Hacettepe University Graduate School of Social Sciences

Department of Economics

DETERMINANTS OF HOUSEHOLD GREENHOUSE GAS EMISSIONS IN THE EUROPEAN UNION COUNTRIES

Erdener Emin EKER

Master's Thesis

Ankara, 2020

DETERMINANTS OF HOUSEHOLD GREENHOUSE GAS EMISSIONS IN THE EUROPEAN UNION COUNTRIES

Erdener Emin EKER

Hacettepe University Graduate School of Social Sciences

Department of Economics

Master’s Thesis

Ankara, 2020

ACKNOWLEDGEMENTS

First of all, I would like to state that I am deeply grateful to my advisor, Assist. Prof. Dr. Onur YENİ for his guidance and support throughout this process. His mentorship and encouragement have provided me the best possible support that I could hope for, especially during the Covid-19 outbreak.

I am also grateful for the feedbacks and contributions given by the rest of my thesis committee; Assoc. Prof. Dr. Fatih Cemil ÖZBUĞDAY and Assist. Prof. Dr. Mustafa Aykut ATTAR. Their comments and suggestions significantly contributed to this thesis.

I also would to show my gratitude to Assoc. Prof. Dr. Selcen ÖZTÜRK and Assoc. Prof. Dr. Dilek Başar. Their comments and support have helped for me specifically beginning of this journey.

Additionally, I would like to thank my colleague and friend Elizabett SERT. Her help and contributions have helped me a lot during the process.

Last but not least, I would like to thank my mother Hülya EKER and my father Avni EKER for always supporting me.

ABSTRACT

EKER, Erdener Emin. *Determinants of Household Greenhouse Gas Emissions in the European Union Countries*, Master's Thesis, Ankara, 2020

Global climate change is mainly caused by greenhouse gas (GHG) emissions from human activities. Household consumption activities contribute to GHG emissions both directly, i.e., transportation, heating/cooling, etc., and indirectly, i.e., consumption of goods and services other than energy. Recognizing the responsibilities of households; therefore, an analysis of the determinants of the household GHG emission is crucial for carbon reduction efforts and future policy implications in order to fight against climate change. This study aims to investigate the determinants of the household GHG emissions in the European Union. To this end, we employ panel data estimation techniques for the period 2008-2016 and for 24 member countries. We obtained the necessary data from Eurostat (Air Emission Accounts database, European Union Labor Force Survey database, Energy Balances dataset) and World Bank (Climate Change Knowledge Portal). Our findings mainly in line with the related literature and suggest that income, education, energy consumption, July temperature, and the number of children affect direct household GHG emissions positively in the European Union countries. On the other hand, employment and the number of elder people have a negative impact on household emissions.

Keywords

Climate change, Household GHG emissions, Direct emissions

TABLE OF CONTENTS

ABBREVIATIONS

CH_4: Methane

CO_2: Carbon Dioxide

COP: Conference of Parties

CPA: Statistical Classification of Products by Activity in the European Economic Community

EEA: European Environment Agency

EE-IOM: Environmentally Extended Input-Output Model

EKC: Environmental Kuznets Curve

ESA: European System of Accounts

EU: European Union

EU-LFS: European Union Labor Force Survey

EUROSTAT: Statistical Office of the European Communities

FGLS: Feasible Generalized Least Squares

FRED: Federal Reserve Bank of St. Louis database

GDP: Gross Domestic Product

GHG: Greenhouse Gas

GISS: Goddard Institute for Space Studies

H_2O: Water Vapor

HECE: Household Embedded Carbon Emissions

IPCC: Intergovernmental Panel on Climate Change

N_2O: Nitrous Oxide

NACE: General Industrial Classification of Economic Activities within the European Communities

NASA: National Aeronautics and Space Administration

O_3: Ozone

OECD: Organization for Economic Cooperation and Development

Ppm: Parts per Million

PPP: Purchasing Power Parity

PPS: Purchasing Power Standard

SIEC: Standard International Energy Classification

UK: United Kingdom

UNFCCC: United Nations Framework Convention on Climate Change

US: United States

USA: United States of America

YEP: Young Energy People

YES: Young Energy Savers

TABLES

FIGURES

INTRODUCTION

Changes in the Earth's climate have been happening since the existence of the atmosphere. However, for ages, these changes came from the atmosphere's internal dynamics. Different factors alter the atmosphere's internal dynamics, such as Earth's radiation balance, massive volcanic eruptions, etc. Beyond these factors, after the Industrial Revolution, Earth's climate is changing mostly due to one external factor: changes in the greenhouse gas (GHG) concentration due to increased human activities. With the Industrial Revolution, human activities interfered the internal dynamic of the atmosphere like never before. Human population growth and economic activities accelerated after the revolution and continued to increase sharply for centuries. While economic activities continue to grow, the world's population growth rate almost stabilized over the last three decades. Therefore, economic activities have become a major source of GHG emissions (Le Treut, 2007).

During the past 50 years, human activities as causing factors for climate change, become much more apparent (McCarty, Canziani, Leary, Dokken, & White, 2001). Burning fossil fuels, changes in land use, and deforestation are the leading human activities that emit GHGs (IPCC, 2007). Although there are countries with significant GHG emissions in the world, climate change is a common problem. Therefore, the solution to this common problem requires collective action. In terms of collective action, several attempts were made beginning with the establishment of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992. Following the "virtually ineffective" Kyoto Protocol, which is signed in 1997 and entered into force in 2005, Paris Climate Agreement signed in 2015 and entered into force at the end of 2016. Nevertheless, none of these collective actions achieved to decrease emissions globally to the targeted levels. Moreover, emission reduction scenarios show that in order to limit global mean surface temperature with 2°C, more effective actions are needed to reduce global GHG emissions.

European Union (EU) has a better record in terms of emission reductions when it is compared with the rest of the World. According to the Paris Agreement, countries set their own emission reduction targets; however, these targets are not binding. The EU set a 20% emission reduction target for 2020 compared to 1990 levels within the scope of the Paris Agreement (da Graça Carvalho, 2012). The EU had already met this target in 2018. Policies aiming energy sector and energy use by households facilitate emission reductions since the Energy sector is the highest GHG emitter among economic sectors, and it has the highest GHG emissions intensity. Unfortunately, even though the EU has 28 members, collective action of 28 countries does not suffice to decrease emissions at the global level. Climate change problem requires global collective action (Nordhaus, 2013, p. 129). The EU's experience showed that policies from different perspectives should be employed for climate change mitigation. Consumption side emissions and household emissions enter climate change literature within this context. Calculating emissions from the production side and suggesting policies accordingly failed in meeting emission reduction targets. Calculating emissions from the consumption side and analyzing household emissions can bring new policy options and expand mitigation efforts.

Household emissions literature gained importance after the 1990s. At first, the literature focused on emissions from residential energy use. Over time, emissions from households' consumption expenditures, i.e., indirect emissions, and determinants of household emissions have been mainly analyzed by the related literature (Liu, Qu, Clarke-Sather, Maraseni, & Pang, 2017). Analysis of household emissions in the EU countries matters because the EU constitutes an important portion of the world GDP and world GHG emissions. Moreover, studies focusing on household emissions' determinants mostly concentrated on single country such as China and the United Kingdom. Hence, determining the factors affecting the EU households' GHG emissions can present an opportunity to form a broader set of policy recommendations. There are common determinants found to be significant in the related literature, such as income, household size, age, marital status, dwelling type, urban or rural location, education status, employment status, household size, household composition, etc. Due to restrictions coming from the data, we only analyzed a limited number of determinants, but we also add temperature variables into our analysis. In this study, we analyze the determinants of direct household emissions of the EU countries by employing panel data methods using the data for 24 member countries for the 2008-2016 period. Mainly our results are in line with the literature.

The structure of the study is as follows: the first chapter of the thesis explains the climate change problem with its causes and consequences and then discusses sectoral GHG emission in the EU and highlights the importance of household emissions using a descriptive analysis. Chapter 2 presents a broad literature survey regarding the determinants of the household emissions and discloses the common determinants used in the literature. Finally, Chapter 3 introduces the data and methodology used in the empirical analysis, includes panel data estimations, and discusses the findings of our analysis.

CHAPTER 1

GREENHOUSE GASES AND CLIMATE CHANGE

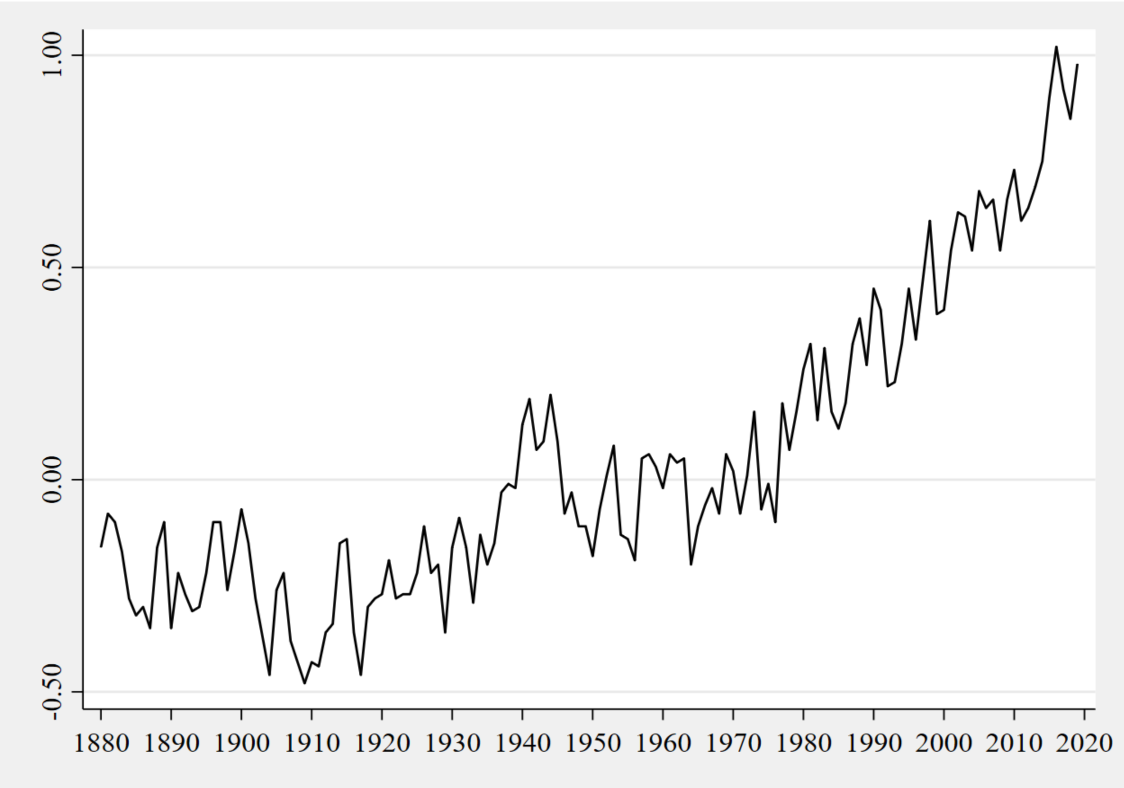
1.1. Climate Change

The Earth's climate is changing since the beginning of history. So change in the climate is not a new phenomenon that we face recently. The new thing is that the climate has been changing due to human activities rather than its own internal dynamics. Human intervention on climate became evident over the last 50 years (McCarty et al., 2001). Nowadays, the term "climate change" is used by the scientific society to address human-induced changes in the climate. IPCC defines climate change as a change in the climate because of human-related and anthropogenic reasons (IPCC, 2007). These human activities can be separated as consumption and production activities. Our way of consuming and producing goods and services creates GHG emissions, which in turn increase concentrations of these gases in the atmosphere. Greenhouses gasses are defined as "… those gaseous constituents of the atmosphere, both natural and anthropogenic, that absorb and emit radiation at specific wavelengths within the spectrum of infrared radiation emitted by the Earth's surface, the atmosphere, and clouds" (IPCC, 2007, p.875). As a result, increased GHG concentration in the atmosphere creates a greenhouse effect and leads to changes in the climate. GHGs trap heatwaves within the atmosphere and reflect them back to the Earth's surface, and eventually, the mean global surface temperatures increase.

The greenhouse effect could be explained using the "blanket" metaphor. A blanket keeps the body warm by trapping the body heat inside it. As GHG concentrations in the atmosphere increased, they become a GHG blanket surrounding the Earth. These GHGs, especially carbon dioxide (CO_2), prevent the longwave radiation coming from Earth's surface to reach outside the atmosphere, therefore trapping it within the atmosphere. GHGs absorb the radiation and eventually reflect them back to the Earth and causes increased heat in the Earth's surface (Ramanathan & Feng, 2009). This process is called the greenhouse effect. When mentioning the greenhouse effect, it is crucial to make a distinction between the anthropogenic greenhouse effect and the natural greenhouse effect. The natural greenhouse effect is crucial for life on Earth. Without the natural greenhouse effect, the average temperature on Earth would be below 0℃ degree. By trapping the heat within the atmosphere, the natural greenhouse effect makes life possible on Earth (Le et al., 2007). On the other hand, as a result of human-induced increases in the GHG concentrations, more heat is trapped within the atmosphere, and eventually, this leads to warmer Earth. This process is called the anthropogenic greenhouse effect. Climate change is a problem because of the anthropogenic greenhouse effect. With increased human activities, especially over the last 50 years, the mean temperatures increased.

Figure 1 shows the deviations in the global surface temperature from 1880 to 2019 from 1951-1980 averages. It can be easily seen from Figure 1 that there is a sharp increase in the global surface temperature from its 1951-1980 averages after the 1970s.

Figure 1: Global Land-Ocean Temperature Index



Source: National Aeronautics and Space Administration's (NASA) Goddard Institute for Space Studies (GISS)

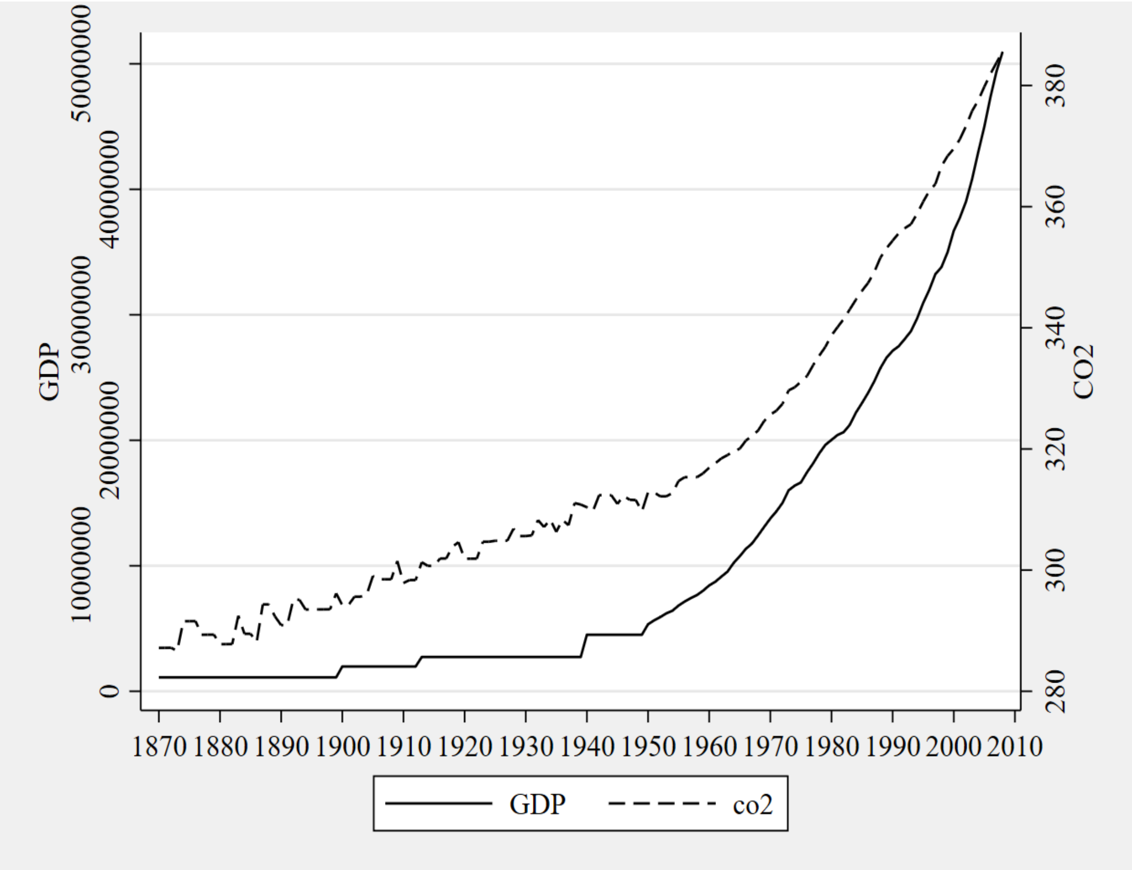
The sharp increase in the global mean temperatures is mainly related to GHG emissions from increased human activities. These are called anthropogenic GHGs. Anthropogenic GHG emissions consist of the emissions released from burning fossil fuels, deforestation, land-use changes, livestock production, fertilization, waste management, and industrial processes. The main drivers of the carbon emissions from fossil fuel combustions are the increased economic activity and population growth along with the globe. While population growth has not changed between the last three decades, economic growth has continued to increase with even higher rates. Therefore, the main driver of emissions is the increase in economic activities (IPCC, 2014a).

Figure 2 shows the link between total World GDP and global CO_2 concentrations from 1870 to 2008. World GDP is in terms of 1990 International Geary-Khamis dollars[1]. CO_2 concentrations show the average concentration of CO_2 in the atmosphere, measured in parts per million (ppm). Emissions released from industrial processes and burning fossil fuels constituted 78% of the total GHG emission increases in the 1970-2010 period (IPCC, 2014a, p.45). Therefore, we can easily conclude that increase in the economic activities, especially after 1970, results with higher anthropogenic GHG emissions in the atmosphere and causes the increase in the global mean surface temperatures.

Until 2010, the highest total anthropogenic GHG emissions observed in the 2000-2010 time period. During this decade, the annual growth of GHG emissions was 1.0 gigatonnes CO_2 equivalent (CO_2e). However, it was only 0.4 gigatonnes CO_2e in the period 1970-2000. In the 2000-2010 period, GHG emissions reduced after the 2008 global economic crises. However, this appeared to be only a temporary reduction. These movements can be seen in Figure 2. Also, CO_2 emissions released within these 40 years (1970-2010) constitute half of the cumulative anthropogenic CO_2 emission for the 1750-2010 time period (IPCC, 2014a, p.7).

