Universidad de Oviedo
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POLLUTION FROM SPANISH HOUSEHOLDS' CONSUMPTION THROUGHT SPACE, TIME, AND GENDER DIMENSIONS

PROGRAMA DE DOCTORADO EN ECONOMÍA Y EMPRESA

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2022

Universidad de Oviedo

Departamento de Economía Aplicada

Pollution from Spanish households' consumption through space, time, and gender dimensions

Memoria para la obtención del grado de doctora en Economía presentada por

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Programa de Doctorado "Economía y Empresa"

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RESUMEN DEL CONTENIDO DE TESIS DOCTORAL

1.- Título de la Tesis	
Español/Otro Idioma: La contaminación del consumo de los hogares españoles a través de la dimensión espacial, temporal y de género.	Inglés: Pollution from Spanish households consumption throught spaces, time, and gender dimension.

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Órgano responsable: Centro Internacional de Postgrado y Comisión académica del programa de doctorado en Economía y Empresa	

RESUMEN (en español)

Motivada por los enormes cambios meteorológicos, extinción de diferentes especies y muertes relacionadas con el cambio climático, es que a lo largo de esta tesis doctoral nos hemos enfocado en las emisiones de gases de efecto invernadero y dado que el consumidor es el principal responsable de la demanda de bienes y servicios y sus emisiones relacionadas, este estudio se enfoca en cómo los cambios demográficos pueden conducir a los hogares a consumir diferente y por lo tanto a tener diferentes niveles de emisión.

Después del capítulo introductorio, en el segundo capítulo se estiman las emisiones derivadas del consumo de cada hogar español entre 1998 y 2018 utilizando bases de datos públicas. Este segundo capítulo enseñará bajo el marco input-output la metodología necesaria para la creación de esta base de datos, además de dar una perspectiva temporal de las diferentes características de los hogares y sus emisiones relacionadas a lo largo de los años. Los resultados de este capítulo señalan la influencia de las características de los hogares en sus niveles de emisión, como lo son los gastos, edad y nivel de estudios. La estimación de esta base de datos es posteriormente utilizada a lo largo de los siguientes trabajos de investigación.

En el capítulo 3, bajo una perspectiva de género y diferentes herramientas econométricas, específicamente la descomposición de Blinder-Oaxaca junto con el estimador de Propensity Score Matching, se quiere analizar si los patrones de emisiones derivados del consumo femenino y masculino son diferentes, además de localizar el tipo de producto que produce estas diferencias. Para esto se han utilizado las bases de datos ya estimadas en el capítulo anterior y dada la falta de información a nivel individual es que utilizamos la información de los hogares unifamiliares españoles entre 1998 y 2018. Los resultados señalan que los hogares unifamiliares femeninos emiten significativamente menos por euro consumido que los hogares unifamiliares masculinos, cuyas diferencias se ven explicadas principalmente por el uso diferenciado de los productos relacionados con el transporte privado en los hogares masculinos.

Dado los resultados de este capítulo es que en el capítulo 4, utilizando las mismas técnicas econométricas que en el capítulo anterior, se analiza si estas diferencias de género influyen en cambios demográficos como es el caso de un aumento de sustentadoras principales mujeres que se ha visto sobre todo en el mundo occidental. En este caso, y dada la carga computacional por la cantidad de hogares, es que se estiman las diferencias utilizando todos los hogares de los años 1998, 2008, 2014 y 2018 independientemente, y no perder así el carácter temporal. Los resultados señalan que los hogares con sustentadoras principales femeninos emiten significativamente menos por euro consumido que los hogares con sustentadores principales masculinos. Esto se ve explicado, nuevamente, por el uso diferenciado de los hogares con sustentador principales masculinos en productos relacionados con el transporte privado.

Finalmente, dado los enormes esfuerzos políticos e importancia de las ciudades en cuestiones medio ambientales, es que en el capítulo 4 se presenta una modificación del Modelo General de Máxima Entropía, que utilizando bases de datos públicas estima las emisiones derivadas del consumo de los hogares a nivel municipal de España. Para esto se han utilizado nuevamente las bases de datos estimadas en el capítulo 2 agregando la información del censo poblacional que nos entrega el nivel geográfico de municipios, forzándonos al mismo tiempo a utilizar el año 2011. Los resultados señalan que, en cuanto a las emisiones directas, los municipios que rodean las grandes ciudades son altamente emisores en promedio, mientras que cuando analizamos las emisiones indirectas, las grandes capitales toman un rol fundamental, donde encontramos patrones geográficos mayormente relacionados con los ingresos de los hogares.

RESUMEN (en Inglés)

Motivated by the enormous meteorological changes, extinction of different species and deaths related to climate change, it is that throughout this PhD thesis we have focused on greenhouse gas emissions and given that the consumer is the main responsible for the demand of goods and services and their related emissions, this study focuses on how demographic changes may lead households to consume differently and therefore to have different emission levels.

After the introductory chapter, the second chapter estimates the emissions derived from the consumption of each Spanish household between 1998 and 2018 using public databases. This second chapter will teach under the input-output framework the methodology necessary for the creation of this database, as well as giving a temporal perspective of the different characteristics of households and their related emissions over

the years. The results of this chapter point to the influence of household characteristics on their emission levels, such as expenditure, age, and education level. The estimation of this database is subsequently used throughout the following research papers.

In chapter 3, using a gender perspective and different econometric tools, specifically the Blinder and Oaxaca decomposition together with the Propensity Score Matching estimator, the aim is to analyse whether the patterns of emissions derived from female and male consumption are different, as well as to locate the type of product that produces these differences. For this purpose, we have used the databases already estimated in the previous chapter and given the lack of information at the individual level, we use the information of Spanish single-family households between 1998 and 2018. The results indicate that female single-family households emit significantly less per euro consumed than male single-family households, the differences being mainly explained by the differentiated use of products related to private transport in male households.

Given the results of this chapter, Chapter 4, using the same econometric techniques as in the previous chapter, analyses whether these gender differences influence demographic changes such as the increase in female main breadwinners that has been seen especially in the Western world. In this case and given the computational burden due to the number of households, the differences are estimated using all households from the years 1998, 2008, 2014 and 2018 independently, so as not to lose the temporal character. The results show that households with female main breadwinners emit significantly less per euro consumed than households with male main breadwinners. This is again explained by the differentiated use of male main breadwinner households in private transport-related products.

Finally, given the enormous political efforts and importance of cities in environmental issues, Chapter 4 presents a modification of the General Maximum Entropy Model, which, using public databases, estimates emissions from household consumption at the municipal level in Spain. For this purpose, the databases estimated in chapter 2 have been used again, adding the information from the population census that gives us the geographical level of municipalities, forcing us at the same time to use the year 2011. The results show that, in terms of direct emissions, the municipalities surrounding large cities are high emitters on average, while when we analyse indirect emissions, the large capital cities play a key role, where we find geographical patterns mostly related to household income.

SR. PRESIDENTE DE LA COMISIÓN ACADÉMICA DEL PROGRAMA DE DOCTORADO

EN ___________________

A el Toro, porque en lo único que ha tenido fe es en sus hijas, siendo un leal y devoto creyente. A la flaca, por traerme al mundo, alimentarme y educarme, porque lo que más me gusta de mí es que me parezco a ti (Pascualina, 1995). A la mayor, por la inspiración, y por ser un gran modelo a seguir, muchas veces inalcanzable. A la menor, por venir al mundo a toda costa, por venir aquí, por llenar mi vida de formas y colores, por ser la amiga que andaba buscando.

A los sabios maestros, por los cafés, comidas y alguna que otra cerveza, por las charlas intelectuales y las no tanto, por la confianza y paciencia, pero sobre todo por el traspaso de conocimiento que a día de hoy ha permitido que escriba mi primer libro.

A la perra de la calle, por sacarme a pasear, llenarme de endorfina y lamer mis heridas. A espalda plateada, por apoyarme y soportarme, por nunca dejar de creer en mí y en mis capacidades, por las risas, bailes, cantos y llantos. Por todo, por la vida que se avecina juntos.

A la madre naturaleza.

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INTRODUCTION

1. MOTIVATION

It is difficult to ignore the effect of climate change, especially the effects of global warming, which is one of the main challenges facing society today. Concern about the relationship between the environment and the economy has grown in recent decades, not only in the scientific community but also in the political arena. This global environmental concern is directly associated with the large number of environmental catastrophes around the world related to global environmental impacts and also with important consequences directly affecting citizens.

Global warming does not simply imply a few degrees warmer on earth given that temperature changes vary geographically and tend to be greatest during the coldest months (Easterling et al., 1997). The extraordinarily hot and cold temperatures that are becoming more common as climate change accelerate are responsible for 5 million deaths globally every year, and while most deaths have been caused by exposure to the cold, the trend is likely to reverse as the planet warms (Zhao et al., 2021), where nowadays 40% of the heat-related deaths are caused by climate change (Vicedo-Cabrera et al., 2021) and this incidents will be highest in the Southern Europe, where its temperature is also expected to increase most rapidly (IPCC, 2022a). Changes in precipitation have also occurred (Trenberth, 2011), where in the north of Europe strong rains caused rivers to burst their banks and wash away buildings in Belgium and Germany and at least 1,300 remained missing (Eddy, 2021), without forgetting respiratory diseases and premature death related to greenhouse gases exposure (Sario et al., 2013).

Household consumption drives modern economies, but unsustainable consumption, production, and resource exploitation have led to multiple crises that threaten the future survival of humanity (Munasinghe, 2010). One of the keys to combating climate change is to involve the consumer as part of the solution. Munasinghe, et al. (2009) expose the role of sustainable consumers and producers, where consumer action can achieve both improved living standards and rapid reduction in carbon emissions, more rapid than can be achieved by governments alone. This work aims to contribute to this line of research, not only providing information on the role played by private consumption in the generation of gas emissions but also studying how different household characteristics explain greenhouse gas emissions locally and globally. More specifically, the thesis presented here follows as strategy a particular case of study, which is the analysis of gas emissions generated as direct and indirect consequence of the consumption of the Spanish household in recent years.

The case study takes place in Spain, which is one of the countries most affected by climate change resulting in large droughts and rising temperatures (Brunet et al., 2007; Noguera et al., 2020). Additionally, it is committed to the different environmental goals and having as one of the objectives to reduce greenhouse gas emissions in 2030 by at least 55% compared to 1990 (Spanish Government, 2022). Moreover, as the fifth most populous country in the European Union, the weight of its inhabitants in climate change responsibility is crucial, where its demographics changes over time, urban areas, and the mainstreaming of women in different spheres should be studied.

This thesis is intended to find empirical evidence that can be used to answer research questions related to the emissions derived from household consumption under different demographic perspectives. To this end, the first chapter presents the estimated databases of emissions derived from the consumption of each Spanish household between 1998 and 2018, where, in addition to presenting and highlighting the potential of the databases, the three main research work developed throughout this thesis arise from here: *Investigating the effect of gender in greenhouse gases emissions patterns*, *Investigating the effect of female breadwinner households in greenhouse gases emissions patterns*, and *Estimation of household emissions at the Spanish municipal level*.

It is important to mention that this study considers indirect emissions from the industrial process necessary to create goods and services, as well as direct emissions from both private car use and the use of gases and other energy goods within the household. While indirect emissions from the industrial process can be located in different geographical areas depending on where different industries are located, direct emissions are those related to local emissions as these are produced at the time of consumption (IPCC, 2022b). Consumer-driven policies tend to focus on local emission reductions, such as energy performance of buildings around all the European countries or Bonus-Malus vehicle incentive system in France (BIO Intelligence Service, 2012). However, indirect emissions are those that provide the largest amount of greenhouse gases (Herendeen and Tanaka, 1976), and it is important to focus on policies that make individuals aware of the responsibility of each product and service they consume and the effect locally and globally (Moran, et al., 2018).

One of the objectives of this work is to study differences in emission patterns between women and men. It should be clarified that the databases used throughout this thesis only allow us to know the «sex» of the individual, a term used to specify purely biological issues, while «gender», although absent in the surveys, will be the term mostly used in this work as it analyses issues of socialisation (Rippon, 2019), as in this case is the purchase of different goods and services under the shadow of "pink" and "blue". The purpose of the title: *Pollution from Spanish households' consumption through space, time, and gender dimensions* is to recognise that the environmental effects of consumption under social processes are observed.

The gender perspective in environmental studies is related in a number of ways. From the 1970s onwards, academics began to theorise the relationship between gender roles and attitudes towards nature inspired by rural women actively resisting deforestation in the global south (MacGregor, 2017; Resurreción, 2017) followed by analyses linking gender and climate change, where women are not only victims derived from their low-income levels but also as agents of change, where they are more resilient, willing to change behaviour, adopt environmental measures, and live more sustainably (Johnsson-Latham, 2007).

The first of the objectives under this perspective is to clarify whether there are differences in the patterns of emissions derived from consumption given purely by gender effects, motivated by the need for studies, programmes and adaptation policies under this approach (OECD, 2021). Secondly, the environmental impact of a structural change within Spanish households is analysed. Derived from an increase in the participation of female labour force in the labour market and their higher levels of education, the number of households with female main providers is increasing, which means that they are the main source of household income, commonly called *breadwinners*. In other words, differences in emission patterns between households with female breadwinner households and male breadwinner households are studied. For both cases, emissions are analysed both in aggregate terms and by product, which allows to identify the type of consumption that is generating the large differences in emissions, providing relevant information for the properly environmental policies focus on consumers.

Finally, given the enormous attention being paid to cities on environmental issues, such as sustainable cities (Wheeler, 2000), energy efficiency in dense areas (Owen, 2004; Chester et al., 2013) and the idea that cities play an important role and have the potential to reduce global greenhouse gas emissions. (Dodman, 2009; Sassen, 2010), different local policies have been put in place (European Commission, 2022). However, in the absence of data, these urban-environmental policies are difficult to assess their environmental effectiveness and have focused too much on city boundaries (Angelo and Wachsmuth, 2020), when a broadening of this boundary would offer a spatially and socially inclusive view of urban futures and the environment (Wachsmuth et al., 2016). Under this perspective, the last chapter of this PhD thesis proposes a methodology to overcome the limitation of small-scale geographical data, which allows obtaining the detail of the emissions derived from the consumption of Spanish cities and small and medium-sized urbanisations.

2. OBJECTIVE

The main objective of this research is to study over the years how household's demographic changes affect their consumption patterns and therefore their emission patterns. This leads to the following four self-contained essays that study the relation between consumers and greenhouse gases, where in chapter 1 the emissions derived from Spanish household's consumption between 1998 and 2018 are estimated, which allows us to observe not only the historical change in emissions from consumption but also gives signals on issues such as age, level of education and expenditure level. From the estimated databases the research options are extensive and varied, focusing throughout this thesis on regional and gender issues. Chapters 2 and chapter 3 studied the gender-related environmental effect and the impact of female breadwinner's households. Chapter 4, a methodological proposal for estimating emissions from consumption at the municipal level is presented, highlighting the importance of cities and other urbanisations.

In order to study the impact of household characteristics on their emission patterns, chapter 1 details the methodology, extensions and databases used to estimate the greenhouse gas emissions derived from consumption of each Spanish household. For this purpose, the input-output framework and its environmental extensions are used, as well as the well-known bridge matrices that connect environmental-industrial information at the micro level, such as household budget surveys that provide details of consumption by product for each household. According to our knowledge, this would be the first Spanish longitudinal series of consumption emissions available with these characteristics.

Although consumption-related activities affect the environment in different ways, this study focuses on air pollutants. Specifically, the six greenhouse gases in which carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulphur hexafluoride (SF_6), hydrofluorocarbons (HFCs) and perfluorocarbons (PFCs) are found. The sum of these gases is homogenised under the unit of kilograms of equivalent CO_2. Therefore, the estimated database presented throughout chapter 1 provides the total of six greenhouse gases measured in kilograms of equivalent CO_2, emitted across 62 industries, and derived from each Spanish household's consumption of 39 product categories between 1998 and 2018. Moreover, the estimates consider both indirect emissions from consumption expenditure and direct emissions from household consumption of energy goods.

Chapter 2 examines differences in emissions from consumption given purely gender effects. For this purpose, Spanish one person households are analysed between 1998 and 2018. From the databases estimated in chapter 1, Blinder-Oaxaca decomposition and the Propensity Score Matching estimator are applied. These methodologies allow gender differences to be analysed subject to the other characteristics of the individual. In other words, it isolates the effect of gender from being influenced by, for example, differences in income. Chapter 3, however, aims to analyse whether these gender effects are replicated in other demographic issues, such as an increase in female breadwinner's households, where under the same econometric methodologies the effect of having a female as the main economic provider is isolated. For this case, all households are used for the years 1998, 2008, 2014 and 2018 independently, these years being strongly influenced by characteristic episodes in female employment rates.

In contrast to other studies, chapter 2 adds a more detailed study to the literature, where the effect of gender is isolated through different econometric techniques without the influence of other aspects and characteristics. Chapter 3, as far as it is known, is the first work to investigate the environmental effect female (or male) breadwinner's households. In chapter 2 and chapter 3, information on emission patterns by products is also provided, which makes it possible to show the type of consumption that produces the emission differences.

Chapter 4 develops a methodology according to small variations of the general maximum entropy model to project emissions from consumption at the micro geographical scale. Direct emissions from the consumption of energy goods and indirect emissions related to the inter-industrial process to produce goods and services are estimated independently, being the first Spanish municipal mapping with these characteristics and hence making it able to detect the different consumers/emitters at municipal level. This study is constrained by the latest census databases, so greenhouse gases are projected at the municipal level for the year 2011.

This methodology not only allows the localisation of large urbanisations, as already presented in previous work, but also distinguishes between small and medium-sized localities and is the first micro-level estimate for the emissions of each household, without major assumptions on income distribution or lifestyle. This makes the environmental impact of other urbanisations visible, making it possible to analyse differences in consumption between households, as well as their own demographic changes within each territory.

Some previous results of this PhD thesis have been presented in several national and international conferences, such as *28th International Association for Feminist Economics, 27th International Input-Output Association Conference*, *III* and *IV Seminar for New Academic Researchers*, *IX Conference of the Spanish-Portuguese Association of Resources and Environmental Economics*, *XLVI International Conference on Regional Science*, and *X Conference of the Spanish-Portuguese Association of Resources and Environmental Economics.* Moreover, will be presented at the forthcoming *9th Hispanic American Conference on Input-Output Analysis.* Some ramifications of chapter 1 were published as "Difference by income in pollution patterns in Spanish households" by elperiodico.com on the differences in emissions based on the income levels of Spanish citizens. Work done for Oxfam Intermón and presented at the Madrid Climate Summit. Derivations of chapter 2 were published as a working paper "Who pollutes more? Gender differences in consumptions patterns". (2019). Research Institute of Applied Economics. Working Paper 06(1): 48

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HOME IS WHERE EMISSIONS START FROM: GREENHOUSE GASES EMISSIONS EMBEDDED IN SPANISH HOUSEHOLDS' CONSUMPTION BETWEEN 1998-2018

1. INTRODUCTION

The responsibility of consumers in pollution through their consumption patterns have increasingly attracted the attention of researchers and debates on environmental issues around the world. Household emissions represents the 59% of national emissions in Canada (Maraseni et al., 2015), 74% in the United Kingdom (Baiocchi et al., 2010) and over 80% in the United States (Jones and Kammen, 2011). Household consumption, therefore, is a crucial element in climate change mitigation. Studies relating households' consumption and environmental impact have been increasing since the pioneering work of Herenden and Tanaka in 1976, who under an input-output framework developed the idea that households consume more energy indirectly thought the purchase of goods and services than directly though the consumption of energy itself.

Economic level of households has been defined as one of the main factors that impact the environment (Duarte et al., 2021) and several studies shown a high correlation between household income and energy requirement or emissions (Vringer and Blok, 1995; Pachauri and Spreng, 2002; Reinders et al., 2003; Bin and Dowlatabadi, 2005; Lenzen et al., 2006). However, household demographic characteristics have also a greatly influence in household environmental footprint even more than the household country or city location (Dubois et al., 2019). Demographics changes —including changes in population size, urbanisation, and the size, age, and sex households' composition— have implications on consumption growth and production activities affecting, consequently, the emissions and land use that drive climate change (O' Neil et al., 2001). Population growth is one of the main demographic changes affecting the environment (Ehrlich and Holdren, 1971; Dietz and Rosa, 1997), also influenced by population age —carbon emissions rise as the shares of older people increase (Menz et al., 2012)—, and the level of urbanisation —relating less developed regions with higher environmental impact (Martinez-Zarzoso and Maruotti, 2011)—. So, changes in demographic characteristics of household might have a great potential to reduce environmental impact.

To mitigate energy and environment pressures caused by household consumption, substantial policies have been implemented in many countries, applying mitigation strategies to reduce climate change with financial incentives or subsidies by such means as taxes, support funds, and premiums, and also non-financial incentives such as regulations, standards and prohibitions (Cardenas et al., 2016). Sathaye and Ravindranath (1998) concluded that the implementation of emission policies requires personalised implementation strategies given the specific condition and combination of barriers and actors in each country or region. According to Shamming and Bullard (2009) the carbon emissions of low-income households are primarily for essential needs (housing, transportation, etc.) while high-income households are mainly derived from the consumption of non-energy goods and services; so, any policy instrument directly affecting the cost of energy products would leads to burden more on the poor.

The status of national economy, geographic location, lifestyles, and attitudes should also be considered for policy development (Zhang and Wang, 2017). For environmental policies focus on mitigated climate change, it would be essential to know the carbon or Greenhouse Gases (GHG) footprints derived from consumption among each household. The main objective of this chapter is to describe the methodology and the databases used to estimate the GHG footprint at individual household level for Spain 1998-2018. Besides this technical description, this chapter also shows the evolution and behaviour of GHG emissions derived from Spanish households' consumption over the 20 years by the mean households' economic and demographic characteristics. This work is not intended to answer a research question or hypothesis, but rather to present in detail the estimated databases that are used in the following chapters and to promote the database potential.

The study focuses on Spain over two decades, from 1998 to 2018, which allows for a longitudinal analysis of the different social and economic developments that the country has undergone over the years. Even before 1998 Spain was going through an expansionary phase of its economy. Due to the introduction of the euro as a unitary currency (Gil et al., 2003) and an increasing demand for employment in the construction sector and some basic services (Alonso and Furió, 2010), Spain's annual GDP growth rate between 1998 and 2007 ranged between 2.7% and 5.2% (World Bank, 2022), which only came to a halt with the financial crisis of 2008 (Padros de la Escosura and Sánchez-Alonso, 2020). Since 2008, the Spanish economy suffered a fall in its macroeconomic indicators (Ortega and Peñalosa, 2012), giving way to a period of recession and crisis which only recovered from 2014 onwards, only to be halted again by the crisis caused by the COVID in 2020 (Hernández de Cos, 2021). Therefore, given the enormous changes that Spain has undergone over the years, it is of interest to study the economy's impact on demographic issues as well as environmental effects.

The data used in this chapter is based on three different resources provided by the Spanish Statistical Agency (INE) and extra information obtained from Denmark Statistik (2019) and Cazcarro et.al., (2021). GHG footprints of each Spanish households between 1998-2004 and 2006-2018 are estimated. A total of 6 GHGs aggregated into CO_2 equivalent units, 62 industries, and 39 products under the Classification of Individual Consumption by Purpose (COICOP) grouped into 12 products categories are considered. Following Wilting et al. (1998), Serrano (2008), and Liu et al. (2021), total household emissions include direct emissions produced by using motor fuels and natural gas, and indirect emissions embedded in the production of goods (food products, clothes, etc.) and services (insurance, public transport, etc.) purchases by households.

The chapter is structured as follows. Section 2 briefly reviews the methodology used to estimate all, direct and indirect, emissions of GHGs embedded in consumption of each Spanish household. Section 3 describes the Spanish database and the needed arrangements to compute the emissions from households' consumption. Section 4 presents the most relevant results and Section 5 summarizes some conclusions.

2. METHODOLOGY

This section aims to show the methodology used to estimate the emissions associated with each household's consumption. This study includes the estimation of indirect GHG emissions derived from consumption expenditure as well as direct emissions from household consumption of energy goods. In other words, I considered GHG emissions produced by buying a car in which indirect inter-industry pollution is considered for producing that good; but also, direct GHG emitted in the process of burning fuels to run that car.

Following Roca and Serrano in 2007 and Eriksson et al. in 2021, direct and indirect emissions of each household ($\mathbf{GHG_{hxp}}$) are defined as a function of h[1] different GHG gases and p different COICOP products as in equation 1.1.

$$\mathbf{GHG} \quad = \mathbf{F} \;\; \mathbf{L} \;\; \mathbf{B} \;\; \hat{\mathbf{c}} \quad + \mathbf{E} \;\; \hat{\mathbf{c}} \quad = \mathbf{M} \;\; \hat{\mathbf{c}} \quad + \mathbf{E} \;\; \hat{\mathbf{c}} \tag{1.1}$$

Direct emissions from households are calculated by $\mathbf{E} \;\; \hat{\mathbf{c}}$, being $\mathbf{E_{hxp}}$ the intensity matrix of direct household emissions, whose elements e_{hp} represent the direct emissions of pollutant h associated with each monetary unit spent on a consumption purpose p, and $\mathbf{c_{px1}}$ represents the expenditure on each of the p COICOP products (see Annex A1.1) from the household consumption basket. Under COICOP classification direct household emissions derives from the consumption of 4.5: "Electricity, gas, and other fuels" and 7.2: "Operation of personal transport equipment". The estimated direct emissions work under the restrictive assumption that one monetary unit spent on any energy good generates the same direct emissions.

Indirect GHG emissions from households' consumption are calculated by $\mathbf{M} \;\; \hat{\mathbf{c}}$ where $\mathbf{M_{hxp}}$ matrix ($\mathbf{M} \quad = \mathbf{F} \;\; \mathbf{L} \;\; \mathbf{B} \;\; \hat{\mathbf{c}}$) summarizes the multiplier effect of emissions defined as indirect emissions generated by a monetary unit spent on each product in the consumption basket of each household. In this expression, $\mathbf{F_{hxn}}$ is the emission coefficient matrix that represents the amount of each of the h atmospheric pollutants generated by one unit of product of industry n. Each element of matrix $\mathbf{F}$ are defined as $f_{hj}=\delta_{hi}/x_j$, where δ_{hi} is the total

[1] Matrices are indicated by bold, upright capital letters; vectors by bold, upright lower-case letters; and scalars by italicized lower case letters. Vectors are columns by definition, so that row vectors are obtained by transposition, indicated by a ^{T}. A circumflex indicates a diagonal matrix with the elements of any vector on its diagonal and all other entries equal to zero.

amount of each atmospheric gas, measured in physical units, emitted by each industry (see section 3.2 in this chapter). $\mathbf{L_{nxn}}$ is the Leontief inverse matrix defined in equation 1.2:

$$\mathbf{L}_{nxn} = (\mathbf{I} - \mathbf{A})^{-1} \tag{1.2}$$

$\mathbf{L_{nxn}}$ is the most useful and powerful tools in input-output analysis since it represents all sectoral interdependencies, revealing indirect effects within the economy. Each element l_{ij} denote to the total output indirectly necessary from sector i to satisfy an extra unit of final demand from sector j. The Leontief inverse matrix is obtained under the domestic assumption. **I** as the identify matrix in the appropriate dimension. $\mathbf{A_{nxn}}$ represents the total technical coefficients matrix recording the economic technology. Each element of matrix **A** represents the amount of input from sector i per unit of product of sector j, and they are defined as $a_{ij} = z_{ij}/x_{ij}$ where z_{ij} are the elements of the inter-sectorial transaction matrix that describe the deliveries through industries.

$\mathbf{B_{nxp}}$ is a composition matrix of aggregated commodity of consumption that relates n products under Classification of Products by Activity (CPA) with p COICOP products (see section 3.4 in this chapter). Matrix **B**, also called bridge matrix, is essential to the analysis since it allows us to connect macroeconomic data classified by industries (or products by activities) —such as matrices **L** and **F**— with data classified by consumption purposes —such as the information from microeconomic databases from vector **c**, that represents the expenditure on each of the p COICOP products.

Due to matrix **B** characteristics, GHG emissions embedded in consumption are calculated at two-digit COICOP detail. Afterwards, however, results are aggregated at one-digit COICOP level for illustration purposes. Because of this aggregation, the outcomes not just depend on the expenditure on each product at two-digit COICOP level, but also to the expenditure distribution on each product within the group at one-digit COICOP level. $\mathbf{GHG_{hxp}}$ is the results considering all the above, of the aggregated six **GHG** in equivalent CO_2 unit.

3. DATA SET AND DATA ARRANGEMENTS

This section details the data used to build a longitudinal series of the 6 GHG emissions derived from Spanish households' consumption basket from 1998-2004 and 2006-2018. The estimated database includes the GHG footprint of the consumption basket composed by 39 COICOP products (see Annex A1.1) of a total of 348,989 households (approximately 17,450 per year) considering the demographic and economic characteristics of each household. The footprint estimation contains indirect GHG emissions derived from consumption expenditure as well as direct emissions from households' consumption of energy goods.

The INE compiles official and open data required to produce the above-mentioned information. This section is dived in five subsections: Section 3.1 gives a brief review of both the Supply and Use Tables (SUT, INE, 2019a) and Input-Output Tables (IOT, INE, 2019b) with the steps implemented to manage these cross-industry matrices. Section 3.2 presents the Atmospheric Emissions Accounts (INE, 2019c) and the procedure to obtain the data at the product-by-product level. Section 3.3 summarises the efforts to manage the longitudinal series of the Household Budget Survey (HBS, INE, 2019d). Section 3.4 presents the Bridge Matrix (BM, Denmark Statistik, 2019; Cazcarro et al., 2021) that connects the macroeconomic indicators given by the IOT and atmospheric emissions accounts with the microdata from HBS. Finally, Section 3.5 provides a brief overview of the RAS technique and its extensions used for data reconciliation needed in some previous sections.

3.1 Supply and use tables and input-output tables

The input-output framework of the European System of Accounts (ESA) consists of three types of tables: supply table, use table and the IOT. The SUT is a statistic summary that provides a complete description of the production process and the resource-employment balance of the national economy at the output level. In other words, it provides a detailed picture of the supply of goods and services by domestic production and imports, and the use of goods and services for intermediate consumption, final use, as well as the value added generated in the production process (income or rents paid to primary production factors).

The SUT relate products and industries and form the basis for deriving IOT when needed by applying certain assumption explained below. The classification used for industries is the

General Industrial Classification of Economic Activities within the European Communities (NACE) and the classification employed for products is the CPA. The IOT is, otherwise, classified in accordance with the SUTs, as the former is a transformation of the latter.

IOT are a summary statistic directly built by statistical offices or derived from the SUT when the IOT is not provided. The IOT presents an exhaustive description of the productive process and the resource-employment balance of the national economy at the product level for homogeneous branches of activity. It assumes a single-product output and are the basis for input-output analysis and necessary to compute the Leontief inverse matrix specifies in equation 1.1

Spanish SUT are annually provided by INE between 1995 and 2018. The Spanish IOT is calculated for 1980, annually from 1985 to 1994, and from 1995 each year ending in 0 or 5, except for the latest update which includes the IOT for 2016 under the 2019 revision. Over the years, the accounting base changed periodically to update weightings measurements as well as to introduce some methodological variants. Accordingly, I estimate an annual series of IOTs from SUTs at different levels of aggregation for the years between 1998 and 2018 (See Annex A1.2 for details), except for those already available at INE, with a total of twenty Spanish IOTs.

To compilate IOT are needed some analytical steps. For the transformation of SUT into IOT, some assumptions must be made, and adjustment are required. The format of an IOT can either be made based on an industry-by-industry or product-by-product classification and can be based on four basic assumptions (Eurostat, 2008, p.347). The most suitable case for this analysis is the product-by-product IOT under the product technology assumption (Model A). This technique assumes that each product has been produced in its own specific way, irrespective of the industry or sector where it is produced.

Figures 1.1 and 1.2 show the general supply and use table’s structure.

Figure 1.1: Structure of a supply table

	Industries	Supply
Products	$\mathbf{V^T}$	$\mathbf{q}$
Output	$\mathbf{g^T}$	

Source: Eurostat (2008, p.348)

Figure 2.2: Structure of a use table

	Industries	Final demand	Use
Products	$\mathbf{U}$	$\mathbf{Y}$	$\mathbf{q}$
Value Added	$\mathbf{W}$		$\mathbf{w}$
Output	$\mathbf{g^T}$	$\mathbf{y}$	

Source: Eurostat (2008, p.348)

$\mathbf{V^T}$ represents the supply matrix product by industries. $\mathbf{g^T}$ is a row vector of industries output. $\mathbf{q}$ represents the column vector of product output. **U** denotes the use matrix for intermediates product by industries. **W** represents the value-added matrix by industries and **w** the value-added column vector. **Y** and **y** are the matrix and row vector of final demand.

The IOT product-by-product is therefore expected to be obtained as shown in Figure 1.3 following the next mathematical steps from equation 1.3 to 1.9.

Figure 3.3: Input-output table – product by product

	Product	Final demand	Output
Products	$\mathbf{S}$	$\mathbf{Y}$	$\mathbf{q}$
Value Added	$\mathbf{D}$		$\mathbf{w}$
Input	$\mathbf{q^T}$	$\mathbf{y}$	

Source: Eurostat (2008, p.348)

$$\mathbf{T} = (\mathbf{V^T})^{-1}\hat{\mathbf{q}} \tag{1.3}$$

$$\mathbf{A} = \mathbf{U}\,\mathbf{T}\,(\hat{\mathbf{q}})^{-1} \tag{1.4}$$

$$\mathbf{R} = \mathbf{W}\,(\mathbf{V^T})^{-1} \tag{1.5}$$

$$\mathbf{q} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y} \tag{1.6}$$

$$\mathbf{S} = \mathbf{U}\,\mathbf{T} \tag{1.7}$$

$$\mathbf{D} = \mathbf{W}\,\mathbf{T} \tag{1.8}$$

$$\mathbf{Y} = \mathbf{Y} \tag{1.9}$$

Despite the data in SUT is given in purchase and basic prices, the resulting IOT satisfy the pricing homogeneity assumption by generating all elements at basic prices (Eurostat, 1996; United Nations, 1999). This method is, however, likely to give some negative values that require the application of numerical algorithms to adjust it. One of these methods is the bi-proportional RAS technique (see section 3.5 in this chapter for details).

3.2 Atmospheric Emissions Account

The atmospheric emissions accounts are a multi-purpose data system that encompasses a conceptual framework and tables describing the interrelationships between the economy and the environment in a manner consistent with the national accounts. In other words, they are an extension of the IOT which makes them consistent with the Leontief model.

INE classifies the activities and sectors of these accounts following the ESA. As in the National Accounts they follow the residence principle, so they account for the emissions of pollutants into the atmosphere generated by the activities of all resident units, regardless of the geographical location in which these emissions are produced. These accounts record the flows of gases and particulates from the national economy into the atmosphere.

The Spanish atmospheric emissions accounts are organized annually. There is information from 1995 to 2019 and an extension for 2020. These accounts should be updated periodically to incorporate relevant methodological and statistical changes, especially changes in the economic accounts base. The pollutants and sectoral level vary according to the base year of reference. Given the longitudinal series, I have worked with different levels of disaggregation to harmonise with the rest of the databases. The economic sectorial information is prepared by adapting the data to the NACE classification and varies given the changes in the economic bases. Table 1.1 summarises the number of different economic sectors and different pollutants available in the atmospheric emissions accounts over the years (more details in Annex A1.2 and Annex A1.3).

Table 4.1: Number of economics sectors and pollutants available in atmospheric emissions accounts. Spain 1998-2018

Years	Number of economics sectores	Number of pollutants
1998-2003	37	12
2004-2007	27	12
2008-2018	63	13

Source: Own elaboration

For the purposes of this study, I use the 6 pollutants related to GHG. Specifically, carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulfur hexafluoride (SF_6), hydrofluorocarbons (HFCs), and perfluorocarbons (PFCs), measured in thousands of tons of equivalent CO_2 (then transformed into kilograms of equivalent CO_2), disaggregated into the different economic activities and households as final consumers. Between 1998 to 2007 the CH_4, N_2O, SF_6, HFCs and PFCs were not available in the equivalent CO_2 unit, so accordance with the global warming potential (GWP100) of each gas as established by the IPCC (IPCC, 1997) the warming potential of CO_2 is equivalent to 1, whereas it is 21 for CH_4, 310 for N_2O, and 23,900 for SF_6. The HFCs and PFCs are grouped by different gases, and for this reason, they do not have one conversion factor. Since NAMEA database does not report information for different gases of HFCs and PFCs groups, I estimate a specific GWP100 for those two groups. For doing so, I have considered the information supplied by Spanish national greenhouse gas inventory report (2020) about emissions and GWP100 of all HFCs and PFCs related gases, and I calculated a warm potential for HFCs and PFCs based in the weight average of each group.

One of the characteristics of the atmospheric emissions account is that are delivered by industry, while IOT estimates are product-by-product (section 3.1). Therefore, a method to transform the atmospheric information from industries to products is required. Like previous sections and following Eurostat (2008, p.347) I applied the product-by-product classification under the industry technology assumption (Model B). This implies the assumption that each industry has its own specific way of producing atmospheric emissions independently of its product mix. The main reason to apply this strategy was the difficulty to solve the negative values with the RAS technic in this context. Although this approach is not the same as procedure followed for the IOT estimations, it does not get too far from the reality either. See Figure 1.4 and Figure 1.5.

Figure 5.4: Environmental extension of a supply table

	Industries	Supply
Products	$\mathbf{V^T}$	$\mathbf{q}$
Output	$\mathbf{g^T}$	
Emissions	$\mathbf{K}$	

Source: adapted from Eurostat (2008)

Figure 6.5: Environmental extension of a product-by-product input-output table.

	Product	Final demand	Output
Products	$\mathbf{S}$	$\mathbf{Y}$	$\mathbf{q}$
Value Added	$\mathbf{D}$		$\mathbf{w}$
Input	$\mathbf{q^T}$	$\mathbf{y}$	
Emissions	$\mathbf{H}$		

Source: adapted from Eurostat (2008)

Where **K** denote the pollutants matrix by industries and the properly transformation is needed to obtain the pollutants matrix by product **H**. From Figure 1.4 I obtain the transformation matrix applied following equations 1.10 and 1.11.

$$\mathbf{T} = (\hat{\mathbf{g}})^{-1}\,\mathbf{V} \tag{1.10}$$

$$\mathbf{H} = \mathbf{K}\,\mathbf{T} \tag{1.11}$$

Finally, I obtain the GHG related gases of Spain between 1998-2004 and 2006-2018 from the different economic sectors and households as final consumers consistent with the NACE/CPA classification.

3.3 Households budget survey

HBS are national surveys that focus primarily on household spending on goods and services. It provides information on the nature and destination of consumption expenditures, as well as various characteristics of household living conditions. Spanish HBS has evolved in different aspects over the years, such as the type of population considered, the sample size, the level of disaggregation and the data collection system together with the design of the questionnaires.

The years chosen throughout this study are limited by this database. I have found files prior to 1998 —even from 1980— but the format is by quarters with no household tracking. From 1998 to 2004 the series is delivered by quarters, however, a reform was implemented to fulfil the needs of users and the recommendations of the Statistical Office of the European Union and adapted longitudinally, leaving 2005 without longitudinally data available. Since then, the HBS are delivered annually.

Bearing in mind that the objective of the survey is to study household consumption expenditures, the basic units of analysis are private households residing in main family dwelling. Consumption is organized according to COICOP European classification, which structures consumption in 12 large products categories with a level of 39 different products. (See Annex A1.1 for more details). Expenditures in HBS are represented at purchase prices, while IOT and GHG emissions are estimated at basic prices. BM, presented in the next section, allow this problem to be solved. Finally, the monetary flows are computed in pesetas from 1998 to 2000, however an exchange rate of 1: 0.00598 was applied to convert them euros.

INE delivered three types of files: household file, member file and expenditure file. Household file collects data on household characteristics such as household size, composition, and other general information about the residential area —such as autonomous community, size of municipality, population density, etc.—. The members file shows information on all the individuals who are members of the households. Finally, the expenditure file shows, as already mentioned, the expenditure of the households of the different families. HBS over the years varies in its socio-demographic and socio-economic information. To obtain a homogenized database I retain the common variables between 1998-2004 and 2006-2018, moreover, all the information available by year independently is stored. The complete size of the sample are 348,989 households.

3.4 Bridge matrix

The BM allow to connect macroeconomic data classified according to the NACE/CPA classification with microeconomic data following the COICOP classification. Since IOT and atmospheric emissions accounts delivered the information under NACE/CPA classification at basic prices, whereas HBS is delivered under COICOP classification at purchases prices, it is necessary to estimate an annual series of BM that homogenises the different classifications and principles. Since the IOT and the atmospheric emissions accounts, as mentioned above, differ their level of NACE/CPA disaggregation over the years, I estimate BM for each year of interest under six different formats for each range of years: 1998-1999, 2000-2003, 2004, 2006-2007, 2008-2015, 2016-2018 (see Table 1.1 and Annex A1.2).

Spanish BM are not available. Given this lack of data I used, under certain assumptions, the annual Danish BM (Danmarks Statistik, 2019) and the recently Spanish BM for 2010 published by Cazcarro et.al (2020)[2]. On the one hand, Danish BM worked under the assumption that the proportion with respect to the totals of each expenditure is the same as in Spain, but on the other hand, Spanish BM for 2010 (Cazcarro et al., 2020) assume that there have not been great technological changes through time. Both cases RAS method, explained in the next section, was needed to align with the national annual information.

3.5 RAS method

The RAS or bi-proportional adjustment is a well-known method for data reconciliation. Its objective is to achieve consistency between the entries of some matrix and to prespecify the row and column totals (Deming and Stephan, 1940; Bregman, 1967). Leontief (1941) proposes a bi-proportional form for the relationship between the values needed by an input-output matrix at different points in time. But the impetus for its use in the construction of IOT was given by Stone in 1962.

Mathematically, RAS is an iterative scaling method whereby a non-negative matrix is adjusted until its columns sum and row sums equal to some pre-specified totals. It multiplies

[2] Spanish BM by Cazcarro et al. (2020) was not available until 2021, I started working with BMs in 2018. However, a proper comparison has been made between the estimated Spanish BM based on the 2010 Spanish BM by Cazcarro et al. (2020) and the Danish BM and not substantial differences were found.

each entry in one row or column by some factor, that is chosen is such way that the sum of all entries in the row or column becomes equal to its target total. This operation is first applied to all row of the matrix. Therefore, the matrix becomes consistent with all target row total Then, the columns are made consistent with their required totals, however, the constraint on the row totals may be violated again. The rows and columns are adjusted in turn until the algorithm converges to a matrix that is consistent with all required row and column totals (Memobust, 2014).

This technique works under the idea of maintaining the initial proportions to the row and column totals, to preserve the structure of the matrix as much as possible. This means that the initial ratios to the row and column totals are kept as close as possible to those given by the initial matrix.

The RAS method was used to deal with the negative values provided by the product-by-product IOT method (section 3.1). I replaced the negative values with the closest IOT values provided by INE and then balanced with RAS[3] subject to the target values of the year of interest. This technique proved to be the most appropriate after contrast with results under RAS extensions such as GRAS. In section 3.4 this procedure was also needed. Danish BM, however, have some negative values but the information to replace with the corresponding positive values it is not available, therefore, RAS extensions such as Generalised RAS (GRAS) method was implemented (Lenzen, 2007). Specifically, an alternative proposal of Lemelin in 2009 was used, this technique offers a GRAS based on entropy theory minimizing the information required to obtain the objective columns and rows.

[3] In this section I have applied the *ipfp* command of RStudio software.

4. RESULTS AND DISCUSSION

The aim of this chapter is to illustrate the estimated results of Spanish households' emission patterns over the twenty years between 1998-2004 and 2006-2018 considering different household characteristics, as well as showing the potential of the estimated database and the possible future perspectives and studies that could be derived from this chapter.

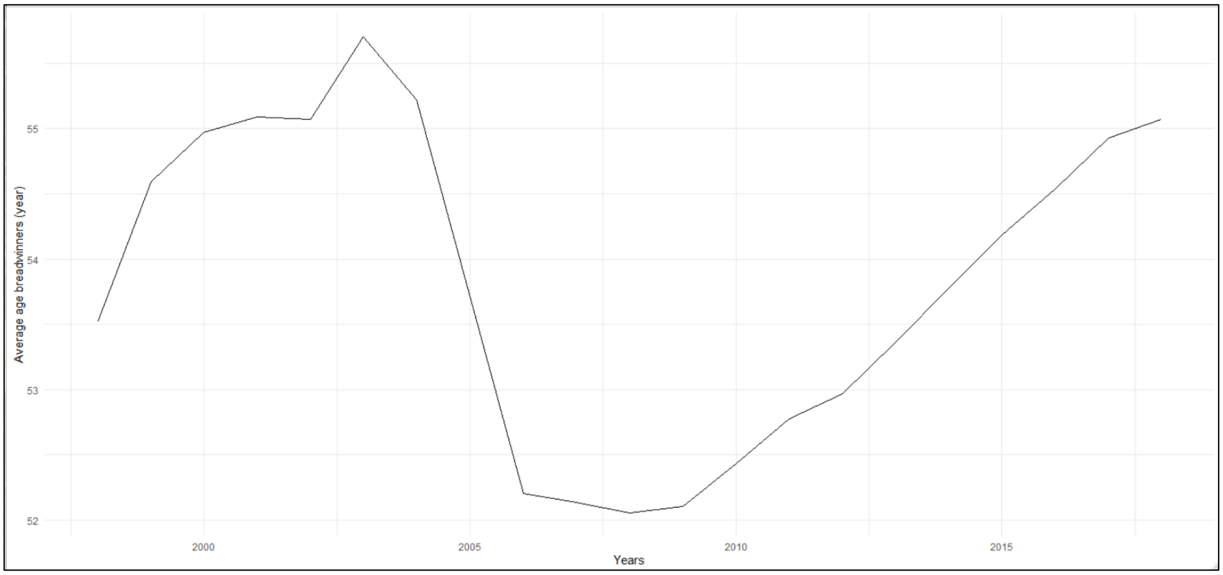
This section is divided intro three subsections. Firstly, HBS information is analysed to contextualise household characteristics (Section 4.1). Secondly, presentation of both indirect emission coefficients of the inter-industrial mechanism to produce each product within the consumption basket and the direct emission coefficients derived from households' consumption of energy goods (Section 4.2). Thirdly, the estimated GHGs emissions measured in kilograms equivalent CO_2 are explored under different perspectives (Section 4.3).

4.1 Household Budget Survey over the years

How have the characteristics of Spanish households changed over the two decades under study from 1998-2004 and 2006-2018? In this section I focused on the age and educational level of the household main breadwinner, the number of members, and level of expenditure of the household.

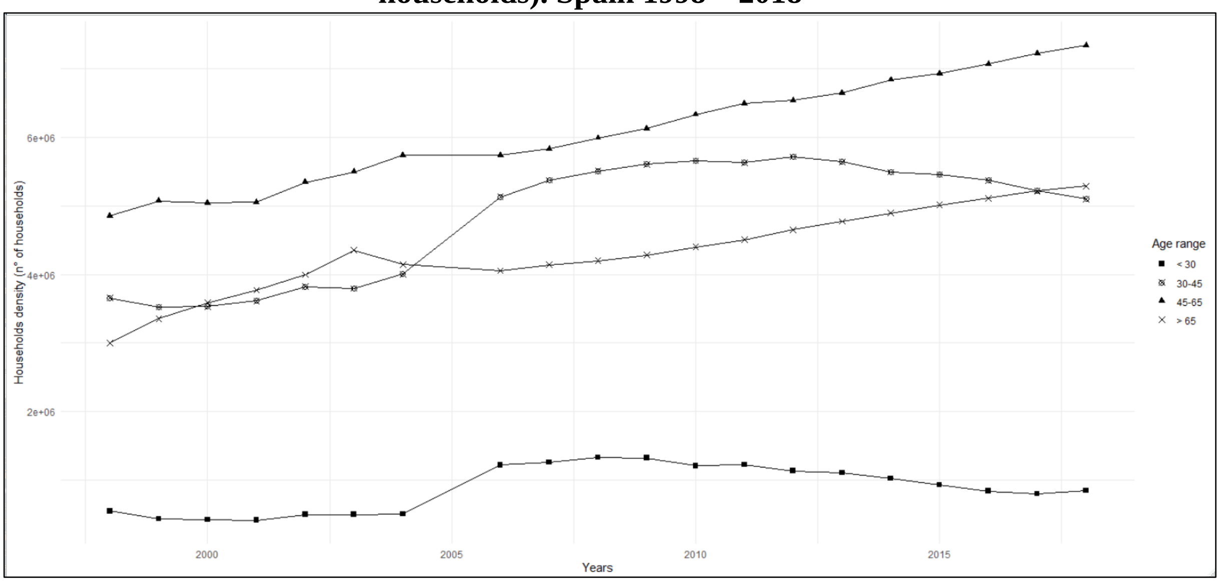
Graphs 1.1 and 1.2 show the average age of household breadwinner and density, measured as the number of households in an age range. Graphs 1.1 indicates that, over the twenty years, the average age of the main breadwinner remained quite constant varying between 52 and 55 years with an average age of 54 years old. Graph 1.2 shows that Spanish households have main breadwinners aged between 45 and 65 years old, this range has a constant growing over the years. From 2004, households with breadwinners between 30 and 45 years old have overtaken the over-65s years old but reversed roles again in 2016. As expected, despite the slight increase from 2006, households with main breadwinners under 30 are the minority.

Graph 1.1: Evolution average age households' breadwinners (years). Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph 1.2: Households densities by age range of household breadwinners (number of households). Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

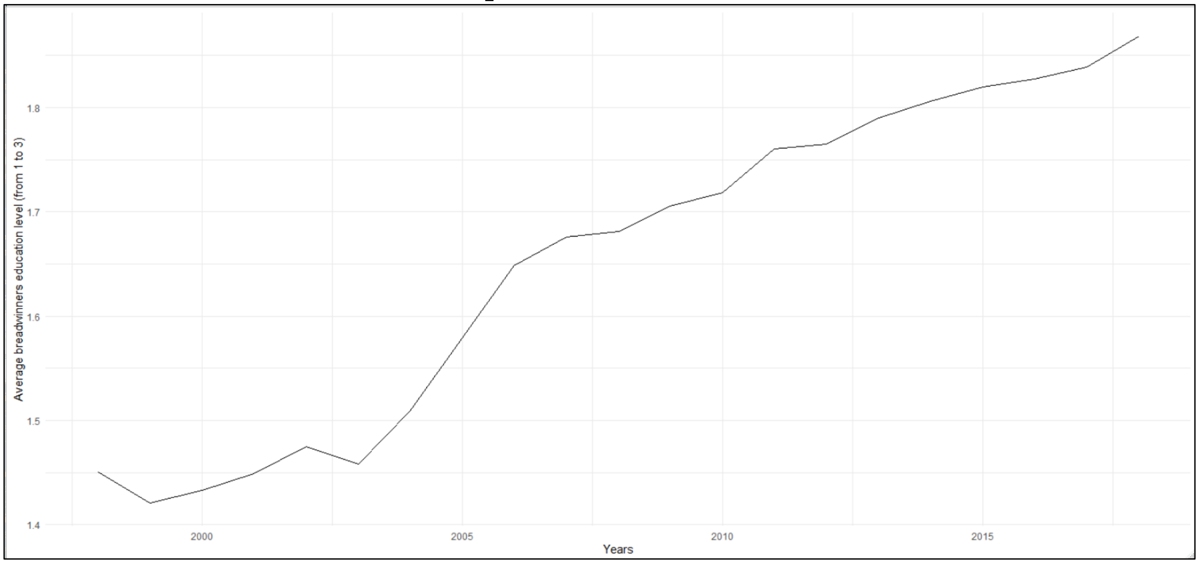
Graph 1.3 presents the breadwinners average educational level over the years and Graph 1.4 the household's density by educational level for the same period. Graph 1.3 shows a clear increase in the average level of education of the households' breadwinners in Spain measured in a scale from 1 to 3 (1 first cycle or less; 2 secondary; 3 university), while education level is a categorical variable their categories are proportional to their education levels, therefore, the "average" gives an a idea about the evolution of educational level of the main breadwinners, well complemented by the density in Graph 1.4, where shows that the highest household's density is found in the least educated group which has remained practically constant over the years. Moreover, it is observing a high growth rate in the number of main breadwinners with a university education.

Regarding the number of members, Graph 1.5 shows the average number of household members and Graph 1.6 de households' density by numbers of members range between 1 to 6 (or more). Graph 1.5 shows a clear decrease in the average number of households members, while from Graph 1.6 it is observed that the households with two members is the most common since 2001, and before the most common households were four member households, which have declined significantly since 2004, being overtaken even by one member households, with one member households being the second most common from 2006 onwards. It follows that there has been a major demographic shift in Spanish households.

Finally, Graph 1.7 shows the average annual households' expenditure and Graph 1.8 by expenditure quintiles. From Graph 1.7 the changes in household spending due to different social and economic events in Spain can be observed, such as the rapid economic growth due to the introduction of the euro, as well as its dramatic decline around 2008 and its recovery from 2014 onwards. Graph 1.8 shows that the highest quintiles are improving their expenditure level faster than other quintiles, and it is twice higher than the second highest quintile and five times larger than the lowest quintiles, gap that has not diminished over the years. Moreover, households within the richest quintiles had greater variability in their expenditures due to economic events, while households in the lowest quintiles remained almost constant. In fact, households in the highest spending quintiles are already affected in

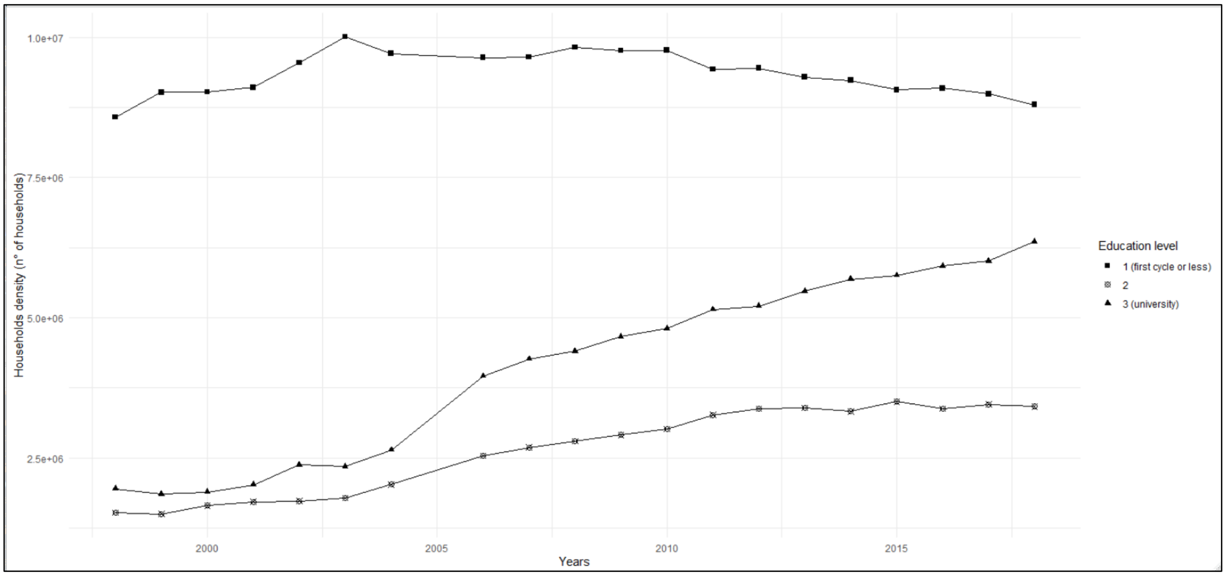
2008, thereafter decreasing their spending faster than the other quintiles. This reproduces that in 2018 inequality in average expenditure does not reach pre-crisis levels.

