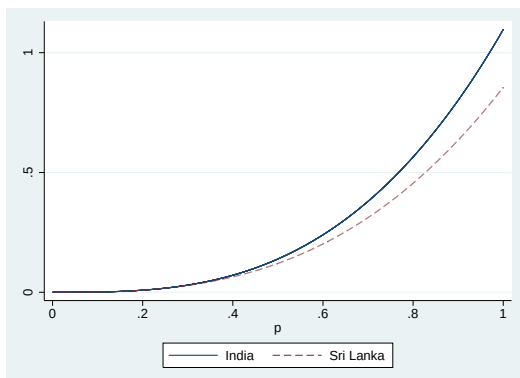


(a) using socioeconomic rank p , $\theta = 1$

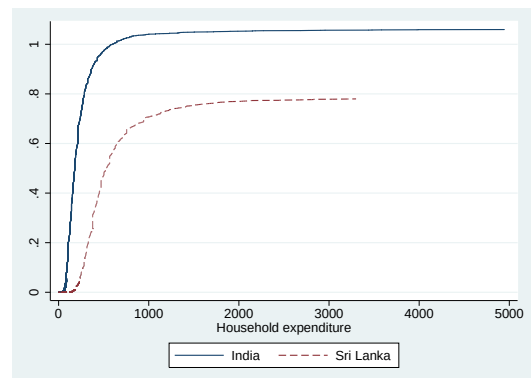


(b) using household expenditure y , $\theta = 1$

Figure 2.132: Third Order Inequality Dominance: India & Sri Lanka

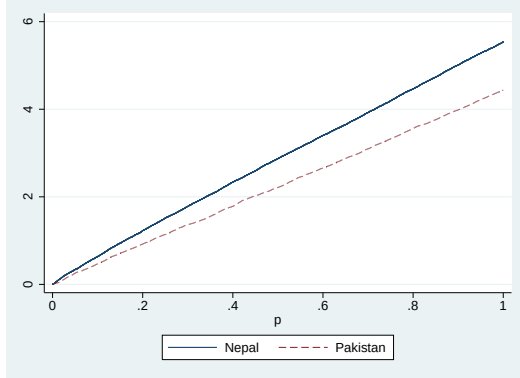


(a) using socioeconomic rank p , $\theta = 1$

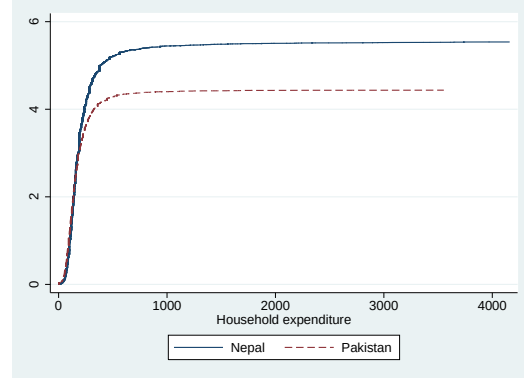


(b) using household expenditure y , $\theta = 1$

Figure 2.133: Fourth Order Inequality Dominance: India & Sri Lanka

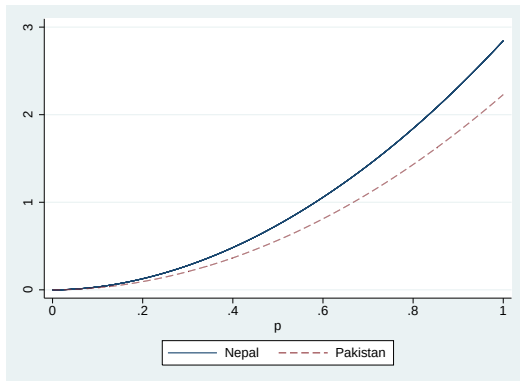


(a) using socioeconomic rank p , $\theta = 1$

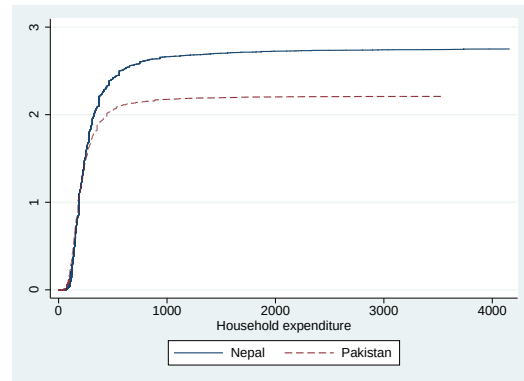


(b) using household expenditure y , $\theta = 1$

Figure 2.134: Second Order Inequality Dominance: Nepal & Pakistan

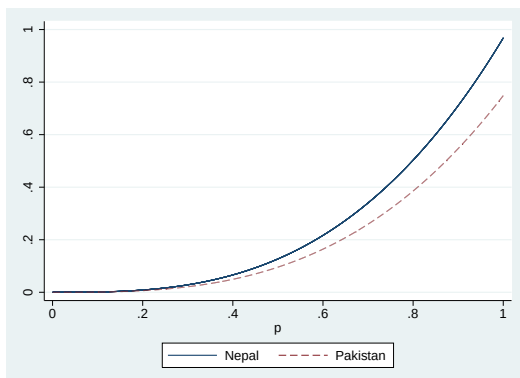


(a) using socioeconomic rank p , $\theta = 1$

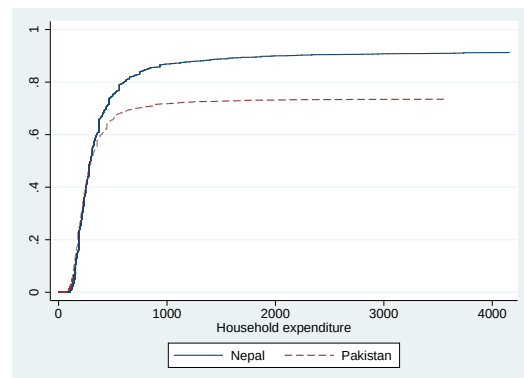


(b) using household expenditure y , $\theta = 1$

Figure 2.135: Third Order Inequality Dominance: Nepal & Pakistan

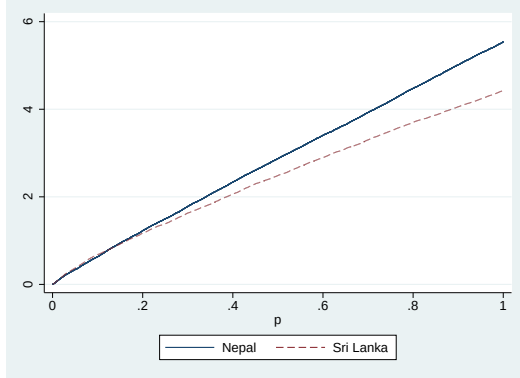


(a) using socioeconomic rank p , $\theta = 1$

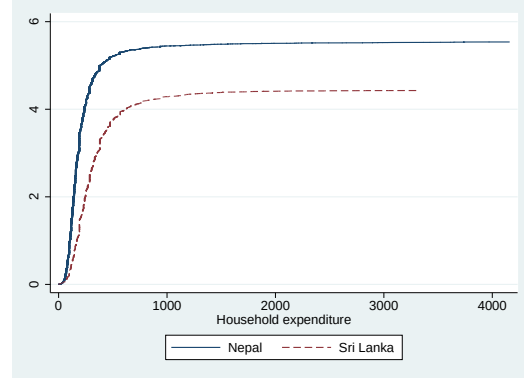


(b) using household expenditure y , $\theta = 1$

Figure 2.136: Fourth Order Inequality Dominance: Nepal & Pakistan

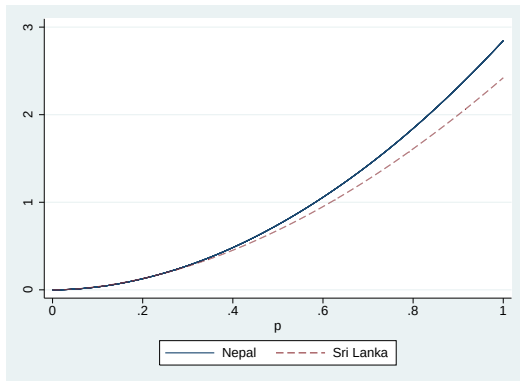


(a) using socioeconomic rank p , $\theta = 1$

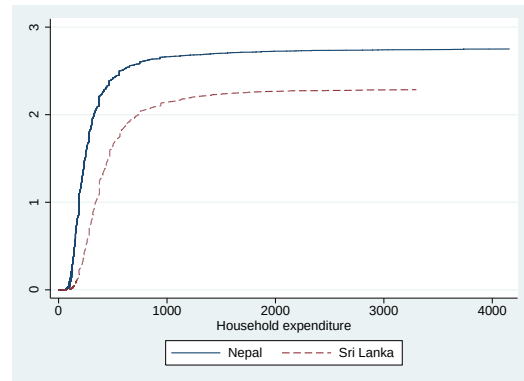


(b) using household expenditure y , $\theta = 1$

Figure 2.137: Second Order Inequality Dominance: Nepal & Sri Lanka

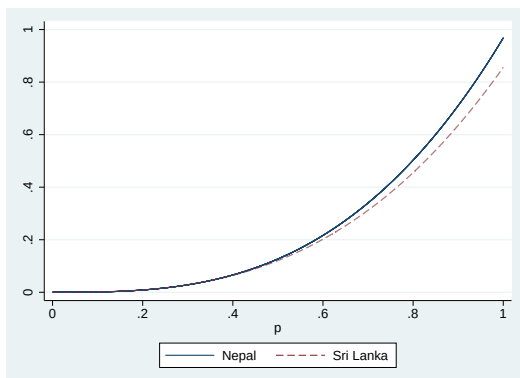


(a) using socioeconomic rank p , $\theta = 1$

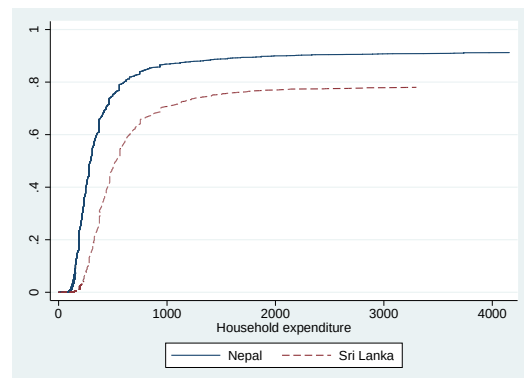


(b) using household expenditure y , $\theta = 1$

Figure 2.138: Third Order Inequality Dominance: Nepal & Sri Lanka

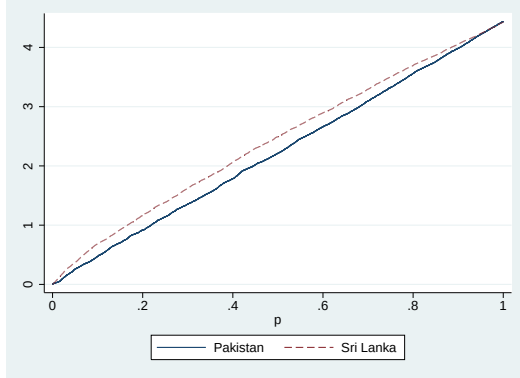


(a) using socioeconomic rank p , $\theta = 1$

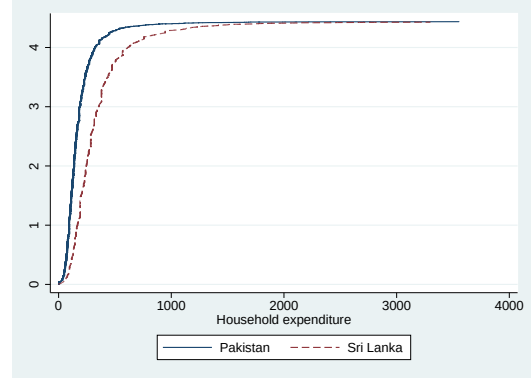


(b) using household expenditure y , $\theta = 1$

Figure 2.139: Fourth Order Inequality Dominance: Nepal & Sri Lanka

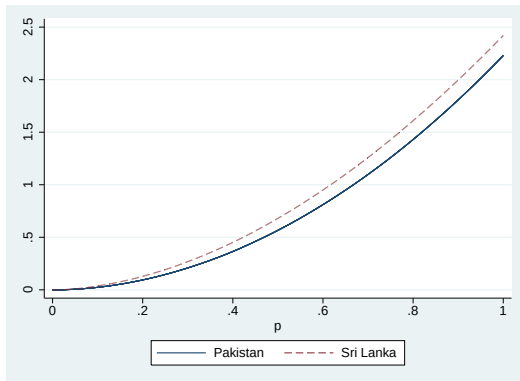


(a) using socioeconomic rank p , $\theta = 1$

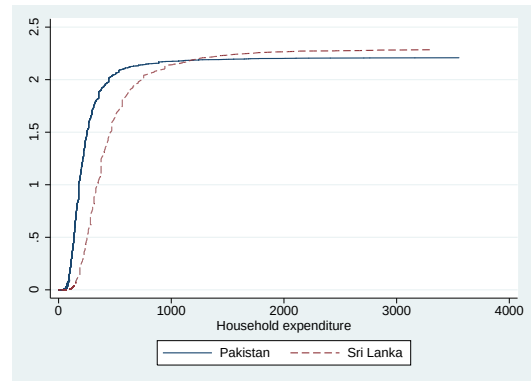


(b) using household expenditure y , $\theta = 1$

Figure 2.140: Second Order Inequality Dominance: Pakistan & Sri Lanka

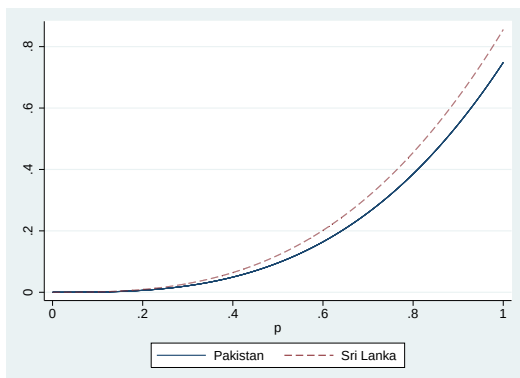


(a) using socioeconomic rank p , $\theta = 1$

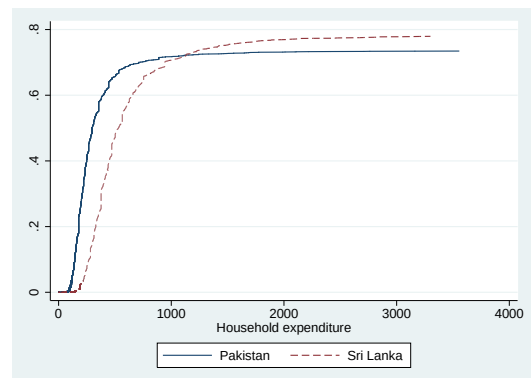


(b) using household expenditure y , $\theta = 1$

Figure 2.141: Third Order Inequality Dominance: Pakistan & Sri Lanka



(a) using socioeconomic rank p , $\theta = 1$



(b) using household expenditure y , $\theta = 1$

Figure 2.142: Fourth Order Inequality Dominance: Pakistan & Sri Lanka

Chapter 3

Economic Evaluations of Public Health Awareness Campaigns

3.1 Introduction

Health care is one of the top-most priorities of governments around the world these days. According to the World Health Organization (WHO), the total expenditure on health care in United States was 17.6% of the GDP in 2009, up from 13.4% in 2000. The health care expenditure in Canada grew from 8.8% to 11.4% of the GDP during that period.¹ One important aspect of public health policies is the prevention of diseases and the promotion of health among population. Because such importance is given to health care, it is of the utmost interest to the government to measure and monitor the health status of the population in the most efficient, cost effective, and accurate way possible. While it is important to maximize the health status of the population in the most effective way possible using the available resources, it is also a priority for the policy makers and health care providers to reduce health inequality between socioeconomic groups to increase social cohesion and the overall well-being of the residents.