[1] This is an International measure for currencies between countries, also known as International dollar

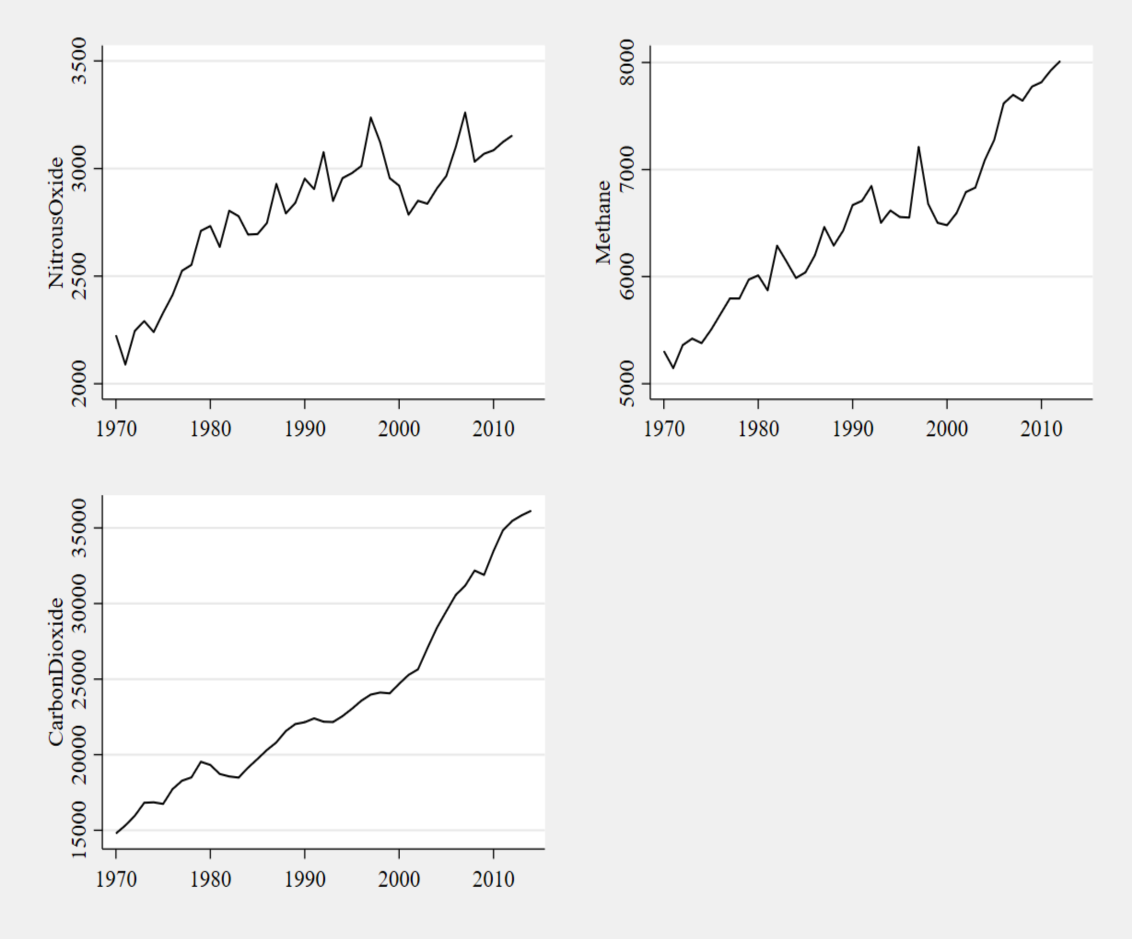
Figure 2: GDP and CO_2 Concentration



Source: The Maddison Database and National Oceanic and Atmospheric Administration- Earth System Research Laboratories

Main GHGs in the atmosphere that cause the greenhouse effect are, carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), water vapor (H_2O), and ozone (O_3). CO_2 constitutes most of the GHGs in the atmosphere. While 75% of the total anthropogenic GHG emissions in 1970 was CO_2 emissions, it increased to almost 76% in 2010. The shares of the remaining GHGs in total emissions in 2010 were 16% for CH_4, 6.2% for N_2O, and 2% for fluorinated gasses (IPCC, 2014a, p.45). Figure 3 shows N_2O, CH_4, and CO_2 emissions since 1970. It is clear from the figure that emissions of all these gases increased since 1970; however, the increase in CO_2 emissions has been sharper than that of others.

Figure 3: Nitrous Oxide, Methane and Carbon Dioxide in million tons



Source: World Development Indicators Database

It is known that natural and human systems are under the threat of climate change. The latest report of the IPCC about impacts of the climate change, reports that due to permanent warmings in the high-altitude and high-latitude regions, melting of the ice and snow masses accelerates and leads to changes in hydrological systems. Climate change also has an impact on crop yields. Even though these impacts can be positive or negative, IPCC reports claim that negative impacts exceed positive impacts. Positive impacts of the climate change on crop yields generally observed in the high-latitude regions, but even in those regions, it is hard to tell that positive impacts outweigh negative impacts. Another impact is the increases in the number and the intensity of extreme weather events such as droughts, floods, heatwaves, storms, etc. (IPCC, 2014b)

So far, we mentioned the observed consequences of climate change globally. One of the latest IPCC report suggests that we will cause global mean surface temperature to increase

1.5 °C above the pre-industrial levels between 2030 and 2052 if we continue to emit GHG emission as we have already done. We have already caused global warming of 1℃ (0.8℃-1.2℃) above the pre-industrial levels (IPCC, 2018, p.45). This special report suggests that if we fail to limit global warming below 1.5℃, there will be more severe consequences of climate change. IPCC (2018) report suggests that to stop global warming before reaching 1.5℃, we need to maintain net-zero global anthropogenic emissions. Therefore, we must understand and analyze the drivers of these emissions to suggest policy options to reach global net-zero emissions.

1.2. Emission Reduction Efforts

Externalities are defined as the cost or benefit that affects a third party who did not choose to incur that cost or benefit. In undergraduate level economics courses, a firm that is polluting a river is given as the most common example of a negative externality. From this point of view, we can argue that climate change is the biggest negative externality of all times. To solve the problem arising from negative externalities, we need regulatory institutions, such as governments. However, if climate change is a global negative externality, and there is no global government, how will we solve this problem?

The only optimal solution for climate change is decreasing GHG emissions globally with the co-operation of the nations (Nordhaus, 2013, p. 197). The first step towards a global co-operation was taken in 1994 by the ratification of the United Nations Framework Convention on Climate Change (UNFCCC). Within its 26 articles, Article 2 of the UNFCCC states that "The ultimate objective of this Convention … is to achieve … stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (Tol, 2019, p. 197). The UNFCCC was the first step, and it was a kind of baby steps since there were no targeted level emission reductions and no obligations.

After a couple of years from the ratification of the UNFCCC, the first emission reduction targets were defined at the Kyoto Protocol in 1997. The aim was set for the 2008-2012 period, and it was decreasing emission levels 5% below the 1990 total emission levels. Nevertheless, this aim was only binding for the high-income countries called as Annex I countries (Nordhaus, 2013, p. 199). Due to several reasons, such as the withdrawal of the

United States from the Kyoto Protocol and increased emissions of the countries that did not sign the Protocol, inconclusive ending of the Kyoto Protocol was inevitable (Nordhaus, 2013, p. 247).

In order to look for a successor agreement for the Kyoto Protocol, during the Conference of Parties (COP) 15 to the UNFCCC in Copenhagen, the Copenhagen Accord was signed in 2009. With this Accord, emission reduction targets were left, and targets were set for global average temperatures. The aim was to limit the increase in global temperatures at the 2℃ level above the pre-industrial levels (Nordhaus, 2013, p. 247). However, since there were no legally binding targets and with the global financial crises, nations hesitated to take necessary action toward decreasing their emissions (Held & Roger, 2018). Therefore the Copenhagen Accord was nothing but a gesture of good intention.

The Kyoto Protocol was ended in 2012. Even though the Copenhagen Accord raised hopes for solutions to climate change, uncertainties for the global climate policy continued. However, in 2015, the Paris Climate Agreement was adopted at COP 21 to cope with climate change. According to the agreement, countries determine their emission reduction targets or their "pledges." The ultimate and long-term aims of the Paris Agreement were limiting the increase in global average temperatures with 1.5 ℃ and 2℃ and reaching zero emissions (Tol, 2019, p. 201). However, as in the Copenhagen Accord, the Paris Agreement was not binding either.

Overall, there is no currently binding international agreement on emission reductions. With the Paris Agreement, countries determine their own emission reduction targets, and if they fail to meet their targets, there are no consequences in terms of global policies. Therefore, with this information, as a matter of fact, one can see that global GHG emissions have still been increasing. Therefore, we can easily assert that international attempts, such as the Kyoto Protocol, the Copenhagen Accord, and the Paris Agreement failed to achieve global emission reductions. To suggest correct policy options, we need to understand drivers and fair distribution of responsibilities of the global emissions. To be able to do that, we need to consider alternative emission calculation methodologies. This will enable us to create broader policy options, especially coming from the consumption side. Before getting into details, we will first explain the production and consumption side calculations of GHG emissions. Then we will try to explain why we should consider the consumption side of the emissions, and in particular, household emissions.

1.3. Production side vs. Consumption side

The distinction between the production framework and the consumption framework arises from the calculation methodologies of the GHG emissions within these frameworks. A production-based framework has been used to calculate GHG emissions since the Kyoto protocol. Nevertheless, studies with consumption-based emission increased, especially after the 2010s. The production-based framework mainly reflects GHG emissions of the countries stemming from the production of goods and services within their national boundaries (Bows & Barrett, 2010). Hence, emissions from imported goods and services were neglected within this framework. The main problem with this framework arises from this fact. When we look at GHG emissions, the main emitters of GHG have been the developed countries except for China. For example, while high-income countries had 13 tCO_2eq/cap median per capita emissions, low-income countries had 1.4 tCO_2eq/cap median per capita emissions in 2010 (IPCC, 2014a, p.46), which means that in 2010, high-level income countries emitted almost 10 times more than the low-income countries. Even though this is the case, when we look at the production-based emissions, we see that developed countries started to decrease their emissions, and there is hope for them to reach emission reduction targets with current policies. However, this is misleading. Because their emissions are not decreasing, they just moved their emissions to developing countries (Davis & Caldeira, 2010). The world's total GHG emissions continue to increase while developed countries decrease their emissions.

As explained in the IPCC (2014a) report, climate change is a global problem that happened because of accumulated GHG emissions over time. Economic agents have their own responsibility within these emissions, and each agent can be affected by the consequences of these accumulated GHG emissions, no matter how much they contributed to GHG emissions in the atmosphere. Therefore, there is no clear-cut responsibility for climate change, such as 'you did it, you pay for it.' This leads to the fact that effective mitigation efforts for climate change require collective action among governments, firms, and households within a nation and require collective action among countries. There is no 'invisible hand' in the context of climate change mitigation efforts.

Even if each nation starts to 'clean their own front yard,' this will be ineffective because, for example, there will be no knowledge spillovers. Since climate change is a 'global commons problem' individual efforts will not be enough for the effective mitigation (IPCC, 2014a).

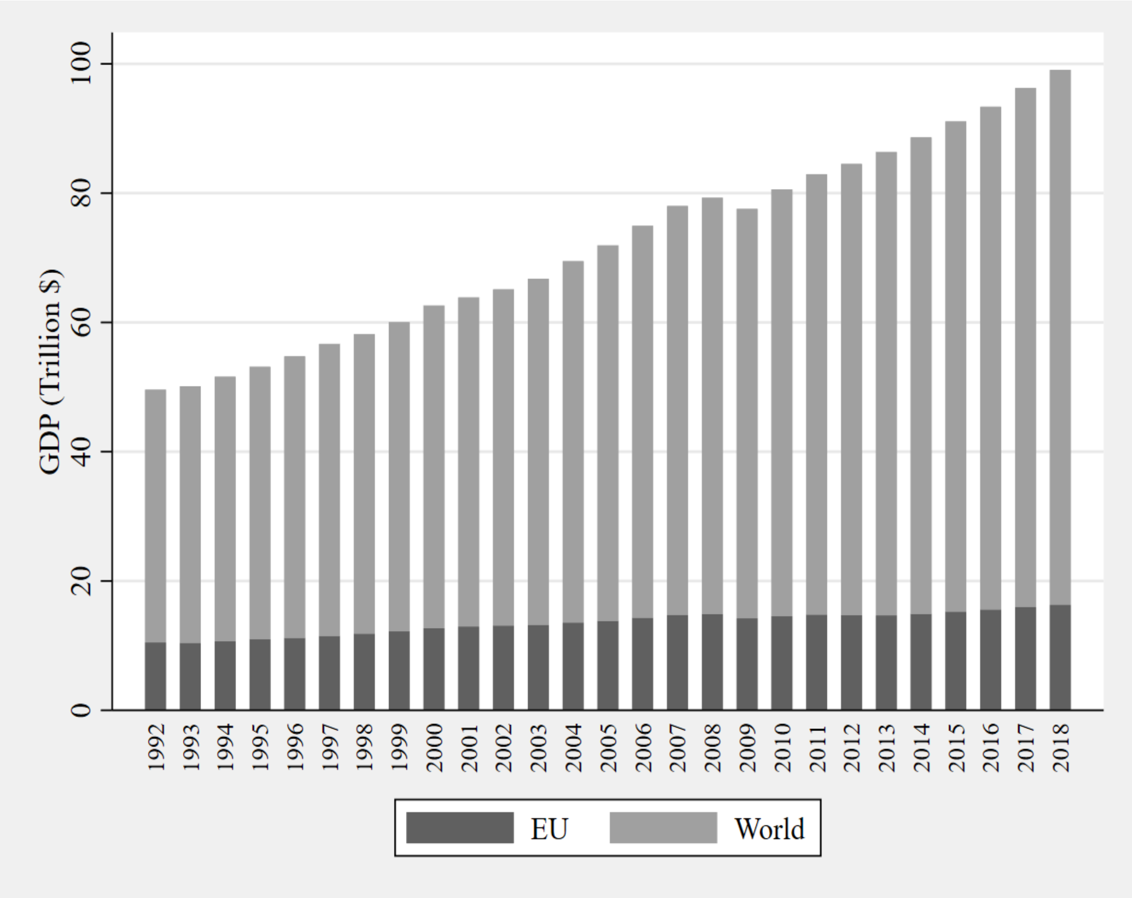
Production-based accounting is misleading in terms of reaching emission reduction targets because developed countries cannot solve the problem itself, and instead, they just try to make it someone else's problem. Moving emissions to developing countries is not a solution to the problem. As we mentioned before, total global GHG emissions have still been increasing. To suggest efficient policy options to reach emission reduction targets, we need a broader perspective and correct assessment of the problem. Therefore, the consumption-based emissions accounting and household sector enter the climate equation within this context.

Consumption-based frameworks do not consider national boundaries. Consumption-based emissions reflect the emissions released from consumed goods and services from a nation's consumers, whether these goods and services produced within or outside the country (Bows & Barrett, 2010). It considers international trade while calculating GHG emissions. In terms of sharing responsibility arising from the climate change problem, a consumption-based framework seems to be more useful than the production-based framework. For example, although there are huge differences between the high and low-income countries according to production-based emissions during 2000 and 2010, CO_2 emissions for the OECD-1990 region countries decreased. However, this is not the case for consumption-based emissions; their emission increased within this period in terms of consumption-based CO_2 emissions (IPCC, 2014a, p.354). Therefore, considering the emissions embodied in international trade, the consumption-based emission accounting framework opens a window for broader policy suggestions.

1.4 Greenhouse Gas Emission in the EU

The EU, with its large economies and urbanized cities, expected to have high GHG emissions. The EU was established with the Maastricht Agreement in 1992. Since then, the EU has been one of the largest economies in the world. Figure 4 shows the GDP in terms of 2010 US dollars for the world and the EU. The world's GDP and EU's GDP increased within the time range shown in the figure except for 2009 due to global economic crises in 2008. While in 1992, the GDP of the EU constituted almost 25% of the world's GDP, in 2018, it was 19% of the world GDP.

Figure 4: EU and World GDP (2010 Constant US $)

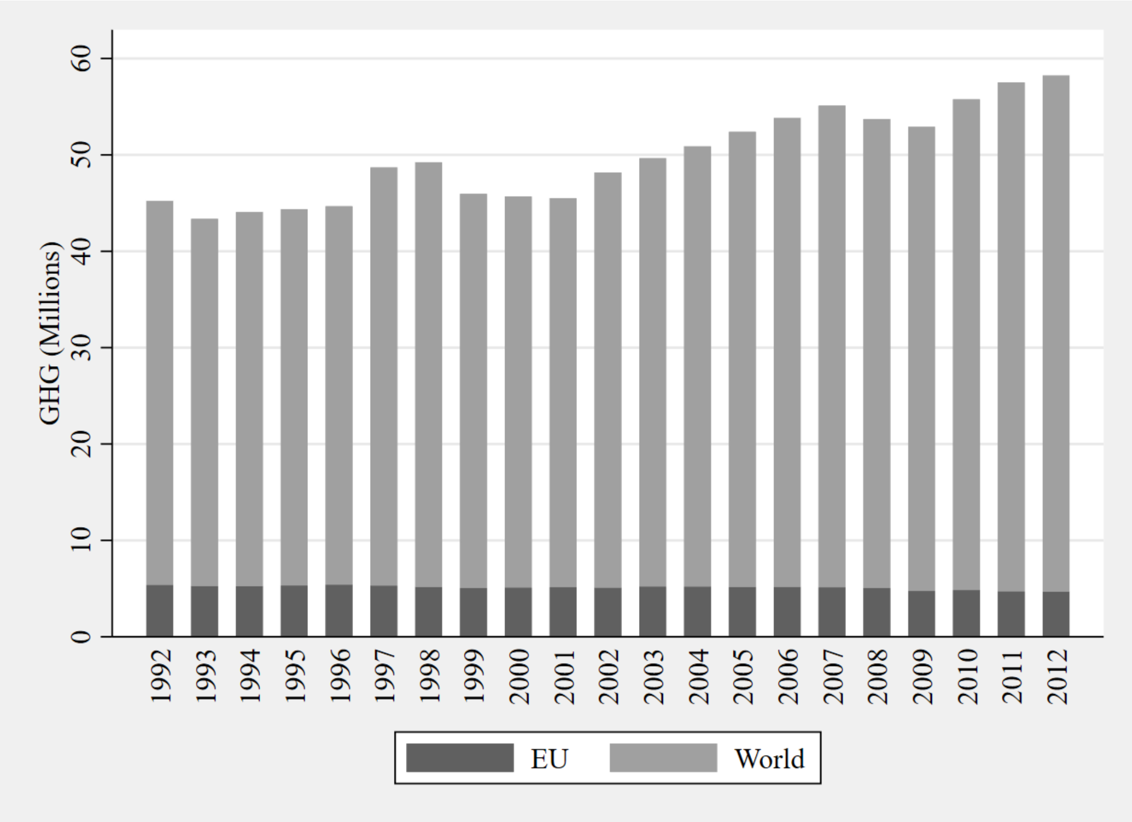


Source: World Development Indicators Database

Considering that the EU is one of the world's largest economies, its GHG emissions also constitute a significant portion of total global GHG emissions. Figure 5 shows the total

GHG emissions for the EU and the world. While there is an increase in total GHG emissions in the world, emissions for the EU follow almost a flat line, and there is a decrease in the emission in recent years. While the EU was responsible for 13% of the total global emissions in 1992, its share decreased to 8% in 2012. The share of the EU's emissions in the total global emissions decreased within time due to two possible reasons: the movement of the production from EU to developing countries and the decrease in emission intensity of production in the EU.