Graph 1.3: Evolution average education level households' breadwinners (from 1 to 3). Spain 1998 – 2018



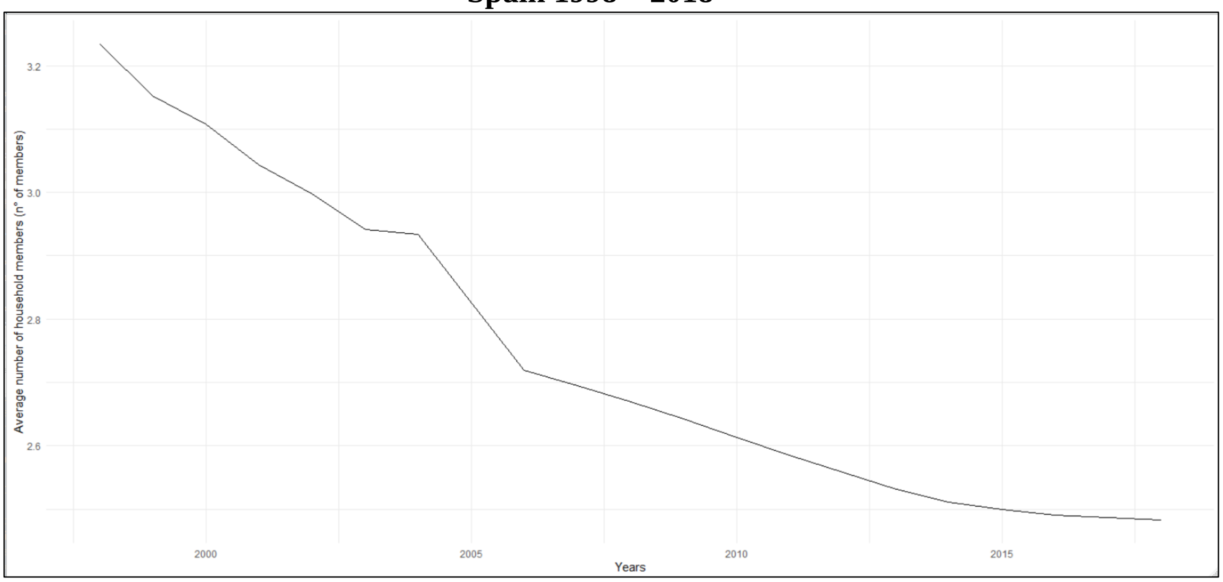
Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph 1.4: Households density by education level of household breadwinners (number of households). Spain 1998 – 2018



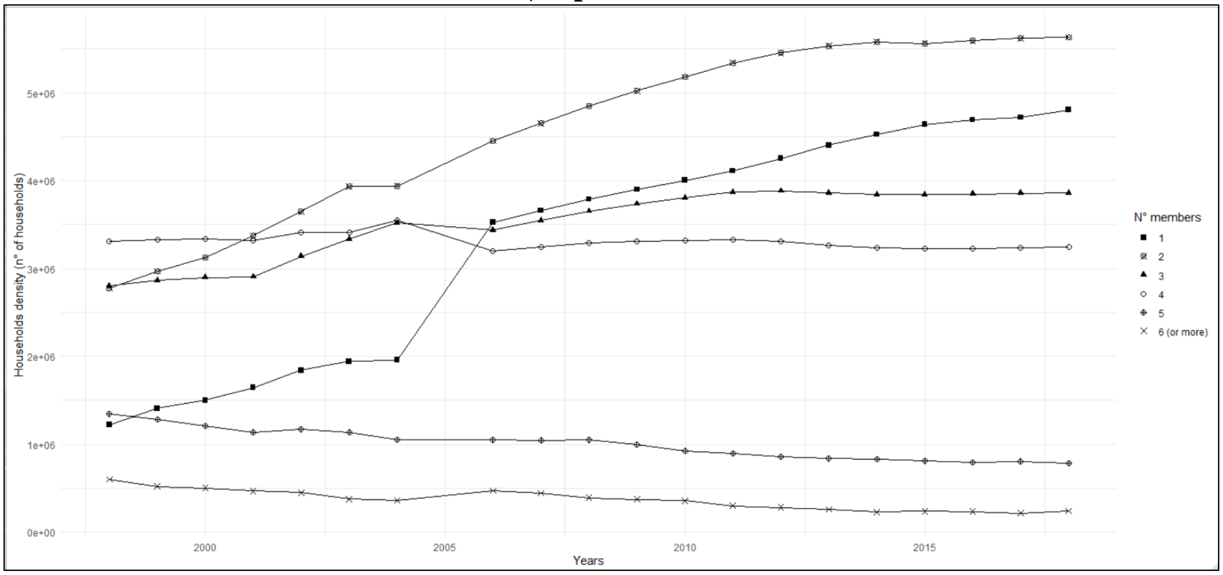
Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph 1.5: Evolution average number of household members (number of members). Spain 1998 – 2018



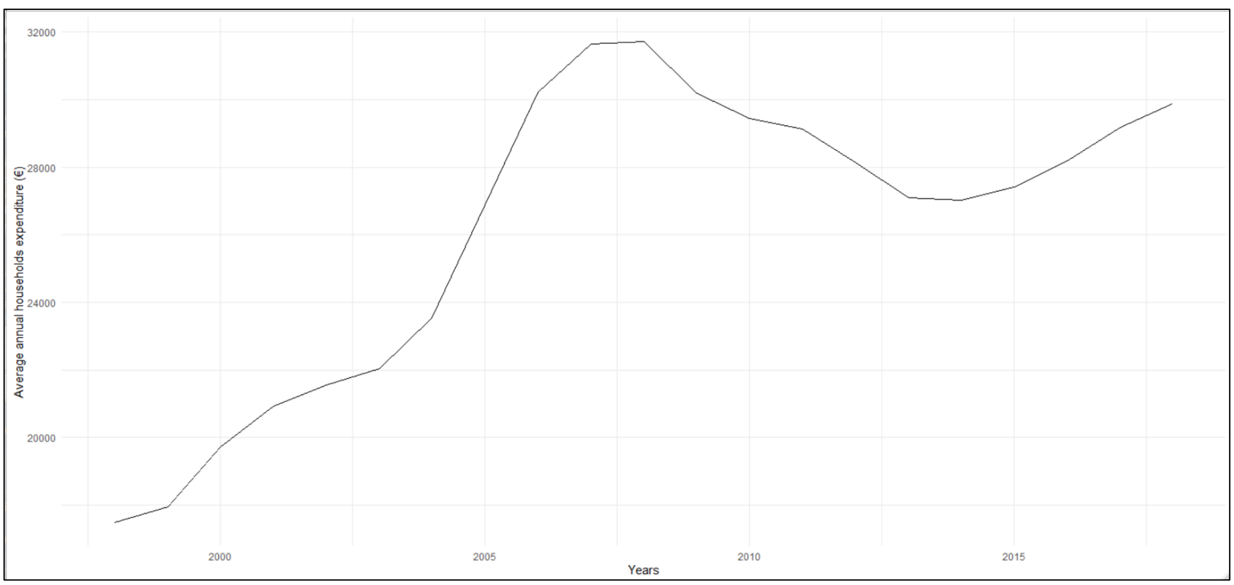
Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph 1.6: Households density by number of household members (number of households). Spain 1998 – 2018



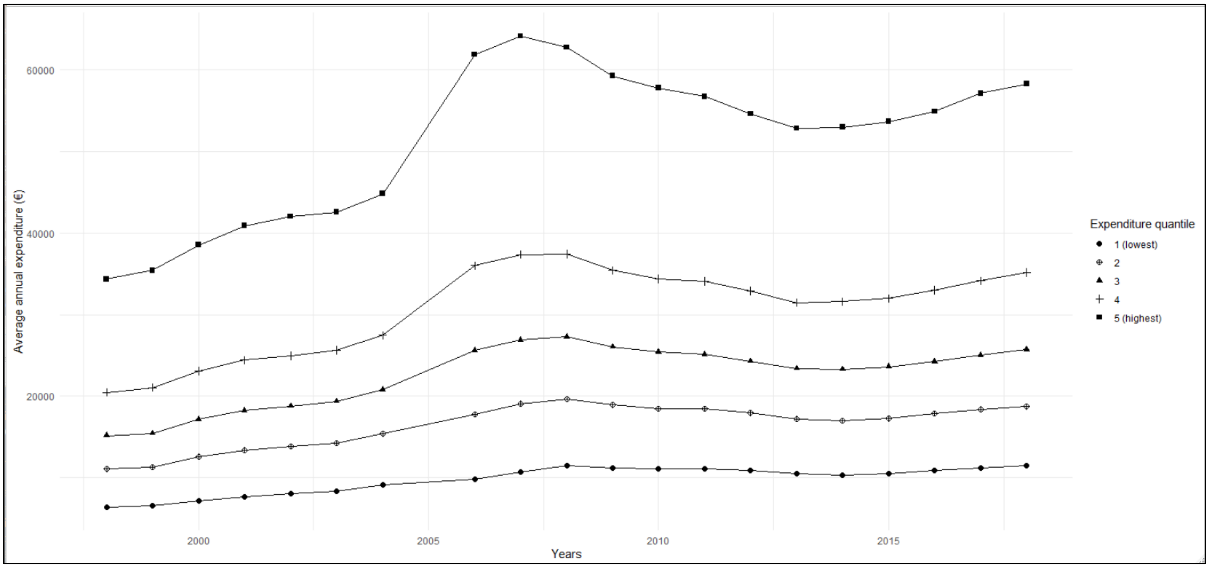
Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph 1.7: Average annual households' expenditure (euros). Spain 1998 - 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph 1.8: Average annual household expenditure by expenditure quintile (euros). Spain 1998 – 2018



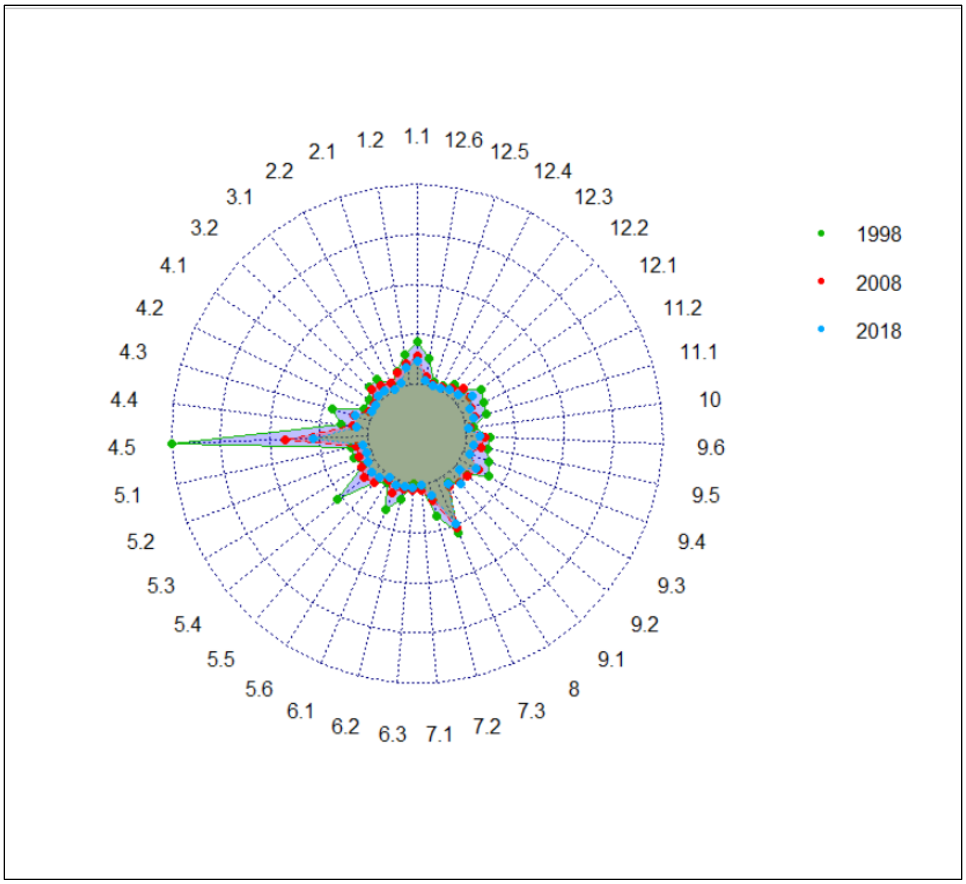
Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

4.2 Emission coefficients

This section has the objective of illustrating the estimated coefficients for both indirect emissions embedded from household consumption expenditure and the direct emissions from households' use of energy goods. These coefficients at COICOP level are constant for all households, allowing to calculate GHG footprints for each household based on their household consumption basket.

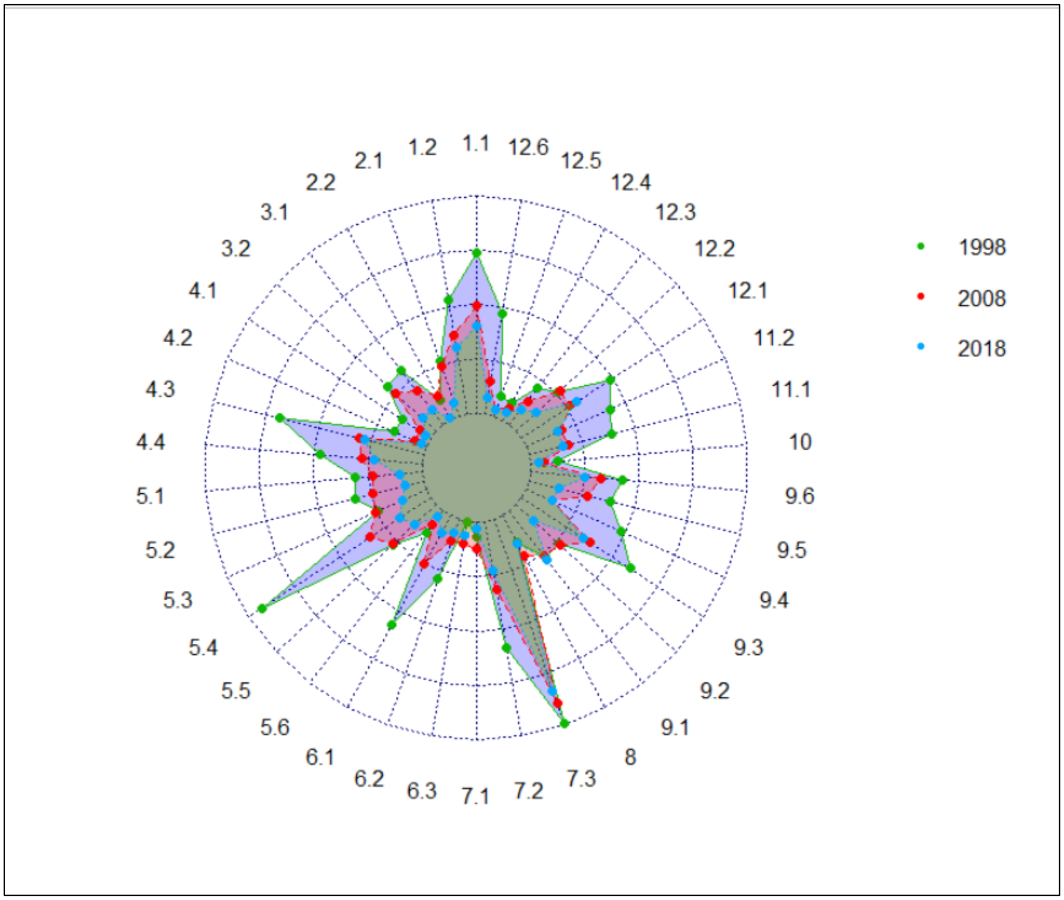
Graph 1.9a and Graph 1.9b (without 4.5 for better visualisation) shows the emissions coefficient derived from the inter-industrial process, illustrated by the matrix **M** in equation 1.1, of 39 COICOP products in 1998, 2008 and 2018. (See Annex A1.4 for details and all years).

Graph 1.9a: Emission coefficient by 39 COICOP products. Spain 1998, 2008 and 2018.



Source: Own elaboration

Graph 1.9b: Emission coefficient by 39 COICOP products (without 4.5). Spain 1998, 2008 and 2018.



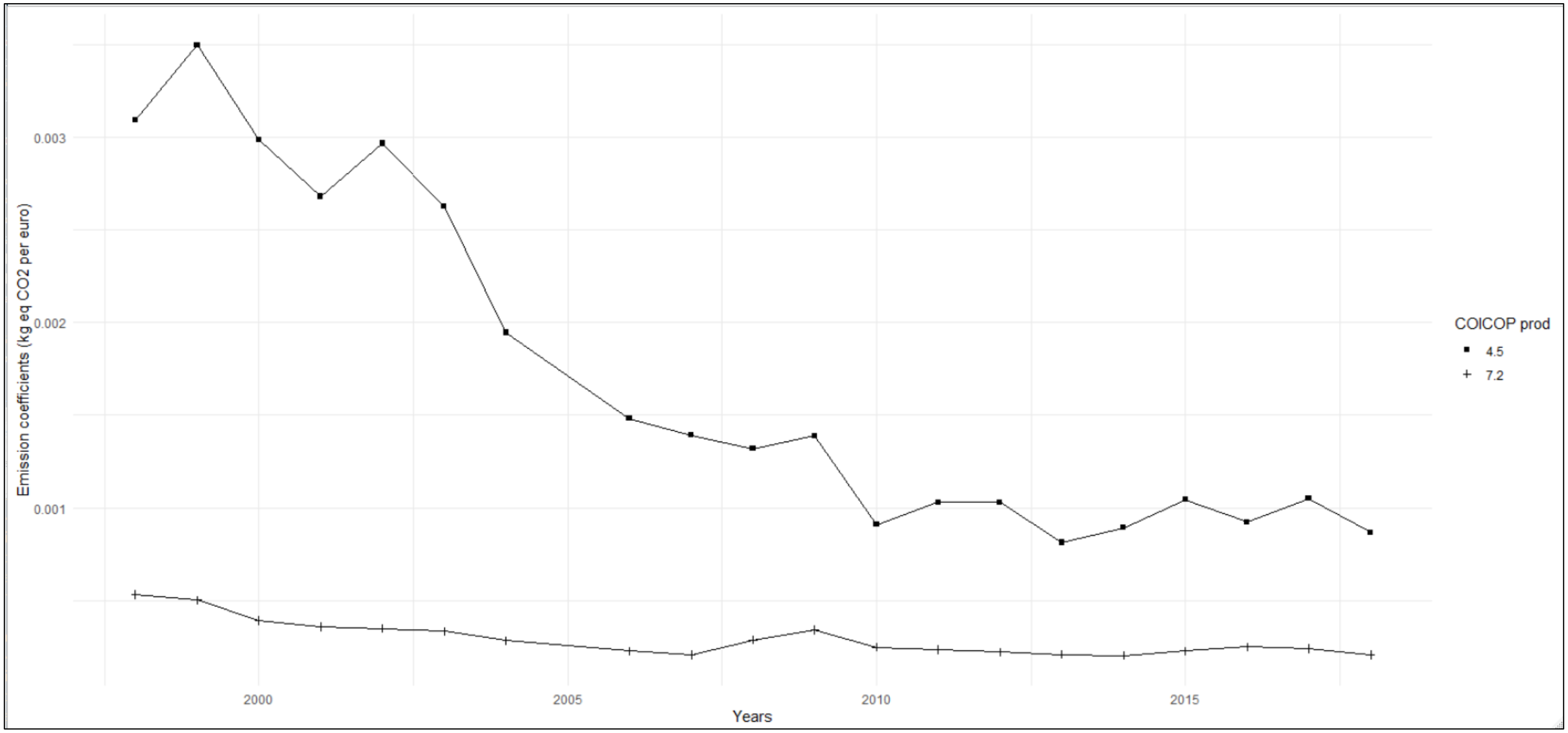
Source: Own elaboration

The variation of emission coefficients over the years is associated with technological changes. Since technological changes have improved the environmental performance of different products, product 4.5: "Electricity, gas, and other fuels" (which includes products such as gas, electricity, and solid and liquid fuels), with the highest emission coefficient over the years, undergoes an abrupt change, significantly improving between 1998 and 2018. It is noted that products such as 7.2: "Operation of personal transport equipment" (vehicle accessories, maintenance, and fuel) do not have coefficients as high as its substitute 7.3: "Transport services" (maritime, air and land transport services), and this last one has not improved considerably over the years.

Since products 4.5: “Electricity, gas, and other fuels” and 7.2: “Operation of personal transport equipment” are directly related to direct emissions, Graph 1.10 shows the evolution of their emission coefficients related to the inter-industrial process to produce each one. It can be concluded that both products have improved their emission coefficients due to the technological investment in the production of these product, even so, it is observed that the emission coefficients associated with 4.5: “Electricity, gas, and other fuels” are considerably higher than that of 7.2: “Operation of personal transport equipment”

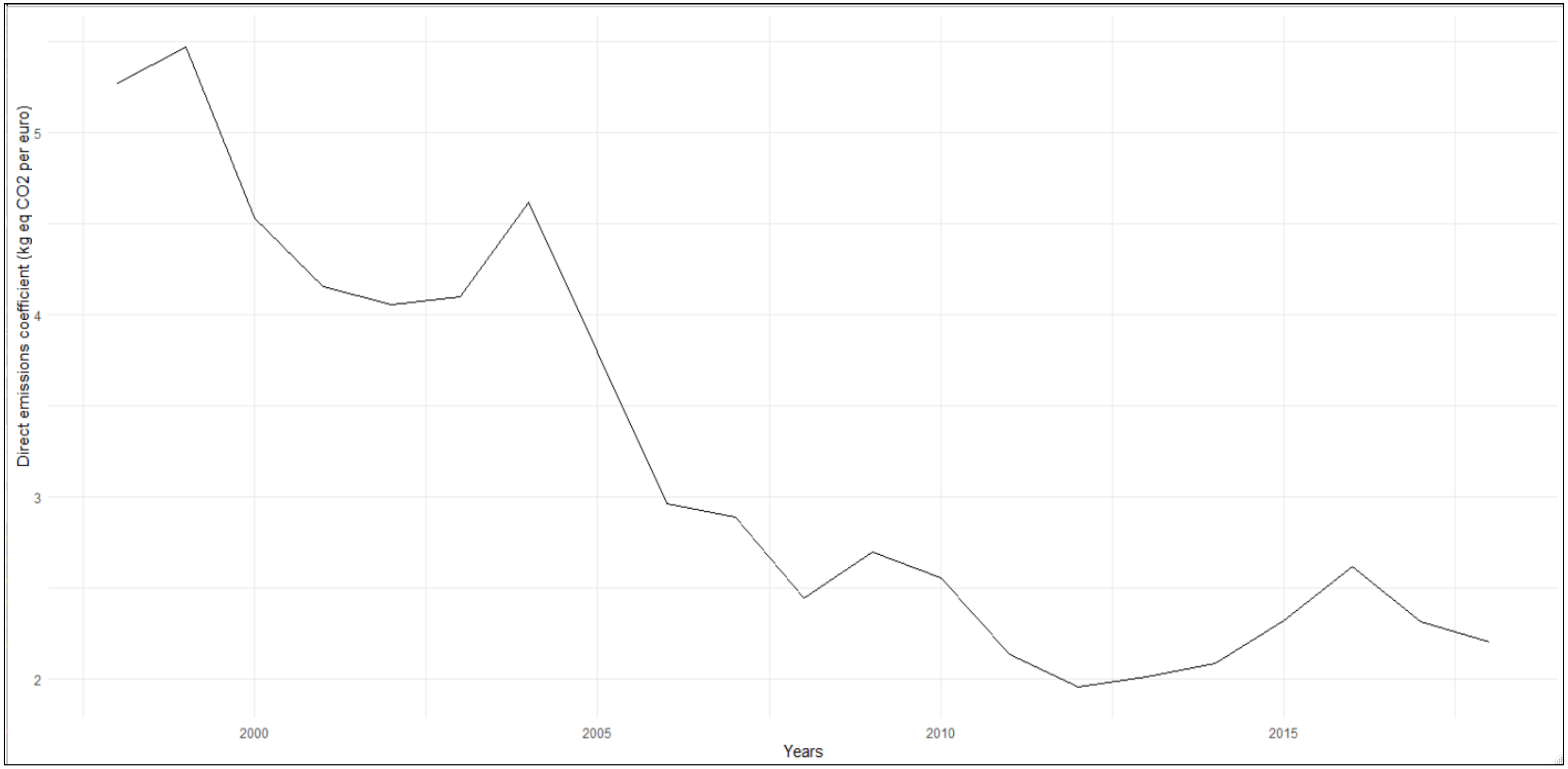
Besides, Graph 1.11 presents the emissions coefficient derived from direct emissions from household consumption of energy goods —for instance, when burning fuels when driving a a car— calculated as the total household direct emission divided by the total expenditure on energy goods. Despite there are two products related with this type of emissions, 4.5: “Electricity, gas, and other fuels” and 7.2: “Operation of personal transport equipment”, the methodology works under the assumption that one monetary unit spent on any energy good generates the same direct emissions. Therefore, it is the same yearly coefficient for both products, and although they have declined over the years, are higher than those shown in Graph 1.10, regardless of the type of product.

Graph 1.10: Emission coefficient by energy good (kgs of eq CO_2 per euro). Spain 1998-2018



Source: Own elaboration

Graph 1.11: Direct emission coefficient of energies goods (kgs of eq CO_2 per euro). Spain 1998-2018



Source: Own elaboration

4.3 Greenhouse gases embedded from consumption

This section presents the estimated final database of GHGs emissions derived from consumption of each Spanish household between 1998-2004 and 2006-2018. The GHGs estimated contains direct and indirect emissions derived from household consumption basket and from household consumption of energy goods.

Graph 1.12 shows the average GHGs emissions, and Graph 1.13 presents the average GHGs emissions for each euro spent, hereafter referred to as emission patterns. Both average emissions and emission patterns have improved considerably over the years. On the one hand, there is a large de-escalation on average emissions since 2006 and an increase since 2014, period related to the 2008 economic crisis. On the other hand, emission patterns are continuously improving, reaching less than 0.3 kilograms of equivalent CO_2 per euro spent (See Annex A1.5 for tables details).

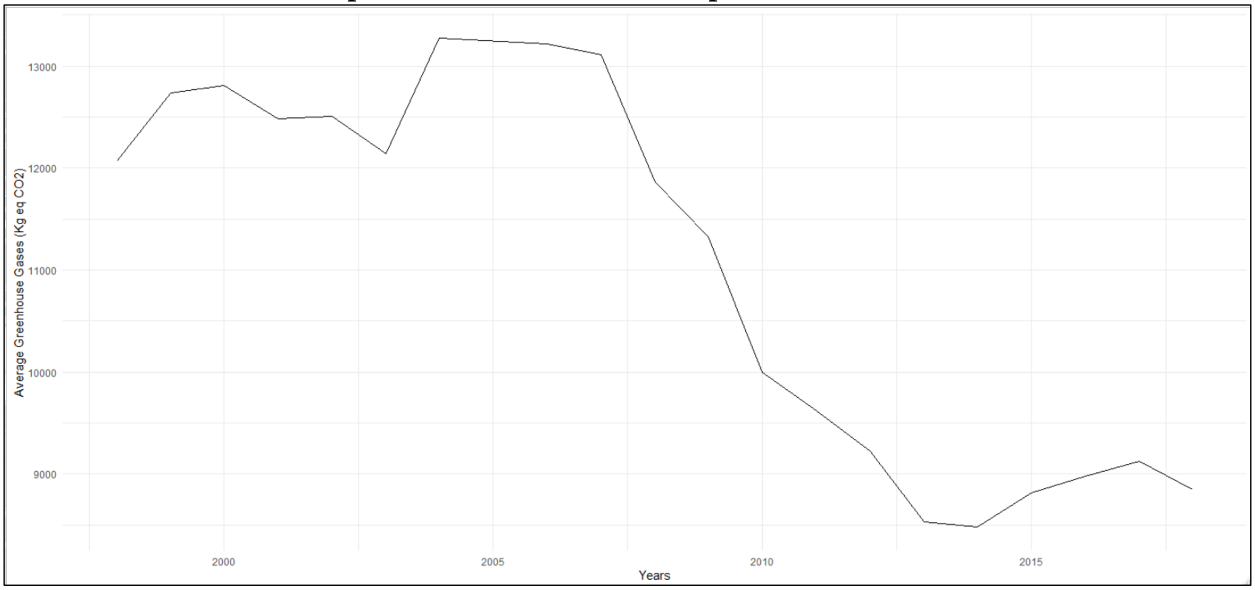
Moreover, looking at household characteristics, Graph 1.14 and Graph 1.15 show the average emissions and emission patterns by household breadwinner age range. Households with breadwinners between 45 and 55 years old are the highest emitters on average, and among the highest emitters in emission patterns. Households with breadwinners older than 65 years old are the lowest emitters both on average and per euro, followed by those under 30 years old.

Graphs 1.16 and 1.17 present the average emission and emission patterns by household breadwinner education level. An inverted pattern is observed, where households with breadwinners with a university education level are the highest emitters on average, but the lowest emitters per euro. The opposite for households with less educated breadwinners, where they are the lowest emitters on average, but have the highest emission patterns.

Graph 1.18 represent the average emissions by number of households members, and Graph 1.19 the average emission patterns by number of households members. It is observed that households with one member are the most eco-friendly, regardless of whether it is look at emissions in absolute terms or per euro, followed by two member households. The highest emissions and emission patterns are found among households with four or more members.

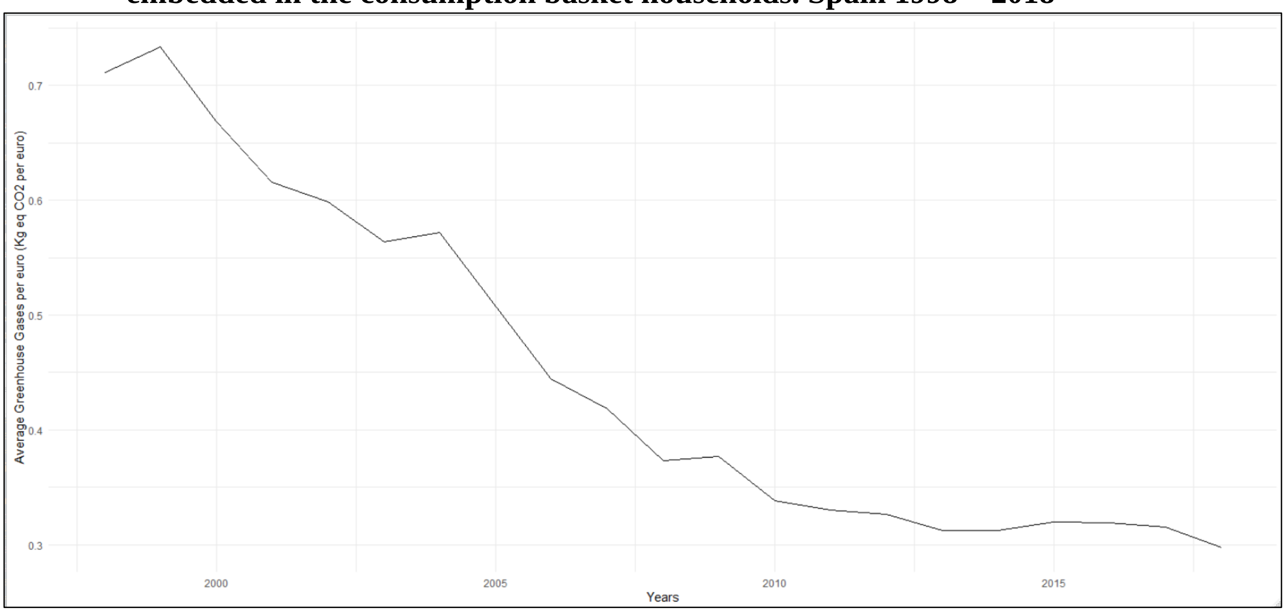
Finally, observing the average emissions and emissions patterns by expenditure levels, Graph 1.20 shows that the higher your expenditure level, the higher your average emissions level. Emitting five times more than households with lower expenditure levels and reporting the 36% of total emissions in 2018 (See Table A1.10, Annex A1.6). However, from Graph 1.21 the highest levels of emissions patterns are disputed between the middle quintiles, while the lowest emissions patterns are disputed between the lowest and highest spending quintiles (See Table A1.11, Annex A1.6).

Graph 1.12: Average of greenhouse gases (kgs of equivalent CO_2) embedded in the consumption basket households. Spain 1998 – 2018



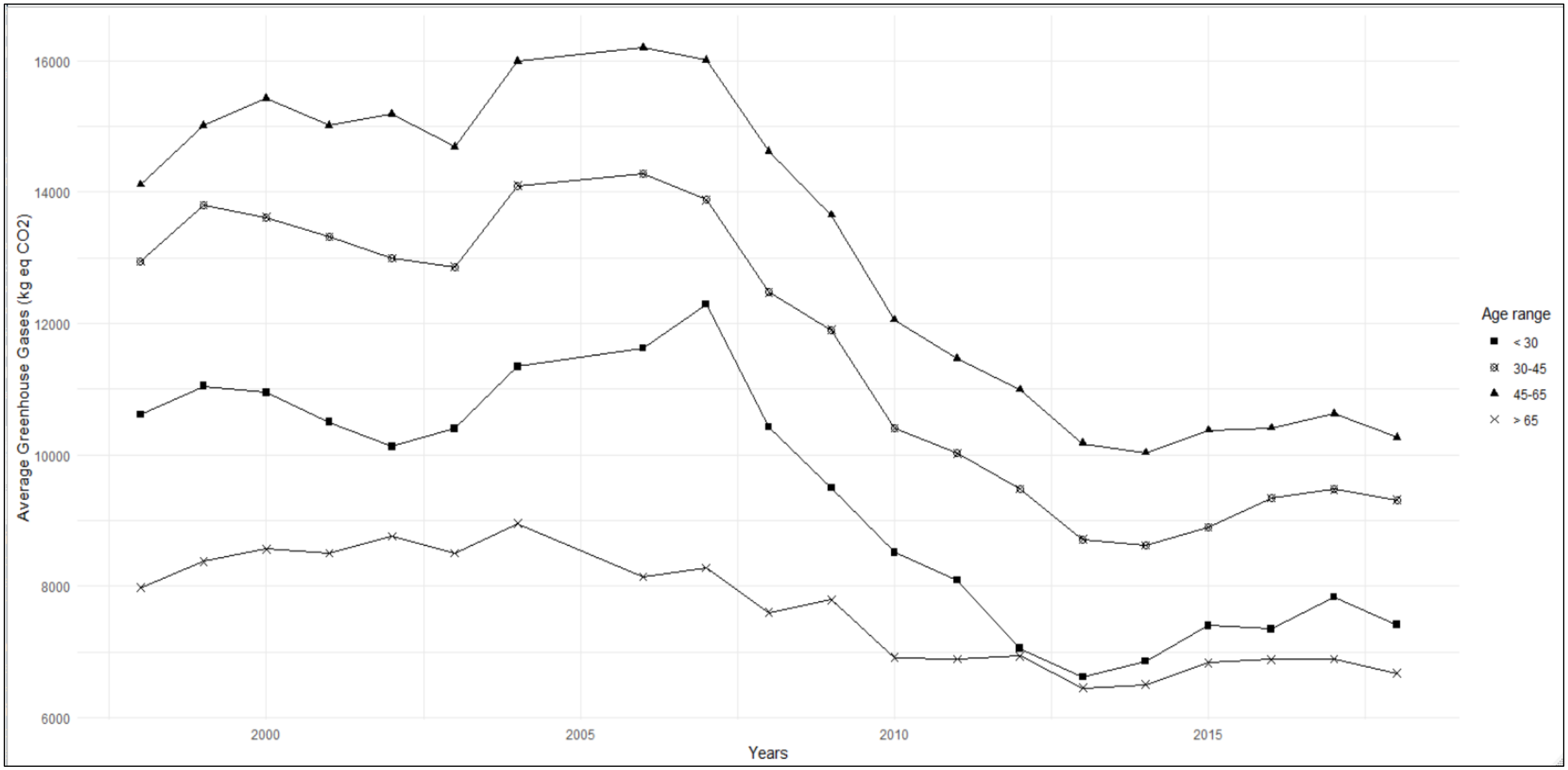
Source: Own elaboration

Graph 1.13: Average of greenhouse gases per euro (kgs of equivalent CO_2 per euro) embedded in the consumption basket households. Spain 1998 – 2018



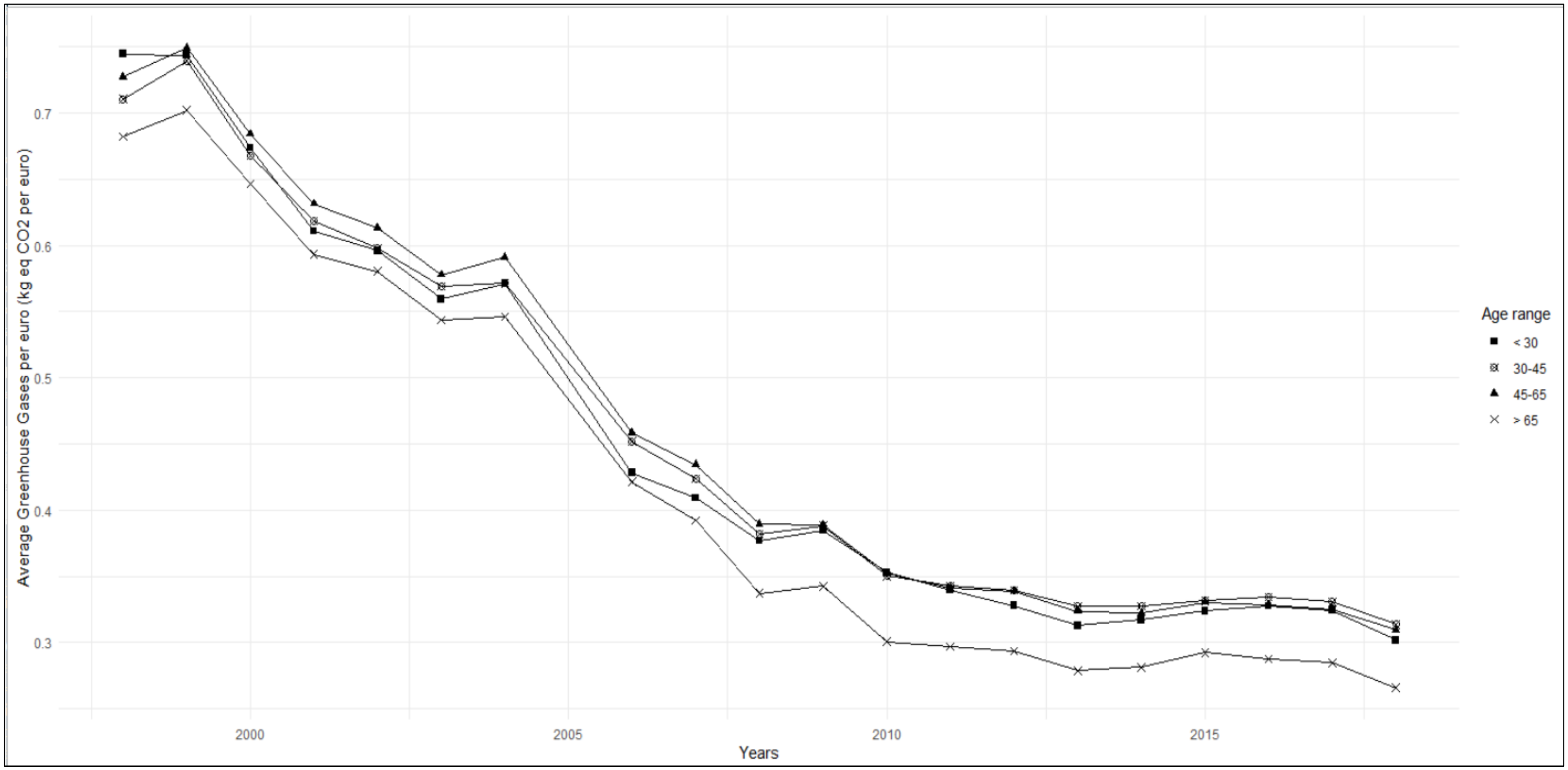
Source: Own elaboration

Graph 1.14: Average of greenhouse gases (kgs of equivalent CO_2) embedded in the consumption basket households by age. Spain 1998 – 2018



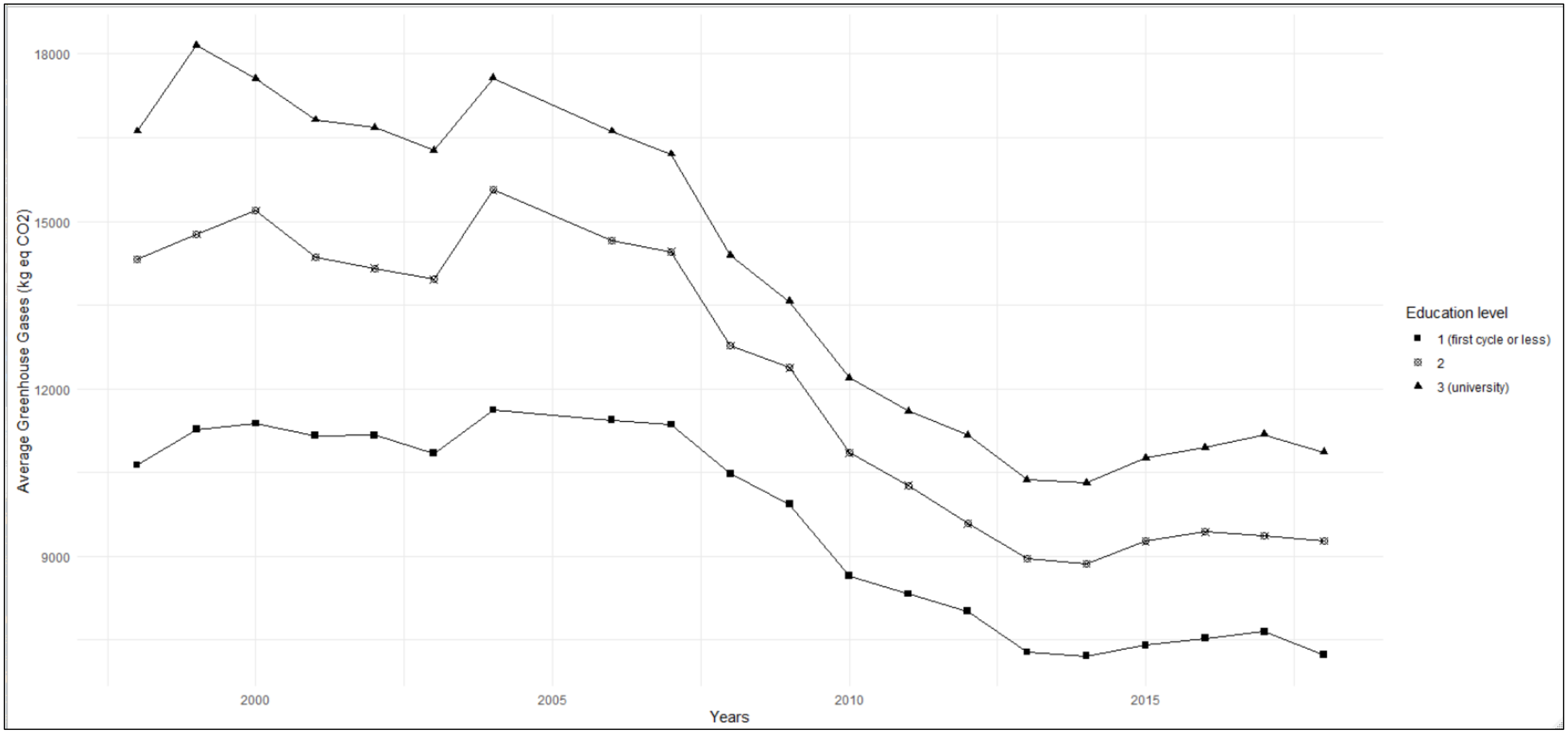
Source: Own elaboration

Graph 1.15: Average of greenhouse gases per euro (kgs of equivalent CO_2 per euro) embedded in the consumption basket households by age. Spain 1998 – 2018



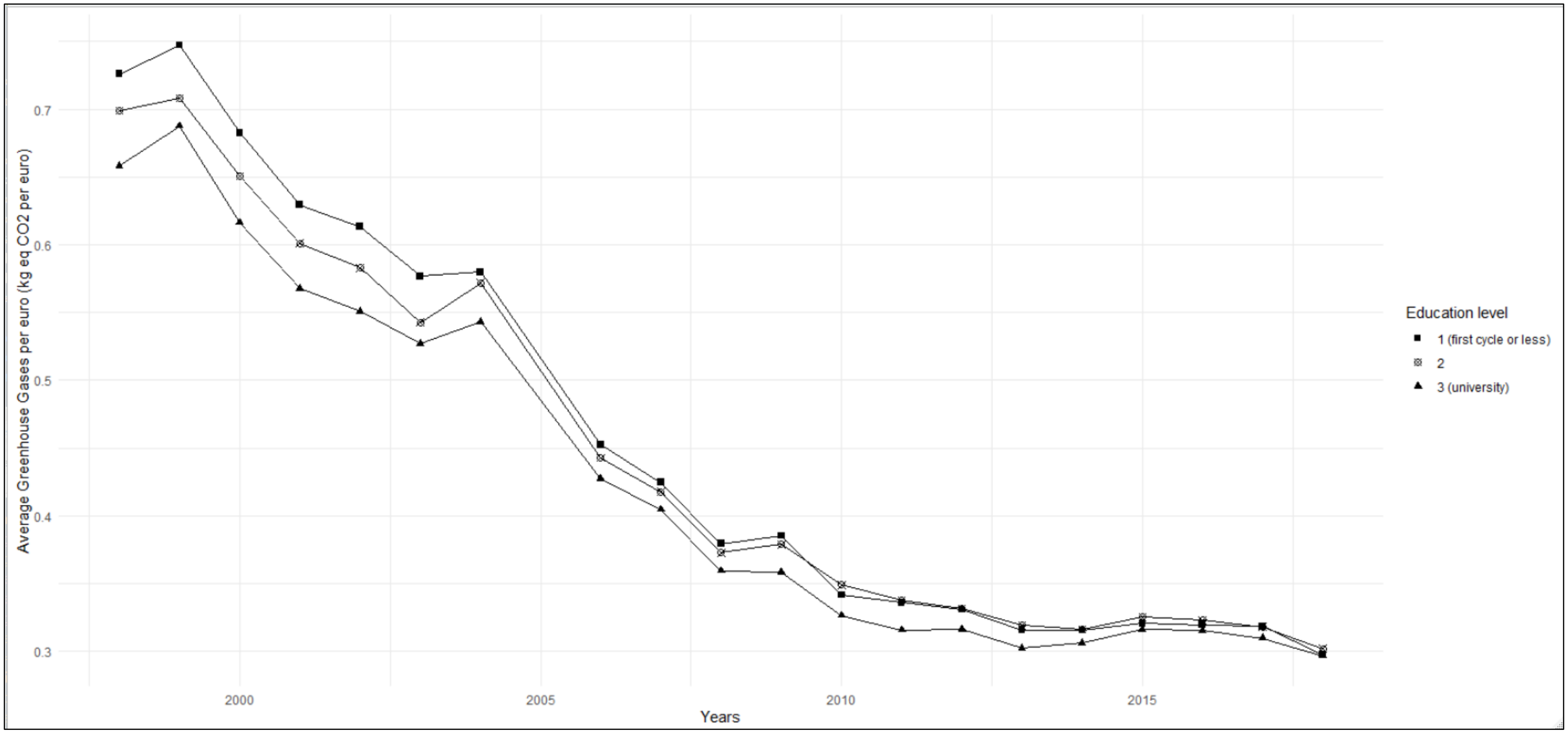
Source: Own elaboration

Graph 1.16: Average of greenhouse gases (kgs of equivalent CO_2) embedded in the consumption basket households by education level. Spain 1998 – 2018



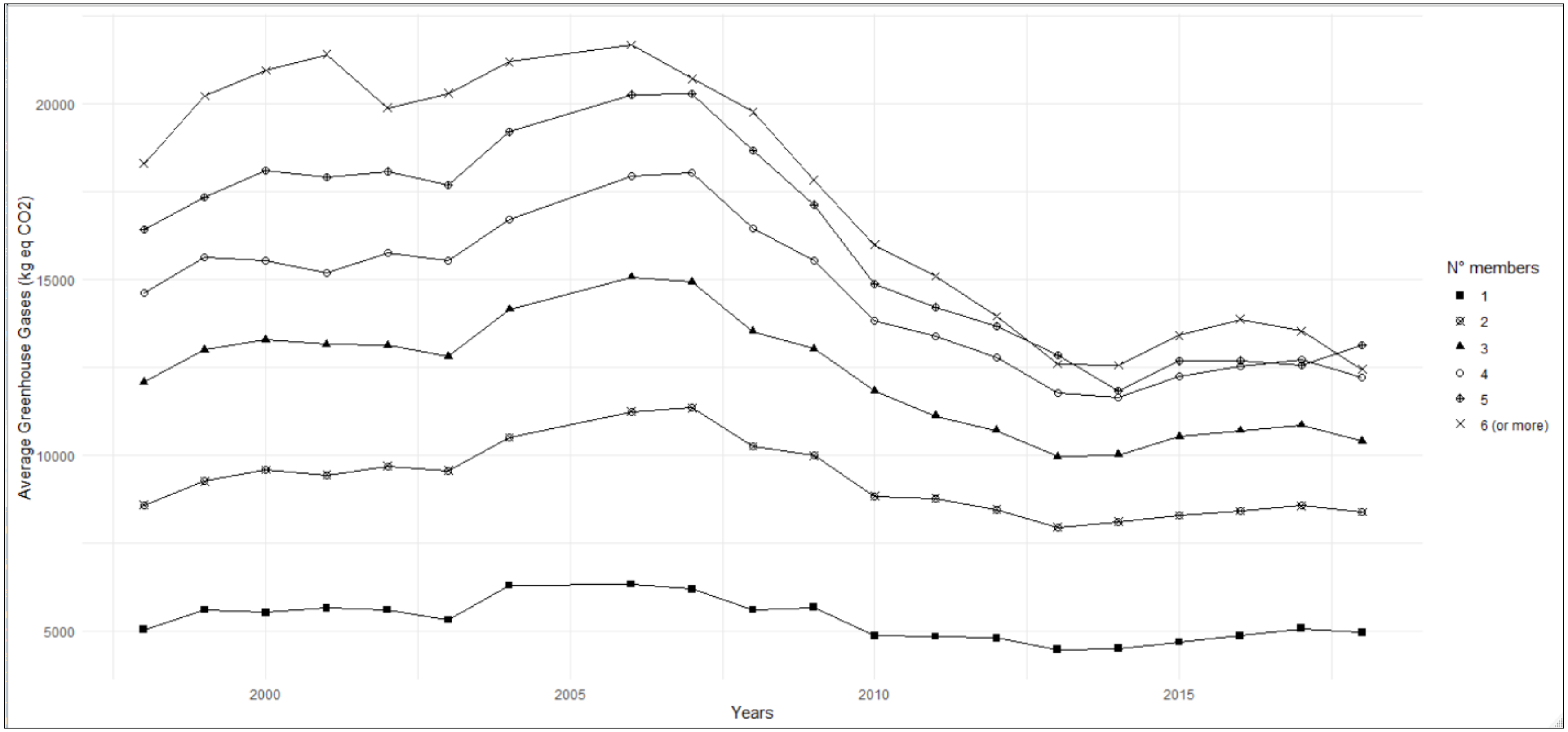
Source: Own elaboration

Graph 1.17: Average of greenhouse gases per euro (kgs of equivalent CO_2 per euro) embedded in the consumption basket households by education level. Spain 1998 – 2018



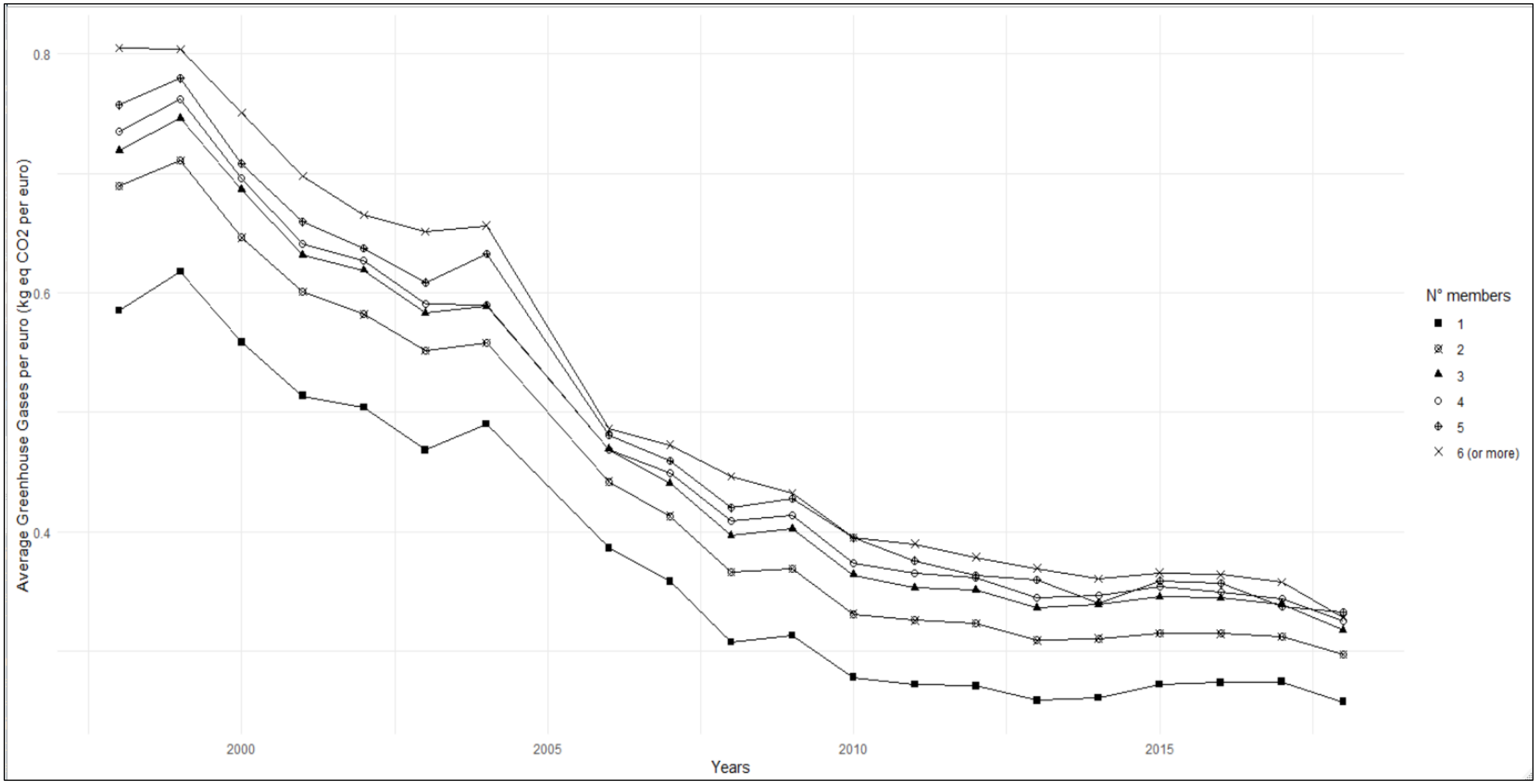
Source: Own elaboration

Graph 1.18: Average of greenhouse gases (kgs of equivalent CO_2) embedded in the consumption basket households by number of households members. Spain 1998 – 2018



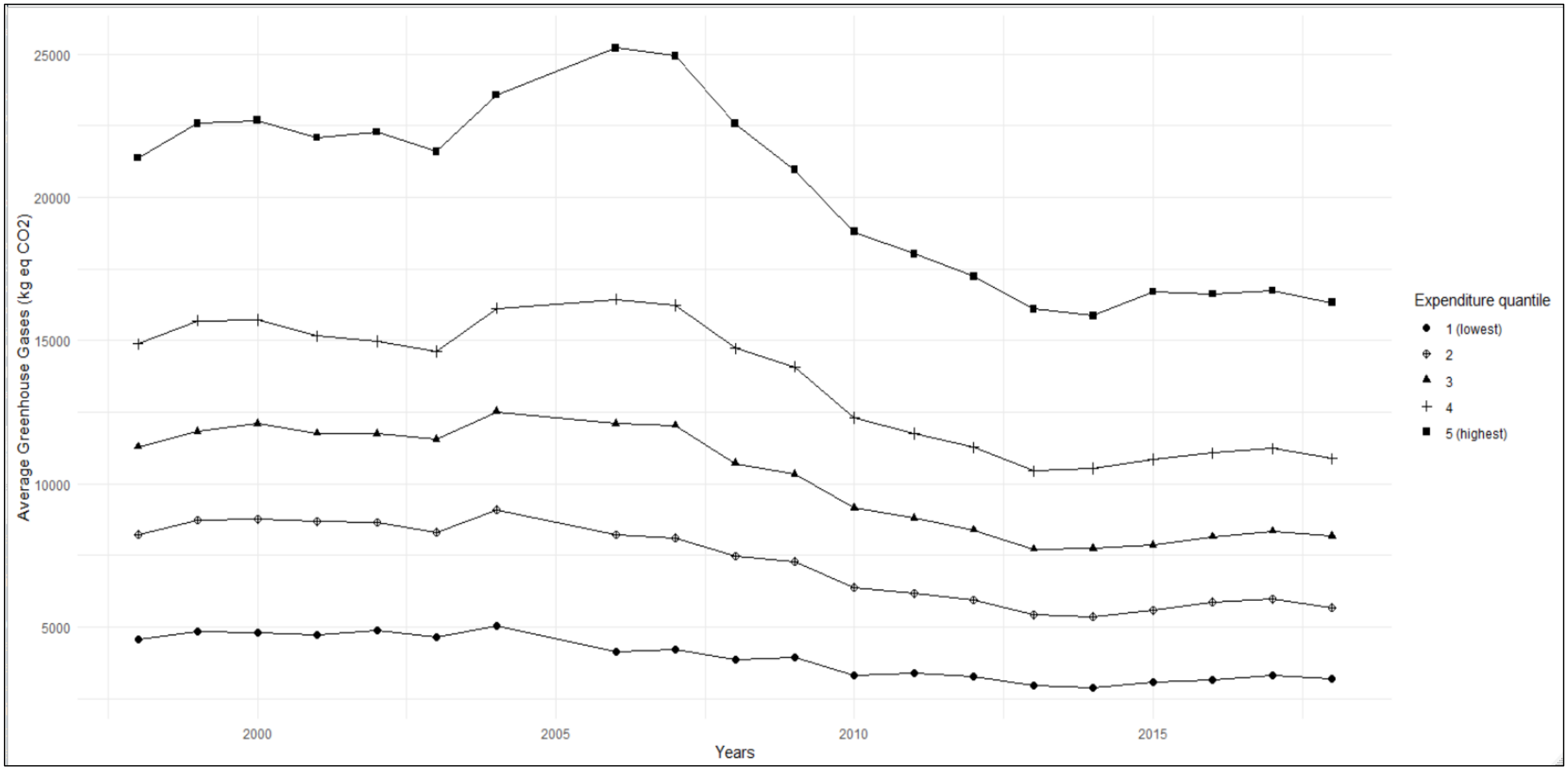
Source: Own elaboration

Graph 1.19: Average of greenhouse gases per euro (kgs of equivalent CO_2 per euro) embedded in the consumption basket households by number of households members. Spain 1998 – 2018



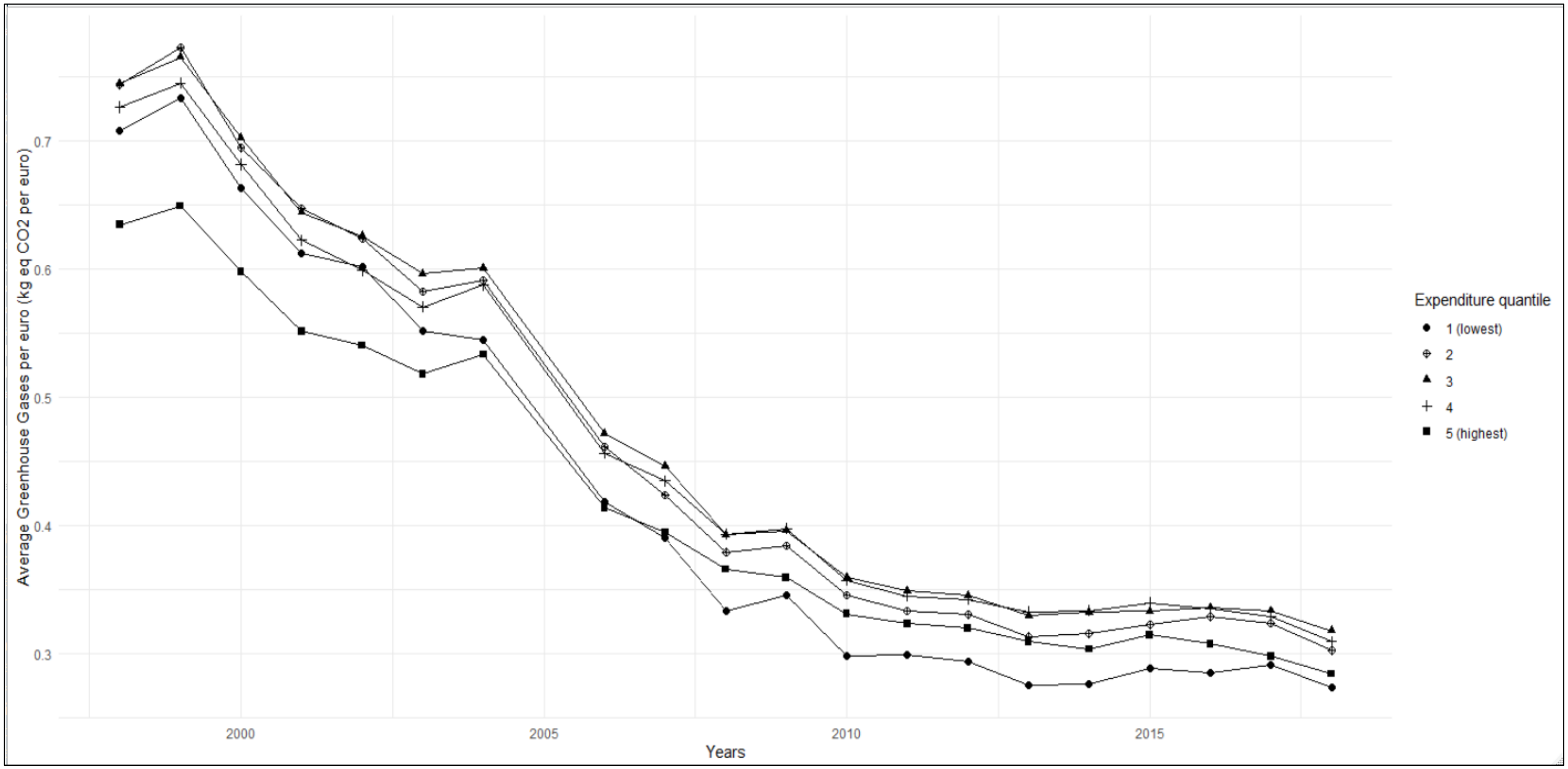
Source: Own elaboration

Graph 1.20: Average of greenhouse gases (kgs of equivalent CO_2) embedded in the consumption basket households by expenditure quintile. Spain 1998 – 2018



Source: Own elaboration

Graph 1.21: Average of greenhouse gases per euro (kgs of equivalent CO_2 per euro) embedded in the consumption basket households by expenditure quintile. Spain 1998 – 2018



Source: Own elaboration

5. CONCLUSIONS

The aim of this chapter is to describe in detail the databases needed, as well as the methodologies and strategies necessary to obtain the GHG emissions measured in kilograms of CO_2 embedded from consumption at the individual household level. Additionally, the results of the estimated database are broadly presented, showing the evolution and behaviour of the emissions derived from each Spanish household consumption between 1998-2004 and 2006-2018.

