Growth, Carbon Dioxide Emissions, Climate and Wellbeing

Dissertation

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Zusammenfassung

Die fünf Essays dieser Dissertation behandeln Themen aus dem Bereich der Entwicklungs- und Umweltökonomie. Alle Essays analysieren wie die Produktion von CO_2 Emissionen beeinflusst oder reguliert werden kann. Das Treibhausgas CO_2 ist eine der größten Externalitäten der Geschichte menschlicher Entwicklung. Die einzelnen Essays zeigen wie lokale Klimaveränderungen das menschliche Wohlbefinden beeinflussen und welche monetären Kosten mit einem Anstieg der Durchschnittstemperatur in Lateinamerika verbunden sind. Außerdem betrachten die Essays Hauptdeterminanten von CO_2 Emissionen auf haushalts- oder nationalem Niveau, und bestimmen den Erfolg aktueller Klimapolitik um CO_2 Emissionen zu reduzieren. Das letzte Essay betrachtet die momentane und zukünftige Verteilung von CO_2 Emissionen wenn verschiedene Politikszenarien realisiert werden würden.

Das erste Essay befasst sich mit dem Effekt von klimatischen Veränderungen auf das Wohlfahrtsniveau in Lateinamerika. Als Wohlfahrtsmaß kommen dabei subjektive Selbstaussagen zum Einsatz. Subjektive Wohlfahrt erfasst nicht nur Veränderungen im Einkommen, sondern auch Veränderungen in anderen Lebensbereichen wie dem Zugang zu Bildung oder Gesundheitseinrichtungen. Generell kommt die Studie zu dem Schluss, dass eine Temperatur im Bereich von 20 Grad Celsius und Niederschlag bis 247mm optimal sind. Höhere monatliche Durchschnittstemperaturen oder Niederschläge sind mit Wohlfahrtsverlusten verbunden. Eine globale Erwärmung von mehr als 2 Grad Celsius wird mit Wohlfahrtsverlusten in Lateinamerika einhergehen.

Das zweite Essay analysiert Haushaltsemissionen in Form des Kohlenstoff-Fußabdrucks in Indien. Dabei liegt das Augenmerk auf dem Effekt von Einkommenswachstum und sozio-ökonomischen Veränderungen innerhalb der Haushalte. Ein höheres Haushaltseinkommen führt zu einem stärkeren Konsumverhalten aber gleichzeitig auch zu weniger CO_2-intensiven Konsummustern. Dennoch kann der Mehrkonsum an CO_2-armen Gütern, wie zum Beispiel Bildung, den Anstieg der Haushaltsemissionen, aufgrund höheren Einkommens, nicht kompensieren.

Das dritte Essay betrachtet in wie fern aktuelle internationale Klimapolitik einen Einfluss auf CO_2 Emissionen genommen hat. Dabei zeigt sich, dass Länder, welche Verpflichtungen im Rahmen des Kyoto Protokolls eingegangen sind, im Durschnitt 6.5%

weniger CO_2 emittiert haben, als vergleichbare Länder mit ähnlichem Einkommens- und Bevölkerungswachstum aber ohne Verpflichtungen.

Das vierte Essay geht auf die Hauptdeterminante des CO_2 Emissionswachstums ein, nämlich Einkommen. Dabei wird aber nicht nur der Effekt von Veränderungen im Einkommen, sondern auch der Effekt von Veränderungen in der Einkommensverteilung auf CO_2 Emissionen untersucht. Einkommensungleichheit wirkt sich abhängig vom gegenwertigen Ungleichheitsniveau auf CO_2 Emissionen aus. Für Länder mit einer hohen Einkommensungleichheit ist der Effekt positiv, das heißt mit sinkender Einkommensungleichheit sinken CO_2 Emissionen. Für Länder mit niedriger Ungleichheit ist der Effekt negativ. Ein weiterer Abbau der Einkommensungleichheit würde dort mit steigenden CO_2 Emissionen einhergehen.

Das fünfte Essay befasst sich mit der globalen Verteilung von pro Kopf CO_2 Emissionen. Dabei geht es darum inwiefern der Energiemix und der sektorale Aufbau einzelner Volkswirtschaften zu dieser ungleichen Verteilung von pro Kopf CO_2 Emissionen beigetragen haben. Der Abbau schwerer Industrie in OECD Ländern und der verstärkte Einsatz von Kohle in nicht-OECD Ländern haben dabei zu einem Rückgang der globalen Ungleichheit in CO_2 Emissionen geführt. Langfristig gesehen kann es sein, dass die Emissionsungleichheit ab 2040 wieder steigen wird.

Jedes Essay trägt in seinem Feld zur betreffenden Literatur bei. Die Essays analysieren wie jegliche ökonomische Aktivität (hauptsächlich Konsum) CO_2 Emissionen verursachen, welche wiederum für Veränderungen im Klima verantwortlich gemacht werden. Diese Veränderungen im Klima gehen mit lokalen Wohlfahrtsverlusten einher. Nationale Politikmaßnahmen wie zum Beispiel Maßnahmen zur Einkommensumverteilung können einen ambivalenten Einfluss auf CO_2 Emissionen haben. Politikmaßnahmen um das Konsumverhalten und Konsummuster zu beeinflussen könnten ein effizientes Mittel zur Regulierung von CO_2 Emissionen in reichen Ländern darstellen. Generell könnten internationale Klimapolitikmaßnahmen nationale Politikmaßnahmen katalysieren.

Summary

The five essays of this dissertation combine topics from development and environmental economics. All essays treat the overall topic on how to influence and regulate the production of CO_2 emissions. The green house gas CO_2 is one of the biggest externalities from human development during the last century. The essays give insight on how changes in local climate conditions affect human wellbeing and what are the potential monetary loses from a rise in average temperature in Latin America. They further analyze the major drivers of CO_2 emissions at the household as well as national level and assess how current international climate policy has contributed to reduce CO_2 emissions. The last essay gives an overview on how unequal emissions are globally distributed and what will be the future distribution of CO_2 emissions when taking different policy scenarios into account.

The first essay analyzes how changes in local climatic conditions affect the level of welfare in Latin America. Self reported wellbeing levels are used as a proxy for individual welfare. Subjective wellbeing does not only account for changes in individual income but also for changes in other areas, which determine overall welfare, such as the access to health care or schooling. The study finds that a temperature up to 22 degrees Celsius and rainfall up to 247mm are beneficial for human wellbeing. Higher temperatures or rainfall go in line with welfare loses. A global average warming of 2 degrees Celsius would go in line with welfare loses in Latin America.

The second essay analyzes household emissions from consumption, the so-called carbon footprint, in India. The study focuses on the effect of changes in income and the socio-economic composition of the household. A higher household income leads to higher consumption but at the same time the goods, which are consumed change towards lower carbon intensive goods. Still the change in the consumption pattern does not offset the higher carbon footprint due to overall higher consumption rates with rising income.

The third essay evaluates how current international climate policy did influence CO_2 emissions. Countries with obligations from the Kyoto Protocol did indeed emit on average 6.5% less CO_2 than comparable countries with similar income and population growth but without any commitments from Kyoto Protocol.

The fourth essay analyzes the main determinant of rising CO_2 emissions, namely income. The focus is not on changes in income but on changes in the income distribution within a country and its effect on CO_2 emissions. The relationship between carbon dioxide

emissions per capita and income inequality is U-shaped: for countries characterized by high income inequality, reductions in income inequality are associated with lower per capita emissions. For less unequal societies, reductions in income inequality are associated with increases in carbon emissions per capita.

The fifth essay studies the global distribution of per capita CO_2 emissions. The focus is on the effect the energy mix and the sectoral composition have on emission inequality. The decline of heavy manufacturing in OECD countries and the rise of using coal in non-OECD countries led to a decline of global inequality in per capita CO_2 emissions. In the long run there is the possibility that emission inequality will rise again.

Each essay contributes to the literature in its specific field. They analyze how economic activities (mostly consumption) influence CO_2 emissions, which are considered responsible for changes in climatic conditions. At the same time those changes in climatic conditions affect human wellbeing and go in line with monetary loses. National policies such as redistributive policies can have an influence on national CO_2 emissions in both directions and have to be well planned. Policies to influence consumption habits towards less CO_2 intensive goods could be efficient to regulate CO_2 emissions but might only be feasible in richer countries. International climate policies have shown an impact on CO_2 emissions among participating countries. International policies can help to get national policies to reduce CO_2 emissions on the way.

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Introduction

Motivation and Objectives

Kellogg stated already in 1987 that "there is now a strong consensus that the observed increase in the atmospheric concentrations of carbon dioxide and other infrared-absorbing trace gases is indeed warming the earth, and that this change is caused by mankind" Kellogg (1987, 113). The increasing share of CO_2 emissions in the atmosphere is attributed to burning fossil fuels, which is directly or indirectly involved in almost any economic activity. The green house effect refers to a rise in average global surface temperature due to the increasing amount of green house gas (GHG) emissions in the atmosphere. The most common GHG is CO_2, which accounted for 81.1% of total GHGs in 2009. Further important GHGs, which are regulated under the Kyoto Protocol, are methane (NH_4) and nitrous oxide (N_2O). Those two gases are released in smaller quantities than CO_2 but exhibit a higher global warming potential (IPCC 2007b; UNFCCC 2010).[1]

Recent data from the Carbon Dioxide Information Analysis Center (CDIAC 2012) reveals that globally emitted CO_2 increased by more than 50% between 1980 and 2008. Global gross domestic product (GDP) in purchasing power parities did almost triple in the same time. And world population, another important determinant of CO_2 emissions, did almost double. During the last decades GDP and CO_2 emissions followed the same steeply rising trend. GDP growth is a synonym for development and rising welfare. Cutting CO_2

[1] The global warming potential refers to the measure of how much heat a certain GHG traps in the atmosphere relative to how much heat is trapped by the same quantity of CO_2.

emissions is a difficult topic as it is associated with cutting GDP growth and long run welfare. When turning to average per capita CO_2 emissions and GDP the development appears less dramatic. Per capita CO_2 did slightly rise between 1980 and 2008. The CO_2 emission intensity per unit of GDP did even decline.

What those trends cannot reveal is the distribution of CO_2 emissions. Just as wealth emissions are unequally distributed within and across countries. The Gini coefficient for CO_2 emissions declined from 0.58 to 0.4 between 1980 and 2008.[2] This decline in global emission inequality is due to a rising share of emissions from emerging countries. The world top three CO_2 emitters in 2008 were China, USA and India. In terms of per capita CO_2 emissions they rank only 78, 12 and 139 respectively (CDIAC 2010).

Currently GHGs are regulated on the basis of the emissions produced in a country. In 2008 China's exports accounted for 35% of its GDP meanwhile its imports accounted only for 27% (World Bank 2012). Hence part of the emissions, which were released in China, were consumed elsewhere. To account for the consumed rather than the produced emissions Hertwich & Peters (2009) estimate the total emissions consumed by households. When applying this accounting method the average US household is ranked first with the highest emissions based on consumption.

With the above introduction on the evolution and accounting of CO_2 emissions I point to the complexity of the subject and the difficulties how to regulate GHG emissions. Chapter 2 to 4 present a method on how to account for CO_2 emissions, which are consumed by households, and also show how current international and national policies do influence CO_2 emissions.

There are large uncertainties on the costs of climate change and how to estimate them. Various studies analyze the welfare effects of climate change. Nordhaus (1994) developed a dynamic integrated model of climate and the economy (DICE). His model allows an assessment of the costs and benefits from climate change while controlling for changes in economic behavior, concentrations of GHGs and the impact of policies to regulate those gases. The 2007 version of the DICE model estimates average damage costs of 3% of global GDP in 2100. This damage is related to a projected rise in global mean temperature

[2] The Gini coefficient is coded between 0 and 1, with 1 indicating total inequality and 0 indicating total equality.

by 3.1°C until 2100. Sterns (2007) model estimates potential damages from climate change of 5% of annual GDP. Nevertheless, the potential costs of climate change vary by region. Those countries with a large agricultural sector and those located closer to the equator will face higher costs than those countries located further away from the equator (Tol 2002).

All those models are useful but none of them considers that wellbeing consists of more than GDP per capita. Furthermore none of the models analyses the level of the individual as they all analyze potential losses of country or regional averaged GDP per capita. Subjective wellbeing allows measuring individual welfare in a broader scope. It refers to self-reported levels of life satisfaction. Life satisfaction is mostly determined by individual income. Apart from income, individual characteristics as well as family- and social relations matter. Thus subjective wellbeing covers more than one dimension of human wellbeing. Climate has a direct influence on subjective wellbeing through physiological and psychological effects like the willingness to engage in social activities or individual mood (Sanders & Brizzolara 1982). Furthermore it has a direct effect on individual income through opportunity costs, which arise for example from higher heating or cooling expenses (Nord & Kantor 2006).

This thesis consists of five empirical essays, which cover research topics from development as well as environmental economics, which currently experience a range of overlapping research topics due to the economics of climate change. Even though the methods and the datasets applied differ largely, the main hypotheses are all built around four key variables GDP, CO_2 emissions, Climate and Wellbeing. The aim of the dissertation is to contribute in each of the fields of the different essays. The hypotheses are:

1. Do changes in the current climatic conditions have an effect on individual welfare measured by subjective wellbeing?
2. What are the determinants of different CO_2 emission levels between households and over time in emerging countries?
3. Is there an effect from current climate policy on CO_2 emissions or did the Kyoto Protocol fail?
4. How much and where will CO_2 emissions rise when poor countries face rising incomes or declining levels of income inequality?
5. How did the global distribution of CO_2 emissions change during the last decades and what are the determinants of this change?

Outline

Chapter 1 refers to the potential costs of climate change and analyzes the relationship between self-reported levels of subjective wellbeing as a non-income welfare measure and climate variables such as temperature, precipitation rates, wind or the number of cloud covered days. It estimates the effects from events related to differences in the local climate on subjective wellbeing and identifies possible welfare losses and gains due to climate change. A linear probability model and a pseudo panel approach are applied to analyze survey data from the Latinobarómetro, which covers the years 1997-2008. The different models control for individual characteristics as well as cohort effects and the macroeconomic environment. The findings indicate an inverse N-shaped relationship between an increase in temperature as well as precipitation rates and subjective wellbeing. At turning points of 22°C and 247mm higher monthly mean temperatures or higher monthly precipitation rates lead to declining levels of subjective wellbeing. Those results remain robust even after controlling for generational fixed effects via cohorts or when applying a different climate dataset. To offset the negative effect of a mean temperature rise by 1°C, GDP per capita growth would have to rise 10%. This effect is large and depends on the current mean temperature levels in each country.

Chapter 2, which is joint work with my colleagues Mirjam Harteisen, Jann Lay, Jan Minx and Sebastian Renner, deals with the question of how to account for CO_2 emissions and what are the major determinants behind rising emissions? Therefore we estimate total emissions, which are attributed to the expenditure of single households in India during 2004/05 and 2009/10. We analyze the effect of rising income, household characteristics or changes in the composition of household consumption. First, we apply input-output energy analysis in combination with household expenditure survey data to calculate the carbon footprint of households. Second, we analyze the respective emission drivers such as income and household characteristics. We further decompose the rise in household emissions between 2004/05 and 2009/10 to isolate the effect of income and potential changes in composition of household consumption. Finally we estimate income elasticities for a number of important consumption sub-categories, differentiating between households by income quintiles. By disaggregating household expenditure, we reveal how consumption patterns change when households become more affluent. The increasing in household income between 2004/05 and 2009/10 explains most of the rise emissions and changes in the consumption patterns cannot offset this effect. But there is evidence that consumption is less carbon intensive with rising income.

Chapter 3, which is joint work with Inmaculada Martinez-Zarzoso, analyses the impact of the Kyoto Protocol on CO_2 emissions. A dynamic panel data estimator and a difference-in-differences estimator with matching are applied for a cross-section of 213 countries over the period 1960 to 2008. The model specifically considers the endogeneity of the policy variable. To provide causality we apply two different approaches. First, number of financed projects from the Clean Development Mechanism (CDM) is used as an external instrument. Second, we match the countries based on GDP and population to create a suitable counterfactual and re-estimate the model for the matched sample. The main results indicate that obligations from the Kyoto Protocol have a measurable reducing effect on CO_2 emissions and indicate that a treaty often seen as "failed" in fact may be producing some non-trivial effects.

Chapter 4, which is joint work with Stephan Klasen, Inmaculada Martinez-Zarzoso and Chris Muris, builds on the model from Chapter 3. Instead of a policy variable now income inequality is analyzed. We document a U-shaped relationship between income inequality and CO_2 emissions per capita, using a newly available panel data set on income inequality (Gini) with observations for 138 countries over the period 1960-2008. Our findings suggest that, for high-income countries with high-income inequality, pro-poor growth and reduced per capita emissions levels go hand in hand.

Last but not least Chapter 5, which is joint work with Michael Jakob and Ioanna Mouratiadou, analyzes the evolution of inequality in global CO_2 per capita emissions from 1971 to 2008. It decomposes the Gini index of total emissions by primary energy carriers and by economic sectors. Within a sample of 90 countries the results indicate that the Gini index declined from about 0.6 in 1971 to slightly above 0.4 in 2008. From the perspective of primary energy carriers this can be mainly attributed to a significant reduction in the contribution of emissions from oil and coal, explained by declining shares of emissions from coal and oil in total emissions and the decreasing Gini coefficient of emission from each of these sources. From the perspective of economic sectors, the decline in overall inequality is almost entirely due to a pronounced decline of the contribution of emissions from manufacturing & construction, for which the declining share of emissions from this sector and the declining Gini within this sector are of comparable importance. Our analysis also suggests that an equally spread emission reduction from any one source (i.e. primary energy carrier or economic sector) would not have a major impact on overall emission inequality. Finally, we find that for plausible future scenarios, emission inequality is projected to increase again from 2030 on, regardless of whether business as usual or stabilization of the atmospheric greenhouse gas concentration at 450ppm CO_2 is assumed.

Chapter 1: Subjective Wellbeing and Changes in Local Climate Conditions

1.1 Introduction

Today, climate change related risks for growth and development are widely acknowledged. The likely consequences of rising sea levels, increasing mean temperatures, more extreme weather events or desertification have been investigated and attempts have been made to assess the economic costs of climate change. Early studies estimated substantial cost of 2% of global income by 2100 (Pearce et al. 1996) but largely ignored potential benefits of global warming and the mitigating effects of adaptation. Depending on the assumptions made, recent studies, which explicitly consider the more complex interplay between climate change and economic responses, vary a lot regarding the predicted costs. The Stern Review (2007) on the economics of climate change forecasts large damages, which are equivalent to 5% of global GDP per year. Other studies arrive at much lower costs of 0.2% of global GDP (Mendelsohn & Williams 2004; Tol 2002). The 4th Assessment Report on Climate Change by the IPCC (2007a) assesses the potential costs of climate change mitigation. Costs vary largely depending on the respective stabilization target of CO_2 concentrations in the atmosphere e.g. 500ppm or 650ppm by 2030 or 2050.[3] The ambitious target of 500ppm by 2050, which is required to prevent a long run global mean temperature rise of more than 2°C, may cost up to 5.5% of global GDP. But the less ambitious target of 650pp by 2030 on the other hand may cost up to 1.2% of global GDP (IPCC 2007a). Since there are many uncertainties regarding the magnitude of climate change effects and when they will fully materialize, the underlying assumptions need to be clearly spelled out when interpreting these estimates.

In terms of regional distribution of climate change effects, previous studies concluded that some countries and regions are more vulnerable than others. In particular, countries with a relatively large agricultural sector and regions located in low latitudes will be affected more severely. Since both facts apply to many developing countries, it is safe to reason that the poorest in Africa and Southeast Asia will have to face the bulk of damages from climate change, whereas estimates for advanced countries suggest zero or even positive net market impacts (Maddison & Rehdanz 2011; Mendelsohn et al. 2006).

Evaluating the economic costs is a useful exercise to estimate the financial consequences of climate change and evaluating alternative mitigation strategies. However, to fully

[3] Parts per million refers to the concentration of CO_2 emissions in the atmosphere.

capture overall welfare impacts of climate change, a solely monetary approach is unlikely to suffice. Conceptual as well as empirical research has demonstrated that welfare is not necessarily an objective phenomenon that can be captured by monetary measures alone, but rather an encompassing concept and closely associated with the subjective assessment of the current state of being (Frey & Stutzer 2002; Kapteyn et al. 1988). Extensive empirical research on determinants of subjective wellbeing (SWB) verified the impact of individual, regional and national factors on personal welfare. It is now very well understood that besides financial resources, SWB is determined by personal characteristics like age, gender, education or health, as well as the broader economic conditions like inflation, unemployment or the level of income inequality (Dolan et al. 2008).

Few studies such as Ferrer-i-Carbonell & Gowdy (2007), Rehdanz & Maddison (2005) and Frijters & Van Praag (1998) have looked at the impact of environmental aspects like pollution and climatic conditions on SWB and their results suggest that these factors are equally important. Two studies close to this analysis are Brereton et al. (2008) and Becchetti et al. (2007). The former one uses data on individual life satisfaction of about 1500 households in Ireland in 2001 and combines this data with gridded climate data.[4] Their findings suggest a positive effect from increasing temperatures and a negative effect from rising wind speed on life satisfaction. Becchetti et al. (2007) use data on individual happiness with about 120000 observations from more than 50 different countries in 2000/01 from the World Value Survey and match it with county averaged climate data. They find that an increasing mean temperature and wind speed have both a negative effect on happiness but a rise in the annual number of months with temperatures above 20°C has a positive effect on happiness.

Although my research question is similar to Brereton et al. (2008) and Becchetti et al. (2007), this study differs in a number of points. First, it applies a much larger time frame from 1997 to 2008 and is regionally focused on Latin America. This more homogeneous group of countries with similar historical background may facilitate a comparative analysis of life satisfaction. Second, it controls for generation-specific effects in form of cohorts to account for unobserved individual characteristics. Third, I rely on two alternative climate

[4] Gridded climate data refers here to data, which assigns each grid of $5km^2$ global surface to one climate data point.

data sets namely FAOClim-NET from the FAO (2010) and another dataset by Mitchell et al. (2004). I analyze the climate conditions, which were present during the month when the interview concerning individual life satisfaction was taken. Earlier studies analyzed average temperature or precipitation during the year when the interview was conducted. I therewith believe to capture a more sensitive effect of climate conditions on SWB.

The remainder of the chapter is as follows. After giving an overview on the related literature I will present the methodology and the data applied before I present the results and conclude.

1.2 Related Literature

Easterlin (1974) analyzes differences in wellbeing across countries and over time and points out that human wellbeing does not depend exclusively on income. Within countries his findings suggest a positive relationship between income and SWB, but when analyzing across countries this relationship diminishes. The Easterlin Paradox refers to this finding. Easterlin (1974) concludes that individuals compare their own wealth with the wealth of their peer group. Hence, relative income matters more for wellbeing than absolute income. Frey & Stutzer (2002) analyze the relationship between SWB and income in a cross county setting. They find that higher income on average contributes to SWB but at a diminishing rate. Therefore, one may expect large gains in SWB at lower levels of income. Frey & Stutzer (2002) conclude that individuals' aspirations adjust thus they always strive for more and these wants are insatiable. Di Tella et al. (2003) and Di Tella & R. MacCulloch (2006) test the effect of the macro-economic environment on SWB. They find that recessions create strong psychic loses besides the decline in GDP and the rise in unemployment. Finally, Di Tella & R. MacCulloch (2008) bring together macro and micro variables and disprove the Easterlin Paradox. After controlling for macroeconomic stability, crime rates, environmental degradation, working hours and life expectancy they find increasing rates of SWB with rising income even across countries.

Frijters & Van Praag (1998) investigate the impact of climate variables on life satisfaction. They analyze the impact of changes in temperature, humidity and precipitation on life satisfaction with a panel of 3727 households in Russia and find that a rise in annual minimum temperatures would lead to lower heating expenses and higher life satisfaction. Rehdanz & Maddison (2005) use country-averaged data on happiness provided by the World Database of Happiness by Veenhoven (2001) to analyze the impact of climate variables on happiness for 67 countries over the period from 1972 to 2000. Regarding the variables for climatic conditions, they apply various indices on temperature and precipitation as well as locational parameters like absolute latitude. Results from a panel-corrected least squares approach do not prove a significant effect of changes in annual average temperature or rain on happiness. But they find a negative effect of an increase in the mean temperature of the annual hottest month and a positive effect on happiness due to an increase in the mean temperature of the coldest month. By applying predicted changes in temperature and precipitation levels for 2039 and 2069, they calculate the change in income required to keep happiness at a constant level. Their results support earlier findings that high-latitude countries will benefit from climate change, but low-latitude countries are likely to suffer most. Maddison & Rehdanz (2011) analyze potential GDP per capita loses and gains based on climate change scenarios in another country panel study. In this analysis they do not refer to the hottest and coldest month's temperature as the variable of interest but refer to the number of "degree months" which represent the deviation from a generally appreciated temperature of 18.3°C. Again they find that countries located in northern Europe might gain, meanwhile African countries may have to face GDP loses based on the climate change scenarios. Becchetti et al. (2007) provide a similar setting as Maddison & Rehdanz (2011) but do not average the data on happiness over countries. They use the individually reported data on happiness and find, that a rise in the number of hot months, with temperatures above 20°C, or the number of rainy days has a positive effect on happiness; meanwhile an increase in mean temperature shows a negative effect. Brereton et al. (2008) analyze the relationship between life satisfaction and climate variables such as temperature, precipitation and wind speed in Ireland. With a geographic information system they match an individuals' place of residence precisely with the climate data and find that an increase in the temperature of the annually coldest and hottest month leads to gains in life satisfaction meanwhile a rise in wind speed leads to a decline.[5]

There are concerns about the analysis of SWB. First of all, there are two commonly used measures of SWB, which are treated equally in the literature. One, which asks for the level of life satisfaction, and a second one, which asks for the level of happiness. Stevenson & Wolfers (2008) point out that those measures should not be treated equally since they tend

[5] For an overview on the studies concerning SWB and climate refer to
Table A.1 in the Appendix to this chapter.

to measure different things. The former accounts for the individual's perception of how his or her life has been so far. Meanwhile the later one captures the current sensation of life or a state of mood when the individual is asked: "How happy are you with your life?" This difference in the perception of the question might explain the low correlation between the two variables. Another major issue is the inconsistency of the data. Krueger & Schkade (2008) tested the correlation between test and the re-test results and conclude that there is either a strong unobserved bias when answering the questions or the people are very inconsistent in their perception of SWB. Ferrer-i-Carbonell & Frijters (2004) address methodological issues and point out that the assumption of cardinal or ordinal scales makes little difference, but allowing for individual fixed effects changes the results.

The results of the studies regarding life satisfaction or happiness and climate vary a lot. This could be due to the different methods and samples applied. Rehdanz & Maddison (2005) and Maddison & Rehdanz (2011) use country averaged data on happiness and life satisfaction. They cannot control for individual characteristics such as being married or unemployed but they can control for the macroeconomic country environment such as GDP per capita growth and inflation. Frijters & Van Praag (1998) and Brereton et al. (2008) analyze individual life satisfaction in Russia and Ireland. Hence they look more homogenous but smaller samples. They can control for individual characteristics but not for the respective macroeconomic environment.

None of the studies uses the climate data from the specific month when individuals were questioned regarding their level of SWB and none of the studies controls for generation specific effects over time. I close this gap in the literature by constructing a pseudo panel and controlling for the cohort specific effect on SWB. My findings regarding monthly mean and maximum temperature as well as precipitation remain robust over all model specifications. I find an inverse N-shaped[6] relationship between mean monthly temperatures and SWB with a turning point at 22°C. Most of the observations have already past this turning point and a further rise in mean temperatures would on average lead to a decline in levels of SWB for this sample of 18 Latin American countries.

[6] The inverse N-shaped relationship describes a curve with initially declining levels of SWB until the lower turning point, which is a minimum point. After passing through the minimum levels of SWB rise until the upper turning, which is a maximum point.

1.3 Methodology

There is no profound theory, which describes how climate affects individual wellbeing, but reviewing the early literature from different disciplines reveals that weather and climatic changes affect SWB through two major channels. First from a physiological and psychological point, Gagge et al. (1967) find that the comfort temperature for undressed human beings ranges between 28 and 30°C. At this temperature there is no physiological effort needed to regulate body temperature. When deviating from this comfort temperature level the sensation of heat or cold increases and causes discomfort. Sanders & Brizzolara (1982) find that high temperatures and high humidity leads to feelings of reduced physical energy and lower interest in social contacts. Second, form an economic point of view, there are costs arising from heating or cooling when temperature or humidity levels deviate from the comfort zone. Dubin & McFadden (1984) analyze household energy demand in the US and control for heating degree-days, which they define up to an outside temperature of 18°C. Above this threshold they assume that there is no energy consumed for heating. Nord & Kantor (2006) study food insecurity of US households and find that low-income households located in states with a high number of heating and cooling degree months are more prone to suffer from food insecurity. Hence, weather and climate variables affect wellbeing directly through physiological and psychological channel and indirectly though higher expenses on energy or the construction and maintenance of homes.

1.3.1 Subjective Wellbeing as a Measure of Welfare

Initially psychologists and sociologists measured individual welfare with self-reported life satisfaction or happiness scores before economists turned their attention to this method. In the Latinobarómetro individuals indicate their level of life satisfaction on a scale from 1 to 4, with 4 being the highest level and 1 the lowest level of life satisfaction. Psychologists mostly interpret the answers as cardinal, hence a switch from level 1 to 2 for one individual is treated the same as a switch from level 3 to 4 for other individuals. Meanwhile economists assume the answers to ordinally comparable thus the relative difference between the life satisfaction responses is unknown but all individuals share the same interpretation of the possible responses on the answer scale (Ferrer-i-Carbonell & Frijters 2004).

Three main assumptions have to be made for the interpretation of the questions regarding SWB:

1. "SWB is a positive monotonic transformation of the underlying concept of welfare W and if $SWB_{il} < SWB_{ih}$ then $W_{il} < W_{ih}$
2. SWB is interpersonally ordinally comparable so if $SWB_i < SWB_j$ then $W_i < W_j$
3. SWB is interpersonally cardinally comparable so $(W_i - W_j) = f(SWB_i, SWB_j)$ with $f(.)$ being a function, which is known up to a multiplicative constant" (Ferrer-i-Carbonell & Frijters 2004, 643).

The first assumption refers to that what is measured by the SWB question is indeed reflecting individual welfare. Hence, the choice of the answer referring to high h or low l life satisfaction is correlated with the level of objective welfare. The second assumption refers to that individuals have a common understanding of SWB. In other words being very satisfied or very happy has to be understood in the same way by the individuals. Last but not least the third assumption amounts to assume that a change in SWB levels from 1 to 2 is the same as a change from 3 to 4. Furthermore a statistical assumption has to be made. There are time-invariant individual characteristics ϑ_i, which are related to the initial level of the observables $cov(\vartheta_i, x_{it}) \neq 0$ and there are time varying unobserved factors ε_{it}, which are unrelated to the observed factors $cov(\varepsilon_{it}, x_{it}) = 0$ (Ferrer-i-Carbonell & Frijters 2004).

1.3.2 Cross Sectional Analysis

I first estimate a linear probability model to allow for a strait forward interpretation of the coefficients. Robust standard errors are used to control for heteroscedasticity. Since the linear probability model does not constrain predictions between 0 and 1, an ordered probit model estimated and the results are presented in the Appendix. The linear probability model is given by:

$$SWB_{it} = \alpha + \beta_1 Indivdual\ Controls_{it} + \beta_2 GDP\ Growth\ pc_{ct} + \beta_3 Inflation_{ct} + \beta_4 Temperature_{it} + \beta_5 Hot\ Months_{it} + \beta_6 Cooling\ Months_{it} + \beta_7 Precipitation_{it} + \beta_8 Wind_{it} + \beta_9 Year_t + \beta_{10} Country_c + \beta_{11} Month_t + \varepsilon_{it} \quad (1.1)$$

where the dependent variable SWB is life satisfaction of individual *i* in year *t,* measured on a scale from 1 to 4 with the later being the highest level. The data does not have a panel structure, thus individuals vary across years. In line with Brereton et al. (2008) I control for individual characteristics such as age in years, dummies for being married, unemployed, a high school or university graduate, and being religious or male.[7] Age is associated with a non-linear effect. In younger years getting older leads to lower levels of life satisfaction, which might be due to high aspirations. After passing a certain threshold life satisfaction rises again with increasing age. Being married is generally associated with a positive coefficient, being unemployed on the other hand is associated with a negative coefficient. Years of schooling or a dummy for higher or lower education reveals that lower education levels are positively correlated with life satisfaction. Income plays a major role even though there are opposing results concerning the potential level of saturation for income where it would no longer lead to higher levels of life satisfaction (Ferrer-i-Carbonell & Frijters 2004; Dolan et al. 2008).

In the absence of a real income variable I apply the subjective economic situation, the subjective income and the objective wellbeing, which is the pollster's perception of the economic situation of the household to account for the individual income. All those income variables are categorical variables on a scale from 1 to 4 or 5.[8] Further I introduce GDP per capita growth and inflation at the country level c to control for macroeconomic shocks, which have been intensive in Latin American countries during the time of observation. I do not introduce GDP per capita and the literacy rate among adult individuals since those two variables are strongly correlated (>0.8) with the temperature variables in our dataset. Entering those variables simultaneously could cause multicollinearity problems.[9] All these micro- and macroeconomic variables are identified to have a major influence on SWB. (Dolan et al. 2008)

As Brereton et al. (2008), I introduce climate variables such as temperature (monthly mean, maximum and minimum), monthly precipitation rates and monthly mean wind speed to analyze the impact of climate on life satisfaction. Those variables enter the model as well in squared and cubic terms to control for non-linearities in the relationship between

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[7] We did apply years of schooling but did not find a significant result.

[8] The variables enter simultaneously into the analysis since they are not too strongly correlated. In a separate analysis I control relative income to control for the national level of subjective income. The results are available on request.

[9] For the table of cross correlations refer to Table A.4 to in the Appendix to this chapter.

climate and SWB. In order to test our specification we also run the analysis with a squared but without cubic weather variables and found a similar relationship between temperature and SWB with a maximum 0.9°C lower than in the model with the cubic temperature variable. Following Becchetti et al. (2007) I control for the annual number of hot months with temperatures above 20°C. Maddison & Rehdanz (2011) refer to so called cooling and heating (degree) months to account for deviations from generally appreciated climate conditions of 18.3°C. The cooling (degree) months are defined as:

$$Cooling\ Mths. = positive(Tmp.Jan. - 18.3) + \cdots + positive(Tmp.Dec. - 18.3) \quad (1.2)$$

where the monthly temperatures above 18.3°C are summed up over each year. For reason of multicollinearity each of the different temperature variables enter the regression analysis separately.

Country dummies account for country-fixed effects and the year as well month dummies account for fixed effects during the time when the life satisfaction data was gathered. Further I try to control for generation- specific effects by following cohorts over time in a pseudo panel analysis, which is described in the next section.

1.3.3 Pseudo Panel Analysis

The model specified in the previous section does not account for unobservable individual time-invariant effects such different perceptions and concepts of SWB among different generations. A way to control for individual specific effects is by constructing a pseudo panel. A linear panel estimator has the following form:

$$SWB_{it} = X'_{it}\beta + \vartheta_i + \varepsilon_{it}, \qquad t = 1, \dots, T \quad (1.3)$$

where subscript *i* indicates the observed individuals over a period of T years. X'_{it} represents the set of control variables measuring individual characteristics such as age or being married and ε_{it} is the error term. The individual time-invariant effect is captured by ϑ_i. Since panel data sets contain data for the same individual over various periods of time, it is possible to eliminate the individual specific effect by applying a within or a first difference estimator. In the Latinobarómetro dataset this is not possible since the individuals, which were asked in each wave of the survey, vary. Nevertheless, one can find the same relationship as in Equation 1.3 for cohort specific effects (Agnus Deaton 1997).

Cohorts are generated among individuals with one or more characteristics in common. I chose to generate cohorts among individuals, which were born during the same 20-year interval from 1922 to 1982 in the same country and which share the same gender. After assigning each individual to one specific cohort h I take the mean of the variables measuring the individual characteristics and get the following equation:

$$SWB_{ht} = \bar{X}'_{ht}\beta + \bar{\vartheta}_{ht} + \bar{\varepsilon}_{ht}, \qquad \mathrm{h} = 1, \dots, \mathrm{H} \text{ and } t = 1, \dots, T \tag{1.4}$$

where $\bar{X}'_{ht}$ represents the mean cohort characteristics, $\bar{\varepsilon}_{ht}$ is the mean cohort error term. The cohort specific effect $\bar{\vartheta}_{ht}$ may not be constant over time since in each survey period a different set of individuals were questioned. This implies that the mean individual effect of each cohort varies over time and is not constant. Under this condition taking first differences does not eliminate the cohort specific effect but Deaton (1997) considers the time variation of the cohort effects to be negligible if the number of individuals per cohort is large. Then Equation 1.4 changes to:

$$SWB_{ht} = \bar{X}'_{ht}\beta + \bar{\vartheta}_{h} + \bar{\varepsilon}_{ht}, \qquad \mathrm{c} = 1, \dots, \mathrm{C} \text{ and } t = 1, \dots, T \tag{1.5}$$

which would allow me to estimate SWB with a first difference or within estimator and therewith to control for the cohort specific effects $\vartheta_h$in the sample.

Another bias arises from the observed cohort mean variables, which are "error ridden" estimators of the real unobserved population cohort means. Deaton (1985) applies a so-called errors-in-variables estimator to correct for this measurement error. Verbeek & Nijman (1992) test the impact of this measurement error and find that, if the cohort size is large enough, then the results from the within estimator come close to the ones from the errors-in-variables estimator. Having a large number of observations within one cohort comes first at the price of reducing observations in the pseudo panel and second the individuals within the same cohort become more heterogeneous. Generally individuals within one cohort should be as homogenous as possible and individuals between cohorts should be as heterogeneous as possible (Verbeek & Nijman 1992).

The average cohort size in this sample is about 213 individuals. Verbeek & Nijman (1992) consider this large enough to apply the within estimator. Choosing this large number of individuals in each cohort leads to a number of 532 observations, which is still higher compared to taking averages over countries. Nevertheless, this step comes at the price of averaging SWB over the cohorts. Therefore, the depended variable is no longer categorical but continuous between 1 and 4 and Equation 1.1 changes to:

$$SWB_{ht} = \alpha + \beta_1 \overline{Indivdual\ Controls}_{ht} + \beta_2 GDP\ Growth\ pc_{ct} + \beta_3 Inflation_{ct} + \beta_4 \overline{Temperature}_{ht} + \beta_5 \overline{Hot\ Months}_{ht} + \beta_6 \overline{Cooling\ Months}_{ht} + \beta_7 \overline{Precipitation}_{ht} + \beta_8 \overline{Wind}_{ht} + \beta_9 \overline{Cloud\ Covered\ Days}_{ht} + \beta_{10} Year_t + \vartheta_h + \varepsilon_{ht} \quad (1.6)$$

All the control variables that vary across individuals remain the same but are now represented by cohort averages. Therewith, I analyze the share of individuals being married, unemployed, high school or university graduates and being religious among one cohort. The income variables are now continuous instead of categorical between 1 and 4 or 5. Age and the male dummy are dropped since those are reflected in the cohort specific effect. With this procedure the within cohort dynamics are neglected but I gain the opportunity to control for generational unobserved heterogeneity Deaton (1997).