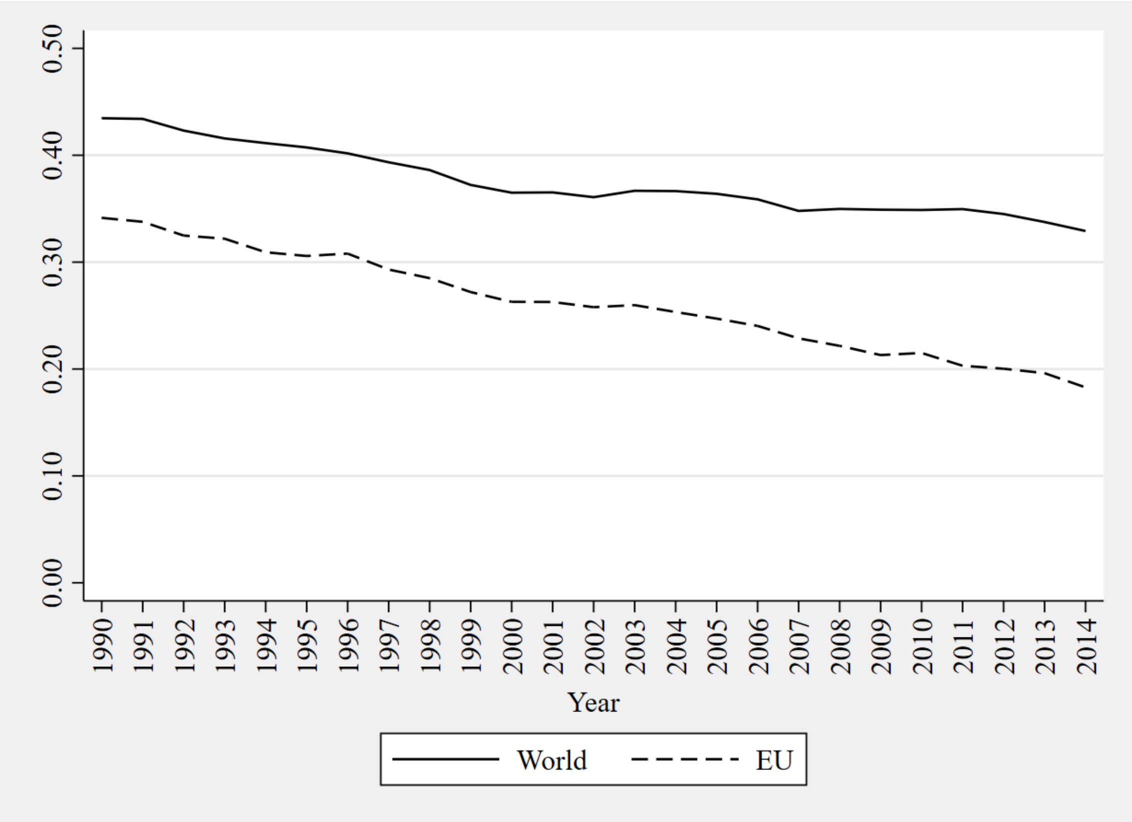
Figure 5: Total GHG emissions for EU and World (kt of CO_2 equivalent)



Source: World Development Indicators Database

Emission intensities show the amount of emission per unit of GDP. Figure 6 shows CO_2 emission per unit of GDP for the world and EU for the period 1990-2014. The carbon intensity of the EU has always been smaller than that of the world throughout the observed period. Both the carbon intensity of the World and EU decreased over time. While the world's carbon intensity was 0.435 kg/$ in 1990, it was 0.340 kg/$ in the EU. However, in 2014, carbon intensities of the world and the EU were 0.329 kg/$ and 0.183 kg/$, respectively. As seen from the figure, the EU managed to reduce the carbon intensity of production more rapidly than the world, especially after the year 2000. This is not a surprising outcome since the total GHG emissions increased for the world and decreased for the EU (Figure 5).

Figure 6: CO_2 Emissions intensity (kg per 2017 PPP $ of GDP) for World and EU

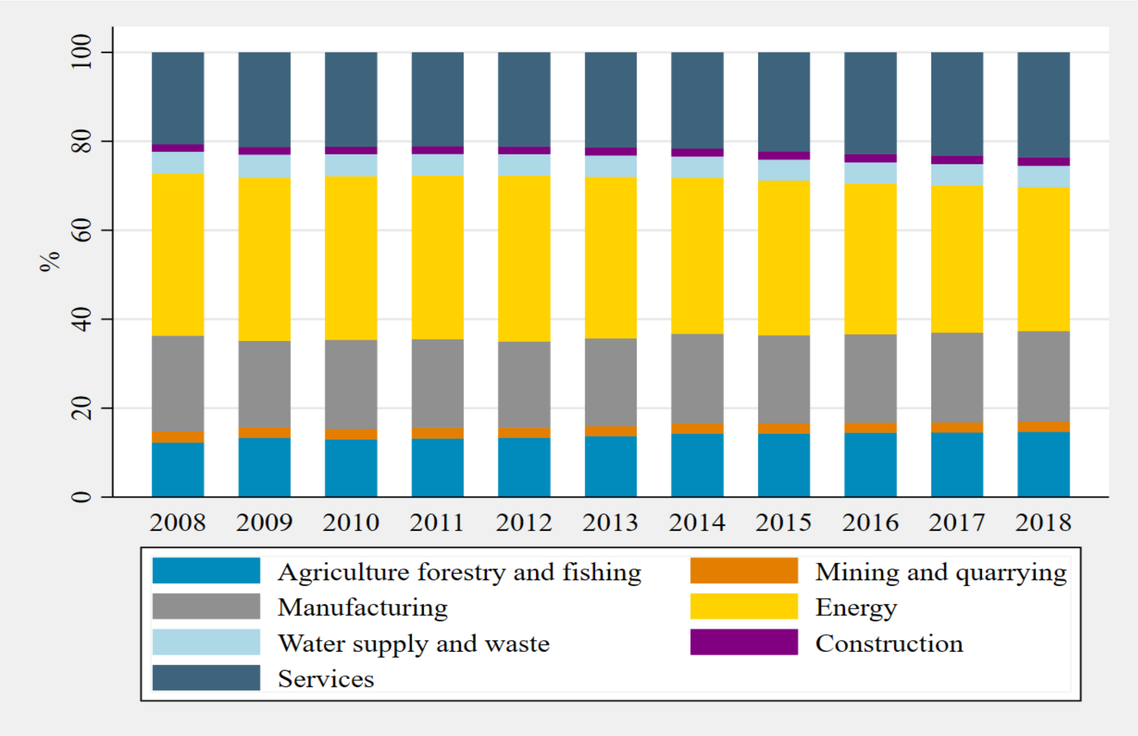


Source: World Development Indicators Database

1.4.1. Sectoral Analysis of GHG emissions in the EU

In order to show the sectoral components of the EU's total emissions, using the Eurostat Air Emission Accounts data according to NACE Rev.2 categories, we constructed Figure 7. Under the level 1 codes of the Statistical Classification of Economic Activities in the European Community Rev. 2, there are 21 sections corresponding to different economic sectors. In the following figure, Agriculture, forestry and fishing (A), Mining and quarrying (B), Manufacturing (C), Water supply; sewerage; waste management and remediation activities (E), and Construction (F) were directly obtained from the source dataset. On the other hand, Energy and Service sectors were calculated by hand. In order to construct the Energy sector, we summed Electricity, gas, steam and air conditioning activities (D) and manufacture of coke and refined petroleum activities (C19)[2]. Also to construct the Service sector we summed up the following activities: Wholesale and retail trade; repair of motor vehicles and motorcycles (G), Transportation and storage (H), Accommodation and food service activity (I), Financial and insurance activities (K), Real estate activities (L), Professional, scientific and technical activities (M), Administrative and support service activities (N), Public administration and defense; compulsory social security (O), Education (P), Human health and social work activities (Q), Arts, entertainment and recreation (R), and Other service activities (S). Due to the missing observations and data, Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use (T), and Activities of extraterritorial organizations and bodies (U) were removed from the analyses, throughout this subsection.

Figure 7: Sectoral GHG Emissions in the EU



Source: EUROSTAT

We can see from Figure 7 that the Energy sector has the biggest share in the total emission among all NACE Rev.2 activities from 2008 to 2018. The Energy sector was responsible for 36.44% of the total emissions in 2008 and 32.42% in 2018. Although the share of the

[2] Manufacture of coke and refined petroleum activities subtracted from Manufacturing activities

energy sector decreased, it remained as the top emitter among all economic sectors. While the Manufacturing sector constituted 21.57% of the total emissions in 2008, the Service sector was responsible for 20.69% of the total emissions. However, starting in 2009, the Service sector became the second-largest emitter. Following the abovementioned sectors, Agriculture, forestry and fishing sector ranked fourth with respect to emissions shares. The construction sector has the lowest share in the total emissions after the Mining and quarrying sector. We can easily divide analyzed sectors into two groups, the one with the high-emitters and the one with the low-emitters. Water supply; sewerage, waste management and remediation activities, Construction, and Mining and quarrying sectors constitute 8-9% of the total emissions from 2008 to 2018. Also, throughout the period, shares of these sectors remain more or less the same individually. The same observation also applies to the Manufacturing sector. On the other hand, the share of the Agriculture, forestry and fishing sector and the Service sector increased within the period, whereas the share of the energy sector started to decrease after 2012.

Assessing the industries' emission performances by looking only at their shares in the total emissions can be misleading and insufficient. Therefore, to detail our analysis regarding economic sectors, we calculated the emission intensities of the sectors. To calculate the emission intensity of the one particular industry, we divided the total emissions of the industry to its production value. For emission data, we again used the Eurostat Air Emission Account database. We obtained data from the Eurostat National Accounts Aggregates by Industry dataset in terms of chain-linked volumes (2015) to calculate production value. We deflated the value-added production for each industry with the Producer Price Index for the EU (Index=2015) obtained from the Fred database[3]. The results can be seen in Table 1. At first glance, it can be easily noticeable that emission intensities present a different picture than sectoral GHG emissions.

[3] Federal Reserve Bank of St. Louis database.

Table 1: Sectoral GHG Emission Intensities in the EU, kg/2015€

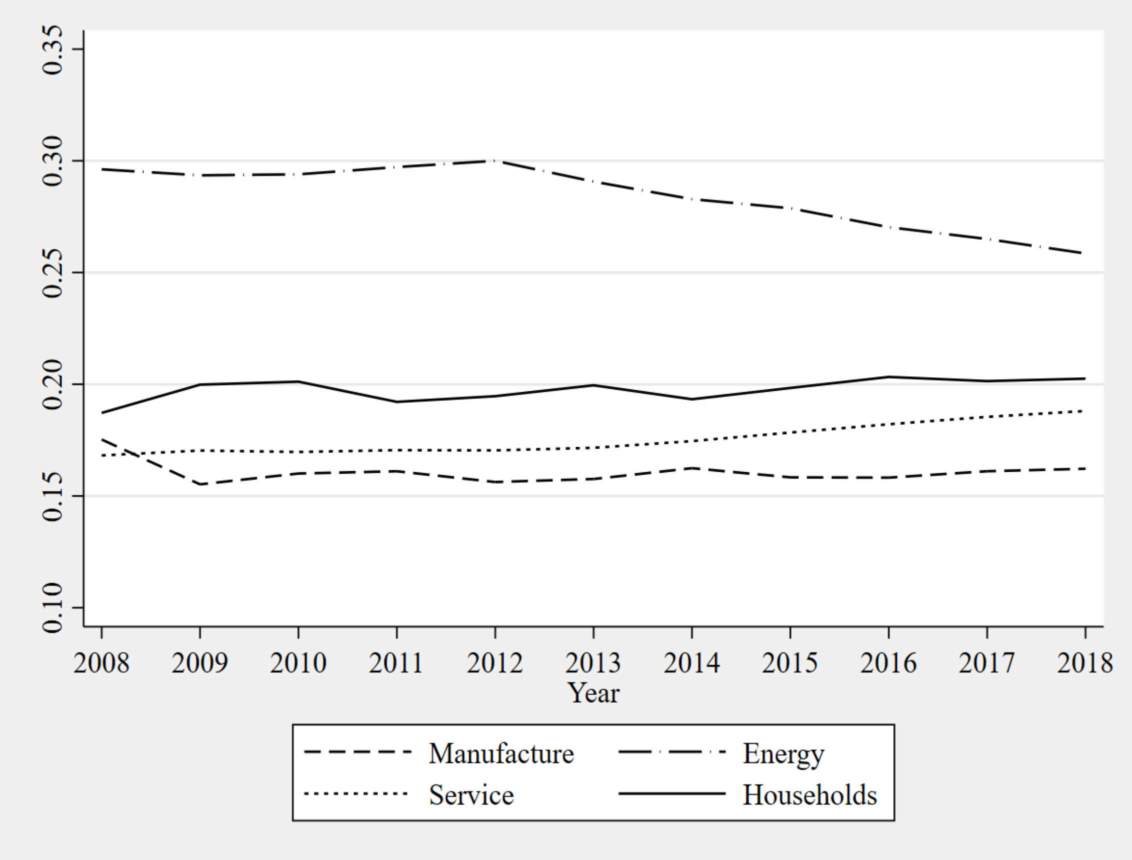
Sectors/Years	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Agriculture, forestry and fishing	248.91	237.53	249.24	251.88	269.14	261.08	246.01	244.00	246.44	252.06	255.56
Mining and quarrying	116.89	113.97	115.15	126.81	128.85	128.64	130.24	133.91	128.26	133.09	141.32
Manufacturing	44.20	40.74	40.39	39.45	39.43	39.11	37.17	34.83	33.50	33.97	33.04
Energy	543.11	477.10	496.13	536.07	532.93	517.30	484.61	460.66	420.16	428.50	477.19
Water supply and Waste	158.88	150.42	149.32	149.65	150.33	143.86	137.89	130.92	124.15	127.86	126.90
Construction	8.35	8.05	8.56	9.35	9.93	9.91	9.52	9.62	9.34	9.70	9.48
Service Sector	9.34	8.69	9.00	9.01	9.04	8.82	8.42	8.37	8.28	8.52	8.50

Source: Author's calculation

The energy sector has the highest emission intensity, as in the case of the share of total emissions. In 2008, 1€ worth of economic activity in the Energy sector resulted in 543.11 kg of GHG emissions. The emission intensity of the Energy sector decreased during the period 2008 to 2018. However, due to its nature, the sector had the highest emission intensity, with 477.19 kg/€ in 2018. Following the Energy sector, Agriculture, forestry and fishing sector ranked second among sectors with respect to emission intensity. This is surprising because Agriculture, forestry and fishing sector constituted 12 to 14% of total emissions in the total economic activities from 2008 to 2018. However, as in the sectoral shares of GHG emissions case, the emission intensity of Agriculture, forestry and fishing sector increased throughout the analyzed time period with the exception of the year 2009. This is expected due to global economic crises that happened in 2008; in fact, all sectors experienced decreases in their emission intensities in 2009. Water supply; sewerage, waste management and remediation activities has the third-highest emission intensity in 2008 with 158.88 €/kg, but as we reached to 2018 emission intensity of the sector decreased to 126.90 €/kg, As a result of increased emission intensity in the same period, Mining and quarrying sector left behind Water supply; sewerage, waste management and remediation activities in 2017 and ranked third with emission intensities of 133.09 kg/€ and 141.32 €/kg, respectively in 2017 and 2018. While the Construction sector exhibited a slight increase in emission intensity, the Service sector's emission intensity slightly decreased in the analysis period. In the case of Manufacturing, however, a significant drop in emission intensity experienced from 44.2 kg/€ in 2008 to 33.04 kg/€ in 2018.

Since the focal point of this thesis is the household emissions, we also calculated emission intensity for the households. However, before, we calculated the share of emissions from the total activities by households in total emissions. The results of our calculations are presented in Figure 8. Total activities by households constituted 18.7% of total emissions in the EU in 2008. The share of household emissions in total increased from 2008 to 2018 and reached to 20.2% in 2018. The share of household emissions in total becomes the second largest when we compare it to sectoral emissions.

