Three Essays in Environmental and Development Economics

by

Meijuan Wang

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
August 4, 2018

Keywords: Air pollution, winter heating, children malnutrition, gender difference, greenhouse gas emissions, environmental efficiency

Approved by

Denis A. Nadolnyak, Chair, Associate Professor of Agricultural Economics
Emir Malikov, Co-chair, Assistant Professor of Agricultural Economics
Valentina Hartarska, Alumni Professor of Agricultural Economics
Ruiqing Miao, Assistant Professor of Agricultural Economics

Abstract

This dissertation consists of three empirical essays as three chapters on environmental issue and hunger problem in developing countries.

Chapter 1 examines whether the central winter heating causes the air pollution in the Northern China. we measure this impact and the data are the daily Air Quality Index (AQI) records for mid-November when the heat is turned on and mid-March when heat is turned off in over 150 cities. The results show that winter heating contributes significantly to air pollution, especially in the period when central heating is switched on. The central heating causes AQI 27.6% higher in northern cities, which indicates more air pollution; the air is 12.47% more likely to be unhealthy for sensitive people and 5.4% more likely to be unhealthy for all. When central heating is turned off, the air quality in southern cities gets slightly better.

Chapter 2 focuses on the issue of gender preference in terms of children malnutrition. We use the Demographic and Health Survey data in Ethiopia and run two rounds of regression, the first one is over stunting, underweight and wasting and the second round is over z-scores of height for age, weight for age and weight for height. The data description shows that nearly one-half of children in our sample are stunted. Children at the age of 2 and 3 are more likely to be short or too skinny compared to normal children at the same age. Our decomposition model estimates show that under in the same living environment, if a girl were to be a boy, the odds ratio of being wasted would increase by 1.34, the odds ratio of being stunted would increase by 1.03 and the odds ratio of being underweight would increase by 1.04. It suggests that boys under

5 in Ethiopia in our sample are more malnourished than girls in the same socio-economic environment.

Chapter 3 aims to assess the environmental performance across countries and over time. A directional distance function framework is applied to measure the technical environmental efficiency (TEE). We use data from the World Bank for the period 1990–2012. There are three inputs—capital, labor, and energy consumption and one good output—GDP; GHG, CO_2, and N_2O are treated as bad outputs and estimated separately in three models, each with five different direction vectors. The main findings are as follows. 1. The relationship between TEE and GDP per capita performs a shallow U shape curve. 2. No significant distributional change in TEE with different direction vectors in GHG and CO_2 models, but results from the N_2O model show that countries are generally more efficient when the direction in GDP is smaller, which indicates that the more we emphasize the importance of N_2O emissions, the lower score in environmental performance evaluation. 3. The GHG efficiency trend over time is ambiguous across different direction vectors, while the CO_2 efficiency is generally decreasing over time and N_2O efficiency is increasing over time. Technical change, the shadow price of bad output, and Morishima elasticity are also computed in this chapter.

Acknowledgments

This dissertation could never have been completed without the help of my advisors, friends, and family, who have helped me climb to reach the shoulder of the giants. I would like to express my sincere appreciation to them.

Thanks to Dr. Nadolnyak, for his understanding and continuous encouragement.

Thanks to Dr. Malikov, for his valuable academic advice, patient and detailed guidance.

Thanks to Dr. Hartarska and Dr. Miao, for their insightful comments and suggestions.

Thanks to all the faculty and stuff, for their dedicated teaching and responsive service during my PhD study.

Thanks to the China Scholarship Council and my department for giving me financial support; thanks to my colleagues, friends and the Student Counseling Service for their psychological support.

Lastly but most importantly, thanks to my family, who are the motivation to keep me going on and on.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AQI	Air Quality Index
CNEMC	China National Environmental Monitoring Center
CRS	Constant Return to Scale
DDF	Directional Distance Function
DEA	Data Envelopment Analysis
DHS	Demographic and Health Survey
DODF	Directional Output Distance Function
EKC	Environmental Kuznets Curve
FAO	Food and Agriculture Organization
GHG	Green House Gas
HDF	Hyperbolic Distance Function
IPCC	International Panel on Climate Change
MDG	Millennium Development Goal
NCHS	National Center for Health Statistics
PM	Particulate Matter
SFA	stochastic frontier analysis
TEE	Technical Environmental Efficiency
TSP	Total Suspended Particulates

USEPA	United States Environmental Protection Agency
WHO	World Health Organization

Chapter 1 The Impact of Central Winter Heating on Air Quality in China

1. Introduction

Fueled by rapid urbanization and industrialization, China has experienced a near 10% average annual growth in the last three decades (Zheng et al. 2014). From 1990 to 2013, the population increased by 322 million, the urban population rate increased by 26 percentage points, and the energy consumption per capita increased by 165%. Following the economic growth, however, is the environmental degradation, such as air pollution, water pollution, and land deterioration. Like many other developing countries, China faces a serious air pollution problem. One notorious pollutant is particulate matter (PM), with $PM_{2.5}$ (particulate matter with diameter less than 2.5 micrometers) and PM_{10} (particulate matter with diameter less than 10 micrometers) concentration are commonly used in air quality reports. In 2014, the population-weighted average exposure to $PM_{2.5}$ in China was 52 $\mu g/m^3$ while it was 10.75 $\mu g/m^3$ in the US, 14.82 $\mu g/m^3$ in the eurozone and 31.54 $\mu g/m^3$ in the world (World Bank 2014).

This paper focuses on the relationship between coal consumption and air pollution. In North China, haze has become the most frequent weather in winter. According to the China National Environmental Monitoring Center (CNEMC) Air Quality Report (CNEMC 2015), in 2014 the Jing-Jin-Ji area experienced 156 days of poor air quality, and the PM_{10} index was 70$\mu g/m^3$ which was much higher than the air quality standard (average 50$\mu g/m^3$ in 24 hours). In Beijing, air quality in nearly half a year was reported as "unhealthy" (Air Quality Index>150) in 2014. In some other cities, it was even worse. Haze lasted for more than two-thirds of the year in Xi'an

(278 days) as well as Shijiazhuang (323 days). Air pollution is more prominent in winter, especially in the northern[1] cities; the coal-based central heating contributes to the formation of pollutants while cold weather in winter impedes the dissipation of air pollutants, which eventually causes the accumulation of haze.

There is rich literature on the relationship between energy consumption, economic growth, and environmental issues, providing insights into the energy and environmental policy (Tiba and Omri 2017). The multi-country and country-specific studies have found that energy consumption and economic growth have a bi-directional causality and there is a positive relationship between greenhouse gas emissions and energy consumption (Auffhammer and Carson 2008; Zheng et al. 2011). Direct energy consumption can be divided into three components: transportation, industrial and residential use. In the industrial sector, the concentration of industrial activities drive the fast economic growth followed by the deteriorated environmental quality (Zheng et al. 2014; Cao et al. 2011). In the transportation sector, the car stock and travels promote the concentration of pollution in urban areas (Han and Hayashi 2008; Viard and Fu 2015). Households' use of biomass for cooking also generates indoor pollutant emissions (Malla 2013). China's development relies heavily on energy consumption, with the coal accounting for up to 70% of the total energy sources, and it is much higher than the coal use in developed countries (20%-30%). Coal combustion is one of the most important sources of air pollution (He, Huo and Zhang 2002; Tian et al. 2012) and it contributes as much as 51% to the average $PM_{2.5}$ in the whole country (Hu and Jiang 2013) as well as 16.7% to the PM_{10} concentration (Zheng et al. 2014).

[1] Later in this paper, the "northern" and "southern" represent the relative relationship to the Qinling Mountrain-Huai River line (or simply called Huai River line), which is the central line dividing the heating and non -heating areas.

Air pollution has a variety of negative effects, which include economic costs (Quah and Boon 2003; Wang and Mauzerall 2006), infant mortality (Luechinger 2014; Arceo-Gomez, Hanna and Oliva 2012; Cesur, Tekin and Ulker 2015), adverse health and happiness impacts (Mukhopadhyay and Forssell 2005; Matus et al. 2012; Li, Folmer and Xue 2014), etc. To alleviate air pollution, researchers propose setting a higher levy rate (Li, Wu and Zhang 2015), moving the dominant energy supply to natural gas, nuclear and renewable energy (van Vliet et al. 2012), etc.

This paper seeks to answer the following question: to what extent does the coal-based central winter heating affect local air quality? Different from the impact analysis of air pollution in the above literature, we use the hazard level[2] to describe the health impact of air quality change caused by winter heating. Every year, the central winter heating in Northern China is turned on on Nov. 15th and keeps running until Mar. 15th of the next year, which causes a much higher coal consumption comparing to other seasons. The purpose of this paper is to use empirical data to test whether China's central winter heating has a significant negative effect on the local air quality. The hypothesis is that the winter heating aggravates the air pollution in the urban area. We take the Huai-river Policy as a quasi-natural experiment, in which the central heating is considered as the treatment, and this treatment applies only to the cities in the north, which constitute the treated group, while cities in the south constitute the control group. The central winter heating policy has long been considered as a low-cost way for household heating, but very few studies focus on its negative impact on air quality. This paper will fill this gap.

The rest of this article is organized as follows. The next section provides a brief description of the central heating policy and the related literature. The third section describes the data, and the

[2] The hazard level standard is defined by EPA (2009) and detailed introduction is provided in section 3.

forth section introduces the model and reports the results. The last section is the conclusions and further discussion.

2. The Central Heating Policy

The central winter heating system was established during 1950-1980s and ran by state-owned enterprises (Chen et al. 2013). Urban areas are supplied with central heating every year during winter, but the heating is not throughout the country. On the issue of central heating, China is divided into two parts by the Qinling Mountain-Huai River line, along which the average temperature in winter is 0° Celsius. This division is named the “Huai-River Policy.” According to the policy, every year from Nov. 15th to Mar. 15th of the following year, hot steam is piped to households in the northern cities, and residents only need to pay a relatively low fee based on the size of their houses (around \$3/m^2/month in 2014). Cities located to the south of the Huai River are not provided with central heating.

The central heating system is coal-based and technically inefficient. Most heat is provided by coal-fired, heat-only boilers or combined heat generators which are less efficient in energy conversion compared to electric, gas, and oil heating systems (Wang, Lin and Lee 1995). When the heating is switched on, there is a sharp rise in the coal combustion, which results in a large amount of Total Suspended Particulates (TSP), as well as nitrogen oxides and sulfur dioxides, being released into the air and forming the main components of air pollutants. Researchers in the chemical science and environmental economics consistently agree that coal combustion can release hazardous air pollutants, especially when the process is incomplete. The incomplete combustion of coal in the boilers causes a release of at least three measured types of air pollutants (Bi et al. 2007). The bad outputs from coal combustion include substantial TSP emissions, SO_2, NO_2, and cause significant air pollution (Muller, Mendelsohn and Nordhaus 2011).

The impact of winter heating has long been overlooked, and there is little research focusing on the environmental effects of the coal-based winter heating system. In recent years, some economists have tried to look into this issue. By analyzing Beijing's haze weather, Duan and Tan (2013) find that winter heating is among important reasons for air pollution. By analyzing the data on air pollution in China in 1981-1993, Almond et al. (2009) find that northern cities have relatively higher TSP concentration, but the result does not hold for SO_2 and NO_2. The models in their paper do not include variables of the city characteristics, which indicates that there may be endogeneity. Chen et al. (2013) study the mortality data in China during 1991-2000 and find that due to the "Huai-river Policy," people in the north bear a longer sustained exposure to air pollution, and their life expectancy is about 5.5 years lower owing to an increased incidence of the cardiorespiratory mortality. At the same time, there are arguments from some researchers supporting winter heating policy. Xiao et al. (2015) argue that the central heating system contributes less air pollution compared to other heating activities because central heating is more efficient than family level self-heating and due to the emission control technologies applied in the central heating system such that there are fewer air pollutants emitted than fugitive emissions from individual heating devices.

3. Data Sources and Descriptive Statistics

Data on environmental air pollution in China are relatively scarce compared to developed countries, and the data quality is considered questionable (Zheng and Kahn 2013; Ghanem and Zhang 2014). One encouraging development in 2011 was that China Environment Agency established a system to measure $PM_{2.5}$, PM_{10}, O_3, NO_2, and CO in the air. Monitor centers were built to provide hourly reports of air quality index in most cities. In this paper, we obtained the daily report of the Air Quality Index and hazardous level records from the Ministry of

Environmental Protection of the People's Republic of China. This dataset is reliable since the data are directly generated by the air quality monitors established in each city and uploaded to the website with the lowest suspicion of manipulation. In the records, for the 2014-2015 winter around the time central heating is turned on there are 158 cities (Nov. 10^{th}- Nov. 19^{th}), and 357 cities in the period when it is turned off (Mar. 10^{th}- Mar. 19^{th}).

In the introduction section, we use haze weather frequency as an indicator of air pollution, while in research air pollution indicators are more complex. Most studies employ an integrated index composed by the density of $PM_{2.5}$, PM_{10}, SO_2, NO_x, CO, O_3. The standards on air quality levels are slightly different across countries, and in this paper, we employ the Air Quality Index (AQI)[3] and the corresponding levels of health concern. Based on the Clean Air Act, United States Environmental Protection Agency (USEPA) calculates AQI using five major air pollutants: particulate matter, carbon monoxide, nitrogen dioxide, sulfur dioxide and ground-level ozone. The relative scales of AQI are shown in Table 1.1.

Hazard levels are designated based on AQI with higher values of AQI corresponds to higher hazard level, which means that the air is more polluted and more harmful to individual's health. At the "good level," air quality is considered satisfactory, and the pollution has little or no risk. At the "moderate" level, air quality is considered acceptable, but the pollution may cause health concerns for a certain group of people. At "unhealthy for sensitive groups" level, people with lung disease, older adults, and children are exposed to a greater health risk. At the "unhealthy" level, the pollution could harm everyone exposed to the air. At the "very unhealthy" level, everyone may experience more serious health effects. At the "hazardous" level, air would trigger

[3] We do not talk about how to calculate AQI here in detail but for more information please refer to (USEPA, 2006, 2009). A quick access can also be found at: http://www.iqa.mddefp.gouv.qc.ca/contenu/calcul_en.htm

a health warning of emergency conditions. The entire population is more likely to be affected. By defining the dependent variable in this way, we could obtain a rough estimation of the health concern caused by central heating.

Other controlled variables such as city characteristics, including GDP per capita, population, number of buses and taxis, etc. are from the China City Year Book. GDP per capita is converted into the 2014 constant dollars. To construct population variable, we only count the people living in the urban area, since the heating facilities are constructed only in the urban area, while the rural households use heating from other sources, such as biomass and electricity. By using the GDP per capita, we seek to allow for an Environmental-Kuznets-Curve-like environment deterioration. Further, since Automobiles account for the largest sources of particulate matter, it is reasonable to include the total number of automobiles in the analysis. Given the limited available data, the number of taxis and buses is used instead of the total number of automobiles. Greenland represents the green covered area (1000 hectare). The number of industrial enterprises (in thousands) and the total amount of electricity consumption for industrial use (in 10^4 GWh) are employed to control for the industrial productivity. Since the geographical location of the cities is related to their climate and the use of heating in the winter time, we also control for the city latitude (north). Table 1.2 reports the descriptive summary statistics for the variables.

For City characteristics, we use only data in 2014; the AQI are collected in two periods. Due to the development of monitor system, the number of observation increases in the second period.

Like event study, we assemble two windows for the switch-on and switch-off periods, each window contains ten days, five days before and five days after the treatment event. The detailed introduction of the model is given in the next section. In the first window in 2014 fall, when heating is switched on, the AQI ranges from 13 to 404 with the mean 99, standard deviation 48 and number of available observations in this period is 1460; there are 77 out of 156 cities in which the average AQI in continuous 10 days exceeds 100 (unhealthy for sensitive groups) and 58 cities in which AQI over 100 lasts more than 5 days. In the second window in 2015 spring, the monitor system expanded and covered around 271 cities. At this switch-off period, the AQI ranges from 21 to 339, with the mean 90.16, standard deviation 42.74 and number of available observations in this period is 2588. There are 88 cities in which the average AQI is unhealthy for the sensitive group, and in 62 cities this unhealthy-for-the-sensitive-group air condition lasts more than five days. The latitudes of the cities are between N 18.25 and N 50.25.

4. Empirical Model and Results

As we mentioned in earlier chapters, in this study the treatment is central heating, it is switched on in the first 10-day window in 2014 November and is switched off in the second 10-day window in 2015 March. The treated group consists cities located to the north of the Huai-River line and the control or untreated group is composed by cities located to the south. Our main model is

$$\log AQI_{it} = \alpha + \beta \boldsymbol{X}_{it} + \delta Heat_t + \theta North_i + \rho Heat_t * North_i + \epsilon_t \ , \tag{1}$$

where AQI is the Air Quality Index for city i at time $t,$ Hazard Level is the corresponding categories which are defined in Table 1.1. $\boldsymbol{X}$ denotes socio-economic characteristics for city i, including GDP per capita, squared GDP per capita, population, number of taxis and buses, green land area etc. $North$ is a dummy variable indicating whether city i is to the north of the Huai River or to the south. $Heat$ is a dummy variable indicating whether heating is provided, in equation (1), when heating is switched on,

$$Heat_t = \begin{cases} 0 & t = Nov.10 - Nov.14 \\ 1 & t = \ Nov.15 - Nov.19 \end{cases}, \tag{2}$$

and when heating is switched off,

$$Heat_t = \begin{cases} 1 & t = Mar.10 - Mar.14 \\ 0 & t = \ Mar.15 - Mar.19 \end{cases} . \quad (3)$$

Since we have two periods of data, the first period covers Nov. 10-Nov.19 in 2014 and Nov. 15 is the day when heating is turned on, we have $Heat = 0$ and 1 for before and after Nov. 15; the second period covers Mar. 10-Mar.19 in 2015 and Mar.15 is the day when heating is turned off, we have $Heat = 1$ and 0 for before and after Mar. 15.

We run two models, one uses the AQI which is continuous and ranges from 1 to 500, another one uses the hazard level which is discrete and has six values in order (see Table 1.1). The OLS model can be used as the baseline estimation and the ordered Logit model shows how winter heating and health concerns are related. We estimate each model for both windows in November and March. Table 1.3 reports the results with the columns labeled accordingly to indicate the time period used in the estimation. Our interest lies in the coefficient of the interaction of two dummy variables: north and heat, which identifies the effect of central heating to air quality.

The results in Column 1 show that both control and treated group experience an increase of AQI when in the first window. Before the heating is turned on, AQI in treated group is 21.1% higher compared to control group, which is likely due to geographical climate differences and the history of energy-intensive heavy industry development in the north. After the central heating is turned on, the average AQI in control group increases by14.9% and in treated group it increases by 27.6%. The AQI gap between two groups increases by 33.8% compared to the gap before treatment, this indicates that AQI at the mean of 80 in the south increases to 103 (Hazard level from 2 to 3) and AQI at the mean of 101 in the north increases to 129. Column 2 shows the results from the OLS model estimated using the data in the second window. We expect that when heating is switched off, the AQI decreases for both groups, yet column 2 tells a slightly different story. When the central heating is off, the AQI in the control group decreases by 14.9%; This means the air quality gets better. Again, the AQI in treated group is higher than that in control group, 19.8% before heating is off, and this gap increases to 41.7% after the heat is switched off. On average, the AQI still keeps an upward trend when heat is off, and it grows at a slow rate of 7%. This does not align with our expectation that when heating is off, the air quality should turn better. It might be explained that, although central heating ends and no heating-use coal combustion, the existed particulate matter, nitrogen dioxide, sulfur dioxide, etc. are still floating in the air; it is also possible that when the central heating is shut down, residents choose alternative heating resource, i.e., coal stoves and biomass burning. These offset the decrease of pollutants emission from central heating plants.