Health inequality measurement is an important consideration in developing health policies. Most of the research papers dealing with this issue use the concentration index as a measure of health inequality. But, using the concentration index poses three important measurement problems. As shown by Wagstaff [2002], the first problem arises from the fact that the concentration indices do not account for the average level of health in the population. As a result, any health policy that would improve the average level of health in the population, while keep the relative distribution of health constant, would be considered neutral in impact when the concentration index is used. To solve this, Wagstaff [2002] proposed the use of an achievement index that accounts for the average level of health status and the socioeconomic inequality of its distribution simultaneously. The second measurement problem is the widely

¹Source: World Health Organization: World Health Statistics Report 2012, pages 136, 142.

known *mirror* problem identified by Clarke et al. [2002]. This problem results in inconsistency between the rankings of health gains and health shortfalls when the concentration index is used. Lambert and Zheng [2011] have shown that no index of relative inequality can avoid this problem. In this paper I am only interested about the inequality in health gains, so I believe this issue will not have any serious impacts on my results. The last measurement problem found in the literature is the *arbitrariness of the concentration index* identified by Erreygers [2006] and Zheng [2008]. From the empirical perspective, most health surveys provide information on health status in the form of categorical variables. However, many measurement approaches in the health status and health inequality assume the existence of a ratio-scaled variable.² As a result, applying the information from health surveys to develop health status profiles may lead to *arbitrariness* in the health concentration index's value. To solve this, I follow Makdissi and Yazbeck [2014] by redefining the health status variable so that it captures the socioeconomic inequality in the health attainments. Following this method not only gets rid of the arbitrariness problem of the concentration index, but also develops more realistic health profiles that are more representative of the true health statuses of individuals.

In this study, I apply simple simulation techniques to understand how a public health intervention may change the socioeconomic health status and health inequality. I think of this intervention in the form of a health awareness campaign that is undertaken by the government to raise awareness among the population about a particular health issue. Simulation is a powerful tool that lets us project different scenarios and estimate outcomes that will evolve based on the criteria that I put to the model as parameters. Simulation is widely used

²Categorical variables can take a limited, and usually fixed number of possible values and do not have a clear definition of 0. Ratio-scaled variables has a clear definition of 0; for example, *weight* is a ratio-scaled variable because a value of 0 means no weight. However, *temperature* is *not* a ratio-scaled variable since 0 temperature does not mean *no temperature*; or, a temperature of 100 degrees is *not* twice as hot as 50 degrees.

in different sectors, for example, manufacturing, defence, health care etc. However, one interesting thing about the use of simulation in health care sector is the lack of stakeholder engagement. This paper is not proposing to use the simulation techniques to impose any sudden changes in policies or hierarchies. Numerous public health awareness campaigns are already being implemented in various jurisdictions around the world, and this study shows how these campaigns might have an impact on population health status and socioeconomic health inequality. The data I have used in this paper are publicly available and reflect the population of United States comprehensively.