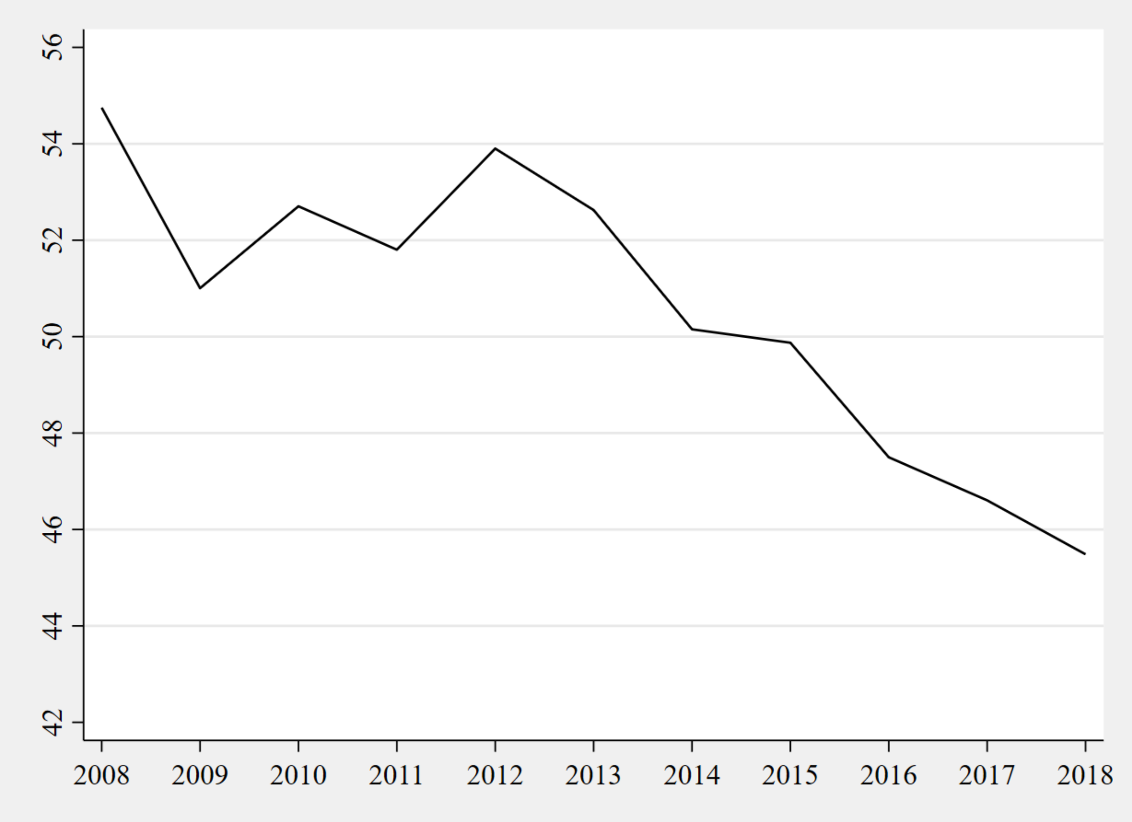
Figure 8: Share of Sectoral GHG Emissions within All NACE Rev 2. Activities



Source: EUROSTAT

In order to calculate emission intensity for household consumption expenditures, we obtained emission data from the Emissions of greenhouse gases and air pollutants from the final use of CPA08 products - input-output analysis, ESA 2010 database of EUROSTAT. The total emissions from total CPA products and direct emissions by private households divided by final consumption expenditure of households after deflating it with implicit deflator with the base year 2010. From 2008 to 2018, there is a negative trend for the emission intensity of household emissions. While the emission intensity of household consumption was 54.75 kg/€ in 2008, it decreased to 45.49 kg/€ in 2018. Therefore, we can observe a clear negative trend in the emission intensity of the households' consumption expenditures. This negative trend directly comes from the reduction in household emissions. Households' consumption expenditures stayed almost stable in the period 2008-2018, but there was a significant reduction in emissions. While, in 2008, emissions from Total CPA products plus direct emissions by private households were 3.91 billion tones, it decreased to 3.32 billion tones in 2018. Le Quéré et al. (2019) showed that the main reduction in the emission for the 18 developed countries (15 of which are the EU member countries) mainly related to the reduction in energy use and strong policies that supporting renewable energy resources. Reductions in the emission intensities are mainly related to targets that were set in 2008 by the EU. The EU adopted a binding legislation that is called the "2020 climate & energy package" in 2008, in order to decrease emission 20% below the 1990 levels, increase the energy sources from renewables by 20%, and improve energy efficiency by 20% by the year 2020.

Figure 9: GHG Emission Intensity of the EU Households' Consumption Expenditures (kg/2010 €)



Source: Author's calculation

The EU reached a total emission level that is 23.2% below the 1990 levels in 2018. The decrease in emissions mainly stemmed from the reductions in fossil fuel combustion and the increase in the usage of renewable energy resources in electricity generation processes. Additionally, lower emissions from the transportation sector accelerated emission reductions due to the shift towards fuel-efficient passenger cars across the EU.

Moreover, to reach energy efficiency targets, building insulation regulations, and avoiding carbon-intensive fuel use in the home heating systems improved energy efficiency (EEA, 2020). In summary, a combination of these targets and policies made possible the reductions in the emissions and emission intensities for the EU.

1.5. Conclusion

Firstly, the causes and consequences of the climate change problem are briefly explained in this chapter. There is no doubt that human activities result in high GHG concentration in the atmosphere, and hence increase the mean global temperatures. In order to decrease global emissions, global action is necessary. Secondly, we explained that global effort aiming to reduce emissions failed so far. However, the EU performed better than the rest of the world in terms of emissions and emission intensities. However, efforts of one country or one organization do not suffice to decrease global emissions. Moreover, we argued that the way we understand and assess this problem from a production-based perspective has been preventing effective mitigation efforts. UNFCC and IPCC seek the new policy options for climate change mitigation to meet the zero-emission target and limit the mean global surface temperature increase with the 2°C. New mitigation policies and perspectives needed because the old ones were proved to be ineffective in solving the problem since there is no observed significant reduction in global emissions. Considering the production-based emissions alone and policies based on this type of emissions-accounting failed to meet determined targets. We need to consider consumption-based emissions in order to create more effective policy options. Finally, we showed that emissions from households constitute a larger share of the total emissions than the Service, Construction, and Manufacturing sectors in the EU. Therefore, household emissions are needed to be taken into account when assessing the climate change problem. Considering and analyzing household emissions is necessary to improve emission reduction efforts and suggest new policies with a broad perspective.

CHAPTER 2

LITERATURE REVIEW

2.1. Introduction

Households' GHG emissions have been an important concept in the studies of climate change economics. Determining the impacts of household behaviors and characteristics on household emissions are important for reducing carbon emission efforts. Therefore, over the past two-decades, the literature on the determinants of household GHG emissions has been expanding. Liu, Qu, Clarke-Sather, Maraseni, and Pang (2017) separated household emissions literature into three periods between 1991 and 2017. During the first decade, carbon emissions raised from residential usage were mainly studied by the related literature. In the second decade, the literature focused on emissions from the consumption side, namely indirect emissions, by developing several methods, such as input-output method, consumer lifestyle methods, and IPCC reference method. In the last period literature is mostly concentrated on determinants and influencing factors of the household emissions.

GHG emission accounting methods are crucial in order to calculate correct measurements of GHG emissions. There are two known accounting perspectives; production perspective and consumption perspective (Druckman & Jackson, 2016). Production-based accounting reflects the emissions released from the production of goods and services within the national boundaries. In the production perspective, emissions related to imported goods and services are neglected. However, consumption-based accounting includes emissions from imported goods and services and excludes emissions from exported goods and services (Peters & Hertwich, 2008). Davis and Caldeira (2010) found that in 2004, 23% of the global carbon emissions traded internationally, mostly as exports from developing countries to developed countries. In their study, they showed the biggest net exporters and importers of the emissions traded globally. As expected, China, Russia, and the Middle East were the biggest exporters of global emissions, whereas the US, Japan, and the UK were the biggest importers. Therefore, the main difference between consumption and production frameworks comes from the emissions embodied in trade. Consumption-based accounting reflects the goods and services consumed by national residents, whether the goods and services are produced within the country or outside the country (Bows & Barrett, 2010). These two approaches are important in the sense that, if we only consider the production-based accounting, then we might observe that national emissions in developed countries are decreasing and emission reduction targets are satisfied, but when we consider the consumption-based accounting, this is not the case. In fact, emissions are increasing, and emission reduction targets are hard to reach. Peters and Hertwich (2008) argue that using a consumption perspective in GHG accounting has several advantages over the production perspective. One of the main advantages is that while production-based accounting reflects that only producers responsible for the emissions, consumption-based accounting also considers consumers and makes more fair shared responsibility between consumers and producers. In this way, consumption perspective accounting reduces the 'carbon leakage' that arise from international trade. Therefore, to meet emission reduction targets and implement realistic policies to fight against climate change, it is important to consider the emissions coming from the consumption side.

Household emissions are calculated from the consumption perspective. In the consumption perspective, household emissions are separated into direct emissions and indirect emissions. Direct emissions are related to emissions released from direct energy usage of households, including heating, cooling, and transportation activities (Druckman & Jackson, 2016). However, indirect emissions mainly reflect embedded emissions from the consumption of goods and services. Emissions released from the whole production and distribution processes of these goods and services consumed by households are indirect emissions (X. Zhang, Luo, & Skitmore, 2015). In household emissions, share of indirect emissions are bigger than the share of direct emissions (Druckman & Jackson, 2016). Jones and Kammen (2011) found out that indirect emissions constitute 77% of the total household emissions in the US. Also, Baiocchi, Minx, and Hubacek (2010) calculated that in 2000 in the UK, 70% of the total emissions were indirect emissions, and the remaining 30% were direct emissions. Ala-Mantila, Heinonen, and Junnila (2014) found that in 2006 direct emissions of the Finnish households constituted 38% of the total emissions while the share of indirect emissions in total was 62%.

In order to calculate household emissions, there are several methods for direct and indirect emissions. Calculating indirect emissions are trickier than calculating direct emissions. Direct emissions are mainly generated with the IPCC reference method (Change, 2006) but indirect emissions calculated with input-output models and consumer lifestyle approaches (Li et al., 2016). To calculate indirect emissions, usage of different methods, and micro-level datasets on household consumption are required. Therefore, studies that include indirect emissions mostly analyze single country or specific regions of a country. For example, Wilson, Tyedmers, and Spinney (2013) analyzed indirect and direct household emissions in Halifax Regional Municipality, Nova Scotia, Canada, with survey data from 1,920 respondents. Qu et al. (2013) assessed direct and indirect household emissions of the Gansu, Qinghai, and Ningxia provinces in China. Another study by Li et al. (2016) also analyzed both direct and indirect household emissions in Northwest China using survey data from 1,199 questionnaires. Baiocchi et al. (2010) focused on direct and indirect carbon emission differentials caused by distinctive consumer behaviors in the United Kingdom. Xu, Tan, Chen, Yang, and Su (2015) calculated direct emissions of the Yangtze River Delta region of China using survey data obtained from nearly 350 households.

Apart from the previous chapters, in the following subsection of this chapter, we only focus on a certain part of the literature that we interested in. The next subsection will summarize the studies that analyzed the determinants of households' GHG emissions.

2.2. Determinants of Household Emissions

Regardless of the direct or indirect emissions, there are common main determinants of households’ GHG emissions in the related literature, such as income, household size, household composition, rural/urban location, diet type, and type of energy supply (Druckman & Jackson, 2016). Also, employment status (Büchs & Schnepf, 2013; Gough, 2013; Gough, Abdallah, Johnson, Ryan-Collins, & Smith, 2011; Han, Xu, & Han, 2015; Pohlmann & Ohlendorf, 2014; Seriño & Klasen, 2015; Xu et al., 2015), education level (Ahmad, Baiocchi, & Creutzig, 2015; Baiocchi et al., 2010; Büchs & Schnepf, 2013; Duarte, Mainar, & Sánchez-Chóliz, 2012; Fremstad, Paul, & Underwood, 2019; Irfany & Klasen, 2017; Liu et al., 2018; Meangbua, Dhakal, & Kuwornu, 2019; Wu, Liu, & Tang, 2012; H. Zhang et al., 2020) and age (Ahmad et al., 2015; Golley & Meng, 2012; Seriño, 2017; Yang, Fan, & Zheng, 2016) are found to be important determinants of the household emissions.

The literature on the determinants of household emissions mostly consists of studies focusing on China. Feng, Zou, and Wei (2011) used a Consumer Lifestyle Approach to calculate direct and indirect emissions for urban and rural Chinese households between 2005 and 2007. They found out that carbon emissions differ between urban and rural locations, but the effect of income on emissions is strong for both direct and indirect emissions. Their findings suggest that increases in the direct emissions in urban areas are faster than the rural areas. Also, for urban areas, indirect emissions are greater than the direct emissions. Golley and Meng (2012) analyzed carbon dioxide emissions between different income groups in Chinese households for 2005. Their findings were also in line with the related literature. As income level goes up, per capita carbon dioxide emissions also go up. To investigate household embedded carbon emissions (HECEs), Han et al. (2015) employed representative survey data in urban China in 2011. Their results suggest that income was the main determinant that increases HECEs. Other than income, car-ownership, employment status, and education level were determined to have a significant positive effect on per capita HECEs. However, house ownership, household size, and retirement were found to have significant negative effects on per capita HECEs. Li et al. (2016) analyzed the household carbon emissions for Northwest China by using survey data for 2011-2012 period and employing spatial econometric models. They showed that per capita income, carbon intensity, urbanization, and July average temperature had significant positive effects on per capita household carbon emissions. Liu, Wu, Wang, and Wei (2011) analyzed carbon emissions between 1992 and 2007 for both Chinese urban and rural households. To calculate direct and indirect carbon emission, they utilized the input-output method and found that increase in population, urbanization, and household consumption expenditures increased indirect carbon emissions of Chinese households. Unlike the related literature, Qu et al. (2013) calculated the household emissions for peasants and herdsmen households in several cities in China by employing survey data for 2008-2009 and input-output methodology. Their results also showed that while income had a positive effect on per capita emissions, the effect of family size on emissions was negative. Wu, Liu, and Tang (2012) collected sociodemographic survey data from 120 households in Lijiang City, China, in 2011 and calculated direct emissions of the households from energy sources such as firewoods, biogas, and electricity by using IPCC reference method. Their findings regarding income differ from the related literature. The findings of the study suggest that as income increases, households switch their energy sources from firewood to electricity, and thus emissions decrease. They also found that an increase in education level decreases household emissions, but emissions rise with household size. Xu et al. (2015) also analyzed the urban household emissions for Nanjing, Ningbo, and Changzhou in the Yangtze River Delta of China in 2011. By employing survey data from the 1,061 households and employing the IPCC reference method, they calculated emissions for urban households. According to their findings, significant independent variables that had an impact on household emissions were income, age, household size, and dependency ratio. All these variables were determined as positively related to urban households' emissions. Yang et al. (2016) calculated carbon emissions for Beijing households in 2009 and analyzed determinants of the emissions. They showed that there was a significant positive relationship between household carbon emissions and income, age, and household size. Other than common variables in the literature, they also analyzed the building types, neighborhood, and location characteristics. Liu et al. (2017) calculated per capita household emissions for China by using the IPCC reference method for the period between 1997 and 2014. Employing spatial panel data econometric methods, they showed that income, education, urbanization have a significant positive effect on per capita household emissions and household size have significant negative effects on household's per capita emissions. In another study by Liu et al. (2018), the authors estimated direct and indirect per capita household emissions for 31 provincial capital cities in China between 2011 and 2013 by using survey data. While they utilized the IPCC reference method for direct emissions, they used the input-output method to calculate indirect emissions. Utilizing a spatial econometric method, they suggest that per capita income, urban and rural structure, household size, education level, and age structure had a significant impact on per capita carbon emissions. One of the most recent studies in the related literature, H. Zhang et al. (2020) estimated carbon emissions for the Chinese household for the 2012-2016 period. They analyzed the influencing factors of the household's carbon emission by employing the Oaxaca-Blinder method. Similar to the previous literature, they showed that income, urban location, senior secondary education, college education and above were found positively related; however, household size, age, marriage status, under primary education level and primary education level were found negatively related to the per capita household emissions. Other than these common determinants, they also found that type of fuel and type of housing were also significant. In another recent study, H. Zhang, Zhang, Wang, and Shi (2019) calculated indirect carbon emissions and scrutinized key drivers of emissions for older Chinese households in 2013. They pointed out that income, marriage status, urban location, and education level are significant positive drivers of carbon emissions, but age and household size are significant negative drivers of the older Chinese household's per capita emissions.

The United Kingdom is the second most common country that was studied in the related literature. Baiocchi, Minx, and Hubacek (2010) analyzed the direct and indirect emissions of UK households in 2000 by applying the input-output method. They found out that sociodemographic variables such as income, age, and education are significant in analyzing household emissions. Their findings suggest that CO_2 emissions differed between UK households with respect to their consumption behaviors and lifestyles. Büchs and Schnepf (2013) calculated home energy, transport and indirect carbon emissions for UK households between 2006 and 2009 by using a representative UK expenditure survey and showed that income, household size, age, employment status, education level, and rural/urban location had significant effects on household carbon emissions. Their results showed that all kind of household emissions increased with income, high education, and rural location. Magnitudes of the coefficients differ according to emission type. In another study, Gough et al. (2011) calculated embodied emissions in consumption for UK households in 2006 for the first time by combining the input-output model and UK Expenditure and Food Survey. They found out that income, household composition, and employment were the main drivers of UK households' GHG emissions.

Other than China and the United Kingdom, studies are focusing on single countries. Ahmad et al. (2015) showed determinants and patterns of the GHG emissions of 60 cities in India by using household micro-level data between July 2009 and June 2010. Their findings reflect that emissions from direct energy usage increased with income and household size. Also, population density, availability of urban services such as water, electricity access, and social and cultural variables explain household emissions. Ala-

Mantila et al. (2014) analyzed the Finnish households' carbon footprint in 2006 by combining household expenditure data with an environmentally extended input-output model (EE-IOM). They aimed to investigate determinants of both direct and indirect emissions of the Finnish households. Regardless of the type of emission, per capita emissions increase with expenditure, but the effect of the urban/rural location on emissions differs between direct and indirect emissions. Christis, Breemersch, Vercalsteren, and Dils (2019) analyzed direct and indirect carbon emissions of the households in the Flanders Region, Belgium, using household budget survey data in 2010. Employing input-output analysis, they found that income and other socio-cultural variables such as household size, employment status, and age had strong relationships with household emissions. Duarte et al. (2012) calculated carbon emissions of the Spanish households in 1999 and found that income, education level, social class, and urban/rural location determine household emissions in Spain. Lenzen (1998) studied the energy and GHG requirements for the Australian households for 1993-1994 time period by employing input-output method and using expenditure survey data and calculated the energy and GHG expenditures for the 8 consumption categories: Shelter, Food, Clothing, Care, Mobility, Recreation, Community and Other. In this study, he also analyzed how the different characteristics for households such as urban-rural location, household composition, and household income affect energy and GHG requirements for the Australian household. The study results revealed that rural households' energy requirements are smaller than the urban households’. Households with large compositions save more energy and GHG requirements than the single-person households, and finally, GHG and energy expenditures increase with income. Olaniyan, Sulaimon, and Ademola (2018) estimated direct household emissions for Nigerian urban-rural households at the national level using Linear Multiplier Factor Method and survey data. Their results showed that in 2015, at the national level, direct emissions for a Nigerian household were significantly determined by income, household size, literacy rate, gender, and the number of vehicles. They also showed that while age was a significant determinant for urban households, it was the opposite for the rural households and at the national level. Pohlmann and Ohlendorf (2014) calculated total and indirect emissions for German households by utilizing EE-IOM and survey data from 2008. The findings of their study showed that income and household size are the most important determinants for German households, both total and indirect emissions. Nevertheless, the effect of the socio-economic variables such as education, age, gender, and social status on the household emissions differ with respect to emission types. Seriño and Klasen (2015) estimated households' carbon emissions from consumption of the goods and services in the Philippines for 2000 and 2006 by implementing the input-output method. Their findings showed that income, age, marital status, household size, education level, and rural/urban location were the significant factors that explain household emissions in the Philippines. In another study, Seriño (2017) calculated indirect emissions for Philippian households for 2000 and 2006 by employing the input-output method. Using the quantile regression method, he analyzed the determinants of household emissions. His results suggest that income, age, gender, marriage status, household size, education level, urban-rural location, access to electricity, and dwelling type were the significant variables that explain variations in the household carbon emissions. Wier, Lenzen, Munksgaard, and Smed (2001) also calculated direct and indirect emissions by employing the input-output method for Danish households in 1995. They found out that expenditure, urban-rural location, age, employment status, and education levels had significant effects on household emissions. Wilson, Tyedmers, and Spinney (2013) calculated direct GHG emissions for the households from Halifax Regional Municipality, Nova Scotia, Canada, by employing the survey data from 1,920 respondents between April 2007 and May 2008. Their results showed that there was a significant relationship between households' direct GHG emissions and income, household size, age, marital status, and community zone. Fremstad, Underwood, and Zahran (2018) estimated carbon emission at the USA's household level for the 2012-2014 period. They found that expenditures, household composition, and urban density are significant determinants for per capita emissions. They also found that whether a household is a renter or not and included residential energy (heat, natural gas, and electricity) in rent were significant determinants for per capita emissions. A recent study by Fremstad et al. (2019), focused on the linkage between working hours and carbon emissions for American households between 2012 and 2014. They showed that household emissions increased with working hours. The other determinants found to be significant in their analysis were household size, hourly wage, urban-rural location, and education level. Meangbua et al. (2019) estimated direct and indirect carbon emissions for households in Thailand by employing the input-output method. They analyzed the period between 1995 and 2010. Their results suggest that income, household size, education level, temperature, and urban-rural location were significant determinants for direct and indirect household emissions, with age being only significant for direct emissions. Another single country study, Irfany and Klasen (2017) estimated the carbon emissions for Indonesian households by utilizing the input-output method for the 2005-2009 period. Their results revealed that expenditure, age, household size, education level, marital status, and gender were significant determinants for Indonesian households' emissions. In another study by Koide et al. (2019), using expenditure-based survey data from 2005, carbon emissions for more than 47,000 Japanese households were calculated. They showed that income, savings, family size and composition, age, house size, car ownership, marriage, and employment status were significant determinants for explaining the carbon footprint of Japanese households. Nässén (2014) studied the determinants of Swedish households' GHG emissions between 1993 and 2006 by estimating emissions with the input-output method. Results of the study revealed that consumption, household size, age, education level, urban-rural location were significant for explaining indirect emissions of the Swedish households.