The coefficients of both GDP per capita and the square term are negative and significant except for the first term; this shows that as the GDP per capita increases, the AQI decreases and air quality gets improved. At the mean of 11.4 thousand dollars (all cities in two periods included), per 114 dollars increase of GDP per capita suggests a 44% (0.028+2*0.204) reduction of AQI, while in the second window the reduction is around 34.4. This does not align with EKC, yet it provides another evidence that when income increases the environmental qualities get improved. (Stern and Common 2001; Costantini and Monni 2008).

The population also impact air quality, the estimate is significant though the magnitude is small. For an increase of one million in the population in the urban area causes a 5.8% increase in the AQI. Number of buses and taxis are used to represent the automobiles; buses contribute to the air pollution yet we find that the more taxes, the lower AQI is, considering that more taxies indicate a larger city and taxi is a substitution for private automobiles, the mixed effect makes the outcome to be positive. Industrial enterprises and electricity usage estimators show that the more industry productivity, the higher risk of air pollution. Green cover, which counts the green area in urban cities, contributes to the air clearing process, per 1000 hectare increase in grassland indicates a decrease of 2.4% in AQI. Cities located in higher latitude are more polluted than those in a lower latitude.

Column 3 and Column 4 in Table 3 shows the Ordered Logit regression estimation with the discrete variable-hazard level. The Ordered Logit estimation results show that air pollution in the treated group is likely to be more hazardous, the central winter heating aggravates the health concern in both treated and control group cities. We also calculate the marginal effect of central winter heating at means in two windows, as shown in Table 1.4. Generally, the heating causes lower probability of the air to be "healthy" and a higher probability of being "unhealthy." After heating, the health concern level of ambient air condition to be 13.96% less likely to be moderate, 12.47% more likely to be unhealthy for sensitive groups, 5.4% more likely to be unhealthy and 1.85% to be very unhealthy. In the heating switch-off period, the probability of air to be unhealthy or unhealthy for sensitive groups decrease by 1.19% and 3.75% respectively, the probability of the air to be moderate and good increase by 2.88% and 2.44% respectively. Other variables perform similarly as they are in OLS model, an increase of GDP per capita indicates a higher probability of air quality being more hazardous. Cities with higher GDP per capita have relatively better air quality.

To check the sensitivity of outcome in respect to different cutoff point (Nov. 15th and Mar 15th), we have a robustness check. In this part we spread each window into four quarters, that is, day1-2 and day 3-5 (before heat starts), day 6-8 and day 9-10 (after heat starts) at first time window in November and same for the second time window in March, which denotes a new dummy variable of date. The regression results are reported in Table 1.5.

All the tests show that cities in treated group are more polluted than cities in the control group, there is no significant AQI change over first two quarters for all cities; in the third and fourth quarter, there is no significant change in southern cities, yet the AQI drops dramatically by 46% on average in northern cities. In the rest of the time subperiods, the interaction terms are not significant. These results corroborate our hypothesis that the increase of AQI is caused by the central heating, the change in control group before heating is not significant. In the second period in March, we find a drop of AQI when comparing the last two quarters. For other quarters of the time window, the AQI keeps increasing in northern cities even after the central heating is switched off, which might be caused by slow dispersion of air pollutants.

5. Conclusion

We study the impact of central winter heating on air quality in China and start a new viewpoint on China's air pollution dynamics. The Huai-River policy is considered as a natural experiment and a model is designed regarding the time difference (heating switches on and off) and geographic difference of cities (north and south). We find that cities located in northern China are more polluted than cities in the south; before heating is switched on, the health impact of the air is moderate to health on average, the central heating causes 27.6% higher AQI in northern cities, and the air is 13.47% more likely to be unhealthy to the sensitive group. When the heating is switched off, AQI in southern cities decreased by 14.9% yet there is still an increasing trend in northern cities. We also find that air quality in cities with higher GDP per capita is better. More crowed cities, more buses and electricity used by industry also contribute to air pollution.

Central heating has a long history with the citizens living to the north of Huai-River, it is cleaner than self-heating provided by coal or wood (which is common in the rural area), and it is much cheaper than air conditioner-based heating. For households in the city, warmth generated by the central heating is the same as air conditioning, but the expenses are less, such that residents have no incentive to reject central heating. However, cheaper central heating is not necessary cheaper if we include the external social cost of air pollution. Central heating and burning coal, or air conditioning with electricity, which one is more socially cheaper? There might be no exact answer. However, we suggest that cleaner energy should be explored to generate heat for households in northern China, such as solar and cleaner electricity.

As many environment scholars suggest, temperature, mildness, wind direction will all influence the air quality, though we have assumed that within observed periods these factors are static. Expanding the analysis to include these contributions is lest for future research.

TABLES:

Table 1.1 Air Quality Index and Corresponding Hazardous Level

Air Quality Index (AQI Values)	Levels of Health Concern
0-50	Good
51-100	Moderate
101-150	Unhealthy for Sensitive Groups
151-200	Unhealthy
201-300	Very Unhealthy
301-500	Hazardous

Table 1.2 Summary Statistics for Key Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
AQI (Nov.10-19, 2014)	1460	99	48	13	404
AQI (Mar.10-19, 2015)	2588	90.164	42.744	21	339
Pollution level (Nov.10-19, 2014)	1460	2.466	0.953	1	6
Pollution level (Mar.10-19, 2015)	2588	2.294	0.875	1	6
GDP per capita (thousand)	2588	11.66	8.886	1.665	75.871
Population (million)	2588	1.455	1.842	0.15	17.87
Industrial enterprises (thousand)	2588	0.559	1.082	0.010	9.642
buses(thousand)	2588	1.48	3.072	0.046	30.590
taxies(thousand)	2588	3.29	6.262	0.125	67.046
green land (thousand hectares)	2588	0.702	1.469	0.003	13.144
Industrial electricity use (10^4 gwh)	2588	0.651	0.962	0.001	7.995
Latitude (North)	2588	33	6.557	18.250	50.250

Table 1.3 Winter Heating Impact on Air Quality (Logged AQI) and Health (Hazard Level)

	(1) Heat switch-on period (Nov. 10-Nov. 19)	(2) Heat switch-off period (Mar. 10-Mar. 19)	(3) Heat switch-on period (Nov. 10-Nov. 19)	(4) Heat switch-off period (Mar. 10-Mar. 19)
	Log(AQI) (OLS)		Hazard level (Ordered Logit)	
GDP per capita	-0.028	-0.116***	-0.224*	-0.538***
	(0.027)	(0.017)	(0.137)	(0.085)
GDPpc square	-0.204***	-0.114***	-0.960***	-0.583***
	(0.030)	(0.015)	(0.157)	(0.076)
Population	0.058***	0.033***	0.212***	0.152***
	(0.009)	(0.012)	(0.040)	(0.061)
Industry enterprises	0.109***	-0.002	0.442***	-0.014*
	(0.018)	(0.002)	(0.094)	(0.008)
Buses	0.018***	0.002***	0.099***	0.007***
	(0.005)	(0.000)	(0.024)	(0.003)
Taxi	-0.023***	-0.001***	-0.100***	-0.005***
	(0.003)	(0.000)	(0.013)	(0.002)
Greenland	-0.024**	-0.003***	-0.110**	-0.010**
	(0.009)	(0.001)	(0.047)	(0.005)
Electricity used by industry	-0.003	0.0001***	0.062	0.005***
	(0.019)	(0.000)	(0.098)	(0.001)
Latitude	0.013***	0.004**	0.061***	0.016*
	(0.003)	(0.002)	(0.015)	(0.010)
Heat	0.149***	0.149***	0.510***	0.675***
	(0.026)	(0.022)	(0.135)	(0.108)
North	0.211***	0.417***	0.833***	1.784***
	(0.045)	(0.028)	(0.225)	(0.137)
North*Heat	0.127***	-0.220***	0.768***	-0.939***
	(0.042)	(0.032)	(0.210)	(0.154)
Constant	3.855***	3.157***		
	(0.084)	(0.119)		
Observations	1460	2588	1460	2588

Note: Robust Standard errors in parentheses, * p<0.1 ** p<0.05 *** p<0.01

Table 1.4 Marginal Effects of Central Winter Heating at Means

Hazard Level	Health Concern	Heat switch-on period	Heat switch-off period
1	Good	-5.93%***	-2.44%***
2	Moderate	-13.96%***	-2.88%***
3	Unhealthy for Sensitive Groups	12.47%***	3.75%***
4	Unhealthy	5.40%***	1.19%***
5	Very Unhealthy	1.85%***	0.35%***
6	Hazardous	0.16%**	0.03%*

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

Table 1.5 Robustness Check in the OLS Process

	Before Heat Starts	After Heat Starts	Before Heat Ends	After Heat Ends
	Day1-2 vs. Day 3-5	Day 6-8 vs. Day 9-10	Day1-2 vs. Day 3-5	Day 6-8 vs. Day 9-10
Heat	0.017	0.008	0.204***	-0.167***
	(0.041)	(0.036)	(0.033)	(0.028)
North	0.440***	0.344***	0.172***	0.409***
	(0.072)	(0.058)	(0.041)	(0.039)
Heat*North	-0.474***	0.082	0.047	0.001
	(0.063)	(0.051)	(0.040)	(0.039)

Note: Robust Standard errors in parentheses = "* p<0.1 ** p<0.05 *** p<0.01"

Chapter 2 Is there Gender Inequality in Children Malnutrition in Ethiopia?

1. Introduction

In many developing countries hunger is a prominent issue. There were some improvements since the 1990s, yet the global number of undernourished propulation is still very large (Black et al. 2013). Child undernutrition is an important public health problem; it is the priority among the world's top ten important challenges reported by the Copenhagen Consensus (T. Sohnesen et al. 2016). One-quarter of children aged under five in the world are stunted (an estimated 162 million in 2012); 15% are underweight, and 8% are wasted. Many countries in Africa are reported of high child stunting prevalence rates, 30% or more. The worst-affected countries are concentrated in Eastern Africa (te Lintelo and Lakshman 2015). In recent years an increasing number of multilateral summits and academic meetings are held on this issue, children malnutrition is considered to be a long-term crisis, and it is estimated to cause 45% of child death (Black et al. 2013). Ethiopia has 80% of the labors in the rural area. In recent years, with the rapid increase of population, farmland per capita has become smaller and the situation is worse due to declining soil fertility caused by intensive subsistence farming (Kebede 2006). The Human Development Index in Ethiopia is 0.442 which is among the lowest countries and it is also among the countries in the world with the highest child undernutrition rates. Taken all together, about 48 percent of children under the age of five were undernourished in 2014, that is, about 6.3 million children are in malnutrition (FAO 2016). The food price volatility of 2008 and of 2010-2011 also caused households welfare lose in rural Ethiopia and aggregated hunger issue (Bellemare, Barrett and Just 2013; Arndt et al. 2016). It is very important to study the children malnutrition issue in Ethiopia.

Policies and commitments are made to fight children hunger issue. In 2000, the Ethiopian government signed the Millennium Development Goal (MDG) declarations, in which it is planned that by 2015, the mortality of children under five should decrease from 140 to 67 out of 1000 live births. There are food aid programs, such as free distribution and "food for work" targeted to poorer households (Yamano, Alderman and Christiaensen 2005), and Productive Safety-Net Program (PSNP) aiming to support the chronically food-insecure households with predictable income transfers (Kebede 2006). Research through the Demographic and Health Surveys implemented in 2000, 2005 and 2011 provide the evidence that there are substantial improvements in the children nutrition status (Ambel et al. 2015), However, the earning from food aid programs are invested differently for boys and girls in one household (Quisumbing 2003), adult consumption behavior in Ethiopia is also found to be related to gender bias (Koohi-kamali 2008), there are still inequalities among regions and between the rich and the poor.

There is rich literature in empirical research on children malnutrition. Studies show that more than one-third of the world's malnourished children live in India (Davey et al. 2014; Panagariya 2013). In the case of Senegal, sustainable nutrition interventions have to be long-term and yield higher returns the earlier they reach children (Rieger and Wagner 2015). Kenya continues to experience warming and drying, malnutrition rates will increase, and investments in infrastructure and expansion of education can mitigate the negative impacts of climate change (Grace et al. 2012). A study of Egypt in period 1992-2008 shows that child and household-level characteristics are more important than aggregate economic conditions (Rashad and Sharaf 2015). There are also a few studies in developed countries, in U.K. and the U.S., findings are that there is a positive relationhsip between adults' height, earnings and good nutrition in early childhood contributes to the height-earnings gap (Case and Paxson 2008). Family income, socio-economic factors, parents' education, breast-fed duration and child age, etc. are commonly considered as factors impact children's health status (Kebede 2005; Atsbeha, Nayga and Rickertsen 2015; Zewdie and Abebaw 2013). In addition to the description of current status, studies have been carried out regarding the negative effects of malnutrition. Alderman, Hoddinott, and Kinsey (2006) found that Child undernutrition may delay in their physical growth and mental development; lower intellectual quotient (IQ), greater behavioral problems and deficient social skills; susceptibility to contracting diseases. Furthermore, the labor market in the future will be affected. Teller, Charles, and Yimer (2015) show that the links among poverty, food insecurity, diseases and child malnutrition can have direct consequences for the future of human resource development policies of Ethiopia. So, effects made to discover more about and decrease children malnutrition is meaningful.

A part of literature studies the inequality of children malnutrition concerning income groups (May and Timæus 2014), socioeconomic inequality (Pulok, Sabah and Enemark 2016; Wagstaff and Watanabe 2003), rural and urban divergence (Smith, Ruel and Ndiaye 2005), etc. while children nutrition gender inequality is less explored. In this paper, we aim to contribute to filling this gap using the case of Ethiopia. It is widely known that gender inequality exists in many dimensions, one prominent aspect is schooling (Dercon and Singh 2013; Chaudhury, Christiaensen and Asadullah 2006; Tesfu and Gurmu 2013). Findings are that boys get a higher chance to obtain education compared to girls, this indicates the potential parents' preference over boys for girls and it may directly cause the disparity in health status over gender.

There are several studies that mention the nutrition inequality over gender. In the case of Malawi, within household nutritional differences exist along gender, age and birth order, so as to rural and urban areas as well as religious groups; the gender of a child is a determinant factor of nutrition within a family (Mussa 2015). In South Asia, the empirical evidence of this gender bias is conflicting as it depends on where the study was conducted (Dancer et al. 2008). Most studies conducted find that a girl child is more likely to be malnourished than a boy child while some Sub-Saharan African studies find reverse results (Garrett and Ruel 1999). The reason behind the gender nutritional inequality can be explained by three concerns of parents (Park and Rukumnuaykit 2004)--equity, efficiency, and preferences. The equity concern reflects the desire of parents to ensure that children are equally well off. If nutritional needs differ by gender, then observed gender bias might be due to equity bias. The efficiency concern relates to differences in returns to investment in child health. If these returns differ for boys and girls, gender bias can arise from efficiency bias (Oyekale 2014). In Ethiopia, there exists considerable diversity in gender norms which mostly favor men regarding acquisition and inheritance of properties (Pathak and Singh 2011).

Based on the knowledge above, we come up with the hypothesis that in Ethiopia, the girls are more likely to be malnourished than boys. As Ethiopia's economy relies greatly on agriculture which requires higher musical quality labor force, and the expected economic return of boys are higher than the return of girls, such that the allocation of food source bias to boys and boys are relatively better nourished. The contributions are three-fold. Firstly, most studies focus on the impact of socio-economic environment on children' nutrition status; rarely we find literature emphasizes the importance of parent's gender preference that causing the children nutrition difference. Secondly, we introduce the Oaxaca Decomposition into the gender inequality in children malnutrition. This method is mostly used in gender-wage-gap analysis but here we show that it can be applied to more varied issues. Thirdly, our findings do not agree with most earlier literature and this can be referred by other researchers for future study.

The remining of this paper is organized as follows. In section 2, we give a short description of the development of Oaxaca Decomposition method and explain the children malnutrition measure employed in this study. In section 3, we introduce the dataset and provide the preliminary results with basic statistics description. The last two sections provide the model estimates and the conclusion.

2. Empirical Model

In this paper, we would like to use a decomposition method to estimate the difference in gender regarding predicted probability of being in malnutrition. Following Blinder (1973) and Oaxaca (1973), firstly we construct two models that are fitted separately for two groups, girl and boy:

$$Y_b = \boldsymbol{X}_b \beta_b + e_b, \tag{1}$$

$$Y_g = \boldsymbol{X}_g \beta_g + e_g. \tag{2}$$

The overall outcome difference can be decomposed by the following equation

$$\overline{Y_b} - \overline{Y_g} = (\boldsymbol{X}_b - \boldsymbol{X}_g)\beta_b + \boldsymbol{X}_g(\beta_b - \beta_g) \ , \tag{3}$$

where the left-hand side is the predicted malnutrition status difference, at right-hand side the first item shows the difference in malnutrition status between girls and boys due to observable characteristics, and the second term shows coefficient difference. Changing the reference group, an alternative expression can be

$$\overline{Y_g} - \overline{Y_b} = \left(\boldsymbol{X}_g - \boldsymbol{X}_b\right)\beta_g + \boldsymbol{X}_b\left(\beta_g - \beta_b\right) . \tag{4}$$

Equation (3) and (4) are not appropriate when our outcome variable malnutrition indicator is not continuous variable, in such case the Blinder-Oaxaca decomposition is rewritten in the nonlinear (NL) form (Sinning, Hahn and Bauer 2008):

$$\Delta_b^{NL} = \left\{E_{\beta_b}(Y_b|\boldsymbol{X}_b) - E_{\beta_b}(Y_g|\boldsymbol{X}_g)\right\} + \left\{E_{\beta_b}(Y_g|\boldsymbol{X}_g) - E_{\beta_g}(Y_g|\boldsymbol{X}_g)\right\}, \tag{5}$$

$$\Delta_g^{NL} = \left\{E_{\beta_g}(Y_b|\boldsymbol{X}_b) - E_{\beta_g}(Y_g|\boldsymbol{X}_g)\right\} + \left\{E_{\beta_b}(Y_b|\boldsymbol{X}_b) - E_{\beta_g}(Y_b|\boldsymbol{X}_b)\right\}. \tag{6}$$

Finally, Daymont and Andrisani (1984) extend the decomposition to three components:

$$\overline{Y_b} - \overline{Y_g} = (\boldsymbol{X}_b - \boldsymbol{X}_g)\beta_g + \boldsymbol{X}_g(\beta_b - \beta_g) + (\boldsymbol{X}_b - \boldsymbol{X}_g)(\beta_b - \beta_g) = E + C + CE, \tag{7}$$

where E is the part of raw differential that is due difference in endowments, C displays that difference in coefficients, and the last item, CE, represents the interaction effect of E and C. In the nonlinear case, the components are:

$$E = \left\{E_{\beta_g}(Y_b|\boldsymbol{X}_b) - E_{\beta_g}(Y_g|\boldsymbol{X}_g)\right\},$$

$$C = \left\{E_{\beta_b}(Y_g|\boldsymbol{X}_g) - E_{\beta_g}(Y_g|\boldsymbol{X}_g)\right\},$$

$$CE = \left\{E_{\beta_b}(Y_g|\boldsymbol{X}_g) - E_{\beta_g}(Y_b|\boldsymbol{X}_b)\right\} + \left\{E_{\beta_b}(Y_g|\boldsymbol{X}_g) - E_{\beta_g}(Y_g|\boldsymbol{X}_g)\right\}. \tag{8}$$

In the empirical analysis, our first step is to estimate the model for two subgroups, boys and girls, to obtain coefficients for each group separately. Then we predict the conditional y value for both boys and girls by applying the other group's coefficients. Our main interest lies in the coefficient difference (part "C"), which is also called "unexplained difference" or "structural difference," and this displays the potential gender inequality in children nutrition status. In the following sections, we infer this difference of $C = \widehat{\beta_b}X_g - \widehat{\beta_g}X_g = Pr^{g|b} - Pr^g$ if response variable is binary and $C = Z^{g|b} - Z^g$ if response variable is continuous (Z-score), as "what if a girl were to be a boy, will the propensity of being malnourished higher, or lower?"