The studies found in the health care literature often use the simulation tool to focus on a particular health problem. For example, Tengs et al. [2004] conducted a hypothetical simulation study of the anticipated health gains or losses in the population in the presence of a federal policy mandating safer cigarettes. Examples involving specific policy issues are Ihori et al. [2011], who simulated reforms of Japanese public health insurance policies, and Muldoon and Stoddart [1989] who presented a simulation analysis of publicly-financed competition in the Canadian health care delivery system. In this paper, I take a different approach by using simple simulation techniques to demonstrate the effects of policy changes on not just a particular health problem, but on the comprehensive *public health* status of the population which is channelled through a number of health problems at the same time. This way, this study is able to demonstrate what the expected effect will be because of a single change in the government policy on a number of health problems and the corresponding effects on socioeconomic health inequality.

Being able to use publicly available data and readily see how a single alternative decision may affect the population health will be helpful to the health planners and decision makers in gaining a quick insight into the effectiveness of a proposed health policy.³ While I am interested about maximizing the health gains and reducing health inequalities, it is important to be aware of the cost effectiveness of such public health improvement measures. Any extra funding by the government will surely impact the health achievements in the population, but to what extent this spending remains effective is something that cannot be overlooked.

The analytical tool of cost effectiveness analysis in health care is the incremental cost effectiveness ratio (ICER), which gives the difference in costs between two health care interventions divided by the difference in outcomes between the two interventions. Assessing the effectiveness of any public health awareness campaign relies on survey data, and thus it is important that the measured health status of individuals who participate in the survey are calculated as accurately as possible. As mentioned previously, most health surveys provide information on individuals' health status in the form of categorical variables whereas most of the measurement approaches in health status and socioeconomic health inequality assume the information of health status to be ratio-scaled. In this paper I propose a measure of cost effectiveness named the *count-approach incremental cost effectiveness ratio (C-ICER)* which is developed using the redefined health status variable that is free from this *arbitrariness* problem, and therefore the measured cost effectiveness of proposed public health campaigns are more accurate.

The remaining of the paper is organized as follows. In the next section I develop the theoretical measurement framework. Section 3 proposes a measure of cost effectiveness of public health interventions. In section 4 I present a simulated empirical illustration using

³This paper presents an exploration of the possible effects of public health awareness campaigns on aggregate health achievement index and socioeconomic health inequality. The simulation estimates presented here are subject to simplified assumptions.

the National Health Interview Survey (NHIS) data for 2010. In section 5 I summarize the findings and talk about policy implications for the health planners, and talk about directions of further research.