In the related literature, there are only a few studies focusing on more than one country. Ottelin, Heinonen, Nässén, and Junnila (2019) analyzed how urbanization affects the carbon footprint of EU households. They estimated carbon emissions for EU households by employing an environmentally extended input-output method. Their findings showed that the effect of urban-rural location on carbon footprint differs between Eastern and Western European households. They also found out that income, expenditure, age, and household size had significant effects on the carbon footprints of EU households. Chancel (2014) studied the effects of the date of birth and income on the direct carbon emissions of the households in the USA and France by employing household budget survey data between 1980 and 2000. The finding of the study showed that for both countries, the richest 10% of the population have higher emissions than the poorest 10% of the population. Although there is no significant effect of generations on the carbon emissions for the USA, in France, the generation born between 1920 and 1960 emits more than the other generations. Kerkhof, Benders, and Moll (2009) calculated household emissions for the Netherlands, the UK, Sweden, and Norway by using an input-output model for the year 2000. Their findings pointed out that households of the UK and Netherlands emit more than the households of Sweden and Norway on average. Differences in the emission patterns between the countries are mainly related to country-specific characteristics such as Carbon intensity of the energy supply of those countries and differences in population densities

In order to visualize the common determinants used in the related literature, we constructed Table 2. In this table, we show the studied location, methodology, and the common determinants that were significant in the studies mentioned above. Certainly, in the related literature, there are variables that were found to be significant other than the variables in the table. However, we constructed the table by considering variables that have been used commonly in the reviewed studies. Since the signs and magnitudes of the relationship between emissions and the related determinants may differ with respect to the emission types and the studied locations, we only consider whether the determinants found to be significant or not.

Table 2: Literature Summary Table

#	Study	Method	Location	Income	Size	Age	Education	Employment	Marriage	Urban/Rural
1	Ahmad et al. (2015)	Regression Analysis	India	✓[1]	✓	✓	✓		✓	
2	Ala-Mantila et al. (2014)	Regression Analysis	Finland	✓	✓					✓
3	Baiocchi et al. (2010)	Regression Analysis	UK	✓	✓		✓			
4	Büchs and Schnepf (2013)	Regression Analysis	UK	✓	✓	✓	✓	✓		✓
5	Christis et al. (2019)	Input-Output Analysis	Belgium	✓	✓	✓		✓		

6	Duarte et al. (2012)	Linear SAM Model	Spain	✓			✓			✓
7	Feng et al. (2011)	Grey Relational Analysis	China	✓						✓
8	Fremstad et al. (2019)	Regression Analysis	USA	✓	✓	✓	✓	✓[5]		✓
9	Golley and Meng (2012)	Regression Analysis	China	✓	✓	✓[3]	✓[3]			
10	Gough et al. (2011)	Regression Analysis	UK	✓	✓[4]			✓		
11	Han et al. (2015)	Quantile Regression Analysis	China	✓			✓	✓	✓	
12	Irfany and Klasen (2017)	Regression Analysis	Indonesia	✓[1]	✓	✓[3]	✓[3]		✓[3]	✓
13	Li et al. (2016)	Spatial Analysis	China	✓						✓
14	Liu et al. (2017)	Spatial Analysis	China	✓	✓		✓			✓
15	Liu et al. (2018)	Spatial Analysis	China	✓	✓	✓	✓			✓
16	Meangbua et al. (2019)	Regression Analysis	Thailand	✓		✓[3]	✓[3]			✓
17	Nässén (2014)	Regression Analysis	Sweden	✓[1]	✓	✓	✓			✓

18	Olaniyan et al. (2018)	Regression Analysis	Nigeria	✓	✓	✓[3]	✓[3]			✓[6]
19	Ottelin et al. (2019)	Regression Analysis	EU	✓	✓					✓
20	Pohlmann and Ohlendorf (2014)	Regression Analysis	Germany	✓	✓	✓	✓	✓	✓	✓
21	Qu et al. (2013)	Input-Output Analysis	China	✓	✓					
22	Seriño (2017)	Quantile Regression Analysis	Philippines	✓	✓	✓[3]	✓[3]		✓	✓
23	Seriño and Klasen (2015)	Regression Analysis	Philippines	✓	✓	✓	✓		✓	✓
24	Wier, Lenzen, Munksgaard, and Smed (2001)	Univariate Regression Analysis	Denmark	✓[1]	✓	✓	✓	✓		✓
25	Wilson et al. (2013)	Regression Analysis	Canada	✓	✓	✓			✓	
26	Wu et al. (2012)	Regression Analysis	China	✓	✓		✓			
27	Xu et al. (2015)	Regression Analysis	China	✓	✓	✓				
28	Yang et al. (2016)	Regression Analysis	China	✓	✓	✓[3]				

29	H. Zhang et al. (2020)	Regression Analysis	China	✓	✓	✓[3]	✓[3]		✓[3]	✓
30	H. Zhang et al. (2019)	Quantile Regression Analysis	China	✓	✓	✓[3]	✓[3]		✓[3]	✓

[1] These studies used consumption expenditures as a proxy for income variable
[2] In this study date of birth is used instead of age variable
[3] These variables reflect the household head
[4] Household composition selected in order to compare larger and smaller households
[5] In this study working hours used as a proxy for employment
[6] This study used urban and rural households as dependent variables for different models.

2.3. Conclusion

In this chapter, we summarize the literature on the determinants of households' GHG emissions. Although there is a broad literature on household emissions, we only focused on the studies that analyzed the drivers and determinants of household emissions. As one can see from Table 2, income is the main determinant for the household emissions in the literature. All the studies analyzed in this chapter used income as a determinant for household emissions. Household size is the second most common variable that was used in the studies examined. Age, education, marriage status, employment status, and urban-rural locations are other common variables that were used in the related literature. There are some other variables that were found to be significant but less commonly used in the literature, such as population density, gender, temperature, car ownership, household composition, number of vehicles, dependency ratio, energy intensity, and number of children.

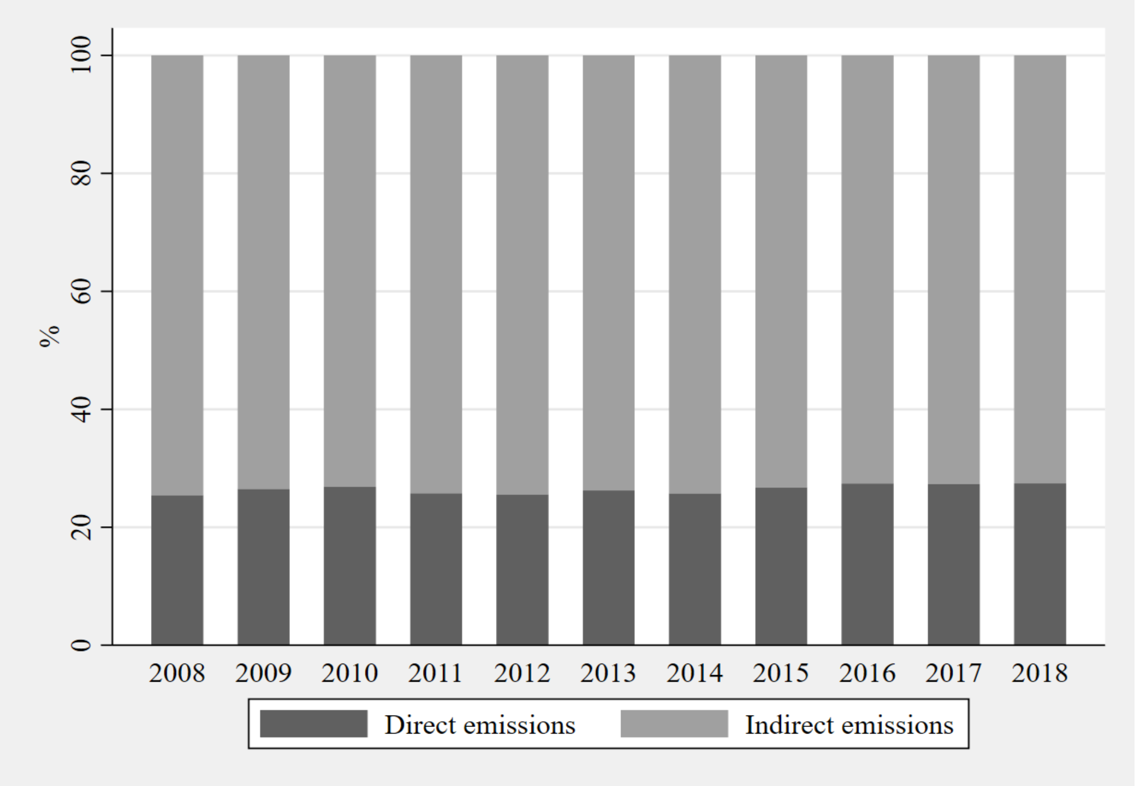
As a result, since we analyze the determinants of direct household emissions in 24 European Union member countries in this study, we determined income, household size, employment status, age, and education level as explanatory variables. In addition to these common variables in the literature, we also include average temperatures in January and July and energy consumption as explanatory variables to our empirical analyses. In the next chapter, we explain the data obtaining process and present our empirical analysis and its results

CHAPTER 3

EMPIRICAL ANALYSIS

This chapter begins with the explanation of the data and the variables used for the analysis, and in the following pages, it will go on to the methods and the results of the empirical analysis. Before starting with definitions and descriptions of the dataset, we would first like to highlight that emission data we employed in the empirical analysis represents direct emissions of the EU households. As mentioned in the previous chapters, household emissions are divided into direct and indirect emissions. Indirect emissions constitute a larger portion of the total household emissions than direct emissions. This is also prevailing for the EU countries. Figure 10 shows direct and indirect emissions for the aggregated EU economy.

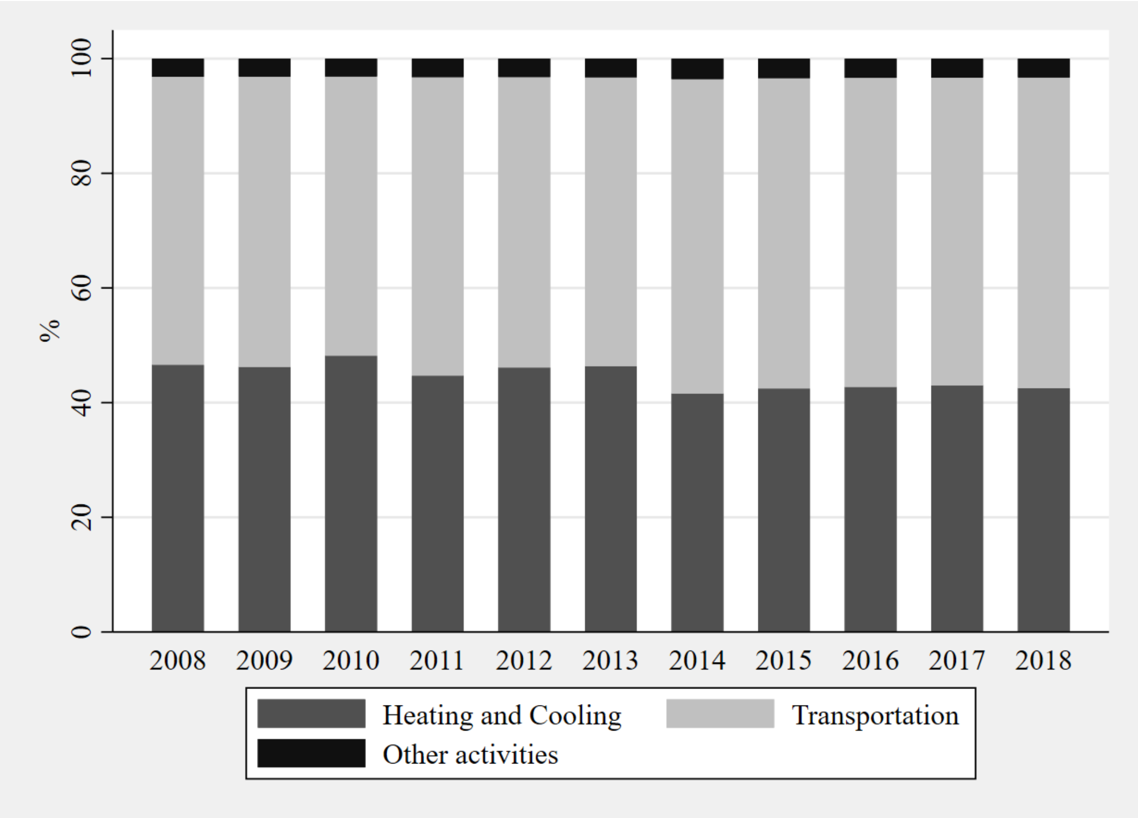
Figure 10: Emission Compositions for the EU (2008-2018)



Source: EUROSTAT

At first glance, it is easily noticeable that indirect emissions constitute a larger portion than the direct emissions within the total emissions. Between 2008 and 2018, direct emissions constitute around 25% to 29% of total emissions. Since our focal point is the determinants of direct GHG emissions of the EU households, our results explain only approximately one-fourth of total household emissions. It is beyond the scope of this study to examine the indirect emissions. Due to practical constraints that are explained below, this thesis cannot provide the empirical analysis of the indirect emissions. Figure 11 reflects the emissions categories in direct emissions. It can be seen from the figure that heating/cooling activities and transportation activities constitute a larger portion of the direct emissions. Emissions from other activities have a small portion within the direct emissions for the EU households.

Figure 11: Emission Categories



Source: EUROSTAT

3.1. Data and Variables

This subsection of the chapter presents the data and the variables that are used for the empirical analysis. First, we will introduce the variables and their abbreviations, and then we will explain data sources and data generation process. Since the analysis focuses on EU households, the research data in this thesis is mostly drawn from EUROSTAT.

Average direct GHG emissions of European households is the dependent variable of the empirical model. Furthermore, explanatory variables that are trying to explain changes in the dependent variable are; average household size, average adjusted gross disposable income, the average number of persons per household with primary level education, the average number of persons per household with secondary level education, the average number of persons per household with tertiary level education, average total energy consumption per household, the average number of employed persons per household, the average number of persons per household who are under 15 years old, the average number of persons per household who are over 65 years old, and dummy variables for average temperature in July and January. Descriptions and units of the variables can be seen in Table 3.

Table 3: Descriptions and Units of Measurements of the variables

Variables	Description	Units or Measures	Source
avhhghg	Average GHG emissions per household, total activities by household	CO_2, N_2O, CH_4 in CO_2 equivalent, tons	EUROSTAT
avhhsize	The average number of persons per household	Number of persons per household	
income	Average adjusted gross disposable income of households per capita,	Purchasing power standard per inhabitant, Euro	
avprimary	The average number of persons who have less than primary, primary and lower secondary education level per household	Number of persons per household	

avsecond	The average number of persons who have upper secondary and post-secondary non-tertiary education levels per household	Number of persons per household	
avtertiary	The average number of persons who have tertiary education level per household	Number of persons per household	
avengcons	Average final energy consumption in households	Thousand tons of oil equivalent	
avemploy	The average number of employed persons per household	Number of persons per household	
less15	The average number of persons younger than 15 years old	Number of persons per household	
over65	The average number of persons older than 65 years old	Number of persons per household	
djuly	Dummy variable takes value 1 if the July temperature of that year is higher than the 1966-2016 average July temperature.	D=1 if condition satisfied D=0 if not	Climate knowledge portal World Bank
djan	Dummy variable takes value 1 if the January temperature of that year is higher than the 1966-2016 average January temperature.	D=1 if condition satisfied D=0 if not	

To achieve the maximum number of observations, the dataset is constructed for the period 2008-2016, annually. Croatia, Denmark, Malta, and Sweden had to be excluded from the analysis because they have missing observations during the analysis period. Hence, with 24 countries and 9 years, this thesis employs balanced panel data with 216 observations.