Measure of malnutrition

The most commonly used method of measuring children malnutrition are wasting, stunting, and underweight (World Food Programme (WFP) and Center for Disease Control and Prevention (CDC) 2005) and they are related to height-for-age, weight-for-age, and weight-for-height in respect. HAZ, WAZ and WHZ are standards used in the main body for papers studying children malnutrition (Block and Webb 2009; Salvucci 2015; Lazzaroni and Wagner 2016). Measured by these indices, children with a score of below minus two standard deviations (-2SD) from the reference population are considered as moderately malnourished[4].

Wasting: <-2 WHZ (Z-score for weight-for-height).

Stunting: <-2 HAZ (Z-score for height-for-age);

Underweight: <-2 WAZ (Z-score for weight-for-age);

The Z-score is calculated in by the following formula:

$$Z - score = \frac{\text{observed value} - \text{median value of the reference population}}{\text{standard deviation value of reference population}}$$

It is a normalized health index that gives a comparison of the individual to a reference group of the children of the same sex at the same age. The reference population database for comparison was used to be the National Center for Health Statistics (NCHS), and it is called NCHS/WHO international reference population. Before 1980's, the reference group consisted of healthy well-nourished US children, the sample for ages 0 to 23 months is based on the children in the Ohio Fels Research Institute Longitudinal Study from 1029 to 1975 and for ages 2 to 18 years is based on the cross-sectional surveys from 1960 to 1975 in the USA. Because of the

[4] Z-score below 3 is defined as severe malnutrition for children under five, we found very few paper using severe malnutrition as the standard in studies of huger problem or children health. Hence, in this paper, we use 2 as the critic value to define the malnutrition status.

growing evidence that the normal pattern of growth for the healthy preschool children from the diverse ethnic background is very similar, the WHO adopted the reference base of NCHS for international use and it is widely promoted in measuring children health condition. In recent years, some drawbacks of the reference population sample come up with and an international effort is underway to develop a new international growth reference, yet before that, the NCHS/WHO growth reference curves will remain the reference values developed earlier.

Wasting is a short-term indicator and captures adequate malnutrition status in the period immediately preceding the survey; it is often associated with acute starvation and/or severe disease. It may also be the result of a chronically unfavorable condition. This, for example, could arise due to weight loss causing illness such as diarrhea. Stunting is an indicator of chronic malnutrition or a lack of adequate nutrition for a long period in the population, reflects a process of failure to reach linear growth potential because of suboptimal health and/or nutritional conditions. This measure is not sensitive to short-term dietary changes. High level of stunting is associated with poor socioeconomic conditions and increased risk of frequent and early exposure to adverse conditions such as illness and/or inappropriate feeding practices. Underweight reflects body mass relative to chronological age and captures both short and long term effects of malnutrition, it does not work well in distinguishing between thin, tall children and short, fewer weight children, but it is worth analyzing when there is less wasting or stunting information.

As our dependent variables (stunting, underweight and wasting) are 0 and 1, we will use logit model in estimation. To check the robustness of our results, we also use the standard deviation scores which are continuous to perform OLS regressions.

3. Data Source and Preliminary Results.

We use household survey data from Ethiopia Demographic and Health Survey (DHS) 2011[5]. The survey was conducted in 11 regions. It contains over 900 questions and around 10 thousand observations. As Ethiopia has 80% of labor in the agriculture sector and it is very likely to be affected by drought, we created an approximate dummy variable indicating whether the household is in drought area (Seleshi and Zanke 2004).

The following table provide the basic findings.

Table 2.1 shows a summary of malnutrition status of children in Ethiopia, classed by regions. In general, there are nearly half of the children population are stunted; it is most serious in northern regions such as Tigray, Affar and Amhara. The distribution of underweight is similar to stunting. One possible factor is that in the north area, rain is relatively less compared to south area, the drought in the north occurs more frequent.

Table 2.2 provides information on the malnutrition status classed by age. Children at the age of 2 and 3 are more likely to be short compared to those normal children at the same age or have weight less compared to same-aged children in the reference group. The newborn babies are more likely to be wasted, which means they have smaller weight compare to the referred group.

Figure 2.2 shows the distribution of z-scores of stunting, underweight, and wasting. And as we note in the second section, if one child's z-score is lower than 2, then the child will be included in the malnourished group.

A comparison of malnutrition rate by gender and age at the mean is provided in the appendix, see figure A1-1.

---

[5] We also have DHS 2000 and DHS 2005 dataset, yet they do not provide the z-scores for the children. We analyzed the gender ratio in each dataset and the information is provided in appendix, see table A1. It shows that over years the gender composition in the surveys does not vary much from 0.5. We also find the temperature and rain around survey year were the same to the past 5 years (See appendix, figure A1-2). The weather in survey year is normal as we expect.

As shown in Figure 2.2, there is nearly half of children population in our sample are stunted, which means they are shorter than normal children. The ratios of underweight and wasting are relatively small yet they are still a large group. Detailed information is given in Table 2.3.

Table 2.3 shows that in the survey sample, girls account for 49.1%, the ratio of the children being stunting, underweight and wasting are 42.3%, 30.1%, and 11.8%, in respect. 84.1% of the children are living in rural places, which coincide with the Ethiopia economy report as we mentioned earlier. In the survey year, there is no strong draught in Ethiopia, the variable draught is an indicator that the area is prone to be dry in the history years, there are 25.8% of the households in the drought area. Family wealth score serves as an indicator of wealth levels and it is consistent with expenditure and income measures (Rutstein 1999). The wealth score is widely used in many DHS country-level surveys[6], it ranges from -22 to 39 and the mean is 3.23. The average education[7] of parents is 2.92 years. Children aged at 0-12 months, 13-24 months, 25-36 months, 37-48 months and 49-60 months account for 20.4%, 8.6%, 1.95%, 2.13% and 2.03%, in respect. Milk is a dummy variable, the value is 1 if the parents gave child tinned, powdered or fresh milk. Meat is also a dummy variable indicating that the parents gave child meat (beef, pork, lamb, chicken, etc.). The Welch t-test[8] over gender, see table 2.4, show that malnutrition rates are different over genders, but other living environment conditions, such as family wealth, parents' education, access to milk, etc., are not significantly different.

4. Results

---

[6] For detailed information on how wealth score is generated, see Ethiopia Demographic and Health Survey Report 2011.

[7] Here the number of years of education is the sum of parents'.

[8] Compare to Student's t-test, the Welch's t-test can be used to test the hypothesis that two population have equal means when the two samples have unequal variances and unequal sample sizes.

We begin with estimating children malnutrition using stunting, underweight and wasting as the response variables, as they are binary variables, we adopt the logit model. The dataset is divided into two groups by gender. Firstly, we run regressions for girls only, then we calculate the predicted probabilities ($\widehat{Pr}$) for the whole dataset. In this process of decomposition, we get the predicted probability of being stunting, underweight or wasting of girls, as well as the probability of boys' being stunting, underweight or wasting as if they were girls, that is the $Pr^{b|g}$. If we repeat this process for boy group, then we will have Pr^{b} which is the predicted probability of boys being malnourished as well as the $Pr^{g|b}$ meaning the probability for girls being malnourished as if they were boys. Corresponding to Eq (7), We also calculate the endowment difference, and interaction difference and they are reported in table 2.5.

As mentioned earlier, the wasting indicates short-term food shortage effect, stunting shows a chronic illness or inadequate nutrition effect, and underweight is an index indicating both short-term and long-term nutrition status. In table 2.5, the first column is the results of Logistic regression over wasting, the second column is stunting and the third column is underweight.

It is expected that the malnutrition rate in rural and draught area would be higher compare to the urban and non-draught area, yet our results show that most of the coefficients are not significant, in urban areas the draught does not cause higher malnutrition rate. Both boys and girls in rural and draught area have a higher probability of being stunted, for the girls, the odds of probability of being stunted increases by 34%, and it is 54.7% for boys than those in the urban and non-draught area. However, we find that children in the rural area have a smaller probability of being wasted, especially for boys; compare to the children living in urban areas, children at the same height in rural areas have higher body weight. We do not find any difference in the probability of being underweight between children in rural and urban, draught and non-draught areas.

A very prominent result is that, for all three aspects of malnutrition, wasting, stunting, and underweight, household wealth and parent's education have a significant positive effect on children's nutrition status, for both boys and girls. The marginal effect of family wealth on malnutrition status is similar for boys and girls, and it shows a greater effect on wasting and underweight compared to stunting. Per unit increase in wealth score indicate and decrease of odds of probability being malnourished by 4.1%-8.6%. For rich families, there is less likely of being in a food shortage, and the child is less likely to be malnourished. The higher education of parents indicated a lower probability of children being stunted and underweight, and the effect is slightly higher to girls compared to boys, one more year of education indicates a decrease of 3%-4% in probability odd of being stunted or underweight. Parents' education has a positive effect to boys' wasting status, yet there is no significant effect for girls. Better educated parents can bring higher income to the family, and the mother will have relatively more knowledge in nutrition, medicine and how to take good care of children.

If the household head is female, the girls tend to be more likely to be underweight and wasted, and the boys have a higher probability of being stunted and wasted. This might be explained that if the mother is household head, she has to spend much time on work and less time to take care of children. Generally, the access to pipe water does not show a positive effect on children's nutrition status. Drinking milk does not affect the short-term weight, but it shows a long-term effect on a child' height. Both boys and girls who are given milk by parents are less likely to be stunted, but for underweight and wasting, the effect is not clear. We create five dummy variables for children's age and find that compared to children under 12 months, elder children are less likely to be wasted, but all with a higher probability of being stunted and underweight. Children at the age of 25-36 months and age of 37-48 months have a higher probability of being malnourished compare to children younger than 12 months.

Our interest lies in the last part of Table 2.5, for each type of malnutrition, the endowment difference is close to 0 and statistically insignificant, this coincides with the Welch-test results of the socioenvironmental variables. The inequality between girls and boys does not come from the living conditions, neither is the interaction term significant. The most interesting part is the coefficient differences, they are positive and significant. The estimates indicate that with the similar home characteristics, if the girls were boys, set all rest living conditions equal, the probability odd ratio of being wasted increases by exp (0.294), which is 1.34; the probability odd ratio of being stunted increases by exp (0.033), which is 1.034; the probability odd ratio of being underweight increases by exp (0.038), which is 1.039; Notice that in this round of regression we use the dummy dependent variables, and the higher probability means worse nutritional status, then we can conclude that the girls are better treated compared to boys.

We also use the z-score to run OLS models, the process is same as above and the results are provided in table 2.6.

Table 2.6 tells the similar story with table 2.5 but in this table, the dependent variables are z-scores of children's height for age, weight for age and weight for height; if the coefficients are positive means the item contributes to improving children's health. Again, we find that household wealth and parents' education are important contributors to children's nutrition condition. Children from the female-leaded family are more likely to be malnourished, and children who drink milk are less likely to be stunted.

The decomposition results for predicted z-scores align with our findings in Table 2.4. The endowment difference and the interaction terms are not significant. We focus on the coefficient difference, that is $C = Z^{g|b} - Z^{g}$. With the similar home characteristics, if the girls were boys, their z-score of weight for height decreased by 0.113, the z-score of height for age decreased by 0.103, and the z-score of weight for age decreased by 0.087. Then we can conclude that the girls are better treated compared to boys. We also process the decomposition for different age groups and the results are reported in table 2.7. Children undernutrition gender differences are significant for children aged under 36 months, but the gender differences are not significant for elder ones. The weight for height index (wasting) which represents the short-term food insecurity effect, differences between boys and girls are outstanding.

5. Conclusion

Children undernutrition is the priority among the world's top 10 important challenges reported by the Copenhagen Consensus, one-quarter of children aged under five in the world are stunted 15% are underweight, and 8% are wasted. African countries are reported to be the most severe area. In Ethiopia, there is about 48 percent of children under the age of five were undernourished, that is, about 6.3 million children are in malnutrition.

In this paper, we use the data from Demographic and Health Survey 2011 Ethiopia to look into the gender difference in the issue of children malnutrition. We find that girls are better treated: under the same condition, if a girl were a boy, the odds ratio of being wasted increases by 1.34, the odds ratio of being stunted would increase by 1.03 and the odds ratio of being underweight increases by 1.04. Our z-score OLS models also agree with these findings. This surprising results may come from the preference of parents, we explored many other literature to find reasonable explanation for this phenomenon--girls are preferred in a family can be as a result of the future marriage pressure that the groom' side have to be rich to obtain a "good" bride (Fafchamps and Quisumbing 2005), the family also has to invest more on boy's schooling (Tesfu and Gurmu 2013). It is also found that the in Ethiopia, boys tend to have greater dropout rate than girls in immunization (Abebaw 2014). These are the potential reasons for girls being better nourished than boys.

We also find that wealth is important in supporting a child's nutrition status. Food aid and monetary support are necessary to improve the health status, but the effect might not last long. Invest in education would have a long-last effect in the future to mitigate children malnutrition problem in Ethiopia.

FIGURES:

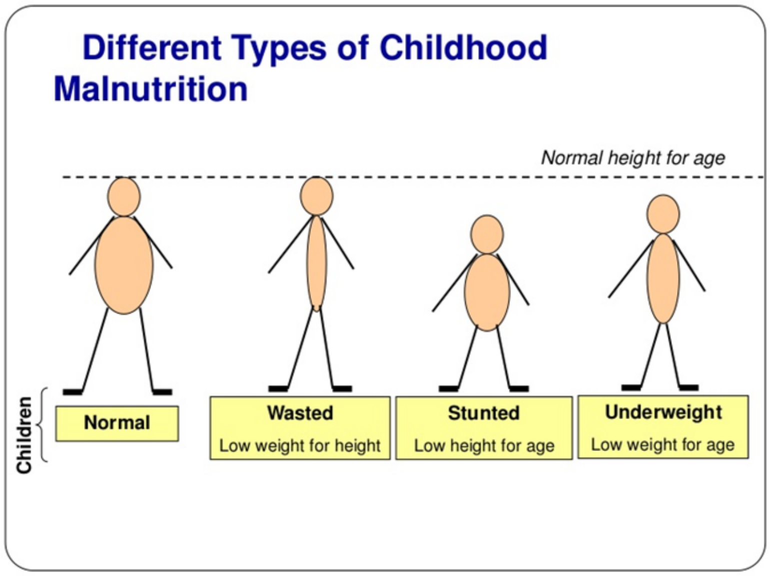


Figure 2.1 Different Types of Children Malnutrition
Source: https://www.slideshare.net/nfpcsp/topic-21-diet-diversity

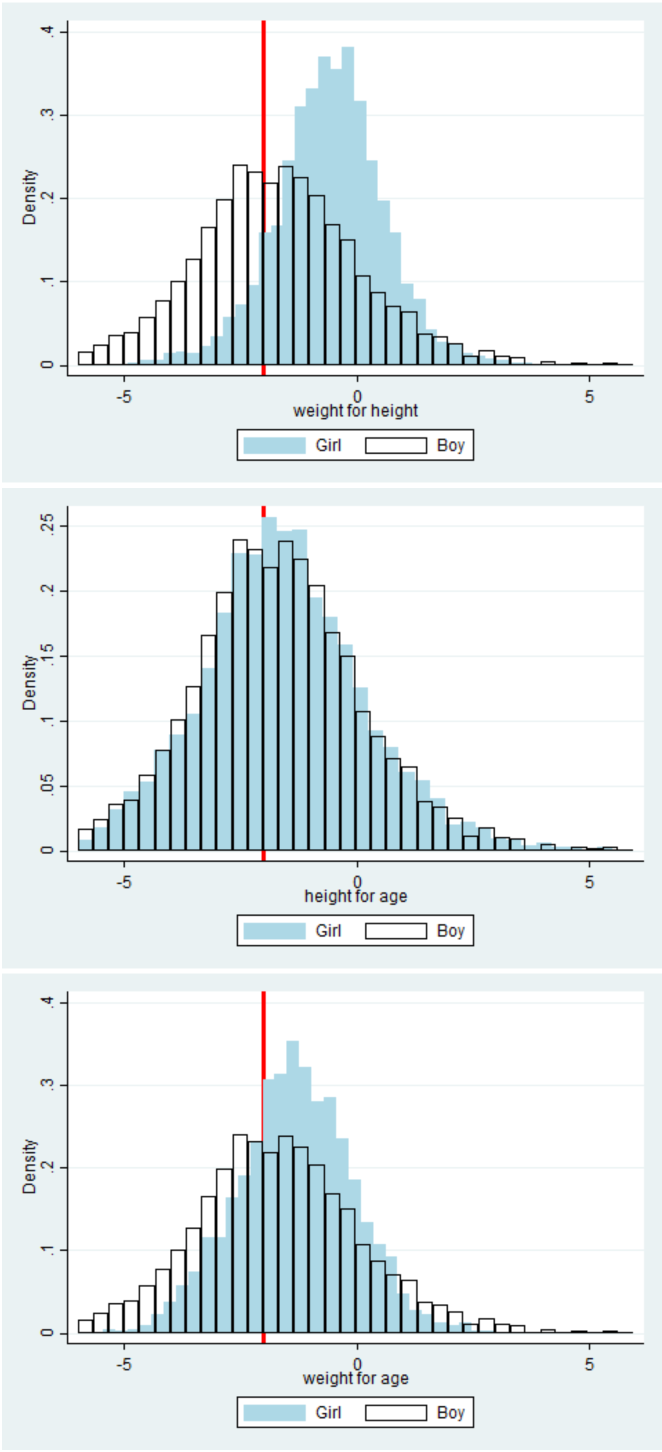


Figure 2.2 Distribution of z-scores of Stunting (Height for Age), Underweight (Weight for Age) and Wasting (Weight for Height).