3.2 Theoretical Framework

To develop the health profiles of the individuals, I follow the adaptation of the class of health achievement and socioeconomic health inequality indices proposed by Wagstaff [2002], as shown by Makdissi and Yazbeck [2014].⁴ Let $F(y)$ represent the cumulative distribution of income y and $p = F(y)$ be the socioeconomic status of an individual with income y . The health information for an individual with the socioeconomic status p is categorical and provides information on K health attributes. The health profile for an individual at the socioeconomic rank p is $H(p) = (h_1(p), h_2(p), \dots, h_K(p))$. Assume that there exists a methodology $\phi(H(p))$ that transforms the information on the K health attributes into a scalar that represents the individual's health status.⁵ After obtaining this scalar, a measure of population health can be written in the following form:

$$A(H) = \int_0^1 v(p)\phi(H(p))dp, \quad (3.1)$$

where $v(p) \geq 0$ is a weight function associated with the socioeconomic rank p such that $\int_0^1 v(p)dp = 1$. This weight function is decreasing in the socioeconomic status p , which implies that the population health measure $A(H)$ displays socioeconomic health inequality aversion.

⁴The income-dependent health index proposed in chapter-2 is not employed in this chapter as chapter-2 is not published yet. Because the contributions presented in this chapter are not on the particular index, it is better to rely on the index that is already used in the literature.

⁵The use of such transformation is common in epidemiology to compute health-related quality of life indices such as the Health Utility Index (Torrance et al. [1996]), the Quality of Well Being Index (Kaplan et al. [1976]), the EQ-5D (Rabin and Charro [2001]), and the SF-6D (Brazier et al. [1998]).

Including this inequality aversion in the population health measure is important because critics of the ICER often mention the lack of fairness in the availability of medical interventions (Gafni and Birch [2006]). The National Institute for Clinical Excellence (NICE) provide guidelines in the UK to use different threshold ICER values based on a case-by-case basis (Rawlins and Culyer [2004]) and treat them as only one input into the decision-making process. NICE is concerned with both the maximization of health gains from the use of National Health Service (NHS) resources and removing the unfairness in the availability of technologies. NICE guidelines address equity issues in three ways: the distribution of potential benefits from the intervention by clinical and social status; the distribution of personal costs on patients and their families; and the distribution of NHS costs by social groups (National Institute for Health and Clinical Excellence [2009]). Including the weight function in the population health measure enables to account for this equity consideration (i.e., more weight is put on individuals with lesser socioeconomic status).

Using the methodology mentioned may often create problems, as it can arbitrarily assign numerical values to the health categories. As a result, the rankings of individual health statuses produced by the aggregation method will not be robust to monotonically increasing transformations $g_k(h_k(p))$ of the numerical value associated with the health attribute h_k . To solve this, I follow Makdissi and Yazbeck [2014] and change the dimension in which the health status is calculated in order to derive a measure for the width of the health problems. The aggregation method $\phi(H(p))$, based on this new measure, will produce the same value for any monotonic transformation $g(h_k(p))$ of any health attribute and thus provide a consistent ranking.

To derive information on the width of the health problems, I count the dimensions in which an individual is considered to have a health status that is below a previously specified acceptable threshold. For each health attribute, I assume that there is a specific threshold

category τ_k , below which the person is considered to have a health problem in that attribute. Consider the following transformation:

$$\gamma(H(p)) = (\iota(h_1(p) < \tau_1)), (\iota(h_2(p) < \tau_2)), \dots, (\iota(h_k(p) < \tau_k)) \quad (3.2)$$

where $\iota(h_k(p) < \tau_k)$ is an indicator function that assumes a value of 1 if $h_k(p) < \tau_k$ and 0 otherwise. Using this indicator function enables to consider the depth of each health problem (i.e., whether the severity of this problem is enough to have an impact on the overall health status). It is obvious that $\gamma(H(p)) = \gamma(g(H(p)))$ for any increasing monotonic transformation $g(\cdot)$ because I know that $g_k(h_k(p)) < g_k(\tau_k)$ if and only if $h_k(p) < \tau_k$. Let $\Theta = (\theta_1, \theta_2, \dots, \theta_K)$ be a vector of weights for health attributes where the taxicab norm $\|\Theta\|_1$ is equal to K .⁶ The width of health problems is then given by $s(H(p))$, where $s(H(p)) = \gamma(H(p))\Theta'$ is the weighted sum of health attributes in which an individual has a health problem. Finally, following Makdissi and Yazbeck [2014], I use the following aggregation procedure that is invariant to any monotonic transformation applied to the numerical values of health categories:

$$\phi(H(p)) = \frac{K - s(H(p))}{K} \quad (3.3)$$

$\phi(H(p))$ is the weighted proportion of an individual's health attributes without any problems (i.e., the health achievement). Following the parametric class of health achievement indices by Wagstaff [2002], the aggregate population health index can be derived as

$$A_\eta(H) = \int_0^1 \eta(1-p)^{\eta-1} \phi(H(p)) dp, \eta > 1 \quad (3.4)$$

⁶The taxicab norm of the vector $x = (x_1, x_2, \dots, x_n)$ is defined by $\|x\|_1 := \sum_{i=1}^n |x_i|$. I am using the taxicab norm following Makdissi and Yazbeck [2014].

where η is a parameter of socioeconomic health inequality aversion (Yitzhaki [1983]). This is the weight function of the Wagstaff [2002]’s class of health achievement indices, and the choice of using this is motivated by the fact that it is the most widely used class in the health inequality literature. This weight function is compatible with what Khaled et al. [2017] call pro-poor higher order health transfer principles; and different from what Khaled et al. [2017] call pro-extreme rank higher order health transfer principles. These principles are compatible with Erreygers et al. [2012]’s class of symmetric indices. The weight function of this chapter is equivalent to a symmetric index only when $\eta=2$. Equation (3.4) shows that the aggregate population health index is the sum of the weighted proportion of all individuals’ health attributes without any problems where these individuals are ranked based on their socioeconomic status (p). And, the socioeconomic health inequality index is given by:

$$I_{\eta}(H) = \frac{1}{\mu_{\phi}} \int_0^1 [1 - \eta(1 - p)^{\eta-1}] \phi(H(p)) dp, \eta > 1 \quad (3.5)$$

where $\mu_{\phi} = \int_0^1 \phi(H(p)) dp$ is the average health status.