1.4 Data

I use data on life satisfaction from the Latinobarómetro (2009), which covers 18 Latin American countries over the period from 1997 until 2008.[10] The survey contains about 1000-1200 households per wave and country. The SWB variable life satisfaction is coded on a scale of 1 to 4. The question is: *"In general, would you say you are satisfied with your life? Would you say you are: 1 Very satisfied, 2 Fairly satisfied, 3 Not very satisfied, 4 Not satisfied at all"*[11]

Figure 1.1 describes the development of life satisfaction over time in the 18 Latin American countries. The left side of Figure 1.1 shows a strong rise in average life satisfaction by about 0.75 points on the 1 to 4 points scale from 1997 to 2008. The right side of Figure 1.1 indicates that there is a strong positive change in overall life satisfaction between the years 2000 and 2001. The number of individuals reporting to be "not satisfied at all" declines by about 75% between 2000 and 2001 and the number of individuals reporting to be "fairly satisfied" increases by about 90%. Part of this change can be

[10] The countries are Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay and Venezuela. Our data on climate conditions from the FAO (2009) does not cover the countries Mexico and Panama, which leads to an exclusion of those two. The waves 1998, 1999 are missing since there was no question regarding life satisfaction. For a list of all the variables and their origin as well as coding refer to Table A.2 and for a list of summary statistics of all the variables refer to Table A.3 in the Appendix to this chapter.

[11] The coding was reversed for matter of interpreting the results.

explained by having Chile, Guatemala and Honduras gradually entering the survey between 2000 and 2008. From 2007 to 2008 a slight overall decline in life satisfaction can be observed again.

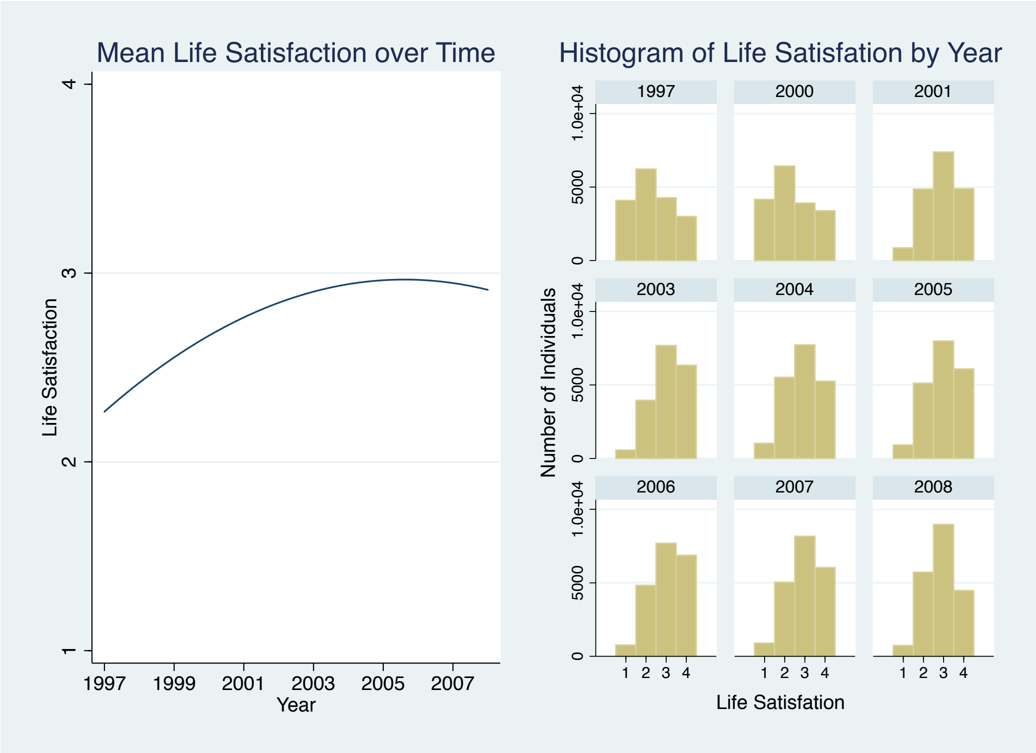

Figure 1.1: Life Satisfaction over Time in Latin America

Source: Latinobarómetro (2009). Note: The variable life satisfaction is coded on a scale of 4 to 1 with: 4 Very satisfied, 3 Fairly satisfied, 2 Not very satisfied, 1 Not satisfied at all".

There are not only differences across countries and over time, but also generational differences in the levels of life satisfaction among our individuals, which are depicted in Figure 1.2. With the example of Paraguay, it is worth to note that individuals born between 1962 and 1981 are on average more satisfied with their lives and experience less shocks to life satisfaction than individuals born between 1922 and 1941. Interestingly, life satisfaction of female cohorts born between 1962 and 1961 varies less over time compared to their male counterparts, which face stronger ups and downs during the time of observation.

Figure 1.2: Life Satisfaction by Cohort in Paraguay

Source: Latinobarómetro (2009). The variable life satisfaction is coded on a scale of 4 to 1 with: 4 Very satisfied, 3 Fairly satisfied, 2 Not very satisfied, 1 Not satisfied at all".

GDP per capita growth and inflation are from the World Development Indicators (World Bank 2012). Overall life satisfaction is strongly correlated with income therefore I take a closer look on how the subjective income on a scale of 1 to 4 and GDP per capita in international dollars develop for the countries under observation between 1997 to 2008.

Figure 1.3 shows the evolution of average GDP per capita over time. Until 2001 a strong downward trend is observed but after 2001 there is a steady rise in mean GDP per capita within our sample. Subjective income performs similarly only with a lag of two years. Mean subjective income declines until 2003 and rises steadily afterwards. The lag of two years can be explained by the time, which is required, until the individuals feel a national macroeconomic shock followed by declining GDP per capita in their personal perception of their income.

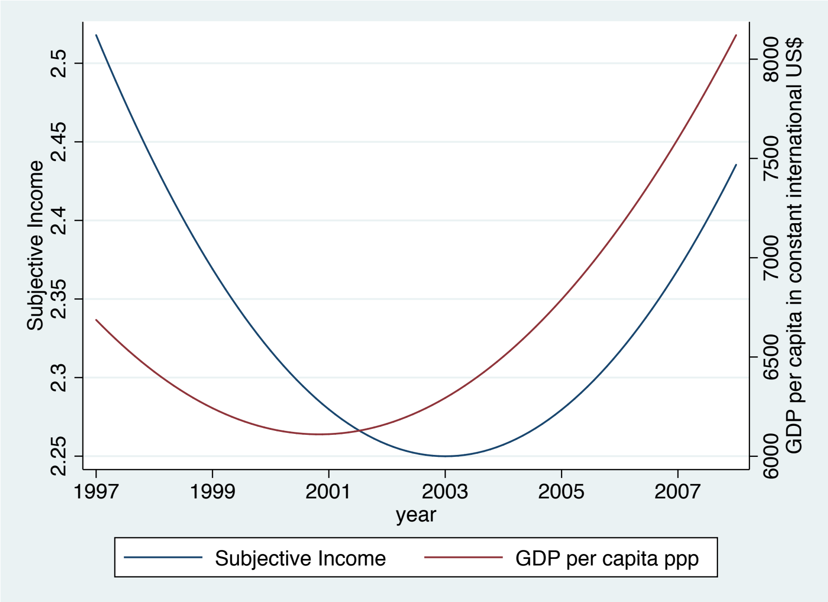

Figure 1.3: Subjective Income and GDP per Capita over Time

Source: Latinobarómetro (2009) and World Bank (2012). Note: The variable subjective income is coded on a scale of 4 to 1 coded: 4 Sufficient and enough to save money, 3 Sufficient, 2 Not sufficient, 1 Not sufficient causing big problems".

The climate data sets are from two different data sources. The first one is from the FAOClim-NET database and includes: monthly mean temperature as well as monthly mean of daily maximum and minimum temperatures in degrees Celsius (°C), monthly total precipitation rates and monthly mean of daily average wind speed in km/h 2m above ground (FAO 2010). The weather stations that report the data are chosen to be located as close as possible to the location of residence of the individuals questioned.[12] The second climate dataset by Mitchell et al. (2004) contains country averaged observed weather data for the years 1901 until 2000 and estimated data[13] for the years 2001 until 2100. Additional to the variables above this dataset contains monthly percentage of cloud covered days.

The data from FAO (2010) presents two advantages with respect to the data by Mitchell et al. (2004). First, the former dataset contains observed data from 1990 to 2009 whereas the latter contains observed data only until 2000. Second, the data from FAOClim-NET allows

[12] There was very limited information on the residence of the individuals and in most cases this information was only available for individuals residing in the main population centre of a country. Therefore the climate data does not vary within a country.

[13] The observed data depends on the climate change scenario and the model, which was applied to estimate the data. We apply the climate change model from the Hadley Centre and the climate change scenario, which assumes a moderate GDP growth and a slow application of green technology.

me to choose climate data from a specific weather stations and it does not contain country averages. The bias, which could arise from averaging the climate data over countries, is displayed in Figure A.1 to Figure A.3 in the Appendix to this chapter. Indeed, bigger countries such as Brazil and those countries with extreme differences in altitude of population centers like Colombia show a relatively high heterogeneity in the climate data from different countrywide weather stations.

A second bias can arise from applying annual mean climate data instead of climate data from the specific month when the SWB data was obtained. Figure 1.4 summarizes the monthly mean, maximum and minimum temperatures FAO (2010). Naturally, countries located further away from the equator, like Argentina or Paraguay, face a higher amplitude in temperatures, which is indicated by the size of the box plots, than those located closer to the equator like Colombia or Ecuador. When applying yearly average temperature data the variance is lost but apart from that the monthly data allows us to apply the temperature data from the month when individuals were questioned regarding their life satisfaction. Therewith we can control for seasonal differences, which matter especially for those countries further away from the equator.

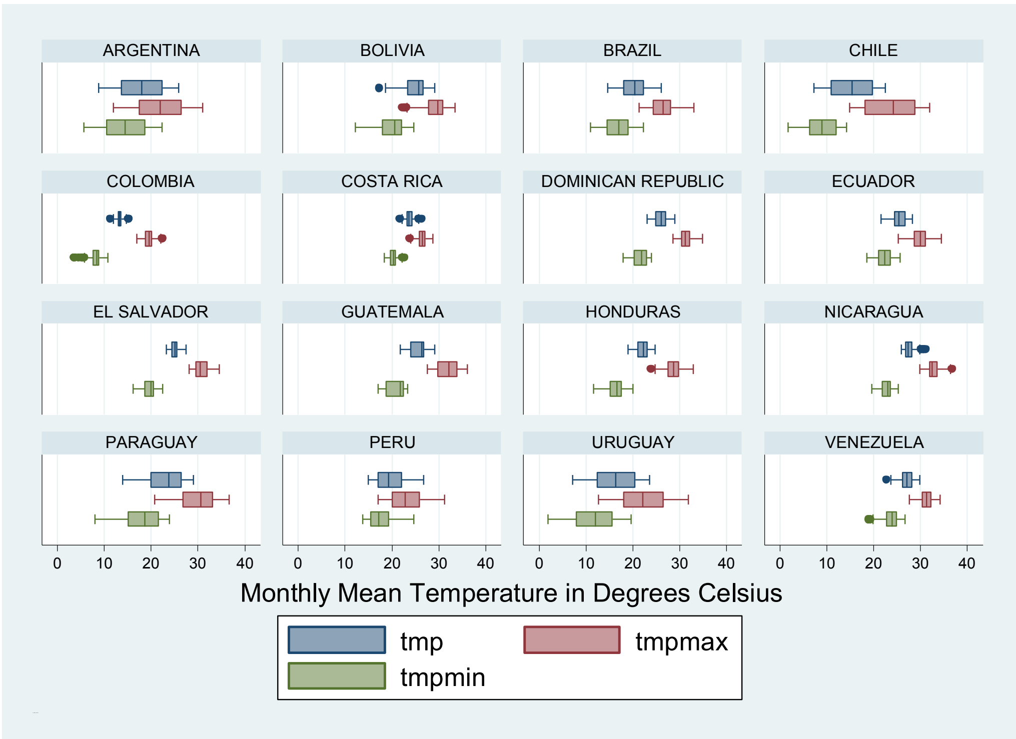

Figure 1.4: Monthly Mean, Maximum and Minimum Temperatures 1990-2009

Source: FAO (2010).

Figure A.4 in the Appendix shows the annual mean, maximum and minimum temperature. Compared to Figure 1.4 there is less variance in the data shown in Figure A.4 in the Appendix, which contains only annual averages. The data on precipitation rates and wind speed shown in Figure A.5 to Figure A.8 in the Appendix follows the same pattern. By applying the climate data from the month when the individuals were questioned regarding their life satisfaction, I try to reveal the true relationship between climate and life satisfaction.

1.5 Results

This section presents two sets of results to evaluate the effect of climate variables on life satisfaction. First, a linear probability and an ordered probit model are estimated with the pooled data. And second, a pseudo panel model is estimated to control for generational heterogeneity. The results from both sets of models will be estimated first with the FAO (2010) and second with the data by Mitchell et al. (2004).

1.5.1 Results from the Pooled Model

I start with the results from the linear probability as well as the ordered probit model. Column 1 in Table 1.1 presents a standard SWB regression (baseline) with the socio-economic control variables estimated with ordinary least squares (OLS). In line with the literature I find that being married or religious affects SWB positively and being unemployed negatively.

In Table 1.1, column 1 high school graduates show slightly lower levels (-0.013) of SWB than elementary school graduates but university graduates show again higher levels (0.013) of SWB compared to elementary school graduates. Male individuals exhibit on average slightly higher levels of SWB than their female counterparts (0.01 points). The results on age and age squared imply that SWB declines during life but after passing through a minimum at the age of 46, individuals face higher levels of SWB as they get older. Being unemployed has a strong effect on SWB, which is confirmed to be time persistent by the literature; meanwhile the negative effect of a divorce diminishes over time. In the sample unemployed individuals face on average 0.08 points lower levels of SWB than those individuals, which are not unemployed. Surprising is the large effect of being religious, which refers to attending one of the three major religious groups such as Christianity, Islam and Judaism. Being religious can almost level of the negative effect of being unemployed.

Table 1.1: Results from the Linear Probability

Life Satis.	(1) LPM Baseline	(2) LPM Extended	(3) LPM (Mitchell)	(4) LPM (FAO)
Married	0.044***	0.045***	0.044***	0.044***
Unemployed	-0.084***	-0.085***	-0.084***	-0.073***
High School	-0.013**	-0.011**	-0.01	-0.006
University	0.013**	0.012*	0.007	0.020***
Religious	0.076***	0.072***	0.071***	0.095***
Obj. Wellbeing	0.044***	0.042***	0.042***	0.038***
Subj. Eco. Sit.	0.243***	0.238***	0.239***	0.236***
Subj. Income	0.120***	0.120***	0.122***	0.131***
Male Dummy	0.011**	0.009*	0.008	0.016**
Age	-0.009***	-0.009***	-0.009***	-0.011***
Age^2	0.000***	0.000***	0.000***	0.000***
GDP Growth		0.006***	0.006***	0.009***
GDP $Growth^2$		0.001***	0.000**	0.000***
Inflation		-0.004***	-0.002***	-0.014***
$Inflation^2$		0.000***		0.000***
Temperature			-0.161***	-0.092**
$Temperature^2$			0.011***	0.006***
$Temperature^3$			-0.000***	-0.000***
Precipitation			-0.000**	-0.002***
$Precipitation^2$			0.000***	0.000***
$Precipitation^3$			-0.000***	-0.000***
Wind				0.021***
Cloud Covered Days			0.035**	
Cloud Covered $Days^2$			-0.000***	
Cloud Covered $Days^3$			0.000***	
Constant	1.078***	2.340***	1.895***	2.649***
Observations	117,907	114,579	118,328	70,542
R-squared	0.232	0.236	0.234	0.240

Source: Authors Estimations. Note: The dependent variable is individual life satisfaction and *, **, *** denote significance at 10%, 5% and 1% level, respectively. The dependent SWB variable life satisfaction is coded on a scale of 4 to 1 with: 4 Very satisfied, 3 Fairly satisfied, 2 Not very satisfied, 1 Not satisfied at all". All the model specifications include country, year and month dummies.

All the income variables such as objective wellbeing, which is the pollster's perception of a household's economic situation, subjective income or the subjective economic situation, which is a subjective judgment of the own economic situation, are positive and highly significant. The coefficients of the subjective economic situation 0.24 and the one of subjective income 0.12 reveal the strongest effect on SWB. Thus, a switch on the scale of subjective income from 2 insufficient to 3 sufficient would lead to an average rise in SWB by 0.12. For comparison overall SWB increased by 0.75 during the period of 1997 to 2008.[14]

Column 2 in Table 1.1 introduces macroeconomic control variables, namely GDP per capita growth and inflation and their respective squared terms. In line with the literature, GDP per capita growth has a positive but small effect and inflation a small negative effect on SWB. In column 3 to 4 the climate variables such as mean temperature and precipitation rates enter the analysis (Equation 1.1). Column 3 presents the dataset by Mitchell et al. (2004), which further contains the data on the percentage of cloud covered days and column 4 presents the data by FAO (2010), which apart from others contains data on wind speed. The coefficients of the socio- and macro-economic variables hardly change in column 3 and 4 except for the two educational dummies such as being a high school or university graduate and the male dummy. There is an inverse N-shaped relationship between mean temperature and SWB with turning points at 12 and 23°C for the data from Mitchell et al. (2004) in column 3 and at 11 and 22°C for the data from FAO (2010) in column 4. Hence a rise in monthly mean temperature between 11 and 22°C may lead to higher levels of SWB, meanwhile a rise in temperatures beyond 22°C may lead to declining levels of SWB. Most of the observations in the sample are beyond the turning point, thus an average increase in temperatures would lead to declining levels of SWB.

The average mean temperature in the sample is 22°C with a standard deviation of 4 degrees. The effect of a rise in mean temperature to 23°C on SWB equals a loss of 0.084 points on average. To neutralize this negative effect, GDP per capita growth would have to increase by 10%. This effect is large and only holds if everything else remains constant. From an individual perspective the loss in SWB due this rise in mean temperature more than equals the negative effect of being unemployed and is still below the effect a rise in subjective income form 2 insufficient to 3 sufficient with a coefficient of 0.13. Therefore a rise in temperature shows a significant negative effect on SWB, which is large.

In addition, there is an inverse N-shaped relationship between precipitation rates and SWB with turning points at 112 and 305mm in column 3 and at 61 and 247mm in column 4. Thus, precipitation rates above 247mm may result in declining levels of SWB. Only 6% of

[14] In a separate analysis I control for relative subjective income since the variable is too strongly correlated. The coefficient of relative income is 0.3. The results are available on request.

the observations surpass this turning point, therefore higher precipitation rates lead on average to higher levels of SWB in the sample. In Column 3 there is an N-shaped relationship between the percentage of cloud covered days and SWB. Levels of SWB decline when the percentage of cloud covered days rises beyond 38%, which covers about 65% of the observations. Higher wind speed in column 4 contributes to a small rise in SWB, which is contrast to the findings by Brereton et al. (2008) and Becchetti et al. (2007). The model in column 4 is the preferred one since it does not apply country averaged or estimated climate data. Nevertheless, the results in column 3 and 4 are similar and the model in column 4 explains slightly more of the variance in SWB.

To verify the selection of our method I estimate all the models presented in Table 1.1 with an ordered probit estimator in Table A.5 in the Appendix. The signs and the significance levels of the coefficients are the same. The coefficients are slightly higher in the ordered probit model but cannot be interpreted directly. This confirms the results from the linear probability model to be robust.

Next, the effect of temperature on SWB is examined in more detail using the climate data from FAO (2010). Table 1.2 presents the results obtained from the linear probability model as in Equation (1.1) adding the variable temperature in five different specifications.

In Table 1.2, column 1 the coefficients of maximum temperature indicate that the level of SWB is increasing with a rise in maximum temperatures between the two turning points at 19 and 28°C. About 50% of the observations on maximum temperature months surpass this turning point of 28°C. Hence, the overall effect of a rise in maximum temperatures depends on the respective country's level of maximum temperatures. In column 2 the effect of monthly minimum temperature on SWB is analyzed and I find a rise to be SWB enhancing until a turning point of 13°C, which lies again below the majority of observations in our sample. Therefore a rise in monthly maximum and minimum temperatures can increase SWB on average but many of our observations have surpassed the turning points of 28 and 13°C and therewith an increase in monthly temperatures would lead overall to a loss in SWB. In column 3, I add the number of hot months, which show a negative effect on SWB if the number of months with temperatures above 20°C rises. Becchetti et al. (2007) on the other hand find that a rise in the number of hot months leads on average to higher happiness levels. Interestingly the turning point of the variable temperature is 22°C, which indicates a sort of threshold for the effect of temperature on SWB. In column 4, the variable cooling (degree) months enters the analysis. A rise in the positive monthly deviation from 18.3°C has a negative effect on SWB, which is in line with the findings by Maddison & Rehdanz (2011).

Table 1.2: Results from the extended Linear Probability Model with FAO Data

	LPM (FAO)			
Life Satis.	(1)	(2)	(3)	(4)
Married	0.044***	0.044***	0.043***	0.042***
Unemployed	-0.073***	-0.073***	-0.074***	-0.075***
High School	-0.005	-0.007	-0.007	-0.01
University	0.022***	0.017**	0.017**	0.025***
Religious	0.096***	0.095***	0.096***	0.086***
Obj. Wellbeing	0.038***	0.039***	0.039***	0.039***
Subj. Eco. Sit.	0.236***	0.235***	0.236***	0.241***
Subj. Income	0.131***	0.130***	0.131***	0.127***
Male Dummy	0.016**	0.016**	0.016**	0.02***
Age	-0.011***	-0.011***	-0.011***	-0.01***
Age^2	0.000***	0.000***	0.000***	0.000***
GDP Growth	0.006***	0.007***	0.007***	0.008***
GDP $Growth^2$	0.000***	0.000***	0.001***	0.001***
Inflation	-0.014***	-0.013***	-0.014***	-0.018***
$Inflation^2$	0.000***	0.000***	0.000***	0.000***
Max Temperature	-0.325***			
Max $Temperature^2$	0.014***			
Max $Temperature^3$	-0.000***			
Min Temperature		0.025***		
Min $Temperature^2$		-0.000***		
Months > 20°C			-0.025***	
Cooling Months				-0.005***
Precipitation	-0.001***	-0.001***	-0.002***	-0.002***
$Precipitation^2$	0.000***	0.000***	0.000***	0.000***
$Precipitation^3$	-0.000***	-0.000***	-0.000***	-0.000***
Wind	0.022***	0.016**	0.03***	0.026***
Constant	4.852***	2.424***	2.728***	2.337***
Observations	70,542	70,542	70,542	67,005
R-squared	0.241	0.240	0.240	0.247

Source: Authors Estimations. Note: *, **, *** denote significance at 10%, 5% and 1% level, respectively. Note: The dependent SWB variable life satisfaction is coded on a scale of 4 to 1 with: 4 Very satisfied, 3 Fairly satisfied, 2 Not very satisfied, 1 Not satisfied at all". All the model specifications include country, year and month dummies.

In Table A.6 in the Appendix I apply the same model specification as in Table 1.2 but use the climate data by Mitchell et al. (2004). I find similar but slightly smaller coefficients for the climate variables such as temperature and precipitation. This dataset also includes the percentage of cloud-covered days, which have an overall negative effect on SWB. Nevertheless, the constructed climate variables such as the number of hot months and the variable cooling (degree) months show the opposite sign. Regarding the number of hot months this is in line with the finding of Becchetti et al. (2007). This bias in the results can steam from the difference in the datasets. I prefer the FAO (2010) data since it exhibits the more precise data on the climate variables but these opposing findings on the number of hot months and cooling (degree months) reveal the sensitivity of the results.

1.5.2 Results from the Pseudo Panel Model

The results from the within estimator as in Equation 1.5 are presented in Table 1.3. Our findings concerning the effect of temperature on SWB are confirmed.

Table 1.3: Results from the Pseudo Panel with FAO Data

			FE (FAO)		
Life Satis.	(1)	(2)	(3)	(4)	(5)
Married	0.124	0.137	0.145	0.139	0.152
Unemployed	-0.003	-0.047	-0.091	-0.089	-0.109
High School	0.03	0.028	0.005	0.015	0.024
University	-0.017	-0.02	-0.032	-0.021	-0.025
Religious	-0.34	-0.343	-0.596*	-0.558*	-0.707**
Obj. Wellbeing	-0.021	-0.041	-0.02	-0.016	-0.033
Subj. Eco. Sit.	0.187**	0.234**	0.175*	0.157*	0.180**
Subj. Income	0.115	0.127*	0.119	0.148**	0.138*
GDP Growth	0.011**	0.007*	0.009**	0.01**	0.011**
GDP Growth^2	0.001*	0.001**	0.001**	0.001**	0.001**
Inflation	-0.01***	-0.01***	-0.014***	-0.012***	-0.015***
Inflation^2	0.000**	0.000**	0.000***	0.000***	0.000***
Temperature	0.048***				
Temperature^2	-0.001***				
Max Temperature		-0.174*			
Max Temperature^2		0.008**			
Max Temperature^3		-0.000**			
Min Temperature			-0.007		
Months > 20°C				-0.005	
Cooling Months					-0.002
Precipitation	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
Precipitation^2	0.000***	0.000***	0.000***	0.000***	0.000***
Precipitation^3	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
Wind	0.027**	0.026*	0.024*	0.024*	0.025**
Constant	1.865***	3.385***	2.678***	2.539***	2.724***
Observations	408	408	408	408	390
R-squared	0.805	0.809	0.799	0.798	0.797
Number of cohortid	78	78	78	78	78

Source: Authors Estimations. Note: *, **, *** denote significance at 10%, 5% and 1% level, respectively. Note: The dependent SWB variable life satisfaction is coded on a scale of 4 to 1 with: 4 Very satisfied, 3 Fairly satisfied, 2 Not very satisfied, 1 Not satisfied at all". All the model specifications include year dummies.

In Table 1.3, column 1 I find a positive effect when mean temperatures rise with a turning point at 18°C and maximum temperatures rise with a turning point at 26°C. Precipitation levels beyond 250mm can lead to a decline in SWB. Nevertheless, the effect of a change in minimum temperatures, the number of hot months with mean temperatures above 20°C as well the variable of cooling (degree) months are not significant anymore. This leads me to question the predictive power of this variable. The results for precipitation rates and wind hold.

Again GDP per capita growth and inflation remain significant and the coefficients hardly change size. Due to the loss of variance in the data when controlling for the cohort specific effects, the positive effect of being a high school graduate or being married, unemployed as well as objective wellbeing, which represents the pollsters perception on a households economic wellbeing, do not show a significant effect on SWB anymore. The control, which remains to play a role for SWB is solely the subjective economic situation. These results challenge the selection of the preferred model. Since my focus is on the climate variables and not on the socio-economic variables I consider these results as another confirmation of the importance of climate for SWB. For studies with focus on the socio-economic control variables the contribution of the pseudo panel approach might be small. There are no other studies, which analyze SWB and climate meanwhile controlling for cohort specific effects.

I repeat the analysis in Table 1.3 with the climate data by Mitchell et al. (2004) and represent the results in Table A.7 in the Appendix with similar findings. The results on subjective economic situation as well as the findings on mean and maximum temperature remain robust. Nevertheless, the results on the number of hot months switch sign and the results on the cooling degree month's loose significance.

1.5.3 Robustness Analysis

In Figure 1.1 I find that there is a strong rise in SWB between 1998 and 2000. In order to test if this influences the results I drop the first two cross sections of the sample and present the results from the linear probability model of the reduced sample in Table 1.4.

In Table 1.4 all the signs of the socioeconomic and macroeconomic control variables are the same and the magnitude of the coefficients varies only slightly compared to the results with the full sample in Table 1.2. The positive effect of the male dummy and the negative effect of being unemployed are slightly higher in the reduced sample, than in the full sample. The climate variables such as mean, maximum or minimum temperature show again the non-linear relationship. The upper turning points are now at 24, 29 and 20°C, which is slightly higher than in the full sample except for the minimum temperature, which is 7°C higher than in the full sample. The number of months with high temperatures above 20°C is not significant anymore but the variable measuring cooling (degree) months remains significant but of smaller size. The variable precipitation remains the inverse N-shaped relationship with the respective turning points at 99 and 311mm, which is similar as in the results from the whole sample. Also the variable wind speed shows the almost same coefficient as in the whole sample.

Table 1.4: Results from the Linear Probability Model with FAO Data (Reduced Sample)

	LPM (FAO)				
Life Satis.	(1)	(2)	(3)	(4)	(5)
Married	0.039***	0.039***	0.039***	0.039***	0.039***
Unemployed	-0.092***	-0.093***	-0.093***	-0.094***	-0.093***
High School	-0.002	-0.001	-0.003	-0.004	-0.006
University	0.027***	0.028***	0.025***	0.023***	0.023***
Religious	0.126***	0.122***	0.135***	0.131***	0.119***
Obj. Wellbeing	0.043***	0.042***	0.043***	0.044***	0.044***
Subj. Eco. Sit.	0.233***	0.233***	0.233***	0.233***	0.235***
Subj. Income	0.116***	0.116***	0.115***	0.115***	0.115***
Male Dummy	0.019***	0.019***	0.019***	0.019***	0.019***
Age	-0.009***	-0.01***	-0.009***	-0.009***	-0.01***
Age^2	0.000***	0.000***	0.000***	0.000***	0.000***
GDP Growth	0.005***	0.004**	0.005***	0.003**	0.003
Inflation	-0.014***	-0.017***	-0.008***	-0.011***	-0.012***
$Inflation^2$	0.000***	0.000***	0.000**	0.000***	0.000***
Temperature	-0.184***				
$Temperature^2$	0.011***				
$Temperature^3$	-0.000***				
Max Temperature		-0.527***			
Max $Temperature^2$		0.023***			
Max $Temperature^3$		-0.000***			
Min Temperature			0.027***		
Min $Temperature^2$			-0.001**		
Months > 20°C				0.005	
Cooling Months					0.002**
Precipitation	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
$Precipitation^2$	0.000***	0.000***	0.000**	0.000***	0.000**
$Precipitation^3$	-0.000***	-0.000***	-1.63e-08***	-0.000***	-0.000***
Wind	0.023***	0.036***	0.0110	0.017**	0.018**
Constant	3.317***	5.221***	1.988***	2.165***	2.103***
Observations	57,936	57,936	57,936	57,936	56,754
R-squared	0.175	0.175	0.174	0.174	0.176

Source: Authors Estimations. Note: *, **, *** denote significance at 10%, 5% and 1% level, respectively. Note: The dependent SWB variable life satisfaction is coded on a scale of 4 to 1 coded: 4 Very satisfied, 3 Fairly satisfied, 2 Not very satisfied, 1 Not satisfied at all”.

1.6 Conclusion

In the first section I pointed out that there is a need to apply not only monetary measures to estimate potential gains and losses from climate change. Climate is a strong determinant of human wellbeing. A change in long run climate conditions might be difficult to adapt to and affects wellbeing negatively. Following the analysis of Maddison & Rehdanz (2011), Brereton et al. (2008) and Becchetti et al. (2007) I introduce the concept and the measures of SWB as a non-income based welfare measure and point to the advantages and shortcomings in terms of reliability of this measure.

This analysis differs from earlier studies since it applies the climate data from corresponding month of the SWB assessment and controls non-linearities in the climate SWB relationship. It further controls for generational fixed effects. The analysis differs from Maddison & Rehdanz (2011) since it does not use country averaged SWB data, which allows me to control for individual characteristics such as being married or unemployed. It also differs from Brereton et al. (2008) since it uses data on 16 different countries over the period of 1997 to 2008 instead of one country, which enables me to control for the macroeconomic environment. Thus, differences in the results compared to earlier studies might be due to different specifications of the climate variables or to the SWB data under observation. I aim to provide an assessment of earlier findings and I do present new results regarding the 16 Latin American Countries under observation.

I find that increasing monthly mean temperatures has a negative effect on SWB. Higher annual average wind speed on the other hand seems to SWB enhancing. The findings are robust as they hold in the linear probability model as well as the ordered probit model even when applying two different climate datasets or dropping the first two cross sections. The results further hold when controlling for generational changes via cohort fixed effects again with two different datasets. The variables hot months and cooling (degree) months, which capture deviations from an appreciated temperature around 20°C are not robust throughout the analysis. The findings show that there is a threshold in precipitation and temperature levels. The effect of a rise in precipitation levels turns negative once a threshold of 247mm is passed. The threshold for mean temperatures is around 22°C when a further rise in temperature leads to a decline in SWB. Whether a rise in temperature is overall positive or negative for SWB depends on the actual temperature levels in each country under observation. The sample at hand exhibits already rather high mean temperatures of 22°C. A rise in mean temperature to 23°C goes in line with a loss in SWB of 0.08 on a scale from 1 to 4. At first sight this effect does not appear very large since overall SWB was rising on average 0.75 during the time of observation. Nevertheless, when holding everything else constant it would cost 10% of GDP per capita growth to neutralize the negative effect of rise in mean temperature by 1°C. Climate change is associated with a rather small rise in average global temperature but one may not underestimate its effect on SWB and the macroeconomic environment.

Chapter 2: The Carbon Footprint of Indian Households

Joint work with Mirjam Harteisen, Jann Lay, Jan Minx and Sebastian Renner

2.1 Introduction

Household income in India has increased considerably in line with economic growth over the last decades. The ministry of statistics and program implementation (MOSPI) reports that wages have been rising between 2004/05 and 2009/10 by 187%.[15] In line with wages also household expenditure has been rising especially in the urban areas where richer households are located.[16] We expect a large share of households to pass the critical income level of 2 Dollars per day and that carbon emissions from Indian households will account for a significant share of global greenhouse gas emissions (GHG) in the future. This rise in carbon emissions will be correlated with increasing direct and indirect energy requirements of households. However, energy consumption and carbon footprints vary with what and how households consume. Therefore, we identify consumption patterns, their dynamics, and their respective carbon intensities for different groups of households.

We apply input-output (IO) energy analysis in combination with household expenditure survey data from India for the year 2004/05 and 2009/10. For the analysis we calculate the carbon footprint of households and analyze the respective emission drivers. First we apply quantile regression analysis to explain the large differences within the household carbon footprint in 2004/05. Household income (total expenditure) appears to be the major determinant of the carbon footprint. Nevertheless, the elasticity of income is above one for households with a low, and below one for those with a high footprint. To analyze the rise in emissions between the two years under observation we apply a Blinder-Oaxaca decomposition. We find that increased income (total expenditure) explains 47% of the rise in household emissions between 2004/05 and 2009/10. Second, we estimate income elasticities for a number of different consumption categories, differentiating between households by income quintiles. By disaggregating household expenditure, we reveal how consumption patterns change when households become more affluent. We observe a disproportionately high increase in the demand for emission-intensive goods and services in comparison to less emission-intensive consumption categories. Such a non-linear increase of carbon-intensive consumption is of great significance given that India has a

[15] Urban wages were rising only by 173 % between 2004/05 and 2009/10.

[16] Mean total household expenditure has been rising by 150% in our sample.

large emerging middle class ready to spend its increasing discretionary income on a variety of emission-intensive consumption items.

The remainder of the chapter is as follows. After the literature review we present the IO analysis as well as the expenditure analysis. In the results section we estimate the carbon footprint and determine the carbon intensive consumption items before we close with the conclusion.

2.2 Literature Review

For an excellent survey on recent literature concerning input-output analysis and the carbon footprint, see Minx et al. (2009). Although our particular focus is on India, most studies focus on developed countries due to data availability.

Earlier carbon footprints for Indian households have been calculated by Parikh et al. (1997). Combining IO-data from 1989-90 and household data for the year 1987-88, their paper presents differences in consumption patterns across income groups and their carbon dioxide implications. A main finding is that the rich have a more carbon intensive lifestyle with the urban emission levels being 15 times as high as those of the rural poor. Apart from carbon footprints, closely related energy requirements of Indian households have been calculated by Pachauri & Spreng (2002) for the years 1983-84, 1989-90 and 1993-94. Based on IO-analysis, they find that household energy requirements have significantly increased over time identifying growing income, population and increasing energy intensity in the food and agricultural sectors as the main drivers. Based on this analysis, Pachauri & Spreng (2002) present cross-sectional variations in total household energy requirements. Using household consumption expenditure data for 1993-1994 matched with energy intensities calculated by Pachauri & Spreng (2002), an econometric estimation reveals income levels as the main factor determining variation in energy requirements across households.

Generally, carbon emissions, which are closely related to direct and indirect energy requirements of households, have been the subject of research since the 1970s. Herendeen and Tanaka (1976) use input-output and household expenditure data to calculate energy requirements of U.S. households. Additional to energy intensities, GHG intensities have been calculated by Lenzen (1998b) for Australian final consumption. Based on IO-analysis and including other GHGs than CO_2 such as CH_4, N_2O, CF_4 and C_2F_6. It is found that most of the GHG emissions are ultimately caused by household consumption.

Close to our approach, household expenditure data and IO derived carbon intensities have been used to calculate household carbon footprints for Australia Lenzen (1998a). Using IO derived carbon intensities from Lenzen (1998b) multiplied with expenditures on 376 commodities, it is one of the first studies calculating carbon footprints on a disaggregated household level. Among the finding that per capita income is the main determinant of household energy and carbon requirements, it is found that on average rural households spend their income on more energy intensive commodities than households in urban areas. Drawing on a similar methodology for energy, Lenzen et al. (2006) focus on the role of income growth in a cross-country analysis. Their motivation is to characterize household consumption patterns with respect to their environmental implications and hereby search for evidence on the Environmental Kuznets Curve (EKC). Their findings support previous research in the EKC energy literature, as energy requirements increase monotonically with household expenditure but no turning point is observed. (Serrano & Roca 2007) apply IO analysis to estimate the emission content of Spanish household consumption from nine different atmospheric pollutants. They analyze the share of each income quintile in emissions and find, except for synthetic green house gases, declining emission intensities of household consumption with rising expenditure. Therewith they find an EKC at the country level.