TABLES

Table 2.1 Rate of Malnutrition by Region

Region	Observation	stunting	underweight	wasting
Tigray	1152	55.38%	41.15%	17.80%
Affar	1025	57.76%	50.05%	30.93%
Amhara	1168	56.08%	40.33%	18.58%
Oromiya	1680	47.14%	33.63%	19.17%
Somali	852	41.78%	41.43%	30.75%
Benishangul-gumuz	937	55.50%	42.80%	21.34%
Snnp	1510	49.60%	35.50%	17.09%
Gamblea	794	38.29%	33.50%	27.46%
Harari	559	36.14%	28.62%	18.78%
Addis	352	28.69%	14.77%	12.78%
Dire Dawa	634	42.74%	35.17%	20.66%

Table 2.2 Malnutrition Status by Age and Child Sex

Child sex\age		0	1	2	3	4
boy	Wasting	19%	19%	11%	9%	9%
	Underweight	19%	36%	39%	33%	33%
	Stunting	15%	49%	56%	53%	47%
girl	Wasting	15%	13%	8%	7%	8%
	Underweight	13%	28%	35%	34%	31%
	Stunting	12%	39%	55%	53%	45%

Table 2.3 Descriptive Statistics on Children Malnutrition in DHS Ethiopia 2011

Variable	Obs	Mean	Std. Dev.	Min	Max
Girl	9450	0.491	0.500	0	1
Weight/height z-score	9450	-0.627	1.214	-5	4.66
Height/age z-score	9450	-1.608	1.760	-6	5.95
Weight/age z-score	9450	-1.360	1.268	-5.68	4.92
Wasting	9450	0.118		0	1
Stunting	9450	0.423		0	1
Underweight	9450	0.301		0	1
Rural	9450	0.841		0	1
Drought area	9450	0.258		0	1
Family wealth score	9450	-3.247	7.338	-22.229	39.263
Years of parents' education	9450	2.927	4.067	0	19
Female household head	9450	0.176		0	1
Access to pipewater	9450	0.253		0	1
Milk (weekly)	9450	0.176		0	1
Meat (weekly)	9450	0.023		0	1
Child age=0-12 mon	9450	0.204		0	1
Child age=13-24 mon	9450	0.086		0	1
Child age=25-36 mon	9450	0.195		0	1
Child age=37-48 mon	9450	0.213		0	1
Child age=49-60 mon	9450	0.203		0	1

Table 2.4 Means and Welch's Test by Child Sex

	Boy	Girl	Difference
Weight/height std.	-0.6862	-0.5658	0.001***
Height/age std.	0.3197	0.2816	0.000***
Weight/age std.	-1.6560	-1.5579	0.007***
Wasting	0.1331	0.1021	0.000***
Stunting	-1.4035	-1.3145	0.002***
Underweight	0.4389	0.4069	0.000***
Rural	0.0743	0.0784	0.4534
Drought area	0.6042	0.5982	0.0994
Family wealth score	-3.2934	-3.1980	0.5274
Years of parents' education	2.9370	2.9166	0.8079
Number of children in the family	3.8130	3.7462	0.1273
Female household head	0.1797	0.1730	0.3919
Access to pipewater	0.2550	0.2514	0.6882
Milk (weekly)	0.2215	0.2143	0.3065
Meat (weekly)	0.1797	0.1717	0.4488
Rural	0.0245	0.0222	0.5491
Obs	4808	4642	

Table 2.5 Estimates of Wasting, Underweight, and Stunting Models

	wasting		stunting		underweight	
	girl	boy	girl	boy	girl	boy
Drural=0 # drought=1	0.281	0.048	0.221	0.362**	0.008	0.199
	(0.320)	(0.282)	(0.191)	(0.183)	(0.233)	(0.219)
Drural=1 # drought=0	-0.351	-0.510***	0.082	0.217	-0.267	0.006
	(0.232)	(0.191)	(0.161)	(0.145)	(0.176)	(0.155)
Drural=1 # drought=1	-0.420*	-0.612***	0.340**	0.547***	-0.032	0.171
	(0.248)	(0.206)	(0.169)	(0.155)	(0.183)	(0.164)
Family wealth score	-0.086***	-0.080***	-0.044***	-0.041***	-0.081***	-0.084***
	(0.017)	(0.015)	(0.010)	(0.010)	(0.012)	(0.011)
Years of parents' education	-0.011	-0.053***	-0.039***	-0.030***	-0.038***	-0.035***
	(0.015)	(0.014)	(0.010)	(0.010)	(0.011)	(0.010)
Female household head	0.265**	0.250**	0.066	0.193**	0.204**	0.003
	(0.125)	(0.110)	(0.087)	(0.083)	(0.091)	(0.086)
Access to pipewater	0.343**	0.154	-0.052	-0.070	0.128	0.096
	(0.143)	(0.130)	(0.096)	(0.095)	(0.102)	(0.097)
Milk (weekly)	0.214*	0.079	-0.234**	-0.442***	-0.088	-0.171*
	(0.124)	(0.110)	(0.093)	(0.089)	(0.098)	(0.090)
Meat (weekly)	-0.213	-0.203	0.389*	-0.073	0.002	-0.240
	(0.382)	(0.296)	(0.221)	(0.202)	(0.251)	(0.219)
Child age=13-24 mon	-0.112	-0.048	1.553***	1.778***	1.002***	0.853***
	(0.137)	(0.121)	(0.123)	(0.116)	(0.125)	(0.110)
Child age=25-36 mon	-0.761***	-0.644***	2.164***	2.001***	1.287***	0.984***
	(0.159)	(0.135)	(0.122)	(0.115)	(0.122)	(0.109)
Child age=37-48 mon	-0.910***	-0.965***	2.050***	1.888***	1.197***	0.700***
	(0.157)	(0.142)	(0.119)	(0.113)	(0.119)	(0.108)
Child age=49-60 mon	-0.682***	-0.875***	1.755***	1.657***	1.119***	0.693***
	(0.152)	(0.138)	(0.121)	(0.113)	(0.122)	(0.108)
Constant	-2.056***	-1.340***	-2.065***	-1.948***	-1.985***	-1.678***

	(0.267)	(0.229)	(0.191)	(0.181)	(0.205)	(0.188)
Cluster	yes	yes	yes	yes	yes	yes
Observations	4642	4808	464 2	4808	4642	4808
Endowment diff	0.002		0.000		0.002	
Coefficient diff	0.294***		0.033***		0.038***	
CE	0.000		-0.001		-0.001	

Robust standard errors in parentheses “* p<0.1 ** p<0.05 *** p<0.01”

Note: the child age ranges from 0 to 60 months, age of 0-12 month is considered as the baseline.

Table 2.6 Estimates of Z-scores Models

	weight for height		height for age		weight for age	
	girl	boy	girl	boy	girl	boy
Drural=0 # drought=1	-0.016	-0.018	-0.140	-0.328***	-0.093	-0.214**
	(0.091)	(0.093)	(0.122)	(0.122)	(0.091)	(0.092)
Drural=1 # drought=0	0.240***	0.286***	0.084	-0.198*	0.198**	0.063
	(0.082)	(0.078)	(0.109)	(0.103)	(0.081)	(0.078)
Drural=1 # drought=1	0.197**	0.263***	-0.189	-0.549***	0.005	-0.145*
	(0.086)	(0.084)	(0.115)	(0.111)	(0.086)	(0.084)
Family wealth score	0.036***	0.042***	0.033***	0.027***	0.044***	0.044***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)
Years of parents' education	0.004	0.012**	0.037***	0.026***	0.024***	0.023***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)
Female household head	-0.175***	-0.004	-0.021	0.003	-0.140***	0.017
	(0.046)	(0.046)	(0.061)	(0.061)	(0.046)	(0.046)
Access to pipewater	-0.067	-0.090*	-0.069	-0.005	-0.085*	-0.064
	(0.051)	(0.053)	(0.068)	(0.070)	(0.051)	(0.053)
Milk (weekly)	-0.059	-0.109**	0.165***	0.294***	0.046	0.080*
	(0.047)	(0.047)	(0.063)	(0.062)	(0.047)	(0.047)
Meat (weekly)	0.045	0.042	-0.091	0.142	-0.007	0.117
	(0.118)	(0.114)	(0.158)	(0.150)	(0.118)	(0.113)
Child age=13-24 mon	-0.035	-0.020	-1.362***	-1.468***	-0.640***	-0.665***
	(0.055)	(0.057)	(0.074)	(0.074)	(0.055)	(0.056)
Child age=25-36 mon	0.257***	0.219***	-1.915***	-1.825***	-0.831***	-0.748***
	(0.055)	(0.056)	(0.073)	(0.074)	(0.055)	(0.056)
Child age=37-48 mon	0.216***	0.361***	-1.833***	-1.687***	-0.874***	-0.643***
	(0.053)	(0.055)	(0.071)	(0.073)	(0.053)	(0.055)
Child age=49-60 mon	0.114**	0.255***	-1.653***	-1.528***	-0.854***	-0.662***
	(0.054)	(0.055)	(0.073)	(0.072)	(0.054)	(0.055)
Constant	-0.688***	-0.901***	-0.328***	-0.237*	-0.735***	-0.812***
	(0.091)	(0.093)	(0.122)	(0.123)	(0.091)	(0.093)
Cluster	yes	yes	yes	yes	yes	yes
Observations	4642	4808	4642	4808	4642	4808

Endowment diff	-0.006	-0.000	-0.005
Coefficient diff	-0.113***	-0.103***	-0.087***
CE	-0.000	0.006	0.003

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

Table 2.7 Coefficients Differences by Age

Index\age	0-12mon	13-24mon	25-36mon	37-48mon	49-60mon
wasting	0.0385	0.0429**	0.0366**	0.0163	0.00654
	(1.86)	(2.64)	(2.85)	(1.11)	(0.43)
stunting	0.0237**	0.0892***	0.0110	0.00921	0.0332
	(3.20)	(5.21)	(0.56)	(0.41)	(1.77)
unweight	0.0639***	0.0597*	0.0449	-0.00100	0.0186
	(5.19)	(1.97)	(1.83)	(-0.05)	(0.74)
Weight for height	-0.161**	-0.133*	-0.209***	-0.0230	-0.0173
	(-2.98)	(-2.43)	(-3.63)	(-0.51)	(-0.26)
Height for age	-0.142	-0.223**	-0.0690	-0.0182	-0.0566
	(-1.78)	(-2.80)	(-0.87)	(-0.29)	(-0.99)
Weight for age	-0.175***	-0.178**	-0.105	0.0413	-0.00304
	(-4.97)	(-3.24)	(-1.54)	(0.84)	(-0.05)

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

Appendix 1

Table A1- 1 Gender Ratio in Previous DHS Datasets

Dataset	age	Obs	% of girl	Std.dev
2011	0	2,254	0.50	0.5001
2011	1	1,927	0.49	0.5000
2011	2	2,099	0.49	0.4999
2011	3	2,311	0.50	0.5001
2011	4	2,217	0.47	0.4993
2011	.	846	0.44	0.4969
2005	0	1,926	0.48	0.4999
2005	1	1,697	0.49	0.5001
2005	2	1,693	0.48	0.4995
2005	3	1,879	0.52	0.4998
2005	4	1,807	0.50	0.5001
2005	.	859	0.43	0.4956
2000	0	1,922	0.48	0.4999
2000	1	1,845	0.48	0.4999
2000	2	1,886	0.50	0.5001
2000	3	2,013	0.50	0.5001
2000	4	1,894	0.51	0.5001
2000	.	1,313	0.45	0.4981

Table A1- 2 Summarize Statistics of Malnutrition Indices by Gender

Child sex	Obs	hasd	wasd	whsd	stunting	unweight	wasting
		-1.6560	-1.4035	-0.6862	0.4389	0.3197	0.1331
boy	4,808	(1.77)	(1.28)	(1.24)	(0.50)	(0.47)	(0.34)
		[-6, 5.95]	[-5.68,4.92]	[-5,4.66]	[0,1]	[0,1]	[0,1]
		-1.5579	-1.3145	-0.5658	0.4069	0.2816	0.1021
girl	4,642	(1.75)	(1.26)	(1.19)	(0.49)	(0.45)	(0.30)
		[-5.99,5.84]	[-5.46,4.05]	[-4.92,4.3]	[0,1]	[0,1]	[0,1]

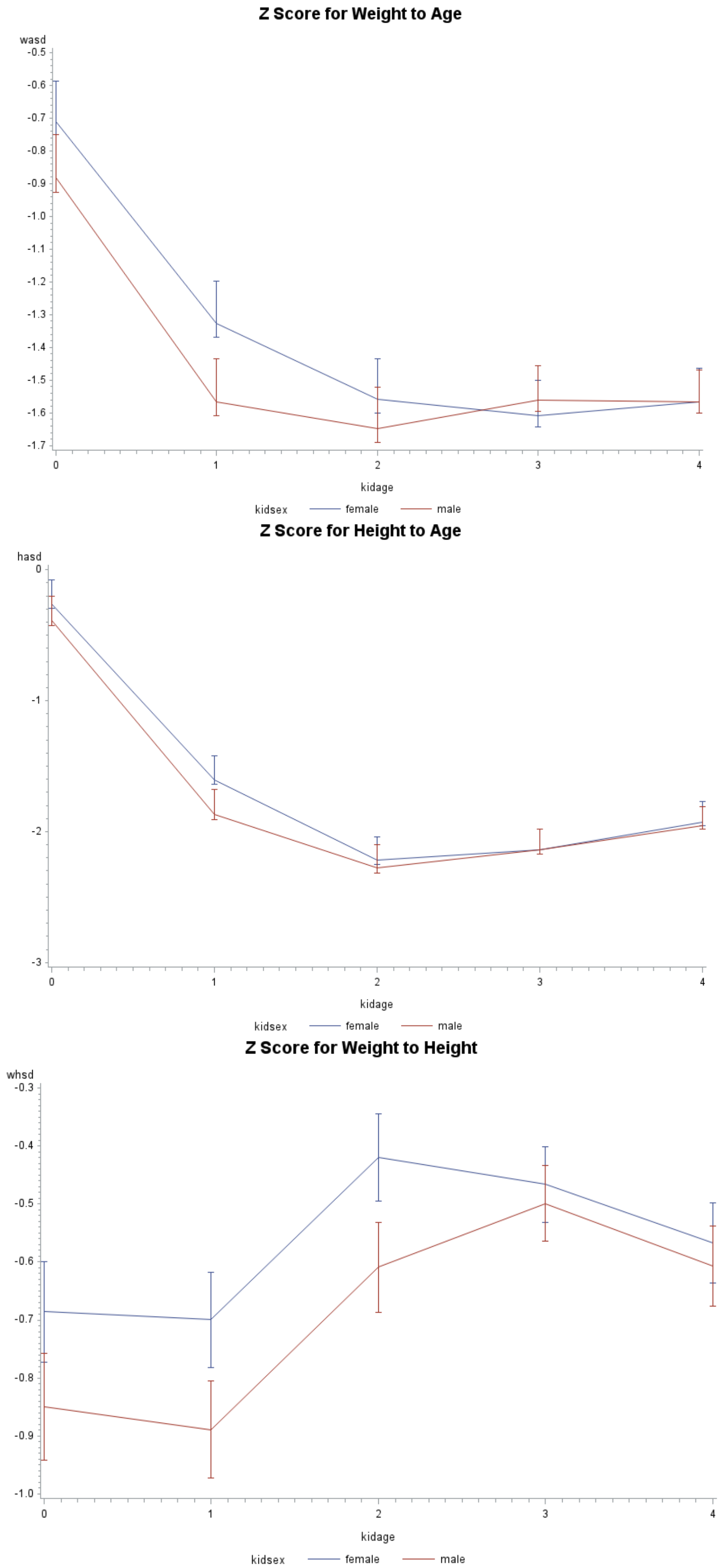


Figure A1-1 Plots of Z-scores by Gender and Age

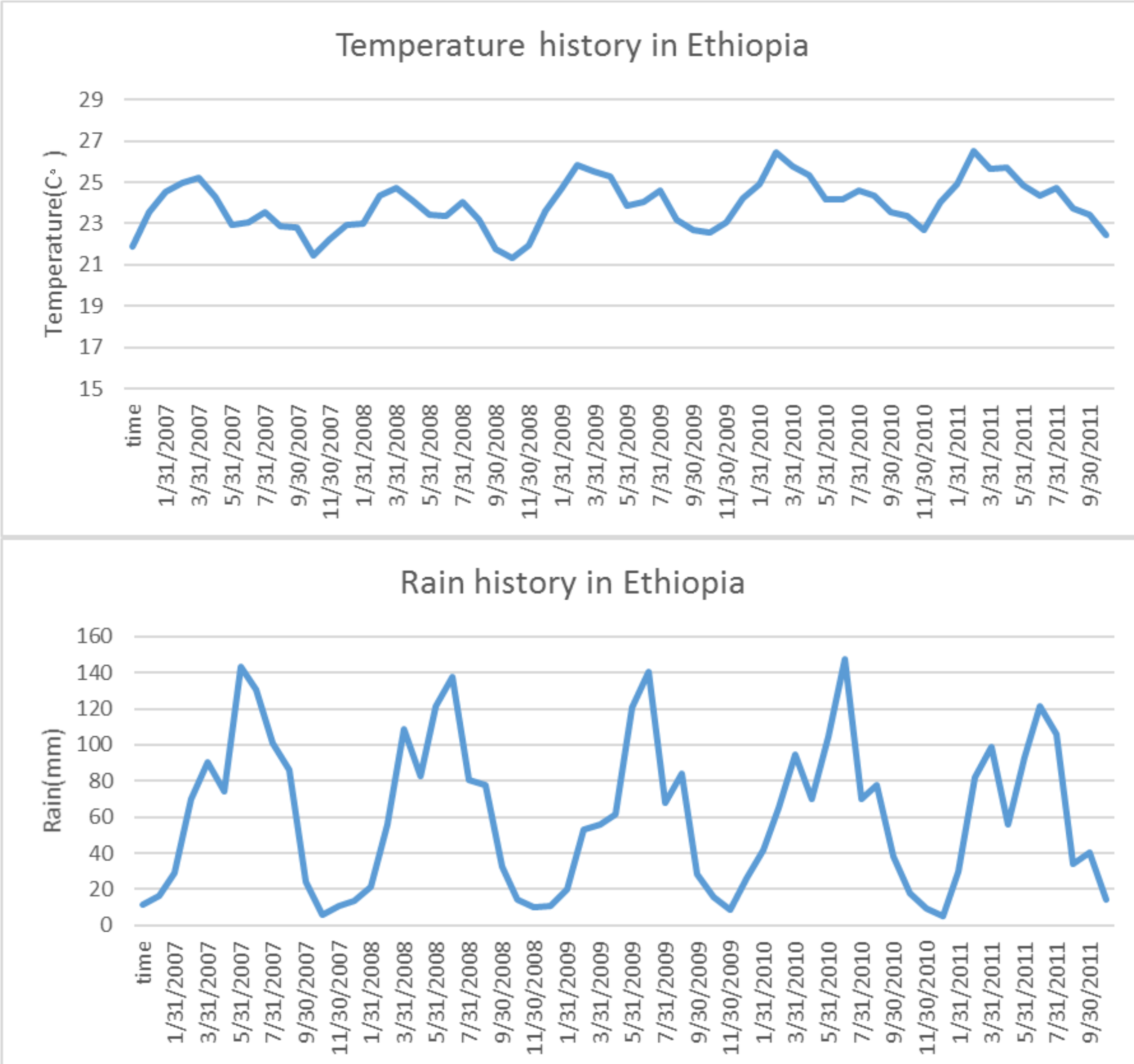


Figure A1-2 Temperature and Rain History in Ethiopia, 2007-2011

Chapter 3 Greenhouse Gas Emissions and Economic Growth: a Measure of Environmental Efficiency Based on the Directional Distance Function

1. Introduction

Environmental issues such as climate change and environmental degradation are important topics in the research of sustainable development. Since the Second Industrial Revolution (also known as Technological Revolution), which is driven by the force of large fossil energy consumption, greenhouse gas (GHG) emissions increases dramatically. Data from the World Bank show that from 1970 to 2012, the volume of GHG emissions doubled and the total energy consumption nearly tripled. In the late 20th century when East Asia became one of the most recently industrialized regions, the GHG emissions from energy consumption significantly increased, leading to a rising concern of global warming and climate change (Kasman and Duman 2014). Hence, a study of the environmental performance is of great importance to provide guides in alleviating the global warming and GHG emissions abatement. We aim at estimating the technical environmental efficiency (TEE) concerning three forms of emissions, GHG, CO_2, and Nitrous Oxide (N_2O). According to the Climate Report from International Panel on Climate Change (IPCC) (Solomon et al. 2007), fossil fuel combustion contributes to around 87% of human sources of CO_2 while agricultural activities cause about 67% of all human sources of N_2O. The use of CO_2 and N_2O in this paper can help the researcher to assess the environmental performance for each country from both industry and agriculture aspects.