The GHG emissions for EU households data are retrieved from Air emission accounts by the NACE Rev.2 activity database of EUROSTAT. This database contains GHG and air pollutants for 64 industries plus households. As air pollutant, this study uses the GHG emissions, which is equal to the sum of Carbon dioxide (CO_2), Nitrous oxide (N_2O), and Methane (CH_4) in CO_2 equivalents. Original data is starting from 1995, and it is available for all NACE activities plus households. Total activities by households refer to the sum of Heating/Cooling activities by households, transport activities by households, and other activities by households. Transport activities represent the emissions from private transportation; emissions from public transportation services are not included. Total household activities are related to emissions released from energy consumption, other than emissions released from the consumption of goods and services. As mentioned in the previous chapter, many researchers have studied indirect emissions by using input-output analysis and consumer lifestyle methodologies, but here direct GHG emissions data is directly obtained from EUROSTAT. To calculate average GHG emissions for EU households, annual GHG emissions of total activities by households divided by the total number of households for each country. So, the variable 'avhhghg' is calculated as follows:

$$avhhghg_{i,t} = \frac{GHG\ emissions\ from\ total\ activities\ by\ households_{i,t}}{Total\ number\ of\ households_{i,t}}$$

$$i: 1,2,3,\dots,24 \quad t: 2008,2009,\dots,2016$$

The data for the household size variable gathered from the European Union Labor Force Survey (EU-LFS) database, Household Statistics of EUROSTAT. Since data is originally in terms of average persons per household, observations for household size variable is directly utilized in the empirical analysis without doing any calculation.

As income variable, adjusted gross disposable income of household per capita income, measured in terms of purchasing power standard (PPS) per inhabitant, is obtained from the EUROSTAT. To control for social transfers and government aids, the adjusted gross national income of household per capita is utilized. Also, in order to control for price level differences between these 24 countries, as a unit of measurement, purchasing power standard (PPS) per inhabitant is selected.

Education variables are 'avprimary', 'avsecond' and 'avtertiary'. These variables are obtained from the European Union Labor Force Survey, Household Statistics of EUROSTAT. The 'avprimary' variable is generated as the total number of people who are at the age of 15 and over, with less than primary, primary and lower secondary education levels divided by the total number of households. The 'avsecond' variable is generated as the total number of adults who are at the age of 15 and over with at least secondary, post-secondary and non-tertiary education levels divided by the total number of households. Similarly, to calculate the 'avtertiary' variable, the total number of adults at the age of 15 and over with tertiary education level is divided by the total number of households. Therefore, education variables were generated as follows:

$$avprimary_{i,t} = \frac{Total\ number\ of\ adults\ who\ attends\ \ primary\ level\ education_{\ i,t}}{Total\ number\ of\ households_{i,t}}$$

$$i: 1,2,3, \dots ,24 \quad t: 2008,2009, \dots ,2016$$

$$avsecond_{i,t} = \frac{Total\ number\ of\ adults\ who\ attends\ \ secondary\ level\ education_{\ i,t}}{Total\ number\ of\ households_{i,t}}$$

$$i: 1,2,3, \dots ,24 \quad t: 2008,2009, \dots ,2016$$

$$avtertiary_{i,t} = \frac{Total\ number\ of\ adults\ who\ attends\ tertiary\ level\ education_{\ i,t}}{Total\ number\ of\ households_{i,t}}$$

$$i: 1,2,3, \dots ,24 \quad t: 2008,2009, \dots ,2016$$

Energy consumption variable obtained from the Energy Balances dataset, EUROSTAT. Within this dataset, we obtained the data representing final energy usage in households for space and water heating, cooling and cooking activities, and electric consumption from different electrical appliances. Due to missing variables in the significant number of Standard international energy classification (SIEC), the 'total' energy consumption classification was selected for the analysis. 'Total' classification includes all other classifications such as Natural Gas, Electricity, Primary solid biofuels, Gas oil and diesel oil (excluding biofuel portion), Heat, Solid Fossil Fuels, Liquefied petroleum gases, Ambient heat (heat pumps), Other kerosene, and Solar thermal. All classifications measured in terms of a thousand tons of oil equivalent. To calculate average total energy consumption per household, total energy consumption for each country divided by the total number of households annually. So, 'avengcons' variable is calculated as follows:

$$avengcons_{i,t} = \frac{Total\ energy\ consumption\ in\ household\ by\ fuel\ type\ _{i,t}}{Total\ number\ of\ households_{i,t}}$$

$$i: 1,2,3, \dots ,24 \quad t: 2008,2009, \dots ,2016$$

The employment variable is also retrieved from the European Union Labor Force Survey, Household Statistics of EUROSTAT. The employment variable shows the average number of employed persons within a household. In order to calculate the average number, the total number of employed persons at the age of 15 and over, divided by the total number of households for each country, annually. Furthermore, 'avemploy' variable is computed as follows:

$$avemploy_{i,t} = \frac{Total\ number\ of\ employed\ persons\ at\ age\ 15\ and\ over\ _{i,t}}{Total\ number\ of\ households_{i,t}}$$

$$i: 1,2,3, \dots ,24 \quad t: 2008,2009, \dots ,2016$$

Age variables are 'less15' and 'over65'. As mentioned in the previous chapter, age is another important variable for household emissions literature. In the European Union

Labor Survey database, age groups are divided into several categories, such as less than 15 years, 15 to 24 years, 15 years or over, 55 to 64 years and 65 years and over, etc. Within these age groups, we obtained the youngest and oldest age categories. It is important to note that these two variables reflect the number of people in a household within a certain age. The data for the age variables are gathered from the European Union Labor Force Survey database, Household Statistics of EUROSTAT. To be able to calculate average terms, the total number of persons under 15 years old and over 65 years old are divided by the total number of households for each country and each period. Therefore, age variables are obtained as follows:

$$less15_{i,t} = \frac{Total\ number\ of\ persons\ under\ \ 15\ years\ old\ _{i,t}}{Total\ number\ of\ \ households_{i,t}}$$

$$i: 1,2,3, \dots ,24 \quad t: 2008,2009, \dots ,2016$$

$$over65_{i,t} = \frac{Total\ number\ of\ persons\ over\ \ 65\ years\ old\ _{i,t}}{Total\ number\ of\ \ households_{i,t}}$$

$$i: 1,2,3, \dots ,24 \quad t: 2008,2009, \dots ,2016$$

Dummy variables 'djan' and 'djuly' are computed from the Climate Change Knowledge Portal of the World Bank. First of all, 1966-2016 average temperatures for January and July are calculated for each of 24 countries. And then, dummy variables are generated. If the average July or January temperature of the year t is higher than the 1966-2016 average temperature of that year t, then dummy variable takes value 1.

$$djan = 1\ if\ T_t \ \ > T_{1966-2016\ average}$$

$$djuly = 1\ if\ T_t \ \ > T_{1966-2016\ average}$$

$$T: temperature\ t: 2008,2009, \dots ,2016$$

Our a priori expectations regarding explanatory variables used in the analysis are as follows; the variables income, energy consumption, number of people less than 15 years old, and the dummy variable for July temperature to be positively related with direct emissions. On the other hand, education variables, employment variable, number of people older than 65, and the dummy variable for January temperature are negatively related to household emissions.

Table 4: Descriptive Statistics

Variables	N	Mean	Min	Max	Sd
avhhghg	216	4.51	1.82	9.29	1.63
avhhsize	216	2.46	2.00	2.90	0.24
income	216	18,263.28	7,468.00	33,075.00	5,697.67
avprimary	216	0.55	0.17	1.62	0.29
avsecond	216	0.85	0.26	1.64	0.29
avtertiary	216	0.45	0.22	0.76	0.12
avengcons	216	4.45	0.15	32.36	7.07
avemploy	216	1.08	0.81	1.43	0.12
djuly	216	0.80	0.00	1.00	0.40
djan	216	0.67	0.00	1.00	0.47
less15	216	0.38	0.26	0.58	0.06
over65	216	0.41	0.30	0.53	0.05

3.2. Methodology

Previous empirical studies in the household GHG emissions literature extensively analyzed a specific region of a specific country or a single country at the national level, by employing survey data (see Chapter 2). However, this thesis focuses on 24 EU member countries. One of the most important features that distinguish this thesis from previous studies is that it contains the analysis of 24 countries. Therefore, due to restrictions coming from the data, this thesis utilizes annual panel data belonging to 24 EU countries and covering the period 2008-2016.

Panel data has two main models according to the assumption on error term of a model; fixed effects model and random effects model (Pillai, 2016). While the fixed effects model assumes that unobserved time and individual heterogeneities are fixed, the random effects model assumes that they are random. Therefore, the fixed effects model does not take into account unobserved characteristics, and those unobserved characteristics are assumed to be fixed (Pillai, 2016). Nevertheless, unobserved characteristics are important in our analysis, because individual units of the analysis are average households of the European Union countries. Since differences across households in different countries might have an influence on their GHG emissions, this thesis employs the random effects model. This is the first rationale behind why we employed the random effects model. The other rationale behind employing the random effects model is that variation in the dependent variable comes from cross-section units rather than time dimension. This can be seen in Figure 12 and Figure 13. We also estimated fixed effects models. Estimation result of the Fixed Effect models with country fixed effects and year fixed effects can be found in the Appendix[4].

[4] Income is significant and positively related in all fixed effects models. In the country FE model over65, avtertiary and djan variables are significant and negatively related with household emission. In the year FE model, while avengcons, less15, and all education variables positively related with household emissions, avemploy variable negatively related. Finally, in country and year FE model other than income variable only less14 variable is significant and positively related with emissions.

Figure 12: Variation across Countries

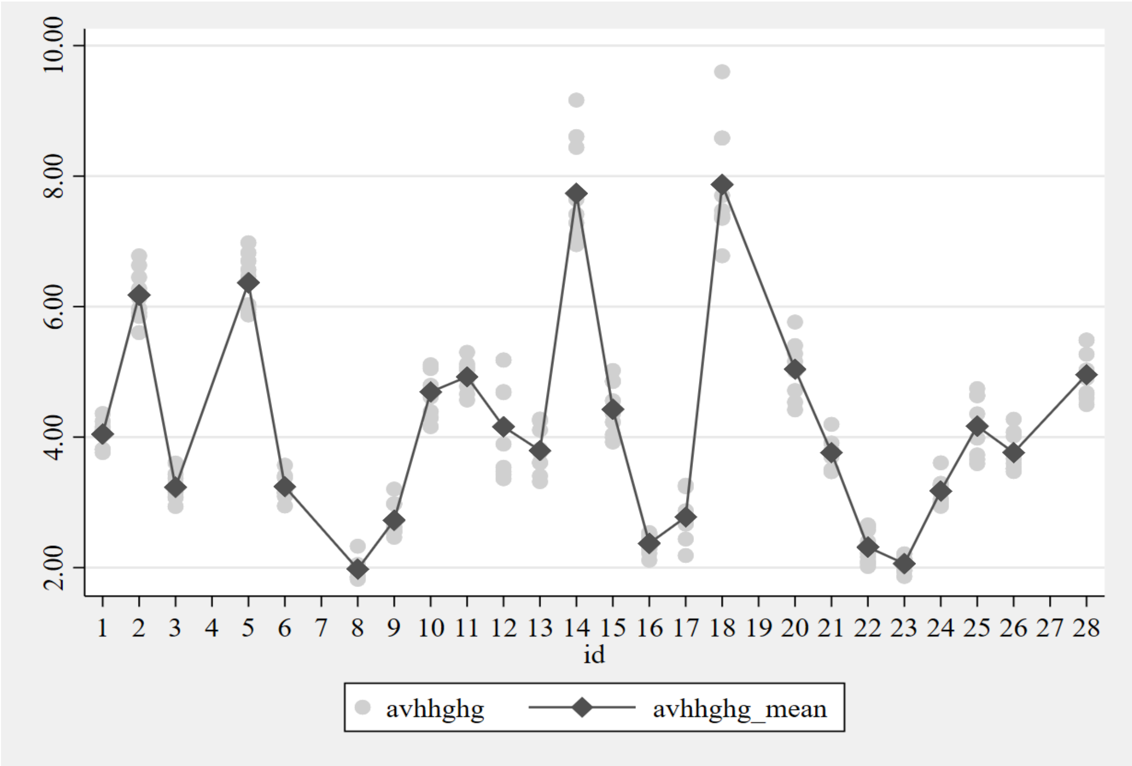
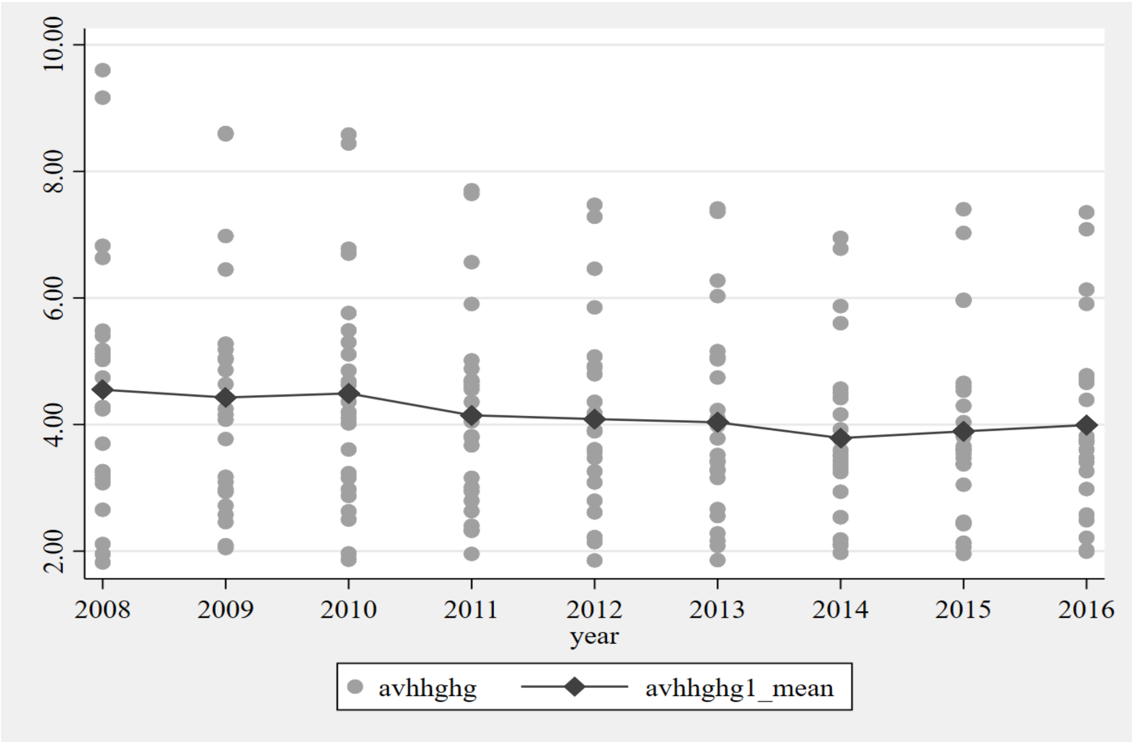
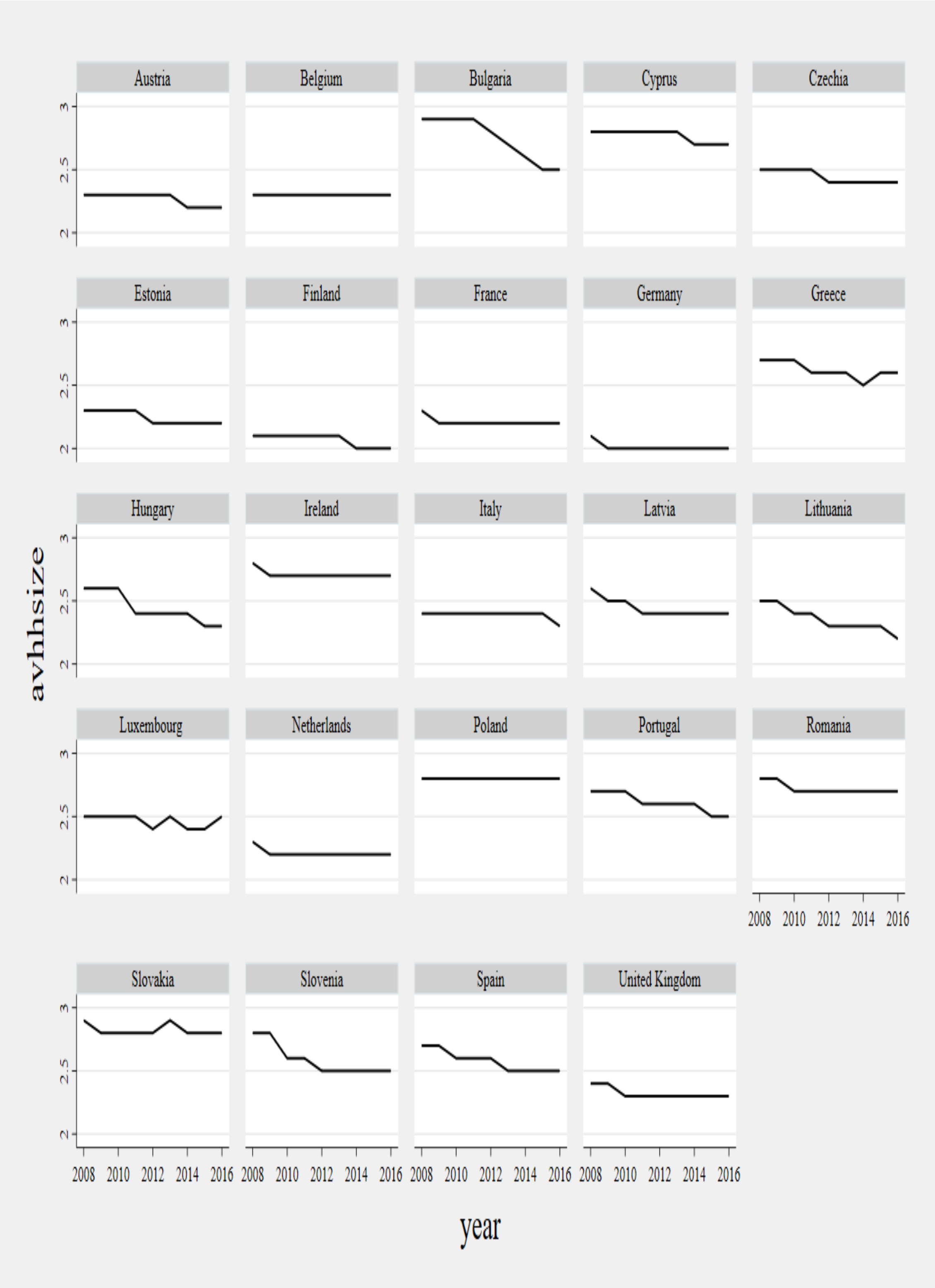


Figure 13: Variation across Years



The model we used in the empirical analysis does not include the household size variable. Household size is one of the most important variable in the related literature. However, in our data set, the variables except temperature, income and energy consumption variables are in terms of the average number of persons in a household. Therefore, using the household size variable, as the average number of persons in a household, creates problems in the empirical analysis. In the related literature, variables such as education level and employment status are represented generally with dummy variables, such as education and employment level of the household head. In our dataset, these variables are in terms of average number of persons in a household. Furthermore, there is a relatively high correlation (see Appendix 1) between the average household size and the employment variable. In addition, since our cross-section units are the average households of the EU countries, the average household size is not changing significantly across the analyzed period. Therefore 'avhhsize' variable fails to explain the variation in the dependent variable. It can be seen from Figure 14 that the variation of the average household size for almost all countries remains limited within the period for 2008-2016.