In general there are several studies combining household expenditure data with IO derived carbon intensities to calculate household carbon footprints. Wier et. al (2001) analyze the carbon footprint of Danish households, identifying household characteristics with a significant influence on CO_2 emissions. Kerkhof et al. (2009) quantify CO_2 emissions of households in the Netherlands, UK, Sweden and Norway by combining a hybrid approach of process and input-output analysis with household expenditure data. Similar approaches recently published are Bin & Dowlatabadi (2005) and Weber & Matthews (2008), both focusing on US households. Hertwich & Glen P. Peters (2009) analyze the carbon footprint of nations by applying IO analysis with data from the Global Trade Analysis Project. They construct a multi regional input output model to estimate the carbon footprint based four major GHGs measured in CO_2 equivalents. The focus is on eight expenditure categories, such as food, clothing and mobility, and their contribution the national carbon footprint.

They find a per capita carbon footprint of about 1.8t CO_2 equivalents for India in 2001 and find that 95% of Indian emissions are from final consumption of households.[17]

2.3 Methodology

2.3.1 Deriving the Carbon Footprint

We combine energy IO analysis with household demand structure to estimate the carbon footprint for Indian households. Therewith, we can trace the carbon content of each final consumption item back to its intermediates and account for the direct as well as indirect emissions from consumption. We focus on carbon emissions from fossil fuels[18] since CO_2 emissions represent the largest share of GHG emissions covert under the Kyoto Protocol.[19] The method which has been applied is based on Leontief (1970) and we follow the approach of Lenzen (1998b) and Lenzen et al. (2004).

First we estimate the CO_2 intensities (in local currency units) of each sector of the Indian economy. We apply a single region IO model based on the Global Trade Analysis Project (GTAP). By using a single region IO model we account for direct and indirect emissions from goods produced and consumed in India as well as for emissions from imported goods.[20]

Figure 2.1 describes the process IO energy analysis. We use IO tables for the year 2004 from the Indian Central Statistical Organization (CSO) which provide us with an [jx1] vector of domestic output x by 130 sectors j, a [jx1] vector of final demand y by 130

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[17] Our per capita carbon footprint is lower since we only analyse CO_2 emissions from the combustion of fossil fuels and we give each household member the same weight not matter of their age.

[18] The CO_2 emissions are derived from following energy sources: coal, crude oil, natural gas, petroleum products, gas, electricity and gas. The share of renewable and nuclear energy in India's electricity was considerably low in 2005.

[19] Figure B.1 and Figure B.2 in the Appendix to this chapter give insight on how much of the major GHGs we are accounting for. In terms of quantities we account for more than 95% of the Indian GHG emissions. In terms of CO_2 equivalents we account for only 60% of the GHG emissions. Other GHGs such as methane CH_4 and nitrous oxide N_2O are released in far lower quantities but their global warming potential is 25 and 298 times higher than the one of CO_2 emissions.

[20] The share of imported goods and services in the Indian GDP equals about 22% in 2005.

sectors j (which includes imports).[21] And a [jxj] matrix of the technical coefficients A, which reflect the input requirements of the jth sector of intermediates from other sectors measured in monetary units.[22] We apply the simple technology assumption and assume that imported goods are produced with the same technology as local goods. We also assume that technology has not changed drastically between 2004 and 2009 since we use the same IO table to estimate the emission intensities of sectors for 2009.[23] Depending on the fuel type the CO_2 emissions per unit of fuel use are represented in the emission coefficient vector c [mx1]. The [mxj] energy use matrix E^{ind} represents the quantitative fuel demand of the 58 sectors per monetary unit of intermediate output from other sectors. The energy use matrix E^{fd} represents the household's quantitative fuel use per monetary unit of final demand from 58 sectors.[24] Total emissions from consumption CO_2 would consist of direct CO_2^{fd} from final demand and indirect CO_2^{ind} emissions from energy use by each sector.

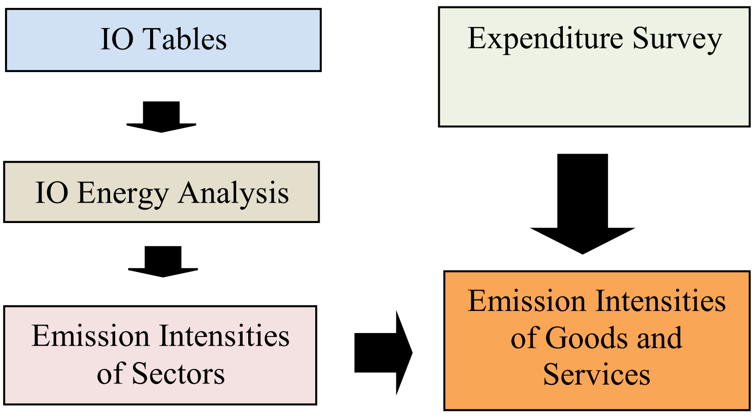

Figure 2.1: IO Energy Analysis with Expenditure Data

Source: After (Kok et al. 2006)

In Table 2.1 the process of the data matching stages is outlined. In the first step we matched the 130 sectors of our IO tables with the energy use data, which is aggregated to 58 sectors in order to get the energy intensity matrix E. In a second step we match the 58 sector emission intensities with the corresponding expenditure categories from the

[21] The 130 sectors include administration and defence.

[22] All the values are in local currency units at 2004 producer prices.

[23] This assumption is confirmed by the emission intensities per sector from the World Input Output database, which neither changed drastically in India between 2004 and 2009 (Erumban et al. 2012).

[24] The data by the GTAB energy volume data is disaggregated into 58 sectors, which were matched with the 130 sectors from the Indian IO tables.

household survey data. The data on household expenditure is rather disaggregated and we match all the 340 expenditure categories with the corresponding emission intensities.[25] Even though the IO tables contain information on monetary fossil fuel and electricity demand we still need to refer to the quantitative energy intensity data from GTAP to gain a more precise estimate on emissions per sector.

Table 2.1: Data Matching Scheme

Coefficient Matrix A
001
002
003
…
130

Energy Intensity E
001
…
058

Expenditure Categories
001
002
003
004
005
…
340

Source: Authors

In our model we consider a single region approach, which assumes that environmental and energy technology is the same as abroad. Therefore, we analyze the sum of direct and indirect emissions from industrial sectors. Direct emissions from final demand *fd* can be characterized as follows:

$$CO_2^{fd} = c'E^{fd}y \tag{2.1}$$

where c' represents the inverse emissions coefficient vector, E^{fd} is the energy use matrix and y is the final demand vector (Suh 2010).

Indirect emissions CO_2^{ind}, which are divided into emissions from domestic production for domestic final demand, emissions from imported intermediates and emissions from imported final demand.[26] The emissions by sector can be estimated by multiplying the demand of each sector represented as vector y with the transposed emissions coefficients vector c and the industrial energy use matrix E^{ind} as well as the with the domestic Leontief inverse $(I-A)^{-1}$:

[25] For an overview on the emission intensities of each economic sector and our matched IO sector please refer to Table B.1 in the Appendix to this chapter.

[26] Exports are excluded.

$$CO_2^{ind} =$$
$$c'E^{ind}\left[(I-A)^{-1}y_{\neq exp} + ((I-A_{tot})^{-1} - (I-A)^{-1})y_{\neq exp} + (I-A_{tot})^{-1}y_{imp_{\neq exp}}\right] \quad (2.2)$$

where $A_{tot}=A+A_{imp}$, $y_{tot}=y+y_{imp}$ and $y_{\neq exp}$ is domestic final demand, I represents an identity matrix and A is the technical coefficients matrix, which mirrors the contribution of the intermediates to one final output unit (Suh 2010).

Direct and indirect emissions from consumption can be estimated by:

$$CO_2 = CO_2^{fd} + CO_2^{ind} \quad (2.3)$$

$$CO_2 = c'\left[E^{fd} + E^{ind}\left((I-A)^{-1}y_{\neq exp} + ((I-A_{tot})^{-1} - (I-A)^{-1})y_{\neq exp} + (I - A_{tot})^{-1}y_{imp_{\neq exp}}\right)\right] \quad (2.4)$$

In order to estimate the carbon footprint of each household i we deduct the value added tax VAT from the household expenditure Exp and multiply each consumption category j with the respective carbon intensity CO_{2j} of the respective sector. [27] Summing up over all the expenditure categories, which yields the household carbon footprint CO_2^{hh} in kg of CO_2:

$$CO_2{}^{hh}{}_i = \sum_{i=340}^{j}\left(CO_{2\,j}(Exp_{ij} - VAT)\right) \quad (2.5)$$

where i represents the household and j the different expenditure category.

2.3.2 Determinants of the Household Carbon Footprint

Wier et al. (2001) show in a descriptive analysis that Danish households have differing CO_2 requirements depending on their characteristics, which they subdivide in economic, demographic and socio-cultural variables. Namely they analyze expenditure, urbanity, household size, type of accommodation and age as well as education. We follow the approach of Wier et al. (2001) but apply a semi parametric regression analysis to explain the differences in the household carbon footprint.

The regression model has the following form:

[27] For the consumption categories rice, wheat and kerosene we applied marked prices on those quantities, which households received at subsidized prices via the public distribution system (PDS).

$$\ln\left(CO_{2_i}^{hh}\right) = \alpha + \beta_1 \ln(Income_i) + \beta_2 PDS_i + \beta_3 Urban_i + \beta_4 HHSize_i + \beta_5 Age_i + \beta_6 Female_i + \beta_7 Education_i + \beta_8 Energy\ Source_i + SD_s + \varepsilon_i \quad (2.6)$$

where $ln(CO_2{}^{hh})$ represents the carbon footprint of household i in natural logs. The major determinant of the household emissions is income, which is here proxied by total household expenditure in natural logs and which represents the economic variable. Additionally we also control if a household is considered income poor and receives subsidized consumption goods such as kerosene from the public distribution system (PDS). Apart from income the location in either rural or urban areas, the household size and the age as well as gender of the household head explain the differences due to demographic variables. To control for socio-cultural impacts on consumption and therewith emission patterns we control for the education of the household head. One of the major direct energy needs arises from the energy source used for cooking. These energy sources do not vary largely in industrialized countries, but in our sample some of the households use electricity, some kerosene and some dung cake as an energy source for cooking. Thus, we add control variables for the type of energy source for cooking of the household.[28] Finally *SD* represents the state s dummies and ε_i the error term. We also introduce squared and cubic terms to control for non-linearities and we interact income with being located in urban areas, household size and education to able to differentiate between the effects on low- and high-income households from the respective variables.

We apply quantile regression for the analysis for two reasons. First the distribution of the household carbon footprint is highly skewed and quantile regression analysis is more robust to outliers than ordinary least squares regression (OLS) since it does not assume the data to be normally distributed. Second, it allows us to study the impact of the regressors, such as income, on the location and the scale parameters of the model. The OLS estimator minimizes the sum of the squared error term $\sum_i e_i^2$ and quantile regression "minimizes the sum that gives the asymmetric penalties $(1-q)|e_i|$ for overprediction and $q|e_i|$ for underprediction" (Cameron & Trivedi 2010, 206).

[28] Households can pick from various major energy sources for cooking in the questionnaire or indicate that have no major energy source for cooking at al.

We assume that the impact of an increase in income for households with a low carbon footprint is a different one than for households with a high carbon footprint. Quantile regression allows us to estimate the impact of a one-unit change in income on a specific quantile q of our response variable the household carbon footprint.

The q^{th} quantile regression estimator minimizes over β_q via linear programming

$$Q(\beta_q) = \sum_{i:y_i \geq x_i'\beta}^{N} q\left|y_i - x_i'\beta_q\right| + \sum_{i:y_i \leq x_i'\beta}^{N} (1-q)\left|y_i - x_i'\beta_q\right| \qquad (2.7)$$

where $0 < q < 1$ and the choice of q (we choose 0.1 and 0.9 in our analysis) estimate different values of β. If $q=0.9$ then more weight is placed on prediction for observations with $y_i \geq x_i'\beta_q$ (Cameron & Trivedi 2010).

While the estimated relationship is useful to separate the different determinants of the household carbon footprint, it has two important drawbacks. The first originates from a theoretical standpoint. Households target their consumption at goods which fulfill their needs, while CO_2 emissions represent an externality that is neither explicitly taken into account nor is it an aim to maximize the carbon footprint.[29] To deal with this wrong behavioral assumption in Equation 2.6, we adopt a real household consumption perspective by estimating the demand elasticities for various consumption items. The second drawback of this first approach is the missing information about the consumption categories driving the household carbon footprint. We expect some categories to drive the carbon footprint more than others, revealing valuable information for further energy and climate mitigation policies.

2.3.3 Demand Analysis

Based on the Theory of Consumption by Deaton & Muellbauer (1980) demand functions derived from the utility maximization of the consumer depend on prices and income of the individuals. Since we do not have the data on prices of the household expenditure items we estimate the engel curves without prices, only dependent on income and socio-economic

[29] To some extent carbon emission are taken into account via energy prices leading to different prices of goods.

characteristics of the households.[30] Having no prices available, there is no necessity to meet the homogeneity restriction, with the adding-up restriction leading to linear budget constraints as the necessary requirement left for the equation to estimate. The model to be estimated has the following form:

$$w_{ij} = \beta_0 + \beta_{1_{ij}} \ln(y_i) + \beta_{2_{ij}} X_i + \varepsilon_{ij} \tag{2.8}$$

where w_{ij} represents the share of total expenditures allocated to the jth consumption category by the *ith* household, $log\ y_i$ the income of household i in natural logs, X_i a vector with household characteristics and the error term ε_{ij}. With no income information available in the data, we follow the standard approach and use total household expenditure as a proxy for income. The engel curves should preferably be estimated in a complete demand system to secure efficient estimates. However, our specification is in line with the adding-up restriction even if we estimate equation by equation with ordinary least squares.

Besides the choice of functional form we are facing econometric problems, caused by the data and the estimated specification under consideration. The first problem, present in most household surveys is measurement error. A second problem is the potential endogeneity of our main explanatory variable. These are common problems in demand estimation and can be solved with instrumental variable techniques, but our data does not offer candidates for valid instruments.

Deaton (1997) points to another source of potential simultaneity bias, which is caused by richer household buying high quality products, which are more expensive. In other words, as households get richer they do not consume more of a certain good and cause more carbon emissions but they consume higher quality goods, which may not have to be related with higher carbon emissions than the lower quality items of the same consumption category. To control for this quality bias we split the sample for the analysis in rural and urban since we find that the majority of the urban households are income poor. We further split our sample into income quintiles. Following Easterly (2001) we take this relative definition of different income classes instead of taking an absolute approach such as the

[30] We derived prices by dividing the household expenditure on a certain item through the number of items bought, but we received very unreliable results. The variance in the derived unit price was too large to be reliable.

number of households living of less than two dollars a day. Banerjee & Duflo (2008) point out that relative measures draw the wrong image of the society and the low-income class or the people living in poverty underrepresented. Nevertheless, we do not intend to define who is poor and who is not, we try to reveal what happens to consumption patterns and therewith the carbon footprint when household income is rising.

2.3.4 Decomposing the Changes in the Carbon Footprint

As a last step of the analysis we apply a Blinder-Oaxaca decomposition to analyze to the changes in the carbon footprint between 2004/05 and 2009/10. Blinder (1973) and Oaxaca (1973) explain the gap in the mean of an outcome variable between two groups, which will be applied to two time periods in this case. The gap is decomposed into the part due to the differences in the magnitudes of the explanatory variables and the part due to the differences in the coefficients of these variables. Hence, the rise in the carbon footprint between 2004/05 and 2009/10 could be due to quantitative changes in our explanatory variables such as higher average household expenditure and increasing average household size in 2009/10. Or it could be due to unexplained factors such as changes in the consumption patterns.

O'Donnell et al. (2008) present the method as follows. The gap between the mean carbon footprint in the first period $CO_2^{hh'}$ and the second period $CO_2^{hh''}$ is equal to

$$CO_2^{hh''} - CO_2^{hh'} = \beta''x'' - \beta'x' \tag{2.9}$$

where x'' and x' are vectors of explanatory variables evaluated at their mean values in period two and one while assuming the error term to be zero. From the point of view of the second period the difference in the carbon footprint can be displayed:

$$CO_2^{hh''} - CO_2^{hh'} = \Delta x\beta'' + \Delta\beta x'' + \Delta x\Delta\beta = E + C + CE \tag{2.10}$$

where the gap between the mean household carbon footprint in the first and second period is decomposed into the gap due to differences in the endowments *E*, the gap due to the differences in the coefficients *C* and the interaction of endowments and coefficients *CE*.

2.4 Data

We apply IO data for 2004 from the Central Statistical Organization in India. The IO tables are disaggregated into 130 economic sectors.[31] The data on energy demand per sector and the conversion into CO_2 emissions is derived from GTAP.[32]

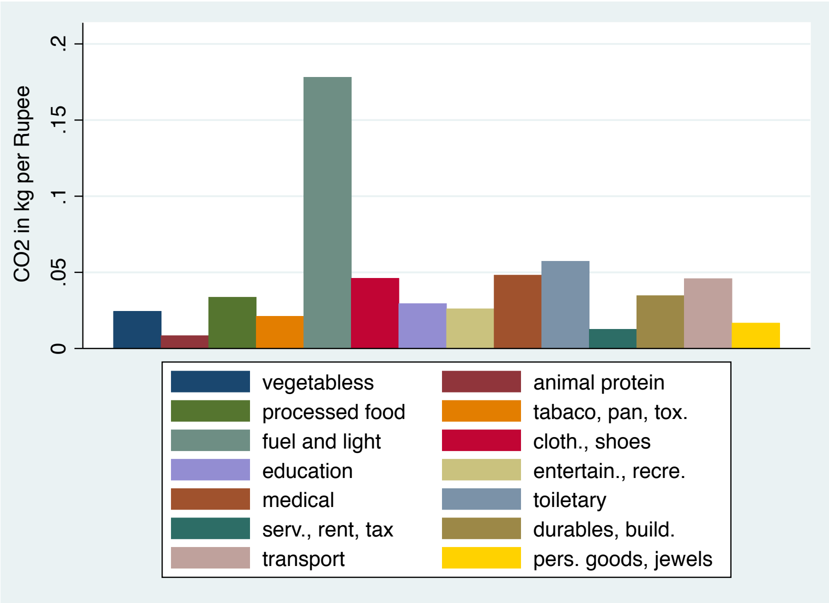

Figure 2.2: Emission Intensities of the Expenditure Categories
Source: CSO (2005) and NSS (2006).

We estimated the emission intensities for 58 economic sectors, which were matched with the household expenditure categories and are displayed in Figure 2.2. Emission intensities vary strongly between the consumption categories with the highest emission intensity per currency unit for light and fuel. Further, toiletry, medical and clothing as well as transport items exhibit high carbon intensities due to the manufacturing process of those goods. Animal protein, which accounts for dairy as well as any kind of meat or fish products, reveals a low emission intensity since we only account for emissions from fossil fuels and not for methane.[33] The carbon intensity of the category vegetables, which includes all non-animal agricultural produce, is higher than the one of animal protein since the input from

[31] For a list of the IO sectors and the corresponding emission intensities refer to Table B.1 in the Appendix to this chapter.

[32] The data on energy demand and CO_2 emissions by sectors is available upon request.

[33] Erumban et al. (2012) find that methane emission account for more 50% of the total GHG emissions from the agricultural sector in India in 2004.

other emission intensive sectors such as machinery is high in the category vegetables. We observe low emission intensities for all food categories as well as for expenses on education or entrainment and recreation.[34]

The household expenditure analysis is based on data from the National Sample Survey, which consists of data on the expenditure of about 125000 households, which is disaggregated to around 340 consumption categories and 40 sub-categories.[35] The survey is a representative sample of the Indian economy and we apply two waves, which were conducted in 2004/05 and 2009/10.[36] The households are to 64% located in urban areas and 69% of the households live of less than 2 dollars per person each day. The poor households are concentrated in rural areas. There are 11% of the households, which are headed by a woman. The average household size consists of 5 members, 46% of the households consist of 3 to 6 members and 39% are households with up to 43 members.[37] The household heads are to 76% of Hindu, 12% of Muslim or 7% of Christian religion. The average years of schooling of the household head is 4 years and 30% of the household heads received only 1 year of schooling. The average monthly per capita expenditure equals 3880 Rupee in 2004/05 and 5831 Rupee in 2009/10.

Figure 2.3 gives an overview on what households spent their income on in 2004/05.[38] Between 2004 and 2010 overall expenditure has been rising by about 50%. The structure of the expenditure shares varies largely between rural and urban households in Figure 2.3. Rural households spent a larger fraction of their income on food items and a much smaller share on services, rent and taxes than urban households. Figure B.3 in the Appendix to this chapter reveals that expenditure shares for education as well as entertainment and recreation are increasing between the two time periods for both rural and urban households. The overall pattern of consumption has hardly changed between the two time periods

[34] Our Carbon Intensities by category are higher than the data by Murthy et al. (1997) but closer to the ones by Kerkhof et al. (2009).

[35] For an overview on household expenditure categories refer to Table B.2 in the Appendix to this chapter.

[36] For summary statistics refer to Table B.3 and Table B.4 in the Appendix to this chapter.

[37] A household is defined as people sharing one kitchen.

[38] Figure B.3 in the Appendix to this chapter presents the shares for 2009/10, which are very similar even though total expenditure has been increasing strongly.

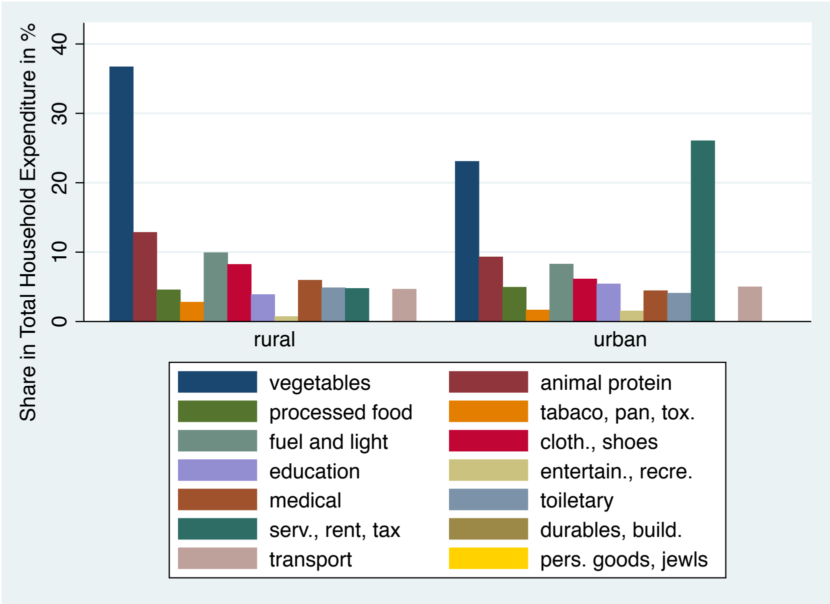

Figure 2.3: Expenditure Shares of the Expenditure Categories 2004/05

Source: CSO (2005) and NSS (2006).

When turning to the household carbon footprint, which consists of the sum of all expenses from the 40 sub expenditure categories multiplied by the respective emission intensities, we find large differences between the household carbon footprint of different income quintiles as displayed in Figure 2.4. Apparently, the carbon footprint of the 20% richest households 4.5t CO_2 is six times as high as the carbon footprint of the 20% poorest households with 0.75t CO_2 and still about 2.5 times as high as the one of the median. The gap between urban and rural households is only 1.2t CO_2 per year.[39] Considering these large differences we want to analyze the determinants of the strong rise in the household emissions between the different income quintiles.

[39] Figure B.4 in the Appendix to this chapter gives an overview on the average share of each consumption category of the total household carbon footprint.

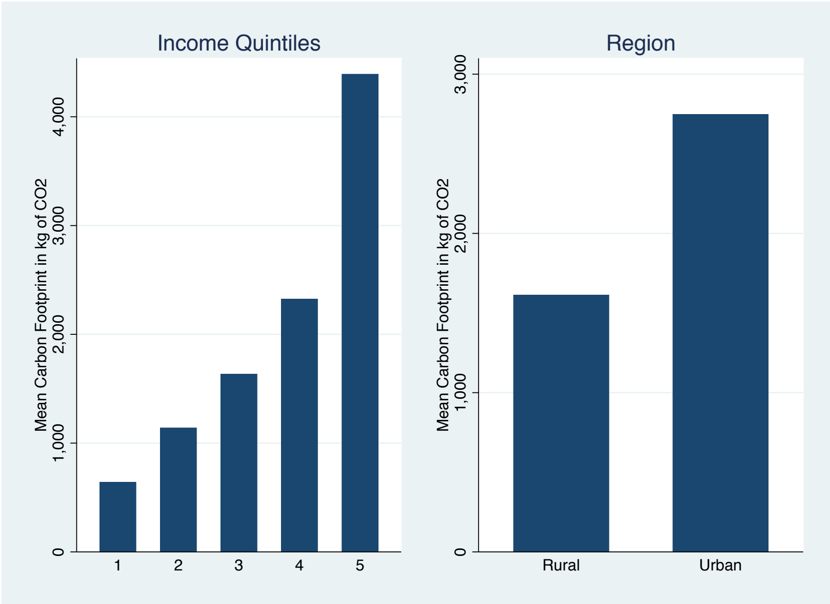

Figure 2.4: Household Carbon Footprint by Income and Location 2004/05
Source: CSO (2005) and NSS (2006).

2.5 Results

First we will present the results from the analysis, which attempts to reveal the effect of changes in major determinants of the household carbon footprint such as income, demographic as well as socio-cultural variables and the major energy source for cooking of the household. Second we present how much of the rise in the household carbon footprint between 2004/05 and 2009/10 was due to changes in total expenditure. Last but not least we present the results on how much the composition of household expenditure changes when total expenditure is rising.

2.5.1 Determinants of the Household Carbon Footprint

Table 2.2 shows the results from the analysis of the household carbon footprint and its main determinants. Column 1 presents the results from OLS regression and a model specification containing similar variables as analyzed in Wier et al. (2001). For comparison we find that living in an urban area leads on average to a 13% higher carbon footprint in our sample. In contrast Wier et al. (2001) find that Danish urban households emit on average less than their rural counterparts.[40]

Table 2.2: Determinants of the Household Carbon Footprint 2004/05

$lnCO_2^{hh}$	(1) OLS	(2) Beta Coef.	(3) QR (q=0.1)	(4) QR (q=0.9)
lnIncome	1.775***	1.547	2.723***	0.789***
$lnIncome^2$	-0.04***	-0.723	-0.084***	0.004
PDS Dummy	-0.068***	-0.043	-0.07***	-0.059***
Urban Dummy	0.128***	0.078	0.063***	0.119***
Income*Urban	0.000	0.004	0.000***	0.000***
HH-Size	-0.007***	-0.023	0.009***	-0.024***
$HH\text{-}Size^2$	0.001***	0.034	0.000	0.002***
$HH\text{-}Size^3$	-0.000***	-0.024	-0.000***	-0.000***
Income*HH-Size	0.000***	0.029	0.000***	0.000***
Age-Head	-0.015***	-0.265	-0.012***	0.001
$Age\text{-}Head^2$	0.000***	0.608	0.000***	0.000
$Age\text{-}Head^3$	-0.000***	-0.311	-0.000***	-0.000
Female Dummy	0.041***	0.017	0.023***	0.054***
Edu.-Head	0.035***	0.123	0.02***	0.027***
$Edu.\text{-}Head^2$	-0.001***	-0.049	-0.000*	-0.001***
Income*Edu.	-0.000***	-0.062	-0.000***	-0.000***
LPG	0.115***	0.066	0.171***	0.096***
Gas	0.034*	0.002	0.081***	-0.007
Dung	-0.023***	-0.006	-0.009	-0.043***
Charcoal	0.058**	0.002	0.199***	-0.022
Kerosene	0.019***	0.005	0.062***	0.012*
Electricity	0.368***	0.016	0.255***	0.491***
Constant	-6.783***		-12.55***	-1.064***
Observations	124,589		124,589	124,589
R-squared	0.863			

Note: The dependent variable is the household carbon footprint in natural logs and *** p<0.01, ** p<0.05, * p<0.1, state dummies are included.

The OLS results in column 1 are providing only a benchmark and allow us to report the standardized beta coefficients to compare the effect of the independent variables. In column 2 the standardized beta coefficient of income (0.83) and years of education of the household head (0.07) as well as the urban dummy (0.08) show the highest magnitudes. Hence a change in one standard deviation of the variable income is related with a change in 0.8 standard deviations of the carbon footprint. All other variables show lower standardized beta coefficients, which points to the importance of the income variable.

[40] Nevertheless, their analysis differs in many ways. First the sample is from an industrialized country, second they do not control for the other variables such as education. Finally they only analyse deviations from the mean carbon footprint.

In column 3 and 4 we display the results from the quantile regression. Column 3 presents the effect of a unit change of the explanatory variables on the 10^{th} quantile of the predicted variable household carbon footprint and column 4 the effect on the 90^{th} quantile respectively. In column 3 an increase in income by 1% is related to a rise of the carbon footprint by about 2.6% for the 10^{th} quantile and a rise by about 0.8% for the 90^{th} quantile. This implies that at the positive effect of a rise in income is higher for lower quantiles of the carbon footprint. When comparing those results with the OLS results in column 1 the OLS estimator underestimates the effect of an increase in income for the 10^{th} quantile and overestimates it for the 90^{th} quantile of the household carbon footprint. The squared coefficient of income in column 3 could indicate a decline in emissions after reaching a maximum. Nevertheless, this turning point is out of sample, which indicates steadily rising emissions with rising income. The coefficients of the demographic and socio-cultural control variables do not vary as much for the different quantiles in column 3 and 4. Being eligible for goods from the public distribution system (PDS) has a small negative impact on the household carbon footprint. Being located in an urban area explains slightly higher emissions, especially for households with high emissions. Higher income accelerates this effect. Concerning the household size, an increase by another household member leads to a considerable small rise in emissions and again higher income accelerates this effect. The age of the household head seems to be only relevant for households with low emissions. There are two turning points at 31 and 74 years of age, which determine the range where rising age of the household head goes in line with increasing emissions. Female-headed households cause on average slightly higher emissions, which is stronger for households with a higher level of emissions. The more educated the household head the higher the emissions with a turning point of 12 years of education for households in the 10^{th} quantile of the carbon footprint distribution. Nevertheless higher income paired with higher education contributes to a slight decline in emissions.

We also analyze the major energy sources used for cooking again differentiating for the effects on the 10^{th} and 90^{th} quantile. Using electricity or charcoal leads on average to higher carbon footprints. The positive effect of kerosene or LPG is smaller and using dung cake affects carbon footprint negatively as one might expect.[41]This result indicates that

[41] None of the energy source variables is dropped from the regression since households can choose to use now major energy source at all.

switching energy sources could contribute to lower the carbon footprint. In Table B.7 in the Appendix to this chapter we present the same household carbon footprint regression for the period 2009/10. The coefficients remain very similar for the second period. The coefficient for income is now even larger for households in the 10th quantile and smaller for households in the 90th quantile. In other words, the household carbon footprint is even more sensitive to changes in the income. To account for the effect of the variables change over time we present a pooled regression with both time periods where we interact each variable with a dummy variable for the period 2009/10 in Table B.8 in the Appendix to this chapter. All the interacted explanatory variables are significant, which indicates that the change in the magnitude of those variables between 2004 and 2010 plays a role for the carbon footprint. With the following analysis we aim to explain how much of the rise in the carbon footprint is due to the change in the magnitude of those variables and who much is due to other sources.

2.5.2 Changes in the Household Carbon Footprint over Time

Table 2.3 presents the results from the Blinder-Oaxaca decomposition. Column 1 presents the mean prediction for the household carbon footprint, which represents 1503kg in 2004/05 and 2351.5kg CO_2 in 2009/10. There is an increase of about 0.7 tons CO_2, hence mean emissions increased by 57%, which is represented by the coefficient for Difference 1.57 in column 1.[42]

In Table 2.3 column 2 to 4 this rise in emissions is divided into three parts. Column 2 reflects the mean increase in emissions if the households in period one would have had the same magnitude of endowments such as income, household size, age or education as in period two. The coefficient of Total endowments 1.56 indicates that the change in endowments accounts almost for the entire rise (56%) in emissions between the two periods. More precisely income accounts for 47% and the education of the household head for 3% of rise in emissions. As confirmed above, the change in household income is the major determinant of the differences in household emissions between households and over time.

[42] The observed mean household carbon footprint is higher with 2015kg CO_2 in the first and 3078kg CO_2 in the second period. However the rate of change in emissions is similar with 52%. Therefore we consider the results of the decomposition analysis to be reliable.

Table 2.3. Results from the Blinder-Oaxaca Decomposition

CO_2^{hh}	(1) Differential	(2) Endowments	(3) Coefficients	(4) Interaction
Prediction 09/10	2351.469***			
Prediction 04/05	1502.936***			
Difference	1.565***			
Total		1.557***	1.038***	0.968***
lnIncome		1.471***	0.834***	0.993***
PDS Dummy		0.998***	1.017***	1***
Urban Dummy		1.007***	0.988***	1***
HH-Size		0.999***	0.989***	1***
Age Head		1.001***	1.019***	1***
Sex Head		1	1	1
Edu. Head		1.026***	0.98***	1***
LPG		1.012***	1	1
Gas		1	1	1
Dung		1***	1	1
Charcoal		1	1	1
Kerosene		1***	1	1
Electricity		1***	1***	1***
Constant			1.21	
Observations	225440	225440	225440	225440

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, state dummies are included. The dependent variable is CO_2^{hh} in kg.

Column 3 quantifies the rise in emissions when applying the coefficients from the second period to the characteristics from the first period. The coefficients play a minor role when explaining the rise in emissions. Only 3.8% of the difference is attributed to the total coefficients. Column 4 presents the interaction terms, which measure the simultaneous effect of differences in endowments and coefficients.

2.5.3 Income and Carbon Elasticities

The analysis of income elasticities reveals some interesting results. We present in Table 2.4 the OLS results for urban, rural and all India. Negative income elasticities represent a declining expenditure share of the respective expenditure category with rising income. These inferior good categories such as vegetables are in opposition to luxury goods such as medical goods or services and rent. It shows that one of the main priorities when households get richer appears to be housing. When doubling income, the share of total expenditures spent for rent and services would rise by about 10%. However, it has to be stressed that differences between different income classes can be significant, which can be shown by distinguishing between urban and rural households. The decline in spending on vegetables with rising income is stronger for rural households. Urban households show smaller spending responses towards reduced vegetable consumption. The classification into inferior, necessities and luxury goods holds for rural and urban households for the same consumption category. While households generally reduce vegetable consumption relative to their total expenditures when income rises, animal protein gains weight in their consumption basket.

Table 2.4: Income Elasticities of Expenditure Categories

	All India		Rural		Urban	
	coeff	se	coeff	se	coeff	se
Vegetables	-0.161***	-0.001	-0.151***	-0.001	-0.105***	-0.001
Animal protein	0.018***	-0.000	0.049***	-0.001	0.011***	-0.001
Processed food	0.017***	-0.001	0.013***	-0.001	0.019***	-0.001
Tobacco, pan, tox.	-0.001***	-0.000	0.002***	-0.000	0.002***	-0.000
Fuel, light	-0.032***	-0.000	-0.03***	-0.000	-0.026***	-0.000
Clothing, shoes	-0.017***	-0.000	-0.01***	-0.001	-0.009***	-0.001
Education	0.021***	-0.000	0.021***	-0.001	0.026***	-0.001
Entertainment	0.007***	-0.000	0.006***	-0.000	0.007***	-0.000
Medical goods	0.028***	-0.001	0.048***	-0.001	0.024***	-0.001
Toiletry	-0.011***	-0.000	-0.009***	-0.000	-0.008***	-0.000
Services, rent	0.108***	-0.001	0.028***	-0.000	0.03***	-0.001
Durables, building	0.000***	-0.000	0.000***	-0.000	0.000***	-0.000
Transport	0.023***	-0.000	0.032***	-0.001	0.028***	-0.006
Personal goods	0.000***	-0.000	0.000***	-0.000	0.000***	-0.000

Source: NSS 2006 and CSO 2005. Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

In general most of the estimated coefficients are very small, implying that the change in the carbon footprint is caused by overall higher consumption and not by shifts within the consumption basket. Besides the coefficients shown in Table 2.4 and the above discussion of their signs and magnitude can be better understood by showing how a change in income affects the composition of the consumption basket.

Table 2.5 shows that a 10% income rise only marginally affects the composition of the consumption basket. The biggest change can be observed in the consumption of vegetables, a 10% income rise changes the share of vegetables in total expenditures by 1.6%. Other consumption shares change in less dramatic way.

Looking at the mean of the income distribution like in the first column in Table 2.4, average effects for the whole population can be an interesting starting point. If one is additionally interested in carbon footprint changes of different income groups, greater heterogeneity in consumption behavior can be revealed.[43] The poorest group of the

[43] Results for income quintiles are shown in Table B.9 in the Appendix to this chapter.

population significantly reduces the share of vegetable food in total expenditures and increases consumption in most other categories. In general, no shift towards a sustainable consumption with low emission goods can be observed. With the exception of services and rent as low emission intensity consumption categories, high emission intensity consumption increases with income. By moving up the income ladder, a considerable part of the additional income is spent on carbon intensive goods such as transport.

Table 2.5: Consumption Shares and Changes when Income Rises

consumption category	share of total exp (%); before income rise	change in share (% points), 10% income rise	share of total exp (%); after income rise
Vegetables	35.488	-1.61	33.878
Animal protein	10.566	0.175	10.741
Processed food	5.171	0.173	5.344
Tobacco, pan, intoxicants	2.596	-0.008	2.588
Fuel, light	10.46	-0.324	10.136
Clothing, shoes	7.627	-0.166	7.461
Education	3.313	0.214	3.527
Entertainment	0.84	0.072	0.912
Medical goods	4.4	0.277	4.677
Toiletry	5	-0.114	4.886
Services, rent, tax	10.862	1.08	11.942
Durables, building	0.016	0.000	0.017
Transport	3.655	0.232	3.887
Personal goods	0.005	0.000	0.006
Sum	100	0	100

Source: NSS 2006

2.6 Conclusion

First, we apply input output analysis matched with Indian household expenditure data to estimate the carbon footprint of Indian households. Second, we analyze the determinants of the variation in the carbon footprints between households and over time trying to find what, besides income, is a determinant of Indian CO_2 emissions from consumption. To analyze changes over time we decompose into the effect of the change in the magnitude of the variables and possible unexplained effects such as changes in the consumption patterns. Finally, we estimate the income elasticity of major consumption subgroups to be able to investigate the effect of changes in the composition of household consumption and point to consumption items, which are declared as luxury goods and which exhibit a high carbon intensity.

We find that income is indeed the major determinant of household emissions. But, fuel types, which are used for cooking, have an impact on the carbon footprint as well as age, gender and education of the household head. The effect of a rise in income affects households differently. Households with a low carbon footprint tend to observe a stronger rise in emissions as income is increasing. Households with a high carbon footprint reveal an income elasticity lower than one. Hence, they might have passed a point of saturation, which allows increasing consumption to become less carbon intensive. When looking at changes over time we find that the rise in the mean carbon footprint by 57% is mostly due to increased household income (total expenditure), which explains 47% of the rise in emissions. With the analysis of income elasticities of each consumption category we find that those categories, which are classified as luxury goods such as transport, medical goods or entertainment do not exhibit the highest carbon intensities, which leads us to the conclusion that the large difference in the carbon footprint between the fourth and fifth income quintile is mainly due to the overall higher expenditure and not due to changes in the consumption patterns of households as they get richer. We conclude that there is no evidence for sustainable consumption patterns but there is evidence for declining emission intensity as income is rising.