CO_2 emissions are primarily from fossil fuel consumption. It accounts for the largest component of GHG and is associated with climate change as well as global warming. There is a rich literature on the study of the relationship between energy consumption and CO_2 (GHG) emissions (see Tiba and Omri, 2017, for an excellent review). To understand the environmental performance related to CO_2, it is necessary to explore literature on the nexus between energy consumption, economic growth, and CO_2 emissions. There are mainly three strands in the former studies (Omri 2013). A large stream of former research focuses on the validity of the Environmental Kuznets Curve (EKC) hypothesis, which proposes that there is an inverse U-shape relationship between environmental pollution level and economic development. A second strand is about the causality between energy consumption and economic growth. The main findings suggest that higher energy consumption is necessary for economic growth, high energy efficiency requires more developed economy. The third strand of research finds that energy consumption is one determinant of CO_2 emission (Tiba and Omri 2017). In the above literature, the most commonly used methodologies ARDL bonds testing, VECM Granger causality, and cointegration test, etc., and the data are either longitudinal data for a single country or groups of countries such as the OECD countries, OPEC countries, etc. Another important component of GHG is N_2O. N_2O emissions are mainly from fossil fuel combustion, fertilizers, etc. N_2O is very durable and has an estimated atmospheric lifetime of 114 years. Its 100-year time horizon global warming potentials (GWP) is estimated to be 300 times of CO_2 (S Solomon et al. 2007). Recent years there are, though not many, research on non-CO_2 emissions, (Hyman et al. 2002; Marten and Newbold 2012; Maza, Villaverde and Hierro 2015). These papers deduce general causal linkages, yet not deal with the heterogeneity across countries, which potentially harm the validity of the results.

Apart from the causality effect in these three items mentioned above, we are interested in analyzing the relations using a different function form, the production function with “bad” output (undesirable output) to model the environmental performance using the technical environmental efficiency.

In this study, we firstly employ the directional output distance function to model the pollution technology which treats good output and bad output jointly, models with different bad outputs (GHG, CO_2, N_2O) under different directional vectors ((0.1, 1), (0.5, 1), (1, 1), (2, 1) and (10, 1)) are estimated separately. The TEE is estimated parametrically via a quadratic functional form. We also calculate the shadow prices and Morishima elasticities between good output and bad output.

What we care about is the variation of TEE and the cause of it. Regardless of the tools used to measure the performance, studies suggest that there exists highly significant difference among production unit as regards environmental efficiency (Tyteca 1996). Tyteca describes the production unit as an integral black box, on which external and internal pressures can exert various kinds of effect. External pressures include economic context, such as energy price, openness of the economy; internal pressures can be managerial activities, the production unit’s motivation towards environmental protection, etc. We could not observe the details inside the black box, yet interesting patterns can be found regards the environmental efficiencies.

Our objects in following sections are to show how the TEE vary across countries in different models and over time. Firstly, how the TEE is related with GDP per capita. In earlier literature, the EKC hypothesis is tested, and the relationship is verified to be valid in many cases. It is reasonable to predict that in a country with higher GDP per capita, the production efficiency, accounting for the bad output, is higher. Our results show a “U-shape” relationship between mean TEE and GDP per capita.

Secondly, how different directions affect the environmental performance evaluation. Extreme cases are $\boldsymbol{g} = (1{,}0)$ and $\boldsymbol{g} = (0{,}1)$, with which only the credit of one output is counted, regardless of the “contribution” of the other output. We expect the TEE obtained from models with different manually-set direction vectors show how the environmental efficiency changes when environmental preoccupations come as the main priorities. We find direction vectors affect the efficiency estimated only in the N_2O model.

Thirdly, how the TEE evolves. In the second section, we plot the frontier shifts in figure 3.1. The shifts in technical environmental frontier indicate improvements in technology. Under new technology, the equipment is likely to be more efficient than older equipment, if environmental protection concept is involved in the invention of new technology. We expect that the efficiency increases as the environmentally-poorly-behaved countries learn from the more efficient countries.

2. Methodology

2.1 Model

Production efficiency analysis was applied to the environmental performance evaluation since the 1980s when the modern concept of sustainable development was brought out, and the energy and environmental modeling became very popular (Song, Zheng and Wang 2016; Zhang and Choi 2014). To include the pollutants in a production function, the efficiency measure must credit both the increase of good outputs and the reduction of bad outputs. There are two widely used methodologies, the hyperbolic distance function (HDF) and the directional distance function (DDF). The HDF is reciprocal to the Shephard’s distance function, allowing good and bad outputs to vary the same proportion, but in different directions. It provides a Farrell-type efficiency measure (Cuesta, Lovell and Zofío 2009; Cuesta and Zofío 2005; Zelenyuk 2014). However, the HDF efficiency tends to be overestimated in the presence of a slack variable, and it is an overall indicator that could not assign contribution to a specific factor (Zhang and Choi 2014). The DDF was firstly introduced by Chung, Färe, and Grosskopf (1997), and later developed by Chambers, Chung, and Färe (1998) and Färe et al. (2005). This method is mainly to analyze the efficiency in the presence of bad outputs. The main advantage the DDF is that while it remains the property of crediting both increases of good outputs and subtraction of bad outputs, it allows different directions for the factors, which is more flexible and powerful. In this paper, we choose to employ the DDF to evaluate the countries' environmental efficiency and compare the efficiency distribution under different directions.

Following Färe et al. (2005), let's consider a production process where a unit uses inputs **x** to produce two kinds of outputs, good outputs **y,** and bad outputs **b**. The production set can be described as

$$\mathrm{T} = \{(\mathbf{x}, \mathbf{y}, \mathbf{b}) : \mathbf{x} \text{ can produce } (\mathbf{y}, \mathbf{b})\}, \tag{1}$$

subject to assumptions

1. Output set is compact for each input, finite inputs can only produce a finite amount of output;
2. inputs are freely disposable: if $(\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$ and $\mathbf{x}' > \mathbf{x}$ then $(\mathbf{x}', \mathbf{y}, \mathbf{b}) \in \mathrm{T}$;
3. null-jointness: if $(\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$ and $\mathbf{b} = 0$ then $\mathbf{y} = 0$;
4. week disposability of outputs: if $(\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$ and $0 \leq \theta \leq 1$ then $(\mathbf{x}, \theta\mathbf{y}, \theta\mathbf{b}) \in \mathrm{T}$;
5. strong disposability of good outputs: if $(\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$ and $\mathbf{y}' \leq \mathbf{y}$ then $(\mathbf{x}, \mathbf{y}', \mathbf{b}) \in \mathrm{T}$.

The boundary of the technology set is considered as the production frontier, and if one unit stands on the frontier, the productivity is fully efficient. Inefficient production units are confronted with a distance to the frontier, and this distance is calculated by the directional output distance function (DODF) defined as

$$\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g}) = \max\{\beta: (\mathbf{x}, \mathbf{y} + \beta\mathbf{g}_{\mathrm{y}}, \mathbf{b} - \beta\mathbf{g}_{\mathrm{b}}) \in \mathrm{T}\}. \tag{2}$$

This DODF seeks a simultaneous maximum expansion in the good output in direction $\mathbf{g}_{\mathrm{y}}$ and maximum reduction of bad output in the direction $\mathbf{g}_{\mathrm{b}}$, given inputs unchanged. It satisfies the following properties:

1. nonnegative for all feasible output vectors: $\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g}) \geq 0$ iff $(\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$;
2. monotonicity (corresponding to the disposability): If $(\mathbf{x}', \mathbf{y}, \mathbf{b}) \geq (\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$ then $\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}', \mathbf{y}, \mathbf{b}; \mathbf{g}) \geq \vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g})$; If $(\mathbf{x}, \mathbf{y}', \mathbf{b}) \geq (\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$ then $\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}', \mathbf{b}; \mathbf{g}) \leq \vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g})$; If $(\mathbf{x}, \mathbf{y}, \mathbf{b}') \geq (\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$ then $\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}, \mathbf{b}'; \mathbf{g}) \geq \vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g})$;
3. concavity: $\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g})$ is concave in $(\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$;
4. weak disposability of desirable output and undesired output: $\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \theta\mathbf{y}, \theta\mathbf{b}; \mathbf{g}) \geq 0$ for $(\mathbf{x}, \mathbf{y}, \mathbf{b}) \in \mathrm{T}$ and $0 \leq \theta \leq 1$;
5. translation property: $\vec{\mathrm{D}}\mathrm{o}\left(\mathbf{x}, \mathbf{y} + \alpha\mathbf{g}_{\mathrm{y}}, \mathbf{b} - \alpha\mathbf{g}_{\mathrm{b}}; \mathbf{g}\right) = \vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g}) - \alpha$, $\alpha \in \mathcal{R}$.

If we let the direction vector be $\mathbf{g} = (\mathrm{g}_{\mathrm{y}}, \mathrm{g}_{\mathrm{b}})$, if $\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathbf{y}, \mathbf{b}; \mathbf{g}) = 0$, this country is efficient in the $(\mathrm{g}_{\mathrm{y}}, -\mathrm{g}_{\mathrm{b}})$ direction.

Like Feng and Serletis (2014), we allow for the inputs and outputs change over time and add interaction term of time and production factors, then the quadratic form of the distance function is

$$\vec{\mathrm{D}}\mathrm{o}\left(\mathbf{x}, \mathrm{y}, \mathrm{b}, \mathrm{t}; \mathrm{g}_{\mathrm{y}}, -\mathrm{g}_{\mathrm{b}}\right) = \alpha_0 + \textstyle\sum_{i=1}^{3} \alpha_i x_i + \beta_1 y + \gamma_1 b + \delta_\tau t$$

$$+\frac{1}{2}\sum_{i=1}^{3}\sum_{j=1}^{3}\alpha_{ij}x_i x_j+\frac{1}{2}\beta_2 y^2+\frac{1}{2}\gamma_2 b^2+\frac{1}{2}\delta_{\tau 2}t^2$$

$$+\sum_{i=1}^{3}\beta_{i1}x_i\, y+\sum_{i=1}^{3}\gamma_{i1}x_i\, b+\theta_{11}yb+\sum_{i=1}^{3}\alpha_{i\tau}x_i\, t+\beta_{1\tau}yt+\gamma_{1\tau}bt. \qquad (3)$$

To hold the translation property, the restrictions on parameters are

$\beta_1-\gamma_1=-1,$

$\beta_2=\gamma_2=\theta_{11},$

$\beta_{i1}=\gamma_{i1}$ for $i=1,2,3$ and $\beta_{1\tau}=\gamma_{1\tau}$.

We also impose symmetry condition: $\alpha_{ij}=\alpha_{ji}, i, j=1,2,3$.

Equation (3) could not be estimated directly as the left-hand side variable is not observed. By applying the translation property, the following equation holds,

$$\vec{\mathrm{D}}\mathrm{o}(\mathbf{x},\mathrm{y},\mathrm{b},\mathrm{t};\mathrm{g_y},-\mathrm{g_b})=\vec{\mathrm{D}}\mathrm{o}(\mathbf{x},\mathrm{y}+\alpha\mathrm{g_y},\mathrm{b}-\alpha\mathrm{g_b},\mathrm{t};\mathrm{g_y},-\mathrm{g_b})+\alpha. \qquad (4)$$

Add the stochastic part, we have $\vec{\mathrm{D}}\mathrm{o}(\mathbf{x},\mathrm{y},\mathrm{b};\mathrm{g_y},-\mathrm{g_b})=u-v$ where $u\geq 0$ measuring the distance of one producer to the frontier and $v\in N(0,\sigma_v^2)$ is the error term.

Let $\alpha=b/\mathrm{g_b}$, rearrange equation (4),

$$-b=\vec{\mathrm{D}}\mathrm{o}(\mathbf{x},\mathrm{y}+\mathrm{bg_y}/\mathrm{g_b},\mathrm{b}-\mathrm{b},\mathrm{t};\mathrm{g_y},-\mathrm{g_b})-u+v$$

$$=\alpha_0+\sum_{i=1}^{3}\alpha_i x_i+\beta_1\tilde{y}+\delta_\tau t+\frac{1}{2}\sum_{i=1}^{3}\sum_{j=1}^{3}\alpha_{ij}x_i x_j+\frac{1}{2}\beta_2\tilde{y}^2+\frac{1}{2}\delta_{\tau 2}t^2$$

$$+\sum_{i=1}^{3}\beta_{i1}x_i\,\tilde{y}+\sum_{i=1}^{3}\alpha_{i\tau}x_i\, t+\beta_{1\tau}\tilde{y}t+\gamma_{1\tau}bt-u+v, \qquad (5)$$

where $\tilde{y}=y+\mathrm{bg_y}/\mathrm{g_b}$.

We generate Figure 3.1 using the real data from the World Bank to illustrates the technology set and how the DODF is applied. Coefficient Estimates of $\vec{\mathrm{D}}\mathrm{o}(\mathbf{x},\mathrm{y},\mathrm{b},\mathrm{t};\mathrm{g_y},-\mathrm{g_b})$ from equation (5) are used to simulate the production set. Since Japan is relatively efficient all through the study period, we employ the average inputs of Japan. The bad output, GHG, is rearranged to be from 0 to the maximum value with a step of maximum value divided by the number of observations. We set the distances to be zero and obtain a quadratic relation equation between y and b for given inputs. This figure mainly provides three pieces of information: 1. It shows a compact output set and the strong disposability of both good outputs and bad outputs. If an observed country with GDP and GHG emissions inside the feasible set, then any observation with equal GHG emission and less GDP is in this technology set too. 2. There are frontier shifts over the years, which implies an improvement of the environmental technology. We split the data into three periods, 1991-1999, 2000-2007 and 2008-2012, to show that the production feasible set is expanded over the years, allowing to produce more GDP at the same level of GHG emissions. 3. The yellow dot in the output set is an example of the production unit, China, 2010, and the distance is defined as the point toward frontier in the direction of $(g_y, g_b) = (1, 1)$.

2.2 Estimation

Both data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are widely used in recent studies. Papers that applies non-parametric DEA include Seiford and Zhu (2002), Scheel (2001), Färe, Grosskopf and Hernandez-Sancho (2004), Zhou, Ang and Poh (2008). Although the DEA can calculate the efficiency directly, it suffers from two drawbacks: the program is nonlinear if the production is not constant return to scale (CRS), and since the DEA efficiency estimates are serially correlated, a valid inference cannot be made without bootstrapping (Simar and Wilson 2007). The SFA requires a functional form of the distance function and allows for a stochastic variation. It provides parameterized productivity form and support to make further inferences, such as computing elasticities and shadow prices of bad outputs. It is common to set a translog function form in HDF which holds homogeneity property and a quadratic function form in DDF which holds translation property. The study by Färe et al.

(2005) is a classical paper and enlightens many following researchers, such as Njuki, Bravo-ureta and Mukherjee (2016), Matsushita and Yamane (2012), Malikov, Kumbhakar and Tsionas (2016). In this paper, we also start in the same way as introduced in Färe et al.'s paper.

Since the estimation of inefficiency depends on the assumption of the distribution of u, the technical efficiency measure is not consistent. It is also not justified to assume the independency of u and the regressors (Schmidt and Sickles 1984). Consider the model

$$y_{it} = \alpha_t + \boldsymbol{x}'_{it}\boldsymbol{\beta} - u_{it} + v_{it} = \alpha_{it} + \boldsymbol{x}'_{it}\boldsymbol{\beta} + v_{it}, \tag{6}$$

where α_{it} are the intercept of producer i at time t. Following Cornwell, Schmidt and Sickles (1990), $\alpha_{it} = W_t\delta_i$, where W_t is a quadratic vector of t, that $W_t = [1, t, t^2]$ and $\alpha_{it} = \delta_{i0} + \delta_{i1}t + \delta_{i2}t^2$, this allows for the correlation between the effects and the inputs, and no distribution assumption required for the u. In this way we could estimate the individual-specific technical environmental inefficiency in different years.

The time-varying inefficiency $\hat{u}_{it}$ is obtained from

$$\hat{u}_{it} = \hat{\alpha}_t - \hat{\alpha}_{it}, \tag{7}$$

where $\hat{\alpha}_t$ is the maximum α overall production unit at time t, $\hat{\alpha}_t = \max_i(\hat{\alpha}_{it})$, the inefficiency is estimated in a fixed effect frame work.

By solving the revenue maximization problem

$$R(\boldsymbol{x}, p, q) = \max_{y,b}\{py - qb \colon \vec{\mathrm{D}}\mathrm{o}\big(\mathbf{x}, \mathrm{y}, \mathrm{b}, \mathrm{t}; \mathrm{g_y}, -\mathrm{g_b}\big) \geq 0\}, \tag{8}$$

Where p if the price of good output, we obtain the shadow prices (q)

$$q = -p\left[\frac{\partial\vec{\mathrm{D}}\mathrm{o}(\mathbf{x},\mathrm{y},\mathrm{b};\mathrm{g_y},-\mathrm{g_b})/\partial b}{\partial\vec{\mathrm{D}}\mathrm{o}(\mathbf{x},\mathrm{y},\mathrm{b};\mathrm{g_y},-\mathrm{g_b})/\partial y}\right]. \tag{9}$$

In our case since the good output is GDP, the price $(p)$is set constant to \$1.

The Morishima elasticity between good output and bad output is

$$M_{by} = (y + g_y \vec{\mathrm{D}}\mathrm{o}(\cdot)) \left[\frac{\partial^2 \vec{\mathrm{D}}\mathrm{o}(\cdot)/\partial y \partial b}{\partial \vec{\mathrm{D}}\mathrm{o}(\cdot)/\partial b} - \frac{\partial^2 \vec{\mathrm{D}}\mathrm{o}(\cdot)/\partial y \partial y}{\partial \vec{\mathrm{D}}\mathrm{o}(\cdot)/\partial y} \right].^{9} \tag{10}$$

3. Data

Our data are from the World Bank. The country level annual data are used to analysis TEE for each country with available records in each year. There are three inputs, capital stock, labor, and energy. The time range from 1990 to 2012. Since available emission dataset prior 1990 is too small, we limited the time to start from 1990. There is one good output GDP, and the price of GDP is set to be 1 in the shadow price calculation. The bad outputs include GHG, CO_2, and N_2O. The GHG totals are expressed in CO_2 equivalent using the GWP100 metric of the Second Assessment Report of IPCC and include CO_2, GH4, N_2O etc. Carbon dioxide emissions are the by-products of energy production and use, accounting for the largest share of greenhouse gases. Nitrous oxide is another powerful greenhouse gas, mainly from fossil fuel combustion and the overuse of mineral fertilizers and herbicides.

Table 3.1 shows the mean values of each variable over 1991-2012.

All the variables have very large ranges, which can be observed that the standard deviation is larger than the mean. The Lorenz estimates show that in 2012, the top 10% countries, consumed 35% of the energy, fed 70% of the labor in the world, and generated 70% of the total GDP, emitting approximately 75% of GHG, 80% of CO_2 and 65% of N_2O. The average annual growth rate of total GHG in the word is 3%, and CO_2 for 4%, N_2O for 0.5%. Regarding the per person emissions, the GHG per capita increased by 4%, CO_2 creased per capita by 18% while N_2O per capita decreased by 30%.