3.3 Cost Effectiveness of Public Health Campaigns: Introducing the *C-ICER*

Cost effectiveness analysis (CEA) is regarded as a useful methodology to help the decision-makers allocate health care resources effectively. Because there is a given level of resources available (i.e., the health care budget) to provide numerous health care services to the public, the priority of the decision-maker (i.e., the government) is to maximize the total aggregate health benefit of the population. The most commonly used analytical tool in CEA is the incremental cost effectiveness ratio (ICER), which is calculated by dividing the difference in

costs by the difference in effects between two medical interventions. Costs are measured in terms of dollars and the health effects are measured in terms of quality-adjusted life years (QALYs).⁷

A number of studies identify the cost effectiveness analysis and the ICER as a less-dependable resource for a decision-maker who wants to ensure the best use of available healthcare resources. The WZ model developed by Weinstein and Zeckhauser [1973] first used ICER as a cost effectiveness analysis tool. The model showed that under perfect divisibility and constant returns to scale, the total health benefits are maximized when all available interventions are ranked from lowest to the highest ICER and then selected to implement until all available resources are exhausted (i.e., the league table approach). Another approach is that the interventions are selected only when their ICER is less than or equal to a predetermined the critical ratio λ , given by the opportunity cost of the resources at the margin (i.e., the threshold ICER approach). Although this model works as the foundation of using ICER as a tool to implement cost effectiveness, there are problems associated with it. For both the league table approach and the threshold ICER approach, information on the cost and effects of all current and potential interventions would be required. In real world, this information is often missing. Even if we assume that it is somehow possible to estimate costs and effects of potential interventions, we can never have a fixed threshold (λ) value because any change in the healthcare resources would generate a change in λ . Furthermore, the model works under the assumptions of perfect divisibility and constant returns to scale, which are not realistic. For example, under perfect divisibility, any intervention can be purchased by the decision-maker in incremental units (e.g., 1 minute usage of a chemotherapy machine). Under the assumption of constant returns to scale, the marginal health effects of an intervention is

⁷For example, if a treatment costs an extra \$10,000 and increases a person's quality of life from 0.6 to 0.7 for the rest of her life from age 70 and onwards, and her expected lifespan increases from 75 to 77, then the ICER is $= \$10,000 / (7 \times 0.7 - 5 \times 0.6)$ or \$5,263 per QALY

constant (e.g., if one chemotherapy machine produces additional 10 QALYs per year, then 10 machines would produce 100 additional QALYs per year). This linearity is nearly impossible in most decision-making settings as shown by Gafni and Birch [1993]. Using ICERs in such decision-making context would contribute nothing but rather impose an additional cost, while the health benefits would remain unclear. Birch and Gafni [2006] rightly identify ICER in these cases to be information that merely estimates an *average* additional cost per QALY.

Affordability is another concern while using the ICER as an information tool. Laupacis et al. [1992] suggest that in the threshold ICER approach, the threshold (λ) is determined independently of the available resources. They suggest that in the case where the cost of adopting an acceptable threshold exceeds the current health budget, the implication of this exceeder might be that an increase in the health budget is justified. In contrast, Weinstein and Zeckhauser [1973] show that under the conceptual model on which the cost effectiveness model is based, the threshold (λ) is determined by the resources made available for health care technologies. Gafni and Birch [2006] argue that a positive-valued ICER means that the new intervention generally costs more than the existing way of treating the problem in question. To adopt the new intervention, the decision-maker must cancel the use of the existing intervention (that is being replaced) and something else as well (i.e., in health care or elsewhere) in order to keep the budget balanced. Therefore, the threshold approach assumes that additional resources can be found to financially support the proposed new programs if their ICER is less than or equal to λ . This unrealistic assumption implies that using the threshold approach as a decision-making criterion is flawed and inconsistent with our objective. Birch and Gafni [2006] proposed another alternative and simpler approach to practical decision-making which is less data-intensive. This approach is based on the objective that the new interventions would only be adopted in cases where these adoptions lead to an *unambiguous* increase in the health gains. However, following this path would also require information on the incremental costs

and effects of the proposed intervention, which may be inaccurate and difficult to estimate.

The *count-approach incremental cost effectiveness ratio (C-ICER)* proposed in this paper is different from the widely used ICER in various ways. First, the C-ICER is calculated using the redefined health status variable that is free from the *arbitrariness* problem of the concentration index, and the resulting health status values of the population are more accurate. Secondly, I propose to use the C-ICER to measure the effectiveness of a public health campaign undertaken by the government instead of comparing two intervention strategies for any particular health problem. Doing so gets rid of the aforementioned *constant returns to scale* assumptions, because in a public awareness campaign there is no need to assume constant returns to scale. Affordability is not applicable in assessing the C-ICER assuming there is a separate general budget allocated by the government to run health campaigns. However, any new intervention costs would need to be diverted within a fixed budget. A public health awareness campaign would also divert funds from other possible interventions that may or may not be disease-specific. Public health awareness campaigns target both broader health issues that covers more than one disease (e.g., anti-smoking campaigns), or focus on a particular disease (e.g., campaigns on mammograms, flu shots etc). Later in the paper, I discuss the effects of two public awareness health campaigns focusing on smoking and obesity, both of which cover a number of diseases. Although the diseases related to smoking are different than the diseases related to obesity, one can still compare the two C-ICERs associated with these two campaigns and rank them so that the decision maker can readily see which health campaign is more cost effective. This comparison is possible because the focus is on the overall aggregate health status in the society and not on a particular disease.⁸

Now, suppose that the cost of treating k th health attribute where an individual has a

⁸ICERs are also comparable as long as the denominator is the same (e.g., QALY, sick days averted, public health costs saved etc).

problem is c_k . Suppose also that the cost of running a campaign to raise public awareness against a particular health issue (e.g., smoking or obesity) is C_m . I assume a fixed cost for such a campaign because a lump sum amount of such an activity can easily be assessed beforehand, and I also assume such an awareness-building campaign is targeted towards everyone in the society and not towards any specific group of people who might be suffering from the diseases related to the campaign. As defined before, the aggregate population health index is given by:

$$A(H) = \int_0^1 v(p)\phi(H(p))dp \quad (3.6)$$

I assume the campaign has positive effects on n number of diseases. Then, the change in the population health index attributed to the awareness-raising campaign is given by:

$$\Delta A_n = \frac{n}{K} \int_0^1 v(p)\phi(H(p))dp \quad (3.7)$$

It can be seen that the change in the aggregate health status because of improvements in n health attributes, represented by ΔA_n , can be interpreted as the value of the public health awareness. Thus, the count-approach incremental cost effectiveness ratio (C-ICER) can be calculated as:

$$C - ICER_k = \frac{C_m}{N\Delta A_n} = \frac{\text{cost of campaign related to } n \text{ attributes}}{\text{population size x value of campaign related to } n \text{ attributes}} \quad (3.8)$$

3.4 Empirical Illustration

Now I illustrate the calculation of population health achievement and socioeconomic health inequality in the United States using the National Health Interview Survey (NHIS) data for the year 2010 using the count approach, and then simulate hypothetical improvements in public health resulting from educational campaigns on public health awareness run by the government. Such campaigns are important because health communication plays a major role in improving overall public health, disease prevention and the quality of life (Rimal and Lapinski [2009]). The simulation technique shown here uses simple concepts that can be readily understood by the health care managers and policy makers.

The NHIS is a cross-sectional household interview survey that collects comprehensive health status data on a broad range of health topics in the US population. I use the person-level file, which has information on each person's total income in the previous year, which is then used to calculate the individual's socioeconomic rank. I then merge this information using the unique identifier for each person with the sample adult file which has detailed information on each adult's health status in the household. This yields a total of 13,712 observations. Table 3.1 below outlines 36 health problems that I have identified in order to calculate the population health status and socioeconomic health inequality.