Chapter 3: The Effect of the Kyoto Protocol on Carbon Dioxide Emissions

Joint work with Inmaculada Martínez-Zarzoso

3.1 Introduction

Among the six dominant greenhouse gases (GHG) mentioned by the UNFCCC, carbon dioxide emissions (CO_2) are considered to have the strongest impact on climate change. In 2009, total global CO_2 emissions amounted to 31.3 billion tonnes, an increase of almost 405 since 1990, the base year of the Kyoto Protocol. The large regional variation in emission trends resulted in a 535 share for developing countries versus 44% for industrialized countries in 2009. Industrialised countries under Annex B of the Kyoto protocol are due to cut emissions by 5.2% on average below their 1990 levels until 2012, which amounts to 22.5 billion tonnes.[44] Although these countries had reduced CO_2 emissions by about 7% in 2009, a substantial part of the decrease was due to a drop in economic activity in response to the economic crisis. Indeed, emissions could increase toward pre-recession levels as developed countries recover their normal levels of economic activity.

Given the current policy debate and the importance of evaluating the effectiveness of the already established climate agreements, the main aim of this chapter is to analyse to what extent emission commitments from the Kyoto Protocol have an effect on CO_2 emissions. In other words, how much more CO_2 would the countries have emitted in the absence of their Kyoto Protocol ratification? This question is important to evaluate present international climate negotiations and to encourage future climate negotiations, which could introduce binding emission reduction commitments for all countries without jeopardising the growth of developing countries.

From a theoretical point of view, we base our analysis on a more elaborated version of the model proposed by Grossman and Krueger (1991) and (1995). The model assumes that economic growth, measured by GDP, brings an initial phase of rising emissions followed by a subsequent phase of declining emissions. By adding a policy variable, namely commitments from the Kyoto Protocol, we introduce a crucial factor to this model.

Although a small amount of related empirical research does exist, there is, to our knowledge, no previous work that uses our identification strategy to assess the impact of

[44] Annex-B countries are industrialised nations that signed the Kyoto Protocol. Their emission reduction goals are mentioned in Annex-B of the treaty. For a list of all Annex-B countries, please refer to Table A.1 in the Appendix.

the Kyoto protocol on CO_2 emissions. While Mazzanti and Musolesi (2009) and Iwata and Okada (2010) used panel data to control for unobserved heterogeneity, they did not consider the problem of endogeneity of the Kyoto variable. Only Aichele and Felbermayr (2012) address the endogeneity of the policy variable by using an instrumental variable estimator, but rely on an arguably weak identification strategy (see below). The main contribution of this chapter is twofold. First, we use matching combined with difference-in-differences techniques to properly identify the Kyoto effect. Second, to place our results in the existent literature we also use instrumental variable techniques for panel data to control for the endogeneity of the policy variable and propose a number of variables as instruments for Kyoto commitments. As regards the first approach, a difference-in-differences estimator with matching is used to create a suitable counterfactual in order to estimate how a country's emission path would have developed if it had not ratified the protocol. As a robustness check, we estimate an instrumental variable panel data model and use three different variables as external instruments for the Kyoto variable, namely the number of financed projects from the Clean Development Mechanism (CDM), World Trade Organization (WTO) membership and International Criminal Court (ICC) membership. The CDM, as one of the flexible mechanisms from Kyoto Protocol, is correlated with the emission reduction commitments of the investing country, but not with its current CO_2 emissions. Whereas the ICC variable was used by Aichele and Felbermayr (2012), we propose WTO membership as an additional instrument. By using several instruments, we are able to interpret our estimates as causal effects and test for the validity of the instruments. The main results indicate that ratifying the Kyoto Protocol has a significant effect on CO_2 emissions. Countries that face emission commitments emit on average about 7% less than those without.

The rest of this chapter is structured as follows. Section 3.2 reviews the related literature. Section 3.3 presents the empirical strategy and section 3.4 discusses the estimation results. Section 3.5 applies several robustness checks and section 3.6 presents the conclusions of the chapter.

3.2 Literature Review

The Kyoto Protocol was prepared by the annual meetings of the UNFCCC and adopted for use at the 1997 meeting in Kyoto. It finally came into force in 2005 following Russia's ratification, which fulfilled the established prerequisite that a minimum of 55 countries emitting at least 55% of global GHG emissions had ratified the treaty. The long delay between the adoption of the protocol and when it came into force was due to discrepancies over which countries should have binding emission reduction commitments and what those commitments could potentially cost.

Although in the political arena a lot has been said about the reason why countries committed themselves –or not– to participate in the Kyoto Protocol, only two studies have empirically investigated the determinants of the Kyoto-ratification decision. York (2005) and Zahran (2007) analyse the key determinants that led to ratification of the Kyoto Protocol with or without commitments. According to both studies, population growth, education levels, energy consumption and emissions growth are the main factors affecting the decision to ratify the protocol. We will follow these studies and use the variables they propose as main factors to construct the counterfactual in our empirical application.

Another issue concerning the design of the protocol was how to incorporate developing countries such as China, which in 1997 did not account for a large share of global emissions but now does. In order to integrate developing countries, the Kyoto Protocol seeks to enhance sustainable development via the Clean Development Mechanism (CDM). The CDM makes it possible to fulfil a country's GHG emission reduction commitments with Certified Emission Reduction Units (CERs) from any developing country that is a member of the UNFCCC.

Among the vast empirical literature that studies the determinants of CO_2 emissions, to our knowledge only three studies have specifically investigated the effect of the Kyoto Protocol on countries' CO_2 emissions. In the first study, Mazzanti and Musolesi (2009) evaluate the impact of time-related policy events on carbon emissions in European countries. They find that the income-emissions relationship is affected by policy events such as the signing of the UNFCCC in 1992 and the Kyoto Protocol in 1997. Their findings indicate a decline in CO_2 emissions for northern European countries after 1997, which they attribute to the Kyoto Protocol. The main shortcoming of this study is that it focuses exclusively on European countries and fails to address the endogeneity bias of the policy events, including Kyoto. Instead, we will use a larger sample of countries and propose different ways of addressing the potential endogeneity bias of the target variable. The endogeneity bias is related to the fact that countries may self-select into Kyoto if their past emission levels were low.

Second, Iwata and Okada (2010) analyse the effect of ratifying the Kyoto Protocol on major GHGs using data over the period 1990 to 2005 to estimate a dynamic panel data model with fixed effects. When focusing on CO_2 emissions as the dependent variable, they find that Kyoto-ratification has a significant CO_2 reducing effect of about 11 percent. This study has two main weaknesses. On the one hand, it does not control for the abovementioned self-selection problem. On the other hand, it justifies using data only for the period 1990-2005 by arguing that after 2005 countries started to invest in CDM projects and since then emissions have been reduced abroad rather than domestically. We argue instead that the CDM projects start in 2003 and the amount of emissions reduced abroad is very low. Most countries ratified the Kyoto Protocol after 2005, for which reason in our empirical application we extend the sample to cover more recent years.

The third study by Aichele and Felbermayr (2012) analyses the impact of ratifying the Kyoto Protocol on countries' CO_2 emissions between 1997 and 2007. In order to overcome the problem of self-selection into the protocol, the authors instrument the Kyoto variable with a country's membership of the International Criminal Court (ICC) and its spatial lag. The authors restrict the data to a sample of 40 countries. Out of them, only 12 countries do not face obligations from Kyoto and not all the countries that face obligations are represented in the dataset. The timeframe is divided into pre- and post ratification yielding two 4-year averaged time periods. Their findings indicate that countries with Kyoto commitments emit on average about 8% less CO_2 than countries without.

In this study we believe that the sample composition and the time period matter, therefore we do not restrict the sample composition and use data for more countries over a more recent time period without averaging. Furthermore we propose an alternative estimation method that is also able to address the self-selection issue, namely a matching differences-in-differences estimator. In order to identify the channel how the Kyoto commitments reduced emissions we specify an alternative model and find that countries did cut emissions through lowering emission intensity. As a robustness check we compare the results with those obtained by using an instrumental variable and employ alternative instruments besides the abovementioned ICC.

3.3 Empirical Strategy

3.3.1 Model Specification

The empirical model proposed to estimate the effects of the Kyoto Protocol on CO_2 emissions includes income and population variables as the main drivers of emissions. We follow the approach of (Harbaugh et al. 2002) to identify the right empirical specification for GDP per capita.[45] The quadratic specification is selected as it yields more robust results than the cubic specification of GDP per capita.[46] Technological change is not added as an explanatory variable because our policy variable accounts for technological innovations, which are policy-induced. The remaining effect of technological change is modelled in the error term. Our model takes the following form:

$$\ln CO_{2_{it}} = \alpha_i + \lambda_t + \beta_1 Kyoto_{it} + \beta_2 \ln POP_{it} + \beta_3 \ln GDP_{it} + \beta_4 \ln GDP_{it}^2 + \varepsilon_{it} \tag{3.1}$$

where $\ln CO_{2it}$ is the natural logarithm of CO_2 emissions emitted by country i in year t measured in tonnes. α_i and λ_t are country and year-specific effects that control for unobservable country heterogeneity and common time-varying effects that could affect emissions. $Kyoto_{it}$ measures the impact of the Kyoto Protocol on CO_2 emissions. It takes a value of one when country i has ratified the Kyoto Protocol and faces commitments from the treaty at time t, and a value of zero otherwise. The population variable POP_{it} is measured by the number of inhabitants. GDP_{it} and GDP_{it}^2 denote GDP per capita and GDP per capita squared, respectively.[47] The squared term accounts for non-linearities of the pollution-income relationship. Finally, ε_{it} is the error term that is assumed to be independent and identically distributed.

Most of the countries with emission commitments ratified the protocol between 2002 and 2005. It is worth noting that a number of high-income countries, namely the United States, South Korea and Singapore, did not ratify the Protocol or as in the case of Canada withdrew from its obligations. As a result, the Kyoto dummy is not too highly correlated (0.34) with the level of per capita income, which permits the identification of separate

[45] The model is based on the Environmental Kuznets Curve Hypothesis by Krueger (Grossman & Krueger 1995)

[46] The cubic term did not yield significant results.

effects. As the Protocol did not come into force until 2005, when sufficient countries had ratified it, the dummy could be defined as taking a value of one from 2005 onwards for all countries. However, there are several reasons to construct the dummy variable using the year of ratification rather than the year of implementation. First, implementation of the protocol does not have immediate consequences and second, politicians, the media and voters are involved in the ratification process and the relevant domestic policy measures are established immediately after ratification of the Protocol.

We already mentioned in the previous section the problem of self-selection into the Protocol. Countries could self-select into the ratification process and this would bias the estimates of the Kyoto effect. In particular, high emission levels during the time of protocol ratification might have lowered the incentives for countries to ratify and therewith to “select out” of the protocol. In the case of the United States, political pressure not to ratify the already signed protocol was high.

We create a counterfactual or control group as the main way of overcoming the problem of self-selection. We compare the effect of having Kyoto emission reduction commitments with not having commitments. The effect of facing emission commitments is the conditional average treatment effect on being treated (ATT):

$$ATT = \mathbb{E}[Y_i(1) - Y_i(0) \mid Kyoto_i = 1] \tag{3.2}$$

where $\mathbb{E}$ is the expectation operator. In this framework, a quasi-natural experiment, the countries in the control group have to be as similar as possible to the treated group, except for the fact that they do not face any commitments. According to York (2005) and Zahran (2007), the decision to ratify or not is mostly determined by current GDP, population and emission growth. Thus, we use those variables and their higher order to estimate propensity scores for ratifying the Kyoto protocol with reduction commitments. We use a probit estimator to estimate the propensity score to ratify the Kyoto Protocol with emission commitments. The model specification is given by,

$$Treat_i = \beta_1 GDP\ growth_i + \beta_2 Pop\ growth_i + \beta_3 CO_2\ growth_i + \beta_4 GDP\ growth_i{}^2 + \beta_5 Pop\ growth_i{}^2 + \beta_6 CO_2\ growth_i{}^2 + \varepsilon_i \tag{3.3}$$

where $Treat_i$ takes the value one if a country has ratified the Kyoto Protocol with commitments at some point in time and zero otherwise. GDP, population and CO_2 growth are measured as percentages and ε_i represents the error term. We use the nearest neighbour to match countries with Kyoto commitments to comparable countries without commitments.[48] We match the countries for each year separately in order to keep the multi-t panel structure of the data and not having to average over pre- and post-Kyoto periods.

Next we apply a difference-in-differences estimator to the matched sample using the following specification:

$$\widehat{ATT_{PSM}^{DD}} = \frac{1}{N_T}\sum_{i \in T=1}\left[Y_{i2}^{T} - Y_{i1}^{T} - \sum_{i \in C} w_{ij}\left(Y_{i2}^{C} - Y_{i1}^{C}\right)\right] \tag{3.4}$$

where N_T is the number of treated countries T and w_{ij} is the weighting, which is assigned to country j in control group C being matched to country i (Khandker et al. 2009). The efficiency of the ATT estimates can be improved using the inverse propensity score as a sampling weighting (Hirano et al. 2003).

The validity of the ATT is conditioned by the fulfilment of two assumptions. The first assumption, conditional independence, assumes that the selection into treatment is solely based on observable characteristics. We are aware that there could be unobserved variables, which could be correlated with the decision to ratify Kyoto and different from the ones we control for. The second assumption is the common support condition. The common support region includes all the observations where the balancing score has a positive density for both treated and untreated countries. There has to be an overlap between treated and untreated countries in order to match them (Khandker et al. 2009). We present the results on the density distribution of the propensity scores and the common support region in Figure A.1 to A.3 in the Appendix.

In order to analyse through which channel the Kyoto commitments have led to declining emissions we modify the model specification in Equation 3.1 and use the emission intensity, namely the amount of CO_2 emissions per unit of GDP, as dependent variable:

$$\ln\left(\frac{CO_{2it}}{GDP}\right) = \alpha_i + \lambda_t + \beta_1 Kyoto_{it} + \beta_2 \ln POP_{it} + \beta_3 \ln GDP_{it} + \varepsilon_{it} \tag{3.5}$$

[48] The nearest neighbour algorithm applies a weight of one to the counterfactual observation that has the nearest propensity score to the treated observation, in our case, Kyoto commitments.

In this way we analyse how having Kyoto commitments influences a countries' emission intensity. Indeed, technological change, which is in most cases policy induced, does not cut emissions directly but does have an effect on the emission intensity of each unit of GDP.

3.3.2 Data

CO_2 emission data are from the Carbon Dioxide Information Analysis Center (CDIAC 2012) and include emissions from solid, liquid as well as gas fuel consumption and emissions from cement production as well as gas flaring. The panel is unbalanced because the data on CO_2 emissions for economies in transition are only available from 1992 onwards. Therefore, we restrict our dataset to 170 countries over the period from 1992 to 2009 in order to have CO_2 emission data for each country each year.

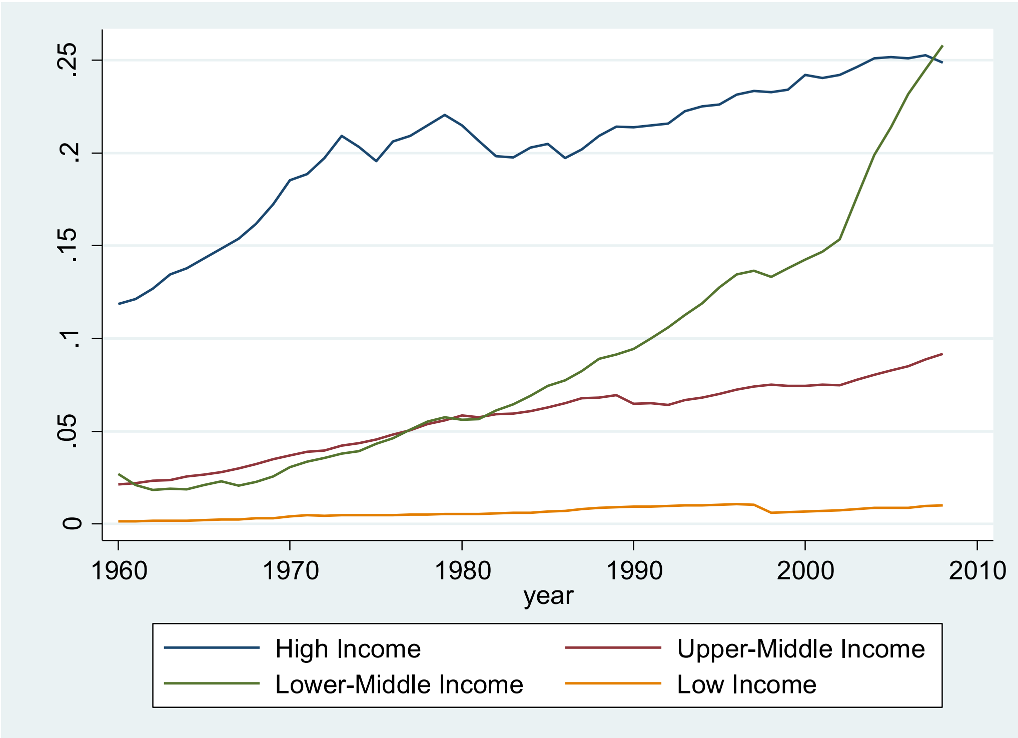

Figure 3.1: Average CO_2 Emissions of High-, Middle- and Low-Income Countries.

Source: CDIAC (2012). Note: The y-axis displays CO_2 emissions from fossil fuels in billion metric tons. Economies in Transition are excluded. Countries are grouped according to 2009 GNI per capita, calculated using the World Bank Atlas method. The groups are: Low Income, $995 or less; Lower-Middle Income, $996-$3,945; Upper-Middle Income, $3,946-$12,195; and High Income, $12,196 or more.

Figure 3.1 shows that CO_2 emissions have steadily increased over the whole period and in all countries. High-income countries emit on average more than 10 times the amount of CO_2 than low-income countries. The lower-middle income countries display a more volatile trend and surpass high-income countries in 2008, mainly due to the upturn in emissions from China and India. The data on Kyoto Protocol ratification and CO_2 emission reduction commitments are from the (UNFCCC 2010) and the data on the number of financed CDM projects by country are from the UNEP Risoe Centre (UNEP 2012). The data on GDP per capita and Population are taken from the Penn World Tables Penn World Tables (Heston et al. 2011). Summary statistics and cross correlations for the variables used in the analysis are presented in Table C.2 and Table C.3 in the appendix to this chapter.

3.4 Main Results and Policy Recommendations

In the first part of this section we present the results obtained using the difference-in-differences estimator with matching and in the second part we discuss how the Kyoto Protocol could have affected emissions.

Table 3.1: Results from Estimating the Propensity Scores for 2009

	Probit
CO_2 Growth	-16.95***
	(5.77)
Population Growth	-10.38
	(52.58)
GDP Growth	-19.38***
	(6.99)
CO_2 Growth^2	-89.52**
	(37.96)
Population Growth^2	-6822.45
	(4297.16)
GDP Growth^2	-44.06
	(66.21)
Constant	-0.73**
	(0.29)
Observations	186
Pseudo R-squared	0.57

Note: The dependent variable is Treat. Robust standard errors are in brackets, ***p<0.01, **p<0.05, *p<0.1.

Table 3.1 presents the results from the probit regression used to estimate the propensity scores for ratifying Kyoto with emissions commitments in 2009. As in Equation 3.3, the dependent variable Treat takes a value of one for the treated units. The three key variables, which influence the decision to ratify Kyoto with commitments, namely growth in GDP, population and CO_2 emissions, are statistically significant.

We choose nearest neighbour matching to create the control group by matching countries with commitments (treated group) to those without commitments and with a similar likelihood of being in the treated group. The quality of the match relies on the balancing property and the test of the difference in means of the independent variables after the match is made. We show that the balancing property is met and the difference in the mean propensity score between the treated and control group is 0.28 points. Table A.4 in the Appendix shows that there is no significant difference between the treated group and the control group in terms of the means of the explanatory variables, namely GDP per capita and population growth, after matching.

Table 3.2: Results Using the Difference-in-Differences Estimator 1992-2009

Dep. Var.	Ln CO_2	Ln CO_2		Ln (CO2/GDP)	
Sample:	Whole	Matched		Matched	
Weights:	-	-	(1/PS)	-	(1/PS)
Kyoto Dummy	-0.194***	-0.1**	-0.065**	-0.121***	-0.087**
	(0.02)	(0.042)	(0.032)	(0.04)	(0.034)
Treat Dummy	0.401**	6.448***	-8.438**	-3.503*	0.916
	(0.169)	(2.246)	(3.414)	(1.908)	(0.741)
Ln Population	1.018***	2.003***	1.739***	1.781***	1.424***
	(0.128)	(0.378)	(0.308)	(0.315)	(0.262)
Ln GDP	1.133***	1.661*	1.499*	-0.391***	-0.430***
	(0.273)	(0.85)	(0.786)	(0.118)	(0.100)
Ln GDP^2	-0.024	-0.064	-0.06		
	(0.016)	(0.043)	(0.039)		
Constant	-20.32***	-36.02***	-18.63***	-16.22***	-17.49***
	(1.91)	(8.598)	(2.871)	(2.182)	(4.076)
Country Dummies	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes
Number of Obs.	3,056	468	468	429	429
Overall R-squared	0.988	0.998	0.999	0.998	0.999

Note: Robust standard errors are in brackets, ***$p<0.01$, **$p<0.05$, *$p<0.1$. PS denotes propensity score.

Next we apply a difference-in-differences estimator to calculate the average treatment effect to be able to control for the unobservable country heterogeneity and common time effects that may also affect emissions. Table 3.2 shows the main results. Column 1 of Table 3.2 presents the results for the whole sample as a benchmark. The estimated coefficient for the Kyoto variable (-0.19) is negative and statistically significant, but its magnitude is considerably high. Column 2 presents the same specification estimated using the matched sample instead of the whole sample. An ATT of -0.10 is obtained, indicating that countries that face emission commitments emit on average 10% less CO_2 compared to the control group of countries, which face similar conditions in terms of GDP and population growth, but do not have to cut emissions. It is worth noting that restricting the sample to the matched countries as a way of controlling for the endogeneity of our policy variable reduces the coefficient from about -0.19 (column 1) to -0.10 (columns 2 and 3). In order to refine our estimate and prove its validity, column 3 of Table 3.2 shows the results obtained by using the inverse of the propensity score (PS) as sampling weights. This refinement lowers the coefficient of Kyoto to -0.065.

Similar to other studies estimating the Kyoto effect, we also obtain that ratifying Kyoto has a negative and significant effect on emissions. In particular, our results show that a country with emission commitments emits on average 6.5% less CO_2 than a country without reduction commitments. This is a lower effect in comparison with the results obtained by Aichele and Felbermayr (2012), -8% (estimate from a fixed effects IV regression) and Iwata and Okada (2010), who find an effect of about -11% for CO_2 emissions (estimate from a fixed effects estimator). Mazzanti and Musolesi (2009) also find the Kyoto Protocol has a negative effect on CO_2 emissions for the northern EU country group.

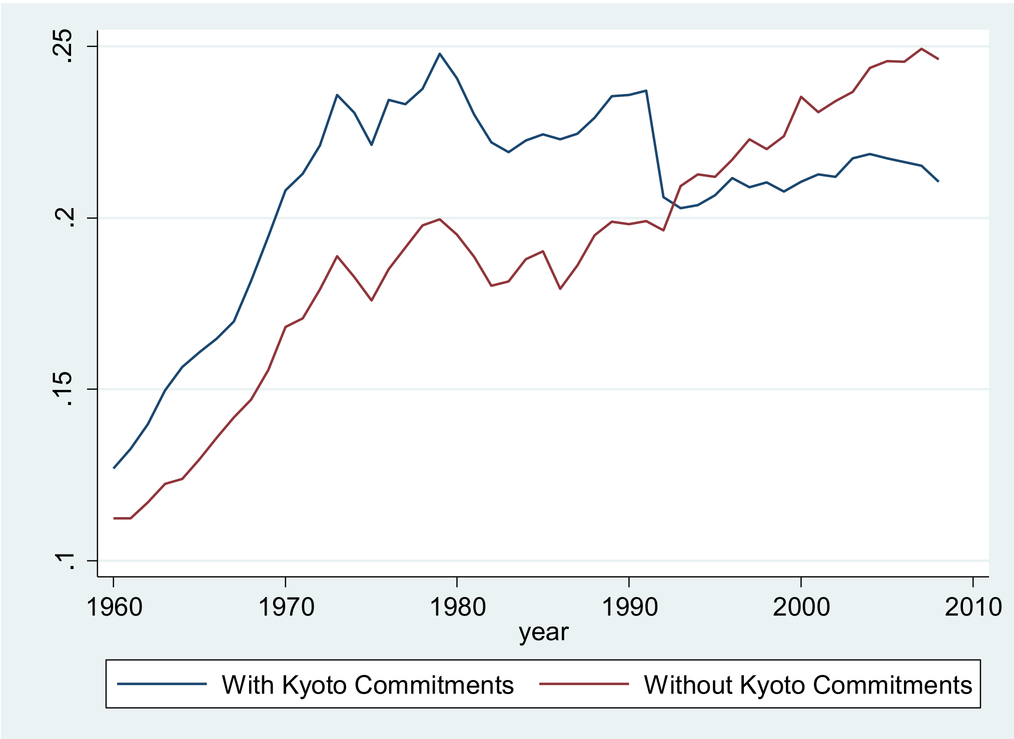

Figure 3.2: Average CO_2 Emissions of High-Income Countries Only

Source: CDIAC (2012). Note: The y-axis displays CO_2 emissions from fossil fuels in billion metric tons.

Interestingly, Figure 3.2 indicates that average emissions of these two country groups mainly diverge from the early nineties onwards, whereas before that date outcomes moved in tandem, with almost parallel trends. Hence, the existence of similar emissions trends for “similar” countries between the treatment and comparison groups before the policy change validates the use of matching techniques as the preferred model to estimate the Kyoto effect.

When turning to column 4 and 5 in Table 3.2 we find that the estimated Kyoto effect when using emission intensity as dependent variable is slightly larger. Countries with Kyoto commitments show on average a 9% lower emission intensity per unit of GDP than their comparison group without commitments. This difference in emission intensity could be the channel through which the Kyoto commitments affect countries' emissions. It could be argued that policies such as the Kyoto Protocol induce technological change, which in turn affects emission intensity.

Summarising, we find that Kyoto countries emit less CO_2 than comparable non-Kyoto countries, but the effect is lower than estimated by previous studies. Yet despite the reduced effect, we have been able to find strong indications that the Kyoto Protocol has not failed and that until now it has been the only functioning mechanism to prevent the participating countries from increasing CO_2 emissions.

The main policy recommendation derived from this study is that policy makers should actively work towards finding a way of extending the Kyoto Protocol to a wider range of countries, including the so-called new industrialised nations, which indeed should be renamed "already" industrialised countries. Unfortunately, this is not what is actually happening, as the Doha amendment, which would prolong and renew the commitments from the Kyoto Protocol, did not come into force yet. Many countries did sign but did not ratify the amendment so far.

3.5 Robustness Check

3.5.1 Pre-Kyoto Differences

As a robustness check, we run a placebo experiment to test whether the emission reducing effect from Kyoto is really due to the ratification of the protocol and not to differences in the initial emission levels between countries. Table C.5 in the appendix to this chapter shows the results obtained from estimating the same model using the whole sample of countries over the pre-ratification period, more specifically from 1980 to 1994. The Kyoto dummy takes a value of one for the countries that ratified with commitments at some point in time and zero otherwise. As the coefficient for facing future commitments from Kyoto is statistically significant but positive, we conclude that the Kyoto effect found above is not due to pre-ratification differences in emissions.

3.5.2 IV Estimates

Another option to control for endogeneity is by instrumenting the variable Kyoto with a number of selected instruments. The first proposed instrumental variable is the number of CDM projects financed by the investing country. The CDM, as one of the flexible mechanisms of the Kyoto Protocol, is correlated with the emission reduction commitments of the investing country, but not with its current CO_2 emissions. This is because the amount of emissions reduced by the CDM is very small and even if it did affect a country's emissions, this effect would be on future emissions instead of current ones. Even though it is necessary to ratify the protocol in order to invest in CDM projects, we only exploit the correlation between the two variables.[49] We also use two additional instruments, namely membership of the WTO and, as in Aichele and Felbermayr (2012), membership of the ICC. The instruments must fulfil two conditions. They have to be correlated with the instrumented variable and they must not be correlated with the error term. The first stage of the IV approach is:

$$Kyoto_{it} = \alpha_i + \lambda_t + \beta_1 \ln POP_{it} + \beta_2 \ln GDP_{it} + \beta_3 \ln GDP_{it}^2 + \beta_4 CDM_{it} + \beta_5 WTO_{it} + \beta_6 ICC_{it} + \upsilon_{it} \qquad (3.6)$$

where $Kyoto_{it}$ takes a value one when a country i has ratified the Kyoto Protocol and faces commitments from the treaty at time t, and zero otherwise. α_i and λ_i are country and year-specific effects that control for unobservable country-heterogeneity and common time-varying effects that could affect the decision to ratify Kyoto. The external instruments are CDM_{it}, WTO_{it} and ICC_{it}. In particular, CDM_{it} accounts for the number of CDM projects in which a country invested in year t. WTO_{it} takes a value of one if a country is a member of the WTO in the specific year and zero otherwise. Similarly, ICC_{it} indicates whether or not a country is a member of the ICC. Finally, υ_{it} is the error term. The second stage of the IV approach is:

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[49] CDM projects clearly did not 'cause' participation in Kyoto, but the other way around. However, for an instrument to be valid, all that is needed is for the two to be correlated (and for CDM projects to be exogenous to the emissions path).

$$\ln CO_{2_{it}} = \alpha_i + \lambda_t + \beta_1 Kyoto_{it} + \beta_2 \ln P_{it} + \beta_3 \ln GDP_{it} + \beta_4 \ln GDP_{it}^2 + \mu_{it} \tag{3.7}$$

where $\ln CO_{2it}$ is the natural log of CO_2 emissions emitted by country i in year t measured in tonnes. The variable $Kyoto_{it}$ is instrumented with the variables from Equation 3.6 and a maximum of three external instruments. μ_{it} is the error term.

Column 1 in Table C.6 in the appendix to this chapter presents the benchmark regression without instrumenting the Kyoto variable. Column 2 presents the instrumental variable estimation results (-0.3) using the number of CDM projects in which a country has invested as the instrument. The Kyoto effect is negative and the magnitude of the effect is even greater than in column 1 but inaccurately estimated. When we add WTO membership as an additional instrument in column 3, the effect declines slightly to -0.25. Nevertheless, the Hansen test rejects the validity of our instruments (p-value=0.02).

Similar to Aichele and Felbermayr (2012), we add ICC membership as a third instrument. The result does hardly change (-0.26) but the Hansen test still rejects the validity of the instruments. In order to make the sample more homogenous, we reduce the sample to high-income countries in column 5 Table C.6 in the appendix to this chapter). We find that high-income countries with Kyoto commitments emit on average 11% less CO_2 than those without commitments. This effect is higher than the result obtained by Aichele and Felbermayr (2012), but they use a slightly smaller sample of countries (40). Apparently, the results are sensitive to small modifications in the sample of countries considered. Indeed, by restricting the sample to "similar" countries we obtain a more similar Kyoto estimate to the result obtained for the matched sample, but still biased and much larger (0.11 versus 0.065).

3.6 Conclusions

This chapter tests for an effect of the Kyoto Protocol on CO_2 emissions. Our estimates indicate that countries with emission commitments from the Kyoto Protocol emit on average about 6.5% less CO_2 than similar countries that did not ratify the Protocol. We conclude that there is a potential effect from the Kyoto policy on emissions in those countries. The channel of this effect is the difference in emission intensities between countries with Kyoto commitments and those without. Once a country ratifies the protocol with emission reduction obligations it is more likely to pass green growth policies, which do not immediately cut emissions but reduce emission intensity of GDP. We contribute to the existing literature by using a new identification strategy of the causal effect, namely using matching and difference-in-differences techniques to obtain an accurate estimation of the Kyoto effect.

One matter of concern is whether we can indeed attribute the whole estimated effect to the Kyoto Protocol, as the number of countries that ratified the protocol and face emission commitments (32), is rather small compared to the number of countries that do not face any emission commitments under the Kyoto Protocol (138). It could be argued that Annex B countries could have put the same effort into reducing their CO_2 emissions, even in the absence of the protocol. Indeed, it is often claimed that regulatory stringency is a positive function of per capita income and in the last decade many developed countries have been taking action to reduce emissions, irrespective of the modest commitments required by the protocol. In this line, we leave the inclusion of better proxies for regulatory stringency in the model for further research, which will help to support our findings.

In order to stabilise global warming at 2 degrees Celsius, much more serious measures will have to be taken. Although emissions from the developed countries with reduction commitments have declined and some countries like France, the United Kingdom and Germany have achieved their targets, the decline in emissions is unlikely to be enough to stabilise levels of GHG in the atmosphere. Emissions from emerging countries, namely China and India, are expected to increase substantially in the near future. Even if the involved developed countries achieve their Kyoto target this year, it can only be considered a partially successful agreement that is not going to be sufficient to solve the global warming problem. Possible solutions could be to integrate more countries into the treaty, including developing countries, or to establish an international carbon tax on GHG emissions.

As the first commitment round of the Kyoto Protocol closed last year and we observe large emission reductions which are due to the Protocol, it would be desirable that the Doha amendment comes into force as fast as possible and not 13 years after its signature, such as in the case of the Kyoto Protocol. Finally, we would like to close the discussion by pointing out that according to our findings even a treaty often seen as a "failure" may in fact be producing some non-negligible effects.

Chapter 4: Income Inequality and Carbon Dioxide Emissions

Joint work with Stephan Klasen, Inmaculada Martínez-Zarzoso and Chris Müris

4.1 Introduction

Climate change and absolute income poverty are two major challenges facing mankind in the twenty-first century. As is well known (Bourguignon 2003; Klasen 2008), distribution-neutral growth serves to lower absolute poverty, while growth that is associated with reduced income inequality, or 'pro-poor growth' has a larger poverty-reducing effect. At the same time, literature on the environmental Kuznets curve (EKC) and on climate change suggests that increases in economic activity are responsible for observed and projected climate change; the effect of inequality change on emissions is, however, less clear. Analyzing the role of inequality for emissions is however, critical to understand possible trade-offs between pro-poor growth and climate change.

In this chapter, we analyze the relationship between income inequality and carbon dioxide emissions per capita. To investigate this issue, we use unbalanced panel data for 138 countries for the period 1960-2008 in combination with a fixed effects (FE) panel data model for per capita carbon emissions that introduces nonlinearities in per capita income and income inequality. We contribute to the existing literature on the relationship between income inequality and carbon emissions by using a much more comprehensive data set on income inequality that also deals with consistency issues in these data; in addition, we consider non-linear effects of inequality on emissions, which was not done before and leads to substantially different conclusions. Our main finding is that the relationship between income inequality and carbon dioxide emissions is U-shaped while there is also a (well-known) nonlinear income-emissions relationship (IER). Furthermore, this finding is robust against a wide range of specification changes but differs across countries: in high-income countries the turning point is at much lower levels of inequality so that the possibility of emission-reducing pro-poor growth is more feasible there, while most poorer countries indeed face a trade-off between lowering inequality and increasing per-capita emissions.

Income inequality can influence carbon emissions per capita through various channels whose relative strength might depend on the stages of economic development. An overview of the theoretical arguments for the role of income inequality for emissions can be found in Borghesi (2006). In the next paragraphs we briefly describe two of them, namely aggregation bias and political economy arguments.

Ravallion et al. (2000) point out that in a simple model where the marginal propensity to emit (MPE) falls with income, income inequality enters the income-emissions relationship. There is some evidence that the MPE varies with the level of income, see e.g. Holtz-Eakin & Selden (1995) and Heil & Selden (1999). If the poor have a higher MPE, increasing inequality will improve aggregate environmental quality conditional on average income. A related reasoning can be found in Heerink et al. (2001): if an inverted-U shaped relationship is assumed between household income and household carbon emissions, aggregating over households will also result in a negative relationship between income inequality and carbon emissions per capita.

This effect might be strengthened if the MPE rises with income for the poorer sections of the population in poor countries, e.g. because the poor in a poor country have no access to modern energy. Increasing inequality will then reduce marginal emissions of richer population segments, *and* reduce emissions of poorer segments as they are pushed out of the carbon economy.

Conversely, the MPE might rise with income due to the high energy-intensity of luxury good consumption. As different effects may dominate at different levels of income, the effect of inequality on emission could be U-shaped. Based on the arguments above, it could be the case that the turning point of the U comes later in poorer countries where the carbon economy argument is relatively more important, while in richer countries the rising MPE with rising incomes is reached relatively earlier leading to an earlier turning-point.

Based on political economy considerations, Boyce (1994) and Torras & Boyce (1998) assume that, in more unequal societies, those who benefit from pollution are more powerful than those who bear the cost. Therefore, the cost-benefit predicts an inefficiently high level of pollution. This implies a positive correlation between income inequality and pollution.

These two arguments point towards complex and possibly non-linear effects of income inequality on emissions, which may depend additionally on income levels.

Previous empirical work on the relationship between per capita CO_2 emissions and income inequality is limited. Ravallion et al. (2000) use a pooled OLS model and find that income inequality is negatively associated with carbon emissions. Borghesi (2006) rejects the pooled OLS specification in favor of a FE panel data estimator and finds that there is no statistically significant relationship between income inequality and carbon emissions per capita. Finally, Heerink et al. (2001) use a cross-section and find a negative correlation. None of these authors tested for nonlinearities in inequality.

These studies rely on the Gini income inequality measure from the data described in Deininger & Squire (1996) and estimate the model using a limited number of years. An important contribution of this chapter is the use of a comprehensive data set of comparable Gini coefficients based on Gruen & Klasen (2008). This allows us to use a much larger set of countries (138 instead of 42/37/64) and observations for the period 1960-2008 (compare 1975-1992/1988-1995/1985).

4.2 Data and Model

We use an unbalanced data set covering 138 countries from 1960 until 2008 with 1332 observations. The variables of interest are GDP per capita, CO_2 emissions per capita and income inequality (Gini).

Starting point for the income inequality data is the WIDER World Income Inequality Database, to which the treatment proposed in Gruen & Klasen (2008) is applied. We also apply a regression-based approach that addresses the heterogeneity of Gini coefficients. This deals with, among others, heterogeneity in consistency of the income concept and the unit considered, caused by the fact that the data can be based on either income or expenditure data, and can originate from either individuals or households, or may use some equivalence scales.