---

[9] For detailed calculation of shadow prices and Morishima elasticities, see Färe et al. (2005)

To avoid convergence problems all variables are corrected prior to model estimation, three inputs and both good and bad outputs in each model are normalized. Finally, we use the bad output to impose translation property. In this way, the length of distance estimated in each model is measured as the unit of the bad output, i.e., GHG, CO_2 or N_2O.

4. Results and Discussion

As described earlier, there are three inputs in our model, capital, labor, and energy. One good output is GDP, the bad outputs are GHG, CO_2 and NO.

4.1 Model estimates

We estimate three models with different bad outputs under different direction vectors. Since the most commonly used direction set is (1,1), here we use the outputs from models with (1,1) direction vector for discussion (see Table 3.2). Tables contain all parameter estimates and results of models with other direction vectors are attached in the appendix.

When we test the monotonicity in outputs, 2429 out of 2434 observations in GHG model, all the observations in the CO_2 model and 2431 out of 2434 observations in the NO model satisfy the property. The violation of monotonicity condition is below the tolerance level, so we do not need to worry about this.

The shadow price of a bad output is the lost value when the productivity of one country moves toward the production frontier, or the marginal abatement cost of the bad output. Take the example in Figure 3.1, where China is not efficient. If China moves toward the frontier in the direction of (1, 1), the total value added of the total outputs (GDP and GHG) consists not only the increase of GDP, but also the value of subtracted GHG, the value of emissions abatement is not observed in the data. The shadow price quantifies the relative value of bad output abatement to the good output. In this study the good output is GDP and the price is constant $1, and the shadow price of GHG is \$0.546 per unit for the normalized data at the mean. The mean shadow price of CO_2 is \$0.960 per unit and N_2O is \$0.468 per unit. If we rescale the outputs to original data, the shadow prices of GHG, CO_2, and N_2O per ton are \$919, \$960 and \$524. The shadow price estimates of bad outputs are different from other literature. Maradan and Vassiliev (2005) also employed the directional distance function and cross-country data to calculate the shadow prices of CO_2, they find that the shadow price ranges from \$130 per ton to \$1083 per ton (1987 U.S.\$). Some other studies use state or firm level data and obtain different mean shadow price of CO_2, such as €88 /ton (Molinos-Senante, Hanley and Sala-Garrido 2015), \$237/ton (Lee and Zhou 2015). The derivation of the difference can be result from the use of different methodology and the measures of good output value.

Since we use the Schmidt and Sickles's method to obtain the TEE, the efficiencies should be considered as "relative efficiency": a country with higher TEE is more efficient than the one with smaller efficiency. If all countries were efficient as the most efficient country in all periods of 1990-2012, then there would be approximately 50% reduction of total GHG emissions, and there should be 40% less CO_2 output and 57% less N_2O output. In 2012, the total value of GHG, CO_2 and N_2O abatement, assuming all countries being fully efficient, is 1.98 billion, 3.04 billion and 3.32 million, which account for 16%, 25% and 0.3% of the total GDP in the world.

The definition of Morishima elasticity of substitution is $\partial \ln(q/p) / \partial \ln(y/b)$ and it measures the how the GDP and GHG (CO_2, N_2O) price ratio changes relative to the change of good-bad output ratio. We found the elasticities at the means are negative for all three bad outputs, which indicates that an increase of good-bad output ratio causes a decrease of the shadow prices, and this change is inelastic. The transformation elasticity for CO_2 and GDP is super in-elastic and it implies that the marginal abatement cost of CO_2 emissions is stable when GDP-CO_2 outputs adjust.

4.2 TEE and economic development

We are interested in finding the relationship between TEE and economic development. A graph of all the countries would be too crowded and hard to read, so we choose to scatter a few in stead of all. We estimate the Lorenz and concentration curve and find that the top 25% of countries generated 90% of the total GHG, we care more about the efficiencies of large countries, of which a relative small improvement of technology can produce a large effect on the global emission. So, we graphed the relationship between average TEE and GDP per capita of the “large” countries, which contain countries with the top 25% population. The analysis of TEE over countries at different development level can give information on the change of environmental efficiency over economic growth process.

The first graph in Figure 3.2 shows the TEE obtained from GHG model, at a direction of (1,1), the leading countries are United States, Japan, and the United Kingdom. The second graph shows the TEE obtained from CO_2 model, and the leading countries are France, Kenya, and Tanzania. The third one shows the TEE obtained from N_2O model and the most efficient countries are Japan, United Kingdom, and Colombia. We also found that in each model, both China and India are ranked lowest among the large countries. These findings coincide with Valadkhani, Roshdi and Smyth's (2016) study and provide support to the “paradox of plenty,” whereby countries with most rich natural resources exhibit the lowest economic and environmental efficiency.

In general, there is a U shape curve relationship between TEE and GDP per capita. One widely used model in development economics is the “take-off” model. In this model, Rostow designated a set of states of economic growth: the traditional society, the preconditions for take-off, the take-off, the drive to maturity and the stage of mass consumption (Rostow 1959). The stages are closely related to the sustainable development, economically and environmentally (Rammel and van den Bergh 2003; Elliott 2012). In early stages an economy mainly stands on agricultural outputs, Such as Tanzania, Kenya, and Pakistan (the shares of GDP from agriculture in 2012 are 33.2%, 29.1%, 24.5%, compare to China 9.4%), capital and labor may not be fully utilized but there is less energy consumption. In such circumstance, the economy is relatively environmentally efficient compared to the countries at the middle stages when the force of economic growth is largely based on the use of fossil fuels, whose growth are fast, but emissions increase dramatically and environmental efficiency is hardly achieved. Well-known countries at such “take-off” stage are China and India. Developed countries (at the stage of “mass consumption”), such as the United States, Japan, and United Kingdom are more efficient and the economy in such countries is closer to sustainable development.

4.3 TEE at different directions

In the choice of direction vector for two outputs, the most commonly used vector is (1,1), which we explained earlier. Though there have been some attempts to obtain optimal direction sets (Färe, Grosskopf and Whittaker 2013; Hampf and Krüger 2013; Atkinson and Tsionas 2016), in this paper, we are not going to endogenize the directions or maximize the efficiency. We manually assign five direction vectors to each model, (0.1, 1), (0.5, 1), (1, 1), (2, 1), (10, 1), with which we can make a comparison over the distributions of TEE under different directions. See Figure 3.3.

Under each direction vector in (0.1, 1), (0.5, 1), (1, 1), (2, 1) and (10, 1), for a production unit, if the distance is 1 unit of good output, then this production unit is required to achieve 10, 2, 1, 0.5 and 0.1 unit(s) of emission abatement to reach full efficiency. In other words, a smaller value of g_y/g_b indicates greater importance of bad output deduction. The kernels do not provide much evidence that TEE has a significant change in GHG and CO_2 models with different directions. However, we find that the efficiencies are greater (or the same) when g_y/g_b increases in the N_2O model. That is, when we ignore the bad credits from the undesired output, the efficiency improves. In another word, when we emphasize more about N_2O emissions in assessing the performance of a country, the less efficient that country is; efficiency can be improved if we ignore the environmental concerns and only focus on economic development. At a time when climate issue is emerging, it is of great importance to include environmental concern into policymaking.

4.4 TEE change over time

In earlier section, Figure 3.1 shows shifts of production frontier among three periods. Here we also check the changes of TEE over time via Kolmogorov–Smirnov test. The two sample K-S test provide the equality of two distribution. We separate the data into two periods, 1991-2000, 2001-2012, and test the difference between two time windows. The results are given by Table 3.3.

The time trend of GHG efficiencies is unclear, a weak conclusion is that the TEE is decreasing if GHG is emphasized ($\mathbf{g} = (0.5{:}\,1)$) while it is increasing over time when GDP is much more important than GHG emissions ($\mathbf{g} = (10{:}\,1)$)). In the CO_2 model, the TEE is decreasing over time, consistent for the first three direction vectors, but it is improving over time when g_y is large enough. In the N_2O model, the environmental efficiencies are increasing in general for all the direction vectors. There can be many reasons for efficiency change. Technology progress and promotion of education, such as the wide spread of computer increases labor output per capita; learning by doing such that higher capital return in a well-functioned finance market. Efficiencies are also related to institutional characteristics.

Since 87% of CO_2 emissions are generated by fossil fuel combustion, the decrease of TEE over time can be caused by the over-consumption of energy in the economic growth. From 1970 to 2012, the CO_2 emissions per kilogram of energy (oil equivalent) rise dramatically while N_2O emissions per kilogram of energy (oil equivalent) have a slightly downward slope over time. Since the human-source N_2O emissions are mostly from agriculture productivity, such as crop cultivation (fertilizer) and livestock production (animal waste), the development of agriculture management that precisely quantify the fertilizer needed by crops and scientific dispose of animal waste helps increase the agriculture environmental efficiency. This finding agrees with Dakpo, Jeanneaux, and Latruffe (2017), in which the authors conducted research over sheep farm productivity in French and found that the environmental efficiency is steady over 1987-2012 while the mix warming efficiency is slightly increasing.

5. Conclusion

Technological Revolution pushed a leap in economic development and lead to large consumption of fossil fuels. In the late 20th century, global warming and climate change became an emerging issue due to emissions of GHG, including CO_2, N_2O, CH4 etc. In such circumstances, sustainable development, which concerns not only economic growth, but also environmental and social development, become a new goal.

To evaluate the environmental performance, the directional distance function framework is applied to estimate the production efficiency. We estimate three models concerning GHG, CO_2 and N_2O emissions and calculate the corresponding TEE. There are mainly three findings. 1. The relationship between TEE and GDP per capita performs a shallow U shape curve, that is, the

TEE is relatively high in the early stage of development and the later stage, but a country experiences low efficiency during the “take-off” period. 2. No evidence on the difference between TEE obtained from GHG and CO_2 models when imposing different direction vectors, but results from the N_2O model show that countries are generally more efficient when the direction vector g_y/g_b is set to be smaller, which indicates that the more we emphasize the importance of N_2O emissions, the lower score in environmental performance evaluation. 3. The GHG efficiency trend over time is ambiguous across different direction vectors, while the CO_2 efficiency is generally decreasing over time. N_2O efficiency is increasing. We also find that there is technical change over years, which is shown in Figure 3.1 that there is frontier shifts between 1991-1999, 2000-2007 and 2008-2012.

Environmental regulations such as command-and-control, cap, and trade, etc. help reduce the social cost of pollutions but also hurt the economic growth. Since the primary human activities that generate pollutions are fossil fuel combustion and agriculture productivity, we suggest more research and development in clean energy to reduce the input cost, which can both mitigate energy crisis and increase the environmental efficiency while keeping the economic growth rate. Culture, institute characteristic, and market structure, etc. may also affect the environmental performance the country, which is left for further study.

FIGURES

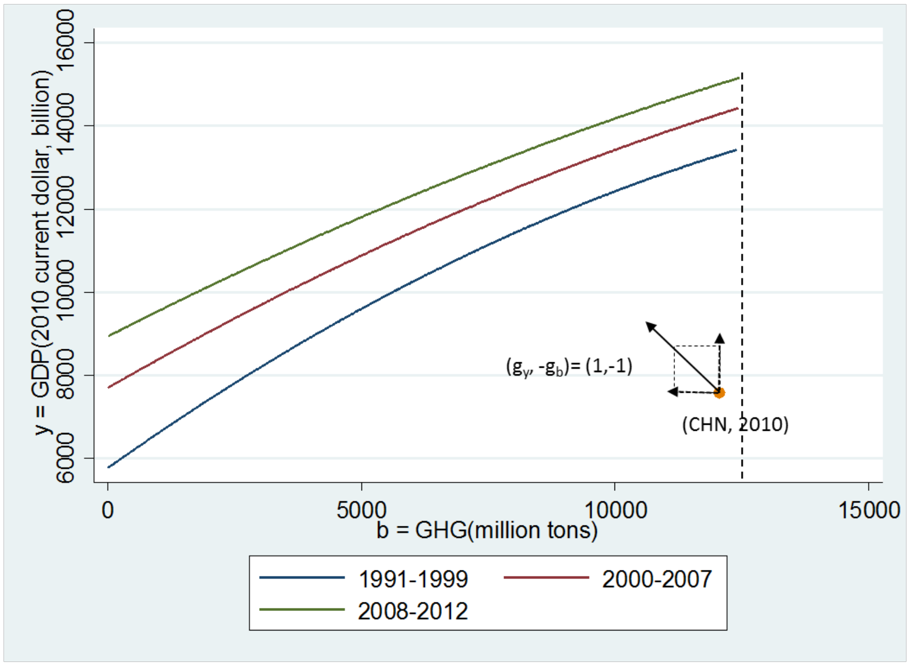
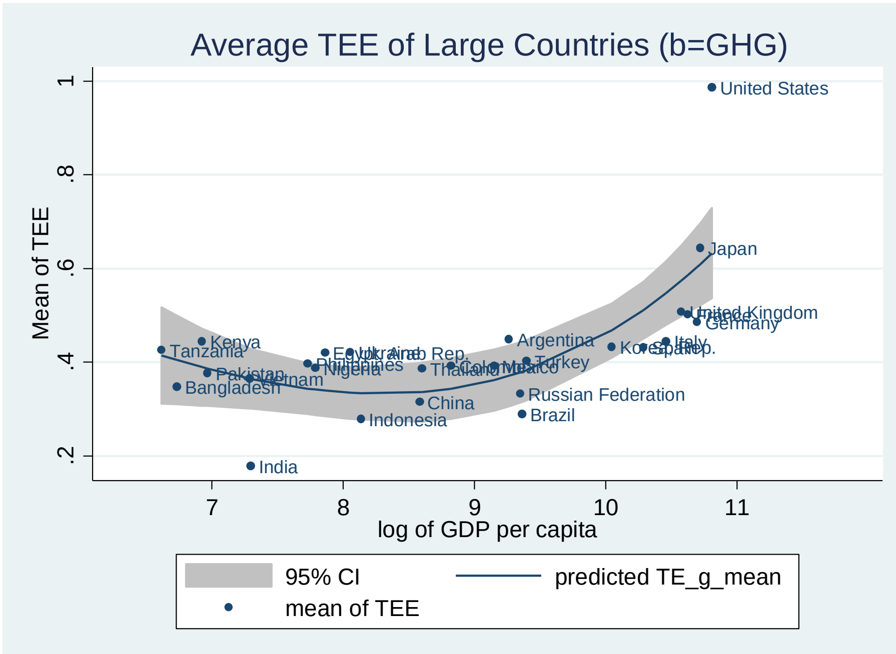
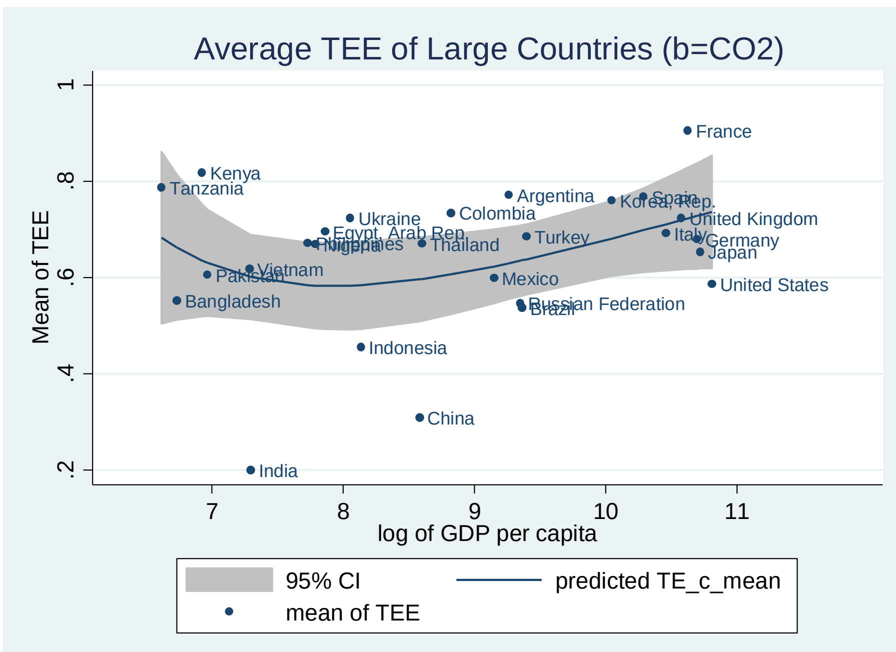


Figure 3.1 Outputs Set of y and b and an Example from Data

(a)


Average TEE of Large Countries (b=GHG)
Mean of TEE
.2
.4
.6
.8
1
7
8
9
10
11
log of GDP per capita
United States
Japan
Germany
Kenya
Tanzania
Argentina
Turkey
Russian Federation
Brazil
China
Indonesia
Bangladesh
India
95% CI
predicted TE_g_mean
mean of TEE

(b)


Average TEE of Large Countries (b=CO2)
Mean of TEE
.2
.4
.6
.8
1
7
8
9
10
11
log of GDP per capita
France
Kenya
Tanzania
Argentina
Ukraine
Colombia
Egypt, Arab Rep.
Thailand
Turkey
United Kingdom
Germany
Japan
Vietnam
Mexico
United States
Bangladesh
Indonesia
China
India
95% CI
predicted TE_c_mean
mean of TEE

(c)

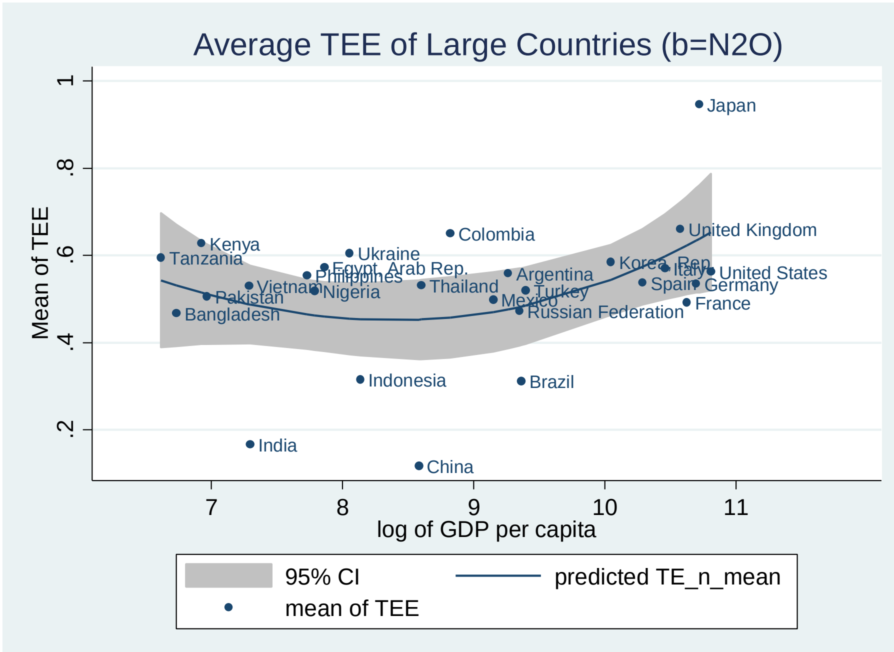
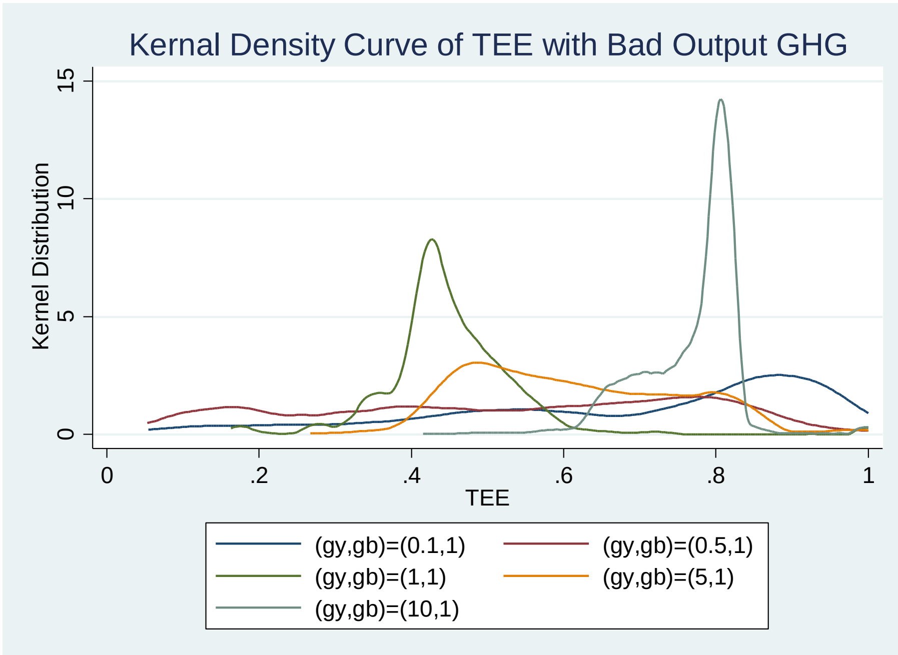