Figure 14: Average Household Size for the period of 2008-2016



Therefore, econometric model used in the empirical analysis[5] is as follows:

$$lnavhhghg_{it} = \beta_0 + \beta_1 avemploy_{it} + \beta_2 lnincome_{it} + \beta_3 avprimary_{it} + \beta_4 avsecond_{it} + \beta_5 avtertiary_{it} + \beta_6 djan_{it} + \beta_7 djuly_{it} + \beta_8 avengcons_{it} + \beta_9 less15_{it} + \beta_{10} over65_{it} + \epsilon_{it}$$

Where i denotes countries i = 1,2,3,...,24 and t denotes time t = 2008,2009,..,2016

First, in order to compare Fixed-effects and Random-effects model estimators, we employed the Hausman specification test. As explained before, we have strong evidence to employ the random effects model. The Hausman test null hypothesis assumes that there is no correlation between error terms and independent variables; hence, random effect models would be consistent and efficient. In line with our evidence, the results of test statistics fail to reject the null hypothesis, and we have strong evidence to use a random effects model.

Autocorrelation and Cross-sectional dependence are common problems observed in the panel data estimations. The autocorrelation problem arises when there is a serial correlation between the error terms. To check whether the autocorrelation problem exists in our model or not, we employed Wooldridge's test (Drukker, 2003). The “xtserial” command presented by Drukker, enable us to check for the null hypothesis that is “no first-order autocorrelation” in the panel data models. As we can see from the results in Table 5, the null hypothesis is rejected at the 95% significance level, and thus the model has an autocorrelation problem.

Table 5: Autocorrelation Test Results

F-statistic	p-value	Significance level
7.54	0.01	0.95

Cross-sectional dependence is another frequent problem observed in panel data analysis because of the unobservable factors and common shocks (De Hoyos & Sarafidis, 2006). To detect the Cross-Sectional dependence problem in the panel data, several different

[5] Level-level models were also used in the anaylsis, results can be found in the Appendix

tests have been employed, such as Pesaran (2004), Friedman (1937), and Frees (1995) tests. However, despite the Pesaran test, Friedman and Frees tests were designed for static panels. However, the Frees test reflects poor results with a small T (De Hoyos & Sarafidis, 2006). Since we have small numbers of T (9) and relatively large numbers of N (24) to check for cross-sectional dependence, we utilized the Friedman test. The 'xtcsd' command in Stata allows us to test for the null hypothesis that:

H_0: Cross-sectional independence

H_A: Cross-sectional dependence

Table 6: Cross-Sectional Dependence Test Results

Friedman's Test of Cross-Sectional Independence	p-value	Significance Level
26.922	0.2593	0.95

As we can see from Table 6 that, we fail to reject the null hypothesis. Thus, there is no cross-sectional dependence for the model at the 95% significance level.

Another common problem observed in the panel data econometrics is heteroscedasticity. Violation of the assumption of constant variance error terms results in the heteroscedasticity problem (Greene, 2003, p. 308). To test whether there is a heteroscedasticity problem in our model or not, we employed the Panel Groupwise Heteroscedasticity test, and we have found that there is a presence of heteroscedasticity in our model.

3.3. Empirical Findings

So far, we have detected autocorrelation and heteroscedasticity problems in the model we are using. The Feasible Generalized Least Squares method developed by Parks (1967) corrects for the autocorrelation and heteroscedasticity problem in panel data models. Therefore by employing the FGLS method with the "xtgls" command in STATA, we obtained our empirical findings that are presented in Table 7.

Table 7: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lnincome	0.76***	0.72***	0.74***	0.69***	0.67***	0.73***	0.73***	0.70***	0.70***	0.70***
	(0.061)	(0.06)	(0.05)	(0.06)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
avengcons		0.01***	0.00**	0.00	0.00	0.00*	0.00	0.01**	0.01**	0.01**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
less15			2.34***	2.07***	1.95***	1.93***	1.39***	1.84***	1.85***	1.83***
			(0.29)	(0.32)	(0.40)	(0.40)	(0.50)	(0.48)	(0.48)	(0.47)
over				-0.79*	-0.99	-0.98	-1.31**	-2.03***	-1.99***	-2.12***
				(0.43)	(0.62)	(0.61)	(0.64)	(0.62)	(0.62)	(0.61)
avprimary					0.04	0.12	0.30**	0.55***	0.56***	0.55***
					(0.08)	(0.10)	(0.14)	(0.14)	(0.14)	(0.14)
avsecond						0.14	0.29**	0.62***	0.63***	0.58***
						(0.09)	(0.13)	(0.13)	(0.13)	(0.13)
avtertiary							0.46*	0.67***	0.68***	0.66***
							(0.25)	(0.24)	(0.24)	(0.24)
avemploy								-1.00***	-1.01***	-0.99***
								(0.19)	(0.19)	(0.19)
djan									-0.03	-0.01
									(0.03)	(0.03)
djuly										0.09**
										(0.04)

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

In our final model, we can see that all variables are significant, with the exception of the dummy variable for January temperatures. Also, other than education variables, our a priori expectations are met in terms of sings of the variables. Also, magnitudes of the number of people within a household who are younger than 15 years old and the number of people within a household who are older than 65 years old variables are the highest. The variables which have the least magnitude effect on the household emissions are energy consumption variable and the dummy variable for the July temperatures.

In the literature, household size is one of the leading determinants that explain the GHG emissions of households. However, we need to state that in our model, the average household size variable is not included in the explanatory variables due to reasons explained before. Variables "less15" and "over65" are both reflecting the number of people in a household and the number of children and old people in the household. Moreover, they are both significant at the 0.01 level in the model 10. As we mentioned earlier, the household size variable is not changing enough; it stays almost the same for the EU countries. Therefore increases and decreases in the household population by 1 person is a respectively big change in the household composition. Since our age variables also reflect the number of people within a household, their high magnitudes are not surprising. As we can see from the table, one more person younger than 15 years old in a household increases direct emissions by 183% in a given year. Furthermore, one more person older than 65 years old in a household, decreases direct emissions by 212%. While households with the children emit more, households with the old people emit less.

Income is the most important determinant of household emissions (Druckman and Jackson, 2016). Consumption expenditures are also used in the related literature, as a proxy for income (Ahmad et al., 2015; Irfany & Klasen, 2017; Nässén, 2014; Wier et al., 2001). Both income and consumption expenditures found to be positively related to household GHG emissions. Our findings suggest that income has a positive effect on household emissions at the 0.01 significance level in all models. As the average income of households increases by 1%, emissions increase by 0.70%.

In the literature, one of the most controversial findings related to the sign of the employment variable. The relation between the employment status and household emissions differs according to the analyzed region, period, and type of emissions. In our analysis, we found that as the number of employed people within a household increases, households' direct emissions decrease. One more employed person within a household results in a -99% decrease in emissions for the households.

Findings regarding education levels also change in the related literature according to emission type, analyzed period, and region. Our results showed the positive relationship between the average number of educated people within a household and direct GHG emissions of households. Furthermore, as the level of education increases, the positive magnitude of education on emissions also increases. The variables “avprimary” and “avsecond” are not significant unless “avtertiary” variable is included into model. We separately estimated the effects of education variables on household emissions while controlling for income and found that while “avprimary” and “avsecond” variables are insignificant, “avtertiary” variable is significant, results can be found in Appendix. In the final model, all education variables, average primary, average secondary, and average tertiary education levels, are significant at the 0.01 level. As the average number of people within a household with a primary education level increases by one, average emissions increase by 55%. As the average number of people within a household who has secondary education level increase by one, average emissions increase by 58%. And finally, as the average number of people who have tertiary level education increases by one unit, emissions increase by 66%. The average number of persons with tertiary level education has the highest positive magnitude effect on the emissions among the education variables.

Temperature is also another determinant that explains household GHG emissions in our analysis. Temperature levels are important because they alter energy demand for households (Li et al., 2016). The January temperature is selected to reflect cold times of the year, related to heating demand, and July temperature is selected to reflect hot times of the year and to reflect cooling demand. Dummy variable for January temperature is negatively related to household emissions, as we expected, but no significant relationship was found. Dummy variable for July temperature is positively related as we expected, and it is significant at the 0.05 level. Hence, if the average July temperature of that year is higher than 1966-2016 average July temperatures, emissions for that year increase by 0.09% for the average household. So, we can say that higher July temperatures are positively related to GHG emissions.

Energy consumption is directly related to household GHG emissions. So, the positive relationship between average energy consumption and average household GHG emissions at the 0.05 significance level is not a surprising result. As average energy consumption goes up by 1 thousand tons of oil equivalent, emissions go up by 1% per year.

3.4. Discussion of the Results

Income is a principal determining factor of household emissions. In the related literature, income is positively related both with direct and indirect emissions. This study confirms that for the EU households, income is also positively related to the direct emissions. However, the magnitude of the increase in income on emissions is low for indirect emissions. A higher magnitude effect of income on household emissions has been found in the studies analyzing indirect emissions.

Age variables have been used extensively in the determinants of the household emissions literature (See Chapter 2). For most of the cases, the age variable is represented by the age of the household head. These studies find that as the age of the household head increases, emissions also increase. Nevertheless, the inverted-U hypothesis applies to the age variable in the context of the determinants of household emissions. (Olaniyan et al., 2018; Seriño & Klasen, 2015; Xu et al., 2015). This means that as household heads' age increases, emissions increase, but as household heads' age continues to increase, emissions start to decrease after a certain age. Here, our age variables do not reflect the age alone. They also reflect the number of people in a household within the particular range of age. "less15" variable might be evaluated as a proxy for the number of children in a household, and "over65" variable might be evaluated as a proxy for the number of old people in a household. Our findings mainly suggest that as the number of children goes up, emissions go up, and as the number of old people goes up, emissions go down. The decrease in the emissions as the increase in the number of old people in a household is explained by the structure of the emission employed in the analysis. Our emission data reflects heating and cooling activities, transport activities, and other activities. Due to changing lifestyle and consumption patterns, old peoples' emissions restricted with mostly home energy demand, thus heating and cooling activities in our data. On the other hand, the number of children in a household increases emission due to increasing demand for all types of emissions activities.

The education variables' results indicate that all the education variables are positively related to emissions, but their magnitudes differ according to their levels. As the average number of educated persons increases for a household, an increase in the emissions also goes up. Education levels of household members play an important role in household direct GHG emissions. However, in the literature, there are controversial results regarding education variables. Since high education brings high income and better living standards, emissions increase with education level (Ahmad et al., 2015; Büchs & Schnepf, 2013; Zhang, Zhang, Wang, & Shi, 2019). On the other hand, as Baiocchi, Minx, and Hubacek (2010) showed, when people become more and more educated, they become more environmentally conscious and decrease their emissions. Our a priori expectations about education variables were negative, but here we found a significant positive relationship between education variables and emissions. The decreasing effect of education level on emissions might be observed in indirect emissions rather than direct emissions.

Employment status is also another controversial determinant in the literature. Both positive and negative effects of the employment status on household emissions found significant in the related literature. Employment status can be positively related with household emissions because, as the number of employed persons within a household increases, their commuting time increases. On the other hand, negative relationship between employment status and household emissions can be explained as the number of unemployed persons within a household increases, their time-spent at home increases therefore their home-energy demand increases (Gough et al., 2011). However, these findings differ according to the study area and the analyzed period. As the number of employed persons within a household increases, household direct GHG emissions decrease. We found that the number of the employed persons in a household is negatively related to direct emissions. This is mainly related to employed people spending less time at home than unemployed people. Another possible explanation of this is that public transportation activities are not observed in our dependent variable; therefore, employed people's emissions from commuting, are not affecting our results.

Temperature is an important factor in terms of energy demand within a household. To observe heating and cooling activities on household GHG emission, we create dummy variables for January and July average temperatures. Our results suggest that if the average July temperature for that year is over the 1966-2016 average temperature in July, GHG emissions increase for households. The higher temperatures increase the cooling demand and then result in an increase in emissions. Another study in the literature analyzed the effects of temperature on household emissions (Li et al., 2016) found that an increase in January average temperature decreases emissions due to lower heating demand. Therefore, we can easily conclude that there is a relationship between temperature and households' direct emissions.

The emissions that we observed in this analysis are coming from the direct emissions. Therefore, the positive relationship between energy consumptions and emissions is not surprising. As energy consumption within a household increases, their emissions from heating and cooling activities increase.

Overall, our findings do not contradict a priori expectations except the education variables, and they are mainly consistent with the findings of the related literature. We find that the main determinants of household GHG emissions literature also stands for EU households. Among all the analyzed variables, the number of children and the number of old people have the greatest magnitude on the household emissions in EU countries.

CONCLUSION

The international scientific community almost unanimously agree that increased atmospheric GHG concentrations from human activities are the main reason behind climate change. Especially after the 1970s, increased atmospheric GHG concentrations have become much more evident. Global GHG emissions have been steadily increasing since the Industrial Revolution, with the exception of several periods of global economic downturn. Although there were international efforts to reduce GHG emissions since 1994, those efforts seem to be inadequate to decrease global GHG emissions. The last step of these international efforts was the Paris Agreement which requires the countries to set their own emission reduction targets to limit the increase in the global mean temperatures with 2°C.

In terms of meeting the emission reduction targets, the EU presents better performance than the rest of the World. After 2008, there were significant reductions in the emissions and emissions intensities of the EU. However, as we argued before reductions in the production-based emissions are misleading because production-based accounting neglects the emissions embodied in trade. There are strong pieces of evidence in the literature showing that developed countries transferred their emissions to developing countries, and they managed to reduce emissions in this way. However, considering consumption-based emission accounting reverses the situation in the case of GHG emissions. Since the household sector represents consumers in an economy, household emissions literature gained importance within the climate change context, especially over the last decade. Due to calculations of GHG emissions from the production side, household emissions have long been neglected. However, as we presented in the first chapter when household emissions are compared with sectoral emissions, total activities by households have the second-highest sectoral share following the Energy sector in the EU, and this share increased in the period 2008-2018.

Household emissions are separated into two as direct and indirect emissions. Indirect emissions constitute a significant portion of the total household emissions, and the remaining part accounts for direct emissions. For the EU countries, the share of direct emissions in the total household emissions is about 25-29%. The emissions used in this study include emissions from energy use in dwellings and private transportation activities of the households. Therefore, emissions data we used only reflects the direct emissions. This is one of the drawbacks of the study. The literature on household emissions mostly depends on survey data and both direct and indirect emissions calculated in these studies by using relevant methodologies. Calculation/estimation of indirect emissions is probably the first best option in analyzing determinants of household emissions, and it may present a broader set of policy implications. However, calculation of consumption-based GHG emissions for all of the EU households across years is an extremely difficult task, and neither national statistical institutions nor Eurostat compiles indirect emissions data at the country level. Because of this, our analyses in this study are restricted to direct household emissions. The other drawbacks of the study also come from the data generation process. Since we do not have survey data, social and demographic characteristics of the households, such as education level, employment status, etc., represented with the number of persons within a household who has these social and demographic characteristics. This problem costs us an important common determinant (i.e. household size) used in the literature. Household size is one of the most important determinants in the literature after income. Since all our variables except temperature variables are in terms of the number of persons within a household, we had to exclude household size from our analysis. The final drawback of the study is that we could not investigate the effects of some common determinants specified in the literature due to restrictions coming from our data. These variables are urban/rural location, marital status, and diet type.

Despite the drawbacks explained above, we found that common determinants specified in the related literature also significantly determine the direct GHG emissions of the EU households. Our findings showed that income, education, energy consumption, July temperature, and the number of children are positively related to direct emissions while employment and the number of elderly individuals in the household are negatively related to the direct emissions of the EU households. Our findings are parallel with the common findings of the literature. The key finding of the study is related to the number of children and the elderly within a household. These are the variables that have the highest magnitude effects on emissions. Income, education, and energy consumption variables present similar results with the findings of the related literature. The most controversial determinant in the literature is employment, and we found that number of employed persons within a household is negatively related to household emissions. We showed that other than households' characteristics, temperature anomalies also significantly determine the direct emissions. As average temperatures in July exceed the July average temperature, direct emissions increase.

Since our dependent variable is direct GHG emissions reflecting the emissions coming from energy use at home and transportation activities of the households, our policy suggestions are oriented around the energy consumption of households and energy efficiency in residential buildings and transportation.

Our empirical findings suggest that household energy consumption is positively related to household GHG emissions. Heating and hot water constitute 79% of total final energy use in EU households. Although cooling has a relatively smaller share in total final energy use, the energy demand of households related to cooling increases in summer due to the increasing temperatures and effects of climate change. Considering that 75% of energy demand related to heating and cooling activities is met with fossil fuels, providing incentives towards the use of renewable energy, thermal insulation of buildings, and promoting increased energy efficiency further in residential buildings seems to be a proper policy option. In fact, as a first step, the European Commission proposed an EU Heating and Cooling Strategy in 2016. Moreover, the renovation of the building stock in the EU is expected to contribute significantly to decarbonization efforts by improving energy efficiency. However, preparations regarding the renovation of buildings have just begun with the roadmap published by the European Commission in May 2020 (European Commission, 2020a, 2020b).

Final energy consumption in transport increased annually by 0.06% on average in the 2005-2017 period in the EU. An examination of individual members reveals that while all of the countries gained accession to the EU after 2008 increased their final energy consumption in transport in the same period, two-thirds of the old members (i.e., except Austria, Belgium, France, Germany, and Sweden) decreased it (European Commission 2020c). Therefore, taking some measures regarding energy efficiency in transportation in the countries with increased final energy consumption will probably limit GHG emissions from the transportation activities of households.

In light of these considerations and findings of the current study, we can suggest more detailed policy options to reduce household emissions. According to our findings, the number of persons in the household who are younger than 15 years and the number of persons in the household who are older than 65 years, among other determinants, have the highest magnitude effect on household emissions. Therefore, our first policy recommendations are related to these variables. According to our findings, as the number of persons younger than 15 years increases within a household, emissions also increase. Accordingly, educating children starting from the young ages regarding energy saving and energy efficiency can reduce the emissions from energy use in dwellings. Several projects implemented under the European Commission, such as Young Energy People (YEP), Young Energy Savers (YES), and Kids4Future, have already presented hopeful results in terms of increasing energy awareness among the children. Extending these projects to the national level, and including education modules regarding energy awareness and energy saving starting from the kindergarten level, especially in new members, can bring huge benefits to the household emissions reduction efforts. In terms of education, our findings suggest that as the education level in a household increases, emissions also increase. However, this finding contradicted with our prior expectations (i.e. as the number of educated people and level of education in a household increase, the household become more energy aware and has lower emissions). Therefore, we can assert that there is still a need for developing energy awareness modules in education, starting from the kindergartens and stick with it through to university education.