Emissions exploited at the micro level can be used for several lines of research, considering that the HBS includes different demographic and economic variables of Spanish households. First, the enormous technological advances over the years can be seen with the emission coefficients for each product having decreased considerably, as well as the average emissions from consumption and emissions per euro consumed. On the other hand, regarding emissions under household characteristics, households with breadwinners between 45 and 55 years old are considerably the highest emitters, both on average and per euro, while the lowest emitters are among the oldest and youngest age group. The education level also points differences in emissions from household consumption. Households with a breadwinner holding an university degree are the highest emitters on average but have the most environmentally friendly emission patterns. On the opposite side, households with breadwinners with the lowest level of education emit the least on average but with the most polluting emission patterns. In the case of household members, both in average emissions and emission patterns, smaller households tend to have lower emission levels, while those with more than four members have higher emission levels. The level of expenditure shows, as expected, that the higher level of expenditure, the higher the average emissions. The most polluting emission patterns, however, are disputed among households with middle expenditure level, and the lowest polluting emission patterns are disputed between households with the lower and higher levels of expenditure.

This chapter showed that emissions are affected by sociodemographic characteristics of the household breadwinner, composition, and expenditure level of the household. However, the characteristics of the breadwinner do not alone determine consumption patterns and derived emissions. Different lifestyles, inter-household relationships, the particular position in the different phases of the life cycle, and household compositions also contribute to shape consumption patterns and emissions. Therefore, future work would help to develop a more detailed analysis regarding household socioeconomic and demographic variables. The aim of this modest chapter is to present the potential of the estimated database and the possible research questions that could be derived from it.

Possible future research questions are extensive and varied, for instance, population ageing and its impact on emissions, expenditure inequality and its environmental consequences, analyse the emission behaviour by cohorts, as well as any demographic changes within Spanish households. Moreover, the impact of the different environmental policies over the years can be analysed, as being able to feed models and generate projections.

This work faces the challenge of estimating an appropriate Spanish BM, which produced strong assumptions, hence one of the future works is to develop appropriate BM for each year of interest, considering the changes in both consumption patterns and technological changes that Spanish society has recently had to face.

Finally, this chapter allowed to present in detail the methodologies and estimates of GHG emissions measured in kilograms of equivalent CO_2 derived from each Spanish household consumption, as a first step for the following chapters. It is from here that the research questions that are developed throughout this thesis derive, where under a temporal analysis the environmental impact is investigated under a gender and spatial perspective.

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7. ANNEX A1

ANNEX A1.1

Table A1.1: List of 39 COICOP products and 12 COICOP products categories.

01 - FOOD AND NON-ALCOHOLIC BEVERAGES

01.1 - Food

01.2 - Non-alcoholic beverages

02 - ALCOHOLIC BEVERAGES AND TOBACCO

02.1 - Alcoholic beverages

02.2 - Tobacco

03 - CLOTHING AND FOOTWEAR

03.1 - Clothing

03.2 - Footwear

04 - HOUSING, WATER, GAS, ELECTRICITY AND OTHER FUELS

04.1 - Actual rentals for housing

04.2 - Imputed housing rentals

04.3 - Regular maintenance and repair of the dwelling

04.4 - Other services relating to the dwelling

04.5 - Electricity, gas and other fuels

05 - FURNISHINGS, HOUSEHOLD EQUIPMENT AND ROUTINE MAINTENANCE OF THE HOUSE

05.1 - Furniture, furnishings and decorations, carpets and other floor coverings and repairs

05.2 - Household textiles

05.3 - Household appliances

05.4 - Glassware, tableware and household utensils

05.5 - Tools and equipment for house and garden

05.6 - Goods and services for routine household maintenance

06 - HEALTH

06.1 - Medical products, appliances and equipment

06.2 - Outpatient services

06.3 - Hospital services

07 - TRANSPORT

07.1 - Purchase of vehicles

07.2 - Operation of personal transport equipment

07.3 - Transport services

08 - COMUNICATION

09 - RECREATION AND CULTURE

09.1 - Audio-visual, photographic and information processing equipment

09.2 - Other major durables for recreation and culture

09.3 - Other recreational items and equipment, gardens and pets

09.4 - Recreational and cultural services

09.5 - Newspapers, books and stationery

09.6 - Package holidays

10 - EDUCATION

11 - RESTAURANTS AND HOTELS

11.1 - Catering services

11.2 - Accommodation services

12 - MISCELLANEOUS GOODS AND SERVICES

12.1 - Personal care

12.2 - Personal effects n.e.c.

12.3 - Social protection

12.4 - Insurance

12.5 - Financial services n.e.c.

12.6 - Other services n.e.c.

ANNEX A1.2

Table A1.2: List of NACE sectors between 1998-1999

Input-Output Table BASE 1995: 1998-1999
1:Agricultura, ganadería y caza
2:Selvicultura y explotación forestal
3: Pesca y acuicultura
4-7: Industrias extractivas
12-16: Alimentos y bebidas
17-19: Industria textil
20:Industria de la madera y el corcho
21:Industria del papel
22:Edición y artes gráficas
8:Coquerías, refino y combustibles nucleares
23:Industria química
24:Industria del caucho y materias plásticas
25-28: Otros productos minerales no metálicos
29:Metalurgia
30:Fabricación de productos metálicos
31:Maquinaria y equipo mecánico
32-35: Industria de material y equipo eléctrico, electrónico y óptico
36:Fabricación de vehículos de motor y remolques
37:Fabricación de otro material de transporte
38:Muebles y otras industrias manufactureras
9-10: Producc. y distrib. electric., gas y vapor
11:Captación, depuración y distribución de agua
40:Construcción
41-43: Vehículos y reparación
44:Servicios de hostelería
45-46: Transporte terrestre
47:Transporte marítimo
48:Transporte aéreo y espacial
49:Otros servicios anexos a los transportes
50:Servicios de telecomunicaciones
51-53: Intermediación financiera
54-58: Inmobiliarias y servicios empresariales
64: Administración pública
59&65: Educación
60&66: Sanidad y servicios sociales
39&61-63&67-69: Otras actividades sociales y servicios
70:Hogares que emplean personal doméstico

Table A1.3: List of NACE sectors between 2000-2003

Input-Output Table BASE 2000: 2000-2003
1:Agricultura, ganadería y caza
2:Selvicultura y explotación forestal
3:Pesca y acuicultura
4-7: Industrias extractivas
12-16: Alimentos y bebidas
17-19: Industria textil
20:Industria de la madera y el corcho
21:Industria del papel
22:Edición y artes gráficas
8:Coquerías, refino y combustibles nucleares
23:Industria química
24:Industria del caucho y materias plásticas
25-28: Otros productos minerales no metálicos
29:Metalurgia
30:Fabricación de productos metálicos
31:Maquinaria y equipo mecánico
32-35: Industria de material y equipo eléctrico, electrónico y óptico
36:Fabricación de vehículos de motor y remolques
37:Fabricación de otro material de transporte
38:Muebles y otras industrias manufactureras
9-10: Producc. y distrib. electric., gas y vapor
11:Captación, depuración y distribución de agua
40:Construcción
41-43: Vehículos y reparación
44-45: Hostelería
46-47: Transporte terrestre
48:Transporte marítimo
49:Transporte aéreo y espacial
50-51: Actividades anexas a los transportes
52:Correos y telecomunicaciones
53-55: Intermediación financiera
56-60: Inmobiliarias y servicios empresariales
67: Administración pública
61&68: Educación
62&69: Sanidad y servicios sociales
39&63-66&70-72: Otras actividades sociales y servicios
73:Hogares que emplean personal doméstico

Table A1.4: List of NACE sectors between 2004-2007

Input-Output Table BASE 2000: 2004-2007
1-3: Agricultura, ganadería y caza
4-7: Industrias extractivas
12-16: Industria de la alimentación, bebidas y tabaco
17-19: Textiles and leather products
20: Industria de la madera y el corcho
21-22: Industria del papel
8: Coquerías, refino y combustibles nucleares
23: Industria química
24: Industria del caucho y materias plásticas
25-28: Fabricación de otros productos minerales no metálicos
29-30: Metalurgia
31: Maquinaria y equipo mecánico
32-35: Industria de material y equipo eléctrico, electrónico y óptico
36-37: Fabricación de material de transporte
38: Muebles y otras industrias manufactureras
9-11: Producción y distribución de energía eléctrica, gas y agua
40: Construcción
41-43: Comercio reparación de vehículos de motor motocicletas y ciclomotores y artículos personales y de uso doméstico
44-45: Hostelería
46-52: Transporte, almacenamiento y comunicaciones
53-55: Intermediación financiera
56-60: Actividades inmobiliarias y de alquiler servicios empresariales
67: Administración pública
61&68: Educación
62&69: Actividades sanitarias y veterinarias servicios sociales
39&63-66&70-72: Otras actividades sociales y de servicios prestados a la comunidad servicios personales
73: Hogares que emplean personal doméstico

Table A1.5: List of NACE sectors between 2008-2015

Input-Output Table BASE 2010: 2008-2015
1: Productos de la agricultura, la ganadería y la caza, y servicios relacionados con los mismos
2: Productos de la silvicultura y la explotación forestal, y servicios relacionados con los mismos
3: Pescado y otros productos de la pesca; productos de la acuicultura; servicios de apoyo a la pesca
4: Industrias extractivas
5: Productos alimenticios; bebidas; tabaco manufacturado
6: Productos textiles; prendas de vestir; artículos de cuero y calzado
7: Madera y corcho y productos de madera y corcho, excepto muebles; artículos de cestería y espartería
8: Papel y productos del papel
9: Servicios de impresión y de reproducción de soportes grabados
10: Coque y productos de refino de petróleo
11: Productos químicos
12: Productos farmacéuticos de base y sus preparados
13: Productos de caucho y plásticos
14: Otros productos minerales no metálicos
15: Productos de metalurgia y productos metálicos
16: Productos metálicos, excepto maquinaria y equipo
17: Productos informáticos, electrónicos y ópticos
18: Equipo eléctrico
19: Maquinaria y equipo n.c.o.p.
20: Vehículos de motor, remolques y semirremolques
21: Otro material de transporte
22: Muebles; otros productos manufacturados
23: Servicios de reparación e instalación de maquinaria y equipos
24: Energía eléctrica, gas, vapor y aire acondicionado
25: Agua natural; servicios de tratamiento y distribución de agua
26: Servicios de alcantarillado; servicios de recogida, tratamiento y eliminación de residuos; servicios de aprovechamiento; servicios de saneamiento y otros servicios de gestión de residuos
27: Construcciones y trabajos de construcción
28: Servicios de comercio al por mayor y al por menor y servicios de reparación de vehículos de motor y motocicletas
29: Servicios de comercio al por mayor e intermediación del comercio, excepto de vehículos de motor, motocicletas y ciclomotores
30: Servicios de comercio al por menor, excepto de vehículos de motor y motocicletas
31: Servicios de transporte terrestre, incluso por tubería
32: Servicios de transporte marítimo y por vías navegables interiores

33: Servicios de transporte aéreo
34: Servicios de almacenamiento y auxiliares del transporte
35: Servicios de correos y mensajería
36: Servicios de alojamiento y de comidas y bebidas
37: Servicios de edición
38: Servicios cinematográficos, de vídeo y televisión; grabación de sonido y edición musical; servicios de programación y emisión de radio y televisión
39: Servicios de telecomunicaciones
40: Servicios de programación, consultoría y otros servicios relacionados con la informática; servicios de información
41: Servicios financieros, excepto seguros y fondos de pensiones
42: Servicios de seguros, reaseguros y planes de pensiones, excepto seguridad social obligatoria
43: Servicios auxiliares a los servicios financieros y a los servicios de seguros
44: Servicios inmobiliarios
45: Servicios jurídicos y contables; servicios de sedes centrales de empresas; servicios de consultoría de gestión empresarial
46: Servicios técnicos de arquitectura e ingeniería; servicios de ensayos y análisis técnicos
47: Servicios de investigación y desarrollo científico
48: Servicios de publicidad y de estudio de mercado
49: Otros servicios profesionales, científicos y técnicos; servicios veterinarios
50: Servicios de alquiler
51: Servicios relacionados con el empleo
52: Servicios de agencias de viajes, operadores turísticos y otros servicios de reservas, y servicios relacionados con los mismos
53: Servicios de seguridad e investigación; servicios para edificios y paisajísticos; servicios administrativos, de oficina y otros servicios de ayuda a las empresas
54: Servicios de administración pública y defensa; servicios de seguridad social obligatoria
55: Servicios de educación
56: Servicios de atención sanitaria
57: Servicios sociales de atención en establecimientos residenciales; servicios sociales sin alojamiento
58: Servicios de creación, artísticos y de espectáculos; servicios de bibliotecas, archivos, museos y otros servicios culturales; servicios de juegos de azar y apuestas
59: Servicios deportivos, recreativos y de entretenimiento
60: Servicios prestados por asociaciones
61: Servicios de reparación de ordenadores, efectos personales y artículos de uso doméstico
62: Otros servicios personales
63: Servicios de los hogares como empleadores de personal doméstico; bienes y servicios no diferenciados producidos por hogares para uso propio

Table A1.6: List of NACE sectors between 2016-2018

Input-Output Table REV 2019: 2016-2018
1: Productos de la agricultura, la ganadería y la caza, y servicios relacionados con los mismos
2: Productos de la silvicultura y la explotación forestal, y servicios relacionados con los mismos
3: Pescado y otros productos de la pesca; productos de la acuicultura; servicios de apoyo a la pesca
4: Industrias extractivas
5: Productos alimenticios; bebidas; tabaco manufacturado
6: Productos textiles; prendas de vestir; artículos de cuero y calzado
7: Madera y corcho y productos de madera y corcho, excepto muebles; artículos de cestería y espartería
8: Papel y productos del papel
9: Servicios de impresión y de reproducción de soportes grabados
10: Coque y productos de refino de petróleo
11: Productos químicos
12: Productos farmacéuticos de base y sus preparados
13: Productos de caucho y plásticos
14: Otros productos minerales no metálicos
15: Productos de metalurgia y productos metálicos
16: Productos metálicos, excepto maquinaria y equipo
17: Productos informáticos, electrónicos y ópticos
18: Equipo eléctrico
19: Maquinaria y equipo n.c.o.p.
20: Vehículos de motor, remolques y semirremolques
21: Otro material de transporte
22: Muebles; otros productos manufacturados
23: Servicios de reparación e instalación de maquinaria y equipos
24: Energía eléctrica, gas, vapor y aire acondicionado
25: Agua natural; servicios de tratamiento y distribución de agua
26: Servicios de alcantarillado; servicios de recogida, tratamiento y eliminación de residuos; servicios de aprovechamiento, de saneamiento y otros servicios de gestión de residuos
27: Construcciones y trabajos de construcción
28: Servicios de comercio al por mayor y al por menor y servicios de reparación de vehículos de motor y motocicletas
29: Servicios de comercio al por mayor e intermediación del comercio, excepto de vehículos de motor, motocicletas y ciclomotores
30: Servicios de comercio al por menor, excepto de vehículos de motor y motocicletas
31: Servicios de transporte terrestre, incluso por tubería
32: Servicios de transporte marítimo y por vías navegables interiores

33: Servicios de transporte aéreo
34: Servicios de almacenamiento y auxiliares del transporte
35: Servicios de correos y mensajería
36: Servicios de alojamiento y de comidas y bebidas
37: Servicios de edición
38: Servicios cinematográficos, de vídeo y televisión; grabación de sonido y edición musical; servicios de programación y emisión de radio y televisión
39: Servicios de telecomunicaciones
40: Servicios de programación, consultoría y otros servicios relacionados con la informática; servicios de información
41: Servicios financieros, excepto seguros y fondos de pensiones
42: Servicios de seguros, reaseguros y planes de pensiones, excepto seguridad social obligatoria
43: Servicios auxiliares a los servicios financieros y a los servicios de seguros
44-44a: Servicios inmobiliarios
45: Servicios jurídicos y contables; servicios de sedes centrales de empresas; servicios de consultoría de gestión empresarial
46: Servicios técnicos de arquitectura e ingeniería; servicios de ensayos y análisis técnicos
47: Servicios de investigación y desarrollo científico
48: Servicios de publicidad y de estudio de mercado
49: Otros servicios profesionales, científicos y técnicos; servicios veterinarios
50: Servicios de alquiler
51: Servicios relacionados con el empleo
52: Servicios de agencias de viajes, operadores turísticos y otros servicios de reservas, y servicios relacionados con los mismos
53: Servicios de seguridad e investigación; servicios para edificios y paisajísticos; servicios administrativos, de oficina y otros servicios de ayuda a las empresas
54: Servicios de administración pública y defensa; servicios de seguridad social obligatoria
55: Servicios de educación
56: Servicios de atención sanitaria
57: Servicios sociales de atención en establecimientos residenciales; servicios sociales sin alojamiento
58: Servicios de creación, artísticos y de espectáculos; servicios de bibliotecas, archivos, museos y otros servicios culturales; servicios de juegos de azar y apuestas
59: Servicios deportivos, recreativos y de entretenimiento
60: Servicios prestados por asociaciones
61: Servicios de reparación de ordenadores, efectos personales y artículos de uso doméstico

62: Otros servicios personales

63: Servicios de los hogares como empleadores de personal doméstico; bienes y servicios no diferenciados producidos por hogares para uso propio

ANNEX A1.3

Table A1.7: List of atmospheric pollutants

Pollutants: 1998-2007	Pollutants: 2008-2018
SOx: Óxidos de azufre (toneladas)	CO2 - Dióxido de carbono (miles de toneladas)
NOx: Óxidos de nitrógeno (toneladas)	CH4 - Metano (toneladas)
COVNM: Compuestos orgánicos volátiles, excluido CH4 (toneladas)	N2O - Óxido nitroso (toneladas)
CH4: Metano (toneladas)	PFC - Perfluorocarbonos o compuestos polifluorcarbonados (miles de toneladas de CO2 equivalente)
CO: Monóxido de carbono (toneladas)	HFC - Hidrofluorocarbonos o compuestos hidrogenofluorcarbonados (miles de toneladas de CO2 equivalente)
NH3: Amoníaco (toneladas)	SF6 - Hexafluoruro de azufre (miles de toneladas de CO2 equivalente)
CO2: Dióxido de carbono (miles de toneladas)	PM2.5 - Partículas de diámetro menor o igual a 2,5 µm (toneladas)
SF6: Hexafluoruro de azufre (kg)	PM10 - Partículas de diámetro menor o igual a 10 µm (toneladas)
N2O: Monóxido de nitrógeno (toneladas)	NOx - Óxidos de nitrógeno (toneladas de NO2 equivalentes)
PM10: partículas en suspensión, diámetro hasta 10 micrómetros (toneladas)	SOx - Óxidos de azufre (toneladas de SO2 equivalentes)
PFC: Compuestos polifluor carbonados (kg)	NH3 - Amoniaco (toneladas)
HFC: Compuestos hidrogenofluorcarbonados (kg)	CO - Monóxido de carbono (toneladas)
	COVNM - Compuestos orgánicos volátiles no metánicos (toneladas)

ANNEX A1.4

Table A1.8: Emission coefficient by 39 COICOP products. Spain 1998-2004 and 2006-2018

COICOP	1998	1999	2000	2001	2002	2003	2004	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
1.1	0.662	0.673	0.660	0.619	0.595	0.568	0.512	0.456	0.427	0.445	0.461	0.401	0.407	0.399	0.386	0.375	0.370	0.382	0.381	0.362
1.2	0.479	0.499	0.489	0.446	0.433	0.402	0.368	0.322	0.320	0.330	0.310	0.277	0.278	0.276	0.263	0.276	0.247	0.285	0.291	0.277
2.1	0.243	0.280	0.243	0.233	0.224	0.212	0.184	0.174	0.169	0.219	0.197	0.168	0.171	0.169	0.155	0.155	0.113	0.071	0.066	0.061
2.2	0.092	0.116	0.100	0.114	0.118	0.102	0.100	0.077	0.079	0.112	0.103	0.062	0.049	0.042	0.039	0.040	0.028	0.011	0.009	0.008
3.1	0.282	0.288	0.284	0.267	0.265	0.251	0.239	0.210	0.204	0.176	0.163	0.136	0.132	0.139	0.121	0.115	0.097	0.082	0.077	0.076
3.2	0.271	0.285	0.280	0.262	0.260	0.250	0.246	0.218	0.212	0.231	0.199	0.140	0.138	0.146	0.126	0.123	0.116	0.094	0.088	0.078
4.1	0.143	0.149	0.157	0.137	0.135	0.125	0.134	0.114	0.106	0.056	0.047	0.045	0.039	0.035	0.030	0.028	0.029	0.026	0.027	0.024
4.2	0.143	0.149	0.157	0.137	0.135	0.125	0.134	0.114	0.106	0.056	0.047	0.053	0.046	0.040	0.035	0.032	0.034	0.026	0.027	0.024
4.3	0.616	0.598	0.589	0.484	0.461	0.459	0.444	0.363	0.320	0.273	0.247	0.291	0.305	0.305	0.315	0.338	0.376	0.275	0.266	0.250
4.4	0.424	0.458	0.323	0.294	0.298	0.284	1.441	1.064	1.078	0.252	0.279	0.213	0.206	0.211	0.208	0.200	0.223	0.236	0.212	0.198
4.5	3.091	3.498	2.988	2.680	2.966	2.626	1.945	1.482	1.391	1.318	1.388	0.909	1.030	1.028	0.812	0.893	1.044	0.923	1.049	0.867
5.1	0.279	0.297	0.258	0.245	0.245	0.236	0.241	0.205	0.201	0.203	0.186	0.147	0.138	0.145	0.128	0.125	0.118	0.107	0.106	0.094
5.2	0.293	0.308	0.284	0.264	0.261	0.246	0.239	0.202	0.191	0.216	0.185	0.139	0.135	0.142	0.124	0.122	0.111	0.080	0.077	0.077
5.3	0.221	0.222	0.225	0.226	0.237	0.218	0.200	0.168	0.165	0.234	0.207	0.153	0.150	0.157	0.138	0.136	0.129	0.124	0.126	0.111
5.4	0.838	0.716	0.277	0.271	0.387	0.257	0.270	0.397	0.495	0.298	0.233	0.174	0.160	0.168	0.152	0.149	0.141	0.154	0.150	0.151
5.5	0.243	0.237	0.223	0.214	0.213	0.199	0.197	0.184	0.176	0.242	0.211	0.158	0.154	0.162	0.143	0.141	0.133	0.141	0.138	0.126
5.6	0.113	0.115	0.103	0.087	0.089	0.085	0.077	0.065	0.060	0.071	0.063	0.041	0.040	0.054	0.052	0.050	0.047	0.045	0.044	0.034
6.1	0.513	0.472	0.431	0.357	0.296	0.274	0.253	0.276	0.251	0.226	0.187	0.147	0.142	0.150	0.130	0.127	0.117	0.088	0.084	0.083
6.2	0.263	0.255	0.249	0.225	0.220	0.203	0.208	0.170	0.152	0.096	0.093	0.082	0.080	0.084	0.073	0.074	0.073	0.064	0.062	0.061
6.3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.095	0.092	0.081	0.079	0.084	0.073	0.074	0.072	0.064	0.062	0.061
7.1	0.063	0.068	0.063	0.064	0.056	0.054	0.084	0.067	0.067	0.109	0.125	0.084	0.091	0.084	0.070	0.065	0.061	0.037	0.032	0.029
7.2	0.531	0.501	0.392	0.357	0.348	0.334	0.284	0.226	0.207	0.288	0.340	0.247	0.235	0.222	0.208	0.203	0.227	0.249	0.239	0.206
7.3	0.894	0.881	0.927	0.889	0.865	0.826	0.474	0.424	0.416	0.806	0.772	0.727	0.704	0.674	0.646	0.642	0.676	0.775	0.801	0.752
8.0	0.125	0.152	0.211	0.201	0.207	0.184	0.428	0.313	0.308	0.190	0.168	0.144	0.145	0.145	0.120	0.119	0.123	0.159	0.138	0.131
9.1	0.243	0.361	0.342	0.312	0.306	0.282	0.247	0.208	0.199	0.237	0.203	0.151	0.149	0.154	0.133	0.130	0.124	0.260	0.247	0.254
9.2	0.239	0.221	0.207	0.266	0.209	0.307	0.179	0.271	0.180	0.247	0.220	0.200	0.196	0.227	0.156	0.163	0.151	0.115	0.114	0.097
9.3	0.535	0.657	0.718	0.613	0.557	0.582	0.565	0.466	0.494	0.341	0.310	0.262	0.232	0.239	0.205	0.199	0.200	0.264	0.264	0.303
9.4	0.427	0.427	0.375	0.358	0.327	0.309	0.340	0.282	0.275	0.116	0.107	0.112	0.114	0.116	0.110	0.113	0.109	0.123	0.118	0.117
9.5	0.351	0.356	0.309	0.302	0.301	0.281	0.321	0.300	0.277	0.252	0.223	0.159	0.158	0.158	0.140	0.133	0.126	0.155	0.147	0.128
9.6	0.382	0.380	0.418	0.383	0.366	0.342	0.474	0.424	0.416	0.291	0.268	0.238	0.218	0.217	0.257	0.244	0.257	0.207	0.229	0.225
10.0	0.113	0.120	0.111	0.095	0.101	0.091	0.077	0.062	0.059	0.060	0.057	0.050	0.039	0.034	0.027	0.027	0.039	0.043	0.039	0.036
11.1	0.353	0.351	0.272	0.249	0.235	0.226	0.198	0.166	0.159	0.170	0.148	0.160	0.163	0.159	0.150	0.147	0.143	0.156	0.153	0.143
11.2	0.379	0.378	0.288	0.264	0.249	0.241	0.206	0.171	0.164	0.164	0.144	0.152	0.155	0.152	0.143	0.141	0.139	0.156	0.154	0.144
12.1	0.441	0.420	0.386	0.365	0.356	0.343	0.366	0.322	0.316	0.240	0.222	0.196	0.181	0.212	0.179	0.184	0.199	0.269	0.263	0.270
12.2	0.234	0.249	0.271	0.293	0.275	0.251	0.244	0.179	0.175	0.248	0.212	0.156	0.152	0.157	0.139	0.137	0.127	0.110	0.102	0.114
12.3	0.190	0.181	0.173	0.158	0.154	0.136	0.151	0.134	0.127	0.124	0.121	0.106	0.108	0.103	0.091	0.096	0.095	0.088	0.085	0.081
12.4	0.083	0.079	0.079	0.066	0.065	0.059	0.061	0.052	0.047	0.055	0.057	0.046	0.050	0.043	0.039	0.037	0.037	0.036	0.038	0.035
12.5	0.090	0.087	0.088	0.073	0.072	0.067	0.069	0.058	0.051	0.029	0.028	0.040	0.044	0.043	0.042	0.040	0.037	0.031	0.028	0.027
12.6	0.419	0.410	0.351	0.342	0.337	0.322	0.381	0.346	0.323	0.138	0.119	0.082	0.077	0.074	0.063	0.063	0.073	0.085	0.076	0.070

Source: Own elaboration

ANNEX A1.5

Table A1.9: Average greenhouse gases emissions (kgs of eq CO_2) and greenhouse gases emissions per euro (kgs of eq CO_2 per euro). Spain 1998-2018

year	Average GHG	Average GHG per euro
1998	12070.781	0.712
1999	12731.381	0.733
2000	12811.396	0.668
2001	12482.029	0.616
2002	12507.403	0.599
2003	12142.167	0.564
2004	13271.556	0.572
2006	13217.296	0.445
2007	13110.125	0.418
2008	11867.349	0.373
2009	11322.329	0.377
2010	9998.200	0.339
2011	9626.110	0.330
2012	9221.491	0.327
2013	8527.323	0.312
2014	8485.057	0.313
2015	8817.158	0.320
2016	8980.467	0.319
2017	9122.750	0.315
2018	8851.502	0.298

Source: Own elaboration

ANNEX A1.6

Table A1.10: Average greenhouse gases emissions (kgs of eq CO_2) by quintile of expenditure. Spain 1998-2018

year	1 (lowest)	2	3	4	5 (highest)
1998	4570.61	8242.57	11291.30	14878.37	21374.41
1999	4829.51	8737.31	11822.71	15697.22	22578.55
2000	4818.17	8757.22	12093.85	15716.97	22679.27
2001	4745.94	8685.29	11759.01	15156.90	22077.47
2002	4879.05	8658.28	11752.36	14980.86	22274.15
2003	4633.25	8314.84	11554.00	14621.40	21598.93
2004	5062.97	9096.14	12517.77	16127.27	23562.04
2006	4142.19	8224.52	12089.67	16434.68	25208.02
2007	4237.41	8115.42	12036.30	16236.62	24929.73
2008	3864.06	7478.64	10715.14	14723.87	22563.41
2009	3947.98	7294.64	10332.56	14082.75	20958.64
2010	3326.71	6398.64	9161.58	12309.23	18797.57
2011	3389.90	6168.57	8795.43	11761.68	18016.69
2012	3263.78	5947.71	8392.78	11272.14	17234.65
2013	2955.04	5418.53	7720.38	10449.89	16094.35
2014	2904.28	5366.81	7752.51	10539.84	15864.52
2015	3088.45	5579.68	7866.88	10849.83	16703.86
2016	3170.45	5885.53	8153.77	11076.98	16618.51
2017	3316.13	5969.68	8350.88	11234.11	16745.39
2018	3188.20	5680.42	8185.70	10878.57	16326.90

Source: Own elaboration

Table A1.11: Average greenhouse gases emissions per euro (kgs of eq CO_2 per euro) by quintile of expenditure. Spain 1998-2018

year	1 (lowest)	2	3	4	5 (highest)
1998	0.708	0.744	0.745	0.727	0.635
1999	0.734	0.773	0.766	0.745	0.649
2000	0.664	0.695	0.703	0.682	0.598
2001	0.613	0.647	0.644	0.623	0.552
2002	0.602	0.624	0.626	0.600	0.541
2003	0.552	0.583	0.596	0.571	0.518
2004	0.545	0.592	0.601	0.588	0.534
2006	0.419	0.462	0.472	0.457	0.414
2007	0.391	0.424	0.447	0.435	0.395
2008	0.333	0.380	0.393	0.394	0.366
2009	0.346	0.384	0.396	0.398	0.360
2010	0.298	0.346	0.360	0.358	0.331
2011	0.300	0.334	0.349	0.345	0.324
2012	0.294	0.331	0.346	0.343	0.320
2013	0.275	0.314	0.330	0.333	0.310
2014	0.277	0.316	0.333	0.334	0.304
2015	0.289	0.323	0.333	0.340	0.315
2016	0.285	0.329	0.337	0.336	0.308
2017	0.291	0.324	0.334	0.329	0.298
2018	0.274	0.303	0.318	0.310	0.285

Source: Own elaboration

PINK IS THE NEW GREEN: INVESTIGATING THE EFFECT OF GENDER IN GREENHOUSE GASES EMISSIONS PATTERNS

1. INTRODUCTION

Environmental objectives are varied and complex. From the United Nations (UN) Framework Convention on Climate Change in 1994, going through the agreement of the Kyoto Protocol adopted in 1997, the Paris Agreement entered in force in 2016, and the last UN Climate Change Conference organized in Glasgow in 2021, several environmental problems caused by emissions have been increasing the attention of all countries. Nowadays, the 2030 Agenda for Sustainable Development, also known as Horizon 2030 (H2030), is established as a roadmap for member states of the UN that decided to create a guide for sustainable development involving the entire international community, including the UN itself, as well as other public and private entities such as companies, universities, and municipal and regional governments (United Nations, 2022a).

Among the formulations and applications of the H2030 plans and strategies, which include both contributions at the national level and adaptation plans and communications, the gender perspective is a fundamental pillar, which several countries have committed to incorporate into their environmental measures (United Nations, 2021). These actions demand disaggregated data collection, gender sensitive analysis, and equal participation in government structures for gender mainstreaming in decision-making (United Nations, 2022b). Furthermore, the need for gender equitable and gender sensitive policies to advance sustainable development strategies is articulated (OECD, 2020).

According to the report from the Organization for Economic Co-operation and Development (OECD, 2021), the gender perspective in environmental objectives should include the analysis of i) specific impacts of climate change, environmental damage, and biodiversity loss on women; and ii) the role of women in sustainable production and consumption. The aim of this chapter is in line with the last point. This chapter aims at testing if emissions embedded in female and male consumption patterns are significantly different from each other due to gender differences exclusively.

If female and male consumption has different impact in terms of GHG emissions, different environmental responsibilities could be allocated between women and men. Therefore, the role that individuals might play in climate change mitigation could be explained by a gender perspective. The gender perspective would be also useful, and necessary, for the correct design of public policies related to the environment, such as product labelling, public information campaigns and specific education programmes. A gender-differentiated plan design would accelerate the contribution of individual citizens towards more sustainable consumption and production (Wong, 2016; Hosein et al., 2020).

European Instituto for Gender Equality (EIGE, 2012) expose that women and men experience environmental effects differently due to different biological characteristic and societal roles; for example in water access, transport use, or even the urban design of a city. Literature shows that women are more likely to recycle, minimise waste, buy organic food and green label products, engage in water and energy saving initiatives, and have more knowledge and concern for environmental issues than men (Yaccato, 2003; Johnsson-Latham, 2007; Kaenzig et al., 2013; Khan and Trivedi, 2015).

There is also difference between women and men regarding consumption. Women are more engaged with brands and make more impulse purchases (Tifferet and Herstein, 2012). They are less likely to order large portions of food, they prefer home cooked dinners, and eat more sweets, and fruit and vegetables; on the contrary, men consume more fats, oils, beverages, and products related to animal intake (Biloukha and Utermohlen, 2000; Baker and Wardle, 2003; Liebman et al., 2003; Wansink et al., 2003). Regarding transport use, women are more likely than men to walk and, in most cities, to use public transport (Goel et al., 2022).

Even though consumption is directly related to emissions (Bin and Dowlatabadi, 2005; Zeng et al., 2021), studies relating environmental impacts of consumption differences between women and men are still scarce. Exceptions are Räty and Carlsson-Kanyama (2010) who estimate energy use derived from consumption of one-person households (OPH) to analyse differences between female and male OPH for four European Union (EU) countries (Germany, Norway, Greece, and Sweden). Results show differences between female and male OPH in Greece and Sweden, where in general male OPH use more energy than female OPH. The largest differences were found in energy use derived from consumption of transport, as well as the consumption of catering, and alcohol and tobacco goods. This study was the first to report gender differences in environmental responsibility derived from consumption of energy use, however, they perform an analysis of average consumptions. Their average analysis does not consider the influence of relevant characteristics not intrinsically linked to gender —such as income and education level— that might influence results.

This chapter, however, overcomes this limitation by comparing female and male OPH consumption using statistics techniques that allows to isolate the effect of household characteristics different from gender. This chapter analyses if GHG emissions embedded in female and male OPH consumption patterns are significantly different from each other due to gender differences exclusively by applying two different techniques: the so-called Blinder-Oaxaca Decomposition —which decomposes mean differences based on linear regression models—, and Propensity Score Matching —that capture differences in emissions between two groups with identical characteristics excepting the classification (treatment) of interest—.

The study focuses on Spain for a period of 20 years, 1998-2004 and 2006-2018. Spain is one of the 193 member states committed to incorporate the gender perspective in H2030 plans and strategies coordinating actions necessary for the fulfilment of the Sustainable Development Goals (SDGs) (Spain Government, 2022). Specifically, in Spanish's National Voluntary Report (2018), submitted to the UN, the Action Plan (2018-2020) for the Implementation of the H2030 includes gender equality as a political holder to accelerate the process to achieve all the SDGs. Data used in this chapter are obtained in chapter 1. In particular, the GHG footprints of Spanish OPH between 1998-2004 and 2006-2018. A total of 6 GHGs aggregated into CO_2 equivalent units, 62 industries, and 39 COICOP products grouped into 12 products categories are considered. GHGs estimated includes indirect GHG emissions derived from consumption expenditure as well as direct emissions from household consumption of energy goods (see details in chapter 1).

The rest of the chapter is organised as follows: Section 2 shows results obtained in chapter 1 closely related with the aim of this chapter. Section 3 provides a brief review of the methodologies of the Blinder-Oaxaca Decomposition and Propensity Score Matching. Section 4 presents the main results, and Section 5 summarises the conclusions of this study.

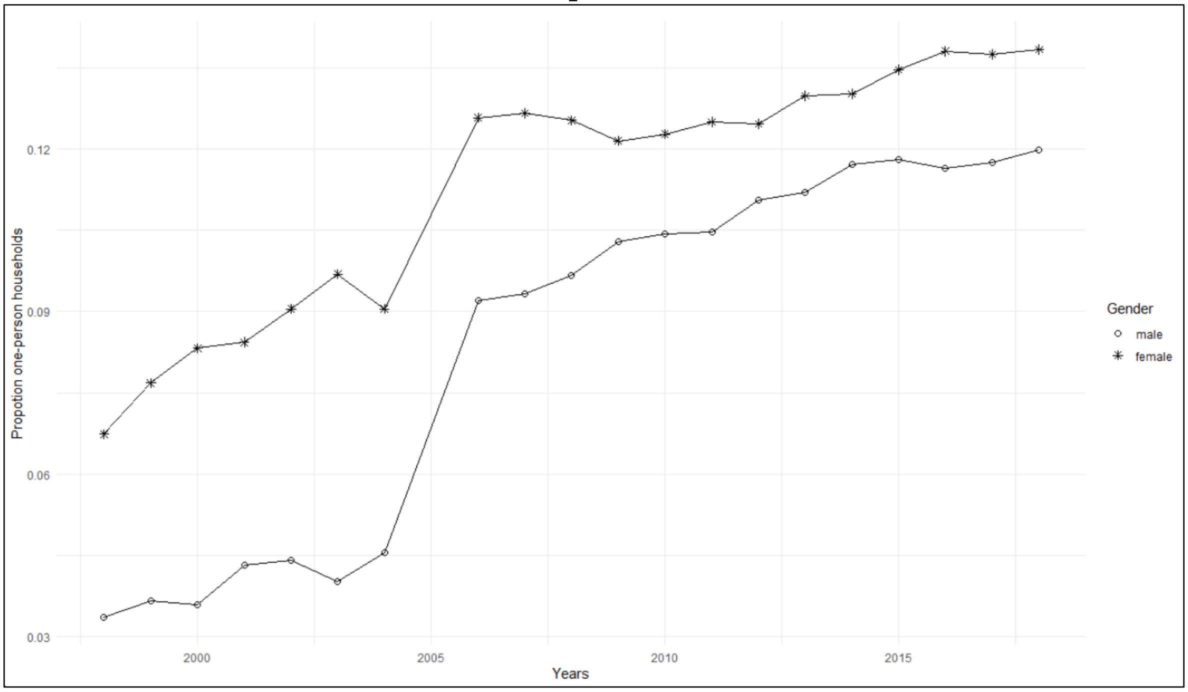
2. DATA SET

This section presents the most relevant information related to this chapter that has been already estimated in chapter 1. Three sources of INE are used to estimate the emissions derived from the consumption of each Spanish household i) Spanish IOT (INE, 2019a), some published by INE and other estimated from SUT (INE, 2019b); ii) Spanish environmental accounts (INE, 2019c); and iii) Spanish HBS (INE, 2019d). Additionally, the BM for the years of interest is estimated from the Danish Bridge Matrices (Denmark Statistics, 2019). For this purpose, the RAS methodology has been used, so that the data are consistent with the aggregate macroeconomic information for Spain (see details in chapter 1). GHG emissions from the consumption of all 39 COICOP products and by the 12 products categories has been estimated applying input-output analysis (see Annex A1.1 in chapter 1). The footprint estimation contains indirect GHG emissions derived from consumption expenditure, as well as direct emissions from household consumption of energy goods (see details in chapter 1).

In this chapter, however, only GHG footprints of female and male OPH are considered, with a final database of 54,562 households. OPH are the only type of households that are not affected by other household members' consumption that might interfere in the analysis of the unique effect of gender. Although OPH cannot represent every single woman and man in Spain, they are the best approximation due to data available. Besides, the current household structural change in developed countries results in an increase of OPH, which is expected to continue increasing (Eurostat, 2022).

Graph 2.1 shows the proportion representation of OPH by gender in Spain between 1998-2004 and 2006-2018 at the population level. OPH has increased from 10% to 26% between the two decades; male OPH have increased by 8% while female OPH have increased by 7% (see details in Annex A2.1).

Graph 2.1: Evolution of female and male one-person households over total households. Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Table 2.1 shows average OPH characteristics by gender between 1998-2004 and 2006-2018. Female OPH spend on average 1,800 euros less per year than male OPH and have a slightly lower level of education. Otherwise, female OPH are older than male OPH and live in less dense areas.

Table 2.1: Average descriptive statistics of household characteristics of female and male one-person households. Spain 1998 – 2018

Variables by gender (weigthed)	Min	Max	Mean	Stand.deviation
Annual expenditure (€)				
Male	673.114	411794.4	17809.330	104.773
Female	248.200	173450.8	15985.120	71.874
Education level SP				
Male	1	3	1.807	0.008
Female	1	3	1.570	0.006
Age in years				
Male	16	97	52.589	0.147
Female	17	99	64.101	0.124
Density				
Male	1	3	1.774	0.007
Female	1	3	1.668	0.005

Note: education level is measured in a scale from 1 to 3 (1 first cycle or less; 2 secondary; 4 university). The density is a categorical variable in a scale from 1 (densely populated area) to 3 (Sparsely populated).

Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

From Annex A2.2, Graph A2.1 to Graph A2.3 show average OPH characteristics evolution by gender between 1998-2004 and 2006-2018 of annual expenditure, education level measured in a scale from 1 to 3 (1 first cycle or less; 2 secondary; 3 university) and average age.

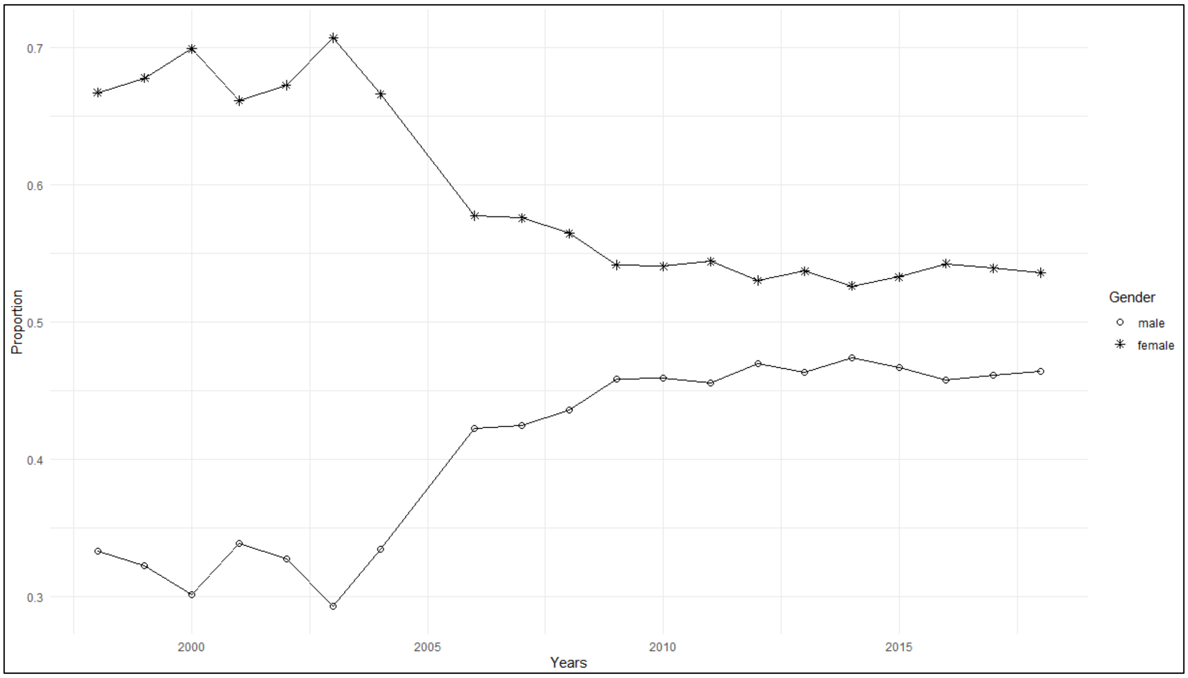
Graph A2.1 shows the expenditure level gender gap. The differences have been decreasing over the years, however, has the highest expenditure gender gap in 2006 with male OPH spending approximately 3 thousand euros more than female OPH, and on average male OPH expend 2,700 euros more than female OPH.

Moreover, Graph A2.2 points clear differences in educational levels between household types, with male OPH having considerably higher levels of education than female OPH, however, both are improving their education levels, with female OPH improving 0.13 points faster than male OPH. Although in 2018 the educational level gender gap is considerably high, second only to the differences in 2000, on average there is a decrease in the differences in educational levels between female and male OPH.

Finally, Graph A2.3 shows the age differences between female and male OPH. The average age of female OPH is around 65 years old, while male OPH do not exceed 60 with average of 54 years old. Even in years such as 2013, differences of up to 12 years in age are found between female and male OPH. Even though both are decreasing in average age, the age average differences between female OPH and male OPH have increased over the years

Graph 2.2 shows the proportion over the twenty years between gender of OPH. In 1998, a large proportion of OPH were female (67%), a gap that has been decreasing over the years, with female OPH representing only 54% in 2018. Moreover, female OPH have different characteristics from male OPH, that might affect emissions patterns by gender. In other words, the differences in characteristics between female and male OPH have evolved over the years, purchasing power gender gap has decreased, both female and male OPH have improved their level of educational level and female OPH are considerable older that male OPH, all of these should affect the difference in consumption, therefore, affect the difference on emissions patterns.

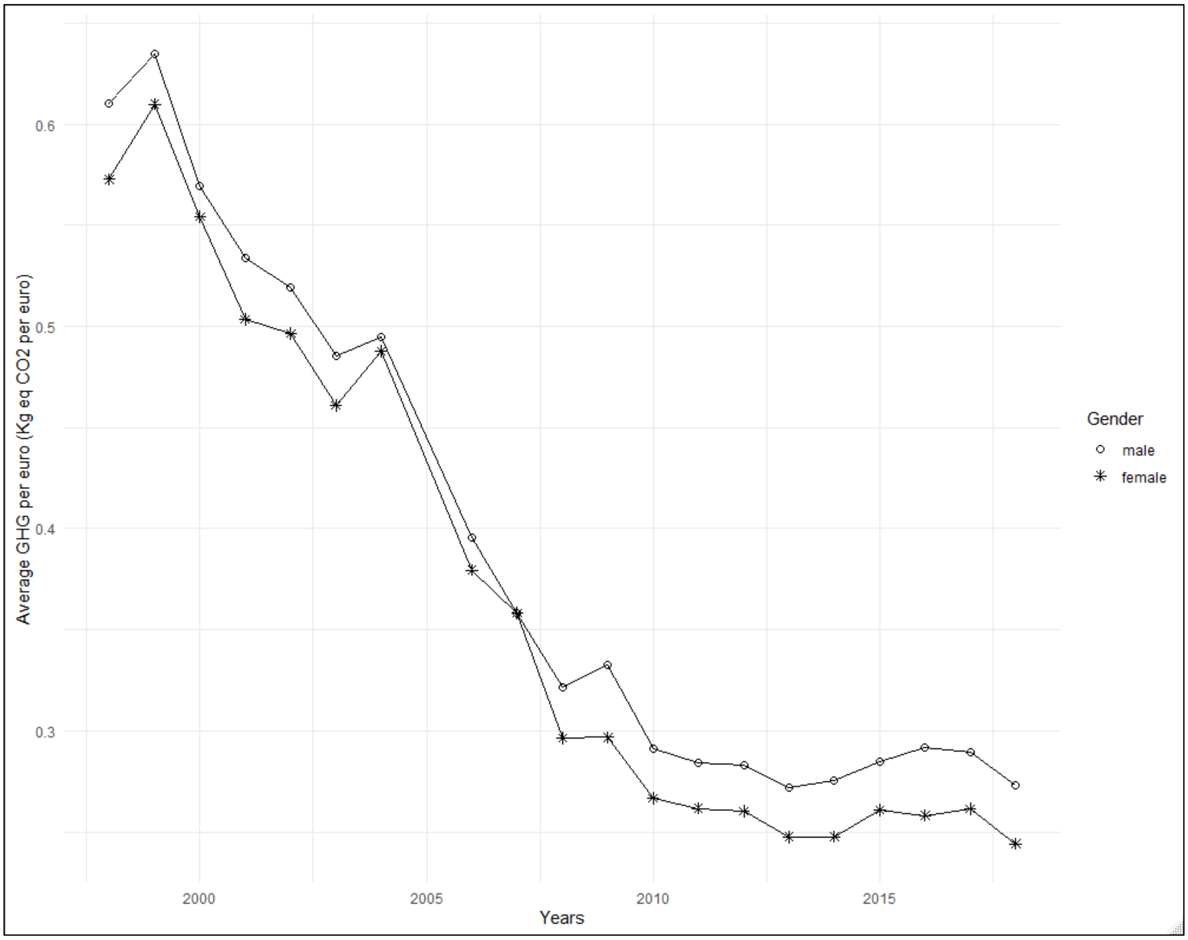
Graph 2.2: Evolution between female and male one-person households. Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

From the environmental point of view Graph 2.3 present the average GHG emissions per euro (i.e., the consumption pattern), distinguishing OPH by gender at population level.

Graph 2.3: Average of greenhouse gases per euro embedded (kgs of equivalent CO_2 per euro) in the consumption basket of female and male one-person households. Spain 1998 – 2018

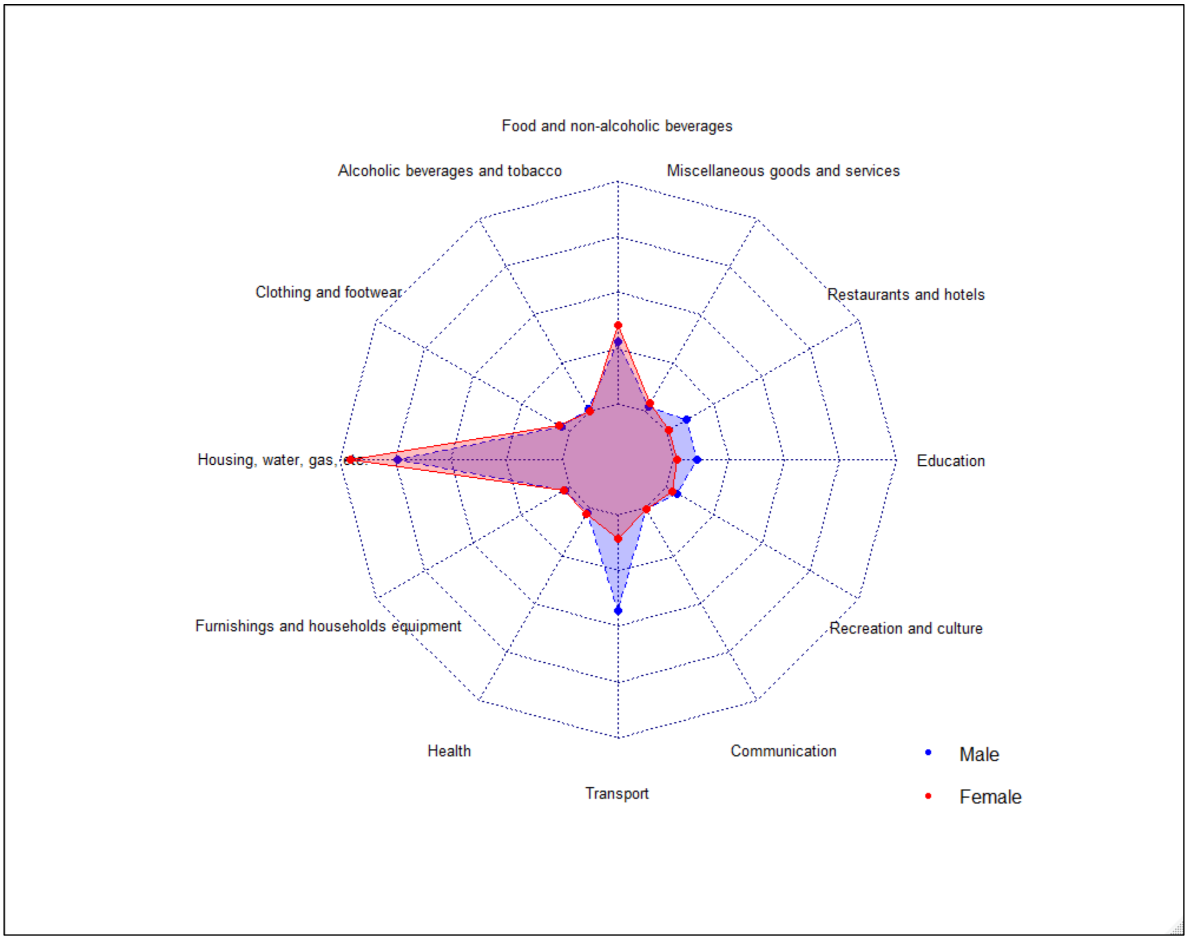


Source: Own elaboration from data presented in chapter 1

Graph 2.3 shows how emissions patterns have been decreasing over the years and that male OPH have emitted more than female OPH per euro spend over the years.

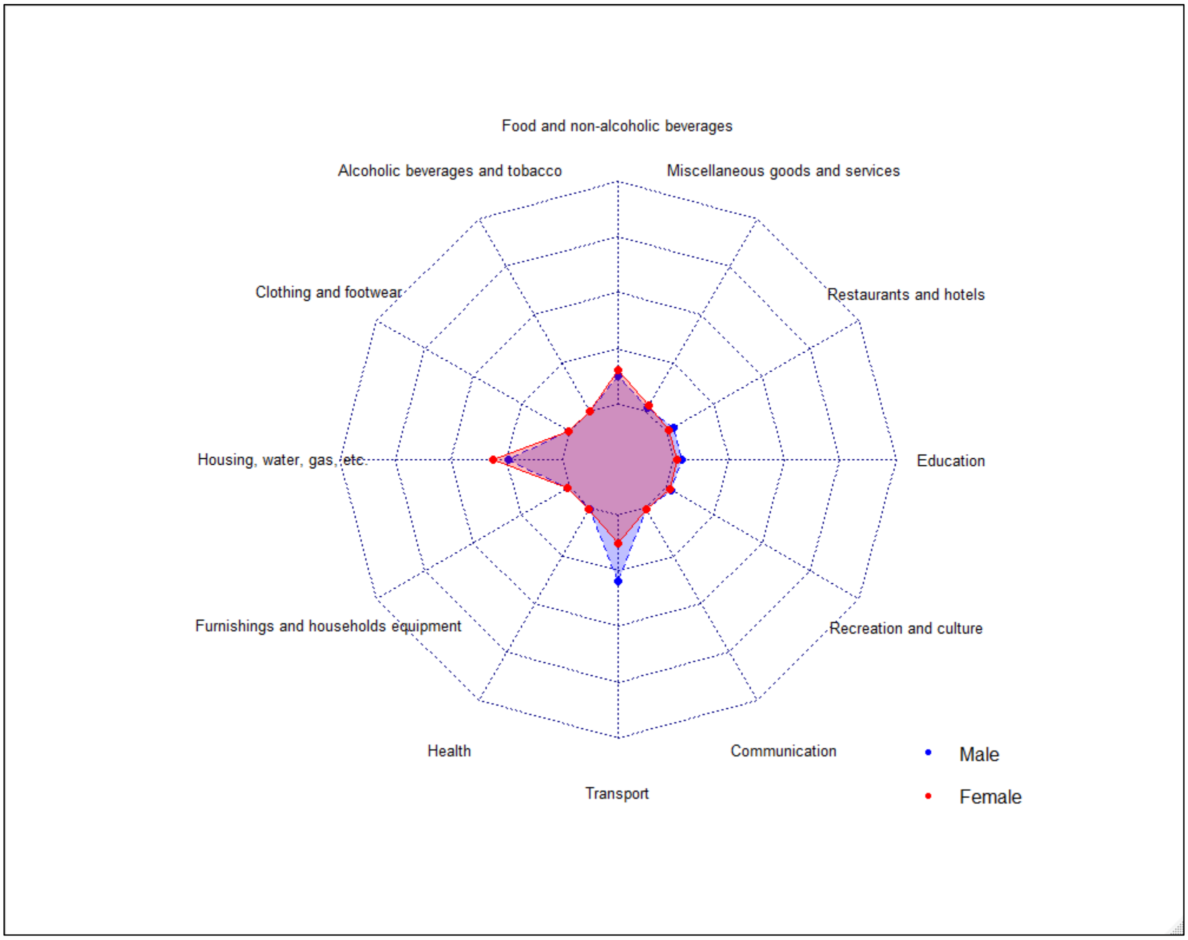
However, this homogeneity of behaviour differs when emissions from consumption are analysed by product categories. Graphs 2.4 and 2.5 show the average emissions per euro expended by type of products in 1998 and 2018.