Figure 3.2 Scatter Plot of Average TEE and the Natural logarithm of GDP per capita with the Direction Vector (1, 1) of Large Countries

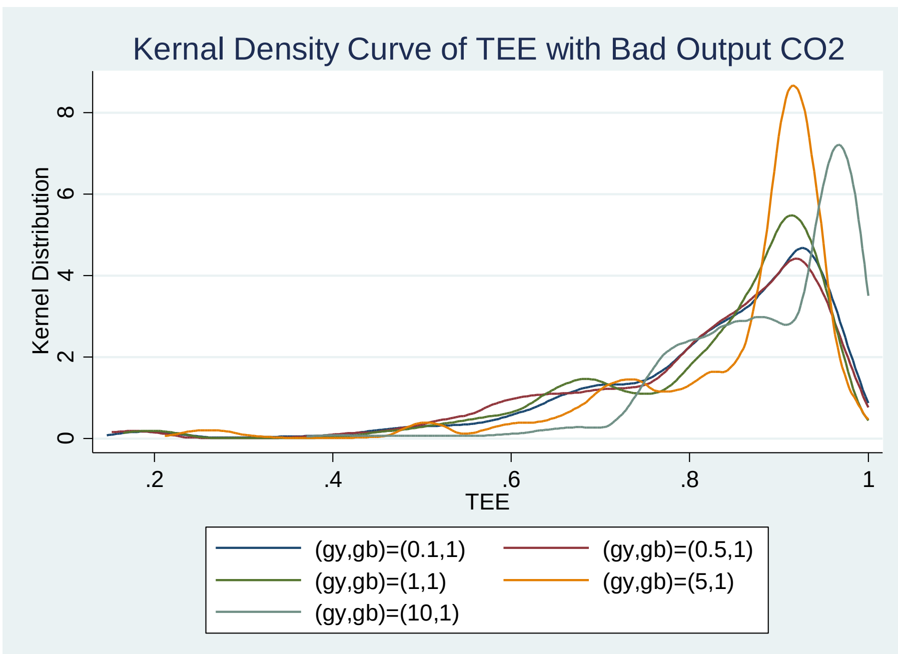
Note: 1) GHG model. 2) CO_2 model. 3) N_2O model. Note: In above three graphs, the fitted line is predicted by the fractional polynomial regression and the shadow area indicates a 95% confidence interval. “Large country” is defined as the country with population among top 25% in the world.

(a)



Kernal Density Curve of TEE with Bad Output GHG
Kernel Distribution
0
5
10
15
0
.2
.4
.6
.8
1
TEE
(gy,gb)=(0.1,1)
(gy,gb)=(0.5,1)
(gy,gb)=(1,1)
(gy,gb)=(5,1)
(gy,gb)=(10,1)

(b)



Kernal Density Curve of TEE with Bad Output CO2
Kernel Distribution
0
2
4
6
8
.2
.4
.6
.8
1
TEE
(gy,gb)=(0.1,1)
(gy,gb)=(0.5,1)
(gy,gb)=(1,1)
(gy,gb)=(5,1)
(gy,gb)=(10,1)

(c)

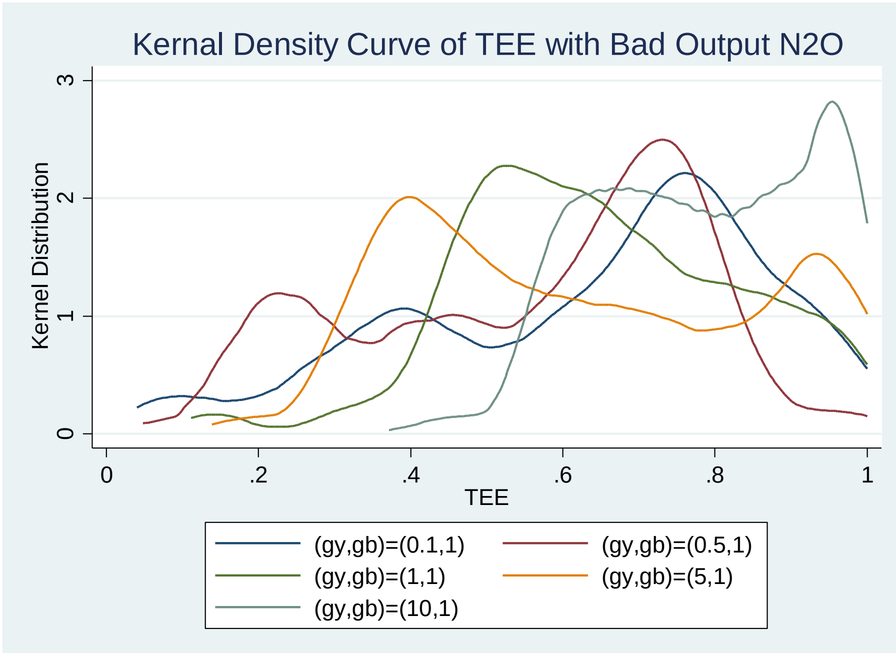


Figure 3.3 Kernel Distributions

Note: 1) Kernel distribution of TEE of the GHG model with different directions 2) Kernel distribution of TEE of CO_2 model with different directions. 3) Kernel distribution of TEE of N_2O model with different directions.

TABLES

Table 3.1 Descriptive Statistics

Variable	Mean	Std.Dev	Min	Max
Capital m	106397.60	333134.20	36.61	3564077.00
Labor t	23389.59	81538.15	91.08	798203.30
Energy	2334.19	2402.04	9.58	18178.14
GDP m	385206.50	1307742.00	365.00	16700000.00
GHG mt (CO_2 equivalent)	357.07	1028.79	0.39	12454.71
CO_2 mt	224.72	775.44	0.05	10249.46
N_2O kt (CO_2 equivalent)	23332.99	59753.66	35.46	587166.4

Table 3.2 Shadow Prices and Elasticity of Transformation, Direction = (1,1)

Variable/Bad Output	GHG Mean	CO_2 Mean	N_2O Mean
$\partial\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathrm{y}, \mathrm{b}; 1, -1)/\partial b$	0.462	0.979	0.514
$\partial\vec{\mathrm{D}}\mathrm{o}(\mathbf{x}, \mathrm{y}, \mathrm{b}; 1, -1)/\partial y$	-1.561	-1.021	-1.512
Shadow Price	0.546	0.960	0.468
Morishima Elasticity	-0.34	-0.001	-0.142
N	2434	2639	2434

Table 3.3 TEE Trends

Directions	GHG Model	CO_2 Model	N_2OModel
0.1:1	↑	↓	↑
0.5:1	↓	↓	→
1:1	↓	↓	↑
2:1	↑	↑	↑
10:1	↑	↑	↑

Note: ↑ increasing ↓ decreasing → ambiguous

Appendix 2

Table A2- 1 GHG Models

Bad Output			GHG		
(g_y,g_b)	0.1:1	0.5:1	1:1	2:1	10:1
α_1	-0.191	1.550***	0.898***	0.385***	0.013
	(0.140)	(0.082)	(0.047)	(0.028)	(0.008)
α_2	3.375***	1.907***	0.424*	-0.123	0.098**
	(0.571)	(0.368)	(0.234)	(0.147)	(0.047)
α_3	-0.301***	-0.422***	-0.286***	-0.163***	-0.018***
	(0.073)	(0.047)	(0.030)	(0.019)	(0.006)
β_1	-0.438***	-1.257***	-0.757***	-0.374***	-0.093***
	(0.070)	(0.033)	(0.015)	(0.006)	(0.001)
β_2	0.019	-0.129***	-0.059***	-0.016***	-0.000***
	(0.014)	(0.006)	(0.002)	(0.001)	(0.000)
α_{12}	0.018	-0.013	-0.072***	-0.092***	-0.027***
	(0.023)	(0.013)	(0.008)	(0.005)	(0.002)
α_{13}	0.090	-0.889***	-0.512***	-0.222***	-0.016***
	(0.097)	(0.060)	(0.034)	(0.019)	(0.006)
α_{23}	-1.345***	-1.304***	-0.852***	-0.380***	-0.026*
	(0.121)	(0.081)	(0.057)	(0.041)	(0.014)
α_{11}	-0.011	-0.271***	-0.209***	-0.129***	-0.016***
	(0.025)	(0.014)	(0.008)	(0.004)	(0.001)
α_{22}	-0.293***	-0.107***	-0.058***	-0.033***	-0.005
	(0.049)	(0.032)	(0.020)	(0.013)	(0.004)
α_{33}	-0.002	-0.004	-0.006	-0.004	-0.000
	(0.011)	(0.007)	(0.005)	(0.003)	(0.001)

δ_{τ}	0.141***	0.083***	0.039***	0.019***	0.005***
	(0.018)	(0.012)	(0.008)	(0.005)	(0.002)
$\delta_{\tau 2}$	-0.005***	-0.004***	-0.001***	-0.000*	-0.000**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
β_{11}	-0.006	0.364***	0.226***	0.100***	0.004***
	(0.031)	(0.015)	(0.006)	(0.002)	(0.000)
β_{21}	-0.025**	0.024***	0.026***	0.011***	0.001***
	(0.010)	(0.006)	(0.004)	(0.002)	(0.000)
β_{31}	0.124**	0.672***	0.270***	0.052***	-0.000
	(0.057)	(0.029)	(0.013)	(0.005)	(0.000)
$\beta_{1\tau}$	0.009*	0.045***	0.017***	0.001	-0.000***
	(0.005)	(0.003)	(0.001)	(0.000)	(0.000)
$\alpha_{1\tau}$	0.001	-0.067***	-0.021***	0.006***	0.007***
	(0.008)	(0.005)	(0.003)	(0.002)	(0.000)
$\alpha_{2\tau}$	-0.008	-0.099***	-0.021	0.017	-0.001
	(0.042)	(0.027)	(0.017)	(0.011)	(0.003)
$\alpha_{3\tau}$	0.003	0.007*	0.007***	0.005***	0.001
	(0.005)	(0.003)	(0.002)	(0.001)	(0.000)
N	2434	2434	2434	2434	2434
Marishima Elasticity	0.041	-0.183	-0.342	-0.023	-0.0001
Shadow Price	0.536	-0.158	0.546	0.483	0.825

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01

Table A2- 2 CO_2 Models

Bad Output		CO_2			
(g_y,g_b)	0.1:1	0.5:1	1:1	2:1	10:1
α_1	0.027	0.031	0.037*	0.019	-0.024***
	(0.022)	(0.022)	(0.021)	(0.018)	(0.009)
α_2	-0.261***	-0.068	-0.052	-0.173***	-0.109***
	(0.087)	(0.081)	(0.073)	(0.063)	(0.037)
α_3	-0.338***	-0.323***	-0.289***	-0.228***	-0.066***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.006)
β_1	0.035***	0.007	-0.029***	-0.056***	-0.061***
	(0.011)	(0.011)	(0.010)	(0.008)	(0.002)
β_2	0.013***	0.004**	-0.001	-0.003***	-0.000***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
α_{12}	-0.013***	0.001	0.004	-0.003	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
α_{13}	0.091***	0.048***	0.004	-0.021	0.010
	(0.015)	(0.016)	(0.016)	(0.014)	(0.006)
α_{23}	-1.531***	-1.388***	-1.150***	-0.793***	-0.127***
	(0.020)	(0.021)	(0.025)	(0.030)	(0.022)
α_{11}	0.010***	0.001	-0.011***	-0.022***	-0.015***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.001)
α_{22}	-0.060***	-0.048***	-0.036***	-0.021***	0.001
	(0.007)	(0.007)	(0.006)	(0.006)	(0.003)
α_{33}	-0.001	-0.000	0.001	0.002*	0.002***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
δ_τ	0.035***	0.037***	0.035***	0.029***	0.011***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
$\delta_{\tau 2}$	-0.001***	-0.001***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_{11}	-0.023***	-0.005	0.011***	0.018***	0.004***

	(0.005)	(0.004)	(0.003)	(0.002)	(0.000)
β_{21}	-0.012***	-0.024***	-0.026***	-0.019***	-0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)
β_{31}	-0.022**	-0.006	0.003	-0.002	-0.006***
	(0.009)	(0.009)	(0.009)	(0.007)	(0.001)
$\beta_{1\tau}$	-0.003***	-0.001	0.001	0.001***	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
$\alpha_{1\tau}$	-0.002	-0.004***	-0.004***	-0.002**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
$\alpha_{2\tau}$	0.009	-0.006	-0.007	0.005	0.008***
	(0.006)	(0.006)	(0.005)	(0.004)	(0.003)
$\alpha_{3\tau}$	-0.000	0.000	0.001	0.001*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
N	2637	2638	2639	2640	2641
Marishima Elasticity	0.012	0.004	-0.001	-0.002	-0.000
Shadow Price	0.992	0.988	0.960	0.923	0.885

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01

Table A2- 3 N_2O **Models**

Bad Output	N_2O				
(g_y,g_b)	0.1:1	0.5:1	1:1	2:1	10:1
α_1	0.145	1.569***	0.682***	0.181***	-0.024***
	(0.155)	(0.078)	(0.044)	(0.026)	(0.007)
α_2	3.405***	1.765***	0.457*	0.071	0.105**
	(0.645)	(0.381)	(0.237)	(0.149)	(0.045)
α_3	-0.201**	-0.305***	-0.183***	-0.097***	-0.008
	(0.082)	(0.048)	(0.030)	(0.019)	(0.006)
β_1	-0.611***	-1.227***	-0.664***	-0.347***	-0.092***
	(0.077)	(0.031)	(0.015)	(0.007)	(0.001)
β_2	-0.062***	-0.168***	-0.068***	-0.016***	-0.000***
	(0.016)	(0.006)	(0.002)	(0.000)	(0.000)
α_{12}	0.107***	-0.006	-0.057***	-0.064***	-0.024***
	(0.025)	(0.013)	(0.007)	(0.005)	(0.002)
α_{13}	0.221**	-0.707***	-0.245***	-0.010	0.013**
	(0.107)	(0.057)	(0.030)	(0.017)	(0.005)
α_{23}	-0.836***	-0.922***	-0.573***	-0.231***	0.015
	(0.136)	(0.079)	(0.050)	(0.033)	(0.011)
α_{11}	-0.154***	-0.310***	-0.201***	-0.114***	-0.015***
	(0.027)	(0.013)	(0.007)	(0.004)	(0.001)
α_{22}	-0.209***	-0.062*	-0.041**	-0.027**	-0.005
	(0.055)	(0.033)	(0.020)	(0.013)	(0.004)
α_{33}	0.000	0.002	-0.001	-0.002	0.000
	(0.012)	(0.007)	(0.005)	(0.003)	(0.001)
δ_τ	0.147***	0.083***	0.043***	0.024***	0.006***
	(0.020)	(0.012)	(0.008)	(0.005)	(0.001)
$\delta_{\tau 2}$	-0.005***	-0.003***	-0.001***	-0.000**	-0.000**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
β_{11}	0.158***	0.404***	0.211***	0.086***	0.004***

	(0.033)	(0.013)	(0.005)	(0.002)	(0.000)
β_{21}	-0.045***	0.075***	0.061***	0.023***	0.001***
	(0.012)	(0.006)	(0.003)	(0.002)	(0.000)
β_{31}	0.175***	0.695***	0.217***	0.010**	-0.003***
	(0.064)	(0.027)	(0.012)	(0.005)	(0.000)
$\beta_{1\tau}$	0.028***	0.045***	0.013***	-0.000	-0.000***
	(0.005)	(0.003)	(0.001)	(0.000)	(0.000)
$\alpha_{1\tau}$	-0.009	-0.052***	0.001	0.021***	0.009***
	(0.009)	(0.005)	(0.003)	(0.002)	(0.000)
$\alpha_{2\tau}$	-0.034	-0.105***	-0.020	0.012	0.001
	(0.048)	(0.028)	(0.017)	(0.011)	(0.003)
$\alpha_{3\tau}$	0.006	0.007**	0.007***	0.004***	0.000
	(0.006)	(0.003)	(0.002)	(0.001)	(0.000)
N	2434	2434	2434	2434	2434
Marishima Elasticity	-0.264	0.051	-0.142	-0.0274	-0.0001
Shadow Price	0.608	0.043	0.468	0.499	0.827

Standard errors in parentheses ="* p<0.1 ** p<0.05 *** p<0.01

References

Abebaw, D. 2014. “SOCIO-ECONOMIC DETERMINANTS OF CHILD IMMUNIZATION IN RURAL ETHIOPIA.” *Journal of International Development* 26(7):1011–1023.

Alderman, H., J. Hoddinott, and B. Kinsey. 2006. “Long term consequences of early childhood malnutrition.” *Oxford Economic Papers* 58(3):450–474.

Almond, D., Y. Chen, M. Greenstone, and L. Hongbin. 2009. “Winter Heating or Clean Air? Unintended Impacts of China’s Huai River Policy.”

Ambel, A.A., C. Andrews, A.M. Bakilana, E. Foster, Q. Khan, and H. Wang. 2015. “Maternal and Child Health Inequalities in Ethiopia.”

Arceo-Gomez, E., R. Hanna, and P. Oliva. 2012. “Does the Effect of Pollution on Infant Mortality Differ between Developing and Developed Countries? Evidence from Mexico City.” *NBER Working Paper* 126(1):1–5.

Arndt, C., M.A. Hussain, V. Salvucci, and L.P. Østerdal. 2016. “Effects of food price shocks on child malnutrition: The Mozambican experience 2008/2009.” *Economics & Human Biology* 22:1–13.

Atkinson, S.E., and M.G. Tsionas. 2016. “Directional distance functions: Optimal endogenous directions.” *Journal of Econometrics* 190:301–314.

Atsbeha, D.M., R.M. Nayga, and K. Rickertsen. 2015. “Can prolonged breastfeeding duration impair child growth? Evidence from rural Ethiopia.” *Food Policy* 53:46–53.

Auffhammer, M., and R.T. Carson. 2008. “Forecasting the path of China’s CO2 emissions using province-level information." *Journal of Environmental Economics and Management* 55(3):229–247.