Table 3.1: Threshold Definitions for 36 Health Problems

Attribute	Threshold met if answered <i>yes</i> to the following question. Did you ever:
Hypertension	been told you have hypertension
Coronary Heart Disease	been told you have coronary heart disease

Continued on next page

Table 3.1 – continued from previous page

Attribute	Threshold met if answered <i>yes</i> to the following question. Did you ever:
Angina Pectoris	been told you have angina pectoris
Heart Attack	been told you had a heart attack
Heart Condition/Disease	been told you had a heart condition/disease
Stroke	been told you had a stroke
Emphysema	been told you have emphysema
Asthma	been told you have asthma
Ulcer	been told you have ulcer
Cancer	been told you have cancer
Diabetes	been told you have diabetes
Prediabetes/Other Symptoms	been told you have prediabetes or other symptoms
Seizure Disorder/Epilepsy	been told you have seizure disorder or epilepsy
Hay Fever	been told you had hay fever in the last 12 months
Sinusitis	been told you had sinusitis in the last 12 months
Chronic Bronchitis	been told you had chronic bronchitis in the last 12 months
Weak/Failing Kidneys	been told you had weak/failing kidneys in the last 12 months

Continued on next page

Table 3.1 – continued from previous page

Attribute	Threshold met if answered <i>yes</i> to the following question. Did you ever:
Liver Condition	been told you had liver conditions in the last 12 months
Dermatitis/Skin Condition	been told you had dermatitis/skin condition in the last 12 months
Joint Pain/Aching/Stiffness	had symptoms of joint pain/aching/stiffness in the last 30 days
Arthritis	been told you have arthritis
Carpel Tunnel Syndrome	been told you have carpel tunnel syndrome
Neck Pain	had neck pain in the last 3 months
Low Back Pain	had low back pain in the last 3 months
Pain in Jaw/Front of Ear	had pain in jaw or front of ear in the last 3 months
Severe Headache/Migraine	had severe headache/migraine in the last 3 months
Head/Chest Cold	had head/chest cold in the last 2 weeks
Stomach Problem with Vomit/Diarrhea	had a stomach problem with vomit or diarrhea in the last 2 weeks
Trouble Seeing	had trouble seeing even with glasses or lenses
Lost Teeth	lost all upper and lower natural teeth
Sadness	felt so sad that nothing cheered you up in the last 30 days

Continued on next page

Table 3.1 – continued from previous page

Attribute	Threshold met if answered <i>yes</i> to the following question. Did you ever:
Nervousness	felt nervous in the last 30 days
Restlessness/Fidgetiness	felt restless in the last 30 days
Hopelessness	felt hopeless in the last 30 days
Effortlessness	felt everything was an effort in the last 30 days
Worthlessness	felt worthless in the last 30 days

3.4.1 Simulation of improvement in diseases related to smoking

Now I simulate the expected change in public health status and socioeconomic health inequality because of a change in government policy towards smoking (i.e., raised awareness about the adverse health effects and diseases related to smoking). It is interesting to note in this context that the Centers for Disease Control and Prevention (CDC) in fact launched a national tobacco education campaign in March 2012 named *Tips from Former Smokers* (*Tips*) that ran for 16 weeks, and the total cost of the campaign was estimated to be \$54 million. The goals of the campaign were to improve public awareness of the health damages caused by smoking and second-hand smoking, and to encourage smokers to quit. The target audience of the campaign were the primary smokers aged 18 to 54, their family members, parents, and adolescents.⁹ McAfee et al. [2013] looked into the effects of the TIPS campaign on the smokers in the U.S. by using baseline and follow-up surveys of nationally representa-

⁹Source: Centers for Disease Control and Prevention (CDC).

tive cohorts of adult smokers and non-smokers. With 3,051 smokers and 2,220 non-smokers participating in these surveys, the study found that nationally 1.6 million additional smokers made a quit attempt, and 220,000 remained abstinent at follow-up, while an estimated 100,000 are expected to sustain their abstinence in the long term, out of a total of 43,700,000 smokers in the country. Therefore, the long term abstinence rate was calculated to be 0.23% among the smokers as a result of the *Tips* campaign. In the simulation exercise shown in this paper, I also use this rate to be the expected effect on smokers because of the health awareness campaign. There are some limitations of this assumption; for example, smokers who quit smoking as a result of the campaign might still be at a higher risk for developing the diseases related to smoking. Also, the health outcomes used are if the person ever had the condition, which implies that smokers who never had developed that particular condition will not have a change in the health status. It should be noted here that the estimates presented here are illustrative examples and not empirical ones.

Firstly, I identify the health diseases that are related to smoking. For this purpose, I use the diseases that were targeted in the *Tips* campaign, which are: Asthma, Buerger's Disease, Cancer, Chronic Obstructive Pulmonary Disease, Diabetes, Heart Disease and Stroke. I match these diseases to the health problems mentioned in Table 3.1; these are: Coronary Heart Disease, Angina Pectoris, Heart Attack, Heart Condition/Disease, Stroke, Emphysema, Asthma, Cancer, Diabetes, and Chronic Bronchitis. Next, I assume that because of a public health awareness campaign run by the government about the harmful effects of smoking, 0.23% of the current smokers decide to quit smoking and remain as non-smokers in the long term. As a result, there is a 0.23% improvement in the smoking related diseases among those people who smoke. For the simulation purposes, I randomly generate¹⁰ this health

¹⁰In reality, it is unlikely that an improvement would be randomly distributed. However, it is difficult to identify and allocate specific improvements for different socioeconomic statuses in the population in the current setting.

improvement in the population over a uniform distribution in the socioeconomic ranks of individuals and calculate the revised health achievement index and health inequality. This step is iterated 1,000 times to calculate the mean value for each health achievement index and a 95% confidence interval is also reported. It would be interesting to see if the decision to quit is *not* random, because hardcore smokers are least likely to quit smoking as a result of such health awareness campaigns. However, it is not possible to identify them in the current setting. Also, time dimensions are not taken into account in the current setting. The results shown in this study are illustrative examples and not empirical ones.

Table 3.2 shows the health achievement index values for four socioeconomic health inequality aversion parameters ($\eta = 1.5, 2.0, 2.5, 3.0$), first in the absence of the campaign (i.e., in the *with no improvement* column), and then the mean health achievement index from the effects of the campaign is reported with a 95% confidence interval. The last column shows the percentage improvement of the new health achievement value compared to the old value (i.e., without any improvement). It can be observed that the most improvement in health achievement occurs when $\eta = 3$; the expected improvement in health achievement is 0.000641%. The inequality aversion parameter η serves as a way to include ethical judgements in calculating the health achievement index; setting the value of $\eta = 2$ gives the standard concentration index (Wagstaff [2002]). When the value of η is set to 1, everyone's health is weighted equally, regardless of their socioeconomic status, and thus the analyst is indifferent to inequality. Raising the value of η above 1 means the weight attached to the health of the persons in the top socioeconomic quantiles falls, and the weight attached to the health of the bottom socioeconomic quantiles rises.¹¹

¹¹The results presented here are possibly overestimates of the health returns as a result of the health awareness campaigns.