Graph 2.4: Average greenhouse gases emissions per euro (kgs of CO_2 equivalent per euro) derived from the consumption of the 12 products groups of female and male one-person households. Spain 1998



Source: Own elaboration from data presented in chapter 1

Graph 2.5: Average greenhouse gases emissions per euro (kgs of CO_2 equivalent per euro) derived from the consumption of the 12 products groups of female and male one-person households. Spain 2018

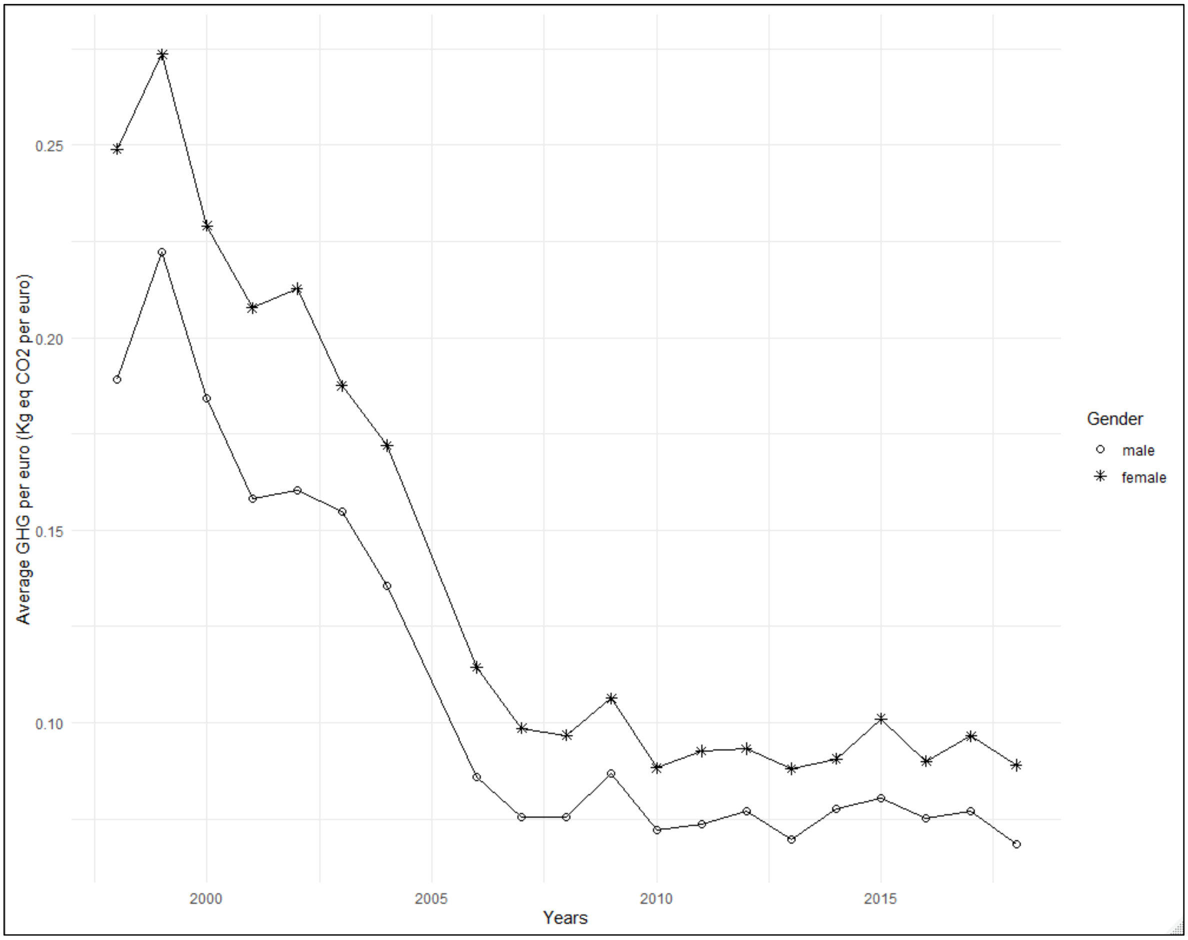


Source: Own elaboration from data presented in chapter 1

Little can be concluded with a quick look at the patterns between the years. There is a larger difference in emissions from transport consumption between female OPH and male OPH along the two decades, with male OPH being higher emitters. Female OPH, otherwise, produce large difference in emissions related from households' commodities consumption. Following chapter 1, it is precisely these categories that include the products that produce direct emissions from household consumption of energy goods, along with, indirect GHG emissions derived from consumption expenditure: 4.5 "Electricity, gas and other fuels" and 7.2 "Operation of personal transport equipment".

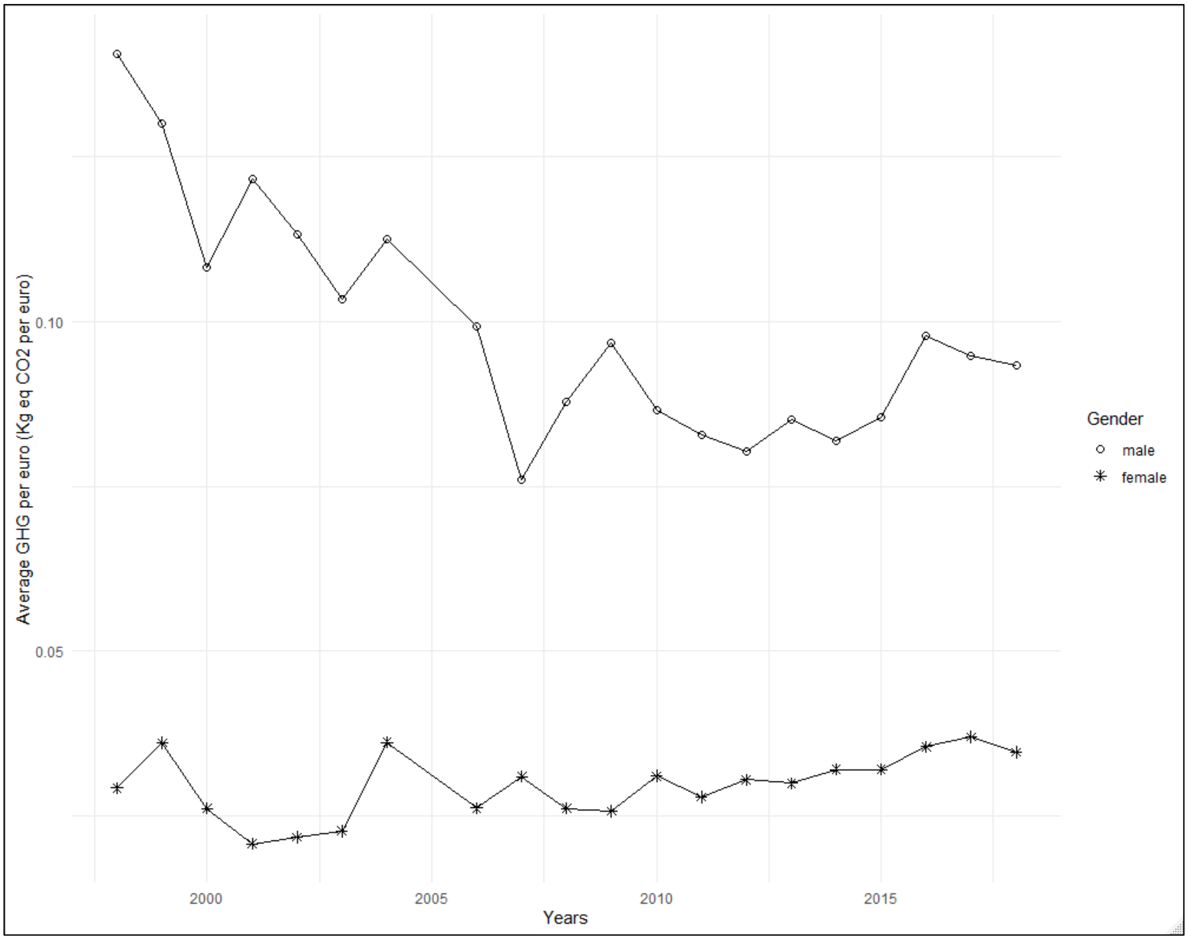
Graphs 2.6 and 2.7 show the evolution by gender of emissions patterns from the consumption of the specific products related to the consumption of energy goods: 4.5 “Electricity, gas and other fuels” and 7.2 “Operation of personal transport equipment”.

Graph 2.6: Average greenhouse gases emissions per euro (kgs of CO_2 equivalent per euro) derived from the consumption of 4.5 “Electricity, gas and other fuels” of female and male one-person households. Spain 1998-2018.



Source: Own elaboration from data presented in chapter 1

Graph 2.7: Average greenhouse gases emissions per euro (kgs of CO_2 equivalent per euro) derived from the consumption of 7.2 "Operation of personal transport equipment" of female and male one-person households. Spain 1998-2018.

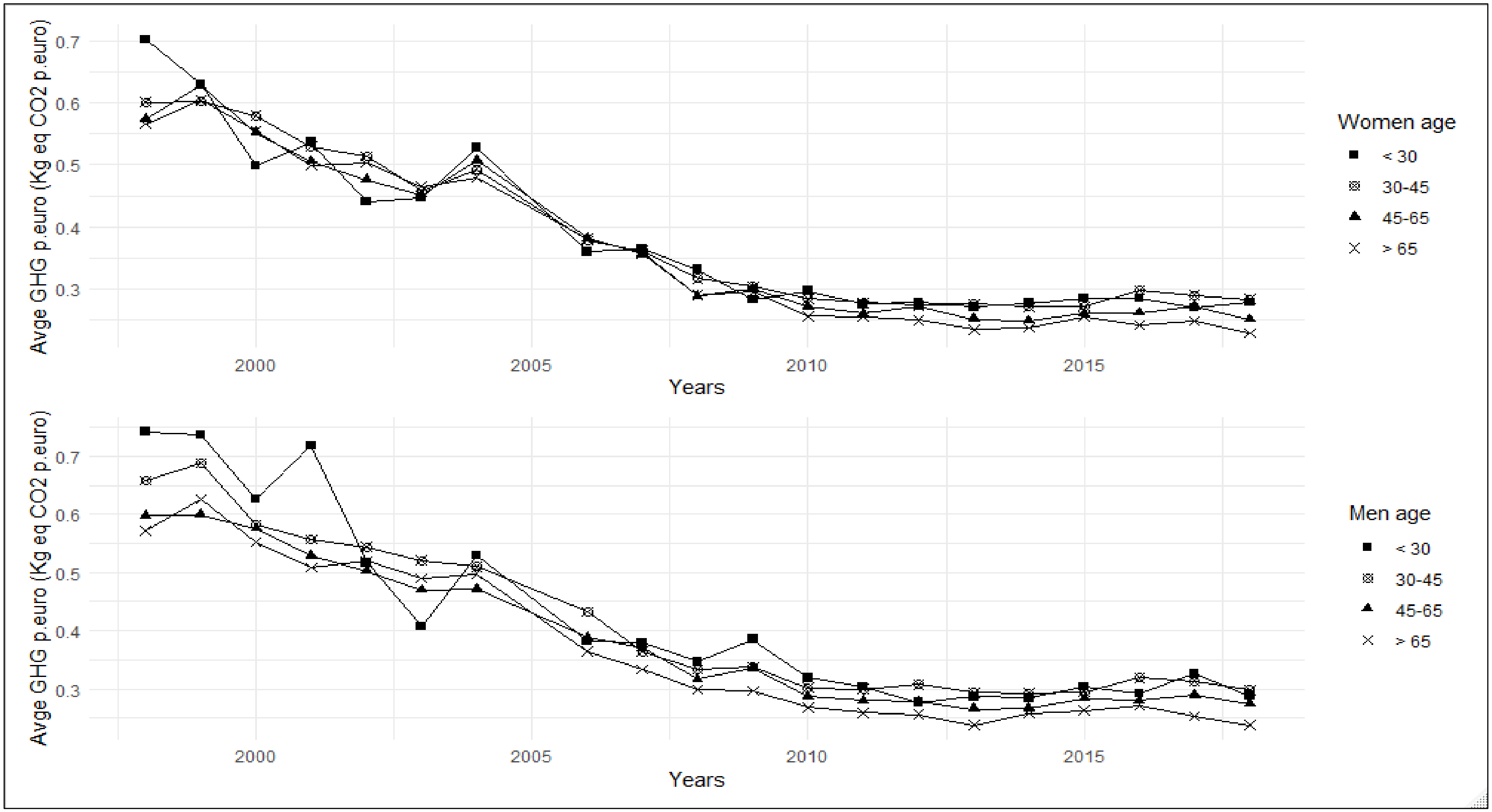


Source: Own elaboration from data presented in chapter 1

Emission patterns from 4.5 "Electricity, gas and other fuels" consumption have been decreasing over the years mainly due to a technological improvement (see comment in chapter 1). Otherwise, emission patterns from 7.2 "Operation of personal transport equipment" consumption have remained almost constant. These results give us an idea of possible gender differences in Spain, although little can be concluded about the differences between female and male OPH at this stage.

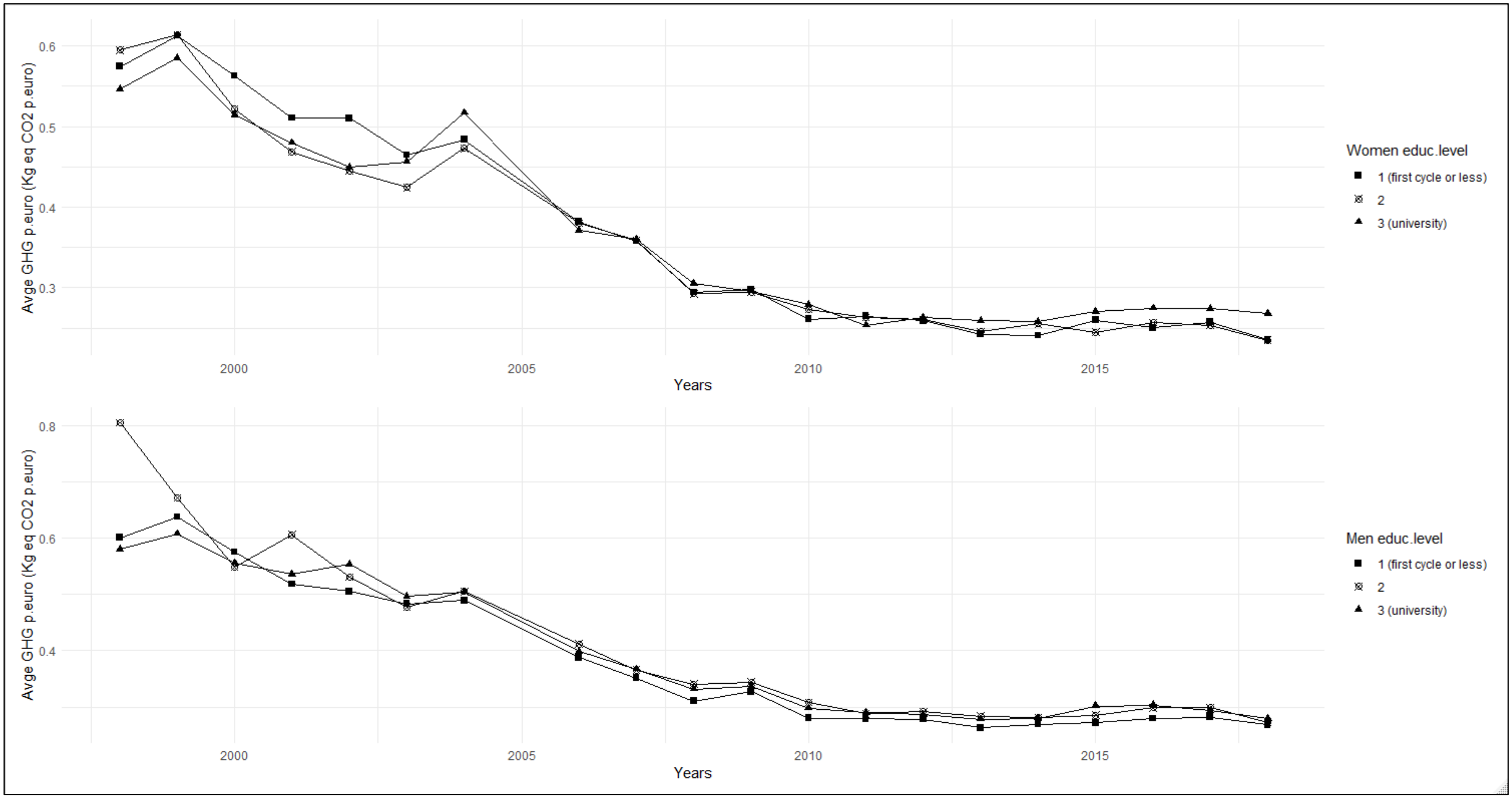
Moreover, GHG emissions derived from consumption are affected by household characteristics. Graphs 2.8, 2.9 and 2.10 show the emissions per euro according to age, education level and expenditure respectively.

Graph 2.8: Average of greenhouse gases embedded per euro (kgs of equivalent CO_2 per euro) in the consumption basket of female and male one-person households by age. Spain 1998 - 2018



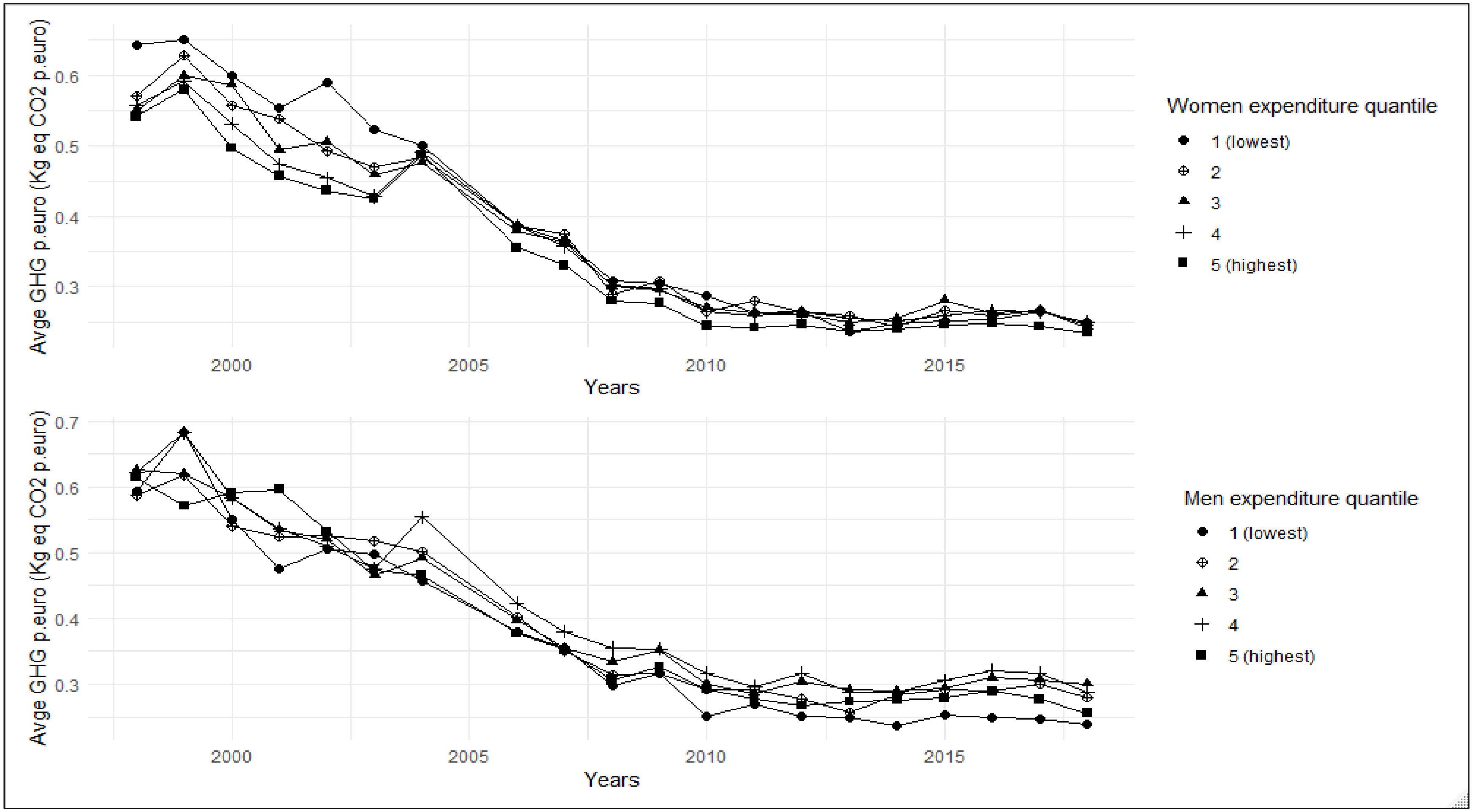
Source: Own elaboration from data presented in chapter 1

Graph 2.9: Average of greenhouse gases embedded per euro (kgs of equivalent CO_2 per euro) in the consumption basket of female and male one-person households by education level. Spain 1998 - 2018



Source: Own elaboration from data presented in chapter 1

Graph 2.10: Average of greenhouse gases embedded per euro (kgs of equivalent CO_2 per euro) in the consumption basket of female and male one-person households by quintile expenditure. Spain 1998 - 2018



Source: Own elaboration from data presented in chapter 1

Regardless of whether you are a female or a male OPH, emission patterns decrease as you get older. Regarding educational level, no clear patterns are found for female OPH, however, male OPH with less education seem to have lower emission patterns. When looking at expenditure quintiles, the lowest quintile of male OPH has lower emission patterns than those male OPH in higher quintiles. The opposite is observed for female OPH, where the lowest quintile of female OPH has the highest emission pattern. Female and male OPH also differ in magnitudes of GHG emissions since they are higher in the male OPH quintiles than in female OPH quintiles.

The analysis of this section shows differences in characteristics and GHG emissions between female and male OPH. However, the analysis of average GHG emissions by gender doesn't lead to solid conclusions since the effect of other characteristics different from gender are not omitted. Therefore, a more detailed analysis controlled by purchasing power, age, educational level, density and region of female and male OPH is performed in the next section by using two different approaches, the Binder-Oaxaca Decomposition and the Propensity Score Matching.

3. METHODOLOGY

Having obtained the emissions derived from the consumption of Spanish households between 1998-2004 and 2006-2018, this section investigates if GHG emissions embedded in female and male OPH consumption patterns are significantly different due to gender differences exclusively. In other words, I want to analyse the difference in GHG emissions from the consumption of female and male OPH without the intervention of other characteristics. The problem is approached under two methodologies: the Blinder and Oaxaca decomposition and the Propensity Score Matching estimator.

Since both methodologies try to capture the gender effect independent of other characteristics, Blinder and Oaxaca decomposition provides the results of the mean differences between households. The mean difference is decomposed in two parts, one explained by the characteristics and the other unexplained. Moreover, besides capturing the average effect of the variable of interest, the Blinder and Oaxaca decomposition also provides relevant information on other characteristics effects present at household level. The Propensity Score Matching is, otherwise, an estimator that separates the results from the confounding factors by providing estimators that are not conditioned by the distributional assumptions of covariance, but valuable information for analysis is missing.

This section is divided into two subsections. Section 3.1 explains the Blinder-Oaxaca decomposition implemented for the analysis of the results; and Section 3.2 refers to all the methodological details to apply the Propensity Score Matching estimator properly.

3.1 Blinder-Oaxaca decomposition

Whenever differences in GHG emissions between female and male OPH can be attributed to gender issues, differences are expected to be found not only due to observable characteristics between individuals, but also due to so-called own consumption decisions attributable by gender differences. “Gender consumption decisions” are not directly observable in databases, being a similar situation as the analysis performed to study the existence of labor market discrimination. In labor market analysis, differences between two groups are, on the one hand, due to individuals own characteristics (such as age, education, region, etc.), and, on the other hand, to an unexplained part that is usually associated with discrimination (Stanley and Jarrell, 1998; Weichselbaumer and Winter-Ebmer, 2005).

One of the most popular methods to capture discrimination is the above-mentioned Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973). This statistical method decomposes the output mean differences between two groups into a part given by the differences in explanatory variables and another given by the differences in coefficient magnitudes. Although Blinder-Oaxaca decomposition originated and has been widely used in the study of labor market discrimination it can be applied to explain differences in any continuous outcome between any two groups as, for instance, immigrant assimilation (LaLonde and Topel 1992), school enrolment rates (Borooah and Iyer 2006), health insurance coverage (Bustamante et al, 2009), smoking prevalence (Bauer et al, 2007), or even local hunting rates (Munn and Hussain 2010). The experience of all these references shows that the application of Blinder-Oaxaca Decomposition is appropriate to study gender differences in GHG emissions generated by consumption patterns.

Equation 2.1 shows the resulting differences between the two groups based on Blinder-Oaxaca Decomposition where *Y* represents GHG emissions per euro and *F* and *M* refer to female and male OPH.

$$\Delta\bar{Y} = \Delta\bar{Y}_F - \Delta\bar{Y}_M \qquad (2.1)$$

Equation 2.1 is decomposed as follows to distinguish the explained from the unexplained part:

$$\Delta\bar{Y} = \underbrace{(\bar{X}_F - \bar{X}_M)'\hat{\beta}_R}_{explained} + \underbrace{\underbrace{\bar{X}'_F(\hat{\beta}_F - \hat{\beta}_R)}_{unexplained\ female} + \underbrace{\bar{X}'_M(\hat{\beta}_R - \hat{\beta}_M)}_{unexplained\ male}}_{unexplained} \qquad (2.2)$$

In equation 2.2 *X* is a vector of characteristics given by the *logarithm of annual household expenditure* measured in euro, *age* (and its square), *educational level*, *density*, and *region* where the individual resides and *year* of survey. β_F and β_M were previously estimated with an Ordinary Least Square (OLS) model for each group separately. β_R is the reference coefficient when estimating the OLS model including both groups (see Annex A2.3 for OLS results).

According to equation 2.2, the decomposition divides the difference in mean outcomes into a portion that is explained by cross-group differences in the explanatory variables, and a part that remains unexplained by these differences.

The unexplained portion of the mean outcomes gap will be attributed to consumption decision due to gender differences. It can be further decomposed into two sub-components, labeled as "unexplained female" and "unexplained male" above. If one interprets the reference coefficient vector to be non-discriminatory, these sub-components measure the part of the mean difference in outcomes that originates from consumption decision of female group and the part that comes from consumption decision of male group, respectively. Farther a detailed, variable-by-variable decomposition can also be estimated:

$$\underbrace{(\bar{X}_F - \bar{X}_M)'\hat{\beta}_R}_{explained} = \underbrace{(\bar{X}_{1F} - \bar{X}_{1M})'\hat{\beta}_{1R}}_{variable\ 1} + \underbrace{(\bar{X}_{2F} - \bar{X}_{2M})'\hat{\beta}_{2R}}_{variable\ 2} + \ldots \tag{2.3}$$

$$\underbrace{\bar{X}'_F(\hat{\beta}_F - \hat{\beta}_R)}_{unexplained\ female} = \underbrace{\bar{X}'_{1F}(\hat{\beta}_{1F} - \hat{\beta}_{1R})}_{variable\ 1} + \underbrace{\bar{X}'_F(\hat{\beta}_{2F} - \hat{\beta}_{2R})}_{variable\ 2} + \ldots \tag{2.4}$$

$$\underbrace{\bar{X}'_M(\hat{\beta}_M - \hat{\beta}_R)}_{unexplained\ male} = \underbrace{\bar{X}'_{1M}(\hat{\beta}_{1M} - \hat{\beta}_{1R})}_{variable\ 1} + \underbrace{\bar{X}'_F(\hat{\beta}_{2M} - \hat{\beta}_{2R})}_{variable\ 2} + \ldots \tag{2.5}$$

Equations 2.4 and 2.5 allow us to visualise the consumption decision by gender effect on other characteristics present in the database.

Blinder and Oaxaca decomposition methodology allows study the emissions differences between female and male OPH given a part explained by the characteristics and an unexplained part associated with consumption decisions due to gender differences. Moreover, analyse the average effect of the other household's characteristics on emissions differences explained by the characteristics and by the consumption decisions by gender effect is allowed.

3.2 Propensity Score Matching

The idea under this methodology is analyses the differences in GHG emissions from the consumption of female OPH compared to male OPH with similar observable characteristics. Therefore, a "treatment effect" problem is faced, which refers to the causal effect of a binary variable (female and male) on an outcome (emissions). In this case, the group of female OPH are effectively the group exposed to the treatment, while the male OPH are the control group and the emissions patterns derived from consumption are the outcomes. The principal econometric problem in the estimation of treatment effects is selection bias, which arises from the fact that treated individuals (or households) differ from the non-treated for reasons other than treatment status per se.

Several methods can be found in the literature to study the treatment effect (Frolich and Sperlich, 2019). In this chapter, however, a problem of selection bias is faced given the non-random participation in the treatment, which produces results that not only show the effect of the female OPH itself, but also the effect of having been "chosen" to live alone. In other words, the fact that a woman lives alone is conditioned by several characteristics that make it difficult to analyse differences with man that live alone (untreated). The previous section shows that on average female OPH have lower expenditure levels, are on average older and have a slightly lower level of education than male OPH. These results limit the type of estimator suitable for measuring differences between households, as results may be affected by treatment choice bias (female OPH) and by differences in the household's characteristics.

Therefore, there is a need for a strategy that identifies the difference in emissions of female OPH with observable characteristics like those of male OPH (Abadie and Imbens, 2006; Cattaneo, 2010; Abadie and Cattaneo, 2018). One of the preferred techniques, which has been replacing the more traditional approaches, is the non-experimental assessment method also named Propensity Score Matching. The Propensity Score Matching is a particular variant of matching techniques based on the idea that bias is reduced when the comparison of results is made with treated and control subjects who are as similar as possible. This method proposes to summarise the pre-treatment characteristics of each subject into a single index (the propensity score or propensity probability) that makes matching possible.

The Propensity Score Matching was proposed by Rosenbaum and Rubin in 1983 as the conditional probability of receiving treatment given pre-treatment characteristics, as shown in equation 2.6

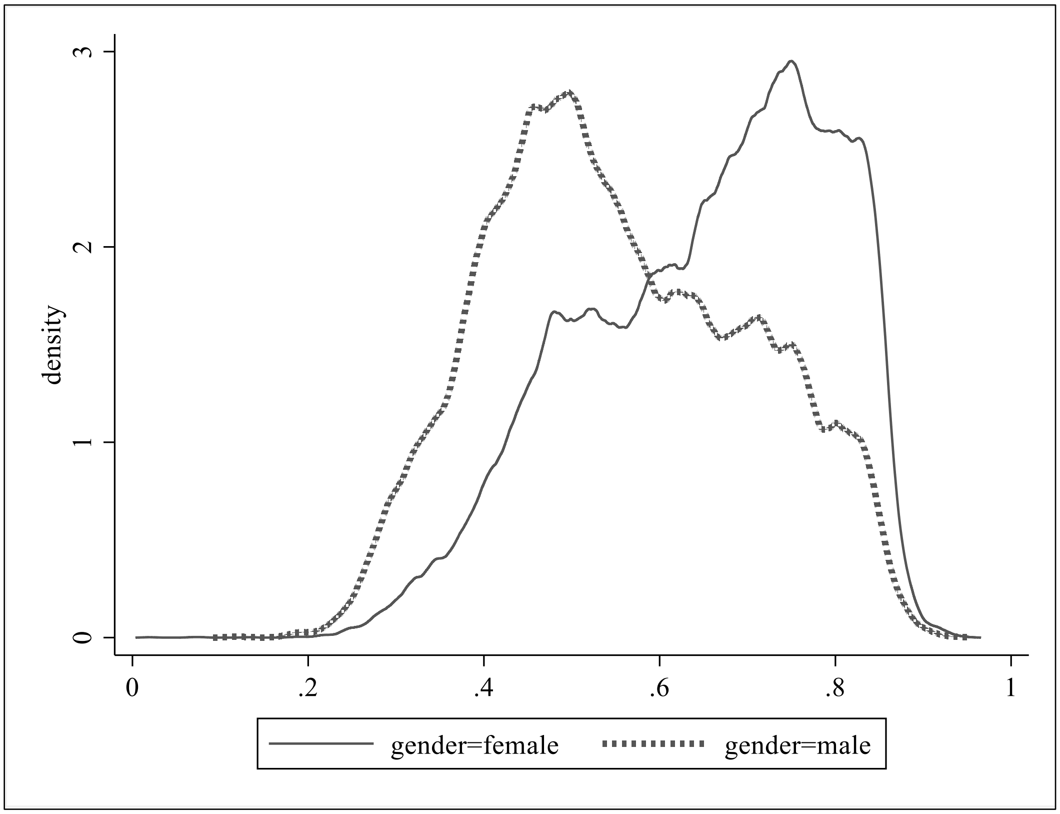
$$p(X) = Pr(W = 1 \mid X) = E(W \mid X) \qquad (2.6)$$

Where $W = \{0,1\}$ is the treatment exposure indicator and X is the multidimensional vector of pre-treatment characteristics. In this case X is given by the *logarithm of annual household expenditure* measured in euro, *age* (and its square), *educational level*, *density*, and *region* where the individual lives and *year* of survey.

Two conditions are needed to properly apply Propensity Score Matching: i) covariates and outcomes must be balanced in both the control and treatment groups; and ii) each sample has a probability of receiving the treatment (or not) greater than zero, well-known as the overlap assumption. The first condition implies that observations with the same propensity probability must have the same distribution of observable (and unobservable) characteristics independent of treatment status. Annex A2.4 shows a summary of the balance of indicators for the covariates considered, which clarifies that it is worked with a well-balanced database with (standardised) mean differences close to zero and variance ratios close to one for all covariates.

Regarding the second condition, the absence of the overlap assumption would imply that for a set of observable covariates, the probability of being in the treated or untreated group is zero (or one). In other words, this would prevent comparing that sample with any other sample, since there would be no real candidate for a potential match. That is, all samples with these characteristics would be in the treated (or control) group and no comparison would be possible. According to Busso, et al. (2014) one way of visually detecting the absence of this assumption is by representing the densities of the treated and non-treated propensity scores and observing densities with too much mass around 0 or 1. Graph 2.11 shows the estimated densities in our sample, suggesting that the overlap requirement holds in our case. Concluding that I am faced with a suitable problem to solve with a treatment effect considering the own characteristics of the database, where the results allow to observe the differences in GHG emissions between households without biasing the results.

Graph 2.11: Estimated densities of propensity scores for the treated and non-treated households. Spain 1998-2018



Source: Own elaboration

4. RESULTS AND DISCUSSION

This section studies the differences in GHG emissions by consumption under Blinder-Oaxaca Decomposition and Propensity Score Matching. GHG emissions, measured in kilograms of equivalent CO_2 per euro consumed, include direct and indirect emissions embedded in households' consumption generated between 1998-2004 and 2006-2018 by Spanish OPH with the objective of analysing the differences in the environmental impact of consumption patterns between female and male OPH. The Blinder-Oaxaca Decomposition application captures the unexplained effect of gender associated with consumption decisions by gender effect, moreover, it provides relevant information on other characteristics effect present at the household level. Otherwise, Propensity Score Matching compares identical households independent of distributional assumptions of covariance.

This section is divided into two subsections. Section 4.1 shows and discusses the results of total GHG emissions per euro (i.e., emissions derived from consumption pattern) applying Blinder-Oaxaca decomposition (Section 4.1.1) and Propensity Score Matching estimator (Section 4.1.2). Similarly, Section 4.2 shows the results of the consumption emission patterns of the 12 products categories, also including the detail for products related to direct household emissions: 4.5 "Operation of personal transport equipment" and 7.2 "Electricity, gas and other fuels". Results at COICOP level are obtained also applying both methodologies: Blinder-Oaxaca decomposition in Section 4.2.1 and Propensity Score Matching estimator in Section 4.2.2.

4.1 Total greenhouse gases per euro

4.1.1 Blinder-Oaxaca Decomposition

Results are presented in Table 2.2, showing a significant negative difference in favour of female OPH. In other words, per euro expend female OPH emits on average 0.004 kilograms of GHGs less than male OPH approximately. This difference is mainly due to the unexplained part, meaning that male OPH produces more GHGs emissions per euro consumed than female OPH partly because of their own characteristics but mainly because they have more polluting consumption patterns than female OPH being explained as consumption decision by gender differences.

Table 2.2: Blinder-Oaxaca decomposition on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) between female and male one-person household. Spain 1998 – 2018

Variable	Total Gas
overall	
women	.32762***
men	.33118***
difference	-.00356*
explained	.00644***
unexplained	-.01***
explained	
l_exp	.00074***
age	-.00668*
sq_age	-0.00491
educ	-.00117***
densi	-.00338***
region	.00128***
year	.02055***
unexplained	
l_exp	-.36471***
age	0.06255
sq_age	-0.02436
educ	-0.00206
densi	.0328***
region	-.04313***
year	-0.00204
_cons	.33096***
*legend: * p<.1; ** p<.05; *** p<.01*	

Source: Own elaboration

Details of each variable considered in this study can be found in the explained and unexplained section of Table 2.2. Note that the sum of each variable gives the total represented in the overall section. Looking at the explained section, the interpretation is that given differences in characteristics as, for instance, expenditure level, female OPH produces more GHG emissions per euro than male OPH. In other words, given that female OPH has a lower expenditure level, they invest each euro less environmentally friendly than male OPH. Unexplained section, however, shows that with equal expenditure level, there exists a difference in the coefficient, associated with consumption decision by gender differences, that produces female OPH to emit less per euro than male OPH. Opposite sign in density variable, that given the difference between municipalities densities, female OPH produces less emissions per euro than male OPH, but the differences associated with the coefficient density differences, associated with consumption decision, cause male OPH to have less emissions patterns than female OPH, something similar apply to region. Coefficient differences related to age (and its square) and educational level are not significant.

4.1.2 Propensity Score Matching

The diagnosis presented in Section 3.2 suggests that the main assumptions required to apply a Propensity Score Matching estimator hold in the sample studied with the specification of covariates considered. Table 2.3 reports results of applying the estimator of gender effect on the total GHG emissions per euro consumed.

Table 2.3: Estimate of the Average Effect on greenhouse gas emissions patterns (in kgs of equivalent CO_2 per euro) of female one-person households. Spain 2018

	Raw sample	Matched
Number of observations (*n*)	54,562	109,124
Male-headed households (control)	21,102	54,562
Female-headed households (treated)	33,460	54,562

	Coefficient	Std. Err.	[95% Conf.	Interval]
Average Treatment Effect (ATE) of female headship	-0.00635	0.00164	-0.00957	-0.00312

Note: Propensity Scores are estimated by means of a probit model.

Source: Own elaboration

Results show the presence of a significant negative effect of female OPH on the GHG emissions patterns. On average, per each euro expend female OPH emits approximately 0.0064 kilograms of GHG less than compared with identical male OPH. In other words, the female OPH studied would emits 0.0064 kilograms of GHG more for euro consumed if they were male, keeping constant the rest of their characteristics (expenditure level, education, age, households, density, and region).

4.2 Greenhouse gases per euro by 12 main COICOP products categories and by product related direct emission

One natural question that might arise from results in Section 4.1 is if the difference of GHG emissions estimated between female and male OPH are distributed uniformly across products or if there are some heterogeneities depending on the product consumed. To answer this question, the previous analysis applying the Blinder-Oaxaca decomposition (Section 4.2.1) and the Propensity Score Matching (Section 4.2.2) is replicated for each one of the 12 products categories identified in the COICOP classification, also considering products related to direct household emissions (see chapter 1 for details).

4.2.1 Blinder-Oaxaca decomposition

Table 2.4 displays results of the Blinder-Oaxaca decomposition for each one of the 12 COICOP products categories and by product related to direct households' emissions: 4.5 "Operation of personal transport equipment" and 7.2 "Electricity, gas, and other fuels". Results are sorted depending on the sign and size of the difference estimated.

Table 2.4: Blinder-Oaxaca decomposition on greenhouse gases emissions patterns (kgs of equivalent CO_2 per euro) by products categories between female and male one-person household. Spain 1998 – 2018

	women	men	difference	explained	unexplained
Products on which women produces less emissions (GHG kg. per total annual consumption in euros)					
Transport	.03881***	.10205***	-.06324***	-.02684***	-.0364***
Others Transport	.00857***	.00998***	-.0014***	-.00292***	.00151***
Operation of personal transport equipment	.03024***	.09207***	-.06183***	-.02392***	-.03791***
Restaurants and hotels	.00592***	.01632***	-.0104***	-.00218***	-.00822***
Recreation and culture	.00918***	.01073***	-.00155***	-.00145***	0
Alcoholic beverages and tobacco	.00088***	.00211***	-.00124***	-.00014***	-.0011***
Education	.0001***	.00014***	-3.5e-05***	-6.9e-05***	3.5e-05***
Products on which women produces more emissions (GHG kg. per total annual consumption in euros)					
Housing, water, electricity, gas and other fuels	.16414***	.12114***	.043***	.02696***	.01603***
Others Households Maintenance	.04406***	.03301***	.01104***	.00818***	.00286***
Electricity, gas and other fuels	.12008***	.08813***	.03195***	.01879***	.01317***
Food and non-alcoholic Beverages	.07337***	.05453***	.01884***	.0096***	.00924***
Miscellaneous goods and services	.01159***	.00611***	.00548***	.00023***	.00525***
Clothing and nootwear	.00832***	.0058***	.00253***	-.00018***	.00271***
Health	.00441***	.00278***	.00163***	.00059***	.00105***
Furniture, householdequipment, etc.	.00596***	.00473***	.00123***	.00019***	.00104***
Communications	.00494***	.00475***	.00019***	-.00029***	.00048***
*legend: * p<.1; ** p<.05; *** p<.01*					

Source: Own elaboration

In Table 2.4, the first block of products corresponds to the groups of “Transport”, “Restaurants and hotels”, “Recreation and culture”, “Alcoholic beverages and tobacco”, and “Education”, for which GHG emissions of female OPH are significantly lower than for male OPH counterparts. Remarkably, GHG emissions associated with the consumption of “Transport” is estimated to be the largest differences between female and male OPH, as well as being one of the most polluting products: per euro, male OPH emits 0.063 kilograms of GHGs more than female OPH.

Moreover, when the emissions related to transport (category 7) are disaggregated by the emissions related to energy product consumption (7.2 “Operation of personal transport” and the other two products grouped as “Others transport”, that is 7.1 “Purchase of vehicles” and

7.3 “Transport services”, which includes public transport, some relevant conclusions can be inferred. Both, the emission related to car use and others transport, have a negative effect meaning that female OPH pollute less. However, “Others transport” shows a negative effect associated with their own characteristics and a positive effect referring to consumption decision by gender differences. In other words, female OPH emits less than male OPH explained by the differences in characteristics between household types, however, female OPH emit more than male OPH given by their own consumption decision but on a smaller scale. Recalling that “Others Transport” includes product group 7.3 about “Transport services” in which emissions associated with public transport services such results are not surprising. Similar conclusions can be adopted for emissions associated to “Education” where female OPH emit less than male OPH given by differences in characteristics, but female OPH emit more than male OPH explained by their own consumption decision but on a smaller scale. Furthermore, the differences in emissions by products are mainly due to the unexplained part, referring to the consumption’s patterns given by gender, except for the emissions related with “Recreation and culture” products where the differences are mainly explained by differences in characteristics.

On the other extreme of the spectrum of categories, female OPH produced more GHG emissions than male OPH for “Housing, water, electricity, gas and other fuels”, “Food and non-alcoholic beverages”, “Miscellaneous goods and services”, “Clothing and footwear”, “Health”, “Furniture, household equipment and other maintenance expenses”, and “Communications”. Highlight the results associated with GHG emissions associated with the consumption of “Clothing and footwear” where there is a negative effect referring to the fact that female OPH, given their own characteristics (e.g., income) emit less than men, but a considerably higher proportion is given by the so-called gender differences. Similarly, emissions associated with “Communications” consumption, but on a much smaller scale.

The GHG emissions associated with the consumption of category 4 “Housing, water, electricity, gas and other fuels” is estimated to be the second largest differences between female and male OPH. Per euro, female OPH emits 0.043 kilograms of GHGs more than male OPH. These differences, however, are mainly explained by the characteristics of the individuals and not for the so-called gender differences. The same conclusion applies, even when product group 4.5 “Electricity, gas and other fuels” related to direct household emissions is disaggregated, and the category "Food and non-alcoholic beverages".

4.2.2 Propensity Score Matching

Propensity Score Matching estimator results for each one of the 12 COICOP products categories and by product related to direct households’ emissions are presented in Table 2.5, sorted depending on the sign and size of the effect estimated. Note that the sum of effects estimated across categories equals the total effect reported in Table 2.3 of section 4.1.2.

Table 2.5: Estimate of the Average Effect on greenhouse gas emissions patterns (in kgs of equivalent CO_2 per euro) of female one-person households by products categories. Spain 2018

Average Treatment Effect (ATE) of female headship	Coef.	Std. Error	[95% Conf. Interval]	
Products on which female one-person households produces less emissions (GHG kg. per total annual consumption in euros)				
Transport	-0.0363	0.0011	-0.0385	-0.0341
Others Transport	0.0011	0.0002	0.0007	0.0015
Operation of personal transport equipment	-0.0374	0.0011	-0.0397	-0.0352
Restaurants and hotels	-0.0084	0.0002	-0.0088	-0.0081
Alcoholic beverages and tobacco	-0.0011	0.0000	-0.0011	-0.0010
Products with non-significant gender differences in emissions (GHG kg. per total annual consumption in Euros)				
Recreation and culture	-0.0003	0.0002	-0.0006	0.0000
Products on which female one-person households produces more emissions (GHG kg. per total annual consumption in euros)				
Housing, water, gas, electricity and other fuels	0.0201	0.0012	0.0177	0.0225
Others Households Maintenance	0.0031	0.0003	0.0025	0.0037
Electricity, gas and other fuels	0.0170	0.0012	0.0147	0.0193
Food and non-alcoholic beverages	0.0094	0.0005	0.0085	0.0103
Miscellaneous goods and services	0.0051	0.0001	0.0048	0.0053
Clothing and footwear	0.0025	0.0001	0.0023	0.0027
Health	0.0011	0.0001	0.0009	0.0013
Furniture, household equipmen, etc	0.0011	0.0001	0.0009	0.0012
Communications	0.0005	0.0001	0.0004	0.0006
Education	0.0000	0.0000	0.0000	0.0000

Source: Own elaboration

Groups of “Transport”, “Restaurants and hotels” and “Alcoholic beverages and tobacco” have emissions patterns of female OPH significantly lower than for male OPH. “Transport” is, as expected, the largest difference between female and male OPH, where per euro male OPH emits 0.0363 kilograms of GHGs more than female OPH under the same characteristics. “Others Transport”, however, have significantly higher emissions patterns of the presence of female OPH. Female OPH, on average, emits approximately 0.0011 kilograms of GHGs per euro expend more that they compared with identical male OPH, but to a smaller dimension than the emissions associated with 7.2 “Operation of personal transport equipment” consumption.

Regarding the second block of categories that groups product groups with no significant differences in the emissions by gender, only “Recreation and culture” consumption is considered.

In the third block of categories, in which female OPH produced more GHG emissions per euro than male OPH households it is found several product groups. For instance, “Housing, water, gas, electricity and other fuels”, “Food and non-alcoholic beverages”, “Miscellaneous goods and services”, “Clothing and footwear”, “Health”, “Furniture, household equipment and other maintenance expenses”, “Communications” and “Education”. These are groups of products on which the estimated effect is significant, but they are not sufficient to offset the effect with opposite sign found for the first block.

5. CONCLUSIONS

Results presented in this chapter contribute to the debate on the gender perspective reflected in emission patterns in Spain over the last 20 years. Evidence is provided on the different emission patterns between female and male OPH considering their characteristics and clarifying the role of gender in sustainable production and consumption. This study contributes to the literature by disaggregating data by gender and providing statistical evidence of differences in GHG emission patterns based on consumption between female and male OPH.

Results between Blinder-Oaxaca decomposition and Propensity Score Matching estimator not only complement each other, but also reinforce their conclusions. Considering the results with respect to total emission patterns, both methodologies confirm that male OPH are higher emitters than female OPH. Blinder-Oaxaca results, moreover, provides information by variable, where a large part of the differences associated with consumption decisions by gender are associated by the level of expenditure.

Moreover, when looking at differences by product categories, both methodologies show the same pattern on the sign and size of the effect estimated, some small differences on “Recreation and culture” being the 3rd larger differences in favor of female OPH under Blinder-Oaxaca estimator, and not significant under Propensity Score Matching. “Education” categories have almost cero effect under Propensity Score Matching against female OPH, however, Blinder-Oaxaca results shows a small but significant difference in favor of female OPH.

Male OPH pollutes more due to emissions embedded in the consumption of products such as "Transport", "Hotels, cafés and restaurants", and “Alcoholic beverages and tobacco”, which are closely related with a life-style outside home and their major emissions. Exceptionally, “Transport”, estimated to be the largest differences between female and male OPH, when it is disaggregated by “Others Transport” and “Operation of personal transport equipment” shows differences between Blinder-Oaxaca and Propensity Score Matching results. Blinder-Oaxaca decomposition shows negative differences in both categories. “Others Transport”, that include: “Transport services” and “Purchase of vehicles”, presents a negative effect associated with their own characteristics and a positive effect referring to consumption decision by gender differences. In other words, female OPH have less emitter patterns principle explained by their own characteristics, but on a smaller scale, higher emitter patterns given by their own consumption decision. Propensity Score Matching, however, shows that “Others Transport” have significantly higher emissions patterns of the presence of female OPH, but not enough to offset the emissions associated with the consumption of car use. Moreover, female OPH have more polluting patterns due to the consumption of products related to the energy consumed within home, food, and clothing under both methodologies.

The results expose the role of women in consumption and in a general more environmentally friendly demand. The role of individuals in climate change mitigation efforts has been described. It also provides information for the correct design of environment-related public policies, such as product labelling, public information campaigns among others under a gender perspective.

There are, however, some limitations of this analysis that should be consider in further studies. On one hand, is the lack of individual consumption data needed to properly analyse the differences in emissions between women and men, on the other hand, average characteristics of women and men living in OPH are not representing the average characteristics of Spanish women and men. However, this sample represent the closest individual information available. Furthermore, this database is not totally free from the influence of other family members, e.g., divorced parents.

Finally, as future work, it would be interesting to analyse the differences in emissions between female and male OPH in different EU countries. Moreover, and given that longitudinal information is available, it would be possible to analyse the impact and the differences of cohort on emissions from a gender perspective, as well as the impact of ageing, among others. It is also possible to compare differences between regions and to analyse whether women and men change their emission patterns with respect to their place of residence.

This study suggests that gender issues associated with consumption difference and emission patterns are important. It has found over the years that the differences between female and male OPH have an effect on the environment. Therefore, it is interesting to analyse how gender issues escalate into other aspects. One structural change in developed countries within households has been a significant increase in female breadwinners, explained by higher education level and greater incorporation into the labor market, where Spain is considered an interesting country to analyse. The increase in female breadwinners' households have been studied from different perspectives, but not for an environmental approach. This research suggests that differences in emissions by gender could produce differences in female and male breadwinner households emissions, which motivate the following research question that will be faced in chapter 3: "*Who bring the emissions home? Investigating the effect of female breadwinners' households in greenhouse gases emissions patterns.*"

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7. ANNEX A2

ANNEX A2.1

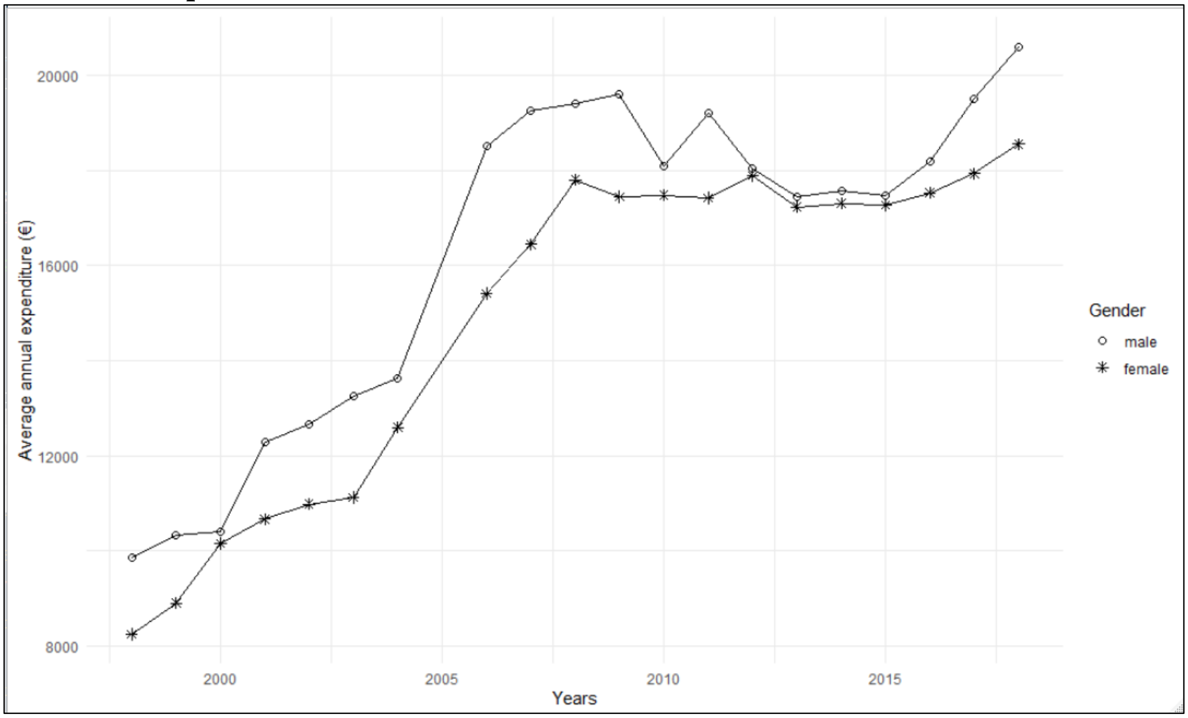
Table A2.1: Percentage of one-person households over total households. Spain 1998-2018 – Population level

Year	female OPH	male OPH
1998	6.74%	3.36%
1999	7.68%	3.66%
2000	8.32%	3.58%
2001	8.43%	4.32%
2002	9.05%	4.41%
2003	9.69%	4.02%
2004	9.05%	4.54%
2006	12.58%	9.21%
2007	12.66%	9.33%
2008	12.53%	9.67%
2009	12.15%	10.29%
2010	12.27%	10.43%
2011	12.50%	10.47%
2012	12.46%	11.05%
2013	12.98%	11.19%
2014	13.01%	11.72%
2015	13.46%	11.80%
2016	13.80%	11.65%
2017	13.75%	11.76%
2018	13.83%	11.98%

Source: Own elaboration

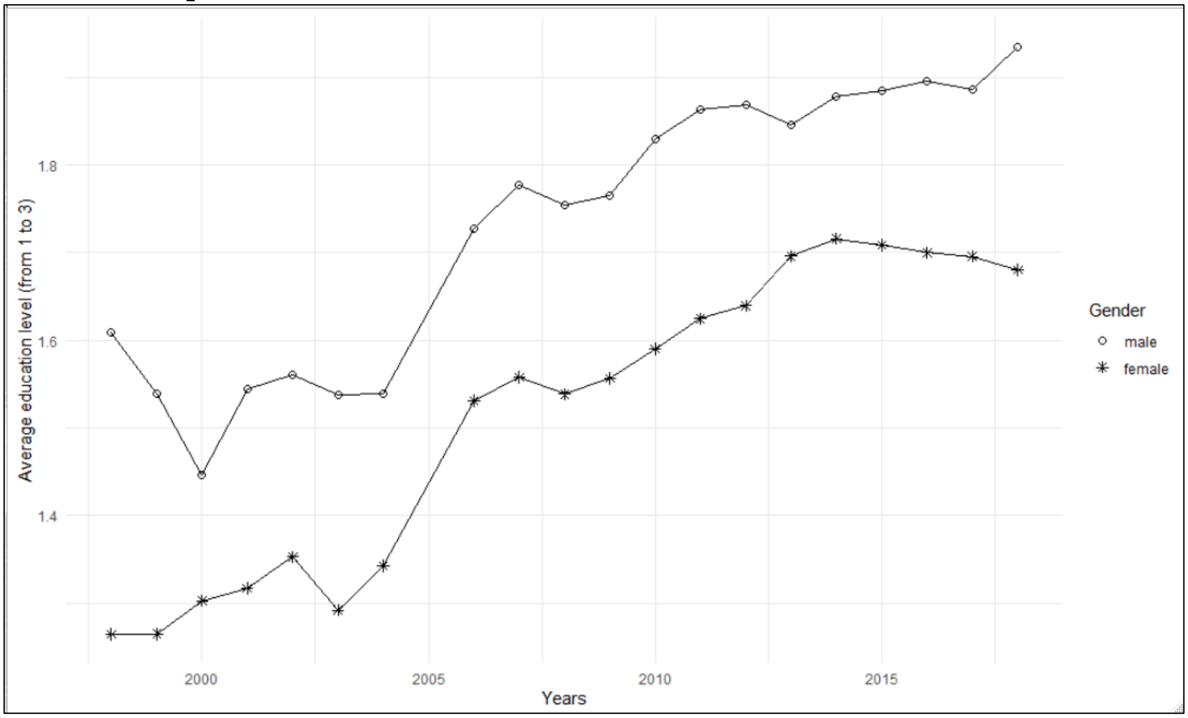
ANNEX A2.2

Graph A2.1: Evolution of average annual expenditure of female and male one-person households. Spain 1998 – 2018



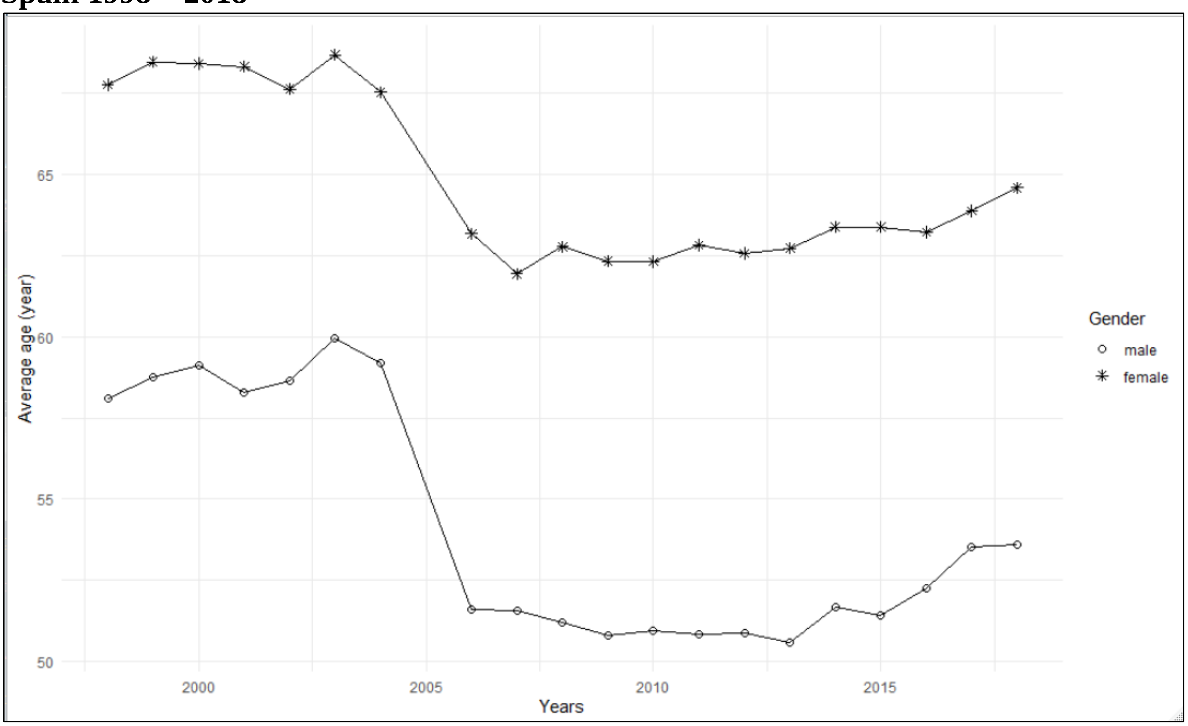
Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph A2.2: Evolution of average educational level of female and male one-person households. Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph A2.3: Evolution of average age of female and male one-person households. Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

ANNEX A2.3

Table A2.2: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for female one-person households. Spain 1998 - 2018