The findings of the study suggest that number of persons in the household who are older than 65 is negatively related to household emissions. This finding is probably related to the patterns of consumption of elderly households, such as having less mobility, adopting a thrifty lifestyle, using public transport, using a blanket instead of setting a higher heater/boiler temperature, etc. This might implicitly suggest that policies promoting lower consumption levels may be effective in reducing household emissions. Additionally, public announcements and broadcasting activities oriented towards energy saving might be of use.

We have also found that as the number of persons employed increases, household emissions decrease. We believe that this might be due to a lower amount of time spent at home and the choice of public transportation to go to work. Therefore, policies discouraging private transportation behavior can help to reduce emissions. Banning cars from city centers in the future seems to be a policy option. Even some of the European cities such as Berlin, Paris, London, Hamburg, Copenhagen, and Oslo have taken similar steps or planning to do so in the coming years. In addition, enhancing public transportation opportunities, promoting zero or low emission means of transportation such as bicycles, electric bicycles, etc. by planning cities and public transport accordingly may be effective in reducing household emissions.

Considering that reducing household GHG emissions is an important step in combatting climate change, understanding the factors driving household emissions in the EU is crucial for mitigation efforts and climate policy formation at the Union and country levels. According to the findings of the study, we have come to the conclusion that policies regarding household GHG emissions should be focused on promoting energy awareness of EU households, shifting patterns of consumption throughout the EU towards a low carbon pattern, and transforming cities into energy-efficient, renewable energy-producing, and public and low-carbon transport based ones.

BIBLIOGRAPHY

Ahmad, S., Baiocchi, G., & Creutzig, F. (2015). CO2 emissions from direct energy use of urban households in India. *Environmental science & technology, 49*(19), 11312-11320. doi:https://doi.org/10.1021/es505814g

Ala-Mantila, S., Heinonen, J., & Junnila, S. (2014). Relationship between urbanization, direct and indirect greenhouse gas emissions, and expenditures: A multivariate analysis. *Ecological economics, 104*, 129-139. doi:https://doi.org/10.1016/j.ecolecon.2014.04.019

Baiocchi, G., Minx, J., & Hubacek, K. (2010). The Impact of Social Factors and Consumer Behavior on Carbon Dioxide Emissions in the United Kingdom. *Journal of Industrial Ecology, 14*(1), 50-72. doi:10.1111/j.1530-9290.2009.00216.x

Bows, A., & Barrett, J. (2010). Cumulative emission scenarios using a consumption-based approach: a glimmer of hope? *Carbon management, 1*(1), 161-175.

Büchs, M., & Schnepf, S. V. (2013). Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO2 emissions. *Ecological economics, 90*, 114-123. doi:https://doi.org/10.1016/j.ecolecon.2013.03.007

Chancel, L. (2014). Are younger generations higher carbon emitters than their elders?: Inequalities, generations and CO2 emissions in France and in the USA. *Ecological economics, 100*, 195-207. doi:https://doi.org/10.1016/j.ecolecon.2014.02.009

Change, I. P. O. C. (2006). *2006 IPCC guidelines for national greenhouse gas inventories*. Retrieved from

Christis, M., Breemersch, K., Vercalsteren, A., & Dils, E. (2019). A detailed household carbon footprint analysis using expenditure accounts–case of Flanders (Belgium). *Journal of Cleaner Production, 228*, 1167-1175.

da Graça Carvalho, M. (2012). EU energy and climate change strategy. *Energy, 40*(1), 19-22.

Davis, S. J., & Caldeira, K. (2010). Consumption-based accounting of CO2 emissions. *Proceedings of the national academy of sciences, 107*(12), 5687-5692.

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *The stata journal, 6*(4), 482-496.

Druckman, A., & Jackson, T. (2016). Understanding households as drivers of carbon emissions. In *Taking stock of industrial ecology* (pp. 181-203): Springer, Cham.

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *The stata journal, 3*(2), 168-177.

Duarte, R., Mainar, A., & Sánchez-Chóliz, J. (2012). Social groups and CO2 emissions in Spanish households. *Energy policy, 44*, 441-450.

European Commission (2020a) https://ec.europa.eu/energy/topics/energy-efficiency/heating-and-cooling_en (accessed 18.06.2020)

European Commission (2020b) https://ec.europa.eu/energy/topics/energy-efficiency/energy-efficient-buildings/renovation-wave_en (accessed 18.06.2020)

European Commission (2020c) https://ec.europa.eu/energy/data-analysis/energy-union-indicators/scoreboard_en?dimension=Energy+efficiency+and+moderation+of+demand&topic=Final+sectors (accessed 18.06.2020)

European Environment Agency (2020) https://www.eea.europa.eu/publications/trends-and-drivers-of-eu-ghg (accessed 05.06.2020)

Feng, Z.-H., Zou, L.-L., & Wei, Y.-M. (2011). The impact of household consumption on energy use and CO2 emissions in China. *Energy, 36*(1), 656-670.

Frees, E. W. (1995). Assessing cross-sectional correlation in panel data. *Journal of econometrics, 69*(2), 393-414.

Fremstad, A., Paul, M., & Underwood, A. (2019). Work Hours and CO2 Emissions: Evidence from US Households. *Review of Political Economy, 31*(1), 42-59.

Fremstad, A., Underwood, A., & Zahran, S. (2018). The environmental impact of sharing: household and urban economies in CO2 emissions. *Ecological economics*, *145*, 137-147.

Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the american statistical association, 32*(200), 675-701.

Golley, J., & Meng, X. (2012). Income inequality and carbon dioxide emissions: the case of Chinese urban households. *Energy Economics, 34*(6), 1864-1872.

Gough, I. (2013). Carbon mitigation policies, distributional dilemmas and social policies. *Journal of Social Policy*, *42*(2), 191-213.

Gough, I., Abdallah, S., Johnson, V., Ryan-Collins, J., & Smith, C. (2011). The distribution of total greenhouse gas emissions by households in the UK, and some implications for social policy. *LSE STICERD Research Paper No. CASE152*.

Greene, W. H. (2003). *Econometric Analysis 7th Edition International edition*: McGraw-Hill. Inc. New York.

Han, L., Xu, X., & Han, L. (2015). Applying quantile regression and Shapley decomposition to analyzing the determinants of household embedded carbon emissions: evidence from urban China. *Journal of Cleaner Production, 103*, 219-230.

Held, D., & Roger, C. (2018). Three Models of Global Climate Governance: From Kyoto to Paris and Beyond. *Global Policy, 9*(4), 527-537.

Irfany, M. I., & Klasen, S. (2017). Affluence and emission tradeoffs: evidence from Indonesian households' carbon footprint. *Environment and Development Economics*, *22*(5), 546-570.

IPCC. (2007). *Climate Change 2007: Impacts, Adaptation and Vulnerability.* Cambridge: Cambridge University Press

IPCC. (2014a). *Climate Change 2014: Mitigation of Climate Change.* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press

IPCC. (20014b). *Climate Change 2014: Impacts, Adaptation and Vulnerability.* Cambridge: Cambridge, United Kingdom and New York, NY,USA: Cambridge University Press

IPCC. Global warming of 1.5°C. An IPCC Special Report: Summary for Policymakers. https://www.ipcc.ch/2018/10/08/ summary-for-policymakers-of-ipcc-special-report-on-global-warmingof-1-5c-approved-by-governments/ (accessed May 15, 2020)

Jones, C. M., & Kammen, D. M. (2011). Quantifying carbon footprint reduction opportunities for US households and communities. *Environmental science & technology, 45*(9), 4088-4095.

Kerkhof, A. C., Benders, R. M., & Moll, H. C. (2009). Determinants of variation in household CO2 emissions between and within countries. *Energy policy, 37*(4), 1509-1517.

Koide, R., Lettenmeier, M., Kojima, S., Toivio, V., Amellina, A., & Akenji, L. (2019). Carbon Footprints and Consumer Lifestyles: An Analysis of Lifestyle Factors and Gap Analysis by Consumer Segment in Japan. *Sustainability, 11*(21), 5983.

Le Quéré, C., Korsbakken, J. I., Wilson, C., Tosun, J., Andrew, R., Andres, R. J., . . . van Vuuren, D. P. (2019). Drivers of declining CO 2 emissions in 18 developed economies. *Nature Climate Change, 9*(3), 213-217.

Le, T. H., Somerville, R., Cubash, U., Ding, Y., Mauritzen, C., Mokssit, A., . . . Prather, M. (2007). Historical overview of climate change science.

Le Treut, H. (2007). Historical overview of climate change. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*.

Lenzen, M. (1998). Energy and greenhouse gas cost of living for Australia during 1993/94. *Energy, 23*(6), 497-516.

Li, J., Huang, X., Yang, H., Chuai, X., Li, Y., Qu, J., & Zhang, Z. (2016). Situation and determinants of household carbon emissions in Northwest China. *Habitat International, 51*, 178-187. doi:10.1016/j.habitatint.2015.10.024

Liu, L., Qu, J., Clarke-Sather, A., Maraseni, T. N., & Pang, J. (2017). Spatial variations and determinants of per capita household CO2 emissions (PHCEs) in China. *Sustainability, 9*(7), 1277.

Liu, L., Qu, J., Zhang, Z., Zeng, J., Wang, J., Dong, L., . . . Liao, Q. (2018). Assessment and determinants of per capita household CO 2 emissions (PHCEs) based on capital city level in China. *Journal of Geographical Sciences, 28*(10), 1467-1484.

McCarty, J. J., Canziani, O., Leary, N., Dokken, D., & White, K. (2001). *Climate change 2001: impacts, adaptation, and vulnerability. Contribution of working group II to the Third assessment report of the intergovernmental panel on climate change* (0521807689). Retrieved from

Meangbua, O., Dhakal, S., & Kuwornu, J. K. (2019). Factors influencing energy requirements and CO2 emissions of households in Thailand: A panel data analysis. *Energy policy, 129*, 521-531.

Nässén, J. (2014). Determinants of greenhouse gas emissions from Swedish private consumption: Time-series and cross-sectional analyses. *Energy, 66*, 98-106.

Nordhaus, W. D. (2013). *The climate casino: Risk, uncertainty, and economics for a warming world*: Yale University Press.

Olaniyan, O., Sulaimon, M. D., & Ademola, W. (2018). Determinants of household direct CO2 emissions: Empirical evidence from Nigeria. *Munich Personal RePEc Archive(2018)*.

Ottelin, J., Heinonen, J., Nässén, J., & Junnila, S. (2019). Household carbon footprint patterns by the degree of urbanisation in Europe. *Environmental Research Letters, 14*(11), 114016.

Parks, R. W. (1967). Efficient estimation of a system of regression equations when disturbances are both serially and contemporaneously correlated. *Journal of the american statistical association, 62*(318), 500-509.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels.

Peters, G. P., & Hertwich, E. G. (2008). Post-Kyoto greenhouse gas inventories: production versus consumption. *Climatic Change, 86*(1-2), 51-66.

Pillai, N. (2016). Panel data analysis with stata part 1 fixed effects and random effects models.

Pohlmann, J., & Ohlendorf, N. (2014). *Equity and emissions. How are household emissions distributed, what are their drivers and what are possible implications for future climate mitigation?* Paper presented at the Degrowth conference Leipzig.

Qu, J., Zeng, J., Li, Y., Wang, Q., Maraseni, T., Zhang, L., . . . Clarke-Sather, A. (2013). Household carbon dioxide emissions from peasants and herdsmen in northwestern arid-alpine regions, China. *Energy policy, 57*, 133-140.

Seriño, M. N. V. (2017). Effects of Affluence on Rising Household Carbon Emission in the Philippines: An Application Using Quantile Regression Approach. *DLSU Business & Economics Review, 26*(2), 147-157.

Seriño, M. N. V., & Klasen, S. (2015). Estimation and Determinants of the Philippines' Household Carbon Footprint. *The Developing Economies, 53*(1), 44-62.

Tol, R. S. (2019). *Climate economics: economic analysis of climate, climate change and climate policy*: Edward Elgar Publishing.

Wier, M., Lenzen, M., Munksgaard, J., & Smed, S. (2001). Effects of Household Consumption Patterns on CO2 Requirements. *Economic Systems Research, 13*(3), 259-274. doi:10.1080/09537320120070149

Wilson, J., Tyedmers, P., & Spinney, J. E. (2013). An exploration of the relationship between socioeconomic and well-being variables and household greenhouse gas emissions. *Journal of Industrial Ecology, 17*(6), 880-891.

Wu, G., Liu, T., & Tang, M. (2012). Analysis of household energy consumption and related CO2 emissions in the disregarded villages of Lijiang City, China. *International Journal of Sustainable Development & World Ecology, 19*(6), 500-505.

Xu, X., Tan, Y., Chen, S., Yang, G., & Su, W. (2015). Urban household carbon emission and contributing factors in the Yangtze River Delta, China. *PLoS One, 10*(4). doi:https://doi.org/10.1371/journal.pone.0121604

Yang, Z., Fan, Y., & Zheng, S. (2016). Determinants of household carbon emissions: Pathway toward eco-community in Beijing. *Habitat International, 57*, 175-186.

Yuan, R., Rodrigues, J. F., & Behrens, P. (2019). Driving forces of household carbon emissions in China: A spatial decomposition analysis. *Journal of Cleaner Production, 233*, 932-945.

Zhang, H., Shi, X., Wang, K., Xue, J., Song, L., & Sun, Y. (2020). Intertemporal lifestyle changes and carbon emissions: Evidence from a China household survey. *Energy Economics*, 104655. doi:https://doi.org/10.1016/j.eneco.2019.104655

Zhang, H., Zhang, L., Wang, K., & Shi, X. (2019). Unveiling Key Drivers of Indirect Carbon Emissions of Chinese Older Households. *Sustainability, 11*(20), 5740. doi:https://doi.org/10.3390/su11205740

Zhang, X., Luo, L., & Skitmore, M. (2015). Household carbon emission research: an analytical review of measurement, influencing factors and mitigation prospects. *Journal of Cleaner Production, 103*, 873-883. doi:https://doi.org/10.1016/j.jclepro.2015.04.024

APPENDIX 1. CORRELATION MATRIX AND REGRESSION RESULTS

Figure 1: Correlation Matrix

	avemploy	lnincome	avprimary	avsecond	avtertiary	davjan	davjuly	avengcons	avhhsize	less15	over65
avemploy	1										
lnincome	-0.211	1									
avprimary	-0.042	0.033	1								
avsecond	0.349	-0.484	-0.621	1							
avtertiary	0.111	0.269	-0.207	-0.343	1						
davjan	-0.036	0.017	0.014	0.02	-0.013	1					
davjuly	0.064	-0.151	-0.099	0.22	-0.082	-0.275	1				
avengcons	0.31	0.176	-0.158	-0.063	0.476	-0.034	0.021	1			
avhhsize	0.583	-0.552	0.296	0.293	-0.038	-0.005	0.134	0.154	1		
less15	0.544	-0.008	0.16	-0.084	0.434	-0.023	-0.044	0.269	0.564	1	
over 65	-0.303	-0.452	0.457	-0.069	-0.416	0.069	0.079	-0.38	0.122	-0.459	1

Table 2: Level-level Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
income	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
avengcon		0.0665***	0.0356***	0.0329***	0.0336***	0.0340***	0.0296***	0.0419***	0.0415***	0.0402***
		(0.0116)	(0.0096)	(0.0098)	(0.0098)	(0.0098)	(0.0106)	(0.0104)	(0.0104)	(0.0103)
less15			12.2703***	11.4833***	10.8982***	10.8824***	9.6727***	11.1824***	11.2942***	11.1694***
			(1.0769)	(1.2282)	(1.5479)	(1.5480)	(1.8940)	(1.8291)	(1.8212)	(1.8045)
over				-2.1572	-3.1824	-3.1867	-3.8770	-6.5150***	-6.1876***	-6.7586***
				(1.6398)	(2.3276)	(2.3269)	(2.4034)	(2.3520)	(2.3501)	(2.3435)
avprimary					0.1953	0.2745	0.6760	1.5820***	1.5955***	1.5812***
					(0.3150)	(0.3806)	(0.5260)	(0.5352)	(0.5325)	(0.5274)
avsecond						0.1258	0.5016	1.6307***	1.6904***	1.5305***
						(0.3397)	(0.4805)	(0.5148)	(0.5137)	(0.5145)
avtertiary							1.0637	1.7885*	1.8489**	1.7897*
							(0.9649)	(0.9303)	(0.9264)	(0.9178)
avemploy								-3.5342***	-3.5686***	-3.5314***
								(0.7411)	(0.7376)	(0.7306)
davjan									-0.1908	-0.1072
									(0.1275)	(0.1325)
davjuly										0.3298**
										(0.1595)

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

Table 3: Regression Results with Education Variables

VARIABLES	(1) lnavghg	(2) lnavghg	(3) lnavghg
lnincome	0.76***	0.78***	0.69***
	(0.06)	(0.07)	(0.06)
avprimary	0.01		
	(0.07)		
avsecond		0.06	
		(0.08)	
avtertiary			0.71***
			(0.16)
N	216	216	216

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

Table 4: Fixed Effect Models

	(1)	(2)	(3)
lnincome	0.38**	0.84***	0.63***
	(0.15)	(0.08)	(0.14)
avengcons	0.02	0.00**	0.00
	(0.01)	(0.00)	(0.01)
less15	1.38	2.24***	1.31*
	(1.00)	(0.41)	(0.75)
over65	-1.24*	-0.52	-0.24
	(0.61)	(0.65)	(0.84)
avprimary	0.35	0.39***	0.18
	(0.24)	(0.13)	(0.20)
avsecond	-0.12	0.62***	-0.16
	(0.25)	(0.13)	(0.22)
avtertiary	-0.52**	0.96***	-0.13
	(0.21)	(0.22)	(0.17)
avemploy	0.02	-1.06***	-0.21
	(0.22)	(0.17)	(0.22)
davjan	-0.02*	0.04	0.00
	(0.01)	(0.04)	(0.01)
davjuly	0.02	0.12**	0.02
	(0.01)	(0.05)	(0.01)
Constant	-2.29	-7.54***	-4.78***
	(1.60)	(1.06)	(1.51)
Observations	216	216	216
R-squared	0.54	0.70	0.63
Number of id	24		24
Country FE	YES		YES
Year FE		YES	YES