Table 3.2: Simulated 0.23% improvement in smoking-related diseases and its impact on health achievement in the United States using 95% confidence interval:

	Original Health achievement	Health Achievement after Simulation			% Improve-ment
		Mean	Lower Bound	Upper Bound	
$\eta=1.5$	0.893327	0.893332	0.893332	0.893332	0.000549
$\eta=2.0$	0.891548	0.891553	0.891553	0.891554	0.000606
$\eta=2.5$	0.890195	0.890200	0.890200	0.890201	0.000607
$\eta=3.0$	0.889093	0.889099	0.889098	0.889099	0.000641

Table 3.3 below shows the expected simulated effects on health inequality because of the same 0.23% improvement in the smoking-related diseases in the population who smoke. I find that the improvement on health inequality is the largest when $\eta = 2.5$ (the negative sign for the improvement values in the last column shows a *decrease* in the health inequality which is desirable); in this case the socioeconomic health inequality gets decreased by 0.022411%.

Table 3.3: Simulated 0.23% improvement in smoking-related diseases and its impact on socioeconomic health inequality in the United States:

	Original Health In-equality	Health Inequality after Simulation			% Improve-ment
		Mean	Lower Bound	Upper Bound	
$\eta=1.5$	0.002750	0.002750	0.002750	0.002750	-0.007273
$\eta=2.0$	0.004736	0.004735	0.004735	0.004735	-0.016892
$\eta=2.5$	0.006247	0.006246	0.006245	0.006246	-0.022411
$\eta=3.0$	0.007477	0.007475	0.007475	0.007476	-0.021399

Looking at the expected changes in health inequalities, it can be seen that all expected values are negative, which implies that socioeconomic health inequality will be reduced as a result of such a health awareness campaign. This reduction in inequality is important from the policy maker's perspective because measures that not only increase the overall health achievement in the society, but also decrease the socioeconomic health inequality at the same

time, are always preferred and consistent with ethically sound principles and norms.

3.4.2 Simulation of improvement in diseases related to obesity

Next I simulate the expected changes in public health achievement and socioeconomic health inequality because of a change in government policy towards obesity (i.e., raised awareness about the adverse health effects and diseases related to obesity). According to the CDC, obesity has dramatically increased in the United States during the last 20 years. More than one-third of the adult population (35.7%) and almost 17% of children and adolescents were obese in 2009-2010 (Ogden et al., 2012). Data from the National Health and Nutrition Survey (2005-2008) show that the prevalence of obesity among men is generally similar at all income levels, while women with higher income are less likely to be obese than those with low income. In this study I do not differentiate between males and females for simulation purposes because I assume that any public health awareness campaign on obesity will affect both males and females in the same way. I also carry out the simulation on overweight and obese individuals separately in order to investigate whether the effects of such a health awareness campaign might have different implications on these two groups. The CDC defines obesity for adults by using weight and height to calculate the *body mass index (BMI)*, since for most people it correlates with their percentage amount of body fat. A person is identified as obese if his/her BMI index is 30 or higher. For those who have their BMI index between 25 and 29.9, CDC treats them to be *overweight*.¹² To identify the adults in the NHIS survey who are obese or overweight, I also follow this measure.

I start by determining which health problems or diseases are related to obesity. Following the National Heart, Lung, and Blood Institute (NHLBI) in the United States, I match ten health problems from Table 3.1 that are related to obesity. These are hypertension, coronary

¹²Source: Centers for Disease Control and Prevention (CDC).

heart disease, stroke, ulcer, cancer, diabetes, liver condition, dermatitis/skin condition, joint pain/aching/stiffness, and lower back pain. Once again, I calculate the public health achievement and socioeconomic health inequality using the count approach. Then, I assume there is a public health awareness campaign by the government about the health risks of obesity. As a result of this campaign, there are improvements in the aforementioned health problems which are related to obesity. To have a better comparison with the campaign against smoking mentioned previously, in this case I also consider the success rate of the anti-obesity campaign to be 0.23% for the simulation (i.e., 0.23% of the people who are overweight or obese will lose weight as a result of the campaign and will not remain as overweight/obese in the long run).

Table 3.4 below shows the expected changes on health achievement assuming a 0.23% improvement in the diseases related to obesity for the individuals who are overweight. Once again this improvement is randomly generated in the population over a uniform distribution in the socioeconomic ranks of individuals, and the revised values of the health achievement index and health inequality are calculated. This iteration is done 1,000 times, and a 95% confidence interval is also constructed. Although the improvements are very close to each other, it can be observed that the largest expected improvement occurs for $\eta = 1.5$; in this case the health achievement index is improved by almost 0.002418%.

Table 3.4: Simulated 0.23% improvement in obesity-related diseases among overweight people and its impact on health achievement in the United States:

	Original Health achievement	Health Achievement after Simulation			% Improvement
		Mean	Lower Bound	Upper Bound	
$\eta=1.5$	0.893327	0.893349	0.893348	0.893349	0.002418
$\eta=2.0$	0.891548	0.891569	0.891569	0.891570	0.002400
$\eta=2.5$	0.890195	0.890216	0.890215	0.890216	0.002348
$\eta=3.0$	0.889093	0.889114	0.889114	0.889115	0.002362

Table 3.5 exhibits what would be the expected changes in socioeconomic health inequality caused by the same 0.23% improvement in obesity-related diseases among the overweight individuals. It is apparent that health inequality actually increases slightly (i.e., positive values of the percentage changes) for all health inequality aversion parameters. However, the most favourable result is obtained (i.e., the least increased health inequality) when the aversion parameter $\eta = 3$. The increase in socioeconomic health inequality in this case might be due to the distribution of overweight people across socioeconomic status levels (i.e., more overweight people might be at the upper socioeconomic status levels which means the improvement in the obesity-related diseases among overweight individuals have proportionately benefited more those individuals who are also at the upper socioeconomic levels).

Table 3.5: Simulated 0.23% improvement in obesity-related diseases among overweight people and its impact on socioeconomic health inequality in the United States:

	Original Health Inequality	Health Inequality after Simulation			% Improvement
		Mean	Lower Bound	Upper Bound	
$\eta=1.5$	0.002750	0.002751	0.002751	0.002751	0.043636
$\eta=2.0$	0.004736	0.004737	0.004737	0.004738	0.027449
$\eta=2.5$	0.006247	0.006248	0.006248	0.006249	0.017608
$\eta=3.0$	0.007477	0.007478	0.007478	0.007479	0.016049

Next I simulate what would be the expected impact on health achievement assuming a 0.23% improvement in the diseases related to obesity for the individuals who are obese. It can be seen that the most improvement in health achievement occurs when $\eta = 2$, and the expected improvement in the aggregate health achievement is 0.002456%. The results of the simulation are reported in Table 3.6.