Variable	Coef.	Std. Err.	[95% Conf.	Interval]
l_exp	-0.025983	0.0019375	-0.029781	-0.022186
age	0.0003935	0.0004029	-0.000396	0.0011832
sq_age	-1.07E-05	3.36E-06	-1.73E-05	-4.11E-06
ed_dummy1	-0.010526	0.002525	-0.015475	-0.005577
ed_dummy2	-0.009976	0.0029177	-0.015695	-0.004257
ed_dummy3	0	(omitted)		
dens_dummy1	-0.031587	0.0021904	-0.03588	-0.027294
dens_dummy2	0	(omitted)		
dens_dummy3	0.0287574	0.0028815	0.0231097	0.0344051
reg1	-0.072362	0.0056546	-0.083445	-0.061279
reg2	-0.007613	0.0066015	-0.020552	0.005326
reg3	-0.028895	0.0061914	-0.04103	-0.01676
reg4	-0.080631	0.0065115	-0.093394	-0.067869
reg5	-0.085585	0.0062683	-0.097871	-0.073299
reg6	-0.029432	0.0066322	-0.042431	-0.016432
reg7	0.0299541	0.0064529	0.0173063	0.0426019
reg8	-0.007901	0.0071234	-0.021863	0.0060607
reg9	-0.030261	0.005843	-0.041714	-0.018809
reg10	-0.067319	0.0057286	-0.078547	-0.056091
reg11	-0.064593	0.0066985	-0.077722	-0.051464
reg12	-0.017503	0.0062099	-0.029674	-0.005331
reg13	-0.031976	0.0057772	-0.0433	-0.020653
reg14	-0.074376	0.0066458	-0.087402	-0.06135
reg15	0	(omitted)		
reg16	-0.053605	0.0056203	-0.064621	-0.042589
reg17	0.0104781	0.0072606	-0.003753	0.024709
year1	-0.040042	0.0109154	-0.061437	-0.018648
year2	0	(omitted)		
year3	-0.052728	0.0102366	-0.072792	-0.032664
year4	-0.104768	0.0096528	-0.123688	-0.085849
year5	-0.109586	0.009975	-0.129137	-0.090035
year6	-0.14323	0.0095699	-0.161988	-0.124473
year7	-0.116169	0.0096561	-0.135095	-0.097243
year8	-0.221101	0.0086194	-0.237995	-0.204207
year9	-0.239244	0.0084699	-0.255845	-0.222643
year10	-0.298734	0.0084377	-0.315272	-0.282196
year11	-0.300247	0.008466	-0.316841	-0.283654
year12	-0.330308	0.0083662	-0.346706	-0.31391
year13	-0.332089	0.0083025	-0.348362	-0.315816
year14	-0.332708	0.0083067	-0.348989	-0.316427
year15	-0.347912	0.0082434	-0.364069	-0.331755
year16	-0.346363	0.0082514	-0.362536	-0.33019
year17	-0.332847	0.0083456	-0.349204	-0.316489
year18	-0.335828	0.0083106	-0.352117	-0.319539
year19	-0.331219	0.008335	-0.347555	-0.314882
year20	-0.347159	0.008397	-0.363617	-0.330701
_cons	0.9253675	0.0227414	0.8807942	0.9699407

Source: Own elaboration

Table A2.3: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for male one-person households. Spain 1998 – 2018

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	0.0121558	0.0024732	0.0073083	0.0170033
age	-0.000583	0.00054	-0.001641	0.0004756
sq_age	-5.81E-06	4.70E-06	-0.000015	3.41E-06
ed_dummy1	-0.010363	0.0032876	-0.016806	-0.003919
ed_dummy2	0.0022311	0.0038572	-0.005329	0.0097912
ed_dummy3	0	(omitted)		
dens_dummy	-0.067255	0.0034586	-0.074034	-0.060476
dens_dummy	-0.030404	0.0040592	-0.03836	-0.022448
dens_dummy	0	(omitted)		
reg1	-0.017893	0.0071137	-0.031836	-0.00395
reg2	0.0331729	0.0089254	0.0156791	0.0506668
reg3	0.0172723	0.0086448	0.0003284	0.0342162
reg4	-0.029278	0.0079596	-0.044879	-0.013678
reg5	-0.026822	0.0078572	-0.042222	-0.011422
reg6	0	(omitted)		
reg7	0.0691112	0.0082347	0.0529711	0.0852514
reg8	0.0280459	0.0094599	0.0095043	0.0465874
reg9	-0.00702	0.0073356	-0.021398	0.0073576
reg10	-0.012217	0.0073987	-0.026719	0.0022843
reg11	-0.003761	0.0093275	-0.022043	0.0145213
reg12	0.0246457	0.008079	0.0088108	0.0404807
reg13	0.0084948	0.0074794	-0.006165	0.0231546
reg14	-0.011366	0.0087391	-0.028495	0.0057629
reg15	0.0292204	0.0091515	0.0112834	0.0471575
reg16	-0.015367	0.0072113	-0.029502	-0.001233
reg17	0.0458127	0.0092482	0.0276862	0.0639393
year1	0	(omitted)		
year2	0.0230368	0.0216724	-0.019441	0.0655149
year3	-0.039998	0.0211584	-0.081468	0.0014729
year4	-0.077379	0.0215551	-0.119627	-0.03513
year5	-0.089351	0.0187406	-0.126082	-0.052619
year6	-0.123668	0.0194499	-0.16179	-0.085546
year7	-0.116921	0.0193643	-0.154876	-0.078967
year8	-0.225009	0.0170184	-0.258365	-0.191653
year9	-0.261159	0.0167495	-0.293989	-0.22833
year10	-0.299883	0.0166409	-0.332499	-0.267267
year11	-0.28814	0.0169705	-0.321403	-0.254878
year12	-0.328667	0.0164224	-0.360855	-0.296479
year13	-0.338409	0.016377	-0.370508	-0.30631
year14	-0.338453	0.0163996	-0.370596	-0.30631
year15	-0.348955	0.0162907	-0.380885	-0.317025
year16	-0.345977	0.0163485	-0.37802	-0.313933
year17	-0.336201	0.0164185	-0.368382	-0.304021
year18	-0.328412	0.0165618	-0.360874	-0.295951
year19	-0.330067	0.0163902	-0.362192	-0.297942
year20	-0.347972	0.0163706	-0.380059	-0.315886
_cons	0.5944114	0.0310917	0.5334713	0.6553514

Source: Own elaboration

Table A2.4: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for one-person households. Spain 1998 – 2018

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.00759	0.0015696	-0.010666	-0.004514
age	-0.00058	0.0003339	-0.001235	0.0000744
sq_age	-3.67E-06	2.82E-06	-9.2E-06	1.86E-06
ed_dummy1	-0.008945	0.0021084	-0.013077	-0.004812
ed_dummy2	-0.00293	0.0024952	-0.00782	0.0019608
ed_dummy3	0	(omitted)		
dens_dummy	-0.03445	0.0019317	-0.038236	-0.030664
dens_dummy	0	(omitted)		
dens_dummy	0.0288542	0.0024386	0.0240747	0.0336338
reg1	-0.073469	0.0044776	-0.082245	-0.064693
reg2	-0.014991	0.0053974	-0.025571	-0.004412
reg3	-0.0335	0.0050833	-0.043464	-0.023537
reg4	-0.083143	0.0050914	-0.093122	-0.073164
reg5	-0.085441	0.0049839	-0.095209	-0.075672
reg6	-0.042315	0.0054601	-0.053016	-0.031613
reg7	0.0219509	0.0051371	0.0118821	0.0320198
reg8	-0.018223	0.005808	-0.029606	-0.006839
reg9	-0.045094	0.0046388	-0.054186	-0.036002
reg10	-0.068244	0.0046106	-0.077281	-0.059208
reg11	-0.063454	0.0055637	-0.074359	-0.052549
reg12	-0.024581	0.0049591	-0.034301	-0.014861
reg13	-0.040003	0.0046326	-0.049083	-0.030923
reg14	-0.0719	0.0054334	-0.08255	-0.061251
reg15	-0.012655	0.0058458	-0.024113	-0.001197
reg16	-0.062843	0.0045162	-0.071695	-0.053991
reg17	0	(omitted)		
year1	-0.033666	0.0102567	-0.053769	-0.013562
year2	0	(omitted)		
year3	-0.056726	0.0095849	-0.075512	-0.037939
year4	-0.104154	0.009577	-0.122926	-0.085383
year5	-0.111462	0.0090042	-0.12911	-0.093813
year6	-0.145746	0.0088724	-0.163136	-0.128356
year7	-0.126399	0.0089744	-0.143989	-0.108809
year8	-0.232741	0.0079503	-0.248323	-0.217158
year9	-0.259395	0.0078137	-0.27471	-0.24408
year10	-0.310213	0.0077548	-0.325413	-0.295014
year11	-0.305693	0.0079309	-0.321238	-0.290149
year12	-0.340974	0.0076703	-0.356008	-0.325941
year13	-0.346395	0.007614	-0.361319	-0.331472
year14	-0.34735	0.0076403	-0.362324	-0.332375
year15	-0.359984	0.0075686	-0.374819	-0.34515
year16	-0.357937	0.0075988	-0.372831	-0.343043
year17	-0.3461	0.0076532	-0.3611	-0.331099
year18	-0.344293	0.0077062	-0.359397	-0.329188
year19	-0.342334	0.0076446	-0.357317	-0.32735
year20	-0.358978	0.0076556	-0.373983	-0.343973
gender	0.0099954	0.0015131	0.0070298	0.0129609
_cons	0.798203	0.0183431	0.7622504	0.8341555

Source: Own elaboration

ANNEX A2.4

Table A2.5: Balance indicators for the covariates under Propensity-Score Matching.

		Standardized differences		Variance	Ratio
Variables		Raw	Matched	Raw	Matched
l_exp		-0.125045	-0.0074268	0.9152432	1.000511
age		0.5849763	-0.015063	0.8905631	1.034117
sq_age		0.5956205	-0.0110515	0.9915367	1.00132
estudredsp					
	2	-0.178582	0.0053275	0.6868611	1.011519
	3	-0.162312	-0.0031381	0.8247994	0.9963555
ccaa					
	2	0.0135301	0.0080601	1.058067	1.034226
	3	0.0396214	0.0186501	1.190905	1.086887
	4	0.0221572	0.0052169	1.107491	1.02416
	5	-0.045925	0.0113703	0.8188846	1.051492
	6	0.0144326	0.0091381	1.07625	1.047726
	7	-0.00135	0.0089872	0.9957594	1.028847
	8	0.0085504	-0.0279904	1.037832	0.8884563
	9	0.0153483	-0.0020116	1.043969	0.9944104
	10	0.0084214	-0.0011473	1.0263	0.9964589
	11	-0.025163	-0.0146357	0.8938921	0.9375128
	12	0.032146	0.0098646	1.12074	1.035318
	13	-0.006322	-0.0085584	0.9787727	0.9718337
	14	-0.016076	-0.0038845	0.9239656	0.9811195
	15	-0.005168	-0.0086659	0.9768431	0.9612686
	16	-0.041137	0.0017171	0.8961439	1.004617
	17	-0.009827	0.0009115	0.9511176	1.004706
densi					
	2	-0.021061	-0.0017557	0.9686147	0.9973091
	3	-0.127661	-0.0196714	0.8977368	0.9832258
anoenc					
	1999	0.0489788	0.0049932	1.412496	1.034979
	2000	0.0547422	0.0043072	1.453975	1.02891
	2001	0.0388859	0.0122747	1.289473	1.082604
	2002	0.0385893	-0.0015781	1.282411	0.9900853
	2003	0.0553831	0.0129668	1.434991	1.087068
	2004	0.0323531	-0.005151	1.234197	0.9676389
	2006	0.0091244	0	1.038498	1
	2007	0.0219753	-0.0092388	1.088833	0.9653542
	2008	0.0176717	0.0030685	1.069718	1.011724
	2009	-0.004622	-0.0082455	0.9830918	0.9703167
	2010	-0.008296	0.0050992	0.9702063	1.018732
	2011	-0.011465	-0.0107565	0.9595208	0.9621787
	2012	-0.017288	-0.000675	0.9403	0.9975933
	2013	-0.016861	0.0034336	0.9436317	1.01191
	2014	-0.040654	-0.0021057	0.8726133	0.9928247
	2015	-0.030686	0.0069225	0.903819	1.023399
	2016	-0.019739	0.001608	0.9380682	1.005237
	2017	-0.029418	-0.010852	0.9111861	0.9661886
	2018	-0.034702	0.0053743	0.8961022	1.017255
l_exp#					
l_exp		-0.128036	-0.0074218	0.9030535	0.9969829
estudredsp#					
l_exp					
	2	-0.177992	0.0051694	0.6876118	1.010975
	3	-0.161486	-0.0032791	0.8259271	0.9958746

Source: Own elaboration

WHO BRINGS THE EMISSIONS HOME? INVESTIGATING THE EFFECT OF FEMALE BREADWINNER HOUSEHOLDS IN GREENHOUSE GASES EMISSIONS PATTERNS

1. INTRODUCTION

The previous chapter has provided empirical evidence that suggest that gender is a relevant dimension on explaining GHG emissions induced by consumption. This chapter departs from this finding and investigates how this could be impacting in the GHG emissions as a consequence of the evolving characteristics of modern western societies. Female Breadwinners Households (FBH), a term used to refer to women being main economic income producer on households, represent a relatively new phenomenon around the world. They represent a significant proportion of households across developed countries today (Winkler et al., 2005; Wang et al., 2013; Wooden and Hahn, 2014). Countries such as Slovenia, Ireland, or Canada already had more than 30% of households with female main breadwinners in 2013 (Kowalewska and Vitali, 2020).

FBH are different in characteristics than Male Breadwinners Households (MBH). FBH are associated with higher levels of education and higher labour participation (Raley et al., 2006; Vitali and Mendola, 2014), older than their counterpart (Bloemen and Stancanelli, 2015), and living in household units with less members (Bianchi et al., 1999).

However, little is known about the determinants and consequences this structural change of households might entail. Regarding the determinants, two are the main reasons that might explain the increase in FBH: (i) an increase in the male unemployment rate, or (ii) a genuine decision driven by women's job ambition and their potential for higher wages relative to men given their higher education level Drago et al. (2005). Vitali and Arpino (2016) analyse these two aspects for 26 European countries in 2011, concluding that in most cases (including Spain) the increase is explained by economic reasons —high male unemployment rates— rather than women's ambition. Additionally, Klesment and Van Bavel (2017) using data from the European Union's Statistics on Income and Living Conditions for 27 countries in 2007 and 2011 deduce that the main reason for this change in households is due to educational issues. Women increased their level of education above men, both in quantity and quality, which allowed women to access better jobs.

Furthermore, the increase of FBH also has consequences in internal household organization. An increase in economic resources provided by women leads to an increase in female bargaining power within the household (Antman, 2014). The income structure also seems to influence household behaviour modifying the structure of household consumption (Bourguignoni et al., 1993), even when the total household income is fixed (Duncan, 1990; Schultz, 1990). An evaluation of a housing reform policy in China, which transferred property rights of rented homes to individuals, increased individual's bargaining power within the household, reducing household consumption of some goods preferred by men when rights were given to women (Wang, 2014).

Therefore, an increase in female main breadwinners might be reflected in decision-making power and, consequently, in the demand for different goods and services such as food, transport, or fashion commodities (Greene-Finestone et al., 2005; Prati, 2018; Alves-Kein et al., 2020).

Since a significant part of GHG emissions is generated by the private consumption made by households (Munksgaard et al., 2000; Long et al., 2021), an increase of FBH might have relevant effects on global GHG emissions. However, the potential effect of the feminisation on GHG emissions have not yet been studied. The fewer exceptions are Dizialo (2017), who analyses gender differences in pro-environmental attitudes, and Koengkan and Fuinhas (2021), who study environmental impact from an inequality perspective. While both studies seem to conclude that a gender perspective contributes to explaining variability in environmental issues, the specific role of consumption in different goods and services has not been studied.

The hypothesis of this chapter is that households with female and male breadwinners present significant differences in GHG emissions embedded in consumption. If this is the case, the increasing participation of women as head of households will not only impact on socio-economic indicators but will also affect the demand for certain types of products associated with environmental consequences.

The case study for this research is developed for Spain, where there has been an important and intensive growing incorporation of women in both the educational and labour system since the 1980s when some socioeconomic structural changes related with the political regime change of 1975 were consolidated. In 2021 women's employment has increased to reach an activity rate of 70.8%, surpassing the peak of women working in 2019. Between 2007 and 2021, adult women (aged 45-54) have experienced a much higher increase in the labour force (59.2%) than men (28.4%). Additionally, women are strongly represented in the labour market at the highest educational levels with an upward trend, reaching the 53.1% of employees with tertiary education. Active women with this level of education have increased by 51.5% since 2007, compared to a smaller increase in men with this level of education (28.3%) (Ministry of Labor and Social Economy, 2021). Therefore, Spain is a particularly interesting country to study, where an increase in female labour participation and higher educational levels are also reflected in FBH, which has increased from less than 14% in the early 1980s to 35% in 2021 (Aldas and Solaz, 2017; INE, 2022a).

As explained in previous chapters, it seems appropriate to use: the Blinder-Oaxaca decomposition and the Propensity Score Matching estimator to measure gender effect on GHG emissions. This chapter aims at studying the differences in emission between FBH and MBH regardless of other economic and demographic characteristics of households. Emission information derived from the consumption baskets of 1998, 2008, 2014 and 2018 Spanish households is used for the aggregation of 6 GHGs, 62 industries, and 39 products grouped into 12 products categories under the COICOP. The estimation includes direct and indirect GHG emissions derived from households' consumption expenditure and households' consumption of energy goods (see details in chapter 1).

Given the computational challenge of estimating differences in emissions for all households over 20 years, crucial years have been chosen with respect to employment levels in Spain. Considering the available database, the largest gender employment gap is in 1998. Around the 2008 crisis, female employment increases while male employment decreases. From 2013 onwards, both female and male employment rates recover and in 2018 the gender gap in employment has decreased considerably (see details in following section). Since the increase in FBH is directly related to female employment rates relative to male employment rates, the years 1998, 2008, 2014 and 2018 are chosen.

The chapter is structured as follows. Section 2 contextualises the database already obtained in chapter 1, in which emissions derived from Spanish household consumption baskets for the year 1998, 2008, 2014 and 2018 are used. Section 3 briefly reviews the methodologies already presented in chapter 2. Section 4 and Section 5 present the main results and summary conclusions of this study.

2. DATA SET

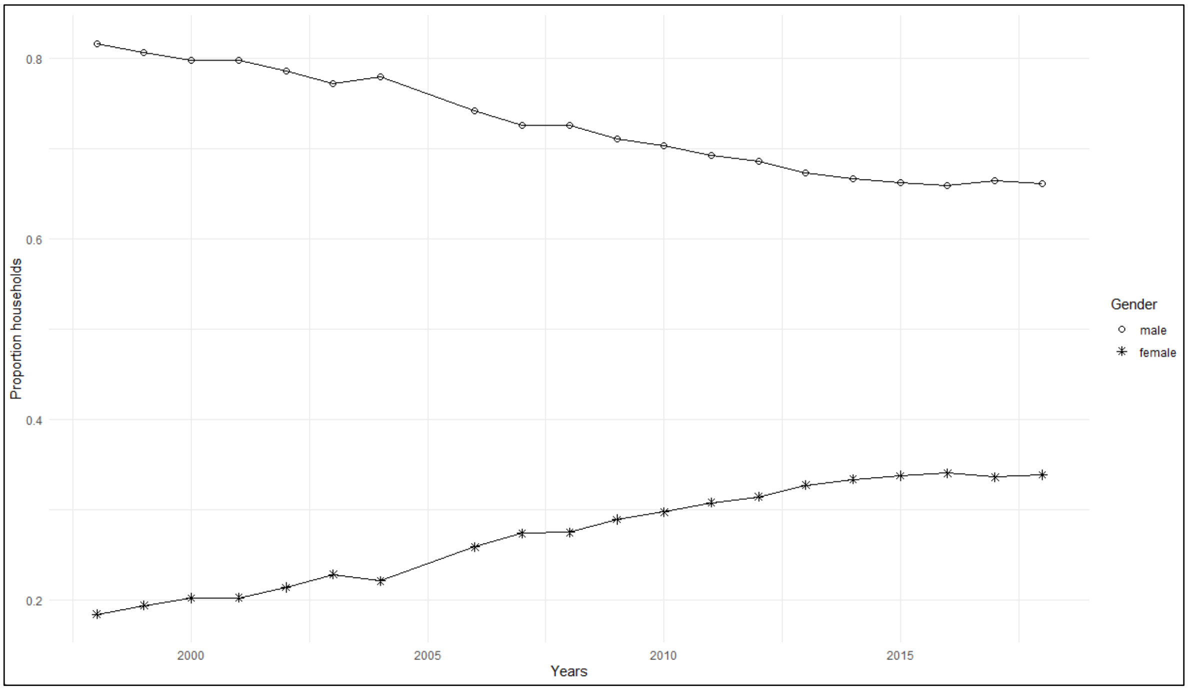
In this chapter, the databases estimated in chapter 1 are used. This section presents the most relevant information and structure of the database related to this chapter.

Three sources of statistical data are used to estimate the emissions derived from the consumption of each Spanish household for the years of interest: i) Spanish IOT estimated from SUT (INE, 2019a), ii) Spanish environmental accounts (INE, 2019b), and iii) Spanish HBS (INE, 2019c). Additionally, the BM delivered by Denmark Statistics (2019)[4] are used as a starting point to estimate the Spanish BM for 1998, 2008, 2014 and 2018. For this purpose, the RAS methodology has been used so that the data is consistent with the aggregate macroeconomic information. GHG emissions from the consumption of 39 COICOP products have been estimated applying input-output techniques, including direct and indirect GHG emissions. See details in chapter 1.

Graph 3.1 shows the proportion of FBH and MBH and how they have evolved over the two decades. In 1998 FBH represented only 18% of households (82% of MBH) to almost 34% in 2018 (66% of MBH), showing an increase (or decrease) of 16% through the years. (See details in Annex A3.1).

[4] For this chapter I also applied Cazcarro et.al (2021) bridge matrix as a starting point to estimate the Spanish bridge matrix for the year 2018. The results change slightly in dimensions but not in conclusions.

Graph 3.1: Evolution of female and male breadwinner households over total households. Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Table 3.1 shows main average descriptive statistics of household by gender breadwinner between 1998-2004 and 2006-2018. FBH spend on average 5 thousand euros less than MBH, have a slightly higher level of education and live in household units with less members. In addition, female breadwinners are older than male breadwinners and live in less dense areas.

Table 3.1: Average descriptive statistics of household characteristics of female and male breadwinner households. Spain 1998 – 2018

Variables by gender (weigthed)	Min	Max	Mean	Stand.deviatio
Annual expenditure (€)				
Male	306.61	419912.62	28127.82	42.022
Female	248.20	332932.61	23025.34	59.708
Education level SP				
Male	1	3	1.660	0.002
Female	1	3	1.728	0.004
Household members				
Male	1	19	2.953	0.003
Female	1	18	2.092	0.005
Age HH in years				
Male	16	99	52.745	0.038
Female	16	99	56.369	0.072
Density				
Male	1	3	1.792	0.002
Female	1	3	1.655	0.003

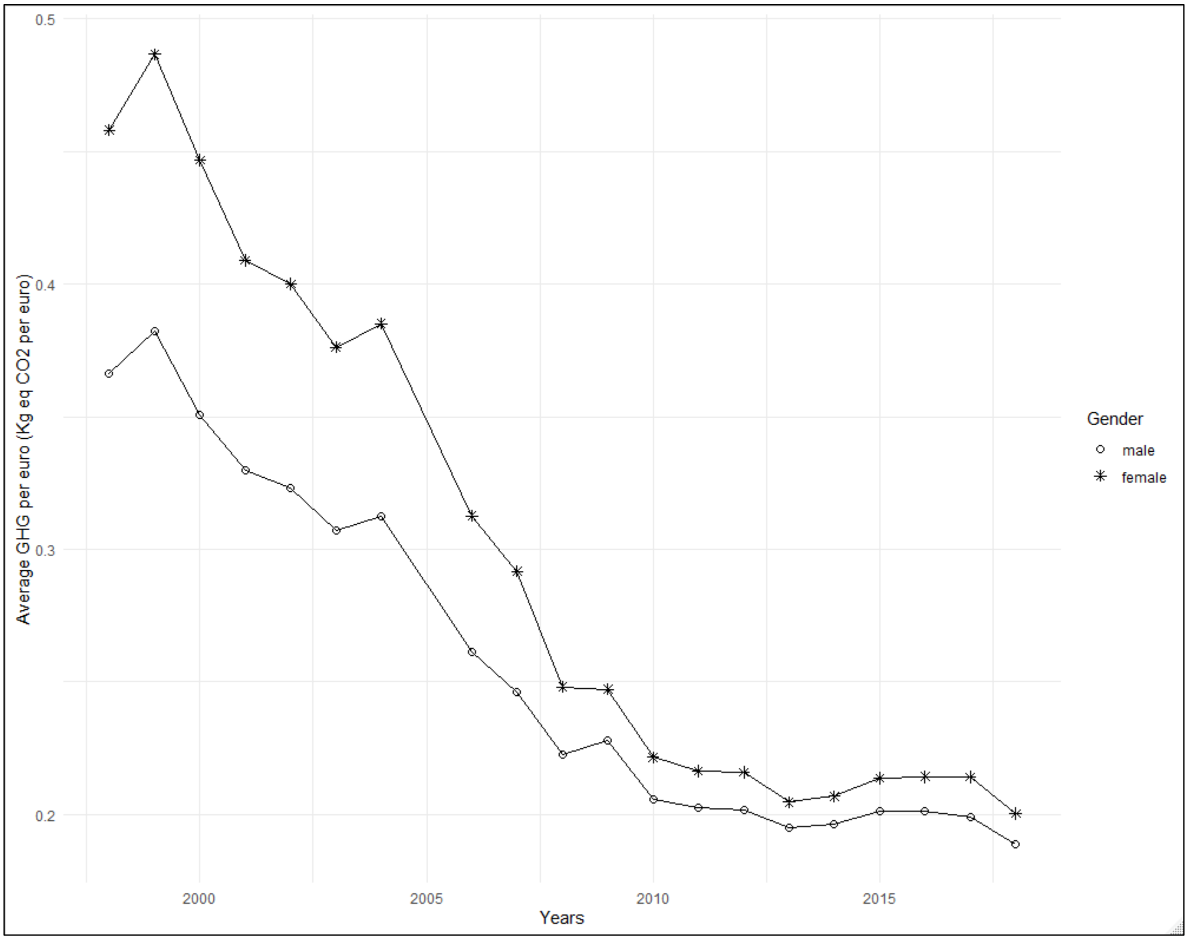
Note: education level is measured in a scale from 1 to 3 (1 first cycle or less; 2 secondary; 4 university). The density is a categorical variable in a scale from 1 (densely populated area) to 3 (Sparsely populated).

Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

From Annex A3.2, Graphs A3.1 to A3.3 show the evolution of average characteristics of FBH and MBH between 1998-2004 and 2006-2018. Graph A3.1 shows differences between FBH and MBH in their expenditure levels. MBH have a considerably higher level of expenditure, differences that have not decreased over the years but increased in many years (see details Annex A3.3). Graph A3.2 shows how the average education level of MBH was slightly higher than of FBH before 2004, but it reversed afterwards being the average educational level of FBH slightly higher. Finally, Graph A3.3 shows that female breadwinners are older than male breadwinners, although this difference has been decreasing over the years. The age difference might be caused by the relatively high percentage of old women living alone who acts as a main female breadwinner.

Graphs 3.2 presents average GHG emissions per euro, distinguishing the type of households at population level with the equivalent household size correction.

Graph 3.2: Average greenhouse gases per euro embedded (kgs of equivalent CO_2 per euro) in the consumption basket of female and male breadwinner households. Spain 1998 – 2018



Source: Own elaboration from data presented in chapter 1

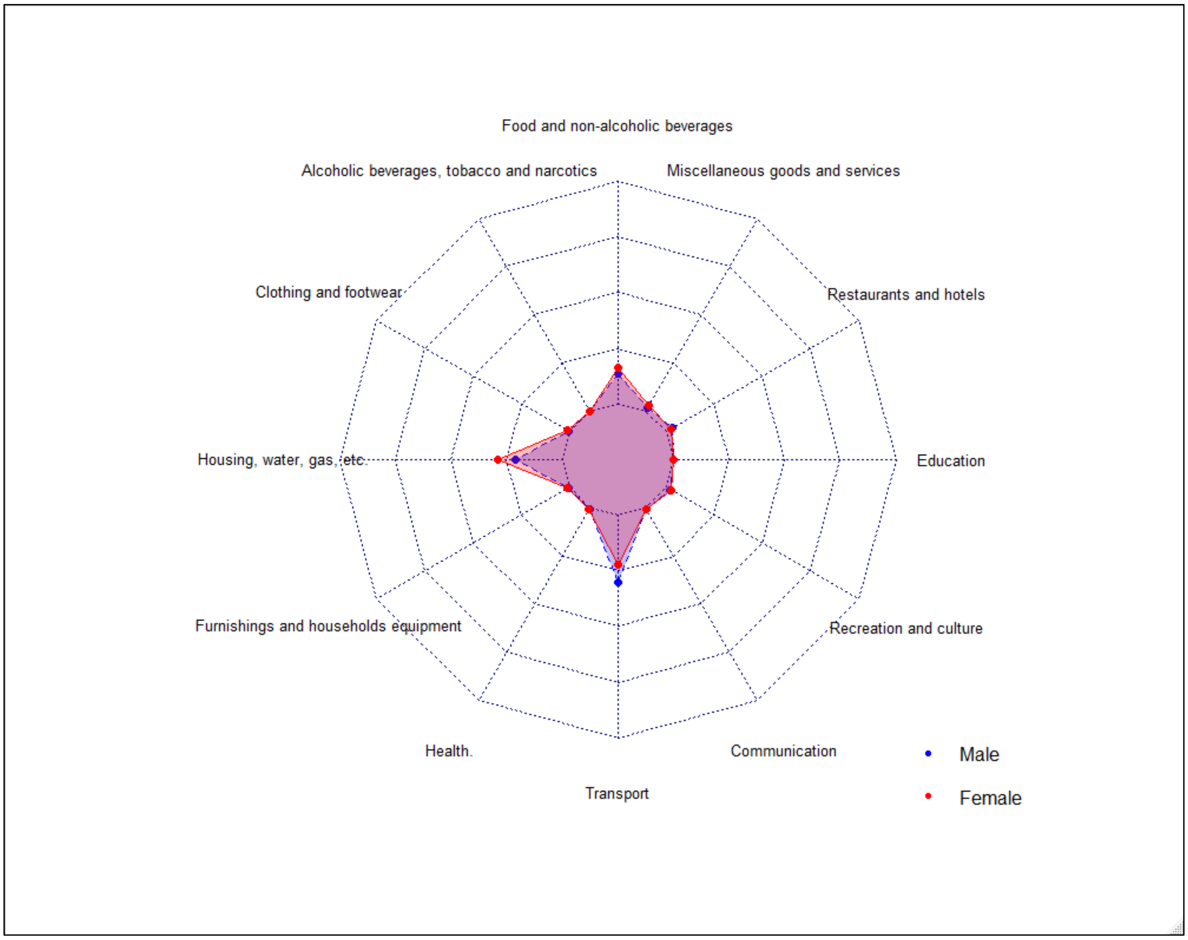
Historically, FBH have more polluting emission pattern than MBH. These differences must be influenced by the different characteristics between household types.

As it was demonstrated in chapter 2, there are some heterogeneities by gender when emissions from consumption are analysed by products categories. To simplify, Graph 3.3 and Graph 3.4 show the average emissions patterns from consumption by 12 products categories (see Annex A1.1 from chapter 1) in 1998 and 2018 households at population level with the equivalent household size correction.

Graph 3.3: Average greenhouse gas emissions per euro (kgs of CO_2 equivalent per euro) derived from the consumption of the 12 products groups of female and male breadwinner households. Spain 1998

Source: Own elaboration from data presented in chapter 1

Graph 3.4: Average greenhouse gas emissions per euro (kgs of CO_2 equivalent per euro) derived from the consumption of the 12 products groups of female and male breadwinner households. Spain 2018.

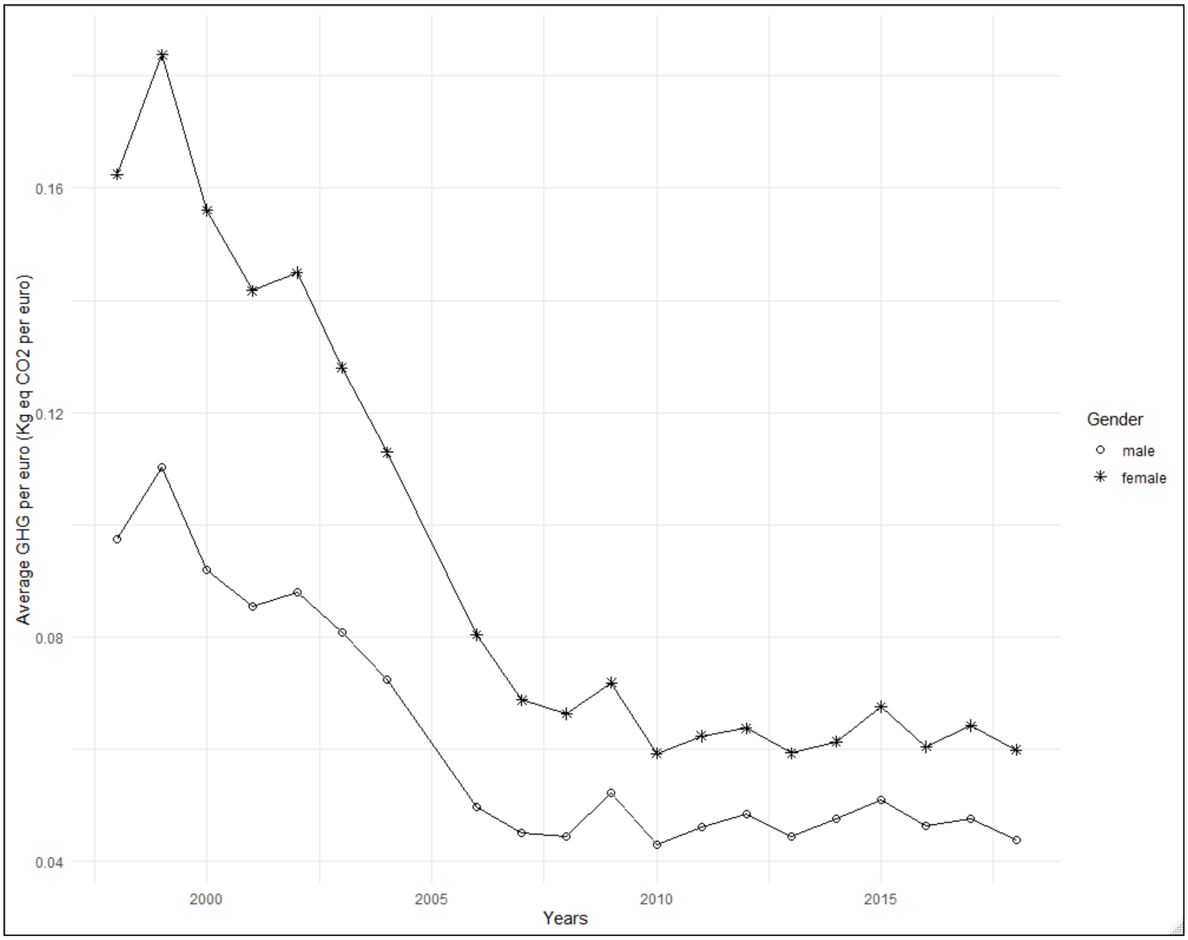


Source: Own elaboration from data presented in chapter 1

Graph 3.3 and Graph 3.4 show large differences in emissions patterns related to "Transport" consumption with MBH emitting more per euro spent, and in emissions related to "Housing, water, gas, electricity and other fuels" consumption, with FBH emitting more per euro spent. Both categories include products that produce direct emissions from household consumption of energy goods, along with indirect GHG emissions derived from consumption expenditure.

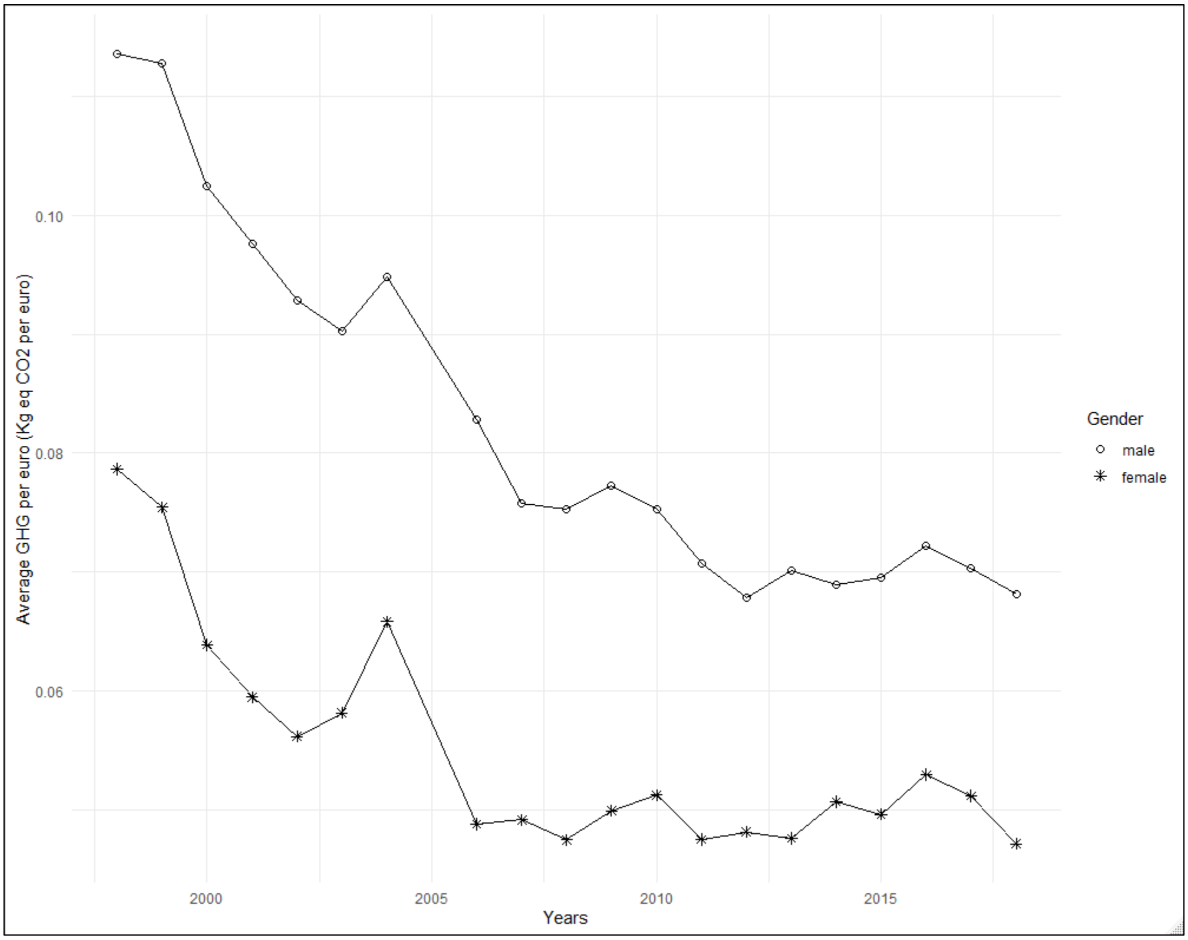
Therefore, Graph 3.5 and Graph 3.6 show the differences between FBH and MBH emissions patterns from the consumption of the specific products related to the consumption of energy goods: 7.2 "Electricity, gas and other fuels" and 4.5 "Operation of personal transport equipment" over the years at the population level with the equivalent household size correction.

Graph 3.5: Average greenhouse gas emissions per euro (kgs of CO_2 equivalent per euro) derived from the consumption of "Electricity, gas and other fuels" of female and male breadwinner households. Spain 1998-2018.



Source: Own elaboration from data presented in chapter 1

Graph 3.6: Average greenhouse gas emissions per euro (kgs of CO_2 equivalent per euro) derived from the consumption of "Operation of personal transport equipment" of female and male breadwinner households. Spain 1998-2018.

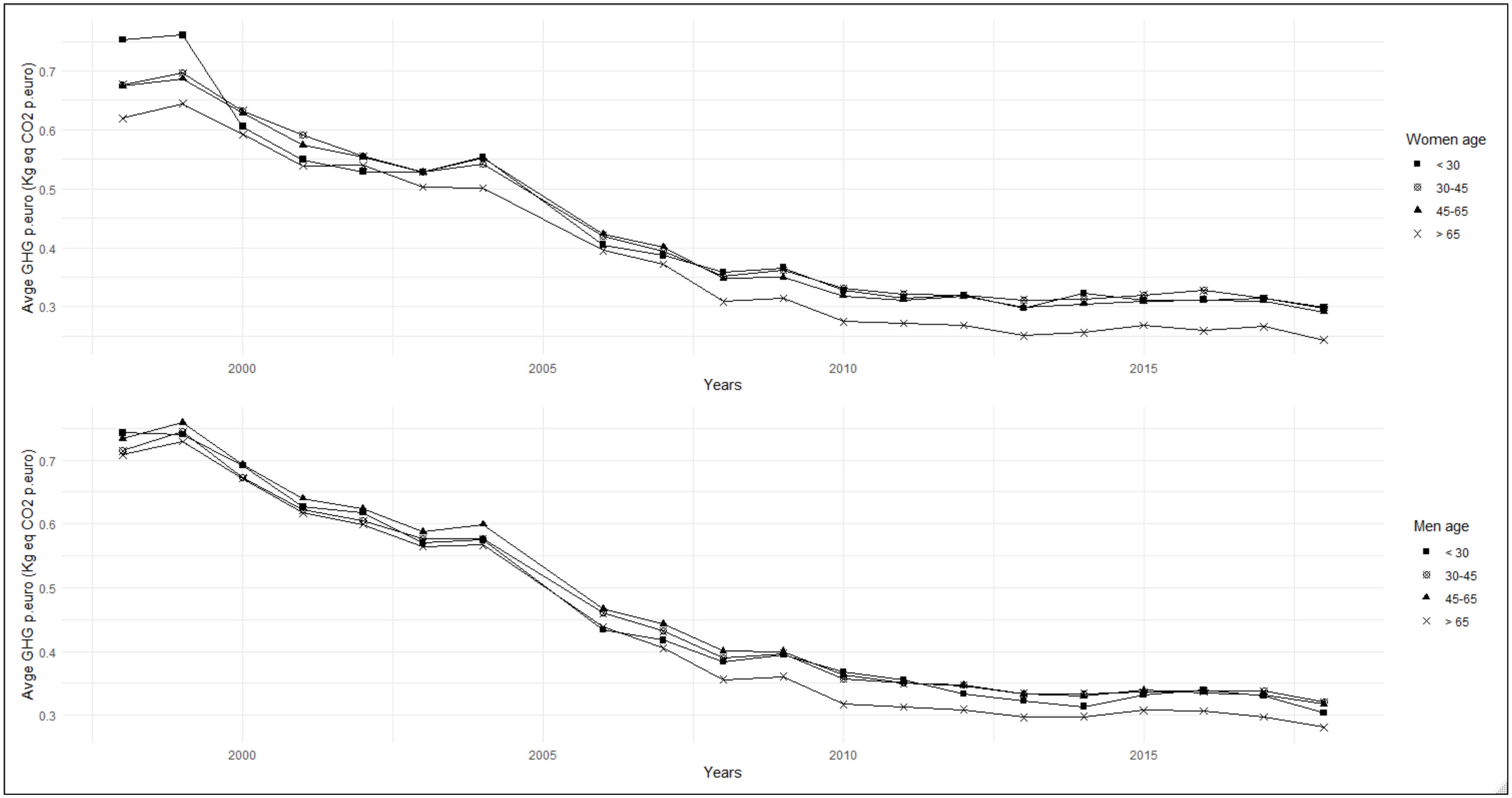


Source: Own elaboration from data presented in chapter 1

Emissions related to household commodities consumption and car use have been decreasing over the years independently of the household type. However, FBH have improved their emissions related to household commodities faster than MBH improve their emissions related to car use. Emission gender gap related to "Electricity, gas and other fuels" is clearly decreasing, although the emission gender gap related to "Operation of personal transport equipment" is almost constant.

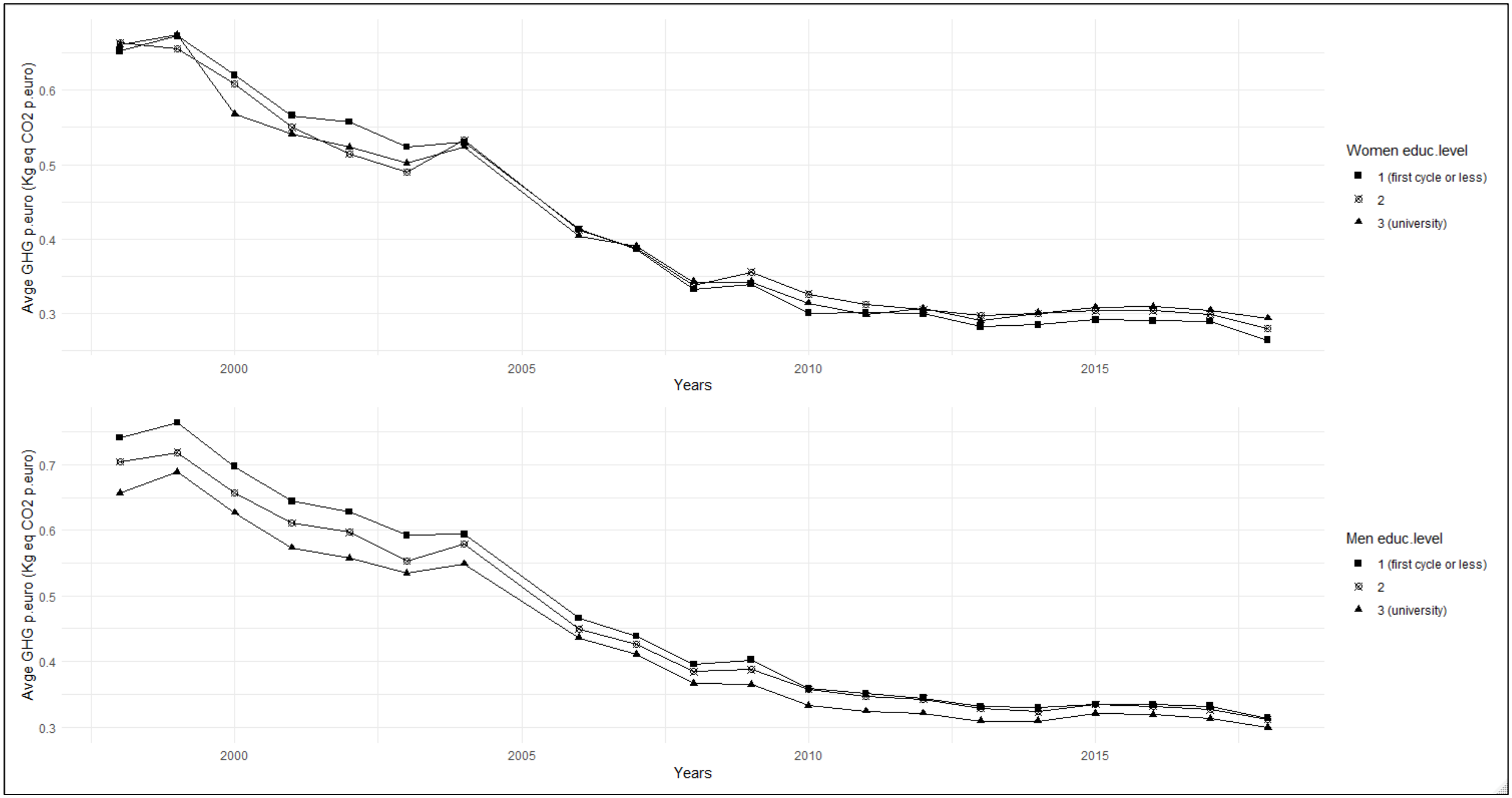
Despite that, all emission patterns should be affected by households' characteristics. Graph 3.7, Graph 3.8, and Graph 3.9 show the emissions per euro according to age range, education level, and expenditure quintiles.

Graph 3.7: Average greenhouse gases embedded per euro (kgs of equivalent CO_2 per euro) in the consumption basket of female and male breadwinner households by age. Spain 1998 - 2018



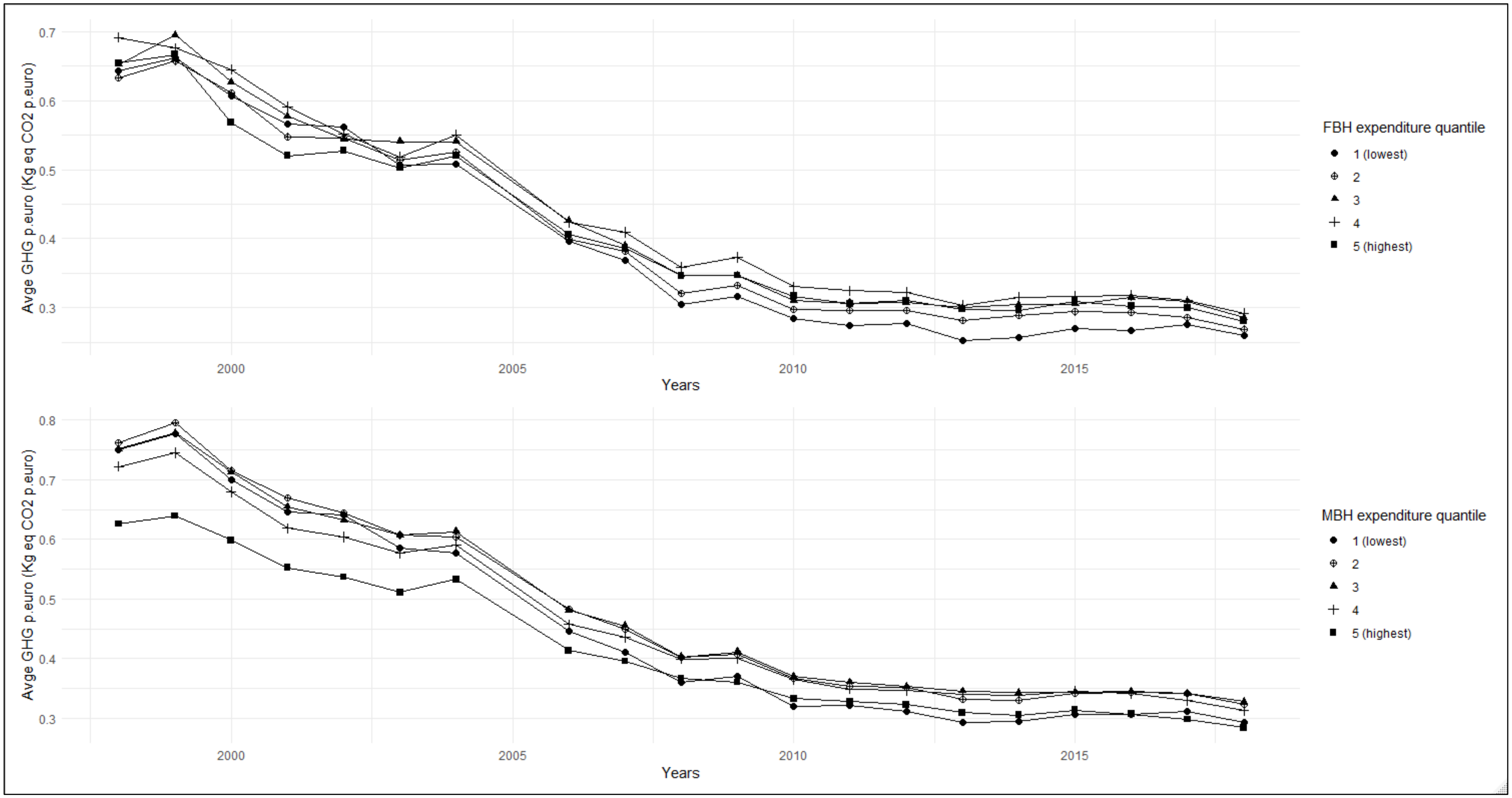
Source: Own elaboration from data presented in chapter 1

Graph 3.8: Average greenhouse gases embedded per euro (kgs of equivalent CO_2 per euro) in the consumption basket of female and male breadwinner households by education level. Spain 1998 – 2018



Source: Own elaboration from data presented in chapter 1

Graph 3.9: Average greenhouse gases embedded per euro (kgs of equivalent CO_2 per euro) in the consumption basket of female and male breadwinner households by quintile expenditure. Spain 1998 - 2018



Source: Own elaboration from data presented in chapter 1

These graphs show that the differences may be affected by the household characteristics themselves rather than simply by the effect of the gender of the main breadwinner. On average “young” breadwinners (less or equal to 30 years old) contribute to more GHG emissions than “old” breadwinners (over 65 years old) independently of the household’s type. Emission patterns with respect to educational level is not so clear in the case of FBH, whereas the most educated MBH have the least polluting consumption patterns, while those with lower education level have the most polluting emission patterns. When it comes to pollution by euro spent, while the two groups of FBHs with the lowest expenditure level have fewer emitting patterns than the rest of the quintiles from 2006 onwards, on the MBH side the lowest emission patterns among the MBH quintiles are led by the highest and the lowest quintile. Therefore, it is necessary to consider all these characteristics to analyze the differences in emissions between different types of households.

Since using the data of every Spanish household over the past 20 years is computationally challenging, only the most relevant years needed to target the objective have been considered. Graph A3.4 in Annex A3.4 shows the employment rate of women and men in Spain between 1998-2018 (INE, 2022b). This data is relevant for analysing the possible scenarios of main breadwinners given that other information provided may bring confusing conclusions, being employment rate the most reliable one.

Employment rate gender gap has been decreasing over the years, with the highest gap in 1998. Between 2007 and 2008, opposite slopes can be noted. In this case, it can be observed that around the financial crisis the female employment rate increased, while the male employment rate decreased. On the one hand, female employment rates have not been affected as much as male employment rates after the crisis, but on the other hand, wage gender gap began to increase (Ministry of Labor and Social Economy, 2021, p.29), probably explained because male unemployment rates increase in the less educated population (INE, 2009). Moreover, from 2013 onwards, both female and male employment rates are recovering, almost at the same speed, thus producing lower employment rate gender gap by 2018. All this justifies the years chosen for this study. Differences in emissions between FBH and MBH in 1998, 2008, 2014 and 2018 independently will be estimated, trying to compare different moments along 20 years

3. METHODOLOGY

After obtaining GHG emissions from the consumption of each household included in the HBS, I want to investigate whether having households with a female breadwinner would have environmental effects. In other words, I analyse the differences in GHG emissions from the consumption of households with female breadwinners compared to male breadwinner households. Therefore, as proposed in chapter 2, the Blinder-Oaxaca decomposition and the Propensity Score Matching estimator are used, as both methodologies capture the effect of gender on intra-household bargaining power on consumption and thus on the production of GHG emissions.

Since the methodologies were previously explained in chapter 2, this section is divided in two sections. Section 3.1 details the variables considered to estimate the differences under Blinder-Oaxaca estimator between FBM and MBH; and Section 3.2 shows the requirements to properly apply the Propensity Score Matching on these samples.

3.1 Blinder-Oaxaca decomposition

As explained and detailed in the previous chapter, the Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973) measures differences between two groups by decomposing, on the one hand, the differences explained by households' characteristics, and on the other hand by unexplained differences, in this case associated with the influence of being a female or male breadwinner on households' emission patterns.

Looking briefly at equation 3.1, β_F; β_M and β_R were previously estimated with an OLS model (see Annex A3.5 for OLS results). X is a vector of the household's characteristics given by *logarithm of the annual household expenditure* measured in euros, the *households' members,* the *kids members*, the *age* of the main breadwinner (and its square), the *level of education* of the main breadwinner, the *region*, and *density*.

$$\Delta\bar{Y} = \underbrace{(\bar{X}_F - \bar{X}_M)'\hat{\beta}_R}_{explained} + \underbrace{\underbrace{\bar{X}'_F(\hat{\beta}_F - \hat{\beta}_R)}_{unexplained\ female} + \underbrace{\bar{X}'_M(\hat{\beta}_R - \hat{\beta}_M)}_{unexplained\ male}}_{unexplained} \tag{3.1}$$

It is also possible to disaggregate equation 3.1 into variable-by-variable decomposition. Blinder-Oaxaca decomposition, therefore, analyses the average effects of the remaining households' characteristics on emissions patterns differences associated by characteristics and by influence of the breadwinner gender (see more details in chapter 2).

3.2 Propensity Score Matching estimator

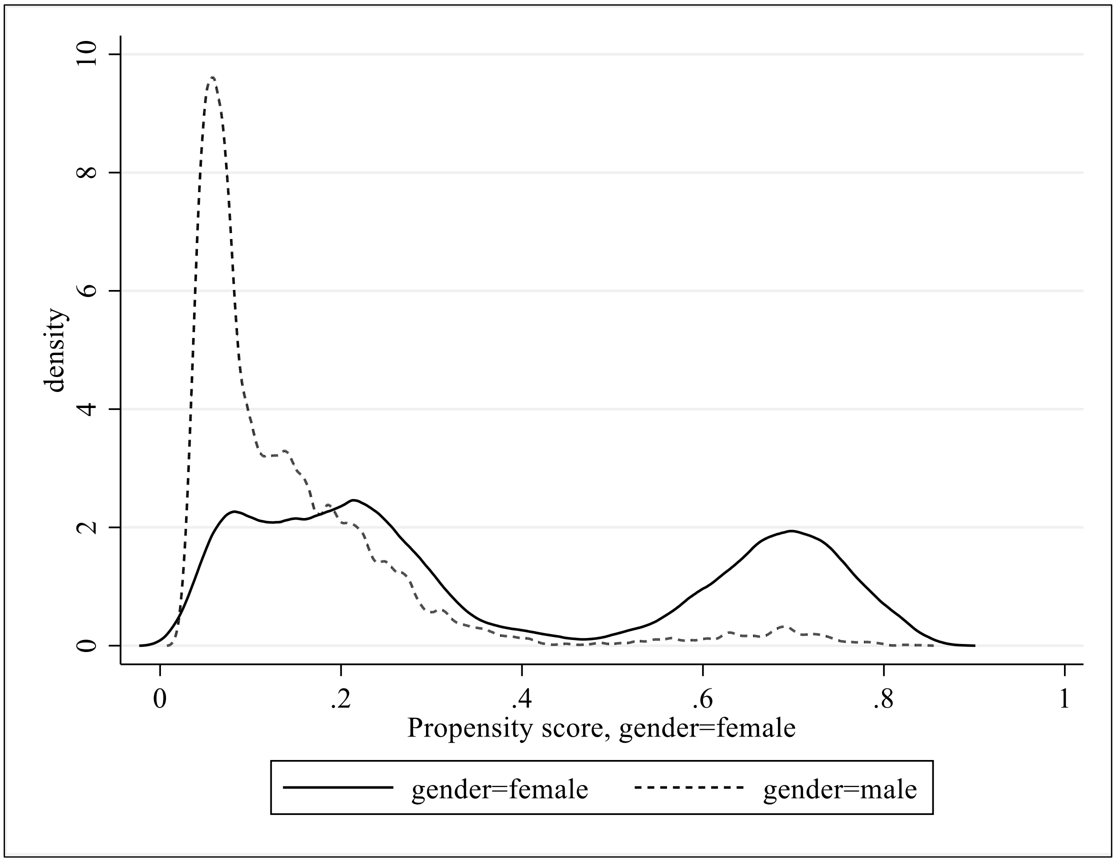
The previous section shows that on average FBH have lower expenditure levels, live in household units with less members, and live in less populated municipalities. Also, female breadwinners are on average older and have a slightly higher level of education than male breadwinners. This limits the type of estimator suitable for measuring differences between households, as results may be affected by treatment choice bias (FBH) and differences in household characteristics.