The data on national CO_2 emissions is taken from the Oak Ridge National Laboratory and covers emissions from fossil fuels, natural gas consumption as well as cement manufacturing. The use of this data set is well established in the literature but faces two major shortcomings. First, it is estimated data, which is based on the consumption of fossil fuels multiplied with the average carbon content of the respective fuel type. And second, it does not account for emissions from agriculture, life stock, deforestation or land use change. Therefore, it might underestimate the CO_2 emissions for countries with a large agricultural sector or where deforestation is a major source of emissions. Real GDP per capita is taken from the Penn World Tables 7.0 and is purchasing power adjusted to allow for international comparison, see Heston et al. (2011).

Our model extends an EKC to allow for an income inequality effect. To approximate a possibly nonlinear function in GDP per capita and Gini, we propose the following second-order approximation:

$$log(CO_2)_{i,t} = \alpha_i + \gamma_t + \beta_1 log(GDP)_{i,t} + \beta_2 log^2(GDP)_{i,t} + \beta_3 log(Gini)_{i,t} + \beta_4 log^2(Gini)_{i,t} + \beta_5 log(GDP)_{i,t} * log(Gini)_{i,t} + \epsilon_{i,t} \quad (4.1)$$

where i denotes an arbitrary country in our sample, t is an arbitrary time period, and α_i and γ_t denote individual and time effects. The coefficients of this model can be estimated using a FE panel data estimator. The interaction effect enters our model naturally because we use a second-order approximation. It allows both the level and the shape of the relationship between CO_2 emissions per capita and income inequality to depend on the value of GDP per capita.

4.3 Results and Conclusion

Our most important finding is that the relationship between carbon dioxide emissions per capita and income inequality is U-shaped: for countries characterized by high income inequality, reductions in income inequality are associated with lower per capita emissions. For less unequal societies, reductions in income inequality are associated with increases in carbon emissions per capita.

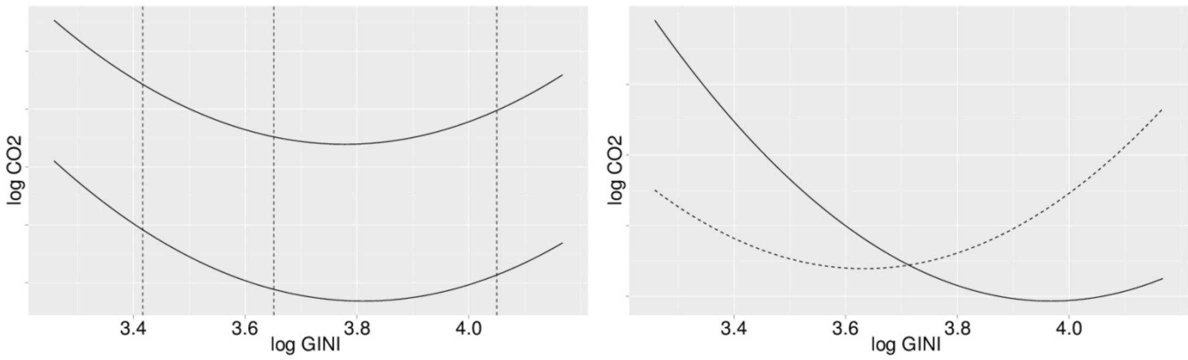

Figure 4.1: Estimated Relationships between Income Inequality and CO_2 p.c.

Note: Left panel: Top line is for the 55th percentile of GDP per capita in 2000; bottom line is 45th percentile. Dotted vertical lines indicate empirical percentiles 10, 50 and 90 of Gini in 2000. Right panel: Curves are normalized to have mean zero. Solid line is for the 1st percentile for GDP per capita in 2000, the dashed line is for the 99th percentile.

The inequality effects are highly significant and thus clearly provide a better fit of the data than a linear effect used in previous research. The level at which reductions in income inequality stop being beneficial will depend on the level of GDP per capita.

Figure 4.1 plots the estimated emissions-inequality relationships. In the left panel, the dashed lines denote 10th, 50th, and 90th percentile of the empirical Gini distribution in 2000, so that we can conclude that the turning point is in-sample. The two curves differ in their level of GDP per capita: the top line is for the 55th percentile of GDP in 2000, the bottom line is for the 45th percentile. This shows that higher values of GDP per capita are associated with higher levels of CO_2 emissions per capita. In the right panel, we plot two normalized emission-inequality relationships for two values of GDP per capita that are further away from each other. The economic significance of the interaction term becomes obvious: for poor countries, the turning point of the relationship shifts to higher values of income inequality (from a Gini of about 0.365 to a Gini of about 0.395 as we move from the 1st to the 99th percentile of per-capita incomes).

Table 4.1: Output from Benchmark Model and Sensitivity Analysis

	Benchmark	RE	Linear	3-year	10-year
ln(GDP)	2.09	0.73	2.57	2.22	1.67
	(0.33)	(0.66)	(0.28)	(0.46)	(0.54)
$\ln^2$(GDP)	-0.11	-0.02	-0.11	-0.11	-0.11
	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)
ln(Gini)	-7.22	-6.38	-0.29	-6.79	-8.84
	(1.31)	(1.98)	(0.08)	(1.60)	(3.09)
$\ln^2$(Gini)	0.79	0.69		0.76	0.86
	(0.13)	(0.15)		(0.18)	(0.40)
ln(GDP)*ln(Gini)	0.14	0.13		0.12	0.27
	(0.08)	(0.13)		(0.07)	(0.07)
Observations	1332	1332	1332	795	410
R2	0.6	0.6	0.61	0.52	0.53
Countries	138	138	138	138	138

Note: Individual and time effects are suppressed. Robust standard errors are in parentheses.

The coefficient estimates for our preferred specification can be found in Table 4.1, column 1. In the adjacent columns, we present a small part of our extensive sensitivity analysis. A Hausman test rejects the specification in column *RE* in favor of our *Benchmark* specification, which suggests that the explanatory variables are correlated with the individual effects. Column *Linear* shows that one would conclude that the relationship between income inequality and per capita carbon emissions is negative if a linear specification is used (Ravallion et al. 2000; Heerink et al. 2001). The last two columns of Table 4.1 show that our results are robust against the level of aggregation of the data: using data aggregated to 3- and10-year averages yield results close to the benchmark output.

This shows that the relationship between inequality and emissions is more complex than the previous literature had surmised. In particular, our findings are consistent with the aggregation bias argument and a more complex relationship between income and the MPE. For example, if there is a section of low incomes where the MPE is first 0 as people are outside of the carbon economy, then rises, then falls, and rises again at very high levels of incomes, this could deliver the results we find here, including the different turning-points for richer and poorer countries. Suggestive descriptive evidence supports this claim. When we divide up our sample in the last year into poorer and richer countries, we find that the unconditional correlation between income inequality and goods proxying the access and intensity of use of the carbon economy (cars or vehicles/1000 population and televisions) is strongly negative for poorer countries, and strongly positive for richer countries. Thus in poorer countries higher inequality reduces access and use of these goods, while in richer countries it increases it, confirming the supposition that the poor in poor countries are largely outside of the carbon economy while in rich countries, higher incomes might be associated with a rising MPE. The findings are also consistent with a combination of the aggregation and political economy arguments, with the latter dominating at higher levels of inequality.

The findings suggest an opportunity for pro-poor, low-carbon development for unequal rich countries. Those countries can promote pro-poor growth and experience declining emissions as a result. For poorer countries, only the most unequal ones could engage in pro-poor growth and reduce per capita emissions. More equal poor countries face a trade-off.

Chapter 5: Decomposition of Global Inequalities in Carbon Dioxide Emissions

Joint work with Michael Jakob and Ioanna Mouratiadou

5.1 Introduction

The question of equity plays a major role in current climate negotiations, involving ethical considerations and a broader analysis than the utilitarian approach to analyze the costs of climate change mitigation (Gardiner 2004). From this perspective, addressing inequality in per-capita emissions across countries is central for a fair allocation of emission rights, and hence the responsibility to reduce emissions, in any future climate agreement. Currently, global emissions are very unequally distributed between countries, with about 1 billion people living in industrialized countries being responsible for roughly half of the global CO_2 emissions (WEO 2010). However, recent growth spurts have caused a sharp increase in developing countries' emissions, closing part of the gap to richer countries, such that for the period 2001-2008 the growth of global emission can almost exclusively be attributed to developing countries (Steckel et al. 2011).

Previous literature has highlighted that in the process of economic development countries undergo characteristic transformations of their energy systems. For instance, while countries at early stages of industrialization predominantly rely on solid fuels, a large part of these fuels is replaced by grid-based, high-quality forms of energy - such as natural gas and electricity - with proceeding industrialization (Marcotullio & Schulz 2007; Grubler 2008). Further, rising per capita income has been found to result in a smaller share of final energy use for the residential sector but larger ones for transportation and the service sector and a reversed U-shape pattern for industry (Schäfer 2005). As convergence in per-capita incomes is closely related to convergence in energy use patterns (Jakob et al. 2012), one should expect the spectacular growth performances witnessed in a number of developing countries to have major impacts on the distribution of CO_2 emissions per-capita across countries.

Given the pivotal role of emissions inequality for climate negotiations, the issue has been investigated in the literature through a variety of methods. (Hedenus & Azar 2005) use the Atkinson index (Atkinson 1970) to find a declining trend in global emission inequality between 1960 and 1999 (from 0.64 to 0.5). This is based on their finding that in 1999 the 20% most emitting countries emitted about 22 times the amount of carbon than the 20% least emitting countries, while in 1960 this gap had been more than twice as large. Various authors use the Theil Index (Theil 1972) to measure and explain global emission inequality (e.g. Padilla and Duro, 2011). The advantage of the Theil index is that it can be decomposed in inequality within and between country groupings (Shorrocks 1982). Duro and Padilla, (2006) use the Kaya identity (1989) to decompose emission inequality across countries into the contributions of carbon intensity of energy, energy intensity and affluence. They find that during the period from 1970 to 1999 income differences were the main drivers of emission inequality between countries, while differences in carbon intensity and energy intensity displayed lower contributions[50]. Padilla and Serrano (2006) also show, using the Gini and the Theil index for country-level emissions, that emission inequality is closely correlated with income inequality and that both follow the same path over time. Finally, Duro, (2012) compares a set of inequality measures such as the Gini coefficient, Theil index, the Atkinson measure as well as the coefficient of variation in terms of their sensitivity to changes in the distribution of CO_2 emissions over time. He concludes that different inequality indicators can yield differing results due to differences in their distributive sensitivity.

A further widely employed measure of inequality is the Gini coefficient. In the case of CO_2 emissions, the cumulative share of global CO_2 emissions is plotted against the cumulative share of the countries from the lowest to the highest per capita emissions. Heil and Wodon, (2000, 1997) follow the methodology of Yitzhaki and Lerman (1991) to decompose the Gini coefficient in a within group and a between group component. The between group component compares rich and poor countries in order to analyze the contribution to the global emission inequality. They find that between group inequality declined slightly, but rich countries would have to reduce emissions by at least 50% to change the ranking of the highest polluting countries.

This chapter adds to the existing literature by investigating how the energy mix and the sectoral composition of a country's energy use determine inequality in global CO_2 emissions. Employing the decomposition of the Gini index pioneered by Lerman & Yitzhaki (1985), economy-wide emissions are disaggregated into contributions by primary energy carriers and economic sectors to estimate the contribution of each source of emission (i.e. each primary energy carrier, or economic sector, respectively) to total inequality. While this empirical methodology is well established in the analysis of income

[50] When Padilla and Duro (2011) apply the Theil index decomposition on emission data from the EU-27, they find that among this more homogeneous group of countries the carbon intensity of energy explains a large share of the emission inequality.

inequality between households (Leibbrandt et al. 2000), this is – to our knowledge – the first essay to employ it to analyze inequality in carbon emissions across countries.

We analyze both past trends using historical data on energy-related CO_2 emissions for 90 countries (which currently account for about 90% of global CO_2 emissions) over the period 1971-2008 and, in order to provide an outlook on how climate policy could affect future emission inequality, we also apply the decomposition method on emission scenarios generated with the integrated assessment model REMIND (Kriegler et al. submitted); (Bauer et al. 2012).

The chapter proceeds as follows: Section 5.2 presents the employed empirical method, and Section 5.3 the used data. Section 5.4 applies the methodology using both historical data, for a global sample as well as for a sub-sample of OECD and non-OECD countries, and results of the REMIND model. Section 5.5 presents the outcomes of a sensitivity analysis, while section 5.6 concludes.

5.2 Methodology

This study adopts the Gini coefficient as a measure of inequality for two main reasons. Firstly, it is arguably the most popular and widely employed inequality measure; for instance, it is adopted by the UNDP in its annual Human Development Reports (UNDP 2010). Secondly, it allows for a straightforward decomposition of total CO_2 emission inequality into contributions of individual sources and an estimation of the marginal effect of a change in any of these sources on overall emission inequality.

The Gini index builds on the concept of Lorenz Curves, which plot the cumulative share of income earned against the cumulative share of the units from the lowest to the highest income (Gini 1912; Lorenz 1905). It can range between 0 and 1, where 0 represents total equality and 1 represents total inequality. The Gini Index for CO_2 emissions has the geometric interpretation as one minus twice the area below the Lorenz Curve for emission distribution across countries and the diagonal line, which represents perfect emission equality.

We apply the decomposition of the Gini index after Lerman and Yitzhaki (1985, 1984) to analyze the effects of each source of carbon emissions (i.e. primary energy carrier and economic sector) on inequality in per-capita CO_2 emissions across countries. Lerman and Yitzhaki (1985, 1984) demonstrate that the Gini coefficient of total emissions can be expressed as a function of (i) the inequality within a given source, (ii) the share of this source in total emissions, and (iii) its rank correlation with total emission inequality. With this Gini decomposition we are able to determine the contribution of each emission source to the Gini index of total per-capita emissions (*G*) between countries:

$$G = \sum_{k=1}^{K} G_k S_k R_k \tag{5.1}$$

Here k is the index denoting the source of emissions (primary energy carrier, or economic sector, respectively), G_k is the Gini of component *k*, S_k is the share of component *k* in total emissions and R_k is the rank correlation between emission component *k* and total emissions[51]. Consequently, the contribution of each single source *k* to overall inequality in per-capita emissions is given by $G_k S_k R_k$.

In addition, this methodology allows analyzing the effect of marginal changes in any single source of emissions, which is useful to assess the impact on inequality in carbon emission across countries that are brought about by policies and/or technological advances that equal percentage reduction of emissions from any one source (see section 4.3). This marginal effect of a change *e* in any source *k* for overall inequality *G* can then be written as:

$$\frac{\partial G}{\partial e_k} = S_k(R_k G_k - G) \tag{5.2}$$

The decomposition method presented above can be applied for any given time period. As we are interested in the evolution of inequality over time, Section 4.1 presents the decomposition of the overall inequality into the contribution of each source of emissions *k* (i.e. primary energy carrier, or economic sector, respectively) for 5-year intervals for the period 1971 to 2008.

In order to gain a deeper understanding of the factors driving the evolution of overall inequality, we employ the Laspeyres decomposition method (e.g. Sun and Ang, (2000) see section 4.2). The Laspeyres decomposition allows us to break down changes in overall emission inequality to changes in its single components *G*, *S*, and *R*. With Δ denoting the difference between the year 2008 and 1971, we can decompose the change in the Gini

[51] The rank correlation R_k ranges between +1 and -1. It will approach +1 (-1) if an emission source is an increasing (decreasing) function of total emissions.

index of total per-capita emissions between two points in time into the joint contribution of three underlying effects E for every source of emissions:

$$\Delta G = \sum_{k=1}^{K}(R_k + \Delta R_k)(G_k + \Delta G_k)(S_k + \Delta S_k) - \sum_{k=1}^{K} R_k G_k S_k \quad (5.3)$$

This can be expressed as:

$$\Delta G = \sum_{k=1}^{K}(E_k^R + E_k^G + E_k^S) \quad (5.3')$$

The individual effects can be derived from carrying out the multiplication in (3) and dividing the residuals (i.e. changes of second and third order) evenly across factors. This is demonstrated exemplarily for E_k^S, i.e. the change in inequality that can be attributed to a change of the share of source k in total per-capita emissions, below:

$$E_k^S = \Delta S_k G_k R_k + 1/2\, \Delta S_k(\Delta G_k R_k + G_k \Delta R_k) + 1/3\, \Delta S_k \Delta G_k \Delta R_k \quad (5.4)$$

5.3 Data

We employ historical data from the International Energy Agency (IEA) on per capita CO_2 emissions from fuel combustion[52] over the period of 1971 to 2008 (International Energy Agency 2011)[53] and emission scenario data over the period of 2005 to 2100 generated by the version 1.4 of the REMIND model (Kriegler et al. submitted); Bauer et al. 2012; Leimbach et al. (2010) under the framework of the RoSE project[54] (Kriegler et al. submitted).

The IEA dataset contains data on CO_2-emissions disaggregated by primary energy carriers (‘coal/peat’, ‘oil’, ‘gas’ and ‘other’) as well as economic sectors (‘manufacturing & construction’, ‘transport’, ‘residential’, ‘other sectors’, and ‘agriculture’). We exclude emissions specified as coming from ‘other’ sources, as this source mainly includes emissions from the combustion of biomass and waste, and there is currently a lively debate

[52] Our analysis focuses on energy-related CO_2-emissions; land-use emissions as well as non-CO_2 greenhouse gas emissions (such as CH_4 and N_2O) are not part of the analysis.

[53] For summary statistics refer to Table E.1and Table E.2.

[54] http://www.rose-project.org/

on how these emissions should be accounted[55]. From the sectoral perspective, the data is organized in a way that it attributes emissions produced in transformation sectors (such as electricity generation, or refining) to final use sectors (e.g. transport or residential) according to the latter sector's consumption of energy from each transformation sector. With the aggregate 'other sectors' being the sum of emissions from the residential and the service sector, we are able to derive 'service sector emissions' by subtracting residential emissions from 'other sectors'. Within the IEA dataset we exclude emissions from the agricultural sector due to a lack of available data. As agricultural emissions account for only a small fraction of energy-related emissions[56] for the large majority of countries, we do not expect this exclusion to seriously bias our results.

In our sample, we only include countries for which there is full information (i.e. no values marked as 'missing') for CO_2 emissions on the level of primary energy carriers as well as economic sectors. We further exclude all countries for which CO_2 emissions from any primary energy carrier or economic sector have zero entries over the entire observation period, as we expect that this might indicate erroneous accounting. We do, however, include countries that display zero observations for some years[57]. For years prior to 1990, we use emission data for the Former Soviet Union and Former Yugoslavia, respectively, while from 1990 onwards, we separately include each constituent state in our sample[58]. This leaves us with a sample of 90 countries (see Table E.3 in the appendix to this chapter), which accounted for approximately 90% of global CO_2 emissions in the year 2008.

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[55] For instance, it has been argued that biomass should be regarded as a zero-emission source of energy, as the associated emissions have been sequestered from the atmosphere during plant growth. However, if one regards the entire life-cycle, this picture changes, as also emissions related to land-use have to be taken into account (Farrell et al. 2006; Searchinger et al. 2008).

[56] Yet, agriculture is an important source of CH_4, N_2O as well as CO_2-emissions from land use, all of which are not part of our analysis.

[57] For instance, it seems plausible that some developing countries report zero emissions from services in early periods, with a formalized service sector only beginning to emerge after a certain threshold of economic development.

[58] Note that different specifications are explored in the scope of the robustness checks in Section 5.

The REMIND data contain information on emissions per primary energy carrier for a business as usual (BAU) and a climate policy scenario (POL). REMIND is a multi-regional global integrated assessment hybrid model, which couples a Ramsey-type optimal growth model with a technology-rich detailed energy system model and a simple climate model. It represents 11 world regions (see Figure E.1 in the appendix to this chapter) and considers the time horizon of 2005-2100[59]. In order to match the regional aggregation of the model to our data, we generate scenarios of future emissions on the country level by means of extrapolation. That is, we apply the changes in emissions from each individual primary energy carrier that are estimated by the model for any of the REMIND regions to each individual country in our dataset that is included in this respective region. As the model's definition of economic sectors does not correspond to the one used in the IEA data, we analyze the inequality of projected future emissions only from the perspective of primary energy carriers. The scenarios analyzed include a BAU scenario that assumes no climate measures and a policy scenario that corresponds to a 450ppm CO_2-eq. concentration stabilization target by 2100. The policy scenario allows for overshoot and full 'when-where-what flexibility' of emissions reductions after 2010 and accounts for the radiative forcing of all radiative substances including Non-Kyoto gases and aerosols.

5.4 Results

5.4.1 Drivers of Changes in Emission Inequality over Time

This section gives an overview of changes in per-capita emissions and the associated Gini index between 1970 and 2008 for our sample of 90 countries. Further, in order to gain a better understanding of the underlying drivers of the developments, it decomposes overall inequality in per-capita emissions in contributions attributable to emissions from specific primary energy carriers or economic sectors.

In Figure 5.1, that gives an overview of how per capita CO_2 emissions have developed, we differentiate between emissions from coal/peat, gas or oil combustion. Overall emissions

[59] The spacing of time-steps is flexible: in the default case, there are five-year time steps until 2050 and 10-year time steps until 2100. The period from 2100–2150 is also calculated to avoid distortions due to end effects. Typically, we only use the time span from 2005–2100 for model applications.

from those three sources are rising, mostly due to an increase in emissions from coal. Additionally, when dividing the sample into OECD and Non-OECD countries we observe a diverging trend between the two groups. Per capita emissions of OECD countries follow a declining trend after 2004, while non-OECD countries show a rising trend after 2002.

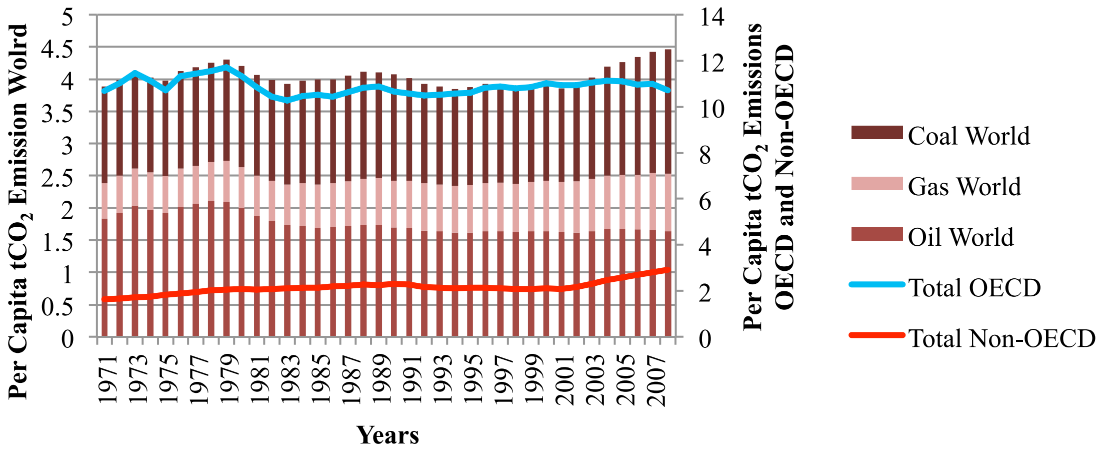


Figure 5.1: Global, OECD and non-OECD Energy-Related CO_2 p.c. CO_2 Emissions

Source: IEA (2011)

Over the entire observation period, the Gini index of per-capita CO_2 emissions declined from almost 0.6 in 1971 to slightly above 0.4 in 2008, indicating that over time, the distribution has become more equal (Figure 5.2). Interestingly, and perhaps contrary to what one could expect, the largest part of this reduction is found to take place in years prior to 1990, i.e. before many emerging economies had started the spectacular growth performance witnessed in recent years.

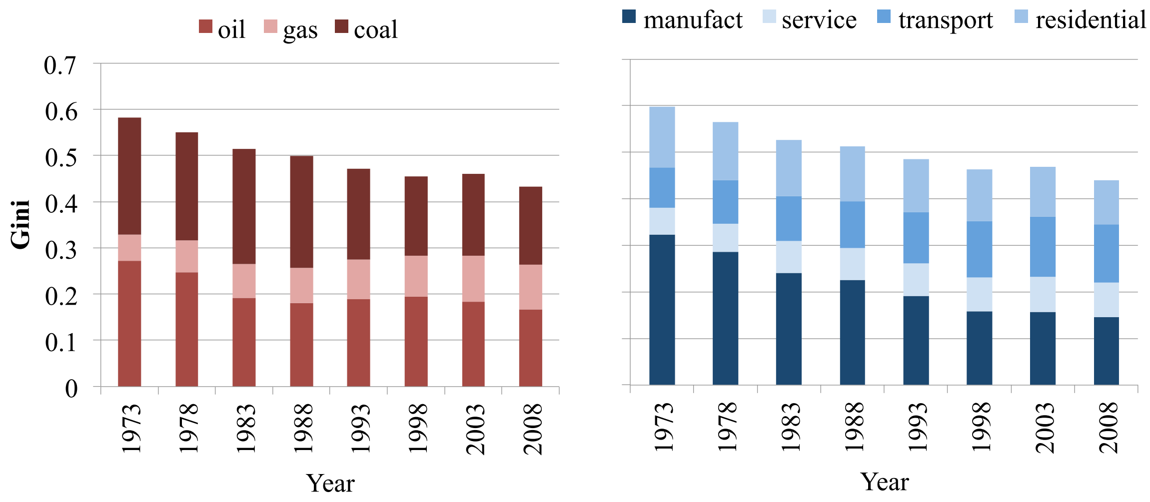


Figure 5.2: Contribution of Primary Energy Carriers and Economic Sectors to Gini of CO_2 p.c.

Analyzing the development of the Gini index disaggregated along primary energy carriers (Figure 5.2 left panel) we observe that the decline in total inequality in per-capita CO_2 emissions can be attributed to (a) a significant reduction in the contribution of emissions from oil, with the most pronounced drop taking place in the period ranging from the mid-70s to the mid-80s and (b) a reduction of similar magnitude in the contribution of emissions from coal/peat, concentrated on the period 1985-2000. Contrary to oil and coal/peat, emissions from natural gas exert an upward influence on total inequality in most years. Consequently, the share of total inequality explained by the contribution from natural gas has increased significantly over the observation period, namely from 8% in 1971 to 23% in 2008.

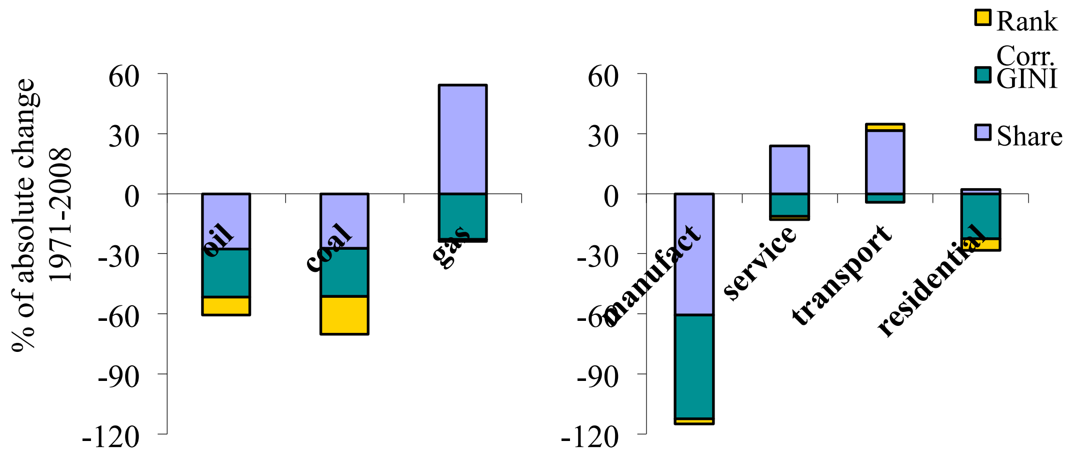
Regarding the evolution of the Gini index of per-capita CO_2 emissions over time along economic sectors (i.e. residential, transport, services, and manufacturing & construction) (Figure 5.2 right panel), the most striking observation is that the declining inequality in CO_2 emissions observed between 1971 and 2008 is almost entirely explained by the pronounced drop of the contribution of emissions from the manufacturing & construction sector, which occurred mainly prior to 2000. While this type of emissions accounted for more than half of total inequality in 1971, this figure drops to one third in 2008. Likewise, the contribution of emissions from the residential sector declines by roughly one third from 1971 to 2008. In contrast, the share of service sector emissions rises from 9 to 16%, and the one for emissions from transportation from 14 to 28%. The contributions of emissions from the service, as well as the transport, sector increase each by almost half over the observation period. However, the effect is quantitatively rather small due to their relatively low initial shares in total inequality.

These findings are very likely explained by the fact that (a) developing countries are increasingly relying on coal/peat and oil to meet their growing energy needs, while for industrialized countries, natural gas plays an increasing role, and (b) structural economic change has resulted in growth of manufacturing and construction in developing countries, but a relative decline of this sector (i.e. a shrinking share of total economic activity) in industrialized countries.

5.4.2 Laspeyres Decomposition

In this section, in order to give a quantitative assessment of the influence of changes in any single factor on total inequality we employ the Laspeyres decomposition. We investigate the contribution of each of the three factors affecting the value of the Gini index to total inequality (i.e. (i) changes in the Gini index within this source, (ii) changes in the share of this source in total per-capita emissions, and (iii) changes in its rank correlation with total emissions) for every individual source of emissions (i.e. primary energy carrier or economic sector). Figure 5.3 presents the respective values for each of the three factors for the first and the last year included in our sample (i.e. 1971 and 2008). The results of the application of the Laspeyres decomposition are shown in Figure 5.3 as the percentage of the absolute value of the total observed change in inequality that can be attributed to each individual factor (i.e. computed over all sources *k*, the changes attributable to individual factors sum up to 100%).

For emissions from oil as well as coal/peat, the declining contribution to the Gini index of per-capita CO_2 emissions is explained by the reduced shares of emissions from these energy carriers in total CO_2 emissions, lower Gini indices within each of these two sources, and to a lesser extent lower rank correlations with total emissions. For natural gas, on the other hand, the increased contribution to the overall Gini index is almost exclusively due to a higher share of emissions from this source in total emissions, while it's declining Gini index works in the opposite direction and the change in the rank correlation is negligible. Consequently, while all three primary energy carriers are characterized by declining 'within' emissions inequality, it is the shift away from coal and oil and towards natural gas that determines the changes in the relative contribution of the three carriers described in the previous section.



(left panel) contributions to absolute change (in%), primary energy carriers

(right panel) contributions to absolute change (in%), economic sectors

Figure 5.3: Laspeyres Decomposition for the Source of Absolute Changes in the Gini of CO_2 p.c.

For emissions from manufacturing & construction, both the sector's reduced share in total emissions and the lower Gini index in 2008 compared to 1971 have comparable impacts on its reduced contribution on overall emission inequality. For emissions from the service as well as the transport sectors, increased shares in total emissions increase inequality in total per-capita CO_2 emissions. On the other hand, decreased Gini indices within both sources work in the opposite direction, without compensating, however, for the previous effect. Finally, for emissions from the residential sector, the reduced inequality of emissions from this sector, and a lower rank correlation with total emissions in 2008 compared to 1971, diminish its contribution of emissions. Its slightly increased share in total emissions causes only a minor increase in the contribution of emissions from this source. Similarly to the decomposition by primary energy carriers, also here we observe that emissions inequality within each of the individual sectors is decreasing over time. However, significant differences are observed between the four sectors, with the Gini coefficient declining more for the manufacturing and residential sector and less for the service and the transport sectors. As a consequence, both diverging changes in the Gini index within each of the four sectors, and changes in the share of each sector in total per-capita emissions, are contributing to differences in overall emissions inequality between countries.

5.4.3 Marginal Effects of Changing Emission Patterns

This section discusses the results of the application of the methodology to determine the marginal effect of an equally spread percentage reduction from any single source of emissions (i.e. primary energy carrier or economic sector) on the Gini index of total per-capita emissions. This kind of analysis could bear importance for the formulation of climate policies, as it allows assessing the impacts of e.g. technological innovations that reduce emissions from one given energy carrier or economic sector (such as more efficient power plants or automobiles), or a global agreement calling for equal percentage reduction of emissions from any particular sector (such as the manufacturing &construction sector).

Table 5.1: Effects of a 1% Decrease of CO_2 p.c. from any Source on the Gini of CO_2 p.c.

Primary Energy Carriers		Economic Sectors	
Oil	0.047	Manufacturing	0.014
Coal	-0.07	Service	-0.014
Natural Gas	0.024	Transport	-0.001
		Residential	0.002

Source: Authors' estimation. Note: 2008 data in %.

The results of this exercise (undertaken for 2008 data) are shown in Table 5.1. The most striking feature is that, regardless of their sign, these marginal effects are relatively small. For instance, an across the board reduction of emissions from coal/peat by 1% would decrease the Gini index of total per-capita CO_2 emissions across countries by no more than 0.07%. For the remaining energy carriers and economic sectors, the respective effects are even less pronounced. Hence, we conclude that an equally spread percentage reduction from any one source of CO_2 emissions would not significantly alter the prevailing pattern of global inequality in per-capita emissions.

5.4.4 Emission Inequality for Different Country Groupings

While the focus of this chapter is clearly on global inequality, we repeat the above procedure for OECD as well as non-OECD countries, respectively. This allows us to assess whether the trends identified above can also be detected for these individual country groupings.

Compared to the full sample, we find a significantly lower Gini index of overall emissions for OECD countries (Figure E.2). In 1971 it lies slightly below 0.4, declining to about 0.25 in 2008. Hence, OECD countries start more homogenously and seem to converge faster to more equal per capita CO_2 emission than non-OECD countries, which start with an initial Gini of 0.6 and a Gini of 0.45 in 2008 (Figure E.3 in the appendix to this chapter).

The overall pattern in terms of the contribution of each energy carrier is similar between the full sample and the two subsamples (Figure E.2 and Figure E.3 left panel in the appendix to this chapter), but OECD countries display a more pronounced reduction in the contribution of coal/peat to overall emission inequality (which declines by almost one half). Furthermore, both country groups display a slight decrease in the contribution of emissions from oil, and a slight increase in the one from natural gas.

From the perspective of economic sectors (Figure E.2 and Figure E.3 right panel in the appendix to this chapter), the declining contribution of emissions from the manufacturing & construction sector turns out to be the main driving force behind the overall decline in CO_2 emission inequality for both OECD and non-OECD countries. It is more pronounced for the former than for the latter. For non-OECD countries the largest part of the reduction takes place between 1990 and 1998, which is possibly related to economic recession in the countries of Eastern Europe and the former Soviet Union. For OECD countries, this declining contribution is partly counterbalanced by an increasing contribution of transport emissions, while this sector displays only little variation for non-OECD countries. The same holds for emissions from the service as well as the residential sector for both country groups.

This analysis suggests that the observed reductions in overall emission inequality reflect global trends. That is, changing patterns of coal/peat consumption and emissions in the manufacturing & construction sector can to a large extent explain changes in inequality in per-capita emissions across countries. This conclusion not only holds on the global level, as shown in the previous section, but also for OECD and non-OECD countries separately.

5.4.5 Application to Emission Scenarios

In order to provide an outlook on the future development in global emission inequality with and without climate policy, we build on scenario data generated with the integrated assessment model REMIND.

Figure 5.4 contrasts the results of a BAU scenario (left panel) and a policy scenario (right panel) with a stabilization target of 450ppm CO_2-eq. by 2100. The BAU scenario indicates that global emission inequality, after an initial slight decline until 2025, is characterized by an increasing trend from then onwards and till the end of the century (slightly above 0.48

in the year 2100). Similarly, in the policy scenario inequality declines until 2020 and then rises again up to 0.46 in 2070 to slightly decline again to 0.44 in 2100. Not surprisingly, a key difference between the two scenarios is the contribution of emissions from the three different primary energy carriers in overall inequality[60]. Under the BAU scenario coal is projected to be the major contributor to emission inequality from 2050 onwards. Meanwhile, with the 450ppm CO_2-eq. target, emissions from coal contribute a diminishing share to overall inequality after 2035, while emissions from oil play a more important role.

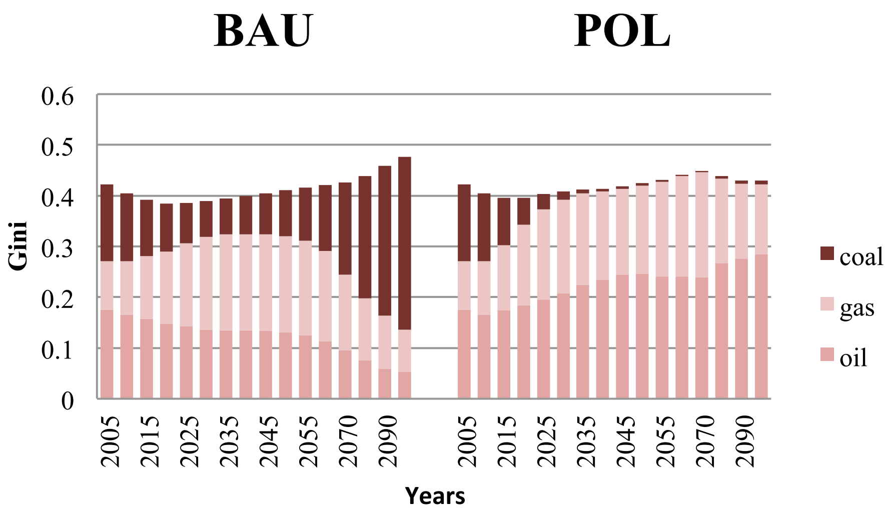
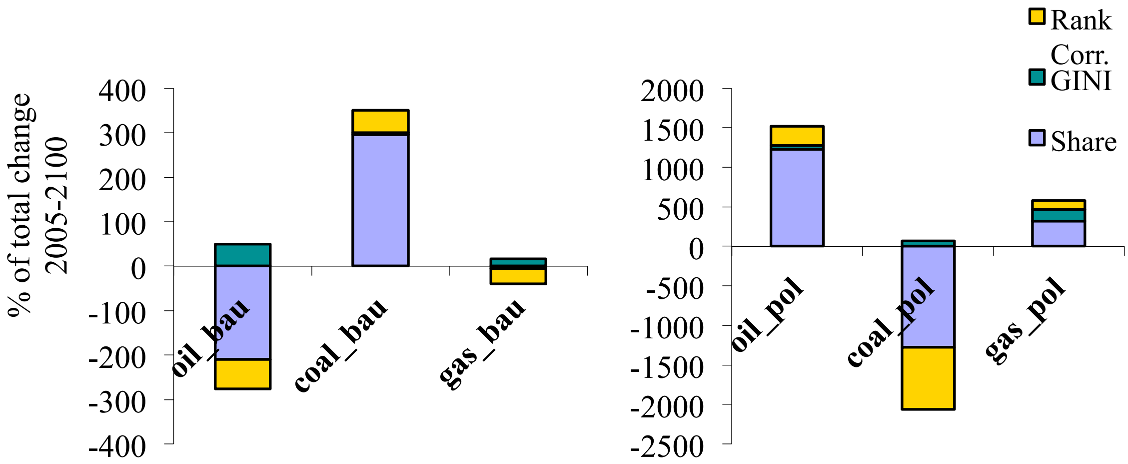


Figure 5.4: Contribution of Primary Energy Carriers to Gini of Future CO_2 p.c.