Table 3.6: Simulated 0.23% improvement in obesity-related diseases among obese people and its impact on health achievement in the United States:

	Original Health achievement	Health Achievement after Simulation			% Improve-ment
		Mean	Lower Bound	Upper Bound	
$\eta=1.5$	0.893327	0.893349	0.893348	0.893349	0.002418
$\eta=2.0$	0.891548	0.891570	0.891569	0.891570	0.002456
$\eta=2.5$	0.890195	0.890217	0.890216	0.890217	0.002415
$\eta=3.0$	0.889093	0.889115	0.889114	0.889115	0.002429

Finally, Table 3.7 shows the expected changes in socioeconomic health inequality because of the 0.23% improvement in obesity-related diseases among the individuals who are obese. It can be seen that unlike the results that I obtained for the effects on health inequality among overweight people, in this case the degree of health inequality is expected to decrease for all values of η except for when $\eta = 1.5$. I also observe that the expected simulated improvements in health achievement are relatively higher for the obese people compared to the individuals who are overweight. When the results are compared to the effects of the campaign against smoking, I find that the campaign against obesity is expected to be more effective in improving the overall health achievement.

Table 3.7: Simulated 0.23% improvement in obesity-related diseases among obese People and its impact on socioeconomic health inequality in the United States:

	Original Health Inequality	Health Inequality after Simulation			% Improve-ment
		Mean	Lower Bound	Upper Bound	
$\eta=1.5$	0.002750	0.002750	0.002750	0.002750	0.003636
$\eta=2.0$	0.004736	0.004736	0.004736	0.004736	-0.006334
$\eta=2.5$	0.006247	0.006247	0.006246	0.006247	-0.008004
$\eta=3.0$	0.007477	0.007477	0.007476	0.007477	-0.005350

3.4.3 Calculating the *C-ICERs* of health awareness campaigns against Smoking and Obesity

After having estimated the expected improvements in health achievement because of the awareness campaigns against smoking and obesity above, now I can calculate the C-ICERs of these campaigns. The aggregate cost of the Tips campaign in 2012 was \$54 million,¹³ and according to McAfee et al. [2013], almost 0.23% smokers quit smoking and sustained their abstinence in the long run. I can use this amount to assess the C-ICERs of both of the proposed anti-smoking and anti-obesity campaigns to obtain a realistic measure. For example, I can consider the case for inequality aversion parameter $\eta = 2$ and a 0.23% improvement in the diseases related to smoking. From Table 3.2, it can be seen that health achievement increases by 0.000005 (or 0.000606%) because of the campaign. The adult population in U.S. in 2010 was 234,564,071¹⁴. Using equation (3.8), the C-ICER related to the anti-smoking campaign is calculated to be \$42,632.¹⁵ Similarly, using Table 3.4 and Table 3.6, I find that the increases in health achievements for $\eta = 2$ are 0.000021 (or 0.002400%) and 0.000022 (or 0.002456%) for the obesity-related diseases among overweight and obese people, respectively. Thus, the C-ICER related to a similar anti-obesity campaign is \$10,758 for the overweight people and \$10,512 for the obese people.

There are some limitations of the study presented here that need to be addressed. Firstly, in this paper I assume equal weights for all health attributes used to develop the overall health status of an individual (i.e., $\theta_1 = \theta_2 = \dots = \theta_k = 1$). A more sophisticated way to determine the health status of individuals would be to assign different weights for each

¹³Source: Centers for Disease Control and Prevention (CDC).

¹⁴Source: United States Census Bureau, Census 2010 Summary File 1.

¹⁵Although the actual and simulated health achievements are calculated for a sample size of 13,712, I assume that the health achievements for the total adult population in the U.S. will not be significantly different because of the comprehensive demographic representation of adult population from all over the country in the NHIS survey.

health attribute, based on their relative importance. However, this complicated methodology is beyond the scope of this paper. Secondly, I assume that the effect of such health awareness campaigns will contribute to changes in the individuals' health profiles by encouraging them to give up smoking or lower their BMI, and consequently affect the diseases related to smoking and overweight/obesity by moving them above the threshold definitions that are used to develop individual health profiles. I understand that doing so overestimates the improvements calculated as a result of the health campaigns discussed here, because the smoking/obesity attributable fractions of diseases may be less than what I assumed (i.e., smoking or obesity is certainly a risk factor for the diseases discussed here, but giving up smoking or changes in the BMI may not be related to improving conditions associated to these diseases on a direct one-to-one basis).

Studies that aim to measure the effectiveness of such public health awareness campaigns are very limited in the literature. Cristofolini et al. [1993] calculated the effects of health campaign for the early diagnosis of cutaneous melanoma in Trentino, Italy that began in 1977 and again repeated in 1981. The paper looked at the cost effectiveness ratio of the campaign by comparing the total costs of the campaign with the expected costs of treatment and found favourable cost effectiveness of the campaign. It determined that 22.3 lives were saved by early diagnosis during the period 1977-1985 and the cost per year of lives saved was calculated to be \$400. A comprehensive study that looks into the effects of the TIPS campaign in the United States is by McAfee et al. [2013]. The authors estimate that as a result of the TIPS campaign, from a third to almost half a million quality-adjusted life years were added to the U.S. population, and the cost per life year saved was less than \$200, making TIPS an extremely cost effective preventive intervention. In other words, this study found that almost 0.23% smokers sustained their abstinence in the long-term because of the TIPS campaign, while it costs less than \$200 to save one life year.

With the simulation illustration shown in this paper, I found that for an estimated 0.23% improvement in the smoking-related diseases with the aversion parameter $\eta = 2$, the C-ICER of anti smoking campaign is \$42,632; in other words, it takes approximately \$42,632 in health awareness campaign costs per person to overcome the threshold in the smoking-related diseases where previously she/he was affected. Although these numbers are not directly comparable, this shows that our estimates are realistic and offer to look at the effectiveness of public health awareness campaigns from a different perspective. One advantage that the C-ICER gives to the policy makers is that by adopting this measure, it is possible to rank a number of health awareness campaigns when the cost of running such a campaign is fixed (e.g., allocated budget for a fiscal year). It also allows to see which campaign would yield the most improvement in the overall health achievement among the residents, and at the same time what would be the expected impact on socioeconomic health inequality because of it.

3.5 Conclusion

In this paper, I have calculated the population health status and socioeconomic health inequality using the National Health Interview Survey data from 2010 in the United States, by adopting Makdissi and Yazbeck [2014]’s counting approach, which takes care of the *arbitrariness* problem associated with categorical health status variables. I then simulate the expected effects of public health awareness campaigns on the harmful consequences of smoking and obesity, and calculate what effects such campaigns may have on the aggregate health status and socioeconomic health inequality among residents in the society. I also develop the framework to calculate the count-approach incremental cost effectiveness ratio (C-ICER) of these public awareness campaigns and show how this new measure is not dependent on unrealistic assumptions like *perfect divisibility* and *constant returns to scale* which are nec-

essary for calculating the traditional ICERs. I present in this paper a simple approach to calculate the expected cost effectiveness of different prospective health campaigns for a given fixed budget, and also the effect of such campaigns on the socioeconomic health inequality. For further research, it would be interesting to see the true effects of the *TIPS* campaign that was run by the CDC in 2012 by calculating the population health achievement, socioeconomic health inequality, and C-ICERs for later years once the data become available and compare how the results measure up against the simulation estimates shown in this paper; and also to develop frameworks to take into account for the limitations outlined here.

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