Therefore, using the non-experimental assessment method, Propensity Score Matching estimator (Rosenbaum and Rubin, 1983) is again appropriated. In the Propensity Score Matching estimator, the matrix of covariates employed has been the same set as in the Blinder-Oaxaca-decomposition detailed in the previous section on this chapter.

Prior to presenting the results and following the same structure as in the previous chapter, some indicators about the suitability of the Propensity Score Matching estimators are presented here. For the proper implementation of the Propensity Score Matching estimator two conditions are needed: i) covariates and outcomes must be balanced in both the control and treatment groups; and ii) overlap assumption, where each sample has a probability of receiving the treatment (or not) greater than zero. Annex A3.6 summarises the balance of indicators for the covariates considered in 1998, 2008, 2014 and 2018, and concludes that it is worked with a well-balanced database. On top of that, Graph 3.10 and shows the estimated densities in 1998 (see Annex A3.7 for 2008, 2014 and, 2018). Following Busso, et al. (2014) suggest that the overlap requirements hold for 2008, 2014 and 2018, but not for 1998, where high density close to zero of MBH propensity score is observed.

Table 3.2 shows the observations that could be violating the overlap assumption. To identify these observations, two checks are performed. The first ensures that the propensity scores are greater than 1e-5 and less than 1-1e-5, while the second ensures that each observation has at least one match in the treatment group. Although the Graph 3.10 suggests that there is an overlap problem, the Table 3.2 does not find any samples that do not satisfy the overlap criteria, therefore, the overlapping requirements are achieved in 1998.

Graph 3.10: Estimated densities of propensity scores for the treated and non-treated households. Spain 1998



Source: Own elaboration

Table 3.2: Overlap violation indicator. Spain 1998

	Freq.	Percent	Cum.
0	9,612	100	100
Total	9,612	100	

Source: Own elaboration

4. RESULTS AND DISCUSSION

Blinder-Oaxaca decomposition and Propensity Score Matching estimator are used to study the differences in GHG emissions patterns, including direct and indirect emissions from households' consumption, between FBH and MBH in 1998, 2008, 2014 and 2018. The objective is analysing the impact of household's breadwinner gender in the intra-household bargaining power on consumption and thus on the production of GHG emissions measure in kilograms of equivalent CO_2 per euro consumed.

Therefore, this section is dived in two subsections. Section 4.1 shows and discusses the results of total GHG emissions per euro and Section 4.2 by GHG emissions per euro disaggregated by the 12 products categories, also including the details for products related to direct households' consumption: 7.2 "Operation of personal transport equipment" and 4.5 "Electricity, gas and other fuels", both by applying the Blinder Oaxaca decomposition (Sections 4.1.1 and 4.2.1) and the Propensity Score Matching estimator (Sections 4.1.2 and 4.2.2) in 1998, 2008, 2014 and 2018 independently.

4.1 Total greenhouse gases per euro

4.1.1 Blinder-Oaxaca Decomposition

Table 3.3 shows the results applying Blinder-Oaxaca decomposition in 1998, 2008, 2014 and 2018 independently. Significative and negative differences in favour of FBH for each year are observed, although they seem to be decreasing over the years. Even if these differences are mainly due by the explained factors, around 43% are related with the unexplained portion. In other words, FBH emits on average 0.045 kilograms of CO_2 equivalent less than MBH. Despite these differences are mainly explained by the differences between the households' characteristics, the unexplained part is significant and represent around the 43% of the differences.

Table 3.3: Blinder-Oaxaca decomposition on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) between female and male breadwinners' household. Spain 1998, 2008, 2014 and 2018

Variable	Total Gas
overall 1998	
women	.6551***
men	.72246***
difference	-.06735***
explained	-.03799***
unexplained	-.02936***
overall 2008	
women	.33548***
men	.3865***
difference	-.05102***
explained	-.03021***
unexplained	-.02081***
overall 2014	
women	.29236***
men	.32244***
difference	-.03008***
explained	-.01922***
unexplained	-.01086***
overall 2018	
women	.27712***
men	.30843***
difference	-.03131***
explained	-.01556***
unexplained	-.01575***
*legend: * p<.1; ** p<.05; *** p<.01*	

Source: Own elaboration

Table 3.4 details each variable. Under the unexplained section, differences associated with differences in consumption patterns by gender effect are associated principle by covariance as *age*, *numbers of adult members*, and *numbers for kids*. In other words, there are some unexplained reasons (gender effect) associated with *age* and *number of kids* that produce FBH have less emitter patterns than MBH, while gender effect associated with number of members produce FBH have more emitter patterns than MBH. Surprisingly, the unexplained impact associated with the *expenditure* covariance is not the most relevant in dimension and in some years even not significant.

Table 3.4: Variables details of Blinder-Oaxaca decomposition on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) between female and male breadwinners' household. Spain 1998, 2008, 2014 and 2018

	1998	2008	2014	2018
explained				
l_exp	.04582***	.00491***	0	.00317***
age	-0.009	.00763***	0	.00439***
sq_age	-0.004	-.0146***	-.00258**	-.00878***
nmiemb	-.08035***	-.02838***	-.01385***	-.0137***
nkids	.01672***	.00491***	.00232***	.00293***
educ	0	0	-.00038***	0
densi	-.00678***	-.00464***	-.00383***	-.00328***
region	0	0	-.00058*	0
unexplained				
l_exp	.25921**	.10852**	-0.047	-0.03
age	-.34563**	-.13644**	-.11588**	-0.087
sq_age	.18059**	.08022**	.05776**	.05152*
nmiemb	.07552***	0.009	.02189***	.01713***
nkids	-.00914***	-.00187*	-.004***	-.00308***
educ	-0.002	-0.003	0	.00656*
densi	-.03003**	-.03137***	.03254***	.02417***
region	-0.023	-.02644*	-0.013	-0.001
_cons	-0.135	-0.019	0.057	0.006

Source: Own elaboration

4.1.2 Propensity Score Matching

After proving that the assumptions necessary to apply Propensity Score Matching hold for each of the years used in this chapter, Table 3.5 shows the results of the effect of FBH on total GHG emissions per euro embodied in consumption.

Table 3.5: Estimate of the Average Effect on greenhouse gas emissions patterns (in kgs of equivalent CO_2 per euro) of female breadwinners households. Spain 1998, 2008, 2014 and 2018.

Average Treatment Effect (ATE) of female breadwinner	Coefficient	Std. Err.	[95% Conf. Interval]	
1998	0.00848	0.01027	-0.01164	0.02860
2008	-0.01381	0.00282	-0.01934	-0.00828
2014	-0.00837	0.00230	-0.01288	-0.00385
2018	-0.01526	0.00225	-0.01968	-0.01085

Note: Propensity Scores are estimated by means of a probit model.

Source: Own elaboration

These results show the presence of a significant negative effect to the presence of female breadwinner on GHG emissions patterns, except for the year 1998 with a positive but not significant effect. On average, FBH emit approximately 0.0125 kilograms less GHG for each euro that identical MBH. Therefore, under the same characteristics (expenditure level, education, age, number of adult members, number of kids members, density, and region), FBH are significantly less emitters than MBH over the years.

4.2 Greenhouse gases per euro by 12 main products categories and by product related direct emission

As mentioned in previous chapters, one of the interesting questions arisen is whether emission patterns between FBH and MBH are evenly distributed across product categories or whether there are some variabilities. For this, the same methodologies from the previous section are replicated for each of the 12 products categories along with the detail of the products directly related to direct household emissions in 1998, 2008, 2014 and 2018 independently.

4.2.1 Blinder-Oaxaca Decomposition

Table 3.6 shows the results under Blinder-Oaxaca decomposition for the 12 COICOP products categories with the desegregation of the products related with direct households' emissions. Results show that there are not significant differences between FBH and MBH in the emissions patterns embedded by consumption of: "Food and non-alcoholic beverages", “Clothing and footwear” and “Furniture, households’ equipment and routine maintenance of the house”. The largest significant differences over the years are found in the emissions patterns related to consumption of: “Housing, gas and other fuels” (being FBH the more polluter group), “Transport” and “Restaurants and hotels” (being FBH the less polluter group).

Differences in emission patterns derived from 4.5 “Housing, gas and other fuels” consumption are positive significative, where MBH produce on average 0.014 kilograms of equivalent CO_2 less than FBH. These differences are mainly due to differences in households’ characteristics, although between the 15% and 31% are due to reasons associated with the breadwinner gender. Moreover, “Transport” has a negative significant effect, meaning that FBH produce 0.0067 kilograms of equivalent CO_2 per euro less than MBH. These differences are mainly because of breadwinner gender for the years 1998 and 2008, and no significant differences unexplained by breadwinner gender are found for the years 2014 and 2018, although looking at the differences between the product 7.2 “Operation of personal transport equipment” between 40% and 55% of the differences are due to breadwinner gender effects.

Table 3.6: Blinder-Oaxaca decomposition on greenhouse gases emissions patterns (kgs of equivalent CO_2 per euro) by products categories between female and male breadwinners household. Spain 1998, 2008, 2014 and 2018

	difference			
Products categories	**1998**	**2008**	**2014**	**2018**
Food and non-alcoholic beverages	-0.003	-0.001	-0.001	-.00136**
Alcoholic beverages and tobacco	-.00124***	-.001***	-.0004***	-.00012***
Clothing and footwear	0	0	0	0
Housing, gas and other fuels	.03167***	.01082***	.00564***	.00643***
Other households maintenance	.01254***	.00589***	.00231***	.00231***
Electricty,gas, and other fuels	.01914***	.00493***	.00333***	.00412***
Furniture, household equipmen, etc.	0	0	.00025***	0
Health	0.001	.00049***	0	.00018**
Transport	-.01186***	-.00839***	-.00343***	-.00324***
Other transport	0	0	.00135***	.00182***
Operation of personal transport equipment	-.01233***	-.00873***	-.00478***	-.00505***
Comunications	.00064***	.00013*	.00026***	.00011**
Recreation and culture	-.00362***	-.00177***	-.0011***	0
Education	-.0005***	0	0	-3.4e-05*
Restaurants and hotels	-.01053***	-.00555***	-.00285***	-.00335***
Miscellaneous goods and services	.00232***	.00199***	.00094***	.00191***
	explained			
Food and non-alcoholic beverages	.00393***	0.001	-.00089***	0
Alcoholic beverages and tobacco	-.00039***	-.00034***	-5.6e-05***	0
Clothing and footwear	-.00174***	-.00148***	-.00058***	-.00045***
Housing, gas and other fuels	.02693***	.00878***	.00369***	.00442***
Other households maintenance	.00958***	.00466***	.00184***	.00167***
Electricty,gas, and other fuels	.01734***	.00411***	.00185***	.00275***
Furniture, household equipmen, etc.	-.0006***	0	0	0
Health	.00034*	0	-.0001***	-4.6e-05*
Transport	-.00864***	-.0067***	-.00288***	-.00269***
Other transport	-.00133***	-.00172***	-.00043***	-.00043**
Operation of personal transport equipment	-.00731***	-.00498***	-.00244***	-.00226***
Comunications	.00027***	0	6.9e-05***	0
Recreation and culture	-.00278***	-.00163***	-.00057***	-.00089***
Education	-.00065***	-.00018***	-8.3e-05***	-.00014***
Restaurants and hotels	-.00734***	-.00222***	-.00106***	-.00132***
Miscellaneous goods and services	0	-.00071***	-.00024***	-.00032***
	unexplaned			
Food and non-alcoholic beverages	-.00677***	-.00142**	0	-.0012**
Alcoholic beverages and tobacco	-.00085***	-.00065***	-.00035***	-.00012***
Clothing and footwear	.00167***	.00186***	.00071***	.00038***
Housing, gas and other fuels	.00475**	.00204***	.00196***	.00201***
Other households maintenance	.00296***	.00123***	.00048**	.00064***
Electricty,gas, and other fuels	0.002	0.001	.00148***	.00137***
Furniture, household equipmen, etc.	.00079*	0	.00025***	0
Health	0	.00056***	.00026**	.00022***
Transport	-.00322***	-.00169***	-0.001	-0.001
Other transport	.0018***	.00205***	.00179***	.00225***
Operation of personal transport equipment	-.00502***	-.00375***	-.00234***	-.00279***
Comunications	.00038***	.00017**	.00019***	8.1e-05*
Recreation and culture	-0.001	0	-.00053***	.0005**
Education	.00015**	.00014***	7.5e-05***	.0001***
Restaurants and hotels	-.00319***	-.00333***	-.00179***	-.00203***
Miscellaneous goods and services	.00229***	.00269***	.00118***	.00223***

Source: Own elaboration

4.2.2 Propensity Score Matching

Table 3.7 shows the results for the 12 COICOP products categories with the desegregation of the products related with direct households' emissions under the Propensity Score Matching estimator. The categories with significant differences are highlighted in grey. One of the main results is that differences in emission patterns resulting from the consumption of 4.5 "Housing, gas and other fuels" are not significant. "Transport" shows, otherwise, a negative and significant negative on the presence of FBH under the same MBH characteristics, except for 1998. In other words, FBH emits on average 0.013 kilograms of equivalent CO_2 per euro invested in "Transport" less than MBH, with similar figures applying to 7.2 "Operation of personal transport". However, "Other transport" has the opposite effect, where FBH emit on average 0.002 kilograms of equivalent CO_2 per euro invested more than MBH, probably explained by gender differences in preferences when using transport services.

From another perspective, in product groups such as "Clothing and footwear", "Miscellaneous goods and services", and "Communications" FBH produce significantly more emissions per euro than MBH under the same characteristics.

Table 3.7: Propensity Score Matching estimator on greenhouse gases emissions patterns (kgs of equivalent CO_2 per euro) by products categories between female and male breadwinner household. Spain 1998, 2008, 2014 and 2018

	Coefficient	Std. Err.	[95% Conf. Interval]		Coefficient	Std. Err.	[95% Conf. Interval]	
Products Categories	**1998**				**2008**			
Food and non-alcoholic beverages	0.0002833	0.0025963	-0.0048052	0.0053719	-0.001785	0.000724	-0.003205	-0.000366
Alcoholic beverages and tobacco	-0.0002485	0.0001849	-0.000611	0.0001139	-0.000335	0.000082	-0.000495	-0.000175
Clothing and footwear	0.0009185	0.0005976	-0.0002529	0.0020898	0.001436	0.000250	0.000947	0.001925
Housing, gas and other fuels	0.0077763	0.004234	-0.0005222	0.0160748	-0.000252	0.001572	-0.003334	0.002830
Other households maintenance	-0.0004019	0.0011787	-0.002712	0.0019082	0.000496	0.000278	-0.000048	0.001040
Electricty,gas, and other fuels	0.0081782	0.0040073	0.000324	0.0160324	-0.000748	0.001553	-0.003791	0.002295
Furniture, household equipmen, etc.	0.0011888	0.0005666	0.0000783	0.0022994	0.000139	0.000209	-0.000270	0.000548
Health	-0.0007199	0.0004773	-0.0016555	0.0002156	0.000445	0.000161	0.000129	0.000760
Transport	-0.0008868	0.0092675	-0.0190508	0.0172772	-0.013483	0.002608	-0.018594	-0.008373
Other transport	0.0016416	0.0006108	0.0004444	0.0028388	0.002389	0.000491	0.001427	0.003351
Operation of personal transport equipment	-0.0025284	0.0093087	-0.0207731	0.0157164	-0.015872	0.002608	-0.020983	-0.010762
Comunications	0.0003837	0.0000901	0.000207	0.0005603	0.000335	0.000065	0.000208	0.000462
Recreation and culture	-0.0007981	0.0006527	-0.0020774	0.0004812	-0.000123	0.000315	-0.000740	0.000495
Education	0.0000164	0.0001112	-0.0002015	0.0002343	0.000060	0.000028	0.000006	0.000115
Restaurants and hotels	-0.0026779	0.0010093	-0.0046561	-0.0006998	-0.002162	0.000270	-0.002691	-0.001633
Miscellaneous goods and services	0.003242	0.0005689	0.0021269	0.004357	0.001917	0.000242	0.001442	0.002391
	2014				**2018**			
Food and non-alcoholic beverages	-0.000366	0.000584	-0.001511	0.000780	-0.000662	0.000534	-0.001708	0.000384
Alcoholic beverages and tobacco	-0.000219	0.000041	-0.000300	-0.000137	-0.000068	0.000016	-0.000098	-0.000037
Clothing and footwear	0.000563	0.000114	0.000340	0.000787	0.000286	0.000079	0.000132	0.000440
Housing, gas and other fuels	0.001046	0.001353	-0.001605	0.003697	0.001033	0.001179	-0.001278	0.003343
Other households maintenance	0.000289	0.000223	-0.000149	0.000726	0.000427	0.000187	0.000061	0.000794
Electricty,gas, and other fuels	0.000757	0.001340	-0.001868	0.003383	0.000605	0.001162	-0.001673	0.002883
Furniture, household equipmen, etc.	0.000144	0.000091	-0.000034	0.000323	0.000109	0.000075	-0.000038	0.000257
Health	0.000183	0.000103	-0.000019	0.000386	0.000207	0.000086	0.000038	0.000375
Transport	-0.009518	0.002076	-0.013585	-0.005450	-0.016601	0.002096	-0.020708	-0.012494
Other transport	0.001777	0.000327	0.001137	0.002417	0.002301	0.000396	0.001525	0.003076
Operation of personal transport equipment	-0.011294	0.002078	-0.015368	-0.007221	-0.018902	0.002099	-0.023015	-0.014788
Comunications	0.000236	0.000038	0.000161	0.000311	0.000172	0.000043	0.000087	0.000256
Recreation and culture	-0.000003	0.000163	-0.000322	0.000316	0.000240	0.000220	-0.000191	0.000671
Education	0.000078	0.000017	0.000045	0.000110	0.000072	0.000021	0.000031	0.000114
Restaurants and hotels	-0.001373	0.000203	-0.001771	-0.000976	-0.001876	0.000214	-0.002295	-0.001456
Miscellaneous goods and services	0.000862	0.000110	0.000646	0.001077	0.001824	0.000149	0.001532	0.002116

Note: Propensity Scores are estimated by means of a logit model.

Source: Own elaboration

5. CONCLUSIONS

Results presented in this chapter contribute to the discussion of environmental effects that a household structural change might have. This chapter goes beyond the analysis of household GHG footprint by analysing how the increase of FBH might induce a change in household demand and thus affecting environment differently. Previous studies show that the incorporation of women in different spheres has socio-economic consequences. Additionally, research also relates women to environmental issues, as they have more environmental attitudes and knowledge than men. Furthermore, there are clear differences between women and men in consumption patterns that would have different environmental consequences.

This study contributes to the literature by collecting data and providing empirical evidence of the environmental effects produced by a structural change within the household derived from women's greater economic power.

If total emission patterns are analysed, the results show that FBH have significantly fewer polluting patterns than MBH over the years under both methodologies: Blinder-Oaxaca decomposition and Propensity Score Matching estimator. Blinder-Oaxaca show that on average FBH emit 0.02 kilograms of GHG per euro less than MBH related with breadwinner gender, while Propensity Score Matching show 0.012 kilograms of GHG emissions per euro less than MBH due to purely gender issues. These results expose the role of women in consumption decisions within the household and thus in a more environmentally friendly demand.

Looking at differences by product categories, the main conclusion regarding differences due to breadwinner gender is that emissions from "Transport" consumption and its disaggregate 7.2 "Operation of personal transport" are less ecologically invested by MBH than by FBH; while emissions patterns from 4.5 "Housing, gas and other fuels" are higher for FBH than for MBH under Blinder-Oaxaca decomposition but not significant under Propensity Score Matching.

Both this chapter and chapter 2 demonstrates an environmental effect associated with gender. Under Blinder-Oaxaca decomposition, it is observed that the differences in emissions between female and male OPH are mainly associated with gender issues and related by covariance such as level of expenditure, while in the case of differences between households breadwinners gender, although the differences are larger than in chapter 2, they are mainly explained by the characteristics of the households, still, on average 43% of these differences are gender related and mainly associated with covariance such as *age* and *number of children*. However, under Propensity Score Matching estimator shows that the influence of having a female breadwinner on household emissions appears to be considerably greater than the effect of being a woman living alone.

When analysing emissions by product type, the difference in emissions related to private car use are the most stable, irrespective of whether they were estimated under Blinder-Oaxaca decomposition or Propensity Score Matching estimator or even if both the pure gender effect in one-person households and the effect of the household's breadwinner gender are studied.

Although guidelines for environmental issues refer exclusively to gender perspective, this work is limited by the fact that it works with households, where the consumption and therefore the emissions related are influenced by the rest of the household members, limiting a pure gender analysis. Nevertheless, it is still a more representative analysis of reality than in previous chapters, as all households are included. Additionally, although the breadwinner gender affects consumption decisions within the household, breadwinners are not necessarily the ones who buy, so emissions would be affected by the consumption decisions of their breadwinner's partners or other household members, and as the gender of the main breadwinner's partner is not included as a determinant factor, other gender effects can be missed in this work.

As future work, it would be interesting to analyse the differences in emissions between FBH and MBH between different countries of the European Union. Furthermore, it could be interesting to extend this analysis with Multiregional Input Output Tables (MIOT) and see the environmental impact of this household's structural change to the rest of the world. Otherwise, given that couples nowadays are more and more varied, it would be interesting to include in the analysis the gender of the breadwinner's partner and study the differences between different types of unions.

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7. ANNEX A3

ANNEX A3.1

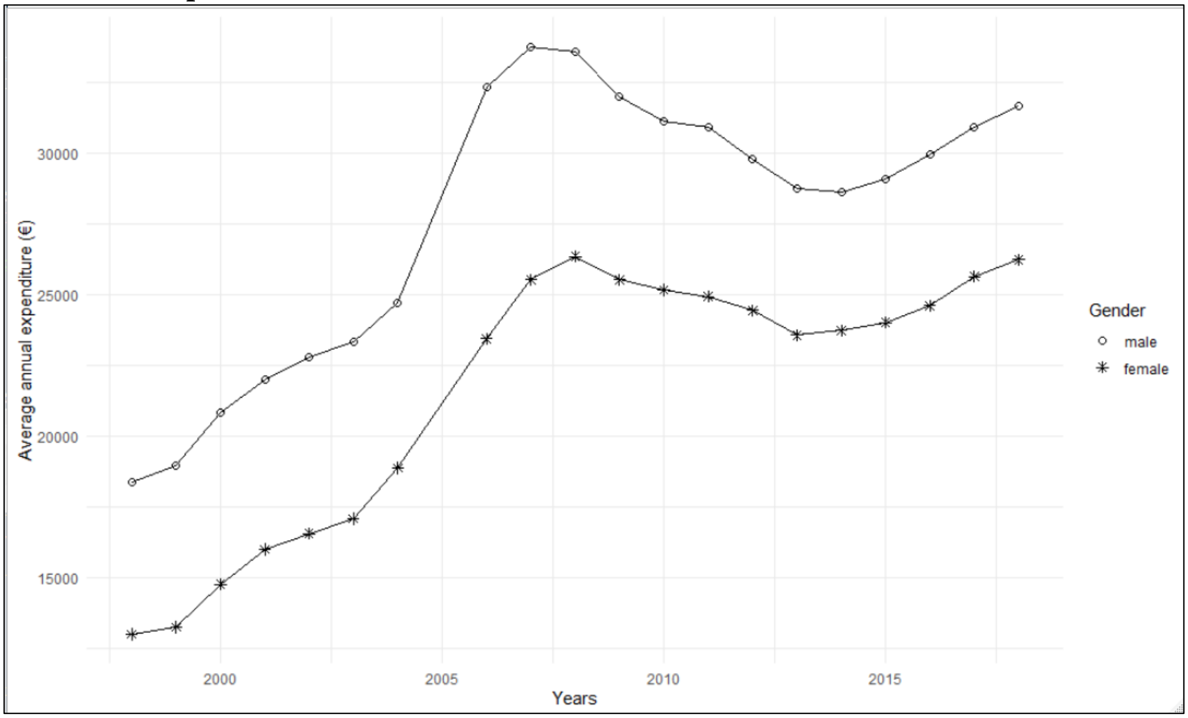
Table A3.1 Evolution of female and male breadwinner households. Spain 1998-2018

year	female	male
1998	2,187,725	9,689,485
1999	2,369,384	9,861,294
2000	2,510,134	9,923,571
2001	2,573,530	10,148,535
2002	2,898,381	10,643,403
2003	3,201,646	10,819,453
2004	3,154,183	11,125,936
2006	4,135,630	11,859,660
2007	4,507,604	11,956,194
2008	4,642,774	12,257,274
2009	4,980,047	12,240,139
2010	5,202,050	12,300,957
2011	5,464,341	12,291,153
2012	5,643,223	12,322,340
2013	5,918,227	12,170,746
2014	6,064,084	12,115,457
2015	6,165,542	12,094,739
2016	6,239,786	12,085,671
2017	6,184,217	12,215,488
2018	6,265,044	12,236,506

Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

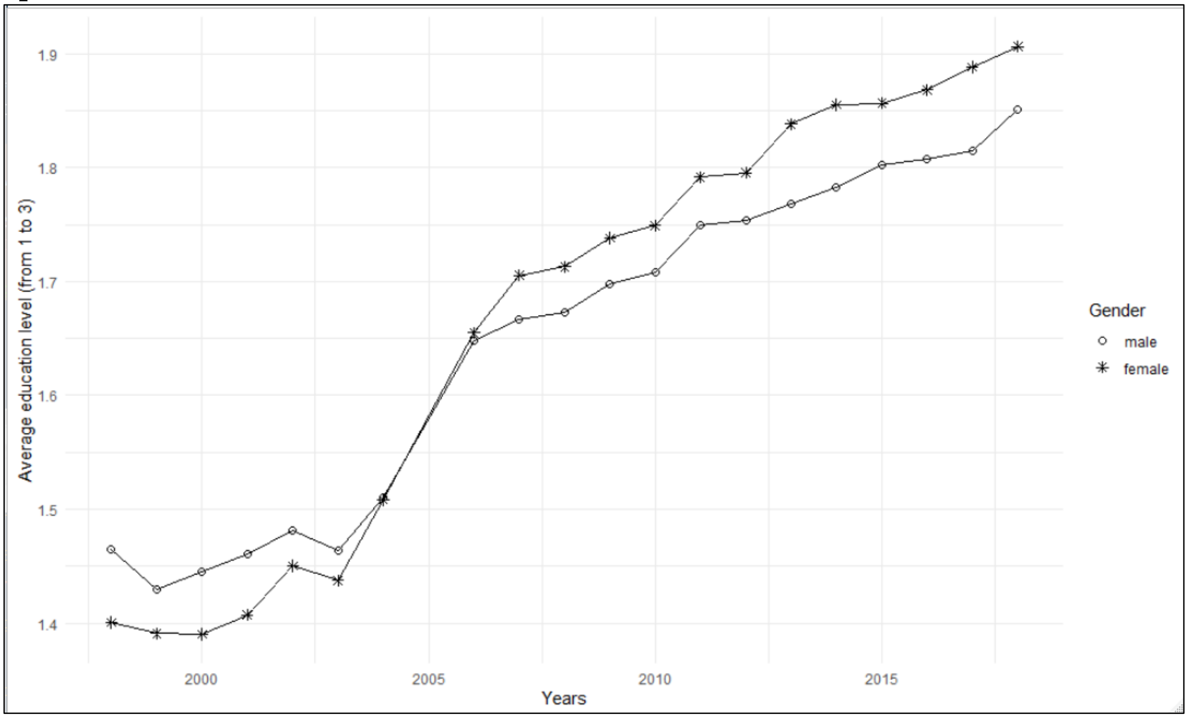
ANNEX A3.2

Graph A3.1: Evolution average annual expenditure of female and male breadwinner households. Spain 1998 – 2018



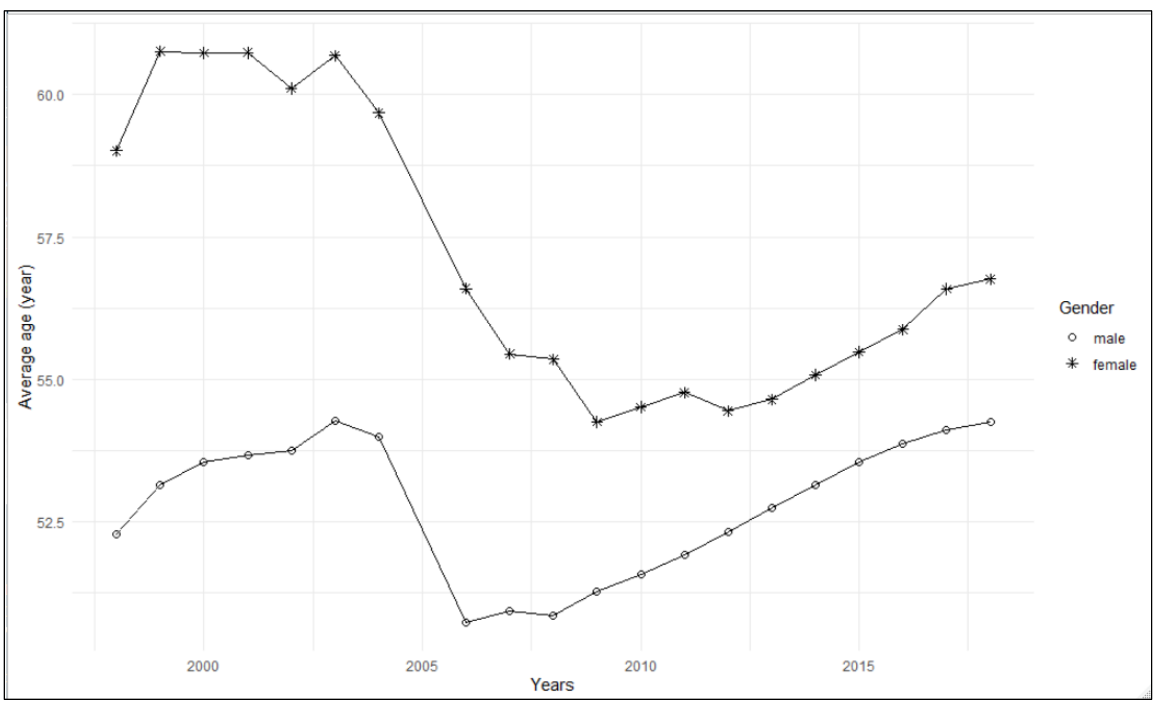
Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph A3.2: Evolution average educational level of female and male breadwinner. Spain 1998 – 2018.



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph A3.3: Evolution average age of female and male breadwinner. Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

ANNEX A3.3

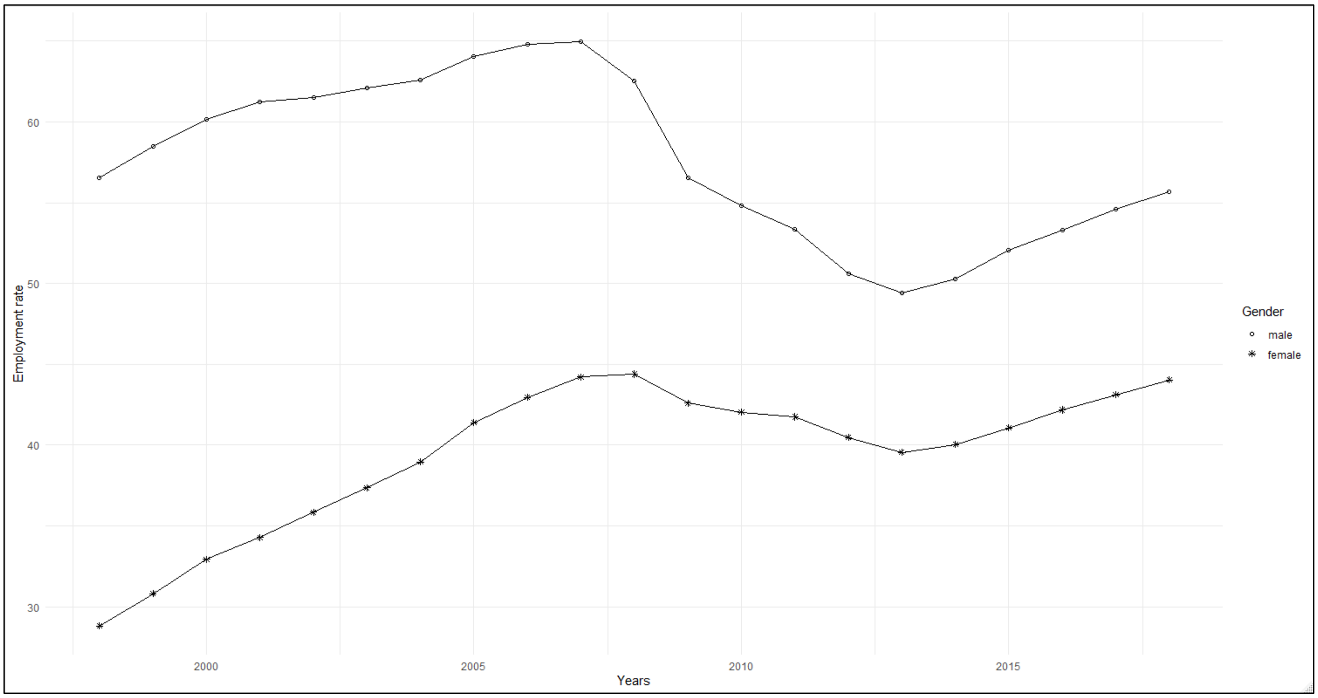
Table A3.2: Evolution average expenditure of female and male breadwinner households. Spain 1998-2018

year	female	male
1998	€ 13,016.60	18,400.38 €
1999	€ 13,267.95	18,966.77 €
2000	€ 14,783.83	20,843.16 €
2001	€ 16,022.07	22,023.47 €
2002	€ 16,569.54	22,782.53 €
2003	€ 17,100.69	23,358.13 €
2004	€ 18,893.51	24,725.38 €
2006	€ 23,457.24	32,347.79 €
2007	€ 25,537.22	33,763.35 €
2008	€ 26,349.68	33,595.64 €
2009	€ 25,532.36	31,991.34 €
2010	€ 25,176.60	31,122.33 €
2011	€ 24,942.92	30,913.36 €
2012	€ 24,449.40	29,783.22 €
2013	€ 23,576.12	28,767.47 €
2014	€ 23,739.75	28,621.66 €
2015	€ 24,024.89	29,090.21 €
2016	€ 24,620.66	29,977.17 €
2017	€ 25,643.33	30,931.36 €
2018	€ 26,242.95	31,687.97 €

Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

ANNEX A3.4

Graph A3.4: Employment rate between women and men. Spain 1998 - 2018



Source: Own elaboration from 1998 to 2018 Spanish Labour Force Survey

ANNEX A3.5

Table A3.3: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for female breadwinner households. Spain 1998

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.096996	0.0113028	-0.119152	-0.07484
age	-0.00535	0.0024139	-0.010082	-0.000619
sq_age	0.00003	0.0000197	-8.71E-06	0.0000687
nmiemb	0.0908931	0.0062607	0.0786209	0.1031653
kids	-0.081288	0.0124238	-0.105641	-0.056935
ed_dummy1	-0.017188	0.0215865	-0.059502	0.025126
ed_dummy2	0	(omitted)		
ed_dummy3	0.0114907	0.0227947	-0.033192	0.056173
dens_dummy	-0.104962	0.015157	-0.134673	-0.075251
dens_dummy	-0.037996	0.0196778	-0.076569	0.0005762
dens_dummy	0	(omitted)		
reg1	-0.097936	0.04018	-0.176697	-0.019175
reg2	0.0001546	0.0435289	-0.085171	0.0854804
reg3	0.0172425	0.0408414	-0.062815	0.0973002
reg4	-0.078455	0.0451835	-0.167024	0.0101146
reg5	-0.135739	0.0417299	-0.217539	-0.05394
reg6	-0.000176	0.0462814	-0.090897	0.0905459
reg7	0.0172166	0.0414597	-0.064053	0.0984863
reg8	-0.040246	0.0461323	-0.130675	0.0501831
reg9	0.0066861	0.0399197	-0.071565	0.0849371
reg10	-0.065357	0.0403147	-0.144382	0.0136684
reg11	-0.08236	0.053757	-0.187735	0.0230149
reg12	-0.041498	0.0407825	-0.121441	0.038444
reg13	0.0251885	0.0403189	-0.053845	0.1042222
reg14	-0.104658	0.0449791	-0.192826	-0.016489
reg15	0	(omitted)		
reg16	-0.04761	0.0416799	-0.129311	0.0340919
reg17	0.0073033	0.0455563	-0.081997	0.0966033
_cons	1.688049	0.1319741	1.429352	1.946746

Source: Own elaboration

Table A3.4: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for male breadwinner households. Spain 1998

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.124639	0.0072982	-0.138945	-0.110333
age	0.0007386	0.0017075	-0.002609	0.0040856
sq_age	-2.16E-05	0.0000151	-5.13E-05	8.08E-06
nmiemb	0.0597736	0.0034393	0.0530318	0.0665154
kids	-0.045752	0.0051085	-0.055766	-0.035738
ed_dummy1	-0.009259	0.0090715	-0.027041	0.008523
ed_dummy2	0	(omitted)		
ed_dummy3	-0.014284	0.0098407	-0.033574	0.0050053
dens_dummy	-0.072575	0.0088041	-0.089833	-0.055317
dens_dummy	0	(omitted)		
dens_dummy	0.0206413	0.0096705	0.0016851	0.0395974
reg1	-0.073806	0.0180481	-0.109184	-0.038428
reg2	0.0443822	0.0211315	0.0029601	0.0858044
reg3	0.0173517	0.0197846	-0.02143	0.0561336
reg4	0.037787	0.0225432	-0.006402	0.0819764
reg5	-0.089146	0.0209623	-0.130237	-0.048056
reg6	0.0127092	0.0230298	-0.032434	0.0578524
reg7	0.0261393	0.0203395	-0.01373	0.0660091
reg8	0.0012923	0.0209217	-0.039719	0.0423032
reg9	0.0221191	0.0186952	-0.014528	0.0587656
reg10	-0.029	0.01883	-0.065911	0.0079104
reg11	-0.081172	0.0218624	-0.124027	-0.038318
reg12	-0.028005	0.0191745	-0.065591	0.0095813
reg13	0.0242001	0.0196367	-0.014292	0.0626921
reg14	-0.051548	0.0216955	-0.094076	-0.00902
reg15	0.0010413	0.0227793	-0.043611	0.0456935
reg16	-0.005267	0.0195864	-0.043661	0.0331263
reg17	0	(omitted)		
_cons	1.822637	0.0802536	1.665323	1.979951

Source: Own elaboration

Table A3.5: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for all households. Spain 1998

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.117269	0.0062591	-0.129538	-0.105
age	-0.001295	0.0013825	-0.004005	0.0014152
sq_age	-5.33E-06	0.000012	-2.89E-05	0.0000182
nmiemb	0.0660665	0.00302	0.0601467	0.0719862
kids	-0.052887	0.004653	-0.062008	-0.043766
ed_dummy1	-0.010262	0.0083568	-0.026644	0.0061189
ed_dummy2	0	(omitted)		
ed_dummy3	-0.009953	0.0090944	-0.02778	0.0078743
dens_dummy	-0.096415	0.0076974	-0.111503	-0.081326
dens_dummy	-0.023852	0.0087408	-0.040986	-0.006718
dens_dummy	0	(omitted)		
reg1	-0.078557	0.0157322	-0.109395	-0.047718
reg2	0.0354304	0.0184481	-0.000732	0.0715926
reg3	0.0189162	0.0170705	-0.014546	0.052378
reg4	0.011824	0.019674	-0.026741	0.0503891
reg5	-0.097609	0.0180111	-0.132915	-0.062304
reg6	0.0105923	0.0199668	-0.028547	0.0497314
reg7	0.0258597	0.0176812	-0.008799	0.0605186
reg8	-0.006007	0.0185012	-0.042273	0.0302592
reg9	0.0189084	0.0162358	-0.012917	0.0507339
reg10	-0.033374	0.0163508	-0.065425	-0.001323
reg11	-0.080537	0.0197094	-0.119171	-0.041902
reg12	-0.028484	0.0166028	-0.061029	0.0040613
reg13	0.0251793	0.0170159	-0.008175	0.0585341
reg14	-0.062231	0.0190132	-0.099501	-0.024962
reg15	0.002101	0.0202651	-0.037623	0.0418248
reg16	-0.013151	0.0171251	-0.046719	0.0204184
reg17	0	(omitted)		
gender	0.0293598	0.0069384	0.0157591	0.0429605
_cons	1.78943	0.0671616	1.657779	1.921081

Source: Own elaboration

Table A3.6: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for female breadwinner households. Spain 2008

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.009718	0.004252	-0.018052	-0.001383
age	0.0000616	0.0009749	-0.001849	0.0019725
sq_age	-9.62E-06	8.66E-06	-2.66E-05	7.35E-06
nmiemb	0.0356649	0.0024369	0.0308883	0.0404414
kids	-0.031527	0.0041313	-0.039625	-0.02343
ed_dummy1	0.0051919	0.0062292	-0.007018	0.0174015
ed_dummy2	0	(omitted)		
ed_dummy3	0.0076745	0.0068249	-0.005703	0.0210519
dens_dummy	-0.069309	0.0068865	-0.082807	-0.055811
dens_dummy	-0.031767	0.0076357	-0.046733	-0.0168
dens_dummy	0	(omitted)		
reg1	-0.05189	0.0130316	-0.077433	-0.026347
reg2	-0.030802	0.0148554	-0.05992	-0.001685
reg3	-0.044644	0.0145723	-0.073207	-0.016081
reg4	-0.061818	0.0145904	-0.090417	-0.03322
reg5	-0.073277	0.0144109	-0.101523	-0.04503
reg6	-0.018533	0.0164465	-0.050769	0.0137037
reg7	0.0176136	0.0146836	-0.011167	0.0463946
reg8	-0.021918	0.0193733	-0.059891	0.0160555
reg9	-0.05708	0.0129727	-0.082507	-0.031652
reg10	-0.057209	0.014266	-0.085172	-0.029247
reg11	-0.048659	0.0172804	-0.08253	-0.014789
reg12	-0.006384	0.0141773	-0.034173	0.0214041
reg13	-0.037891	0.0134041	-0.064164	-0.011618
reg14	-0.06484	0.0155937	-0.095405	-0.034275
reg15	-0.025572	0.0139329	-0.052882	0.0017375
reg16	-0.060877	0.012837	-0.086039	-0.035716
reg17	0	(omitted)		
_cons	0.4813728	0.0479336	0.3874195	0.5753261

Source: Own elaboration

Table A3.7: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for male breadwinner households. Spain 2008

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.020493	0.0029481	-0.026272	-0.014715
age	0.0025998	0.0007084	0.0012113	0.0039884
sq_age	-3.48E-05	6.49E-06	-4.75E-05	-2.21E-05
nmiemb	0.0315456	0.0015108	0.0285842	0.0345069
kids	-0.023712	0.0021354	-0.027897	-0.019526
ed_dummy1	0.012611	0.0033281	0.0060877	0.0191342
ed_dummy2	0.0064185	0.0040963	-0.001611	0.0144475
ed_dummy3	0	(omitted)		
dens_dummy	-0.03679	0.0035371	-0.043723	-0.029857
dens_dummy	0	(omitted)		
dens_dummy	0.028265	0.0041815	0.0200689	0.0364611
reg1	-0.024745	0.0092163	-0.04281	-0.00668
reg2	-0.004253	0.0100194	-0.023892	0.0153858
reg3	-0.002204	0.010702	-0.023181	0.0187729
reg4	-0.038232	0.0104251	-0.058666	-0.017798
reg5	-0.043637	0.0101963	-0.063622	-0.023651
reg6	0	(omitted)		
reg7	0.0246854	0.010204	0.0046848	0.044686
reg8	-0.012339	0.010595	-0.033106	0.0084279
reg9	-0.022993	0.0092949	-0.041212	-0.004774
reg10	-0.029002	0.0094184	-0.047463	-0.010541
reg11	-0.027537	0.0108543	-0.048812	-0.006261
reg12	0.0092903	0.0099721	-0.010256	0.0288362
reg13	-0.008544	0.0092733	-0.02672	0.0096327
reg14	-0.035014	0.0104063	-0.055411	-0.014616
reg15	0.0023059	0.0099621	-0.017221	0.0218324
reg16	-0.032179	0.0090681	-0.049953	-0.014405
reg17	0.0184802	0.0120466	-0.005132	0.0420924
_cons	0.5007399	0.0344119	0.4332901	0.5681896

Source: Own elaboration

Table A3.8: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for all households. Spain 2008

Variable	Coef.	Std. Err.	[95% Conf.	Interval]
l_exp	-0.016797	0.0024165	-0.021533	-0.01206
age	0.0016978	0.0005699	0.0005807	0.0028149
sq_age	-2.62E-05	5.18E-06	-3.64E-05	-1.61E-05
nmiemb	0.0325352	0.0012717	0.0300426	0.0350278
kids	-0.025328	0.0018842	-0.029021	-0.021635
ed_dummy1	0.0086862	0.0028158	0.003167	0.0142055
ed_dummy2	0.002295	0.0035031	-0.004571	0.0091615
ed_dummy3	0	(omitted)		
dens_dummy	-0.037095	0.0029825	-0.042941	-0.031249
dens_dummy	0	(omitted)		
dens_dummy	0.029148	0.003673	0.0219486	0.0363473
reg1	-0.045589	0.0076087	-0.060503	-0.030676
reg2	-0.024745	0.0083286	-0.04107	-0.00842
reg3	-0.0275	0.008753	-0.044656	-0.010343
reg4	-0.057714	0.0085574	-0.074487	-0.040941
reg5	-0.064644	0.0083863	-0.081082	-0.048206
reg6	-0.018177	0.0098362	-0.037457	0.0011025
reg7	0.0099173	0.0084545	-0.006654	0.0264888
reg8	-0.028966	0.0091633	-0.046927	-0.011006
reg9	-0.045592	0.0076513	-0.060589	-0.030595
reg10	-0.049913	0.0079056	-0.065409	-0.034418
reg11	-0.046289	0.009112	-0.06415	-0.028429
reg12	-0.007896	0.0082425	-0.024052	0.0082596
reg13	-0.029793	0.0076979	-0.044882	-0.014705
reg14	-0.056471	0.0087257	-0.073574	-0.039368
reg15	-0.018707	0.0081774	-0.034735	-0.002678
reg16	-0.05354	0.0074945	-0.06823	-0.03885
reg17	0	(omitted)		
gender	0.0208053	0.0025737	0.0157606	0.02585
_cons	0.4849038	0.0275088	0.4309846	0.538823

Source: Own elaboration

Table A3.9: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for female breadwinner households. Spain 2014

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.002713	0.0036737	-0.009913	0.004488
age	-0.001366	0.0007893	-0.002913	0.0001809
sq_age	1.77E-06	6.71E-06	-1.14E-05	0.0000149
nmiemb	0.0315731	0.0019629	0.0277256	0.0354205
kids	-0.02844	0.0034915	-0.035284	-0.021597
ed_dummy1	0.0010702	0.0051671	-0.009058	0.0111981
ed_dummy2	0	(omitted)		
ed_dummy3	0.0009578	0.0051436	-0.009124	0.0110397
dens_dummy	-0.028984	0.0041388	-0.037096	-0.020871
dens_dummy	0	(omitted)		
dens_dummy	0.0359914	0.0057239	0.0247722	0.0472105
reg1	-0.064902	0.0106576	-0.085792	-0.044012
reg2	-0.024147	0.0126804	-0.049002	0.0007071
reg3	-0.026371	0.0126618	-0.051189	-0.001553
reg4	-0.061773	0.0135764	-0.088384	-0.035162
reg5	-0.052973	0.0116603	-0.075828	-0.030118
reg6	-0.045756	0.0115269	-0.068349	-0.023162
reg7	0.0028178	0.0118713	-0.020451	0.0260863
reg8	-0.016213	0.0135378	-0.042748	0.0103217
reg9	-0.045301	0.0108489	-0.066566	-0.024037
reg10	-0.062609	0.0108662	-0.083908	-0.041311
reg11	-0.0536	0.0132809	-0.079631	-0.027568
reg12	-0.015986	0.0127075	-0.040893	0.008922
reg13	-0.038277	0.010851	-0.059546	-0.017008
reg14	-0.046669	0.0126971	-0.071556	-0.021782
reg15	-0.044767	0.0136035	-0.07143	-0.018103
reg16	-0.06784	0.0103732	-0.088172	-0.047508
reg17	0	(omitted)		
_cons	0.3811393	0.0407103	0.3013442	0.4609345

Source: Own elaboration

Table A3.10: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for male breadwinner households. Spain 2014

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	0.0020135	0.0029451	-0.003759	0.0077861
age	0.0007685	0.0006427	-0.000491	0.0020282
sq_age	-1.61E-05	5.55E-06	-0.000027	-5.21E-06
nmiemb	0.0221553	0.001485	0.0192446	0.025066
kids	-0.015087	0.002301	-0.019597	-0.010577
ed_dummy1	0.0074918	0.0036031	0.0004294	0.0145542
ed_dummy2	0	(omitted)		
ed_dummy3	-0.008541	0.0036883	-0.015771	-0.001312
dens_dummy	-0.060011	0.0034403	-0.066754	-0.053267
dens_dummy	-0.032497	0.0039204	-0.040181	-0.024813
dens_dummy	0	(omitted)		
reg1	-0.04349	0.0076563	-0.058497	-0.028483
reg2	-0.007653	0.0093961	-0.02607	0.0107644
reg3	-0.032557	0.0090821	-0.050358	-0.014755
reg4	-0.066534	0.0086746	-0.083537	-0.049531
reg5	-0.05095	0.0086349	-0.067874	-0.034025
reg6	-0.031857	0.0090912	-0.049677	-0.014038
reg7	0.0125842	0.0085481	-0.004171	0.0293391
reg8	0.0055639	0.0091782	-0.012426	0.0235538
reg9	-0.034673	0.0078698	-0.050099	-0.019248
reg10	-0.04551	0.0080268	-0.061243	-0.029777
reg11	-0.035592	0.0100213	-0.055234	-0.01595
reg12	-0.009958	0.0089532	-0.027507	0.0075908
reg13	-0.02184	0.0079615	-0.037446	-0.006235
reg14	-0.033753	0.0091737	-0.051734	-0.015772
reg15	-0.042073	0.0090451	-0.059802	-0.024344
reg16	-0.060426	0.0074721	-0.075072	-0.04578
reg17	0	(omitted)		
_cons	0.32415	0.0327901	0.2598791	0.388421

Source: Own elaboration

Table A3.11: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for all households. Spain 2014

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	0.000582	0.0023068	-0.003939	0.0051035
age	-0.000105	0.0004984	-0.001082	0.0008722
sq_age	-9.21E-06	4.28E-06	-1.76E-05	-8.18E-07
nmiemb	0.0255361	0.0011801	0.023223	0.0278492
kids	-0.019663	0.0019046	-0.023396	-0.01593
ed_dummy1	0.0105213	0.0026877	0.0052532	0.0157895
ed_dummy2	0.0049996	0.0030078	-0.000896	0.010895
ed_dummy3	0	(omitted)		
dens_dummy	-0.061878	0.0028424	-0.067449	-0.056306
dens_dummy	-0.033656	0.0032397	-0.040006	-0.027306
dens_dummy	0	(omitted)		
reg1	-0.013999	0.0050668	-0.02393	-0.004067
reg2	0.023465	0.0066852	0.0103616	0.0365685
reg3	0.0061137	0.0064742	-0.006576	0.0188037
reg4	-0.028413	0.0064331	-0.041022	-0.015804
reg5	-0.013938	0.0058782	-0.02546	-0.002417
reg6	0	(omitted)		
reg7	0.0459385	0.0059379	0.0342998	0.0575772
reg8	0.0352596	0.006721	0.022086	0.0484331
reg9	-0.001553	0.005239	-0.011822	0.0087159
reg10	-0.014545	0.0052769	-0.024888	-0.004202
reg11	-0.004906	0.0072418	-0.0191	0.0092884
reg12	0.0245788	0.0063631	0.0121067	0.037051
reg13	0.0088523	0.0053194	-0.001574	0.0192787
reg14	-0.001643	0.0065479	-0.014477	0.0111917
reg15	-0.006963	0.0066046	-0.019908	0.0059827
reg16	-0.026814	0.004831	-0.036283	-0.017345
reg17	0.035978	0.0071416	0.02198	0.049976
gender	0.0108642	0.0021878	0.0065759	0.0151525
_cons	0.3097501	0.02583	0.2591213	0.3603788

Source: Own elaboration

Table A3.12: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for female breadwinner households. Spain 2018

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.017753	0.0046369	-0.026842	-0.008664
age	0.0007923	0.0007916	-0.000759	0.0023439
sq_age	-1.61E-05	6.65E-06	-2.91E-05	-3.1E-06
nmiemb	0.0281799	0.002092	0.0240793	0.0322804
kids	-0.02966	0.0035618	-0.036642	-0.022679
ed_dummy1	0	(omitted)		
ed_dummy2	0.0010205	0.0049178	-0.008619	0.0106598
ed_dummy3	0.0164967	0.0055487	0.0056207	0.0273726
dens_dummy	-0.031773	0.0046677	-0.040922	-0.022624
dens_dummy	0	(omitted)		
dens_dummy	0.0213441	0.0060119	0.0095604	0.0331278
reg1	-0.05275	0.0118176	-0.075913	-0.029586
reg2	-0.020213	0.0131364	-0.045961	0.0055359
reg3	-0.03832	0.0128246	-0.063457	-0.013182
reg4	-0.058377	0.0128637	-0.083591	-0.033163
reg5	-0.059163	0.0127185	-0.084092	-0.034234
reg6	-0.027537	0.0131841	-0.053379	-0.001696
reg7	-0.000218	0.0125541	-0.024825	0.0243887
reg8	0.0020477	0.0140068	-0.025407	0.0295021
reg9	-0.043415	0.0119813	-0.066899	-0.01993
reg10	-0.06108	0.0122368	-0.085065	-0.037095
reg11	-0.034425	0.0138713	-0.061614	-0.007236
reg12	-0.028	0.0123595	-0.052226	-0.003774
reg13	-0.02099	0.0124815	-0.045455	0.0034742
reg14	-0.047608	0.0133952	-0.073864	-0.021352
reg15	-0.018582	0.0139218	-0.04587	0.0087058
reg16	-0.059499	0.0114993	-0.082038	-0.036959
reg17	0	(omitted)		
_cons	0.460144	0.0450448	0.3718527	0.5484352

Source: Own elaboration

Table A3.13: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for male breadwinner households. Spain 2018

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.014805	0.0029521	-0.020592	-0.009019
age	0.0023437	0.0006805	0.0010098	0.0036775
sq_age	-3.13E-05	5.82E-06	-4.27E-05	-1.99E-05
nmiemb	0.0206473	0.0015596	0.0175902	0.0237043
kids	-0.01843	0.0023894	-0.023114	-0.013747
ed_dummy1	0.0017979	0.0035406	-0.005142	0.0087378
ed_dummy2	0	(omitted)		
ed_dummy3	-0.003784	0.003695	-0.011026	0.0034584
dens_dummy	-0.05394	0.00369	-0.061173	-0.046707
dens_dummy	-0.031006	0.0040899	-0.039022	-0.022989
dens_dummy	0	(omitted)		
reg1	-0.049292	0.0079894	-0.064952	-0.033632
reg2	-0.02247	0.0088345	-0.039786	-0.005153
reg3	-0.035568	0.0091016	-0.053408	-0.017728
reg4	-0.068151	0.0091671	-0.08612	-0.050183
reg5	-0.052322	0.0090929	-0.070144	-0.034499
reg6	-0.014495	0.0100015	-0.034098	0.0051091
reg7	0.0058825	0.008701	-0.011172	0.0229372
reg8	-0.001933	0.0098708	-0.02128	0.0174147
reg9	-0.053551	0.0080452	-0.06932	-0.037781
reg10	-0.046133	0.0083497	-0.062499	-0.029767
reg11	-0.045123	0.0095813	-0.063903	-0.026343
reg12	-0.024935	0.0088246	-0.042232	-0.007638
reg13	-0.021014	0.0083139	-0.03731	-0.004718
reg14	-0.033225	0.0094659	-0.051779	-0.014671
reg15	-0.014981	0.0100318	-0.034644	0.0046821
reg16	-0.0574	0.0078402	-0.072767	-0.042032
reg17	0	(omitted)		
_cons	0.4545643	0.0340977	0.3877303	0.5213984

Source: Own elaboration

Table A3.14: Ordinary Least Square on greenhouse gas emissions patterns (kgs of equivalent CO_2 per euro) for all households. Spain 2018

Variable	Coef.	Std. Err.	[95% Conf. Interval]	
l_exp	-0.015547	0.0024964	-0.02044	-0.010654
age	0.0017507	0.0005171	0.0007372	0.0027643
sq_age	-0.000026	0.0000044	-3.46E-05	-1.73E-05
nmiemb	0.0232072	0.001245	0.0207669	0.0256476
kids	-0.021983	0.0019705	-0.025846	-0.018121
ed_dummy1	-0.0014	0.0029077	-0.007099	0.0042998
ed_dummy2	-0.002508	0.0030258	-0.008438	0.003423
ed_dummy3	0	(omitted)		
dens_dummy	-0.05452	0.0030029	-0.060406	-0.048634
dens_dummy	-0.028299	0.0033913	-0.034947	-0.021652
dens_dummy	0	(omitted)		
reg1	-0.031242	0.0058585	-0.042726	-0.019759
reg2	-0.001844	0.0066925	-0.014962	0.0112738
reg3	-0.017348	0.0067534	-0.030585	-0.004111
reg4	-0.045177	0.0067992	-0.058504	-0.03185
reg5	-0.035538	0.0066729	-0.048618	-0.022459
reg6	0	(omitted)		
reg7	0.0238114	0.0064431	0.0111824	0.0364405
reg8	0.0184603	0.0075051	0.0037497	0.033171
reg9	-0.03065	0.00591	-0.042234	-0.019066
reg10	-0.031656	0.0060823	-0.043578	-0.019734
reg11	-0.02197	0.0072978	-0.036274	-0.007666
reg12	-0.006655	0.0064282	-0.019255	0.0059447
reg13	-0.001761	0.0062484	-0.014008	0.0104868
reg14	-0.017968	0.0071222	-0.031929	-0.004008
reg15	0.0033059	0.0075907	-0.011572	0.0181841
reg16	-0.038913	0.0056349	-0.049958	-0.027868
reg17	0.0195978	0.0079433	0.0040284	0.0351673
gender	0.0157511	0.002196	0.0114468	0.0200554
_cons	0.437582	0.027954	0.38279	0.492374

Source: Own elaboration

ANNEX 3.6

Table A3.15: Balance indicators for the covariates under Propensity-Score Matching. Spain 1998