The nature of these results is explained with the use of the Laspeyres decomposition as displayed in Figure 5.5. For both scenarios we find that the main driver of these changes is changes in the shares of emissions from the different carriers. In the case of the BAU scenario (left panel), an increasing share of emissions from coal is the main cause for the increase in inequality between 2005 and 2100. Inversely, emissions from oil work in the opposite direction, thus leading to a decline in overall emission inequality, which cannot however offset the effect of emissions from coal. The rank correlation with total emissions and the Gini for global coal emissions play a smaller role, and so do gas emissions. For the policy scenario (right panel), the picture is reversed. Here the decreasing share of emissions from coal and its rank correlation with total emissions contribute to a decline in

[60] Note that negative emissions arising from the use of biomass in combination with CCS, which feature in the POL scenario, are not included in this analysis.

overall emission inequality. This effect is offset mainly by the combined effect of the rise in the share of emissions from oil and its increasing rank correlation with overall emissions, and secondarily gas.



(left panel) relative contributions to total change (in %) by primary energy carriers in the business-as-usual scenario (bau)

(right panel) relative contributions to total change (in %) by primary energy carriers in the policy scenario (pol)

Figure 5.5: Laspeyres Decomposition for the Source of Changes in the Gini of CO_2 p.c.

The above analysis indicates that climate change policies can be expected to result in a more equal distribution compared to the BAU scenario. As we saw under the BAU scenario global emission inequality rises by about 0.05, while under the stabilization scenario it rises by only 0.01. This result is due to both a complete phase out of the most carbon intensive fossil (coal) but also due to the overall gradual dramatic reduction in all fossil fuels deployment for all regions under the policy scenario. In specific, emissions from fossil fuels at a global level are almost halved by 2030 under the policy scenario in comparison to the BAU case (about 49260 $MtCO_2$/yr in BAU and 26640 $MtCO_2$/yr in POL), reduced to slightly less than one third by 2050 (about 62140 $MtCO_2$/yr in BAU and 20275 $MtCO_2$/yr in POL), and characterized by a seven-fold reduction by 2100 (61925 $MtCO_2$/yr in the BAU scenario to 9200 $MtCO_2$/yr in POL).

5.5 Sensitivity analysis

In order to assess the robustness of our results with regard to how we select the countries included in our sample, we perform three sensitivity checks.[61]

First, we repeat our estimates excluding the Former Soviet Union and Former Yugoslavia (for years prior to 1990) and its constituent entities (1990 and after) from the overall sample. The results are very similar to those reported above. Therefore we can conclude that the economies in transition do not bias our results for the overall sample.

Second, we include all countries for which data are available, even if zeroes are reported in every single year for a given energy carrier or economic sector. For this enlarged sample of 128 countries, the overall Gini displays a less pronounced decline, from slightly below 0.6 in 1971 to slightly above 0.5 in 2008. This is quite intuitive, as countries reporting zero emissions can be expected to have an upward influence on overall inequality. With regard to primary energy carrier, the general patterns are repeated. Yet, with the larger sample, the decline in the contribution of oil is less pronounced (from 0.21 in 1971 to 0.18 in 2008) and the increase in the contribution of natural gas stronger (from 0.14 to 0.25 in 2008). For economic sectors, we again find that the decline in overall emission inequality is almost exclusively explained by the reduced contribution of the manufacturing & construction sector.

Third, as observations with a zero value might be considered as a sign of reporting errors, we remove all countries that report zero emissions from any single source of emissions in any year from our sample. This smaller sample, which includes only 46 countries, produces a smaller Gini index for overall emissions (slightly below 0.5 in 1971, and slightly below 0.4 in 2008). This can very likely be explained by the fact that countries that report zeroes are predominantly low emitters. Hence, removing these countries from the sample curtails the distribution and decreases overall inequality. For the patterns explaining the observed drop in the Gini index, we again find significantly declining contributions from oil and coal/peat with the contribution of natural gas working in the opposite direction. With regard to the role of economic sectors, the declining contribution of emissions from manufacturing & construction is confirmed to be the dominant factor.

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[61] This section only presents the main conclusions; more detailed information is available on request.

Hence, even though the choice of methods to construct our sample affects some details of the analysis, our overall conclusions appear very robust. For all samples considered, we find that the Gini coefficient declines over time, and that this decline can mainly be attributed to declining contributions from oil and coal/peat (from the perspective of primary energy carriers) or declining contributions of manufacturing & construction (from the perspective of economic sectors), respectively.

5.6 Conclusions

This chapter uses the decomposition of the Gini index proposed by Lerman and Yitzhaki, (1985, 1984) to analyze the contribution of individual primary energy carriers and economic sectors on inequality in total per-capita CO_2 emissions across countries. We analyze past trends using historical data on energy-related CO_2 emissions and also provide an outlook on how climate policy could affect future emission inequality using scenario data from the integrated assessment model REMIND.

For our sample of 90 countries, which represent about 90% of global emissions in 2008, we find that the Gini index of per-capita CO_2 emissions has declined considerably, from about 0.6 in 1971 to slightly above 0.4 in 2008. From the perspective of primary energy carries, this observation can mainly be explained by a considerable reduction in the contribution of emissions from oil and coal/peat. A Laspeyres decomposition reveals that declining shares of emissions from coal/peat and oil in total emissions and the increasing share of emissions from natural gas work in opposite directions. At the same time, emissions inequality is seen to decrease similarly within all three individual carriers, and this is also pushing inequality downwards. From the perspective of economic sectors, decreases in inequality are almost entirely due to the pronounced decline of the contribution of emissions from the manufacturing & construction sector. The most relevant explanatory factors are the declining share of emissions from the manufacturing & construction sector in total emissions, and the declining Gini index of emission from this sector. These observations highlight the importance of changing energy use patterns for inequality in per-capita CO_2 emissions across countries, which had not been analyzed in previous studies.

Our results were found to be robust for different country groupings and marginal effects tests. Firstly, repeating the analysis for OECD and non-OECD countries separately revealed that, while the results are quantitatively different, a similar pattern emerges. As observed also for the whole sample, inequality in per-capita emissions decreased for both OECD and non-OECD countries, and this was mainly due to decreasing contributions from emissions from coal/peat and oil from a primary energy carrier perspective, and a decreasing contribution from manufacturing emissions from a sectoral perspective. Evaluating the marginal effect of an equally spread reduction of emissions from any one source of emissions (i.e. primary energy carries, or economic sectors) on the Gini coefficient of total per-capita emissions, we find that any such reduction would only have minor impacts on overall emission inequality.

Using scenarios of future emissions generated with the integrated assessment model REMIND, we find that climate policy can be expected to result in a more equal distribution of global emissions across countries. The main driver behind this effect is the share of emissions from coal, which under the BAU case is projected to be the major contributor to emission inequality from 2050 onwards, while in the policy case its effect is completely phased out by the end of the century. Changes attributed to oil use are working in the reverse direction, but their effect in overall emissions inequality is not as influential as changes related to coal use. Additionally, notable progressive reductions in global total fossil fuel emissions indicate the considerable diminution in fossil fuel use across all countries. This factor limits the possibility for significant across-country divergence in the level of fossil fuel emissions, in the context of drastic emissions reductions in order to achieve the stabilization target.

Our findings provide a more fine-grained understanding of the underlying drivers of inequality in per-capita CO_2 emissions than previous studies. In particular, they underline the importance of energy system and economic transformations for emissions inequality, by highlighting how changes in the use of primary energy carriers and economic activity between sectors propagates into across-country inequality in per-capita CO_2 emissions.

The issue of inequality in per-capita emissions can be expected to occupy a top spot in the agenda of future climate negotiations. Any future climate agreement faces the challenge of achieving a distribution of emission rights that is recognized as equitable by all participants. Our results indicate that reducing emission inequality is compatible with climate stabilization only if high emitters accept more substantial cuts in their per-capita emissions compared to low emitters. A clear understanding of historical trends and patterns, combined with the integrated assessment of policy scenarios, can form the basis to evaluate the implications of future climate policies. This is where this chapter intends to make a contribution.

Appendix A: Chapter 1

Table A.1: Overview of Studies on SWB and Climate

Authors	Year	Data	Countries	Years	Method	Controls	SWB	Mean Temp.	Max Temp.	Min Temp.	Hot Months	Precipitation	Wind	Sun	Journal
Frijters & Van Praag	1998	Individual	Russia	1993, 94	OLS, OP	Micro	LS		-	+		-	-	n.s.	Climate Change
Rehdanz & Maddison	2005	Country	67	1972-2000	PLS	Micro and Macro	H	n.s.	-	+		n.s.			Ecological Economics
Becchetti et al.	2007	Individual	~50	2000, 2001	MOL	Micro and Macro	H	-			+		-		Working Paper
Brereton et al.	2008	Individual	Ireland	2001	OP	Micro and Macro	LS		+	+		n.s.	-	n.s.	Ecological Economics
Maddison & Rehdanz	2011	Country	79	1981-2008	OLS	Micro and Macro	LS	n.s.	n.s.	n.s.	-	n.s.			Ecological Economics
Grunewald	2012	Individual	16	1997-2008	OLS, OP, FE	Micro and Macro	LS	-	-	-/+		-	+		

Note: The abbreviations are the following: OP Ordered Probit; MOL Multinominal Ordered Logit, PLS Panel Corrected Least Squares; OLS Ordinary Least Squares; FE Fixed Effects; LS Life Satisfaction; H Happiness. The results are the following: + positive coefficient; - negative coefficient; n.s. not significant.

Table A.2: List of Variables

Variable	Unit	Source	Access
Life Satisfaction	1, 2, 3, 4	Latinobarómetro	2009
Married	1, 0	Latinobarómetro	2009
Unemployed	1, 0	Latinobarómetro	2009
Elementary School	1, 0	Latinobarómetro	2009
High School	1, 0	Latinobarómetro	2009
University	1, 0	Latinobarómetro	2009
Religious	1, 0	Latinobarómetro	2009
Obj. Wellbeing	1, 2, 3, 4, 5	Latinobarómetro	2009
Subj. Eco. Sit.	1, 2, 3, 4, 5	Latinobarómetro	2009
Subj. Income	1, 2, 3, 4	Latinobarómetro	2009
Male Dummy	1, 0	Latinobarómetro	2009
Age	years	Latinobarómetro	2009
GDP per capita	constant 2005 int. $	WDI	2012
GDP Growth	annual %	WDI	2012
Inflation	consumer prices annual %	WDI	2012
Literacy Rate	% of people ages 15 and above	WDI	2012
Life Expectancy at Birth	total years	WDI	2012
Monthly Mean Temperature	°C	FAOClim-Net	2010
Monthly Max. Temperature	°C	FAOClim-Net	2010
Monthly Min. Temperature	°C	FAOClim-Net	2010
Monthly Precipitation	mm	FAOClim-Net	2010
Monthly Mean Wind Speed	km/h	FAOClim-Net	2010
Annual Mean Temperature	°C	FAOClim-Net	2010
Annual Max Temperature	°C	FAOClim-Net	2010
Annual Min. Temperature	°C	FAOClim-Net	2010
Annual Precipitation	mm	FAOClim-Net	2010
Annual Mean Wind Speed	km/h	FAOClim-Net	2010
Number of Months > 20°C	1-12	Becchetti et al.	2007
Cooling (degree) Months	°C	Maddison & Rehdanz	2011

Source: Latinobarómetro (2009), World Bank (2012), and FAO (2010).

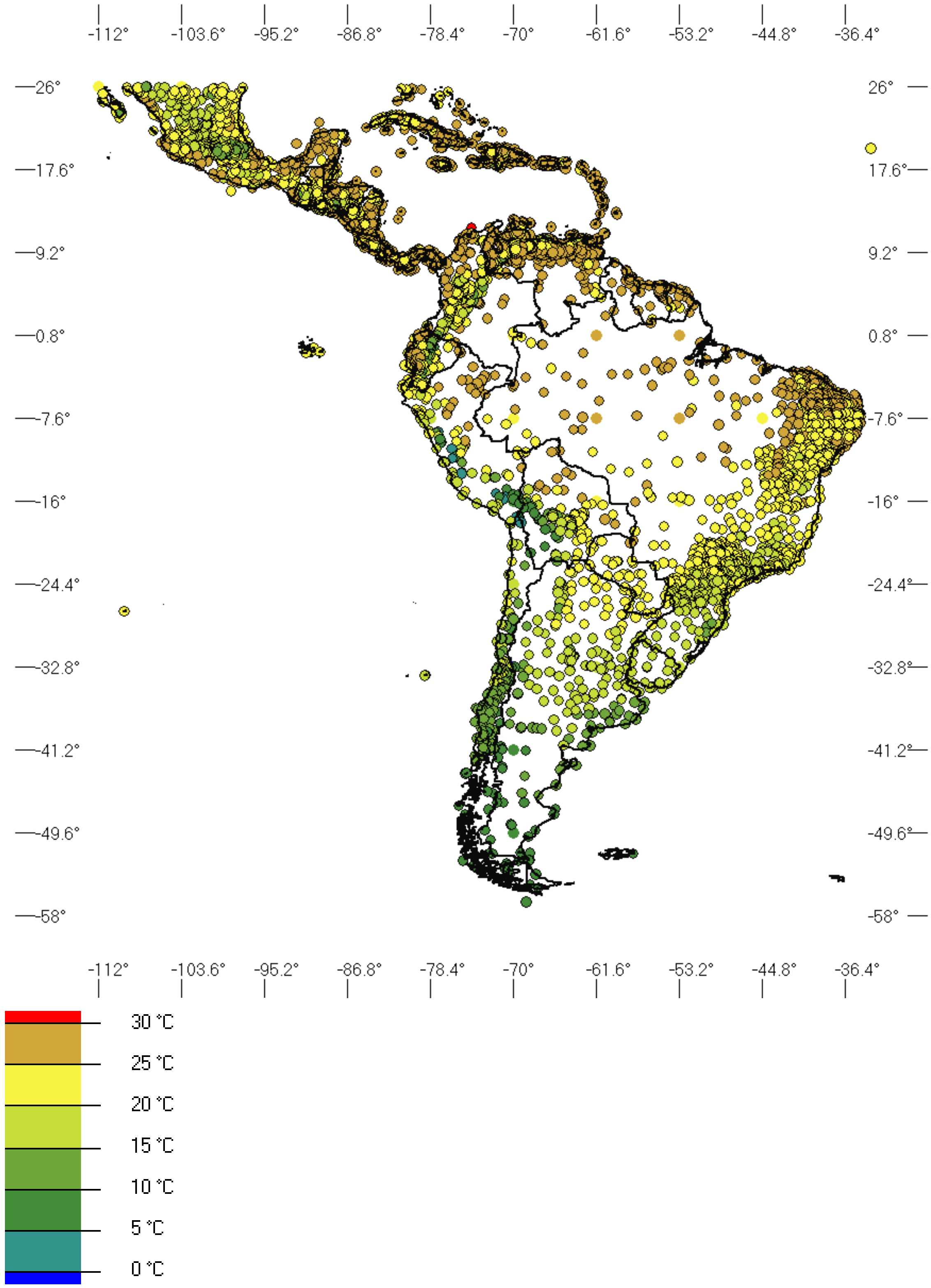

Figure A.1: Average Monthly Mean Temperature in Latin America

Note: The axes on the figure indicate degrees latitude and longitude. The scale at the bottom measures average monthly mean temperature in degrees Celsius. Source: FAO (2012)

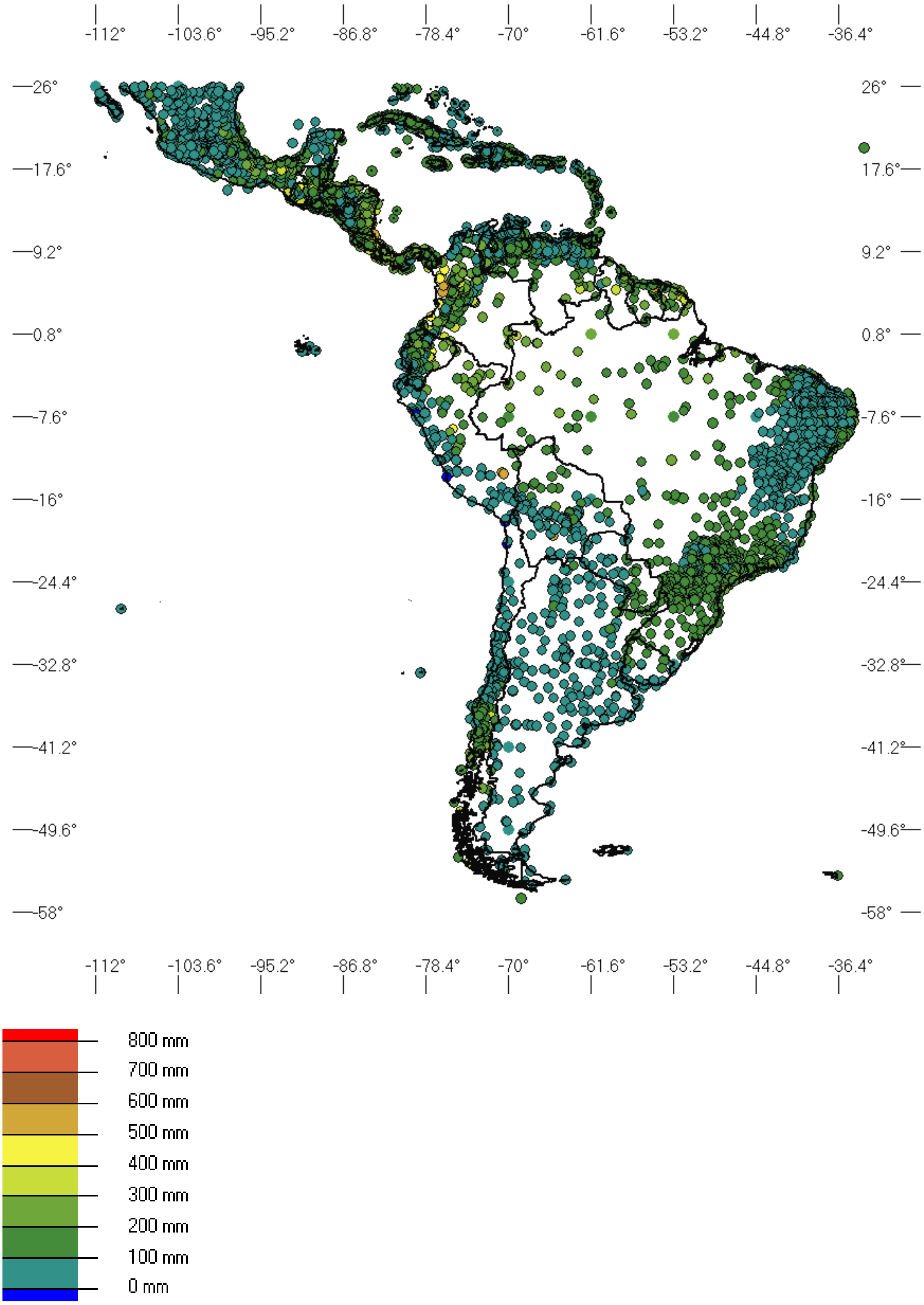

Figure A.2: Average Monthly Precipitation in Latin America

Note: The axes on the figure indicate degrees latitude and longitude. The scale at the bottom measures monthly precipitation in mm. Source: FAO (2012)

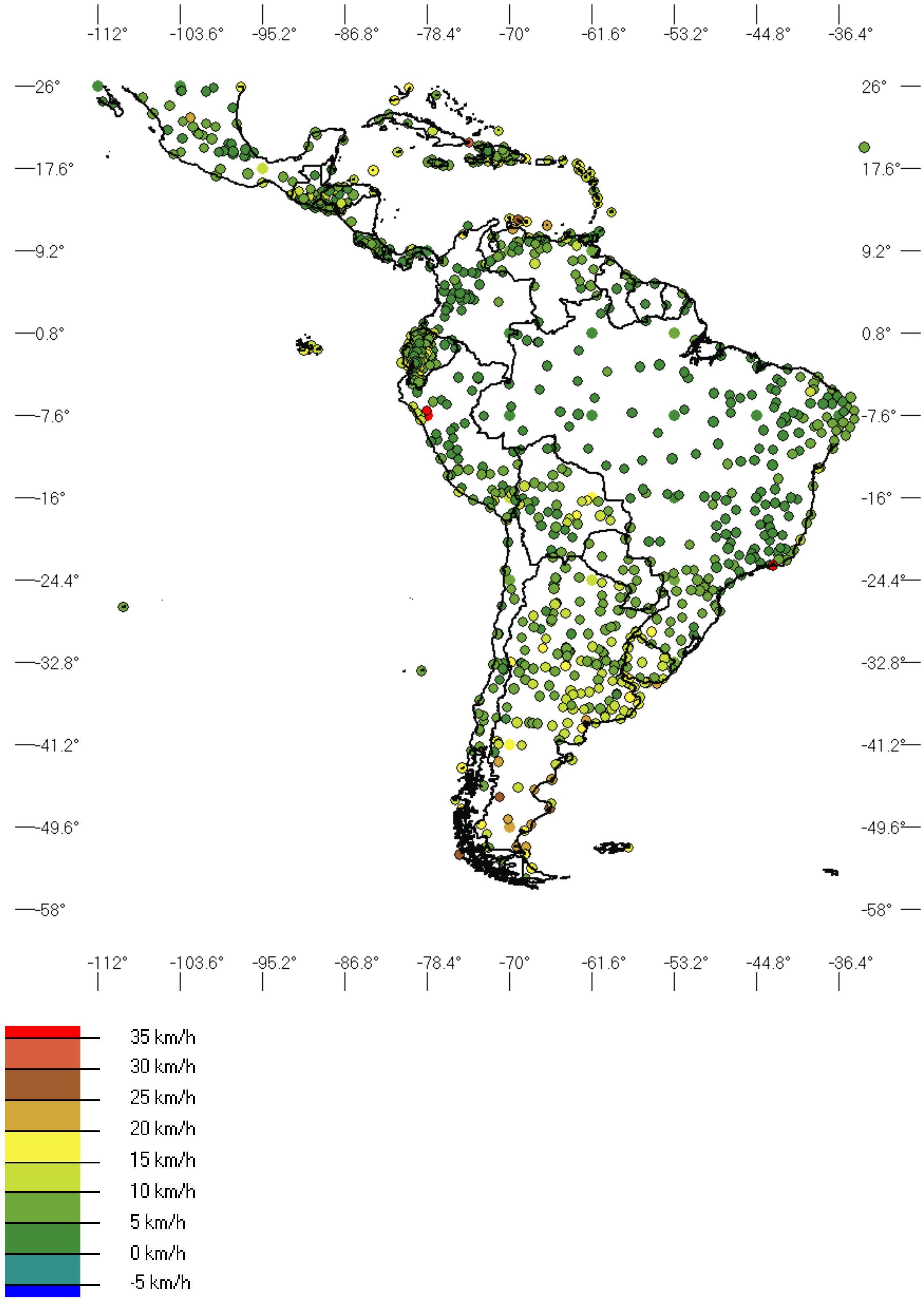

Figure A.3: Annual Monthly Mean Wind Speed

Note: The axes on the figure indicate degrees latitude and longitude. The scale at the bottom measures annual monthly mean wind speed in km/h measured 2m above the ground. Source: FAO (2012)

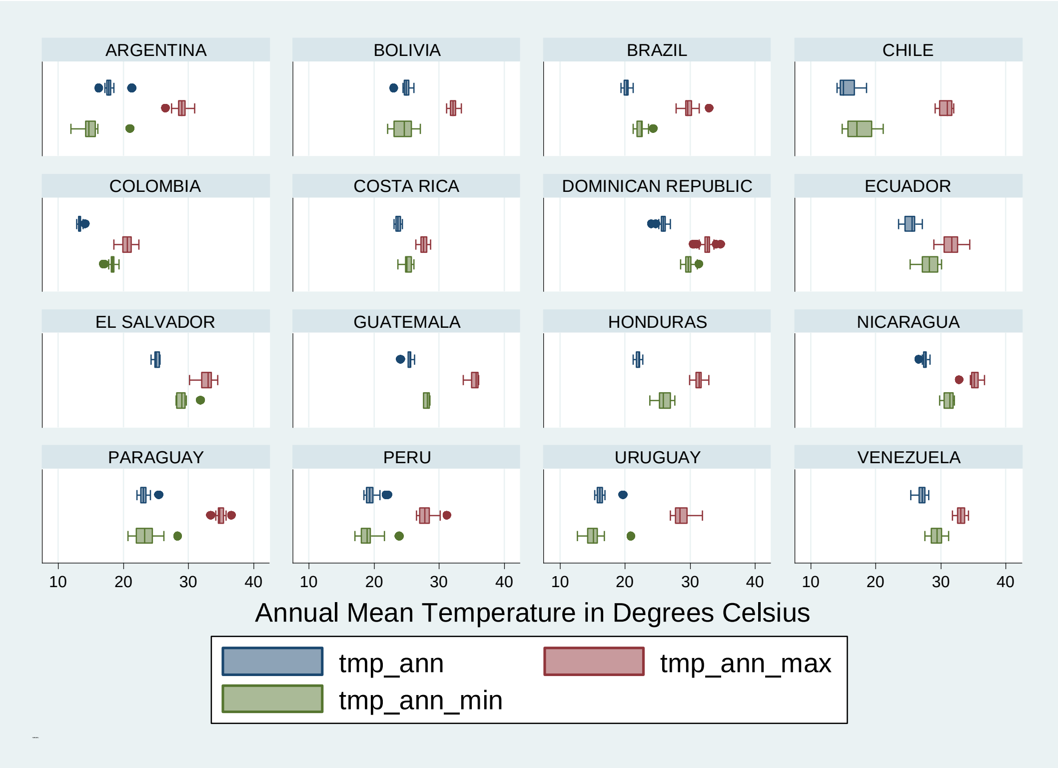

Figure A.4: Annual Mean, Maximum and Minimum Temperature 1990-2009

Source: FAO (2010)

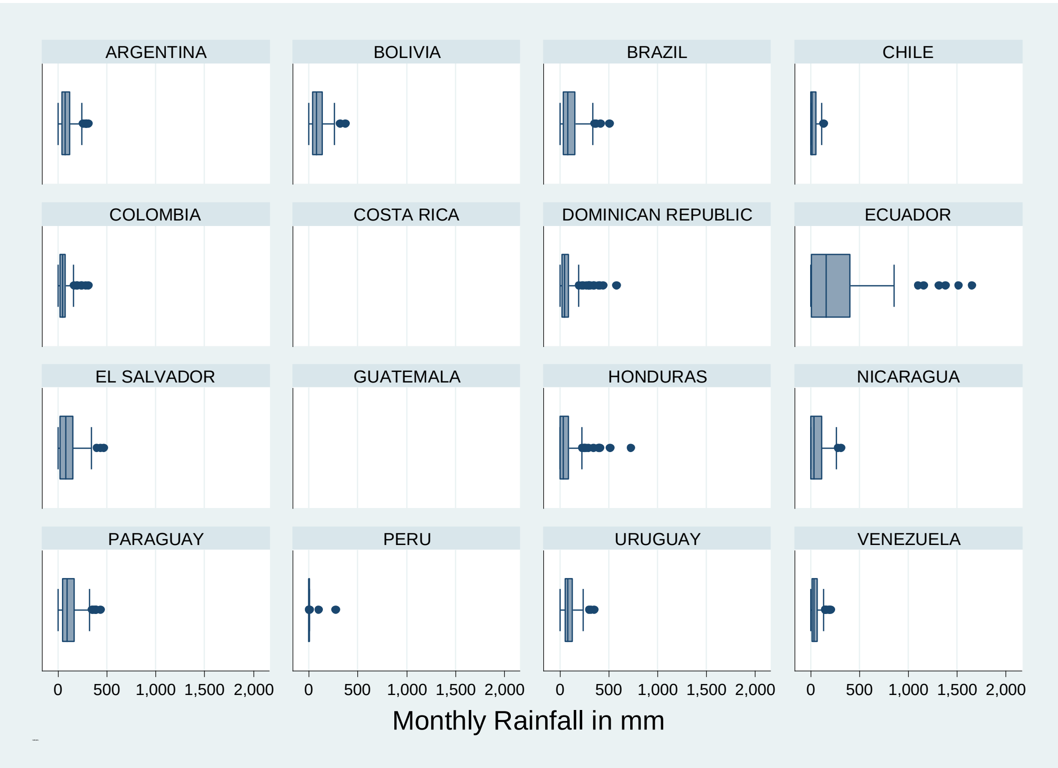

Figure A.5: Monthly Precipitation 1990-2009

Source: FAO (2010)

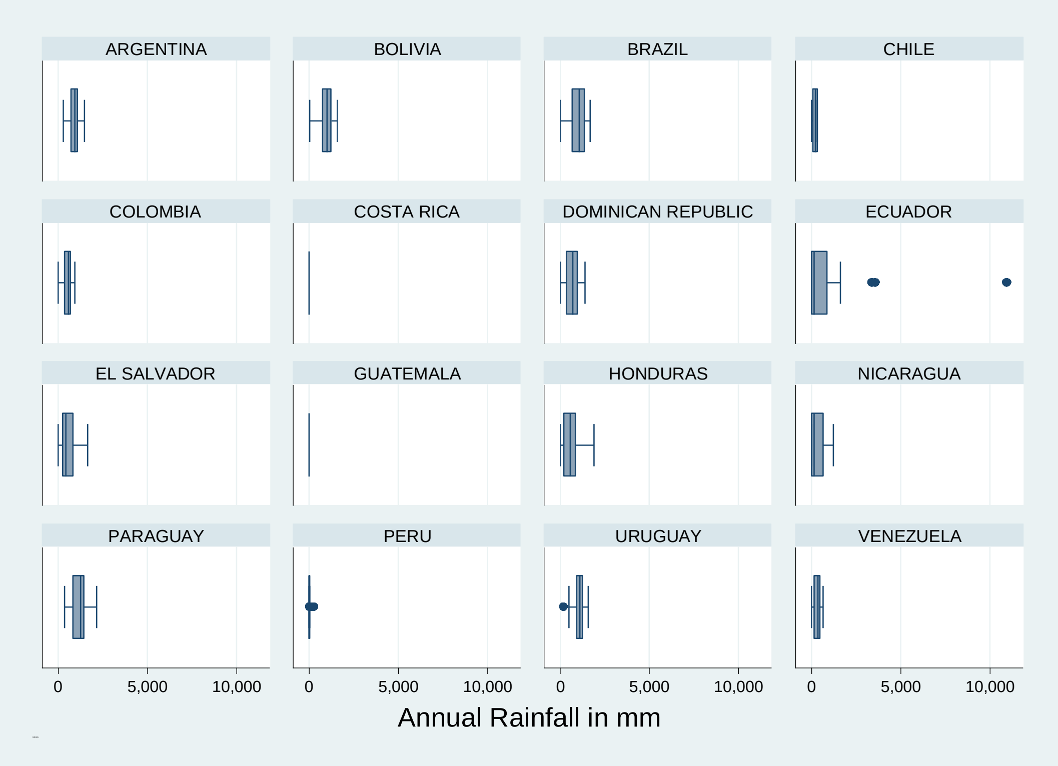

Figure A.6: Annual Precipitation 1990-2009

Source: FAO (2010)

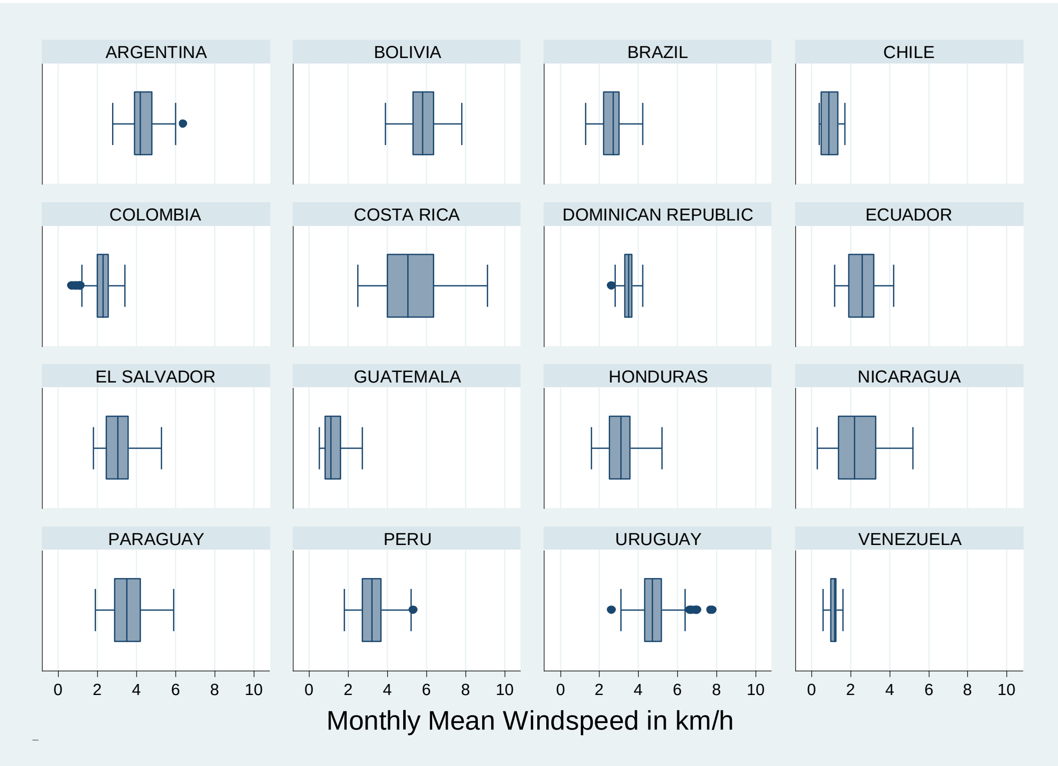

Figure A.7: Monthly Mean Wind Speed 1990-2009

Source: FAO (2010)

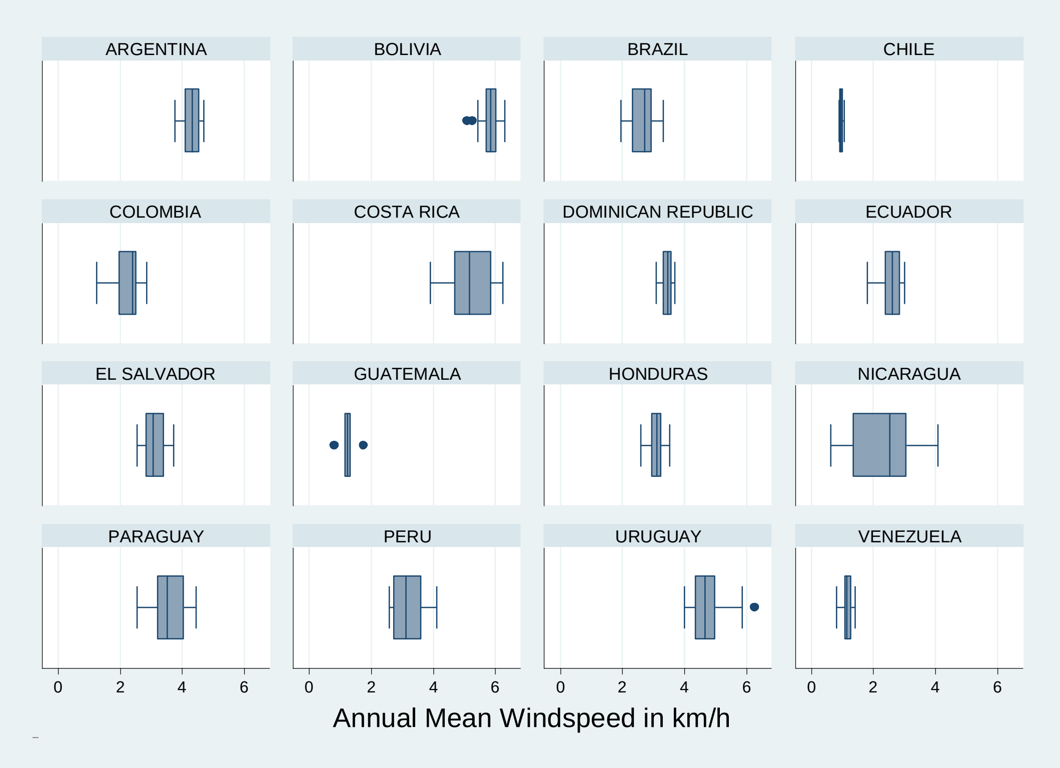

Figure A.8: Annual Mean Wind Speed 1990-2009

Source: FAO (2010)

Table A.3: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Life Satisfaction	138735	2.824	0.917	1	4
Married	139636	0.566	0.496	0	1
Unemployed	139636	0.063	0.243	0	1
Elementary School	139636	0.392	0.488	0	1
High School	139636	0.398	0.489	0	1
University	139636	0.317	0.465	0	1
Religious	139636	0.986	0.119	0	1
Obj. Wellbeing	139592	3.265	0.922	1	5
Subj. Eco. Sit.	121142	2.99	0.814	1	5
Subj. Income	136711	2.355	0.856	1	4
Male Dummy	139636	0.489	0.5	0	1
Age	139623	39.086	16.244	15	101
GDP per capita	139636	6895.118	2895.035	1945.399	13394.13
GDP Growth	139636	3.289	3.221	-9.387	16.236
Inflation	135034	9.916	11.535	-1.067	96.094
Literacy Rate	41097	89.99	5.426	76.677	98.649
Life Expectancy	139636	72.286	3.302	61.866	78.946
Monthly Mean Temperature	136989	21.542	5.357	9.4	29.9
Monthly Max. Temperature	136989	26.578	5.311	15.2	36.7
Monthly Min. Temperature	136989	17.469	5.568	4.3	26.4
Monthly Precipitation	87849	73.449	80.864	0.3	407.2
Monthly Vapor Pressure	136989	0.274	0.089	0.1	0.4
Monthly Mean Wind Speed	136989	3.319	1.572	0.7	7.8
Annual Mean Temperature	139636	21.889	4.422	12.936	28.15
Annual Max Temperature	139636	30.452	3.913	18.6	36.7
Annual Min. Temperature	139636	23.394	5.324	13.2	32
Annual Precipitation	139636	593.29	532.645	0	1669
Annual Mean Vapor Pressure	139636	0.277	0.068	0.136	0.4
Annual Mean Wind Speed	139636	3.34	1.369	0.8	6.182
Number of Months > 20°C	139636	7.626	3.938	0	12

Source: Latinobarómetro (2009), World Bank (2012), and FAO (2010).