Bellemare, M.F., C.B. Barrett, and D.R. Just. 2013. "The Welfare Impacts of Commodity Price Volatility: Evidence from Rural Ethiopia." *American Journal of Agricultural Economics* 95(4):877–899.

Bi, X., Y. Feng, J. Wu, Y. Wang, and T. Zhu. 2007. "Source apportionment of PM10 in six cities of northern China." *Atmospheric Environment* 41(5):903–912.

Black, R.E., C.G. Victora, S.P. Walker, Z.A. Bhutta, P. Christian, M. De Onis, M. Ezzati, S. Grantham-Mcgregor, J. Katz, R. Martorell, and R. Uauy. 2013. "Maternal and child undernutrition and overweight in low-income and middle-income countries." *The Lancet* 382(9890):427–451.

Blinder, A. 1973. "Wage discrimination: reduced form and structural estimates." *Journal of Human resources* (8):427–451.

Block, S., and P. Webb. 2009. "Up in Smoke: Tobacco Use, Expenditure on Food, and Child Malnutrition in Developing Countries." *Economic Development and Cultural Change* 58(1):1–23.

Cao, G.L., X.Y. Zhang, S.L. Gong, X.Q. An, and Y.Q. Wang. 2011. "Emission inventories of primary particles and pollutant gases for China." *Chinese Science Bulletin* 56(8):781–788.

Case, A., and C. Paxson. 2008. "Stature and Status: Height, Ability, and Labor Market Outcomes." *Journal of Political Economy* 116(3):499–532.

Cesur, R., E. Tekin, and A. Ulker. 2015. "Air pollution and infant mortality: evidence from the expansion of natural gas infrastructure." *The Economic Journal*:n/a-n/a.

Chambers, R.G., Y. Chung, and R. Färe. 1998. "Profit, Directional Distance Functions, and

Nerlovian Efficiency." *Journal of Optimization Theory and Applications* 98(2):351–364.

Chaudhury, N., L. Christiaensen, and M.N. Asadullah. 2006. "CSAE WPS/2006-06 Schools, Household, Risk, and Gender: Determinants of Child Schooling in Ethiopia *."

Chen, Y., A. Ebenstein, M. Greenstone, and H. Li. 2013. "Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China 's Huai River Policy." *Massachusetts Institute of Technology Department of Economics Working Paper Series* 13(15):1–53.

Chung, Y.H., R. Färe, and S. Grosskopf. 1997. "Productivity and Undesirable Outputs: A Directional Distance Function Approach." *Journal of Environmental Management* 51(3):229–240.

Cornwell, C., P. Schmidt, and R.C. Sickles. 1990. "Production frontiers with cross-sectional and time-series variation in efficiency levels." *Journal of Econometrics* 46(1–2):185–200.

Costantini, V., and S. Monni. 2008. "Environment, human development and economic growth." *Ecological Economics* 64(4):867–880.

Cuesta, R.A., C.A.K. Lovell, and J.L. Zofío. 2009. "Environmental efficiency measurement with translog distance functions: A parametric approach." *Ecological Economics* 68(8–9):2232–2242.

Cuesta, R.A., and J.L. Zofío. 2005. "Hyperbolic Efficiency and Parametric Distance Functions: With Application to Spanish Savings Banks." *Journal of Productivity Analysis* 24(1):31–48.

Dakpo, K.H., P. Jeanneaux, and L. Latruffe. 2017. "Greenhouse gas emissions and efficiency in French sheep meat farming: A non-parametric framework of pollution-adjusted technologies." *European Review of Agricultural Economics* 44(1):33–65.

Davey, S., A. Davey, S. Adnish, and R. Bagga. 2014. "Study of impact of sociocultural and economic factors of mothers on the nutritional status of their malnourished children in a rural area of Delhi, India." *International Journal of Medical Science and Public Health* 4(2):1.

Daymont, T.N., and P.J. Andrisani. 1984. "Job Preferences, College Major, and the Gender Gap in Earnings." *The Journal of Human Resources* 19(3):408.

Dercon, S., and A. Singh. 2013. "From Nutrition to Aspirations and Self-Efficacy: Gender Bias over Time among Children in Four Countries." *World Development* 45:31–50.

Elliott, J. 2012. *An Introduction to Sustainable Development* 4th ed. London: Routledge.

Fafchamps, M., and A.R. Quisumbing. 2005. "Marriage, Bequest, and Assortative Matching in Rural Ethiopia." *Economic Development and Cultural Change* 53(2):347–380.

Färe, R., S. Grosskopf, and F. Hernandez-Sancho. 2004. "Environmental performance: an index number approach." *Resource and Energy Economics* 26(4):343–352.

Färe, R., S. Grosskopf, D.-W. Noh, and W. Weber. 2005. "Characteristics of a polluting technology: theory and practice." *Journal of Econometrics* 126:469–492.

Färe, R., S. Grosskopf, and G. Whittaker. 2013. "Directional output distance functions: endogenous directions based on exogenous normalization constraints." *Journal of Productivity Analysis* 40(3):267–269.

Feng, G., and A. Serletis. 2014. "Undesirable outputs and a primal Divisia productivity index based on the directional output distance function." *Journal of Econometrics* 183(1):135–146.

Garrett, J.L., and M.T. Ruel. 1999. "Are determinants of rural and urban food security and nutritional status different? Some insights from Mozambique." *World Development* 27(11):1955–1975.

Ghanem, D., and J. Zhang. 2014. "'Effortless Perfection:' Do Chinese cities manipulate air pollution data?" *Journal of Environmental Economics and Management* 68(2):203–225.

Grace, K., F. Davenport, C. Funk, and A.M. Lerner. 2012. "Child malnutrition and climate in Sub-Saharan Africa: An analysis of recent trends in Kenya." *Applied Geography* 35(1–2):405–413.

Hampf, B., and J.J. Krüger. 2013. "Darmstadt Discussion Papers in Economics Optimal Directions for Directional Distance Functions: An Exploration of Potential Reductions of Greenhouse Gases Optimal Directions for Directional Distance Functions: An Exploration of Potential Reductions of Gre."

Han, J., and Y. Hayashi. 2008. "Assessment of private car stock and its environmental impacts in China from 2000 to 2020." *Transportation Research Part D: Transport and Environment* 13(7):471–478.

He, K., H. Huo, and Q. Zhang. 2002. "Urban Air Pollution in China : Current Status, Characteristics, and Progress." *Annual Review of Energy and the Environment* 27(1):397–431.

Hu, D., and J. Jiang. 2013. "A Study of Smog Issues and PM 2 . 5 Pollutant Control Strategies in China." *Journal of Environmental Protection* 4(July):746–752.

Hyman, R.C., J.M. Reilly, M.H. Babiker, A. De Masin, and H.D. Jacoby. 2002. "Modeling non-CO 2 greenhouse gas abatement." *Environmental Modeling and Assessment* 8:175–186.

Kasman, A., and Y.S. Duman. 2014. "CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: A panel data analysis." *Economic Modelling* 44:97–103.

Kebede, B. 2005. "Genetic Endowments, Parental and Child Health in Rural Ethiopia." *Scottish*

Journal of Political Economy 52(2):194–221.

Kebede, E. 2006. “Moving from Emergency Food Aid to Predictable Cash Transfers: Recent Experience in Ethiopia.” *Development Policy Review* 24(5):579–599.

Koohi-kamali, F. 2008. “Intrahousehold Inequality and Child Gender Bias in Ethiopia.” *World Bank Policy Research Working Paper* (October).

Lazzaroni, S., and N. Wagner. 2016. “Misfortunes never come singly: Structural change, multiple shocks and child malnutrition in rural Senegal.” *Economics & Human Biology* 23:246–262.

Lee, C.-Y., and P. Zhou. 2015. “Directional shadow price estimation of CO2, SO2 and NOx in the United States coal power industry 1990–2010.” *Energy Economics* 51:493–502.

Li, X., X. Wu, and F. Zhang. 2015. “A method for analyzing pollution control policies: Application to SO2 emissions in China.” *Energy Economics* 49:451–459.

Li, Z., H. Folmer, and J. Xue. 2014. “To what extent does air pollution affect happiness? The case of the Jinchuan mining area, China.” *Ecological Economics* 99:88–99.

te Lintelo, D.J.H., and R.W.D. Lakshman. 2015. “Equate and Conflate: Political Commitment to Hunger and Undernutrition Reduction in Five High-Burden Countries.” *World Development* 76:280–292.

Luechinger, S. 2014. “Air pollution and infant mortality: A natural experiment from power plant desulfurization.” *Journal of Health Economics* 37(1):219–231.

Malikov, E., S.C. Kumbhakar, and M.G. Tsionas. 2016. “A Cost System Approach to the Stochastic Directional Technology Distance Function with Undesirable Outputs: The Case of us Banks in 2001-2010.” *Journal of Applied Econometrics* 31(7):1407–1429.

Malla, S. 2013. “Household energy consumption patterns and its environmental implications:

Assessment of energy access and poverty in Nepal.” *Energy Policy* 61:990–1002.

Maradan, D., and A. Vassiliev. 2005. “Marginal Costs of Carbon Dioxide Abatement: Empirical Evidence from Cross-Country Analysis.” *Swiss Journal of Economics and Statistics (SJES)* 141(III):377–410.

Marten, A.L., and S.C. Newbold. 2012. “Estimating the social cost of non-CO 2 GHG emissions: Methane and nitrous oxide.” *Energy Policy* 51:957–972.

Matsushita, K., and F. Yamane. 2012. “Pollution from the electric power sector in Japan and efficient pollution reduction.” *Energy Economics* 34(4):1124–1130.

Matus, K., K.M. Nam, N.E. Selin, L.N. Lamsal, J.M. Reilly, and S. Paltsev. 2012. “Health damages from air pollution in China.” *Global Environmental Change* 22(1):55–66.

May, J., and I.M. Timæus. 2014. “Inequities in under-five child nutritional status in South Africa: What progress has been made?” *Development Southern Africa* 31(6):761–774.

Maza, A., J. Villaverde, and M. Hierro. 2015. “Non-CO2 Generating Energy Shares in the World: Cross-Country Differences and Polarization.” *Environmental and Resource Economics* 61(3):319–343.

Molinos-Senante, M., N. Hanley, and R. Sala-Garrido. 2015. “Measuring the CO2 shadow price for wastewater treatment: A directional distance function approach.” *Applied Energy* 144:241–249.

Mukhopadhyay, K., and O. Forssell. 2005. “An empirical investigation of air pollution from fossil fuel combustion and its impact on health in India during 1973-1974 to 1996-1997.” *Ecological Economics* 55(2):235–250.

Muller, B.N.Z., R. Mendelsohn, and W. Nordhaus. 2011. “American Economic Association Environmental Accounting for Pollution in the United States Economy Author (s):

Nicholas Z . Muller , Robert Mendelsohn and William Nordhaus Source : The American Economic Review , Vol . 101 , No . 5 (AUGUST 2011), pp . 1.” 101(5):1649–1675.

Mussa, R. 2015. “Intrahousehold and interhousehold child nutrition inequality in malawi.” *South African Journal of Economics* 83(1):140–153.

Njuki, E., B.E. Bravo-ureta, and D. Mukherjee. 2016. “The Good and the Bad : Environmental E ffi ciency in Northeastern U . S . Dairy Farming.” *Agricultural and Resource Economics Review* 45/1:22–43.

Oaxaca, R. 1973. “Male-female wage differentials in urban labor markets.” *International economic review* (14):693–709.

Omri, A. 2013. “CO2 emissions, energy consumption and economic growth nexus in MENA countries: Evidence from simultaneous equations models.” *Energy Economics* 40:657–664.

Oyekale, A.S. 2014. “Factors Explaining Child Survival in Ethiopia: Application of Two-Stage Probit Model.” *African Development Review* 26(2):237–249.

Panagariya, A. 2013. “Does India Really Suffer from Worse Child Malnutrition Than Sub-Saharan Africa?” *Economic and Political Weekly* 48(18):98–111.

Park, A., and P. Rukumnuaykit. 2004. “Eat Drink Man Woman: Testing for Gender Bias in China Using Individual Nutrient Intake Data.” (May 2016).

Pathak, P.K., and A. Singh. 2011. “Trends in malnutrition among children in India: Growing inequalities across different economic groups.” *Social Science and Medicine* 73(4):576–585.

Pulok, M.H., M.N.-U. Sabah, and U. Enemark. 2016. “Socioeconomic inequalities of child malnutrition in Bangladesh.” *International Journal of Social Economics* 43(12):1439–1459.

Quah, E., and T.L. Boon. 2003. “The economic cost of particulate air pollution on health in

Singapore." *Journal of Asian Economics* 14(1):73–90.

Quisumbing, A.R. 2003. "Food Aid and Child Nutrition in Rural Ethiopia." *World Development* 31(7):1309–1324.

Rammel, C., and J.C.J.M. van den Bergh. 2003. "Evolutionary policies for sustainable development: adaptive flexibility and risk minimising." *Ecological Economics* 47(2–3):121–133.

Rashad, A., and M. Sharaf. 2015. "Does Economic Growth Reduce Child Malnutrition in Egypt? New Evidence from National Demographic and Health Survey." *Working Papers*.

Rieger, M., and N. Wagner. 2015. "Child health, its dynamic interaction with nutrition and health memory - Evidence from Senegal." *Economics and Human Biology* 16:135–145.

Rostow, W.W. 1959. "The Stages of Economic Development." *The Economic History Review* 12(1):1–16.

Rutstein, S. 1999. "Wealth versus expenditure: Comparison between the DHS wealth index and household expenditures in four departments of Guatemala." *Calverton, Maryland: ORC Macro*.

Salvucci, V. 2015. "Determinants and Trends of Socioeconomic Inequality in Child Malnutrition: The Case of Mozambique, 1996–2011." *Journal of International Development*.

S Solomon, M.M. D Qin, Z Chen, M Marquis, KB Averyt, M Tignor, and HL Miller (Eds.). 2007. "Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change." :996.

Scheel, H. 2001. "Undesirable outputs in efficiency valuations." *European Journal of Operational Research* 132(2):400–410.

Schmidt, P., and R.C. Sickles. 1984. “Production Frontiers and Panel Data.” *Journal of Business & Economic Statistics* 2(4):367–374.

Seiford, L.M., and J. Zhu. 2002. “Modeling undesirable factors in efficiency evaluation.” *European Journal of Operational Research* 142(1):16–20.

Seleshi, Y., and U. Zanke. 2004. “Recent changes in rainfall and rainy days in Ethiopia.” *International Journal of Climatology* 24(8):973–983.

Simar, L., and P.W. Wilson. 2007. “Estimation and inference in two-stage, semi-parametric models of production processes.” *Journal of Econometrics* 136(1):31–64.

Sinning, M., M. Hahn, and T.K. Bauer. 2008. “The Blinder–Oaxaca decomposition for nonlinear regression models.” *The Stata Journal* 8(4):480–492.

Smith, L.C., M.T. Ruel, and A. Ndiaye. 2005. “Why Is Child Malnutrition Lower in Urban Than in Rural Areas? Evidence from 36 Developing Countries.” *World Development* 33(8):1285–1305.

Solomon, S., D. Qin, M. Manning, K. Averyt, and M. Marquis. 2007. *Climate change 2007-the physical science basis: Working group I contribution to the fourth assessment report of the IPCC*.

Song, M., W. Zheng, and Z. Wang. 2016. “Environmental efficiency and energy consumption of highway transportation systems in China.” *International Journal of Production Economics* 181:441–449.

Stern, D.I., and M.S. Common. 2001. “Is There an Environmental Kuznets Curve for Sulfur?” *Journal of Environmental Economics and Management* 41:162–178.

Tesfu, S.T., and S. Gurmu. 2013. “Mother’s Gender Preferences and Child Schooling in Ethiopia.” *Atlantic Economic Journal* 41(3):265–277.

Tian, H., J. Gao, L. Lu, D. Zhao, K. Cheng, and P. Qiu. 2012. “Temporal trends and spatial variation characteristics of hazardous air pollutant emission inventory from municipal solid waste incineration in China.” *Environmental science & technology* 46(18):10364–71.

Tiba, S., and A. Omri. 2017. “Literature survey on the relationships between energy, environment and economic growth.” *Renewable and Sustainable Energy Reviews* 69:1129–1146.

Tyteca, D. 1996. “On the Measurement of the Environmental Performance of Firms— A Literature Review and a Productive Efficiency Perspective.” *Journal of Environmental Management* 46(3):281–308.

Valadkhani, A., I. Roshdi, and R. Smyth. 2016. “A multiplicative environmental DEA approach to measure efficiency changes in the world’s major polluters.” *Energy Economics* 54:363–375.

Viard, V.B., and S. Fu. 2015. “The effect of Beijing’s driving restrictions on pollution and economic activity.” *Journal of Public Economics* 125:98–115.

van Vliet, O., V. Krey, D. McCollum, S. Pachauri, Y. Nagai, S. Rao, and K. Riahi. 2012. “Synergies in the Asian energy system: Climate change, energy security, energy access and air pollution.” *Energy Economics* 34(SUPPL. 3):S470–S480.

Wagstaff, A., and N. Watanabe. 2003. “What difference does the choice of SES make in health inequality measurement?” *Health Economics* 12(10):885–890.

Wang, T.J., R.J. Lin, and L.J. Lee. 1995. “Tool Heat Transfer Analysis in Resin Transfer Molding.” *International Polymer Processing* 10(4):364–373.

Wang, X., and D.L. Mauzerall. 2006. “Evaluating impacts of air pollution in China on public health: Implications for future air pollution and energy policies.” *Atmospheric Environment*

40(9):1706–1721.

World Food Programme (WFP), and Center for Disease Control and Prevention (CDC). 2005. “Defining and Measuring Malnutrition •.” *A Manual: Measuring and Interpurtin malnutrition and Mortality* 1:15–32.

Xiao, Q., Z. Ma, S. Li, and Y. Liu. 2015. “The Impact of Winter Heating on Air Pollution in China.” *PLoS ONE* 10(1):e0117311.

Yamano, T., H. Alderman, and L. Christiaensen. 2005. “Child Growth, Shocks, and Food Aid in Rural Ethiopia.” *American Journal of Agricultural Economics* 87(2):273–288.

Zelenyuk, V. 2014. “Directional vs. Shephard’s distance functions.” *Optimization Letters* 8(8):2185–2189.

Zewdie, T., and D. Abebaw. 2013. “Determinants of Child Malnutrition : Empirical Evidence from Kombolcha District of Eastern Hararghe Zone , Ethiopia.” *Quarterly Journal of International Agriculture* 52(4):357–372.

Zhang, N., and Y. Choi. 2014. “A note on the evolution of directional distance function and its development in energy and environmental studies 1997–2013.” *Renewable and Sustainable Energy Reviews* 33:50–59.

Zheng, S., and M.E. Kahn. 2013. “Understanding China’s Urban Pollution Dynamics.” *Journal of Economic Literature* 51(3):731–772.

Zheng, S., C. Sun, Y. Qi, and M.E. Kahn. 2014. “the Evolving Geography of China’S Industrial Production: Implications for Pollution Dynamics and Urban Quality of Life.” *Journal of Economic Surveys* 28(4):709–724.

Zheng, S., R. Wang, E.L. Glaeser, and M.E. Kahn. 2011. “The greenness of China: Household carbon dioxide emissions and urban development.” *Journal of Economic Geography*

11(5):761–792.

Zhou, P., B.W. Ang, and K.L. Poh. 2008. “Measuring environmental performance under different environmental DEA technologies.” *Energy Economics* 30(1):1–14.