	Standardized differences		Variance	Ratio
Variables	Raw	Matched	Raw	Matched
l_exp	-0.651121	-0.008817	1.27323	1.019261
nmiemb	-1.016864	0.0008845	1.037586	1.009439
kids	-0.475731	-0.034408	0.4176364	0.9485481
age	0.4333501	0.0056427	1.346836	1.028066
sq_age	0.469342	0.0091709	1.524991	1.074007
estudredsp				
2	-0.112746	-0.000956	0.7562995	0.9977836
3	-0.034771	0.0485574	0.9373099	1.084653
ccaa				
2	0.0285701	-0.003385	1.124091	0.9858924
3	0.0628389	0.0028003	1.28062	1.01131
4	0.0580875	0.0043092	1.302368	1.020796
5	0.0682838	-0.032961	1.330558	0.8586538
6	0.0458812	-0.006926	1.307737	0.9569657
7	-0.052324	0.0622098	0.844669	1.195903
8	-0.050215	-0.035996	0.801989	0.851873
9	-0.058229	-0.011537	0.8605433	0.9720444
10	0.0021745	0.0258735	1.00673	1.077285
11	-0.036487	0.0137625	0.8251181	1.069781
12	0.0766085	0.0118697	1.258851	1.037361
13	0.0035011	-0.001859	1.011055	0.9945124
14	-0.019283	-0.030531	0.9096999	0.8538616
15	-0.02362	-0.000666	0.8650333	0.9959569
16	-0.033518	-0.024926	0.878706	0.9059147
17	0.0013966	-0.023086	1.008701	0.861997
densi				
2	-0.04338	0.021506	0.9286415	1.035819
3	-0.130087	0.0305399	0.895956	1.022364
l_exp#				
l_exp	-0.6468062	-0.0082811	1.185105	1.02127
estudredsp#				
l_exp				
2	-0.120459	-0.001263	0.7232573	0.9959997
3	-0.04746	0.0499054	0.88402	1.091037
nmiemb#				
l_exp				
2	0.1806166	-0.005331	1.224192	1.003087
3	-0.166874	0.0292067	0.783131	1.042997
4	-0.575485	-0.039297	0.3936195	0.9551297
5	-0.334638	0.0177766	0.325802	1.026333
6	-0.167581	0.0057144	0.346683	1.05426

Source: Own elaboration

Table A3.16: Balance indicators for the covariates under Propensity-Score Matching. Spain 2008

	Standardized differences		Variance	Ratio
Variables	Raw	Matched	Raw	Matched
l_exp	-0.459429	0.0096816	1.325573	1.019608
nmiemb	-0.720688	0.0039448	1.079658	0.994166
kids	-0.263955	-0.027524	0.6588472	0.9338595
age	0.1720702	-0.031154	1.280372	1.009844
sq_age	0.2030736	-0.028699	1.331561	1.007565
estudredsp				
2	-0.029495	0.0291082	0.9444091	1.055771
3	0.0899982	0.0178029	1.102527	1.019892
ccaa				
2	-0.031611	-0.004686	0.8636262	0.9783404
3	0.0131741	-0.0125	1.065524	0.9402477
4	0.0540656	0.0027241	1.293574	1.013679
5	0.0488679	0.0165519	1.232737	1.071085
6	0.0045407	-0.002082	1.02356	0.9890614
7	-0.018276	-0.001118	0.9377198	0.9960812
8	-0.079901	-0.022944	0.7052881	0.907035
9	0.0140166	0.0205152	1.039603	1.057989
10	-0.019474	-0.00582	0.9388593	0.981189
11	-0.028847	-0.016642	0.8767657	0.9262782
12	0.0444727	0.0059831	1.1704	1.021343
13	-0.006906	-0.010014	0.9763307	0.9656344
14	-0.043963	0.0308604	0.8202427	1.13852
15	0.0151559	0.0102056	1.054219	1.03543
16	0.0487769	-0.005951	1.141197	0.9837825
17	-0.00511	-0.011214	0.9733449	0.9408306
densi				
2	-0.036086	-0.01691	0.9508127	0.9769388
3	-0.148522	0.0123217	0.8800368	1.009382
l_exp#				
l_exp	-0.453197	0.0103068	1.267013	1.023054
estudredsp#				
l_exp				
2	-0.038731	0.0291781	0.9045924	1.056291
3	0.0811336	0.0172842	1.071315	1.018079
nmiemb#				
l_exp				
2	-0.018682	-0.009474	0.9840429	0.9984443
3	-0.163042	0.0147708	0.8069245	1.016294
4	-0.424558	-0.002547	0.5040031	1.000039
5	-0.173419	0.0075644	0.4721717	1.023245
6	-0.080695	-0.012788	0.4715174	0.8818472

Source: Own elaboration

Table A3.17: Balance indicators for the covariates under Propensity-Score Matching. Spain 2014

	Standardized differences		Variance	Ratio
Variables	Raw	Matched	Raw	Matched
l_exp	-0.369837	0.0200678	1.126434	1.037239
nmiemb	-0.48097	0.002493	1.106503	0.9990043
kids	-0.15179	-0.03406	0.7593037	0.8672133
age	0.0504829	-0.027661	1.297896	0.9783606
sq_age	0.0838605	-0.029223	1.351904	1.010344
estudredsp				
2	-0.018794	0.0152691	0.9692939	1.024627
3	0.1011445	0.0139069	1.085919	1.011505
ccaa				
2	-0.004123	-0.02704	0.9818863	0.8847138
3	0.0144634	0.0167773	1.069644	1.080026
4	0.0203107	-0.011272	1.105898	0.944402
5	0.0742303	0.0052897	1.354373	1.022194
6	0.0182881	0.012274	1.095901	1.062738
7	-0.002881	-0.009486	0.9901704	0.9671511
8	-0.084222	-0.026741	0.7082088	0.8973689
9	0.0290288	0.0082788	1.084833	1.023714
10	0.027833	-0.005616	1.09009	0.9826398
11	-0.023548	0.0136038	0.9010901	1.062052
12	0.0245706	0.0104303	1.092413	1.038396
13	0.0062507	-0.010026	1.02046	0.9677835
14	-0.058616	0.0032634	0.7531607	1.015338
15	-0.011017	-0.004815	0.9455545	0.9755477
16	0.0025103	0.0064436	1.006708	1.016747
17	-0.036866	0	0.8229841	1
densi				
2	-0.0213	0.016793	0.9743037	1.020229
3	-0.131682	-0.014153	0.8793324	0.9870827
l_exp#				
l_exp	-0.367934	0.0212213	1.091496	1.043938
estudredsp#				
l_exp				
2	-0.028202	0.0164693	0.9313141	1.029944
3	0.0885924	0.0143252	1.047367	1.012869
nmiemb#				
l_exp				
2	-0.055327	-0.008449	0.9397886	0.9923338
3	-0.142813	0.0117068	0.8220735	1.014917
4	-0.283295	-0.002143	0.6291127	1.002041
5	-0.101299	0.0018263	0.6363141	1.005512
6	-0.030164	0.0012737	0.7518524	1.024954

Source: Own elaboration

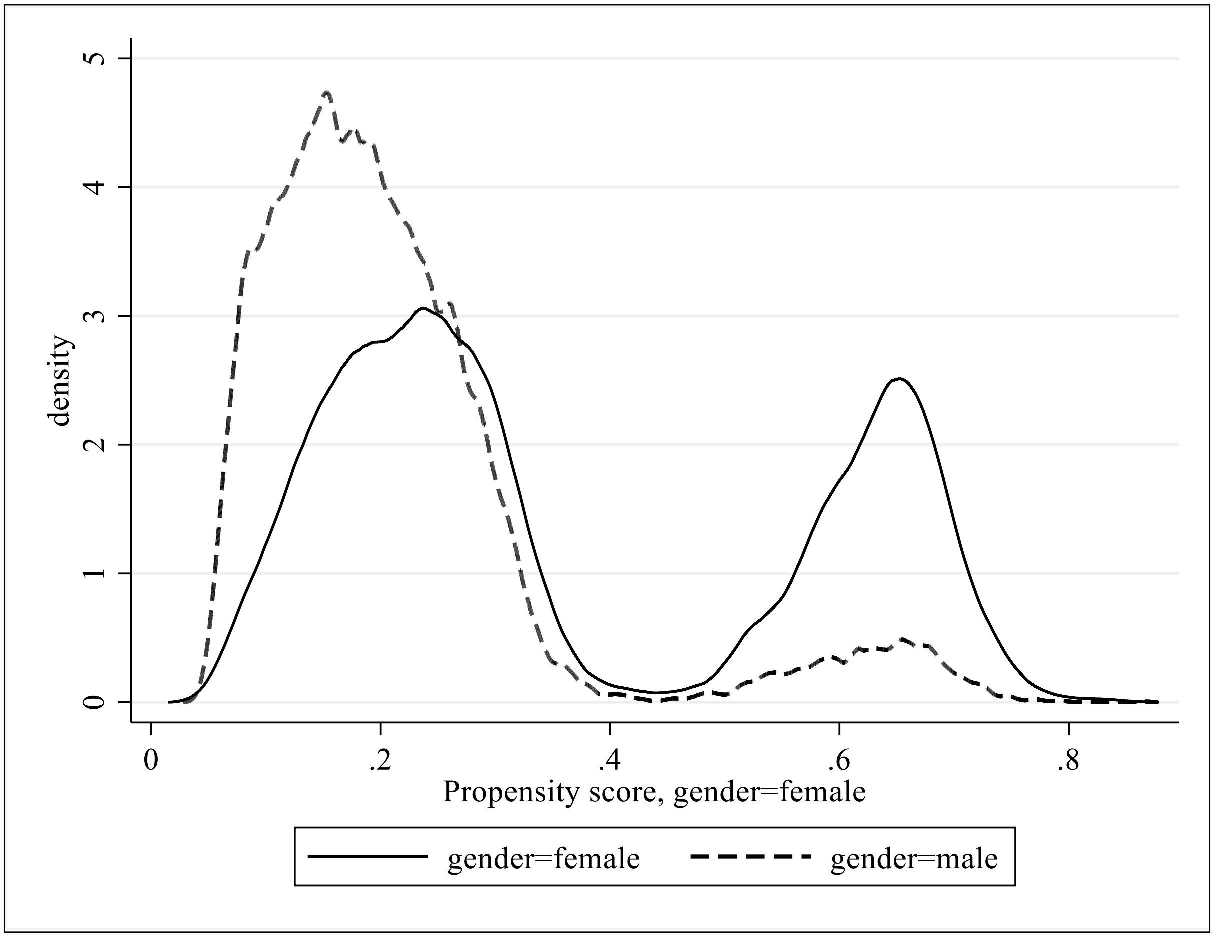
Table A3.18: Balance indicators for the covariates under Propensity-Score Matching. Spain 2018

		Standardized differences		Variance	Ratio
Variables		Raw	Matched	Raw	Matched
l_exp		-0.353841	0.0009123	1.173809	1.044036
nmiemb		-0.515308	0.0002826	1.015877	1.014774
kids		-0.168856	-0.042287	0.7198648	0.9118889
age		0.0844423	0.0014392	1.220629	0.9862098
sq_age		0.1081051	-0.000391	1.279142	1.034685
estudredsp					
	2	-0.054394	0.0075355	0.9120158	1.012127
	3	0.1239501	0.0042302	1.088621	1.003008
ccaa					
	2	-0.018597	-0.01196	0.9214811	0.9485609
	3	0.0220211	0.0110338	1.104479	1.051201
	4	0.0127647	-0.01691	1.072479	0.9080614
	5	0.049031	-0.000671	1.229021	0.99714
	6	0.0106674	-0.001004	1.054561	0.9950941
	7	-0.03654	-0.00454	0.8790329	0.9844653
	8	-0.061439	0.0230183	0.7818768	1.092506
	9	0.032731	-0.014201	1.097097	0.9596888
	10	0.0186151	-0.015647	1.058879	0.9523724
	11	-0.000946	-0.009466	0.9959308	0.9588829
	12	0.0270092	0.0188084	1.100922	1.070316
	13	-0.018413	0.0110583	0.9408116	1.036649
	14	-0.031975	0.0178868	0.8678235	1.0806
	15	-0.04429	-0.017628	0.795156	0.9128238
	16	0.0504876	0.0088661	1.13769	1.02264
	17	-0.025199	-0.012635	0.8724672	0.9336483
densi					
	2	-0.019519	-0.017003	0.9775797	0.9804921
	3	-0.153186	-0.013555	0.8563217	0.9872096
l_exp#					
l_exp		-0.351064	0.0021436	1.130661	1.044797
estudredsp#					
l_exp					
	2	-0.064352	0.0084879	0.8734643	1.016277
	3	0.1141487	0.003543	1.060627	1.00131
nmiemb#					
l_exp					
	2	-0.098364	4.77E-06	0.9161148	0.9985158
	3	-0.128363	-0.016252	0.8334712	0.9789268
	4	-0.288757	0.0040043	0.598548	1.0125
	5	-0.127754	0.0196817	0.5212623	1.095253
	6	-0.047915	-0.010496	0.5663475	0.8775828

Source: Own elaboration

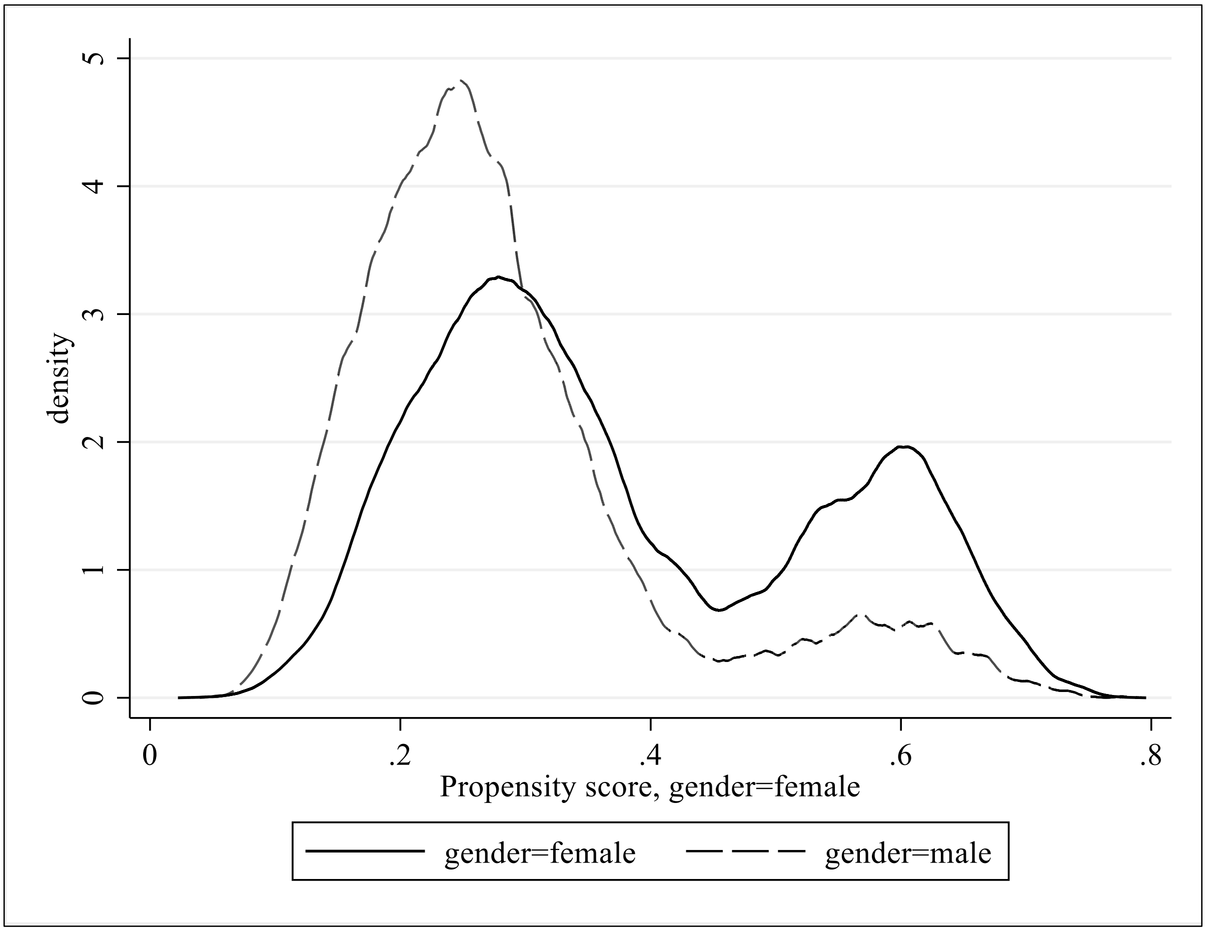
ANNEX 3.7

Graph A3.5: Estimated densities of propensity scores for the treated and non-treated households. Spain 2008



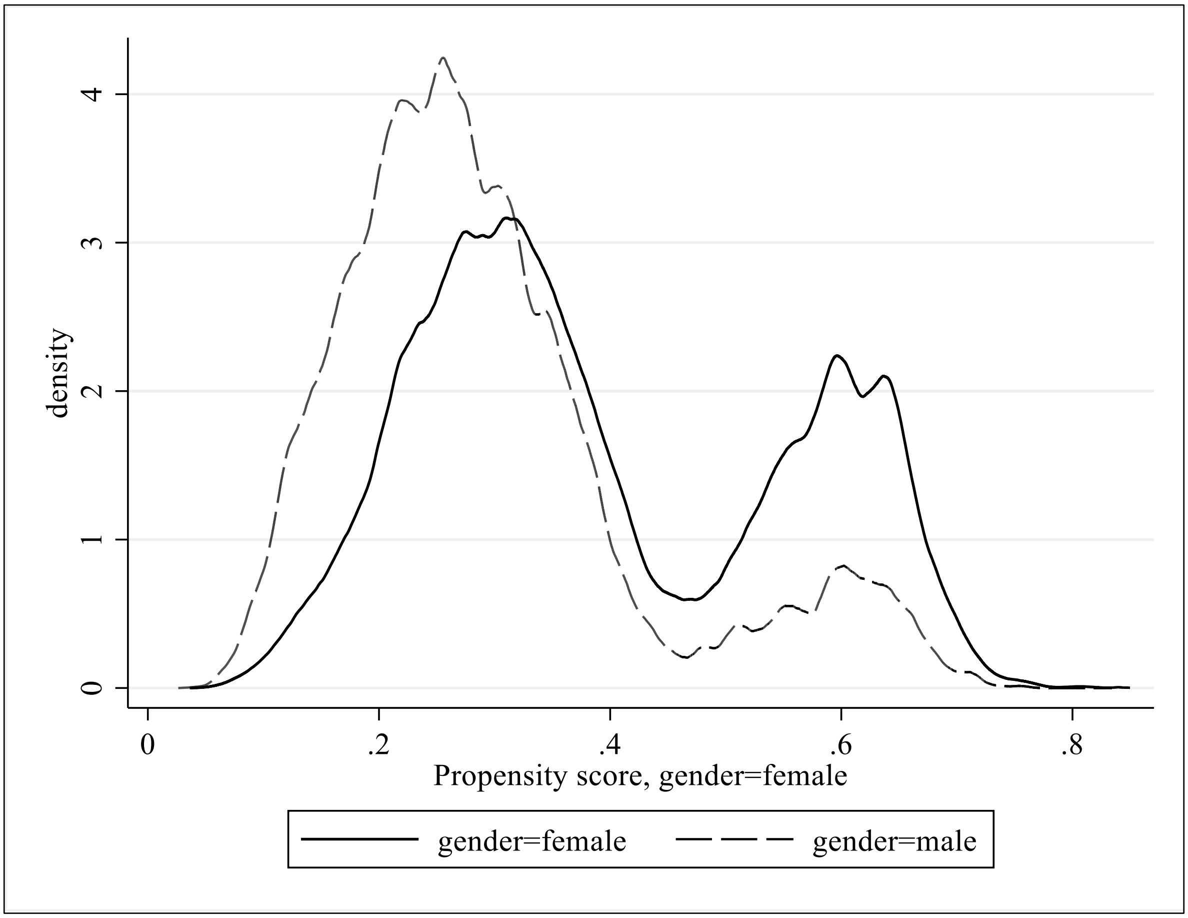
Source: Own elaboration

Graph A3.6: Estimated densities of propensity scores for the treated and non-treated households. Spain 2014.



Source: Own elaboration

Graph A3.7: Estimated densities of propensity scores for the treated and non-treated households. Spain 2018



Source: Own elaboration

WHERE ARE THE EMITTERS? ESTIMATION OF HOUSEHOLD EMISSIONS AT THE SPANISH MUNICIPAL LEVEL

1. INTRODUCTION

Urban areas and cities are home to half of the world's population (World Bank, 2020) and the EU in 2018 has about 40% of the population living in cities, a percentage that continues to increase (Eurostat, 2022). This fact suggests that cities are crucial for proper environmental adaptation. Since urban areas contribute around 74% of CO_2 emissions from global final energy use (Seto et al., 2014), they are more vulnerable to climate change impacts such as extreme temperatures, flooding, droughts and intense storms (World Bank, 2010), and are a key part of the solution (Pattberg and Widerberg, 2015; Nerini et al., 2019) and where mitigation and adaptation in the cities and urban areas are important in the fight against climate change (Grafakos et.al., 2019). However, it is not well understood how emissions are distributed among cities, or how the contribution of GHG production varies by different types of urban areas.

If cities concentrate large amounts of emissions, an opportunity to develop environmental strategies focused on particular local governments could have substantial effects on reducing national, and thus global, emissions (Kamal-Chaoui and Robert, 2009). However, the diversity of cities, regions and types of consumers makes the design and implementation of effective environmental policies problematic, even within a country (Cheng et.al., 2021). Emissions from consumption at a detailed geographical level and the possible differences and consequences have not been fully studied, generally given the lack of reliable data (Pichler et.al., 2017). In this context, the measure of GHG (or other pollutants) footprints embedded from consumption for small geographical areas becomes an important issue, which this chapter aims to overcome.

Although in the literature there are some examples of carbon footprints by cities, they are still rare. Minx et al. (2013) estimated the carbon footprints of 434 municipality areas in the United Kingdom (UK) using geo-demographic information form the MOSAIC database, which distinguishes consumer spending of 61 lifestyle types and 11 lifestyle groups (but not households) at national level. Chen et al. (2016) analysed the carbon footprint of five cities in Australia (Sydney, Melbourne, Brisbane, Perth and Adelaide) and the flow of emissions between them. This study used a singular Australian database that includes input-output tables for multiple cities nested into a global multiregional input-output model. Moran et al.

(2018) applied the so-called Gridded Global Model of Carbon Footprints model to estimate the carbon footprint of 13,000 cities, assuming that all households of a country have the same national average expenditure. However, none of these studies have considered the emissions from non-urban areas or consider the potential different consumption patterns between households.

This study focuses on Spain for 2011, which is composed by 8,131 municipalities. In Spain, large urban areas increased their population by more than five million between 2001 and 2020. This growth accounts for more than the 80% of the overall national increase, making it the main territorial recipient of the demographic increase. The largest percentage increase is in small urban areas, which have increased their population by almost a quarter in the early 21st century. On the one hand, Spanish nonurban municipalities have a regressive demographic dynamic in the same period, where more than the 71% municipalities lost population, 3.3% of which fall very dramatically, with a decrease of more than 50%. On the other hand, there still is a large number of non-urban municipalities with positive dynamics in this period (more than 2,000). Some of these -10.1% of non-urban municipalities- even gained population by more than 25%, (Gobierno de España, 2021).

Moreover, Spain implements environmental policies at the municipal level, e.g., low emission zone in Barcelona (Ajuntament de Barcelona, 2022), energy saving and efficiency policy in Madrid (Ayuntamiento de Madrid, 2022), installation of charging points for electric vehicles and o projects to increase bicycle lanes in Valencia or Bilbao (Ajuntament de València, 2019; Ayuntamiento de Bilbao. 2022). Due to the lack of information at the local level and the focus of these policies on direct and local emissions, it is currently impossible to assess the real environmental effect of such measures. Therefore, there is a need to better understand the role of urban areas in both emissions from direct energy use and indirect emissions from the consumption of goods and services at the municipal level.

Unfortunately, in most of EU countries, official estimates of household consumptions are only available for relatively large regions (NUTS1 or NUTS2 units), and small area estimates are not produced due to lack of reliability and by data privacy issues. Spain is not an exception to this limitation and the consumption figures on the Spanish HBS produced by INE are only available at the scale of NUTS2 area: Autonomous Communities (CCAA, for Spanish acronyms). Consequently, the analysis of household consumption for cities or other spatial units at the level of sub-regions is not possible based on these official aggregate estimates.

This chapter proposes a methodology to overcomes this limitation using a method that predicts emissions embedded from consumption for small areas and being consistent with the observable information. In this chapter the GHG emissions embedded from each households' consumption are projected to the different municipalities applying a modification of the General Maximum Entropy (GME) estimator combining HBS with Population Census (PC), being the latter the one providing the geographic details information.

Part of the data used in this chapter are described in chapter 1 combined with PC. GHG footprints of each Spanish census households in 2011 with a total of 6 GHGs aggregated into CO_2 equivalent units, 62 industries, and 39 COICOP products were estimated. GHGs estimated per municipality are disaggregated for indirect emissions related to the inter-industrial process to create goods and services and direct emissions related to the use of energy goods. This provides the first Spanish mapping distinguishing both types of emissions.

The rest of the chapter is organised as follows: Section 2 shows the data obtained in chapter 1 closely related with the objective of this chapter. Section 3 explains in detail the proposed methodology for obtaining emissions at the micro-geographical level. Section 4 introduces the main results and Section 5 summarises the conclusions of this chapter.

2. DATA SET

The database estimated in chapter 1 is presented in this section, with the most relevant information and structure related with the objective of this chapter. These databases only allow the recognition within the region of the CCAA, if the area of residence is a provincial capital, and the size of the municipality. This allows in some cases the recognition of large cities such as Madrid, but in the case of Catalonia it would not be possible to distinguish Barcelona from Tarragona, leaving invisible in most cases the competencies of cities and large urbanisations, and even worse in the case of small and medium sized municipalities.

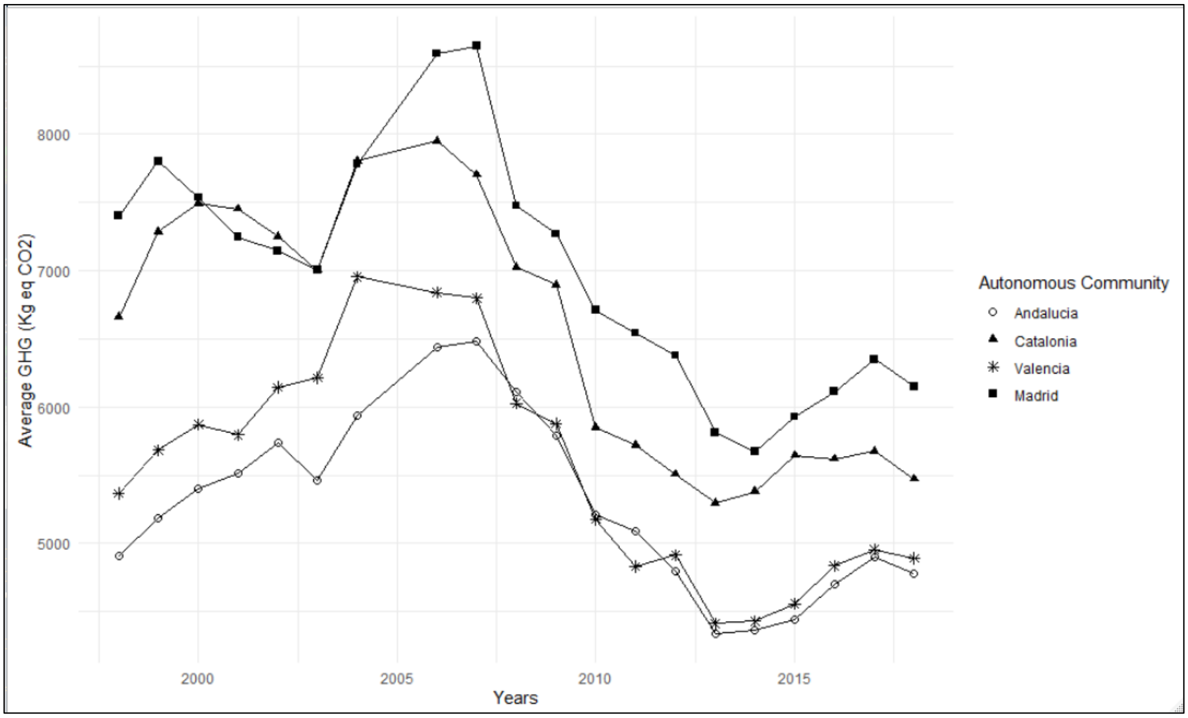
Three sources of statistical data of 2011 are used to estimate the emissions derived from the consumption of each Spanish household: i) IOT estimated from SUT (INE, 2019a), ii) Spanish environmental accounts (INE, 2019b), and iii) Spanish HBS (INE, 2019c). Moreover, the BM delivered by Statistics Denmark (Denmark Statistics, 2019) are used as a starting point to estimate the Spanish Bridge Matrix for 2011 (see details in chapter 1). GHG emissions from the consumption of all 39 COICOP goods and services has been estimated applying input-output techniques, including indirect GHG emissions derived from goods and services consumption as well as direct emissions from households' consumption in energy goods (see details in chapter 1). Finally, as information with geographic detail is needed, the PC (INE, 2011) will be used for applying the methodology presented in the following section.

Both the characteristics of households and their emissions from consumption are expected to be heterogeneous across regions. Given the information available in the HBS and the estimates of emissions from consumption per household developed in chapter 1, it is that from Annex A4.1 Graph A4.1 shows the households breadwinners average age by CCAA between 1998-2004 and 2006-2018. For simplicity, the largest CCAA at the population level are represented: Andalusia, Catalonia, Valencia, and Madrid. It can be observed that since 2006, Valencia has older main breadwinners on average than the other CCAA, but these differences do not exceed 2 years.

Graph A4.2 presents the households breadwinners average education level between Andalusia, Catalonia, Valencia, and Madrid. Historically, Madrid has the highest education level followed by Catalonia. Andalucía has, otherwise, the lowest education level. Moreover, Graph A4.3 shows the average households breadwinners expenditure level, at a population level with the equivalent household size correction. Similar to the education level, Madrid and Catalonia are the communities with the highest levels of expenditure.

Although large aggregates such as the CCAA are presented, the heterogeneity of households among them can be appreciated (see Annex A4.2 for other CCAA). This should affect the emissions derived from consumption. From an environmental point of view, Graphs 4.1 present the average GHG emissions of Andalusia, Catalonia, Valencia, and Madrid, considering the population level with the correction for equivalent household size (see Annex A4.3 for other CCAA).

Graph 4.1: Average households greenhouse gases embedded (kgs of equivalent CO_2) in the consumption basket of Andalusia, Catalonia, Valencia, and Madrid. Spain 1998 – 2018

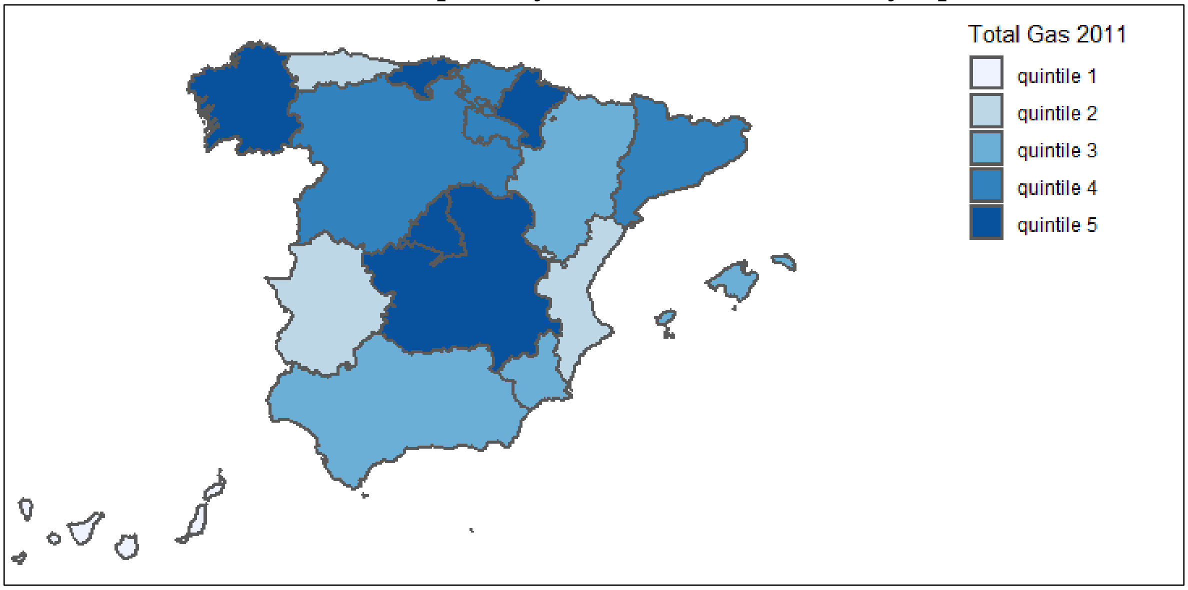


Source: Own elaboration from data presented in chapter 1

Historically, Madrid emits more GHG on average that the rest of CCAA, followed by Catalonia and Andalusia stands out for its low levels of emissions. It can be observed that there are large differences between CCAA, given the diversity of characteristics between them. Even more should be appreciated at more detailed scales, given the great heterogeneity of households within each region.

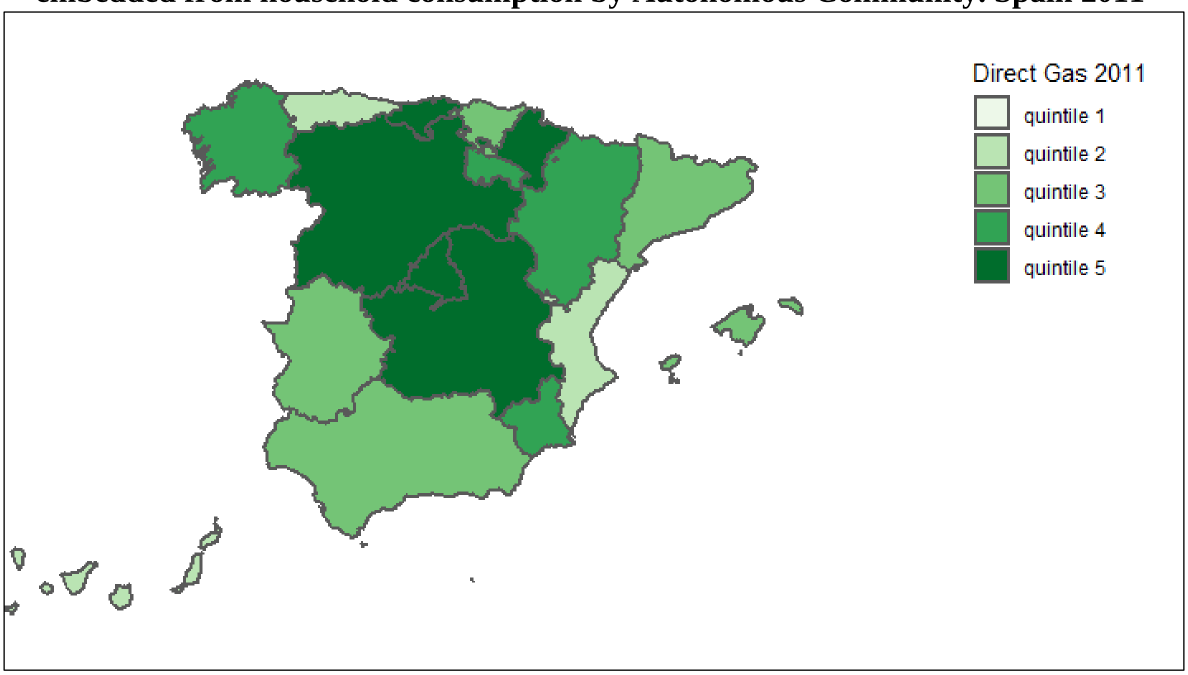
As the aim of this chapter is to calculate emissions from household consumption at a detailed geographical scale of total, direct and indirect GHG emissions, the database is limited to the latest available PC for the year 2011. Map 4.1 shows the average total emissions in 2011 by CCAA at the population level. Maps 4.2 and 4.3 present the direct and indirect emissions in 2011 respectively.

Map 4.1: Average households greenhouse gases (kgs of equivalent CO_2) embedded from household consumption by Autonomous Community. Spain 2011



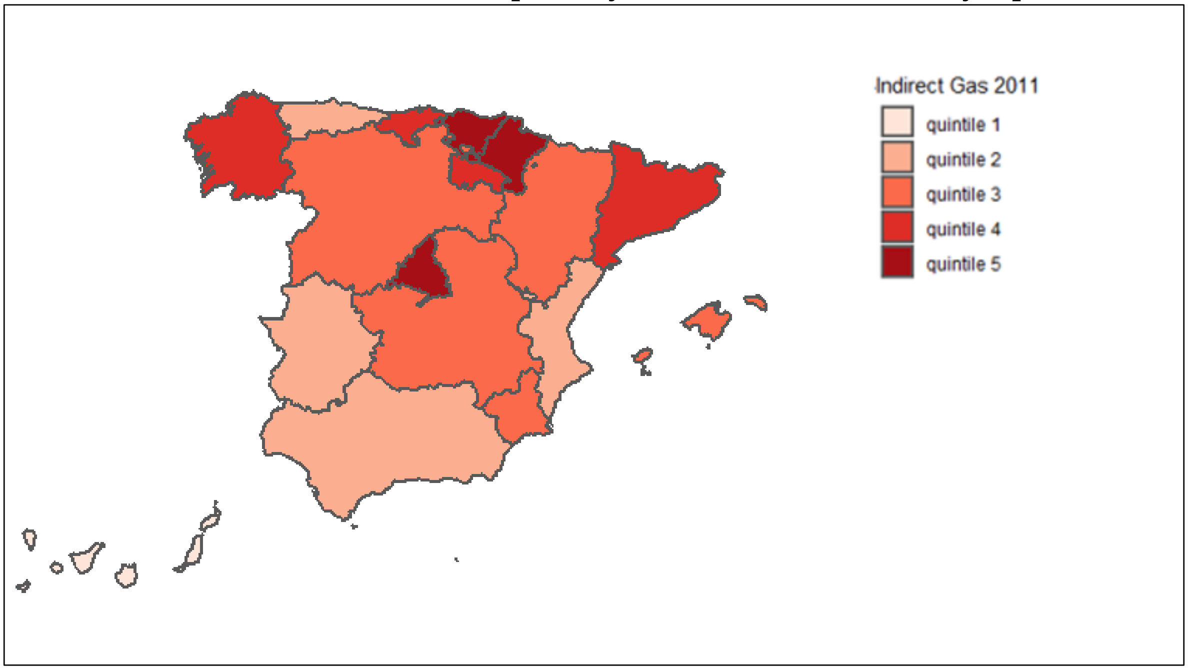
Source: Own elaboration from data presented in chapter 1

Map 4.2: Average households direct greenhouse gases (kgs of equivalent CO_2) embedded from household consumption by Autonomous Community. Spain 2011



Source: Own elaboration from data presented in chapter 1

Map 4.3: Average households indirect greenhouse gases (kgs of equivalent CO_2) embedded from household consumption by Autonomous Community. Spain 2011



Source: Own elaboration from data presented in chapter 1

These figures show the differences between CCAA between type of emissions. Navarre is one of the most emitting CCAA in Spain, regardless of the type of emission observed. Moreover, Catalonia is notable for its high indirect emissions but low direct emissions. A similar case is Madrid, where it has high levels of indirect emissions and medium levels of direct emissions. Andalusia seems to remain with low levels of both direct and indirect emissions.

From here it is observed that emissions from household consumption should be affected by the place of residence. However, homogeneous emissions are assumed within each CCAA, which makes a realistic analysis of the geographical effect on emissions difficult. Differences are expected to be found between each community, especially in large cities. Table 4.1, 4.2 and 4.3 shows, for instance, the emissions of Catalonia, Asturias, and Spain by municipality size, information available on the HBS (see Annex A4.4 for other CCAA).

Table 4.1: Catalonia average households greenhouse gases emissions (kgs of equivalent CO2) by municipality size. Spain 2011

Municipality Size	Total Gas	Direct Gas	Indirect Gas
1 (100,000 inhabitants or more)	4,906.11	1,453.01	3,453.10
2	6,562.81	2,435.09	4,127.72
3	5,967.69	2,284.98	3,682.70
4	6,143.79	2,413.19	3,730.60
5 (less than 10,000 inhabitants)	6,927.94	2,940.38	3,987.56

Note: municipality size is measured in a scale from 1 to 5 (1 100,000 inhabitants or more; 2 between 50,000 and 100,000 inhabitants; 3 between 20,000 and 50,000 inhabitants; 4 between 10,000 and 20,000 inhabitants; 5 less than 10,000 inhabitants

Source: Own elaboration from data presented in chapter 1

Table 4.2: Asturias average households greenhouse gases emissions (kgs of equivalent CO2) by municipality size. Spain 2011

Municipality Size	Total Gas	Direct Gas	Indirect Gas
1 (100,000 inhabitants or more)	5,272.50	1,865.37	3,407.13
2	5,625.64	2,229.71	3,395.93
3	5,620.95	2,369.61	3,251.34
4	5,573.57	2,235.41	3,338.16
5 (less than 10,000 inhabitants)	5,049.61	2,044.32	3,005.28

Note: municipality size is measured in a scale from 1 to 5 (1 100,000 inhabitants or more; 2 between 50,000 and 100,000 inhabitants; 3 between 20,000 and 50,000 inhabitants; 4 between 10,000 and 20,000 inhabitants; 5 less than 10,000 inhabitants

Source: Own elaboration from data presented in chapter 1

Table 4.3: Spain average households greenhouse gases emissions (kgs of equivalent CO2) by municipality size. Spain 2011

Municipality Size	Total Gas	Direct Gas	Indirect Gas
1 (100,000 inhabitants or more)	5,231.67	1,857.15	3,374.52
2	5,694.46	2,182.89	3,511.57
3	5,733.31	2,293.28	3,440.02
4	5,896.95	2,434.69	3,462.26
5 (less than 10,000 inhabitants)	5,999.54	2,632.24	3,367.30

Note: municipality size is measured in a scale from 1 to 5 (1 100,000 inhabitants or more; 2 between 50,000 and 100,000 inhabitants; 3 between 20,000 and 50,000 inhabitants; 4 between 10,000 and 20,000 inhabitants; 5 less than 10,000 inhabitants

Source: Own elaboration from data presented in chapter 1

Although these tables show the differences between municipalities in the same CCAA, it is possible to find differences between municipalities of the same size between CCAA. For example, in the case of Catalonia, the least populated municipalities are the highest polluters on average, while in Asturias, the second most populated municipalities are the highest polluters on average. In order to better understand the role of cities or other spatial units in both emissions from direct energy use and indirect emissions from the consumption of goods and services, it is necessary to improve the estimates and analyse the geographical effect on household consumption, and, consequently, better target environmental policies towards consumption.

3. METHODOLOGY

The database of GHG emissions produced in chapter 1 allows for distinguishing a spatial scale corresponding to the level of NUTS2 regions or CCAA. Even if in some particular cases it is possible to spot large cities (i.e., the city of Madrid for the case of the region of Madrid), since capital cities are identified in the HBS, for most of them this is not possible. (i.e., for the case of Catalonia, it is not possible distinguishing Barcelona and Tarragona just relying on the HBS data). Moreover, considering the level of heterogeneity between spatial units within the same region makes this problem even bigger, where some municipalities will be over or undervalued.

For this purpose, emissions from consumption at the local level will be disaggregated by applying a particular formulation of a Generalized Maximum Entropy (GME) estimator, which will be applied with the same spirit as the methods presented in Elberts, et.al (2003) or Tarozzi and Deaton (2009) for predicting social indicators for small geographical areas. The GME estimator presented in this chapter proposes to combine the HBS, including emissions information, with the PC. One of the advantages of this method is that it allows combining details of geographical information present in the PC, subject to being consistent with some aggregates - moments - of the HBS. One particular feature of the estimator presented here is that it allows to predict the values of a continuous indicator (emissions), which differs from previous formulations of similar GME estimators designed to predict categorical variables (Fernández-Vázquez et.al, 2020).

An overview of Generalized Maximum Entropy Estimators

To illustrate how the GME estimators work, it is useful to introduce a general discussion on the use of these type of estimators in the context of estimating linear regression equations. The starting point for this purpose would be a linear model where the variable of interest y depends on K explanatory variables x_k with *n* observations (*n* can refer to the dimension of a time series or cross-section):

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \tag{4.1}$$

where $\mathbf{y}$ is a $(i \times 1)$ vector of observations, $\mathbf{X}$ is a $(n \times K)$ matrix of observations for the x_k variables, $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_K)$ is the $(K \times 1)$ vector of unknown parameters to be estimated, and $\mathbf{u}$ is a $(n \times 1)$ vector containing the realizations of the random disturbance of the linear model.

The GME estimator requires a reparameterization of equation (4.1) in terms of probability distributions. First, each element β_k of the parameter vector $\boldsymbol{\beta}$ is assumed to be a discrete random variable with $M \geq 2$ possible realizations. These potential values of the unknown parameter are included in a support vector $\mathbf{b'_k} = \{b_{k1}, \ldots, b_{kM}\}$ with corresponding unknown probabilities $\mathbf{p'}_{\mathrm{k}} = (p_{k1}, \ldots, p_{kM})$. The values in b_k are chosen based on priors about the values of β_k. Finally, each parameter β_k is specified as follows:

$$\beta_k = \boldsymbol{b'_k p_k} = \sum_{m=1}^{M} b_{km} p_{km}\,;\ k = 1, \ldots, K \tag{4.2}$$

In turn, the vector $\boldsymbol{\beta}$ can be written as:

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_K \end{bmatrix} = \mathbf{BP} = \begin{bmatrix} \mathbf{b'_1} & 0 & \cdots & 0 \\ 0 & \mathbf{b'_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{b'_K} \end{bmatrix} \begin{bmatrix} \mathbf{p_1} \\ \mathbf{p_2} \\ \vdots \\ \mathbf{p_K} \end{bmatrix} \tag{4.3}$$

where $\mathbf{B}$ and $\mathbf{P}$ are matrices with dimensions $(K \times KM)$ and $(KM \times 1)$ respectively.

A similar approach is followed for the random disturbances. Although the GME procedure does not require specific assumptions about the probability distribution function of $\mathbf{u}$, a set of mild assumptions are still necessary. First, the uncertainty about the realizations of $\mathbf{u}$ is addressed by treating each element u_n as a discrete random variable with $J \geq 2$ possible outcomes contained in a convex set $\mathbf{v}' = \{v_1, \ldots, v_J\}$ which, for the sake of simplicity, will be common for all u_i $(i = 1, \ldots, n)$. Second, it is assumed that these possible outcomes of the random disturbance are symmetric and centred on zero. As a result, $\mathbf{u}$ has mean $E[\boldsymbol{u}] = \mathbf{0}$ and a finite covariance matrix $\boldsymbol{\Sigma}$. Additionally, it is common practice to establish the upper and lower limits of the vector $\mathbf{v}$ applying the three-sigma rule (Pukelsheim, 1994).[5] Under these conditions, the value of the random term for an observation i is:

$$u_i = \mathbf{v}'\,\mathbf{w_i} = \sum_{j=1}^{J} v_j\, w_{ij};\ i = 1, \dots, n \tag{4.4}$$

where, $\boldsymbol{i}$ denotes the probabilities for the values of the support vector of the random disturbance.

In matrix terms:

$$\mathbf{u} = \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix} = \mathbf{VW} = \begin{bmatrix} \mathbf{v}' & 0 & \cdots & 0 \\ 0 & \mathbf{v}' & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{v}' \end{bmatrix} \begin{bmatrix} \boldsymbol{w_1} \\ \boldsymbol{w_2} \\ \vdots \\ \boldsymbol{w_N} \end{bmatrix} \tag{4.5}$$

Therefore, using equation 4.3 and 4.5, equation 4.1 can be rewritten as:

$$\mathbf{y} = \mathbf{XBP} + \mathbf{VW} \tag{4.6}$$

This specification of the original model transforms the estimation of the coefficients of the regression equation (4.1) into the estimation of $K + n$ discrete probability distributions. At this point, the principle of Maximum Entropy (ME) is used to recover the M unknown probabilities $\widehat{\boldsymbol{p}}$ by maximizing the Shannon entropy measure $E(\boldsymbol{p})$ (Shannon, 1948):

$$\underset{\boldsymbol{p}}{\text{Max}}\, E(\boldsymbol{p}) = \sum_{m=1}^{M} p_m\, ln(p_m) \tag{4.7}$$

$E(\boldsymbol{p})$ achieves a maximum when all the M values are equally probable, that is, when $\boldsymbol{p}$ is uniform. However, if some additional data is available, this will lead to a Bayesian update of the uniform solution to $\boldsymbol{p}$. The intuition is that the uniform distribution is the best guess when nothing is known about the distribution. In this case, equal probabilities are assigned to all possible outcomes of the discrete random variable. However, the uniform may not be consistent with the observed data and need to be adjusted. The ME principle sets as solution

[5] This rule sets the support vector for the random term at (-3S, 0, +3S) where S is the sample standard deviation of the dependent variable.

the probability distribution that maximizes the entropy measure subject to being able to generate the observed data.

The GME estimator bases on this principle to estimate the parameters of the re-parameterized equation (4.6). More specifically, matrices $\mathbf{P}$ and $\mathbf{W}$ are estimated by maximizing the entropy function $E(\mathbf{P}, \mathbf{W})$, subject to: (i) being consistent with the sample and (ii) some normalization constraints. That is:

$$\underset{\boldsymbol{P},\boldsymbol{W}}{Max}\, E(\mathbf{P}, \mathbf{W}) = \sum_{k=1}^{K}\sum_{m=1}^{M} p_{km}\, ln(p_{km}) + \sum_{i=1}^{n}\sum_{j=1}^{J} w_{ij}\, ln(w_{ij}) \tag{4.8}$$

subject to:

$$y_n = \sum_{k=1}^{K}\sum_{m=1}^{M} b_{km} p_{km}\, x_{kn} + \sum_{j=1}^{J} v_j\, w_{ij};\;\; i = 1, \dots, n \tag{4.9}$$

$$\sum_{m=1}^{M} p_{km} = 1\,;\; k = 1, \dots, K \tag{4.10}$$

$$\sum_{j=1}^{J} w_{ij} = 1\,;\; i = 1, \dots, n \tag{4.11}$$

The restrictions in equation (4.9) ensure that the estimates can generate the sample data contained in $\mathbf{y}$ and $\mathbf{X}$, while equations (4.10) and (4.11) are normalization constraints. By solving this constrained optimization problem, the solutions $\hat{p}_k$ and $\hat{w}_i$ are found and point estimates $\hat{\beta}_k$ are derived.

A GME estimator for spatial disaggregation

A modified version of this GME estimator can be applied to spatially disaggregate socio-economic indicators. Given the nature of the problem at hand, which consist on the geographical disaggregation of a continuous variable (GHG emissions), let us assume that the objective is to estimate a continuous indicator y for a set of small areas $d = 1,\ldots D$. The problem is that the indicators are not directly observable at a very detailed spatial scale. They are, however, observable in the HBS, but the small area d where a particular household sampled in this survey resides cannot be identified, which prevents the estimation of indicators at this scale by simple aggregation.

Small Area Estimation (SAE) deals with this problem. SAE techniques are increasingly used to provide estimates for local areas of interest (for a recent application, see Durán and Condorí, 2019). Generally speaking, SAE methodologies combine direct estimates with some auxiliary information. The comparative performance of different techniques in this field has been recently evaluated by Guadarrama et al. (2016). Within the group of methodologies that aim at producing social indicators for small areas, there is one in particular that has been widely applied. Specifically, the original proposal by Elbers et al. (2003) and the modification proposed later in Tarozzi and Deaton (2009) has been used by the World Bank to map poverty across small areas in poor countries and it has later been used in several developing countries (see Modrego and Berdegué, 2015) and in other more advanced economies (see Sánchez-Cantalejo et al., 200*; Melo et al., 2016; Morales et al. 2018; for recent examples). The basic idea of these class of estimators consists of "projecting" predictions of the variable of interest for a household survey onto the sample of households that form the population. In a nutshell, the procedure comprises three steps:

1. From the household surveys (HBS in this case), estimate a model of your variable y of interest y=(X), where X is a set of K regressors also observable in the Population Census (PC).
2. Recover the set of K parameters β estimated on the HBS (with some degree of heterogeneity across regions or clusters of households) and take them to the PC.
3. Given the X observable in the PC and the corresponding $\hat{\beta}$, predict the figures of y for the households surveyed in the PC ($\hat{y} = X\hat{\beta}$).

Although this approach is appealing because of its simplicity, the estimates produced are not necessarily consistent with the aggregates that are already observable: for example, the mean value of the estimates of household income produced by the techniques at household level for, say, a given region may not necessarily be equal to the mean regional household income available on the official databases.

In order to overcome this limitation, an alternative methodology is proposed to adjust the estimates to official observable aggregates by incorporating into the estimation problem information on the observable aggregates. It is proposed to perform a correction based on the framework detailed in Golan (2018) and with a procedure similar to the GME estimator presented in Bernadini-Papalia and Fernández-Vázquez (2018). The estimates produced have the advantage of a higher precision than previous methodologies, due to the large number of households in the census (see Tarozzi and Deaton, 2009). Additionally, this large number of estimates allows us studying potential differences between the individuals or households belonging to the same small area.

With this objective in mind, GME disaggregation technique is proposed based on the strategy followed to model categorical variables (see Golan, 2018, chap 11). Consider a sample consisting of n observations of basic units, which for the sake of simplicity will be assumed to be individuals but which can be easily generalized to other types of observations, such as households or firms. Let us assume that the variable of interest is a continuous indicator $\boldsymbol{y}$. For each individual $i = 1, \dots, n$, where variable y_i is defined by the following linear equation:

$$y_i = \sum_{k=1}^{K} \beta_k x_{ki} + u_i \tag{4.12}$$

Which is equivalent, in matrix terms, to equation (4.1).

Equation (4.1) indicates that the observed data in the sample are specified as a function of the structural part that relates the covariates in a matrix $\mathbf{X}$ to $\mathbf{y}$ plus some noise contained in vector $\mathbf{u}$. Our objective is to predict the K elements of vector β based on the observed data, and the predictions of the variable of interest would be $\hat{y}_i = \sum_{k=1}^{K} \hat{\beta}_k x_{ki}$. In order to accommodate these relations between y and X on a flexible way, Golan (2018) proposes the use of the cross-moments equations, which conveniently multiply by matrix $\mathbf{X}^{\mathbf{T}}$ the elements in equation (4.1) and normalize by the sample size n:[6]

[6] Superscript T indicates transposition.

$$\frac{1}{n}X^{T}Y = \frac{1}{n}X^{T}[\mathbf{X\beta} + \mathbf{u}] = \frac{1}{n}X^{T}[\mathbf{XBP} + WV] \tag{4.13}$$

that serve as constraints in the following optimization program:

$$\underset{P,W}{Max}\, Ent(P,W) = -\sum_{k=1}^{K}\sum_{m=1}^{M} p_{km}\ln(p_{km}) - \sum_{i=1}^{n}\sum_{j=1}^{J} w_{ij}\ln(w_{ij}) \tag{4.14}$$

subject to:

$$\begin{aligned} \frac{1}{n}\sum_{i=1}^{n} x_{ik}y_i &= \frac{1}{n}\sum_{i=1}^{n} x_{ik}\left[\sum_{k=1}^{K}\beta_k x_{ki} + u_i\right] = \\ &= \frac{1}{n}\sum_{i=1}^{n} x_{ik}\left[\sum_{k=1}^{K}\sum_{m=1}^{M} b_{km}p_{km}\, x_{ki} + \sum_{j=1}^{J} w_{ij}v_j\right]; k = 1, \ldots, K \end{aligned} \tag{4.15}$$

$$\begin{aligned} &\sum_{m=1}^{M} p_{km} = 1; k = 1, .., K \\ &\sum_{j=1}^{J} w_{ij} = 1; i = 1, .., n; \end{aligned} \tag{4.16}$$

Equations (4.14) to (4.16) depict a GME program, where the set of constraints on equation (4.16) act just as normalization restrictions, the information contained in the sample in the form of cross moments between Y and X is given in the left hand side of equation (4.15). Without this piece of information, the solution of the GME estimator will be a uniform distribution, but this equation "pushes" the solution to be consistent with these observed moments.

Estimating GHG household emissions for small areas, Spain 2011

A modification of the general GME estimator is applied above as an alternative to the methods presented in Elbers et al (2003) or Tarozzi and Deaton (2009) of predicting GHG household emissions for small areas. The GME technique proposed follows the idea of combining household surveys with population census but exploits the information in a different way. One advantage of the method proposed here is that it combines the detailed geographical information present in population census but making it consistent with some aggregates -moments- observable in the household survey.

For the sake of clarity, assuming that the research interest is to estimate an indicator y (GHG household emissions in our case) in a set of small areas $d = 1, \dots D$. The mean value of this indicator in d can be expressed as $\sum_{i=1}^{n_d} y_i^d / n_d$ where n_d represents the number of individuals in this area d. Our problem is that the indicators y_i are not directly observable in a population census. They are observable in the household survey, but the small area d in which the individual lives cannot be identified.

Following equation **¡Error! No se encuentra el origen de la referencia.**, our estimates of the indicator of interest $\hat{y}_i^d$ are defined as $\hat{y}_i^d = \sum_{k=1}^{K} \hat{\beta}_k \, x_{ki}^d$, where $\hat{\beta}_k$ are the predictions of the parameters obtained by the GME estimator. These estimates will be obtained by solving the previously depicted GME program but modifying the constraints on equation (4.15) as follows:

$$\frac{1}{n}\sum_{i=1}^{n} x_{ki} y_i = \frac{1}{N}\sum_{h=1}^{N} x_{kh}\left[\sum_{k=1}^{K} \beta_k x_{kh} + u_h\right] =$$

$$= \frac{1}{N}\sum_{h=1}^{N} x_{kh}\left[\sum_{k=1}^{K}\sum_{m=1}^{M} b_{km} p_{km}\, x_{kh} + \sum_{j=1}^{J} w_{hj} v_j\right]; k = 1, \dots, K \tag{4.17}$$

Or, in matrix notation:

$$\mathbf{\frac{1}{n} X_s^T Y_s} = \mathbf{\frac{1}{N} X_c^T}[\mathbf{X_c \boldsymbol{\beta}} + \mathbf{u}] = \mathbf{\frac{1}{N} X_c^T}[\mathbf{X_c BP} + \mathbf{WV}] \tag{4.18}$$

In equation (4.17) the i and h refer to households observed in the household survey and the population census respectively. From equation 4.18, matrix $\mathbf{X_s}$ -together with $\mathbf{Y_s}$- is collected from the information in the sample, and it has dimension $n \times K$, while matrix $\mathbf{X_c}$ is observable at the population census level and has dimension $N \times K$, where N is the population size. Note that the left-hand side on these equations refers to the cross-moments between Y and the covariates in X, which are observable for the sample of households surveyed. The solutions on the right-hand side must produce, at the census level, cross-moments identical to those observed in the household sample. Since these estimates are obtained with the sufficient geographical detail, it is possible to predict $\hat{y}_i^d$ and make these estimates consistent with the aggregates in $\frac{1}{n} X_s^T Y_s$.

In this particular problem, $i = 1, \ldots n$ refers to the n sampled households in the HBS corresponding to 2011, **X** is a matrix containing a set of covariates available in both the HBS and the PC for that particular year, which include characteristics of the main breadwinner as *age* (in years), *household size* (people), *level of education* (From 1: Lower than the first stage of Secondary Education to 4: Higher education), *gender* and *nationality* (Spanish or foreign). Additionally, contextual characteristics are counted as dummies the *size of the municipality* (From 1: Municipality with 100,000 inhabitants or more to 5: Municipalities with less than 10,000 inhabitants). A regression is estimated for each CCAA independently, which implies that the estimates will be consistent with the cross-moments observed in the HBS for each Spanish region.