Table A.4: Cross Correlations

	Life Satis.	**Married**	**Unempl.**	**Element.**	**H. School**	**University**	**Religious**	**Male**	**Age**	**Obj. Wb.**	**S. Eco. Sit.**	**Subj. Inc.**
Life Satis.	1											
Married	0.002	1										
Unempl.	-0.043	-0.07	1									
Element.	-0.052	0.1	-0.027	1								
H. School	0.011	-0.031	0.038	-0.653	1							
University	0.03	-0.082	-0.008	-0.49	-0.162	1						
Religious	0.02	0.019	-0.007	0.033	-0.008	-0.039	1					
Male	0.041	0.039	0.027	-0.028	0.008	0.022	-0.049	1				
Age	-0.051	0.176	-0.075	0.337	-0.231	-0.136	0.037	-0.024	1			
Obj. Wb.	0.17	-0.016	-0.061	-0.295	0.055	0.282	-0.004	0.004	0.006	1		
S. Eco. Sit.	0.281	-0.042	-0.062	-0.103	0.03	0.07	0.02	0.015	-0.12	0.246	1	
Subj. Inc.	0.188	-0.05	-0.08	-0.215	0.052	0.207	-0.014	0.059	-0.087	0.343	0.371	1
GDP pc	0.04	-0.005	0.033	-0.04	0.087	-0.064	0.063	-0.023	0.164	0.206	0.201	0.097
GDP gr.	0.066	0.000	-0.031	0.158	-0.077	-0.17	0.12	-0.003	0.022	-0.002	0.192	0.022
Inflation	-0.031	0.02	-0.049	0.173	-0.073	-0.113	0.034	0.01	-0.018	-0.131	0.011	0.005
Lit. Rate	0.017	0.017	0.024	-0.089	0.07	0.035	0.094	-0.017	0.16	0.15	0.156	0.069
Life Exp.	0.163	-0.005	0.04	0.037	0.077	-0.168	0.027	-0.019	0.123	0.121	0.106	-0.044
M. Mean. T.	-0.132	-0.01	-0.021	0.035	-0.029	0.046	-0.105	0.018	-0.104	-0.192	-0.213	-0.024
M. Max. T.	-0.117	-0.011	-0.023	0.053	-0.025	0.012	-0.104	0.016	-0.101	-0.175	-0.186	-0.016
M. Min. T.	-0.134	-0.02	-0.015	0.054	-0.034	0.02	-0.104	0.016	-0.099	-0.169	-0.199	-0.012
M. Pre.	-0.146	-0.02	0.01	-0.077	0.008	0.102	-0.051	-0.01	0.007	0.04	-0.005	0.116
M. Vap.	-0.066	-0.002	-0.02	0.05	-0.032	-0.002	-0.095	0.017	-0.132	-0.179	-0.2	-0.07
M.Wind	-0.151	0.018	-0.018	-0.108	0.01	0.211	-0.002	0.01	0.058	-0.141	-0.103	0.038
Mo. > 20°C	-0.171	-0.01	-0.032	0.03	-0.062	0.111	-0.081	0.02	-0.061	-0.204	-0.191	0.02
A. Mean T.	-0.159	-0.013	-0.025	0.047	-0.06	0.07	-0.066	0.02	-0.082	-0.212	-0.197	-0.011
A. Max T.	-0.176	-0.019	-0.009	0.038	-0.026	0.065	-0.071	0.013	-0.001	-0.191	-0.191	0.014
A. Min. T.	-0.047	-0.016	-0.027	0.09	-0.068	-0.036	-0.072	0.018	-0.155	-0.164	-0.145	-0.059
A. Pre	-0.194	-0.008	-0.001	-0.094	0.053	0.112	0.004	-0.007	0.069	0.113	0.084	0.203
A. Vap.	-0.111	-0.011	-0.021	0.041	-0.062	0.057	-0.072	0.02	-0.117	-0.221	-0.218	-0.061
A. Wind	-0.17	0.016	-0.013	-0.117	-0.004	0.252	-0.009	0.012	0.059	-0.144	-0.138	0.041

Source: Latinobarómetro (2009), World Bank (2012), and FAO (2010).

Table A.4 continued: Cross Correlations

	GDP pc	GDP gr.	Inflation	Lit. Rate	Life Exp.	M. Mean. T.	M. Max. T.	M. Min. T.	M. Pre.	M. Vap.	M.Wind	Mo. > 20°C
GDP pc	1											
GDP gr.	0.162	1										
Inflation	-0.327	0.645	1									
Lit. Rate	0.85	0.085	-0.255	1								
Life Exp.	0.709	0.179	-0.173	0.476	1							
M. Mean. T.	-0.79	-0.281	0.319	-0.821	-0.554	1						
M. Max. T.	-0.743	-0.209	0.362	-0.82	-0.48	0.986	1					
M. Min. T.	-0.724	-0.292	0.243	-0.843	-0.495	0.974	0.96	1				
M. Pre.	0.103	-0.08	-0.111	0.089	-0.326	0.038	0.037	0.086	1			
M. Vap.	-0.824	-0.186	0.354	-0.856	-0.451	0.924	0.924	0.891	-0.009	1		
M.Wind	-0.176	-0.099	0.261	0.168	-0.382	0.247	0.18	0.097	-0.031	0.062	1	
Mo. > 20°C	-0.726	-0.184	0.359	-0.686	-0.679	0.866	0.808	0.848	0.035	0.683	0.467	1
A. Mean T.	-0.765	-0.22	0.33	-0.764	-0.604	0.931	0.884	0.925	-0.054	0.797	0.365	0.956
A. Max T.	-0.47	-0.244	0.273	-0.532	-0.326	0.814	0.771	0.837	-0.039	0.621	0.42	0.883
A. Min. T.	-0.842	-0.043	0.323	-0.976	-0.506	0.858	0.855	0.866	-0.146	0.868	-0.051	0.734
A. Pre	0.405	-0.244	-0.255	0.373	-0.248	-0.082	-0.093	-0.033	0.531	-0.284	0.238	0.047
A. Vap.	-0.869	-0.241	0.278	-0.856	-0.583	0.939	0.892	0.921	-0.117	0.876	0.262	0.886
A. Wind	-0.223	-0.293	0.102	0.148	-0.475	0.274	0.177	0.163	0.075	0.067	0.925	0.534

Source: Latinobarómetro (2009), World Bank (2012), and FAO (2010).

Table A.4 continued: Cross Correlations

	A. Mean T.	A. Max T.	A. Min. T.	A. Pre	A. Vap.	A. Wind
A. Mean T.	1					
A. Max T.	0.91	1				
A. Min. T.	0.831	0.61	1			
A. Pre	-0.022	0.081	-0.311	1		
A. Vap.	0.965	0.815	0.902	-0.22	1	
A. Wind	0.42	0.48	-0.073	0.318	0.305	1

Source: Latinobarómetro (2009), World Bank (2012), and FAO (2010).

Table A.5: Results from the Orderd Probit Model

Life Satis.	(1) OP	(2) OP	(3) OP Mitchell et al.	(4) OP FAO
Married	0.058***	0.06***	0.058***	0.06***
Unemployed	-0.109***	-0.11***	-0.108***	-0.094***
High School	-0.017**	-0.015**	-0.012	-0.008
University	0.016*	0.015*	0.011	0.027**
Religious	0.1***	0.095***	0.094***	0.126***
Obj. Wellbeing	0.059***	0.057***	0.055***	0.053***
Subj. Eco. Sit.	0.327***	0.322***	0.322***	0.327***
Subj. Income	0.162***	0.162***	0.164***	0.180***
Male Dummy	0.013*	0.012*	0.01	0.021**
Age	-0.012***	-0.012***	-0.012***	-0.015***
Age^2	0.000***	0.000***	0.000***	0.000***
GDP Growth		0.008***	0.009***	0.012***
GDP Growth^2		0.001***	0.001**	0.001***
Inflation		-0.006***	-0.003***	-0.02***
Inflation^2		0.000***		0.000***
Temperature			-0.210***	-0.158***
Temperature^2			0.014***	0.01***
Temperature^3			-0.000***	-0.000***
Precipitation			-0.002**	-0.002***
Precipitation^2			0.000***	0.000***
Precipitation^3			-0.000***	-0.000***
Wind				0.027***
Cloud Covered Days			0.041**	
Cloud Covered Days^2			-0.001***	
Cloud Covered Days^3			0.000***	
Constant cut1	-0.799***	-0.891***	-1.130**	0.635
Constant cut2	0.444***	0.356***	0.117	-1.808***
Constant cut3	1.553***	1.463***	1.221***	-0.553
Observations	117,907	114,579	118,328	70,542

Source: Authors Estimations. Note: *, **, *** denote significance at 10%, 5% and 1% level, respectively. Note: The dependent SWB variable life satisfaction is coded on a scale of 4 to 1 coded: 4 Very satisfied, 3 Fairly satisfied, 2 Not very satisfied, 1 Not satisfied at all”. All the model specifications include country, year and month dummies.

Table A.6: Linear Probability Model with Data by Mitchell et al. (2004)

	LPM (Mitchell)			
Life Satis.	(1)	(2)	(3)	(4)
Married	0.045***	0.045***	0.045***	0.045***
Unemployed	-0.084***	-0.085***	-0.084***	-0.085***
High School	-0.01	-0.011*	-0.012*	-0.011*
University	0.007	0.005	0.002	0.005
Religious	0.07***	0.066***	0.064***	0.065***
Obj. Wellbeing	0.042***	0.042***	0.043***	0.042***
Subj. Eco. Sit.	0.239***	0.239***	0.239***	0.239***
Subj. Income	0.122***	0.122***	0.122***	0.122***
Male Dummy	0.008	0.008	0.008	0.008
Age	-0.009***	-0.009***	-0.009***	-0.009***
Age^2	0.000***	0.000***	0.000***	0.000***
GDP Growth	0.006***	0.007***	0.005***	0.006***
GDP $Growth^2$	0.000*	0.000**	0.000**	0.000**
Inflation	-0.0012***	-0.002***	-0.003***	-0.003***
Max Temperature	-0.487***			
Max $Temperature^2$	0.022***			
Max $Temperature^3$	-0.000***			
Min Temperature		0.029***		
Min $Temperature^2$		-0.001***		
Months > 20°C			0.036***	
Cooling Months				0.007***
Precipitation	-0.001*	-0.002***	-0.001***	-0.001***
$Precipitation^2$	0.000**	0.000***	0.000***	0.000***
$Precipitation^3$	-0.000**	-0.000***	-0.000***	-0.000***
Cloud Covered Days	0.032**	0.038***	0.057***	0.046***
Cloud Covered $Days^2$	-0.001***	-0.001***	-0.001***	-0.001***
Cloud Covered $Days^3$	0.000***	0.000***	0.000***	0.000***
Constant	4.672***	1.518***	0.741***	0.947***
Observations	118,328	118,328	118,328	118,328
R-squared	0.234	0.234	0.234	0.234

Source: Authors Estimations. Note: *, **, *** denote significance at 10%, 5% and 1% level, respectively. Note: The dependent SWB variable life satisfaction is coded on a scale of 4 to 1 coded: 4 Very satisfied, 3 Fairly satisfied, 2 Not very satisfied, 1 Not satisfied at all". All the model specifications include country, year and month dummies.

Table A.7: Results from the Pseudo Panel with Data by Mitchell et al. (2004)

	FE (Mitchell)				
Life Satis.	(1)	(2)	(3)	(4)	(5)
Married	0.227**	0.216**	0.230***	0.244***	0.228**
Unemployed	-0.012	-0.006	-0.01	0.005	-0.019
High School	0.018	0.025	0.017	0.014	0.021
University	-0.016	-0.006	-0.017	0.009	-0.003
Religious	-0.385	-0.222	-0.411	-0.433*	-0.382
Obj. Wellbeing	-0.031	-0.03	-0.029	-0.015	-0.021
Subj. Eco. Sit.	0.212***	0.229***	0.219***	0.217***	0.218***
Subj. Income	0.210***	0.201***	0.203***	0.192***	0.201***
GDP Growth	0.005**	0.005*	0.005*	0.005**	0.006**
GDP Growth^2	0.001**	0.001**	0.001**	0.001*	0.001*
Inflation	-0.002	-0.001	-0.002	-0.002**	-0.001
Temperature	0.002				
Max Temperature		-0.377***			
Max Temperature^2		0.017***			
Max Temperature^3		-0.000***			
Min Temperature			0.000		
Months > 20°C				0.031**	
Cooling Months					0.007
Precipitation	0.000	-0.000	0.000	0.000	0.000
Precipitation^2	0.072**	0.063**	0.071**	0.078***	0.069**
Precipitation^3	-0.001**	-0.001**	-0.001**	-0.002***	-0.001**
Cloud Covered Days	0.000**	0.000**	0.000**	0.000***	0.000**
Constant	0.219	2.869***	0.304	0.529	-0.127
Observations	678	678	678	678	678
R-squared	0.811	0.814	0.811	0.813	0.812
Number of cohortid	90	90	90	90	90

Source: Authors Estimations. Note: *, **, *** denote significance at 10%, 5% and 1% level, respectively. Note: The dependent SWB variable life satisfaction is coded on a scale of 4 to 1 coded: 4 Very satisfied, 3 Fairly satisfied, 2 Not very satisfied, 1 Not satisfied at all". All the model specifications include year dummies.

Appendix B: Chapter 2

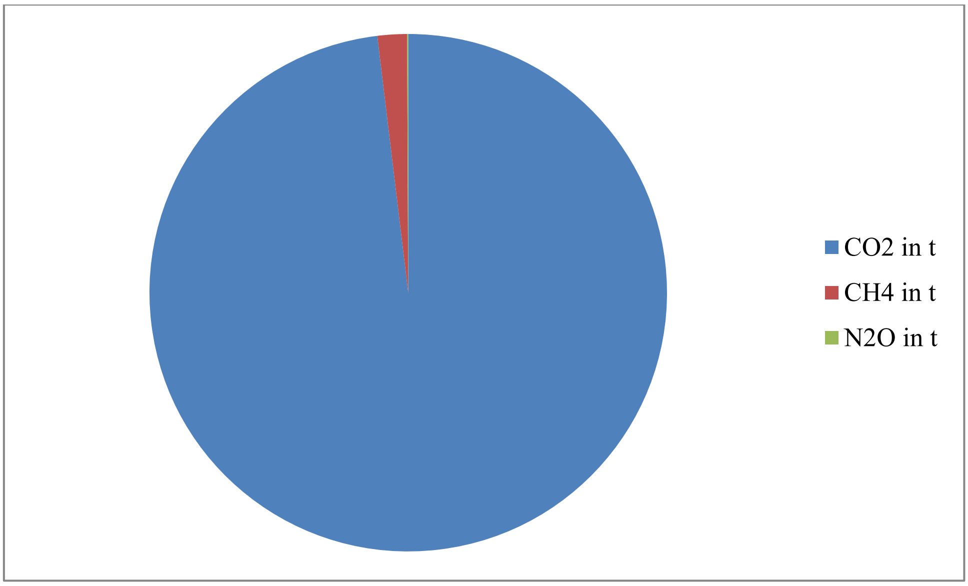

Figure B.1: Share of CO_2, CH_4 and N_2O in Indian GHG Emissions 2004
Source: Erumban et al. (2012)

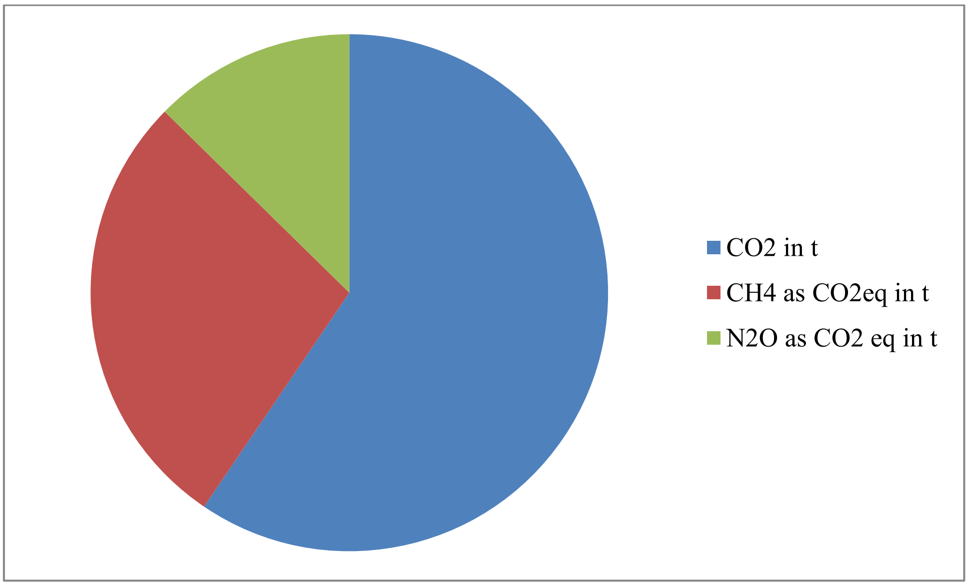

Figure B.2: Share of CO_2, CH_4 and N_2O in Indian GHG in CO_2 equivalents 2004
Source: Erumban et al. (2012)

Table B.1: Emission Intensities by IO Sector

IO Code	IO Description	kt CO_2/100000 Rupee (Rs. Lakhs)
1	Paddy	0.004
2	Wheat	0.005
3	Jowar	0.002
4	Bajra	0.002
5	Maize	0.002
6	Gram	0.001
7	Pulses	0.002
8	Sugarcane	0.002
9	Groundnut	0.001
10	Coconut	0.001
11	Other oilseeds	0.002
12	Jute	0.001
13	Cotton	0.002
14	Tea	0.001
15	Coffee	0.002
16	Rubber	0.001
17	Tobacco	0.001
18	Fruits	0.000
19	Vegetables	0.000
20	Other crops	0.002
21	Milk and milk products	0.001
22	Animal services(agricultural)	0.002
23	Poultry & Eggs	0.000
24	Other liv.st. produ. & Gobar Gas	0.001
25	Forestry and logging	0.000
26	Fishing	0.001
27	Coal and lignite	0.003
28	Natural gas	0.006
29	Crude petroleum	0.001
30	Iron ore	0.004
31	Manganese ore	0.001
32	Bauxite	0.007
33	Copper ore	0.001
34	Other metallic minerals	0.004
35	Lime stone	0.003
36	Mica	0.001
37	Other non metallic minerals	0.001
38	Sugar	0.003
39	Khandsari, boora	0.003
40	Hydrogenated oil(vanaspati)	0.003
41	Edible oils other than vanaspati	0.002
42	Tea and coffee processing	0.005
43	Miscellaneous food products	0.005
44	Beverages	0.004
45	Tobacco products	0.002
46	Khadi, cotton textiles(handlooms)	0.005
47	Cotton textiles	0.007
48	Woolen textiles	0.004
49	Silk textiles	0.003
50	Art silk, synthetic fiber textiles	0.006

Source: Authors estimation based on data from GTAP and CSO (2005)

Table B.1: continued: Emission Intensities by IO Sector

IO Code	IO Description	kt CO_2/100000 Rupee (Rs. Lakhs)
51	Jute, hemp, mesta textiles	0.005
52	Carpet weaving	0.004
53	Readymade garments	0.004
54	Miscellaneous textile products	0.005
55	Furniture and fixtures-wooden	0.003
56	Wood and wood products	0.002
57	Paper, paper prods. & newsprint	0.007
58	Printing and publishing	0.007
59	Leather footwear	0.003
60	Leather and leather products	0.003
61	Rubber products	0.006
62	Plastic products	0.007
63	Petroleum products	0.005
64	Coal tar products	0.006
65	Inorganic heavy chemicals	0.006
66	Organic heavy chemicals	0.005
67	Fertilizers	0.006
68	Pesticides	0.006
69	Paints, varnishes and lacquers	0.006
70	Drugs and medicines	0.005
71	Soaps, cosmetics & glycerin	0.005
72	Synthetic fibers, resin	0.005
73	Other chemicals	0.006
74	Structural clay products	0.014
75	Cement	0.016
76	Other non-metallic mineral prods.	0.013
77	Iron, steel and ferro alloys	0.009
78	Iron and steel casting & forging	0.011
79	Iron and steel foundries	0.009
80	Non-ferrous basic metals	0.003
81	Hand tools, hardware	0.005
82	Miscellaneous metal products	0.006
83	Tractors and agri. implements	0.006
84	Industrial machinery(F & T)	0.004
85	Industrial machinery(others)	0.004
86	Machine tools	0.004
87	Other non-electrical machinery	0.004
88	Electrical industrial Machinery	0.005
89	Electrical wires & cables	0.005
90	Batteries	0.006
91	Electrical appliances	0.005
92	Communication equipment	0.004
93	Other electrical Machinery	0.005
94	Electronic equipments(incl.TV)	0.003
95	Ships and boats	0.001
96	Rail equipments	0.006
97	Motor vehicles	0.005
98	Motor cycles and scooters	0.006
99	Bicycles, cycle-rickshaw	0.006
100	Other transport equipments	0.006

Source: Authors estimation based on data from GTAP and CSO (2005)

Table B.1 continued: Emission Intensities by IO Sector

IO Code	IO Description	kt CO_2/100000 Rupee (Rs. Lakhs)
101	Watches and clocks	0.002
102	Medical, precision&optical instru.s	0.003
103	Jems & jewelry	0.001
104	Aircraft & spacecraft	0.000
105	Miscellaneous manufacturing	0.001
106	Construction	0.005
107	Electricity	0.06
108	Water supply	0.004
109	Railway transport services	0.011
110	Land tpt including via pipeline	0.005
111	Water transport	0.017
112	Air transport	0.007
113	Supporting and aux. tpt activities	0.006
114	Storage and warehousing	0.014
115	Communication	0.002
116	Trade	0.001
117	Hotels and restaurants	0.003
118	Banking	0.001
119	Insurance	0.002
120	Ownership of dwellings	0.000
121	Education and research	0.000
122	Medical and health	0.002
123	Business services	0.002
124	Computer & related activities	0.001
125	Legal services	0.000
126	Real estate activities	0.001
127	Renting of machinery & equipment	0.000
128	O.com, social&personal services	0.001
129	Other services	0.002
130	Public administration	0.000

Source: Authors estimation based on data from GTAP and CSO (2005)

Table B.2: Matched Carbon Emission Intensities with Consumption Categories

NSS Code	NSS Description	IO Code	Erumban (2012) Code
101	rice - PDS	1	1
102	rice - other sources	1	1
103	chira	1	1
104	khoi, lawa	1	1
105	muri	1	1
106	other rice products	1	1
107	wheat/atta - PDS	2	1
108	wheat/atta - other sources	2	1
110	maida	2	1
111	suji, rawa	2	1
112	sewai, noodles	1	1
113	bread: bakery	2	1
114	other wheat products	2	1
115	jowar & products	3	1
116	bajra & products	4	1
117	maize & products	5	1
118	barley & products	2	1
120	small millets & products	4	1
121	ragi & products	7	1
122	other cereals	20	1
129	cereal: s.t. (101-122)		
139	cereal substitutes: tapioca, jackfruit, etc.	20	1
140	arhar, tur	6	1
141	gram: split	6	1
142	gram: whole	6	1
143	moong	6	1
144	masur	6	1
145	urd	6	1
146	peas	6	1
147	soyabean	7	1
148	khesari	7	1
150	other pulses	7	1
151	gram products	6	1
152	besan	6	1
153	other pulse products	7	1
159	pulses & pulse products: s.t. (140-153)		
160	milk: liquid (litre)	21	3
161	baby food	21	3
162	milk: condensed/ powder	21	3
163	curd	21	3
164	ghee	21	3
165	butter	21	3
166	ice-cream	21	3
167	other milk products	21	3
169	milk & milk products: s.t.(160-167)		3
170	vanaspati, margarine	40	3
171	mustard oil	11	3
172	groundnut oil	9	3
173	coconut oil	10	3
174	edible oil: others	41	3
179	edible oil: s.t. (170-174)		
180	eggs (no.)	23	3
181	fish, prawn	26	3
182	goat meat/mutton	22	3
183	beef/ buffalo meat	22	3
184	pork	22	3
185	chicken	23	3
186	others: birds, crab, oyster, tortoise, etc.	23	3
189	egg, fish & meat: s.t. (180-186)		
190	potato	19	3

Source: NSS (2006) Erumban et al. (2012)

Table B.2 continued: Matched Carbon Emission Intensities with Consumption Categories

NSS Code	NSS Description	IO Code	Erumban (2012) Code
191	onion	19	3
192	radish	19	3
193	carrot	19	3
194	turnip	19	3
195	beet	19	3
196	sweet potato	19	3
197	arum	19	3
198	pumpkin	19	3
200	gourd	19	3
201	bitter gourd	19	3
202	cucumber	19	3
203	parwal, patal	19	3
204	jhinga, torai	19	3
205	snake gourd	19	3
206	papaya: green	19	3
207	cauliflower	19	3
208	cabbage	19	3
210	brinjal	19	3
211	lady's finger	19	3
212	palak/other leafy vegetables	19	3
213	french beans, barbati	19	3
214	tomato	19	3
215	peas	19	3
216	chillis: green	19	3
217	capsicum	19	3
218	plantain: green	19	3
220	jackfruit: green	18	3
221	lemon (no.)	18	3
222	garlic (gm)	19	3
223	ginger (gm)	19	3
224	other vegetables	19	3
229	vegetables: s.t. (190- 224)		
230	banana (no.)	18	3
231	jackfruit	18	3
232	watermelon	18	3
233	pineapple (no.)	18	3
234	coconut (no.)	18	3
235	guava	18	3
236	singara	18	3
237	orange, mausami (no.)	18	3
238	papaya	18	3
240	mango	18	3
241	kharbooza	18	3
242	pears, naspati	18	3
243	berries	18	3
244	leechi	18	3
245	apple	18	3
246	grapes	18	3
247	other fresh fruits	18	3
249	fruits (fresh): s.t.(230-247)		
250	coconut: copra	10	3
251	groundnut	9	3
252	dates	18	3
253	cashewnut	9	3
254	walnut	9	3
255	other nuts	9	3
256	raisin, kishmish, monacca, etc.	18	3
257	other dry fruits	18	3
259	fruits (dry): s.t. (250-257)		
260	sugar - PDS	38	3

Source: NSS (2006) Erumban et al. (2012)

Table B.2 continued: Matched Carbon Emission Intensities with Consumption Categories

NSS Code	NSS Description	IO Code	Erumban (2012) Code
261	sugar - other sources	38	3
262	gur	8	3
263	candy, misri	39	3
264	honey	38	3
269	sugar: s.t. (260-264)		
279	salt	37	3
280	turmeric (gm)	20	3
281	black pepper (gm)	20	3
282	dry chillies (gm)	20	3
283	tamarind (gm)	20	3
284	curry powder (gm)	20	3
285	oilseeds (gm)	20	3
286	other spices (gm)	20	3
289	spices: s.t. (280-286)		
290	tea: cups (no.)	42	3
291	tea: leaf (gm)	14	3
292	coffee: cups (no.)	42	3
293	coffee: powder (gm)	15	3
294	ice	44	3
295	cold beverages: bottled/canned (litre)	44	3
296	fruit juice and shake (litre)	44	3
297	coconut: green (no.)	44	3
298	other beverages: cocoa, chocolate, etc.	44	3
300	biscuits	43	3
301	salted refreshments	43	3
302	prepared sweets	43	3
303	cooked meals (no.)	43	3
304	cake, pastry	43	3
305	pickles (gm)	43	3
306	sauce (gm)	43	3
307	jam, jelly (gm)	43	3
308	other processed food	43	3
309	beverages etc.: s.t. (290- 308)		
310	pan: leaf	17	3
311	pan: finished (no.)	45	3
312	supari (gm)	45	3
313	lime (gm)	45	3
314	katha (gm)	45	3
315	other ingredients for pan (gm)	45	3
319	pan: s.t. (310-315)		
320	bidi (no.)	45	3
321	cigarettes (no.)	45	3
322	leaf tobacco (gm)	17	3
323	snuff (gm)	45	3
324	hookah tobacco (gm)	45	3
325	cheroot (no.)	45	3
326	zarda, kimam, surti (gm)	45	3
327	other tobacco products	45	3
329	tobacco: s.t. (320-327)		
330	ganja (gm)	44	3
331	toddy (litre)	44	3
332	country liquor (litre)	44	3
333	beer (litre)	44	3
334	foreign liquor or refined liquor (litre)	44	3
335	other intoxicants	44	3
339	intoxicants: s.t. (330-335)		

Source: NSS (2006) Erumban et al. (2012)

Table B.2 continued: Matched Carbon Emission Intensities with Consumption Categories

NSS Code	NSS Description	IO Code	Erumban (2012) Code
340	coke	64	8
341	firewood and chips	56	6
342	electricity (std. unit)	107	17
343	dung cake	24	1
344	kerosene-PDS(litre)	63	8
345	kerosene - other sources (litre)	63	8
346	matches (box)	56	6
347	coal	64	8
348	LPG	63	8
350	charcoal	64	8
351	candle (no.)	73	9
352	gobar gas	28	8
353	other fuel	63	8
359	fuel and light: s.t. (340-353)		
360	dhoti (metre)	54	4
361	sari (metre)	54	4
362	cloth for shirt, pyjama, salwar, etc. (metre)	54	4
363	cloth for coat, trousers, overcoat, etc. (metre)	54	4
364	chaddar, dupatta, shawl, etc. (no.)	54	4
365	lungi (no.)	54	4
366	gamchha, towel, handkerchief (no.)	54	4
367	hosiery articles, stockings, under- garments, etc. (no.)	54	4
368	ready-made garments (no.)	53	4
370	headwear (no.)	54	4
371	knitted garments, sweater, pullover, cardigan, muffler, scarf, etc. (no.)	54	4
372	knitting wool, cotton yarn (gm)	54	4
373	clothing: others	54	4
374	clothing: second-hand	54	4
379	clothing: s.t. (360-374)		
380	bed sheet, bed cover (no.)	54	4
381	rug, blanket (no.)	52	4
382	pillow, quilt, mattress (no.)	54	4
383	cloth for upholstery, curtain, table- cloth, etc. (metre)	54	4
384	mosquito net (no.)	54	4
385	mats and matting (no.)	54	4
386	cotton (gm)	47	4
387	bedding: others	54	4
389	bedding, etc.: s.t. (380-387)		
390	leather boots, shoes	59	5
391	leather sandals, chappals, etc.	59	5
392	other leather footwear	59	5
393	rubber/ PVC footwear	61	10
394	other footwear	59	5
399	footwear: s.t. (390-394)		
400	books, journals	58	7
401	newspapers, periodicals	57	7
402	library charges	121	32
403	stationery	123	32
404	tuition and other fees (school, college, etc.)	121	32
405	private tutor/ coaching centre	121	32
406	other educational expenses	121	32
409	education: s.t. (400-406)		
410	medicine	70	33
411	X-ray, ECG, pathological test, etc.	122	33
412	doctor's/surgeon's fee	122	33
413	hospital & nursing home charges	122	33
414	other medical expenses	122	33
419	medical - institutional: s.t. (410-414)		
420	medicine	70	33
421	X-ray, ECG, pathological test, etc.	122	33
422	doctor's/surgeon's fee	122	33
423	family planning	122	33
424	other medical expenses	122	33
429	medical - non-institutional: s.t. (420-424)		

Source: NSS (2006) Erumban et al. (2012)

Table B.2 continued: Matched Carbon Emission Intensities with Consumption Categories

NSS Code	NSS Description	IO Code	Erumban (2012) Code
430	cinema, theatre	129	34
431	mela, fair, picnic	129	34
432	sports goods, toys, etc.	105	34
433	club fees	129	34
434	goods for recreation and hobbies	105	34
435	photography	94	34
436	video cassette/ VCR/ VCP(hire)	94	34
437	cable TV connection	94	34
438	other entertainment	129	34
439	entertainment: s.t. (430-438)		
440	spectacles	105	16
441	torch	105	16
442	lock	105	16
443	umbrella, raincoat	105	16
444	lighter (bidi/ cigarette/ gas stove)	105	16
445	other goods for personal care and effects	105	16
449	goods for personal care and effects: s.t. (440-445)		
450	toilet soap	71	9
451	toothbrush, toothpaste, etc.	62	9
452	powder, snow, cream, lotion	71	9
453	hair oil, shampoo, hair cream	71	9
454	comb	62	9
455	shaving blades, shaving stick, razor	82	9
456	shaving cream	71	9
457	sanitary napkins 00 458 other toilet articles	57	9
459	toilet articles: s.t. (450-458)		
460	electric bulb, tubelight	91	14
461	batteries	90	14
462	other non-durable electric goods	91	14
463	earthenware	76	16
464	glassware	76	16
465	bucket, water bottle/ feeding bottle & other plastic goods	62	10
466	coir, rope, etc.	53	10
467	washing soap/soda	71	9
468	other washing requisites	71	9
470	agarbati	71	9
471	flowers (fresh): all purposes	20	9
472	insecticide, acid, etc.	68	9
473	other petty articles	76	9
479	sundry articles: s.t. (460-473)		
480	domestic servant/cook	123	34
481	sweeper	123	34
482	barber, beautician, etc.	123	34
483	washerman, laundry, ironing	123	34
484	tailor	123	34
485	priest	128	34
486	legal expenses	130	34
487	postage & telegram	128	34
488	telephone charges	128	34
490	repair charges for non-durables	123	34
491	grinding charges	128	34
492	miscellaneous expenses	129	34
493	pet animals (incl. birds, fish)	129	34
494	other consumer services excluding conveyance	129	34
499	consumer services excluding conveyance: s.t. (480-494)		

Source: NSS (2006) Erumban et al. (2012)

Table B.2 continued: Matched Carbon Emission Intensities with Consumption Categories

NSS Code	NSS Description	IO Code	Erumban (2012) Code
500	air fare	112	25
501	railway fare	109	23
502	bus/tram fare	97	23
503	taxi, auto-rickshaw fare	97	23
504	steamer, boat fare	111	24
505	rickshaw (hand drawn & cycle) fare	99	23
506	horse cart fare	22	23
507	porter charges	128	23
508	petrol	29	8
510	diesel	29	8
511	lubricating oil	29	8
512	school bus/van	97	23
513	other conveyance expenses	98	26
519	conveyance : s.t. (500-513)		
520	house rent, garage rent (actual)	120	29
521	residential land rent	120	29
522	other consumer rent	120	29
529	rent: s.t. (520-522)		
539	house rent, garage rent (imputed- urban only)	120	29
540	water charges	108	17
541	other consumer taxes & cesses 549	130	34
549	consumer taxes and cesses: s.t. (540-541)		
550	bedstead	54	4
551	almirah, dressing table	54	4
552	chair, stool, bench, table	55	5
553	suitcase, trunk, box, handbag and other travel goods	63	5
554	foam, rubber cushion (dunlopillo type)	61	10
555	carpet, daree & other floor mattings	52	4
556	paintings, drawings, engravings, etc.	69	7
557	other furniture & fixtures (couch, sofa, etc.)	55	6
559	furniture & fixtures: s.t. (550-557)		
560	gramophone & record player	94	14
561	radio	94	14
562	television	94	14
563	VCR/VCP/DVD	94	14
564	camera & photographic equipment	94	14
565	tape recorder, CD player	94	14
566	gramophone record, audio/video cassette, etc.	94	14
567	musical instruments	105	14
568	other goods for recreation	105	14
569	goods for recreation: s.t. (560-568)		
570	gold ornaments	103	12
571	silver ornaments	103	12
572	jewels, pearls	103	11
573	other ornaments	103	11
579	jewellery & ornaments: s.t. (570-573)		
580	stainless steel utensils	82	16
581	other metal utensils	82	16
582	casseroles, thermos, thermoware	82	16
583	other crockery & utensils	82	16
589	crockery & utensils: s.t. (580-583)		
590	electric fan	91	13
591	air conditioner	91	13
592	air cooler	91	13
593	lantern, lamp, electric lampshade	91	13
594	sewing machine	91	13
595	washing machine	91	13
596	stove	91	13
597	pressure cooker/pressure pan	91	13
598	refrigerator	91	13
600	electric iron, heater, toaster, oven & other electric heating appliances	91	13
601	other cooking/household appliances	91	13
609	cooking and household appliances: s.t. (590-601)		

Source: NSS (2006) Erumban et al. (2012)

Table B.2 continued: Matched Carbon Emission Intensities with Consumption Categories

NSS Code	NSS Description	IO Code	Erumban (2012) Code
610	bicycle	99	19
611	motor cycle, scooter	98	19
612	motor car, jeep	97	19
613	tyres & tubes	61	19
614	other transport equipment	100	19
619	personal transport equipment: s.t. (610-614)		
620	hearing aids & orthopaedic equipment	102	14
621	other medical equipment	102	14
629	therapeutic appliances : s.t. (620-621)		
630	clock, watch	101	14
631	other machines for household work	91	14
632	personal computer	115	14
633	mobile phone handset	115	14
634	any other personal goods	93	14
639	other personal goods: s.t. (630-634)		
640	bathroom and sanitary equipment	87	16
641	plugs, switches & other electrical fittings	89	16
642	residential building & land (cost of repairs only)	129	16
643	other durables (specify)	105	16
649	residential building, land and other durables : s.t. (640-643)		
659	durable goods : total (559+569+579+589+609+ 619+629+639+649)		

Source: NSS (2006) Erumban et al. (2012)

Table B.3: Summary Statistics 2004/05

Variable	Obs	Mean	Std. Dev.	Min	Max
HH CO_2	124644	2025.848	1861.983	7.323	110981.5
Income	124644	46560.8	38017.33	171.672	920746.8
PDS Dummy	124644	0.558	0.497	0	1
Urban Dummy	124644	0.364	0.481	0	1
HH-Size	124644	4.892	2.522	1	43
Age Head	124642	45.717	13.576	0	108
Sex Head	124644	0.112	0.316	0	1
Edu. Head	124591	4.166	2.786	1	11
LPG	124644	0.283	0.451	0	1
Gas	124644	0.002	0.043	0	1
Dung	124644	0.051	0.22	0	1
Charcoal	124644	0.001	0.031	0	1
Kerosene	124644	0.04	0.196	0	1
Electricity	124644	0.001	0.034	0	1

Source: NSS (2006) and CSO (2005)

Table B.4: Summary Statistics 2009/10

Variable	Obs	Mean	Std. Dev.	Min	Max
HH CO_2	100855	3078.101	2917.591	45.031	124513.3
Income	100855	69973.31	59234.38	288.985	2089375
PDS Dummy	100855	0.591	0.492	0	1
Urban Dummy	100855	0.414	0.493	0	1
HH-Size	100855	4.646	2.338	1	35
Age Head	100855	46.221	13.462	2	105
Sex Head	100855	0.112	0.316	0	1
Edu. Head	100851	6.22	3.665	1	13
LPG	100855	0.388	0.487	0	1
Gas	100855	0.001	0.0378	0	1
Dung	100855	0.034	0.18	0	1
Charcoal	100855	0.001	0.032	0	1
Kerosene	100855	0.027	0.163	0	1
Electricity	100855	0.002	0.046	0	1

Source: NSS (2012) and CSO (2005)

Table B.5: Cross Correlations 2004/05

	HH CO_2	Income	PDS D.	Urban D.	HH-Size	Age Head	Sex Head	Edu. Head	LPG	Gas	Dung	Charcoal	Kerosene	Electricity
HH CO_2	1													
Income	0.824*	1												
PDS D.	-0.252*	-0.185*	1											
Urban D.	0.293*	0.188*	-0.288*	1										
HH-Size	0.282*	0.365*	0.125*	-0.101*	1									
Age Head	0.188*	0.193*	0.08*	-0.043*	0.214*	1								
Sex Head	-0.071*	-0.094*	0.011*	0.021*	-0.174*	0.086*	1							
Edu. Head	0.372*	0.363*	-0.233*	0.258*	-0.089*	-0.141*	-0.177*	1						
LPG	0.475*	0.413*	-0.354*	0.437*	-0.054*	0.069*	-0.01*	0.457*	1					
Gas	0.021*	0.03*	0.009*	-0.029*	0.017*	0.021*	-0.009*	0.016*	-0.027*	1				
Dung	-0.033*	-0.008*	0.059*	-0.119*	0.102*	0.006*	-0.029*	-0.069*	-0.146*	-0.01*	1			
Charcoal	-0.002	-0.004*	-0.021*	0.024*	-0.003*	-0.009*	0.012*	-0.001	-0.02*	-0.001	-0.007*	1		
Kerosene	-0.046*	-0.065*	0.012*	0.195*	-0.095*	-0.073*	0.013*	-0.007*	-0.128*	-0.009*	-0.047*	-0.006*	1	
Electricity	0.019*	0.002*	-0.021*	0.028*	-0.013*	-0.006*	-0.001	0.021*	-0.021*	-0.001	-0.008*	-0.001	-0.007*	1

Source: NSS (2006) and CSO (2005), Note: * indicates 5% significance level.

Table B.6: Cross Correlations 2009/10

	HH CO_2	Income	PDS D.	Urban D.	HH-Size	Age Head	Sex Head	Edu. Head	LPG	Gas	Dung	Charcoal	Kerosene	Electricity
HH CO_2	1													
Income	0.875*	1												
PDS D.	-0.281*	-0.237*	1											
Urban D.	0.255*	0.176*	-0.348*	1										
HH-Size	0.245*	0.314*	0.132*	-0.108*	1									
Age Head	0.179*	0.17*	0.071*	-0.032*	0.219*	1								
Sex Head	-0.063*	-0.079*	0.017*	0.023*	-0.164*	0.102*	1							
Edu. Head	0.308*	0.3*	-0.284*	0.253*	-0.116*	-0.171*	-0.192*	1						
LPG	0.408*	0.361*	-0.417*	0.448*	-0.056*	0.077*	-0.012*	0.435*	1					
Gas	0.036*	0.042*	0.001	-0.026*	0.022*	0.015*	-0.009*	0.005*	-0.03*	1				
Dung	-0.033*	-0.019*	0.055*	-0.097*	0.076*	0.001	-0.019*	-0.078*	-0.148*	-0.007*	1			
Charcoal	-0.001	-0.004*	-0.018*	0.03*	0.001	0.001	0.012*	0.000	-0.025*	-0.001	-0.006*	1		
Kerosene	-0.044*	-0.053*	0.01*	0.129*	-0.078*	-0.062*	0.003*	-0.026*	-0.133*	-0.006*	-0.031*	-0.005*	1	
Electricity	0.016*	0.003*	-0.031*	0.035*	-0.012*	-0.01*	0.003*	0.006*	-0.037*	-0.002	-0.009*	-0.002	-0.008*	1

Source: NSS (2012) and CSO (2005), Note: * indicates 5% significance level.

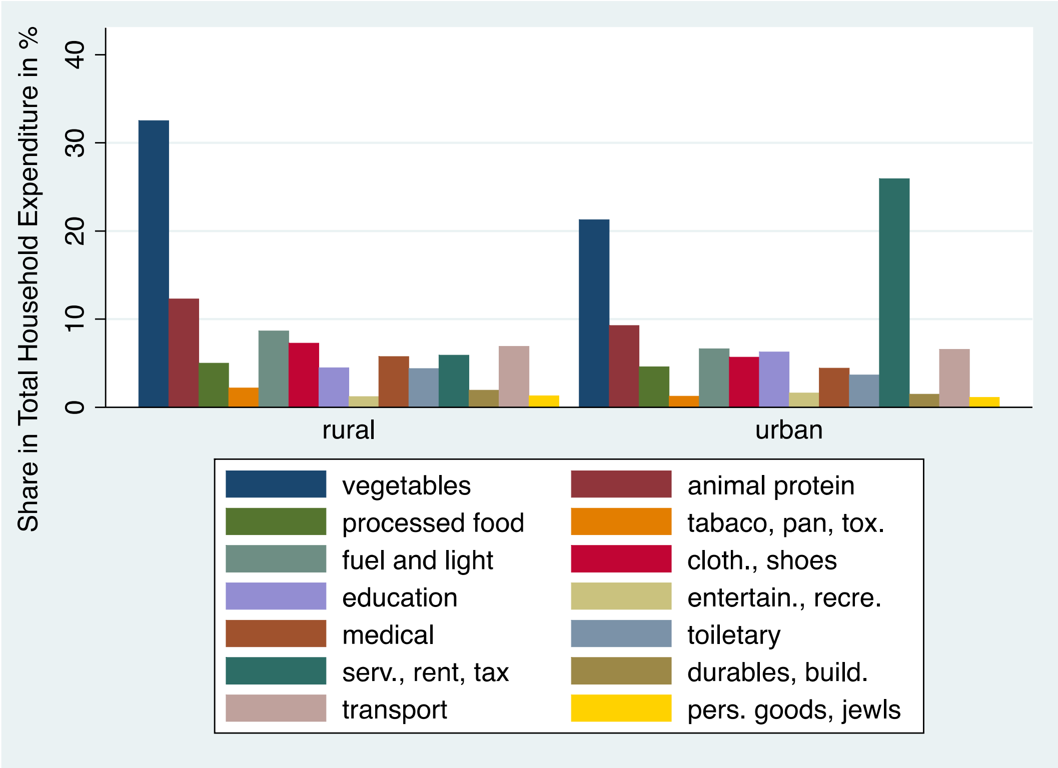

Figure B.3: Expenditure Share of Consumption Categories 2009/10

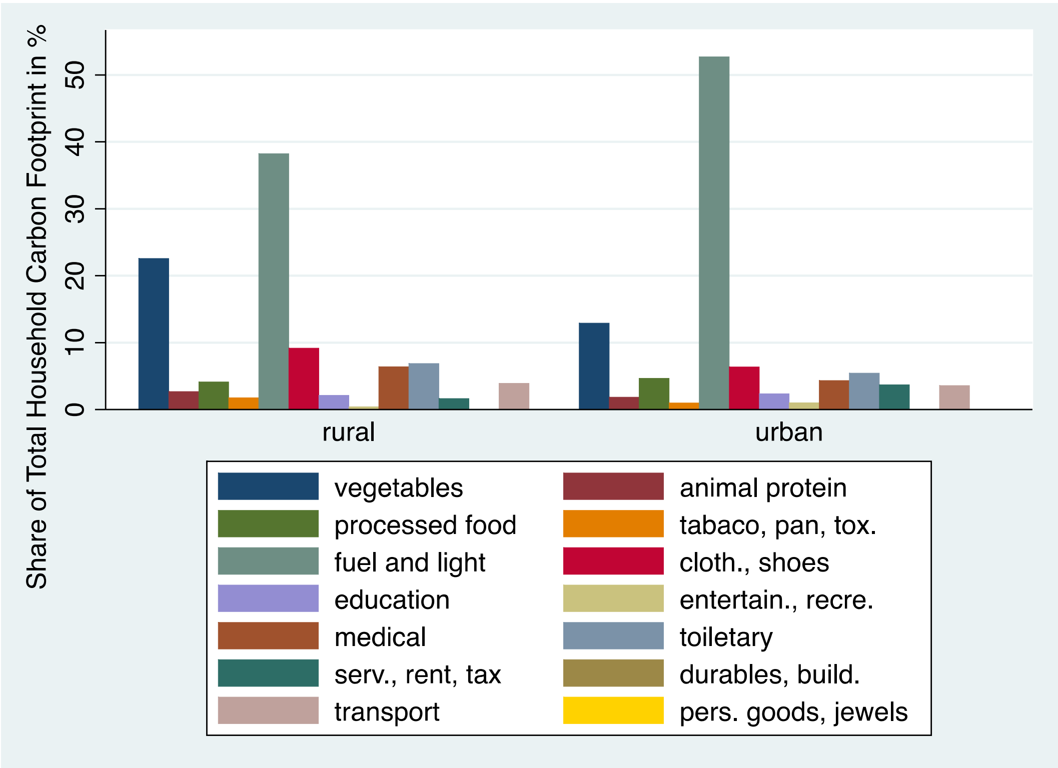

Figure B.4: Carbon Footprint Share of Consumption Categories 2004/05

Table B.7: Determinants of the Household Carbon Footprint 2009/10

	(1)	(2)	(3)	(4)
$lnCO_2^{hh}$	OLS	Beta Coef.	QR (q=0.1)	QR (q=0.9)
lnIncome	1.898***	1.711	3.005***	0.548***
$lnIncome^2$	-0.047***	-0.917	-0.096***	0.014***
PDS Dummy	-0.039***	-0.026	-0.038***	-0.039***
Urban Dummy	0.099***	0.066	0.064***	0.108***
Income*Urban	0.000	0.002	-0.000	0.000***
HH-Size	0.004	0.011	0.018***	-0.013***
$HH\text{-}Size^2$	-0.001***	-0.04	-0.001***	0.000
$HH\text{-}Size^3$	0.000	0.007	0.000	-0.000
Income*HH-Size	0.000***	0.044	0.000***	0.000***
Age-Head	0.000	0.002	0.004***	0.005***
$Age\text{-}Head^2$	0.000**	0.11	-0.000	-0.000
$Age\text{-}Head^3$	-0.000**	-0.065	0.000	0.000
Female Dummy	0.032***	0.014	0.017***	0.025***
Edu.-Head	0.016***	0.08	0.013***	0.007***
$Edu.\text{-}Head^2$	-0.001***	-0.042	-0.001***	-0.000
Income*Edu.	-0.000	-0.000	-0.000***	-0.000
LPG	0.114***	0.076	0.135***	0.109***
Gas	0.057***	0.003	0.057**	0.071**
Dung	-0.025***	-0.006	-0.02***	-0.027***
Charcoal	0.024	0.001	0.048	0.015
Kerosene	0.023***	0.005	0.06***	0.021***
Electricity	0.271***	0.017	0.149***	0.457***
Constant	-7.546***		-14.05***	0.252
Observations	100,851		100,851	100,851
R-squared	0.880		0.683	0.662

Note: *** p<0.01, ** p<0.05, * p<0.1, state dummies are included.

Table B.8: Determinants of the Household Carbon Footprint 2004/05 and 2009/10

	(1)	(2)
$lnCO_2^{hh}$	QR (q=0.1)	QR (q=0.9)
lnIncome	2.736***	0.846***
$lnIncome^2$	-0.084***	-0.000
lnIncome_0910	0.003***	0.006***
PDS Dummy	-0.064***	-0.057***
PDS Dummy_0910	0.015***	0.012***
Urban Dummy	0.083***	0.13***
Urban Dummy_0910	-0.029***	-0.029***
Income*Urban	0.000*	0.000***
HH-Size	0.011***	-0.018***
$HH\text{-}Size^2$	-0.001***	0.001***
$HH\text{-}Size^3$	-0.000	-0.000***
HH-Size_0910	0.002**	-0.004***
Income*HH-Size	0.000***	0.000***
Age-Head	-0.003**	0.003**
$Age\text{-}Head^2$	0.000***	-0.000
$Age\text{-}Head^3$	-0.000***	-0.000
Age-Head_0910	0.000**	-0.000**
Female Dummy	0.023***	0.051***
Female Dummy_0910	-0.011**	-0.024***
Edu.-Head	0.015***	0.017***
$Edu.\text{-}Head^2$	-0.001***	-0.001***
Edu.-Head_0910	0.001**	-0.006***
Income*Edu.	-0.000***	-0.000
LPG	0.151***	0.104***
LPG_0910	0.002	0.006
Gas	0.076***	0.006
Gas_0910	0.009	0.07*
Dung	-0.008	-0.043***
Dung_0910	-0.016*	0.024***
Charcoal	0.192***	-0.065*
Charcoal_0910	-0.131***	0.112**
Kerosene	0.066***	0.018***
Kerosene_0910	0.003	0.000
Electricity	0.251***	0.498***
Electricity_0910	-0.091**	0.002
Constant	-12.43***	-1.364***
Observations	225,440	225,440

Note: *** p<0.01, ** p<0.05, * p<0.1, state dummies are included.

Table B.9: Income Elasticities per Income Quintiles

	Quint 1		Quint 2		Quint 3		Quint 4		Quint 5	
	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se
Vegetables	-0.067***	(0.007)	-0.189***	(0.007)	-0.207***	(0.006)	-0.178***	(0.004)	-0.114***	(0.001)
Animal protein	0.072***	(0.002)	0.074***	(0.005)	0.038***	(0.005)	0.005	(0.004)	-0.04***	(0.001)
Processed fod	0.005	(0.003)	0.004	(0.004)	0.024***	(0.004)	0.014***	(0.004)	0.009***	(0.002)
Tobacco, pan, tox	0.002	(0.002)	0.008***	(0.003)	-0.003	(0.003)	-0.005**	(0.002)	-0.002***	(0.001)
Fuel, light	-0.011***	(0.002)	-0.024***	(0.003)	-0.028***	(0.003)	-0.038***	(0.002)	-0.033***	(0.001)
Clothing, shoes	-0.044***	(0.004)	-0.009***	(0.003)	-0.009***	(0.003)	-0.017***	(0.002)	-0.02***	(0.001)
Education	0.005***	(0.001)	0.024***	(0.003)	0.025***	(0.003)	0.027***	(0.003)	0.028***	(0.002)
Entertainment	0.003***	(0.000)	0.007***	(0.001)	0.01***	(0.001)	0.01***	(0.001)	0.002***	(0.000)
Medical goods	0.018***	(0.001)	0.026***	(0.005)	0.033***	(0.005)	0.039***	(0.004)	0.029***	(0.003)
Toiletary	-0.014***	(0.003)	-0.006***	(0.002)	-0.011***	(0.002)	-0.012***	(0.001)	-0.014***	(0.000)
Services, rent, tax	0.026***	(0.002)	0.06***	(0.006)	0.097***	(0.007)	0.131***	(0.006)	0.135***	(0.003)
Durables, building	-0.000*	(0.000)	-0.000	(0.000)	0.000	(0.000)	0.000*	(0.000)	0.000	(0.000)
Transport	0.006***	(0.001)	0.027***	(0.003)	0.033***	(0.003)	0.024***	(0.000)	0.021***	(0.002)
Personal goods	0.000**	(0.000)	0.000	(0.000)	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)

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

Appendix C: Chapter 3

Table C.1: List of Annex B Countries with Commitments in %

Country	Commitment	Ratified	Country	Commitment	Ratified
Australia	8	2007	Liechtenstein	-8	2004
Austria	-13	2002	Lithuania	-8	2003
Belgium	-7.5	2002	Luxembourg	-28	2002
Bulgaria	-8	2002	Monaco	-8	2006
Canada	-6	withdrawn	Netherlands	-6	2002
Croatia	-5	2007	New Zealand	0	2002
Czech Republic	-8	2001	Norway	1	2002
Denmark	-21	2002	Portugal	27	2002
Estonia	-8	2002	Romania	-8	2001
Finland	0	2002	Russia	0	2004
France	0	2002	Slovakia	-8	2002
Germany	-21	2002	Slovenia	-8	2002
Greece	25	2002	South Korea	-6	2002
Hungary	-6	2002	Spain	15	2002
Iceland	10	2002	Sweden	4	2002
Ireland	13	2002	Switzerland	-8	2003
Italy	-6.5	2002	Ukraine	0	2004
Japan	-6	2002	United Kingdom	-12.5	2002
Latvia	-8	2002	United States	-7	not jet

Source: UNFCCC (1997), 20.

Table C.2: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Kyoto	3935	0.076	0.266	0	1
Treat	3935	0.173	0.378	0	1
CO_2	3487	0.13	0.55	0.000	7.687
Pop	3384	32060.8	121796.4	16.025	1323592
GDP	3351	10822.44	13527.18	1.33	159246.9
CO_2 Growth	3192	0.066	1.069	-0.956	58.375
GDP Growth	3000	0.043	0.08	-0.491	1.295
Pop Growth	3171	0.015	0.014	-0.08	0.137
CDM Projects	3931	1.55	18.247	0	455
ICC	3935	0.249	0.433	0	1
WTO	3935	0.57	0.495	0	1

Table C.3: Cross Correlations

Variable	Ln CO_2	Kyoto	Treat	Ln Pop	Ln GDP	CO_2 Growth	Pop Growth	GDP Growth	CDM	ICC	WTO
Ln CO_2	1										
Kyoto	0.251	1									
Treat	0.409	0.617	1								
Ln Pop	0.750	0.089	0.148	1							
Ln GDP	0.412	0.325	0.476	-0.147	1						
CO_2 Growth	-0.022	-0.019	-0.029	-0.016	-0.019	1					
Pop Growth	-0.153	-0.171	-0.278	0.006	-0.202	0.027	1				
GDP Growth	-0.011	-0.056	-0.084	-0.005	-0.001	0.040	0.141	1			
CDM	0.111	0.285	0.177	0.071	0.117	-0.007	-0.041	-0.035	1		
ICC	0.043	0.435	0.222	0.007	0.134	-0.011	-0.078	-0.003	0.146	1	
WTO	0.168	0.202	0.139	0.141	0.173	0.003	-0.033	-0.017	0.066	0.347	1

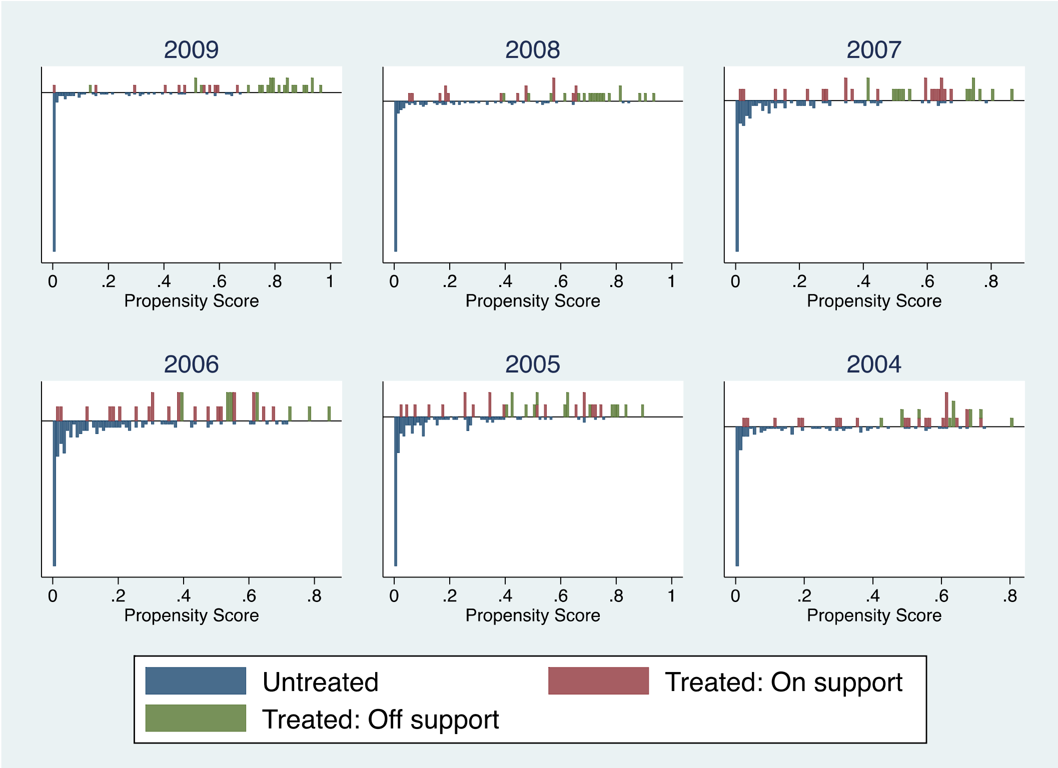

Figure C.1: Region of Common Support 2009-2004

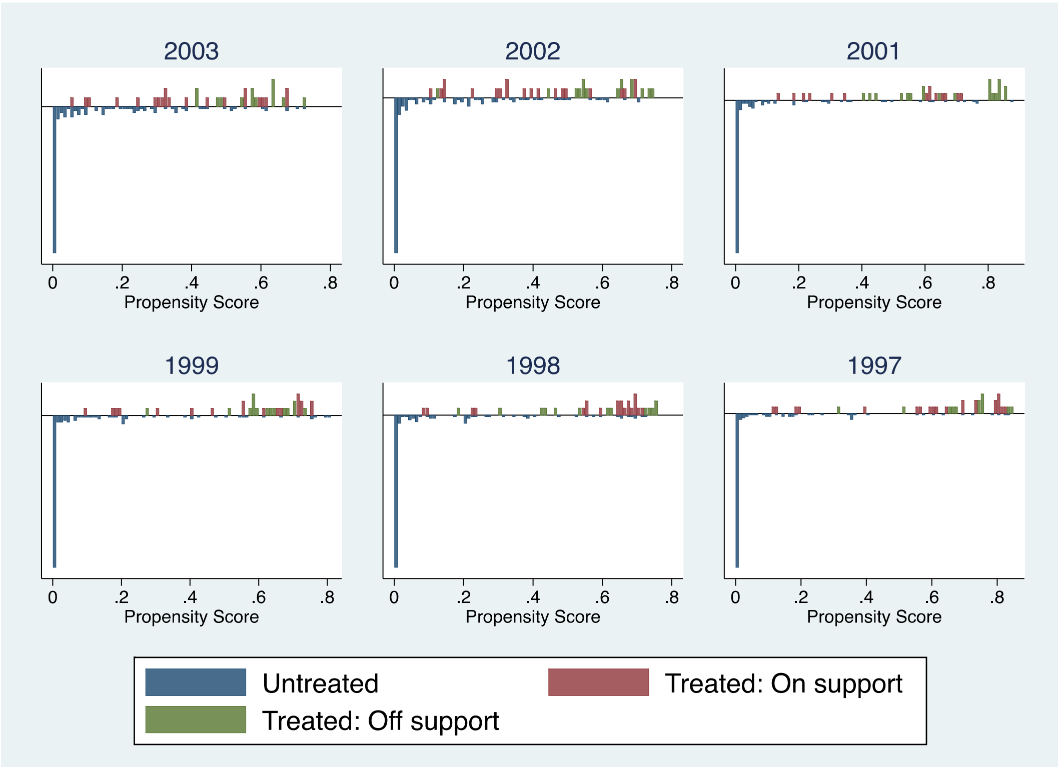

Figure C.2: Region of Common Support 2003-1997

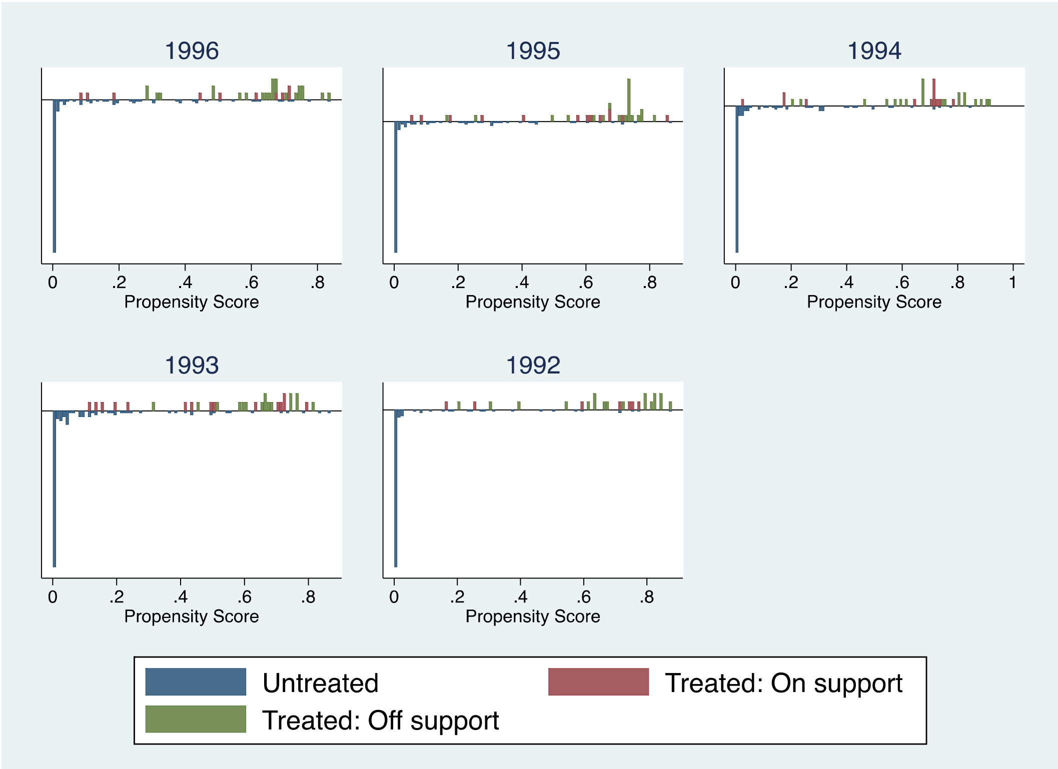

Figure C.3: Region of Common Support 1996-1992

Table C.4: Bias Reduction after the Matching 2009

		Mean			%reduction	t-test	
Variable	Sample	Treated	Control	%bias	in bias	t	p>t
CO_2 Growth	Unmatched	-0.075	0.009	-88.70		-3.88	0.00
	Matched	-0.032	-0.039	7.70	91.30	0.36	0.72
Pop Growth	Unmatched	0.002	0.017	-119.30		-5.11	0.00
	Matched	0.004	0.005	-7.50	93.70	-0.37	0.72
GDP Growth	Unmatched	-0.056	0.017	-149.90		-7.23	0.00
	Matched	-0.033	-0.028	-10.20	93.20	-0.41	0.69
CO_2 Growth^2	Unmatched	0.008	0.015	-19.80		-0.82	0.41
	Matched	0.003	0.003	0.10	99.60	0.01	0.99
Pop Growth^2	Unmatched	0.000	0.001	-31.50		-1.29	0.20
	Matched	0.000	0.000	-0.30	98.90	-0.21	0.84
GDP Growth^2	Unmatched	0.005	0.003	21.40		1.08	0.28
	Matched	0.002	0.002	5.00	76.70	0.40	0.70

Source: Author's estimation.

Table C.5: Pre-Kyoto Estimations

Dep. Var.	$\ln CO_2$	$Ln(CO_2/GDP)$
Sample	80-94 unmatched	80-94 unmatched
Treat Dummy	3.342***	4.030***
	(0.923)	(0.184)
Ln Population	1.406***	1.137***
	(0.145)	(0.111)
Ln GDP	0.742***	-0.186***
	(0.059)	(0.061)
Constant	-24.05***	-17.82***
	(2.272)	(1.287)
Number of Obs.	2,370	2,099
Overall R-squared	0.991	0.993

Note: The dependent variable is Treat. Robust standard errors are in brackets, ***p<0.01, **p<0.05, *p<0.1.

Table C.6: Results from the Instrumental Variables Estimator 1992-2009

Sample of countries:			Whole		High-Income
Instruments used:	None	CDM	CDM, WTO	CDM, WTO, ICC	CDM, WTO, ICC
Kyoto Dummy	-0.194***	-0.301***	-0.247***	-0.257***	-0.113*
	(0.047)	(0.048)	(0.055)	(0.072)	(0.066)
Ln Population	1.018***	0.892***	0.956***	0.943***	1.103***
	(0.33)	(0.144)	(0.155)	(0.150)	(0.168)
Ln GDP	1.133**	1.006***	1.070***	1.057***	3.633***
	(0.529)	(0.278)	(0.275)	(0.295)	(0.712)
Ln GDP^2	-0.024	-0.016	-0.02	-0.019	-0.153***
	(0.035)	(0.016)	(0.016)	(0.017)	(0.039)
Constant	-21.35***				
	(3.216)				
Over ID (H p-value)			0.022	0.055	0.054
Weak ID (F-stat)		29.135	16.523	67.589	28.827
Number of Observations	3,056	3,056	3,056	3,056	833
R-squared	0.387	0.385	0.387	0.386	0.713
Number of countries	170	170	170	170	49

Note: The dependent variable is lnCO_2. Robust standard errors are in brackets, ***p<0.01, **p<0.05, *p<0.1.

Year dummies are included as regressors.

Appendix E: Chapter 5

Table E.1: Summary Statistics IEA Data

Variable	Obs	Mean	Std. Dev.	Min	Max
coal_pc	2935	1.91	3.01	0.00	32.47
gas_pc	2935	0.94	1.26	0.00	6.13
oil_pc	2935	2.62	2.46	0.01	17.09
manufact_pc	2935	1.99	2.60	0.00	38.66
service_pc	2832	0.65	0.74	0.00	3.77
transport_pc	2935	1.12	1.32	0.00	14.73
residential_pc	2935	1.09	1.13	0.00	5.17

Source: (International Energy Agency 2011) Note: Emissions per capita for primary energy carriers and economic sectors in metric tons of CO_2 (tCO_2).

Table E.2: Summary Statistics Scenario Data

Variable	Scenario	Obs	Mean	Std. Dev.	Min	Max
oil_pc	BAU	1248	2.95	2.94	0.09	22.56
gas_pc	BAU	1248	3.22	3.59	0.00	22.52
coal_pc	BAU	1248	2.86	5.79	0.00	67.65
oil_growth	BAU	1170	0.51	1.65	-0.87	13.09
gas_growth	BAU	1170	4.75	17.29	-0.79	164.46
coal_growth	BAU	1170	4.72	16.61	-0.87	119.56
oil_pc	POL	1248	2.16	2.24	0.06	17.09
gas_pc	POL	1248	1.47	1.74	0.00	13.18
coal_pc	POL	1248	0.48	1.15	0.00	10.49
oil_growth	POL	1170	-0.07	0.55	-0.91	3.26
gas_growth	POL	1170	1.34	5.64	-0.85	39.76
coal_growth	POL	1170	-0.71	0.55	-1.00	5.33

Source: (Kriegler et al. submitted) Note : Emissions per capita for primary energy carriers in metric tons of CO_2 (tCO_2) and their respective growth rate (in %).

Table E.3: Country List

Country List IEA		
Albania	Georgia	Peru
Algeria	Germany	Philippines
Argentina	Greece	Poland
Armenia	Hong Kong, China	Portugal
Australia	Hungary	Romania
Austria	India	Russian Federation
Azerbaijan	Indonesia	Senegal
Bangladesh	Islamic Republic of Iran	Serbia
Belarus	Ireland	Singapore
Belgium	Israel	Slovak Republic
Bolivia	Italy	Slovenia
Bosnia and Herzegovina	Japan	South Africa
Brazil	Korea	Spain
Bulgaria	Latvia	Sweden
Canada	Lithuania	Switzerland
Chile	Luxembourg	Syrian Arab Republic
People's Republic of China	FYR of Macedonia	Tajikistan
Chinese Taipei	Malaysia	United Republic of Tanzania
Colombia	Mexico	Thailand
Democratic Republic of Congo	Republic of Moldova	Tunisia
Croatia	Mongolia	Turkey
Cuba	Morocco	Ukraine
Czech Republic	Mozambique	United Kingdom
Denmark	Myanmar	United States
Dominican Republic	Netherlands	Uruguay
Egypt	New Zealand	Uzbekistan
Estonia	Nigeria	Venezuela
Finland	Norway	Vietnam
France	Pakistan	

Source: IEA (2011)

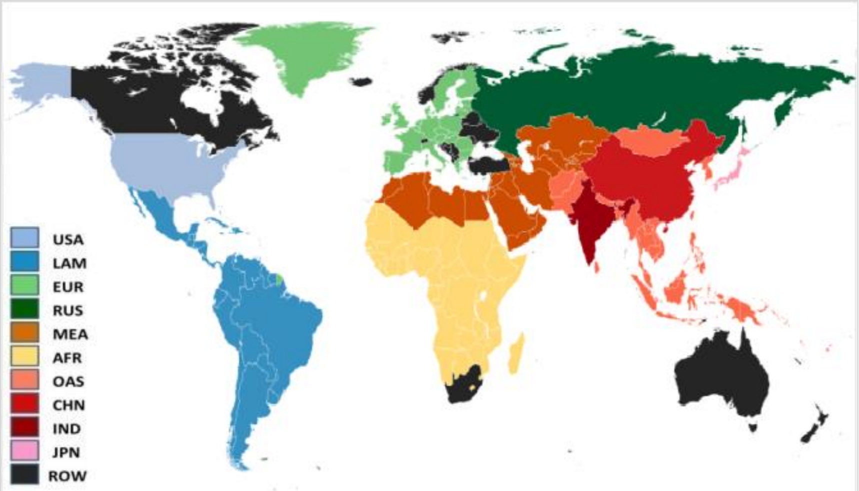

Figure E.1: REMIND Regions

Source: Luderer et al. (2013) Note: The regional acronyms are as follows: *USA* – USA; LAM – Latin America; EUR – Europe; RUS – Russia; MEA – Middle-East; AFR – Africa; OAS – other Asia; CHN – China; IND – India; JPN – Japan; ROW – rest of the World.

Table E.4: Contributing Factors to Changes in the Gini of CO_2 p.c.

	1971			2008		
	Share	GINI	Rank Corr.	Share	GINI	Rank Corr.
Oil	0.53	0.55	0.90	0.43	0.46	0.85
Coal	0.39	0.77	0.93	0.32	0.65	0.81
Gas	0.08	0.84	0.75	0.25	0.53	0.74
Manufact	0.52	0.65	0.95	0.34	0.45	0.94
Service	0.09	0.69	0.93	0.16	0.54	0.90
Transport	0.17	0.53	0.85	0.28	0.50	0.89
Residential	0.21	0.65	0.98	0.22	0.48	0.91

Source: (International Energy Agency 2011)

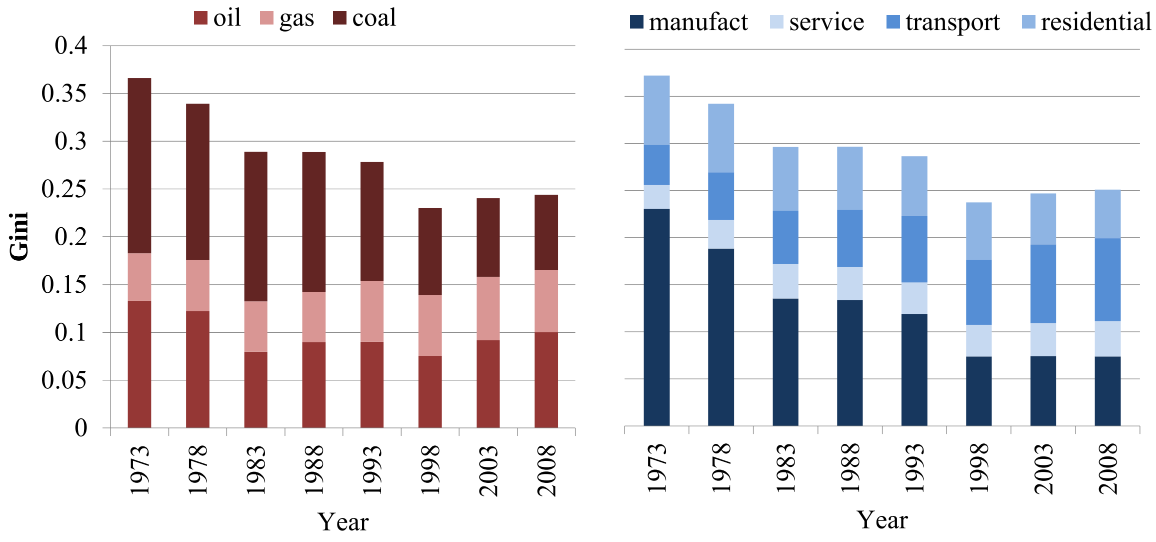

Figure E.2: Contribution of Emissions from Primary Energy Carriers and Economic Sectors to Gini of CO_2 p.c. (OECD Countries only)

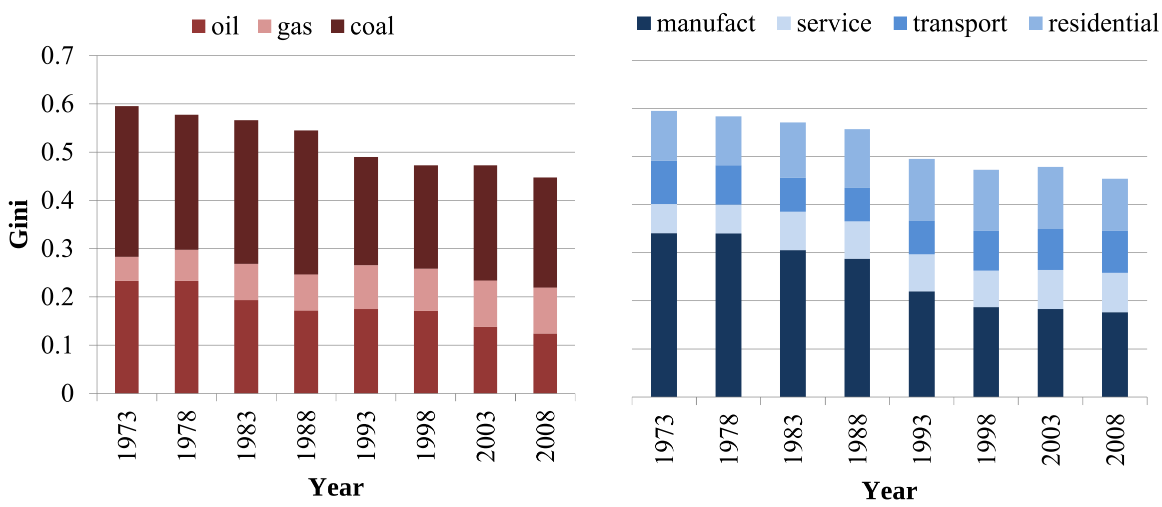

Figure E.3: Contribution of Emissions from Primary Energy Carriers and Economic Sectors to Gini of CO_2 p.c. (non-OECD Countries only)

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Eidesstattliche Erklärung

Hiermit versichere ich, dass ich die vorliegende Arbeit selbständig und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Alle Stellen, die wörtlich oder sinngemäß aus veröffentlichten und nicht veröffentlichten Schriften entnommen sind, sind als solche kenntlich gemacht.

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