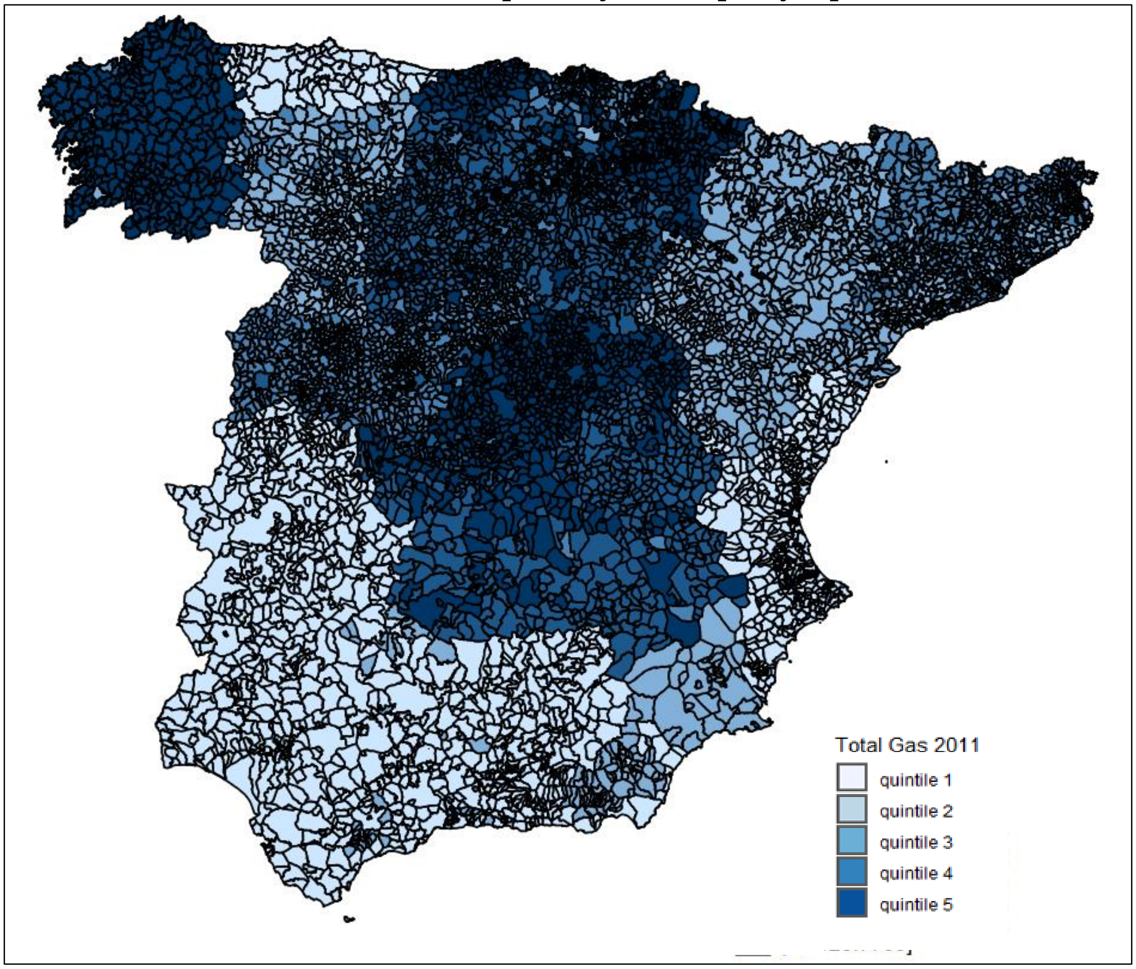
By applying the GME procedure depicted before, it is possible to recover the estimated $\hat{\beta}$ parameters with the information available from the HBS and predict the GHG household emissions for the households surveyed in the Population Census. These predictions will be consistent with the aggregates cross-moment in the HBS. This equivalence in terms of cross-moments between the predictions at small scale and the information contained in the HBS is that the regional means of the predicted GHG emissions will fit with those reported in the HBS, but also the regional means of GHG household emissions across *age*, *level of education* or *gender*, for example. This consistency can be viewed as one of the main comparative advantages of this GME technique.

4. RESULTS

This section presents the results obtained from the estimation under GME to obtain the emissions derived from each household's consumption by Spanish municipality for 2011. Before GME, the database available only allowed the recognition within a CCAA if the area of residence is a provincial capital and the size of the municipality detailed in five broad ranges, impossibility to study many large cities and medium size municipalities.

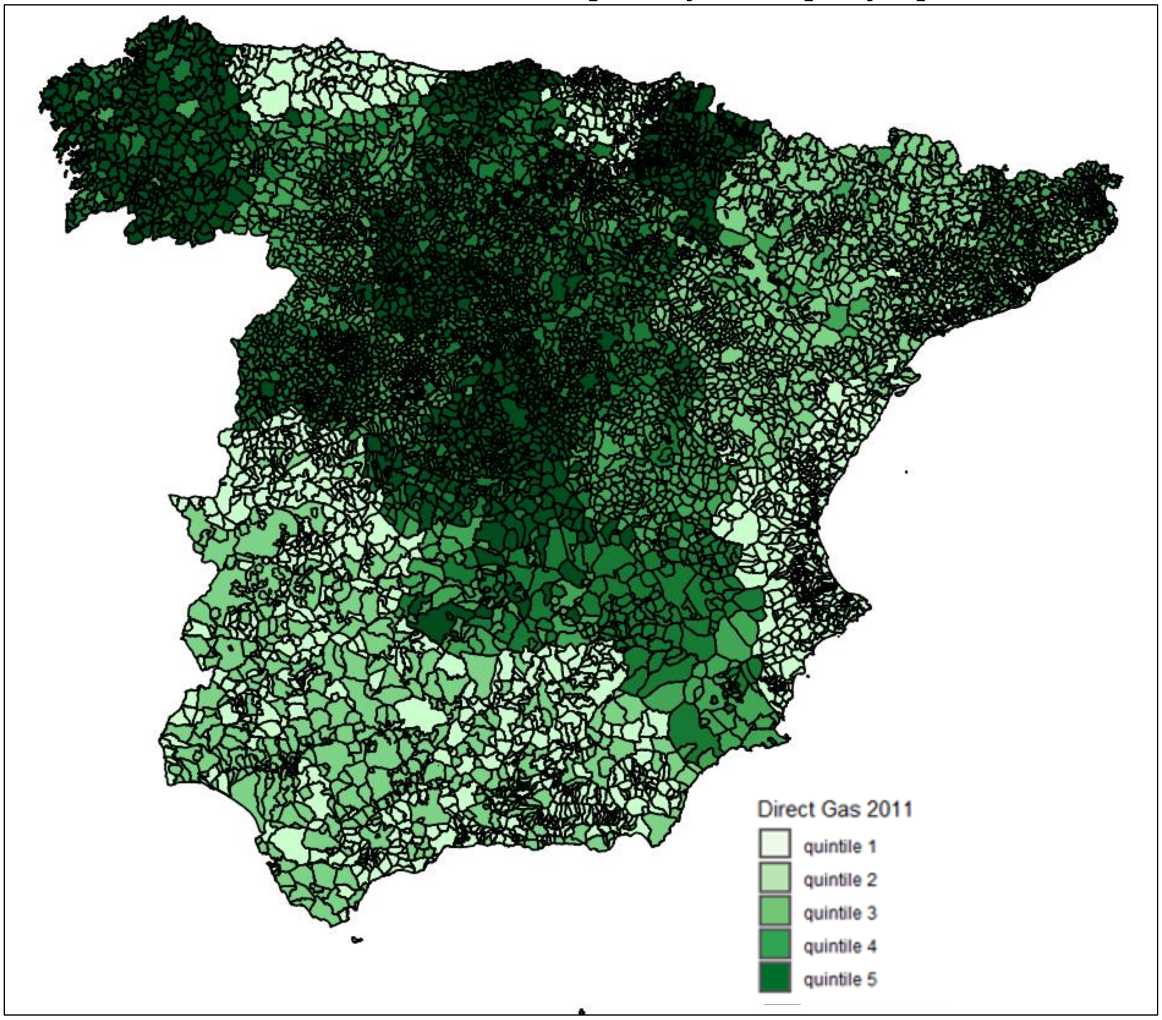
The results are shown at three levels. In Map 4.4 presents the total emissions derived from the final consumption of Spanish households. Map 4.5 shows the indirect emissions embedded from households' consumption expenditure of good and services, while Map 4.6 presents the direct emissions derived from energy goods use (see Annex A4.5 for details of urban areas).

Map 4.4: Average households greenhouse gases (kgs of equivalent CO_2) embedded from household consumption by municipality. Spain 2011



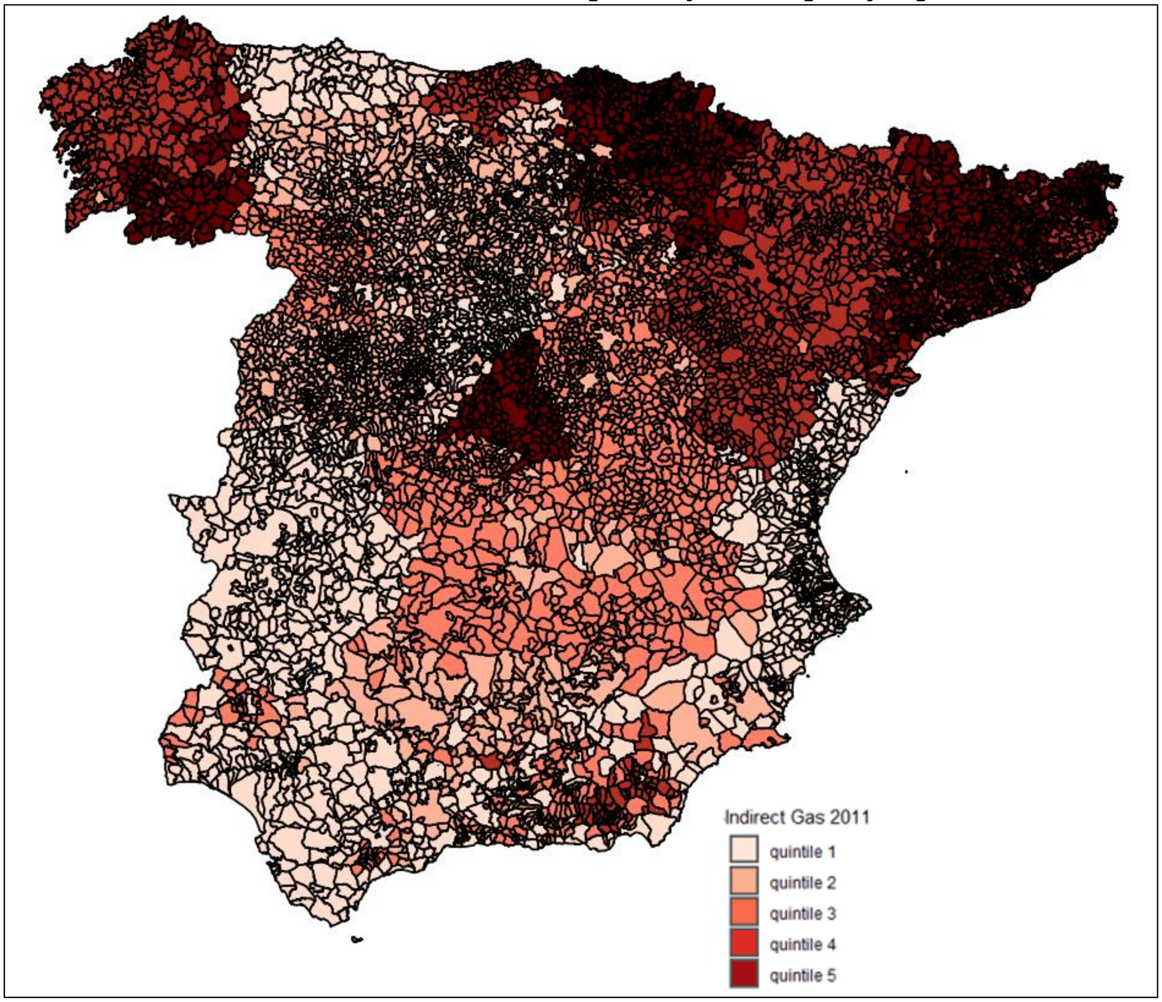
Source: Own elaboration

Map 4.5: Average households direct greenhouse gases (kgs of equivalent CO_2) embedded from household consumption by municipality. Spain 2011



Source: Own elaboration

Map 4.6: Average households indirect greenhouse gases (kgs of equivalent CO_2) embedded from household consumption by municipality. Spain 2011



Source: Own elaboration

From Annex A4.5, it is observed that the twenty-three top emitting Spanish municipalities (with more the 10,000 inhabitant) belong to the CCAA of Madrid, and the capital is not among them, actually household's residents in Madrid city are the ones generate the least direct (and local) emissions. Similar patterns are found in CCAA such as Catalonia and Aragon, where the capital cities are the least direct emitters, and are surrounded by the most polluting municipalities within their region. This can be explained by the fact that direct emissions are related to private car use, therefore, households living in large cities are influenced by the use of public transport and those living in the suburbs to use the private car to travel to the capital cities.

Different patterns are found across regions depending on their characteristics. For example, in Castilla de la Macha the capital Toledo is the second most emitting urban area, with higher mean estimates corresponding to a smaller municipality (Azuqueca de Henares), and with Puertollano as the city with the lowest direct emissions.

Considering the indirect emissions in Map 4.6, Pozuelo de Alarcón, in Madrid, is the Spanish urban municipality with the highest emission levels, and Santa Lucía de Tirajana, in Canaries Island, with the lowest. For this type of emissions, large capitals have a medium level of emissions compared to their neighbours. For instance, within Catalonia, Sant Cugat del del Vallès is the most emitter municipality, producing on average 185 kilograms of CO_2 more than Barcelona city, and Vila-seca (the lowest emitter municipality) emit 97 kilograms of CO_2 less than the capital.

The sum of both types of emissions results in the Map 4.4 where the most polluter municipalities are between the CCAA of Madrid, Navarra, Galicia and Cantabria, where the most pollutants are: Boadilla del Monte, Barañain, Ferrol and Camargo.

These results give us a broad picture of the effect of large capitals on the different types of emissions, and to guide environmental policies in targeting the most problematic areas.

5. CONCLUSIONS

The main objective of this chapter is to study the different types of emissions at a detailed geographical level, which in this case corresponds to the 8,131 Spanish municipalities. Using the data presented in chapter 1 as a starting point, emissions from households' consumption, which under some editions of the GME estimator, can be projected to census levels for the year 2011. The results are presented on three scales: total emissions, direct emissions related to the use of energy goods, and indirect emissions related to the inter-industrial process to produce goods and services.

Direct emissions related to use of energy goods, municipalities close the Madrid city are the top emitting municipalities in Spain, being the capital the least emitter within the CCAA. Similar patterns are found in large capitals such as Barcelona, which produces on average close to 401 kilograms of equivalent CO_2 less than its most emitting neighbour, Cerdanyola del Vallès. Results of indirect emissions embedded from households' expenditure consumption present that municipalities of Pozuelo de Alarcón has the highest emissions levels in Spain, and large cities such as Barcelona and Madrid emit approximately 3% less than their highest emitter municipalities within their CCAA, but they are still considered to be highly indirect polluting municipalities within Spain.

Before applying the methodology proposed in this chapter, previous results presented in section 2 show, for example, CCAA as Madrid stood out for its high levels of direct emissions embedded from use of energy goods, however, the result with the geographical detail shows that the Madrid city has low direct emissions level from energy goods consumption compared with the municipalities that surround it, which gives a more detailed picture of the role of the city and the role of its neighbours.

The main and major limitation of this work is that it is not possible to distinguish within the same CCAA the differences between municipalities with less than 10,000 inhabitants. However, this methodology allows to obtain the geographical detail of at least the large and medium size municipalities with public databases. Furthermore, the results are analysed under averages, without considering the influence of other household characteristics on the effect of emissions by location. A next step would be to analyse these differences under statistical models that control for the other covariates and give clear signals of possible geographic effects.

The possible lines of research and future work are extensive, it is of great interest to obtain emissions per municipality at European level and analyses emission distributions across the continent. As well, considering that the new census 2021 is soon to be published, it would be possible to evaluate possible environmental policies at the municipal level that have been implemented over the last 10 years. Moreover, just as previous chapters have analysed characteristics such as gender, it is of interest to incorporate this perspective across municipalities, where it is expected that, for example, women in small municipalities will behave differently from women in large cities. It is also expected that the differences in emissions between women and men will be heterogeneous across the area, as well as analysing issues related to ageing and educational levels. Given the computational complexity of the methodology proposed in this chapter, it would be interesting to optimize the suggested model and create a package to encourage the use of this methodology in other issues.

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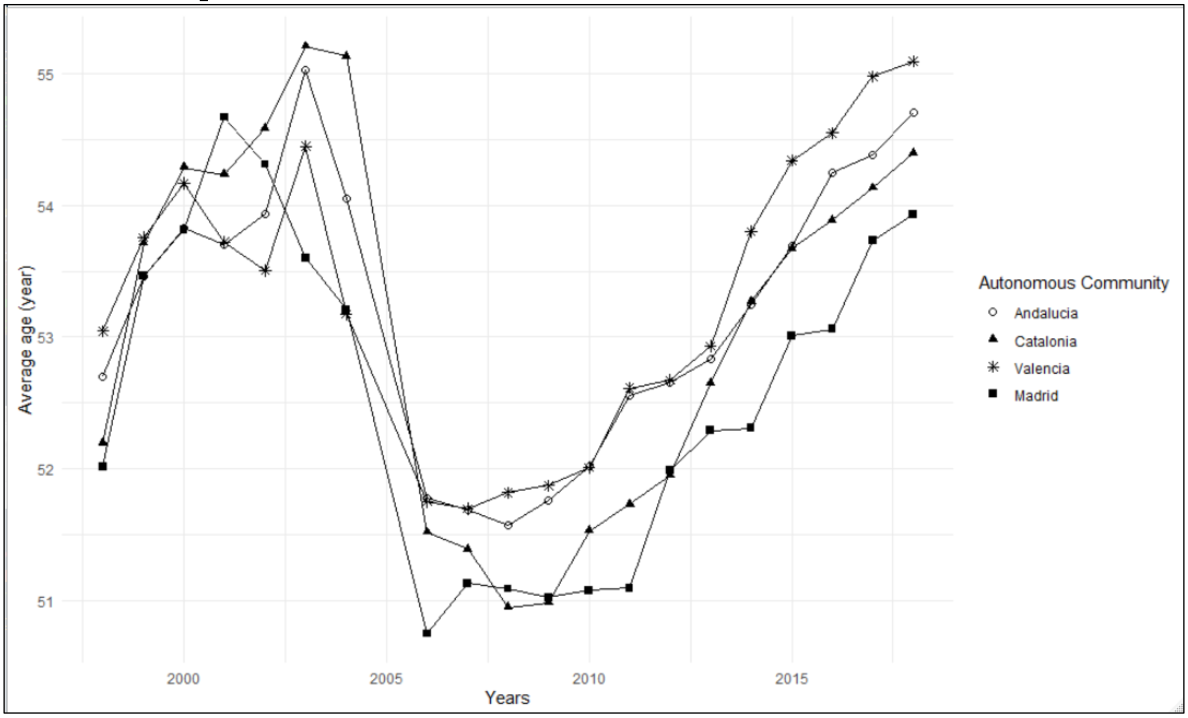
7. ANNEX A4

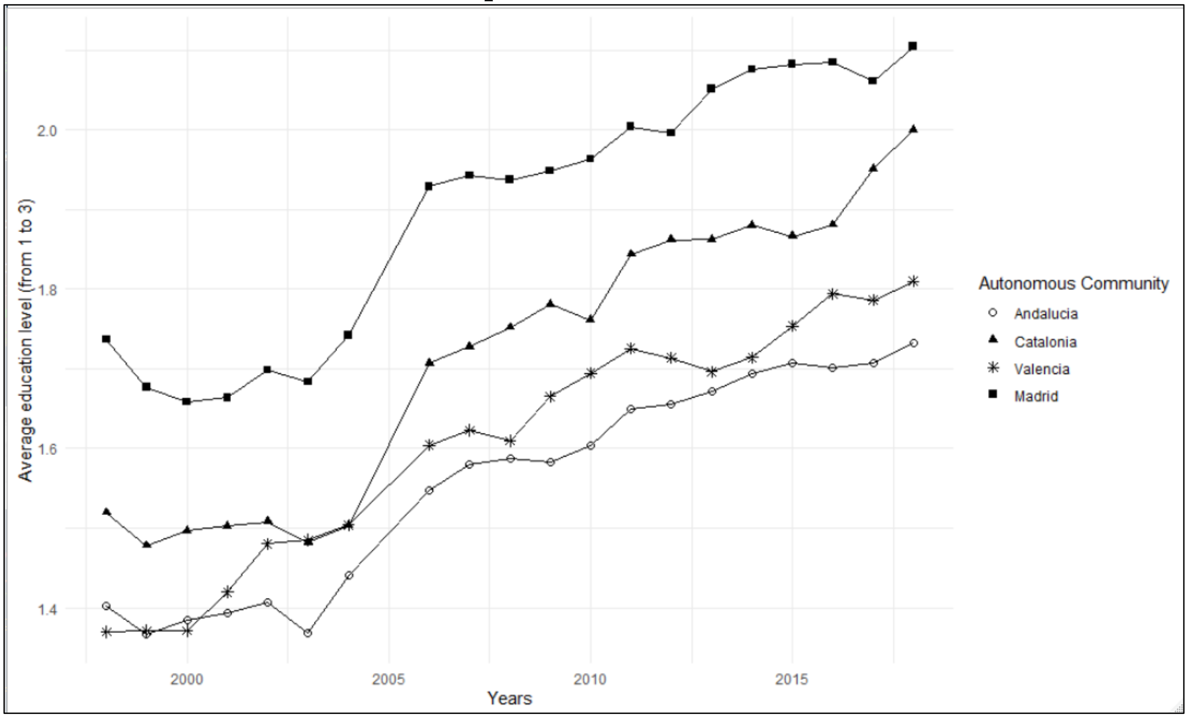
ANNEX A4.1

Graph A4.1: Average households breadwinners age of Andalusia, Catalonia, Valencia, and Madrid. Spain 1998 – 2018



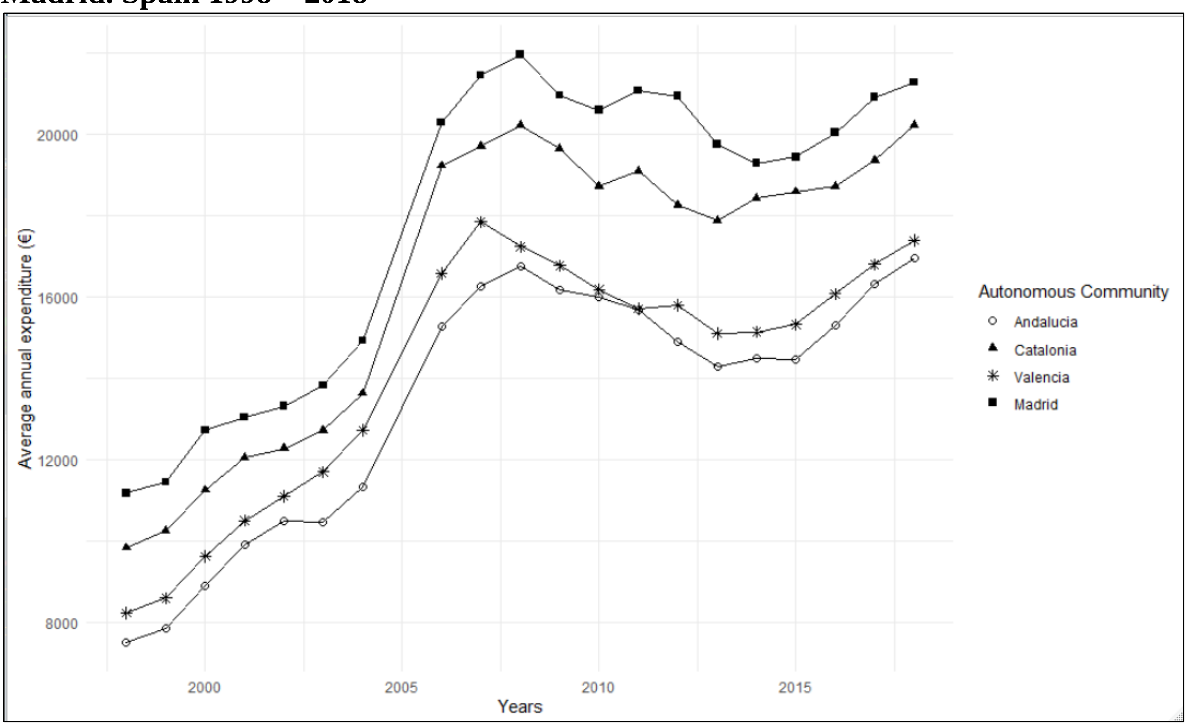
Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph A4.2: Average households breadwinners education level of Andalusia, Catalonia, Valencia, and Madrid. Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

Graph A4.3: Average household expenditure of Andalusia, Catalonia, Valencia, and Madrid. Spain 1998 – 2018



Source: Own elaboration from 1998 to 2018 (without 2005) Spanish Household Budget Survey

ANNEX A4.2

Table A4.1: Average households age, educational level, and expenditure by Autonomous Community. Spain 1998-2018.

Year	Autonomous Community	Age	Educational level	Expenditure
1998	Andalucía	53	1.40	€ 7,495
1998	Aragón	55	1.53	€ 8,604
1998	Asturias	56	1.44	€ 8,846
1998	Baleares	54	1.29	€ 9,233
1998	Canarias	53	1.34	€ 7,809
1998	Cantabria	58	1.42	€ 8,364
1998	Castilla y León	56	1.42	€ 8,017
1998	Castilla La Mancha	56	1.22	€ 7,200
1998	Cataluña	52	1.52	€ 9,818
1998	Comunitat Valenciana	53	1.37	€ 8,218
1998	Extremadura	55	1.23	€ 6,406
1998	Galicia	55	1.34	€ 7,851
1998	Comunidad de Madrid	52	1.74	€ 11,168
1998	Murcia	53	1.28	€ 7,538
1998	Navarra	56	1.45	€ 10,902
1998	País Vasco	53	1.56	€ 10,263
1998	La Rioja	54	1.45	€ 8,545
1998	Ceuta y Melilla	52	1.45	€ 8,735
1999	Andalucía	53	1.37	€ 7,848
1999	Aragón	57	1.46	€ 8,863
1999	Asturias	56	1.37	€ 9,187
1999	Baleares	57	1.30	€ 9,470
1999	Canarias	55	1.36	€ 8,312
1999	Cantabria	58	1.49	€ 9,941
1999	Castilla y León	57	1.40	€ 8,313
1999	Castilla La Mancha	56	1.21	€ 7,342
1999	Cataluña	54	1.48	€ 10,242
1999	Comunitat Valenciana	54	1.37	€ 8,590
1999	Extremadura	57	1.19	€ 6,167
1999	Galicia	55	1.33	€ 8,362
1999	Comunidad de Madrid	53	1.68	€ 11,435

1999	Murcia	55	1.26	€ 8,005
1999	Navarra	56	1.46	€ 10,850
1999	País Vasco	54	1.49	€ 10,859
1999	La Rioja	55	1.45	€ 9,100
1999	Ceuta y Melilla	53	1.55	€ 9,536
2000	Andalucía	54	1.38	€ 8,898
2000	Aragón	56	1.47	€ 10,366
2000	Asturias	57	1.39	€ 9,851
2000	Baleares	57	1.32	€ 10,453
2000	Canarias	55	1.38	€ 9,457
2000	Cantabria	58	1.55	€ 10,969
2000	Castilla y León	58	1.37	€ 8,671
2000	Castilla La Mancha	56	1.24	€ 8,249
2000	Cataluña	54	1.50	€ 11,242
2000	Comunitat Valenciana	54	1.37	€ 9,608
2000	Extremadura	57	1.26	€ 6,937
2000	Galicia	57	1.34	€ 9,355
2000	Comunidad de Madrid	54	1.66	€ 12,710
2000	Murcia	55	1.30	€ 9,445
2000	Navarra	55	1.49	€ 11,501
2000	País Vasco	54	1.52	€ 11,669
2000	La Rioja	56	1.47	€ 10,285
2000	Ceuta y Melilla	50	1.47	€ 11,151
2001	Andalucía	54	1.39	€ 9,889
2001	Aragón	56	1.45	€ 10,910
2001	Asturias	57	1.45	€ 10,959
2001	Baleares	55	1.41	€ 11,325
2001	Canarias	55	1.36	€ 10,202
2001	Cantabria	59	1.44	€ 11,706
2001	Castilla y León	59	1.37	€ 9,357
2001	Castilla La Mancha	56	1.27	€ 9,015
2001	Cataluña	54	1.50	€ 12,050
2001	Comunitat Valenciana	54	1.42	€ 10,494
2001	Extremadura	57	1.25	€ 7,748
2001	Galicia	57	1.35	€ 9,781
2001	Comunidad de Madrid	55	1.66	€ 13,034
2001	Murcia	55	1.29	€ 10,231
2001	Navarra	54	1.47	€ 12,389

2001	País Vasco	54	1.63	€ 12,936
2001	La Rioja	55	1.54	€ 11,594
2001	Ceuta y Melilla	52	1.47	€ 11,610
2002	Andalucía	54	1.41	€ 10,475
2002	Aragón	57	1.51	€ 11,725
2002	Asturias	57	1.45	€ 11,046
2002	Baleares	54	1.39	€ 12,227
2002	Canarias	56	1.35	€ 10,175
2002	Cantabria	58	1.51	€ 12,051
2002	Castilla y León	59	1.39	€ 10,097
2002	Castilla La Mancha	56	1.24	€ 8,913
2002	Cataluña	55	1.51	€ 12,264
2002	Comunitat Valenciana	54	1.48	€ 11,095
2002	Extremadura	56	1.35	€ 8,420
2002	Galicia	57	1.37	€ 10,203
2002	Comunidad de Madrid	54	1.70	€ 13,304
2002	Murcia	54	1.33	€ 10,940
2002	Navarra	54	1.48	€ 12,694
2002	País Vasco	54	1.67	€ 13,649
2002	La Rioja	54	1.56	€ 11,722
2002	Ceuta y Melilla	53	1.45	€ 11,634
2003	Andalucía	55	1.37	€ 10,440
2003	Aragón	57	1.50	€ 12,257
2003	Asturias	57	1.54	€ 11,035
2003	Baleares	55	1.36	€ 12,817
2003	Canarias	57	1.28	€ 10,544
2003	Cantabria	61	1.44	€ 11,744
2003	Castilla y León	60	1.41	€ 10,739
2003	Castilla La Mancha	58	1.21	€ 9,489
2003	Cataluña	55	1.48	€ 12,704
2003	Comunitat Valenciana	54	1.48	€ 11,688
2003	Extremadura	58	1.34	€ 8,522
2003	Galicia	58	1.36	€ 10,796
2003	Comunidad de Madrid	54	1.68	€ 13,818
2003	Murcia	55	1.37	€ 10,885
2003	Navarra	54	1.45	€ 13,270
2003	País Vasco	54	1.66	€ 14,383
2003	La Rioja	54	1.53	€ 11,939

2003	Ceuta y Melilla	53	1.42	€ 11,213
2004	Andalucía	54	1.44	€ 11,323
2004	Aragón	57	1.58	€ 13,583
2004	Asturias	58	1.54	€ 11,961
2004	Baleares	55	1.37	€ 14,067
2004	Canarias	55	1.39	€ 10,918
2004	Cantabria	60	1.60	€ 11,746
2004	Castilla y León	59	1.47	€ 11,467
2004	Castilla La Mancha	57	1.26	€ 10,013
2004	Cataluña	55	1.50	€ 13,620
2004	Comunitat Valenciana	53	1.50	€ 12,712
2004	Extremadura	57	1.41	€ 9,141
2004	Galicia	58	1.43	€ 11,611
2004	Comunidad de Madrid	53	1.74	€ 14,922
2004	Murcia	56	1.36	€ 11,224
2004	Navarra	57	1.47	€ 14,474
2004	País Vasco	53	1.73	€ 15,022
2004	La Rioja	56	1.59	€ 12,929
2004	Ceuta y Melilla	51	1.55	€ 12,989
2006	Andalucía	52	1.55	€ 15,280
2006	Aragón	53	1.62	€ 16,413
2006	Asturias	56	1.60	€ 16,051
2006	Baleares	49	1.65	€ 18,765
2006	Canarias	49	1.66	€ 15,518
2006	Cantabria	54	1.79	€ 16,145
2006	Castilla y León	55	1.53	€ 15,451
2006	Castilla La Mancha	53	1.42	€ 14,186
2006	Cataluña	52	1.71	€ 19,216
2006	Comunitat Valenciana	52	1.60	€ 16,568
2006	Extremadura	54	1.41	€ 13,092
2006	Galicia	55	1.49	€ 15,169
2006	Comunidad de Madrid	51	1.93	€ 20,282
2006	Murcia	51	1.50	€ 15,573
2006	Navarra	53	1.70	€ 19,012
2006	País Vasco	53	1.88	€ 19,061
2006	La Rioja	53	1.54	€ 15,523
2006	Ceuta y Melilla	50	1.65	€ 14,552
2007	Andalucía	52	1.58	€ 16,245

2007	Aragón	53	1.64	€ 17,259
2007	Asturias	54	1.69	€ 16,441
2007	Baleares	50	1.60	€ 20,574
2007	Canarias	49	1.66	€ 16,752
2007	Cantabria	54	1.72	€ 17,817
2007	Castilla y León	55	1.61	€ 16,171
2007	Castilla La Mancha	53	1.46	€ 15,531
2007	Cataluña	51	1.73	€ 19,692
2007	Comunitat Valenciana	52	1.62	€ 17,834
2007	Extremadura	54	1.45	€ 13,904
2007	Galicia	55	1.53	€ 15,869
2007	Comunidad de Madrid	51	1.94	€ 21,438
2007	Murcia	51	1.59	€ 17,362
2007	Navarra	52	1.73	€ 20,218
2007	País Vasco	53	1.88	€ 19,824
2007	La Rioja	53	1.58	€ 16,749
2007	Ceuta y Melilla	51	1.61	€ 15,473
2008	Andalucía	52	1.59	€ 16,734
2008	Aragón	53	1.63	€ 17,834
2008	Asturias	55	1.68	€ 17,613
2008	Baleares	50	1.63	€ 19,498
2008	Canarias	49	1.63	€ 15,839
2008	Cantabria	53	1.78	€ 17,655
2008	Castilla y León	56	1.58	€ 16,925
2008	Castilla La Mancha	53	1.49	€ 15,156
2008	Cataluña	51	1.75	€ 20,208
2008	Comunitat Valenciana	52	1.61	€ 17,228
2008	Extremadura	54	1.48	€ 14,033
2008	Galicia	55	1.55	€ 16,718
2008	Comunidad de Madrid	51	1.94	€ 21,944
2008	Murcia	51	1.57	€ 16,238
2008	Navarra	53	1.76	€ 20,814
2008	País Vasco	53	1.91	€ 20,346
2008	La Rioja	53	1.59	€ 16,854
2008	Ceuta y Melilla	51	1.54	€ 15,985
2009	Andalucía	52	1.58	€ 16,152
2009	Aragón	53	1.67	€ 16,897
2009	Asturias	55	1.68	€ 17,669

2009	Baleares	50	1.71	€ 17,996
2009	Canarias	50	1.71	€ 15,172
2009	Cantabria	53	1.74	€ 18,434
2009	Castilla y León	56	1.64	€ 15,704
2009	Castilla La Mancha	53	1.51	€ 14,767
2009	Cataluña	51	1.78	€ 19,645
2009	Comunitat Valenciana	52	1.67	€ 16,764
2009	Extremadura	54	1.45	€ 13,865
2009	Galicia	55	1.58	€ 16,263
2009	Comunidad de Madrid	51	1.95	€ 20,954
2009	Murcia	51	1.54	€ 15,231
2009	Navarra	53	1.77	€ 20,460
2009	País Vasco	53	1.92	€ 20,014
2009	La Rioja	52	1.67	€ 16,840
2009	Ceuta y Melilla	50	1.47	€ 15,871
2010	Andalucía	52	1.60	€ 15,979
2010	Aragón	53	1.73	€ 16,459
2010	Asturias	56	1.67	€ 18,520
2010	Baleares	50	1.65	€ 17,519
2010	Canarias	50	1.71	€ 14,329
2010	Cantabria	54	1.85	€ 18,185
2010	Castilla y León	56	1.64	€ 15,413
2010	Castilla La Mancha	53	1.53	€ 15,183
2010	Cataluña	52	1.76	€ 18,708
2010	Comunitat Valenciana	52	1.69	€ 16,175
2010	Extremadura	54	1.50	€ 14,211
2010	Galicia	56	1.60	€ 15,994
2010	Comunidad de Madrid	51	1.96	€ 20,579
2010	Murcia	51	1.58	€ 14,909
2010	Navarra	52	1.81	€ 20,277
2010	País Vasco	53	1.93	€ 20,363
2010	La Rioja	52	1.74	€ 17,024
2010	Ceuta y Melilla	52	1.49	€ 15,611
2011	Andalucía	53	1.65	€ 15,680
2011	Aragón	53	1.73	€ 16,916
2011	Asturias	55	1.74	€ 16,722
2011	Baleares	50	1.73	€ 17,539
2011	Canarias	51	1.75	€ 14,004

2011	Cantabria	54	1.82	€ 17,676
2011	Castilla y León	56	1.67	€ 15,823
2011	Castilla La Mancha	53	1.57	€ 14,967
2011	Cataluña	52	1.84	€ 19,081
2011	Comunitat Valenciana	53	1.73	€ 15,704
2011	Extremadura	55	1.43	€ 14,053
2011	Galicia	56	1.63	€ 16,176
2011	Comunidad de Madrid	51	2.00	€ 21,061
2011	Murcia	52	1.64	€ 15,329
2011	Navarra	53	1.86	€ 19,611
2011	País Vasco	54	1.94	€ 20,704
2011	La Rioja	53	1.73	€ 17,144
2011	Ceuta y Melilla	54	1.56	€ 17,821
2012	Andalucía	53	1.66	€ 14,900
2012	Aragón	53	1.76	€ 17,085
2012	Asturias	56	1.70	€ 16,461
2012	Baleares	50	1.73	€ 17,235
2012	Canarias	51	1.77	€ 13,589
2012	Cantabria	54	1.77	€ 17,554
2012	Castilla y León	56	1.67	€ 15,543
2012	Castilla La Mancha	53	1.57	€ 14,243
2012	Cataluña	52	1.86	€ 18,253
2012	Comunitat Valenciana	53	1.71	€ 15,792
2012	Extremadura	55	1.44	€ 13,196
2012	Galicia	56	1.64	€ 15,829
2012	Comunidad de Madrid	52	2.00	€ 20,930
2012	Murcia	51	1.66	€ 15,633
2012	Navarra	53	1.86	€ 18,699
2012	País Vasco	54	1.97	€ 20,278
2012	La Rioja	54	1.70	€ 16,303
2012	Ceuta y Melilla	53	1.65	€ 17,164
2013	Andalucía	53	1.67	€ 14,276
2013	Aragón	54	1.78	€ 16,883
2013	Asturias	57	1.75	€ 16,410
2013	Baleares	50	1.77	€ 16,919
2013	Canarias	51	1.77	€ 13,186
2013	Cantabria	54	1.82	€ 16,463
2013	Castilla y León	57	1.74	€ 15,390

2013	Castilla La Mancha	53	1.63	€ 14,323
2013	Cataluña	53	1.86	€ 17,863
2013	Comunitat Valenciana	53	1.70	€ 15,092
2013	Extremadura	55	1.53	€ 13,576
2013	Galicia	57	1.65	€ 15,506
2013	Comunidad de Madrid	52	2.05	€ 19,746
2013	Murcia	52	1.73	€ 14,770
2013	Navarra	53	1.95	€ 18,661
2013	País Vasco	55	1.98	€ 20,206
2013	La Rioja	53	1.80	€ 16,551
2013	Ceuta y Melilla	55	1.52	€ 13,525
2014	Andalucía	53	1.69	€ 14,475
2014	Aragón	54	1.83	€ 16,259
2014	Asturias	57	1.84	€ 16,669
2014	Baleares	51	1.75	€ 17,435
2014	Canarias	52	1.75	€ 13,667
2014	Cantabria	55	1.84	€ 16,378
2014	Castilla y León	57	1.75	€ 15,679
2014	Castilla La Mancha	54	1.60	€ 14,532
2014	Cataluña	53	1.88	€ 18,424
2014	Comunitat Valenciana	54	1.71	€ 15,132
2014	Extremadura	55	1.59	€ 14,038
2014	Galicia	57	1.65	€ 15,409
2014	Comunidad de Madrid	52	2.08	€ 19,274
2014	Murcia	53	1.69	€ 14,674
2014	Navarra	54	1.89	€ 19,172
2014	País Vasco	55	2.01	€ 19,779
2014	La Rioja	54	1.79	€ 16,391
2014	Ceuta y Melilla	52	1.59	€ 15,516
2015	Andalucía	54	1.71	€ 14,460
2015	Aragón	54	1.86	€ 16,648
2015	Asturias	56	1.85	€ 17,273
2015	Baleares	52	1.78	€ 17,822
2015	Canarias	52	1.79	€ 13,879
2015	Cantabria	56	1.83	€ 17,195
2015	Castilla y León	57	1.75	€ 16,196
2015	Castilla La Mancha	54	1.62	€ 14,792
2015	Cataluña	54	1.87	€ 18,578

2015	Comunitat Valenciana	54	1.75	€ 15,318
2015	Extremadura	55	1.57	€ 13,604
2015	Galicia	57	1.69	€ 15,544
2015	Comunidad de Madrid	53	2.08	€ 19,430
2015	Murcia	53	1.72	€ 15,190
2015	Navarra	54	1.94	€ 18,995
2015	País Vasco	55	2.03	€ 20,610
2015	La Rioja	54	1.80	€ 16,336
2015	Ceuta y Melilla	51	1.70	€ 13,835
2016	Andalucía	54	1.70	€ 15,298
2016	Aragón	55	1.87	€ 17,092
2016	Asturias	57	1.83	€ 17,363
2016	Baleares	52	1.84	€ 19,073
2016	Canarias	53	1.74	€ 14,236
2016	Cantabria	56	1.82	€ 17,460
2016	Castilla y León	57	1.75	€ 16,348
2016	Castilla La Mancha	55	1.65	€ 14,767
2016	Cataluña	54	1.88	€ 18,707
2016	Comunitat Valenciana	55	1.79	€ 16,069
2016	Extremadura	56	1.54	€ 13,994
2016	Galicia	57	1.71	€ 15,737
2016	Comunidad de Madrid	53	2.08	€ 20,033
2016	Murcia	54	1.76	€ 16,157
2016	Navarra	54	1.90	€ 20,109
2016	País Vasco	56	2.04	€ 20,900
2016	La Rioja	55	1.82	€ 16,954
2016	Ceuta y Melilla	50	1.84	€ 17,478
2017	Andalucía	54	1.71	€ 16,308
2017	Aragón	56	1.82	€ 17,390
2017	Asturias	57	1.77	€ 17,118
2017	Baleares	52	1.83	€ 19,762
2017	Canarias	54	1.77	€ 14,494
2017	Cantabria	56	1.90	€ 18,827
2017	Castilla y León	58	1.80	€ 16,806
2017	Castilla La Mancha	55	1.59	€ 14,660
2017	Cataluña	54	1.95	€ 19,343
2017	Comunitat Valenciana	55	1.79	€ 16,790

2017	Extremadura	56	1.57	€ 13,823
2017	Galicia	58	1.73	€ 16,256
2017	Comunidad de Madrid	54	2.06	€ 20,906
2017	Murcia	54	1.79	€ 17,110
2017	Navarra	55	1.88	€ 20,148
2017	País Vasco	56	2.05	€ 20,964
2017	La Rioja	55	1.82	€ 17,463
2017	Ceuta y Melilla	53	1.71	€ 18,454
2018	Andalucía	55	1.73	€ 16,949
2018	Aragón	55	1.88	€ 17,908
2018	Asturias	58	1.83	€ 17,443
2018	Baleares	52	1.82	€ 20,126
2018	Canarias	53	1.77	€ 14,378
2018	Cantabria	56	1.93	€ 18,832
2018	Castilla y León	58	1.83	€ 16,993
2018	Castilla La Mancha	55	1.62	€ 15,082
2018	Cataluña	54	2.00	€ 20,216
2018	Comunitat Valenciana	55	1.81	€ 17,384
2018	Extremadura	57	1.58	€ 14,332
2018	Galicia	58	1.73	€ 16,346
2018	Comunidad de Madrid	54	2.10	€ 21,266
2018	Murcia	54	1.80	€ 17,173
2018	Navarra	55	1.87	€ 21,153
2018	País Vasco	56	2.07	€ 21,517
2018	La Rioja	55	1.86	€ 17,476
2018	Ceuta y Melilla	55	1.82	€ 14,733

Source: Own elaboration

ANNEX A4.3

Table A4.2: Average households greenhouse gases emissions (kgs of eq CO_2) by Autonomous Community. Spain 1998-2018.

Year	Autonomous Community	Total greenhouse gases emissions
1998	Andalucía	4,904
1998	Aragón	6,272
1998	Asturias	6,178
1998	Baleares	6,656
1998	Canarias	4,667
1998	Cantabria	5,808
1998	Castilla y León	6,023
1998	Castilla La Mancha	5,387
1998	Cataluña	6,659
1998	Comunitat Valenciana	5,367
1998	Extremadura	4,499
1998	Galicia	5,426
1998	Comunidad de Madrid	7,403
1998	Murcia	5,115
1998	Navarra	7,267
1998	País Vasco	6,620
1998	La Rioja	5,958
1998	Ceuta y Melilla	4,264
1999	Andalucía	5,182
1999	Aragón	6,675
1999	Asturias	6,178
1999	Baleares	6,772
1999	Canarias	5,048
1999	Cantabria	7,264
1999	Castilla y León	6,305
1999	Castilla La Mancha	6,219
1999	Cataluña	7,285
1999	Comunitat Valenciana	5,684
1999	Extremadura	4,510
1999	Galicia	6,086
1999	Comunidad de Madrid	7,802
1999	Murcia	5,680
1999	Navarra	7,435
1999	País Vasco	7,111

1999	La Rioja	6,728
1999	Ceuta y Melilla	4,422
2000	Andalucía	5,402
2000	Aragón	7,116
2000	Asturias	6,447
2000	Baleares	6,606
2000	Canarias	5,234
2000	Cantabria	7,034
2000	Castilla y León	6,144
2000	Castilla La Mancha	6,237
2000	Cataluña	7,494
2000	Comunitat Valenciana	5,870
2000	Extremadura	4,598
2000	Galicia	6,445
2000	Comunidad de Madrid	7,536
2000	Murcia	6,206
2000	Navarra	7,114
2000	País Vasco	6,938
2000	La Rioja	6,771
2000	Ceuta y Melilla	5,067
2001	Andalucía	5,510
2001	Aragón	6,940
2001	Asturias	6,446
2001	Baleares	6,380
2001	Canarias	5,198
2001	Cantabria	6,542
2001	Castilla y León	6,215
2001	Castilla La Mancha	6,108
2001	Cataluña	7,451
2001	Comunitat Valenciana	5,796
2001	Extremadura	4,770
2001	Galicia	6,190
2001	Comunidad de Madrid	7,246
2001	Murcia	5,935
2001	Navarra	7,045
2001	País Vasco	6,918
2001	La Rioja	6,858
2001	Ceuta y Melilla	4,679
2002	Andalucía	5,741
2002	Aragón	7,056
2002	Asturias	6,583

2002	Baleares	6,450
2002	Canarias	5,142
2002	Cantabria	6,767
2002	Castilla y León	6,408
2002	Castilla La Mancha	6,148
2002	Cataluña	7,250
2002	Comunitat Valenciana	6,145
2002	Extremadura	4,819
2002	Galicia	6,248
2002	Comunidad de Madrid	7,144
2002	Murcia	6,212
2002	Navarra	7,215
2002	País Vasco	7,029
2002	La Rioja	6,688
2002	Ceuta y Melilla	4,520
2003	Andalucía	5,463
2003	Aragón	6,964
2003	Asturias	6,379
2003	Baleares	6,517
2003	Canarias	5,060
2003	Cantabria	6,554
2003	Castilla y León	6,265
2003	Castilla La Mancha	6,039
2003	Cataluña	7,004
2003	Comunitat Valenciana	6,215
2003	Extremadura	4,857
2003	Galicia	6,268
2003	Comunidad de Madrid	7,005
2003	Murcia	5,969
2003	Navarra	7,052
2003	País Vasco	7,176
2003	La Rioja	6,617
2003	Ceuta y Melilla	4,382
2004	Andalucía	5,935
2004	Aragón	7,867
2004	Asturias	6,835
2004	Baleares	7,263
2004	Canarias	5,427
2004	Cantabria	7,220
2004	Castilla y León	6,846
2004	Castilla La Mancha	6,273

2004	Cataluña	7,801
2004	Comunitat Valenciana	6,955
2004	Extremadura	5,322
2004	Galicia	7,220
2004	Comunidad de Madrid	7,781
2004	Murcia	6,481
2004	Navarra	7,548
2004	País Vasco	7,911
2004	La Rioja	7,416
2004	Ceuta y Melilla	5,320
2006	Andalucía	6,436
2006	Aragón	7,281
2006	Asturias	7,141
2006	Baleares	7,802
2006	Canarias	6,071
2006	Cantabria	7,343
2006	Castilla y León	7,608
2006	Castilla La Mancha	6,924
2006	Cataluña	7,951
2006	Comunitat Valenciana	6,839
2006	Extremadura	5,811
2006	Galicia	6,890
2006	Comunidad de Madrid	8,593
2006	Murcia	6,690
2006	Navarra	8,681
2006	País Vasco	7,754
2006	La Rioja	7,333
2006	Ceuta y Melilla	5,780
2007	Andalucía	6,478
2007	Aragón	7,325
2007	Asturias	6,912
2007	Baleares	8,037
2007	Canarias	6,105
2007	Cantabria	7,589
2007	Castilla y León	7,402
2007	Castilla La Mancha	7,037
2007	Cataluña	7,703
2007	Comunitat Valenciana	6,799
2007	Extremadura	5,947
2007	Galicia	7,019
2007	Comunidad de Madrid	8,646

2007	Murcia	7,114
2007	Navarra	8,602
2007	País Vasco	7,508
2007	La Rioja	7,517
2007	Ceuta y Melilla	5,486
2008	Andalucía	6,114
2008	Aragón	6,762
2008	Asturias	6,449
2008	Baleares	6,893
2008	Canarias	5,391
2008	Cantabria	6,752
2008	Castilla y León	7,054
2008	Castilla La Mancha	6,204
2008	Cataluña	7,024
2008	Comunitat Valenciana	6,027
2008	Extremadura	5,705
2008	Galicia	6,798
2008	Comunidad de Madrid	7,476
2008	Murcia	6,127
2008	Navarra	7,953
2008	País Vasco	6,784
2008	La Rioja	6,669
2008	Ceuta y Melilla	5,051
2009	Andalucía	5,791
2009	Aragón	6,535
2009	Asturias	6,456
2009	Baleares	6,320
2009	Canarias	5,250
2009	Cantabria	6,963
2009	Castilla y León	6,701
2009	Castilla La Mancha	6,270
2009	Cataluña	6,895
2009	Comunitat Valenciana	5,875
2009	Extremadura	5,629
2009	Galicia	6,530
2009	Comunidad de Madrid	7,270
2009	Murcia	5,763
2009	Navarra	7,565
2009	País Vasco	6,670
2009	La Rioja	6,704
2009	Ceuta y Melilla	5,252

2010	Andalucía	5,210
2010	Aragón	5,758
2010	Asturias	5,907
2010	Baleares	5,725
2010	Canarias	4,473
2010	Cantabria	6,135
2010	Castilla y León	5,854
2010	Castilla La Mancha	5,587
2010	Cataluña	5,849
2010	Comunitat Valenciana	5,176
2010	Extremadura	5,049
2010	Galicia	5,628
2010	Comunidad de Madrid	6,709
2010	Murcia	5,168
2010	Navarra	6,661
2010	País Vasco	6,092
2010	La Rioja	6,054
2010	Ceuta y Melilla	4,411
2011	Andalucía	5,094
2011	Aragón	5,642
2011	Asturias	5,364
2011	Baleares	5,453
2011	Canarias	4,320
2011	Cantabria	5,989
2011	Castilla y León	5,866
2011	Castilla La Mancha	5,627
2011	Cataluña	5,717
2011	Comunitat Valenciana	4,830
2011	Extremadura	4,943
2011	Galicia	5,601
2011	Comunidad de Madrid	6,542
2011	Murcia	5,275
2011	Navarra	6,755
2011	País Vasco	5,855
2011	La Rioja	5,950
2011	Ceuta y Melilla	4,496
2012	Andalucía	4,794
2012	Aragón	5,486
2012	Asturias	5,182
2012	Baleares	5,213
2012	Canarias	4,162

2012	Cantabria	5,896
2012	Castilla y León	5,794
2012	Castilla La Mancha	5,382
2012	Cataluña	5,506
2012	Comunitat Valenciana	4,914
2012	Extremadura	4,522
2012	Galicia	5,572
2012	Comunidad de Madrid	6,378
2012	Murcia	5,007
2012	Navarra	6,236
2012	País Vasco	5,690
2012	La Rioja	5,504
2012	Ceuta y Melilla	4,010
2013	Andalucía	4,337
2013	Aragón	5,351
2013	Asturias	5,020
2013	Baleares	4,771
2013	Canarias	3,875
2013	Cantabria	5,450
2013	Castilla y León	5,493
2013	Castilla La Mancha	5,241
2013	Cataluña	5,294
2013	Comunitat Valenciana	4,413
2013	Extremadura	4,431
2013	Galicia	5,094
2013	Comunidad de Madrid	5,813
2013	Murcia	4,710
2013	Navarra	6,081
2013	País Vasco	5,341
2013	La Rioja	5,396
2013	Ceuta y Melilla	3,535
2014	Andalucía	4,359
2014	Aragón	5,285
2014	Asturias	5,074
2014	Baleares	5,167
2014	Canarias	3,971
2014	Cantabria	5,161
2014	Castilla y León	5,531
2014	Castilla La Mancha	5,276
2014	Cataluña	5,379
2014	Comunitat Valenciana	4,430

2014	Extremadura	4,585
2014	Galicia	5,252
2014	Comunidad de Madrid	5,672
2014	Murcia	4,647
2014	Navarra	5,823
2014	País Vasco	5,319
2014	La Rioja	5,589
2014	Ceuta y Melilla	3,676
2015	Andalucía	4,445
2015	Aragón	5,292
2015	Asturias	5,321
2015	Baleares	5,447
2015	Canarias	4,118
2015	Cantabria	5,445
2015	Castilla y León	5,956
2015	Castilla La Mancha	5,482
2015	Cataluña	5,644
2015	Comunitat Valenciana	4,556
2015	Extremadura	4,631
2015	Galicia	5,248
2015	Comunidad de Madrid	5,928
2015	Murcia	4,917
2015	Navarra	6,177
2015	País Vasco	5,679
2015	La Rioja	5,649
2015	Ceuta y Melilla	3,885
2016	Andalucía	4,701
2016	Aragón	5,398
2016	Asturias	5,299
2016	Baleares	5,918
2016	Canarias	4,440
2016	Cantabria	5,481
2016	Castilla y León	5,750
2016	Castilla La Mancha	5,363
2016	Cataluña	5,619
2016	Comunitat Valenciana	4,836
2016	Extremadura	4,672
2016	Galicia	5,258
2016	Comunidad de Madrid	6,113
2016	Murcia	5,025
2016	Navarra	6,359

2016	País Vasco	5,734
2016	La Rioja	5,745
2016	Ceuta y Melilla	4,471
2017	Andalucía	4,901
2017	Aragón	5,558
2017	Asturias	5,294
2017	Baleares	5,810
2017	Canarias	4,386
2017	Cantabria	6,161
2017	Castilla y León	5,782
2017	Castilla La Mancha	5,312
2017	Cataluña	5,675
2017	Comunitat Valenciana	4,954
2017	Extremadura	4,635
2017	Galicia	5,315
2017	Comunidad de Madrid	6,349
2017	Murcia	5,259
2017	Navarra	6,577
2017	País Vasco	5,638
2017	La Rioja	5,751
2017	Ceuta y Melilla	4,389
2018	Andalucía	4,780
2018	Aragón	5,461
2018	Asturias	5,056
2018	Baleares	5,454
2018	Canarias	4,042
2018	Cantabria	5,868
2018	Castilla y León	5,680
2018	Castilla La Mancha	5,268
2018	Cataluña	5,472
2018	Comunitat Valenciana	4,892
2018	Extremadura	4,467
2018	Galicia	5,152
2018	Comunidad de Madrid	6,149
2018	Murcia	5,155
2018	Navarra	6,618
2018	País Vasco	5,511
2018	La Rioja	5,627
2018	Ceuta y Melilla	3,722

Source: Own elaboration

ANNEX A4.3

Table A4.3: Average total, direct, and indirect greenhouse gases (GHG) emissions (kgs of eq CO_2) by Autonomous Community and Municipality Size. Spain 2011.

Municipality Size	Total GHG emissions	Direct GHG emissions	Indirect GHG emissions
	Andalucía		
1	4,866.84	1,683.77	3,183.06
2	5,062.08	1,862.48	3,199.60
3	5,165.76	2,066.54	3,099.22
4	5,490.43	2,287.94	3,202.49
5	5,288.97	2,200.04	3,088.93
	Aragón		
1	5,266.95	1,786.40	3,480.55
2	5,882.77	2,190.30	3,692.48
3	5,996.10	2,331.73	3,664.36
4	5,323.57	2,137.68	3,185.89
5	6,368.78	2,838.18	3,530.59
	Asturias		
1	5,272.50	1,865.37	3,407.13
2	5,625.64	2,229.71	3,395.93
3	5,620.95	2,369.61	3,251.34
4	5,573.57	2,235.41	3,338.16
5	5,049.61	2,044.32	3,005.28
	Baleares		
1	4,887.57	1,747.92	3,139.66
2	7,379.96	2,939.70	4,440.26
3	5,777.07	2,150.14	3,626.93
4	5,210.37	2,053.07	3,157.30
5	5,775.58	2,478.75	3,296.83
	Canarias		
1	4,086.15	1,247.18	2,838.98
2	3,772.18	1,241.89	2,530.29
3	4,795.63	1,997.00	2,798.63
4	4,798.37	1,678.59	3,119.79
5	4,607.99	2,003.58	2,604.41
	Cantabria		

1	4,943.65	1,759.64	3,184.01
2	4,856.56	1,725.85	3,130.71
3	6,901.98	3,070.98	3,831.00
4	7,584.67	3,153.59	4,431.08
5	6,541.50	3,076.32	3,465.18
Castilla y León			
1	5,371.41	2,077.72	3,293.69
2	5,239.68	2,165.21	3,074.47
3	6,661.98	2,858.74	3,803.24
4	6,540.63	2,763.36	3,777.26
5	6,218.06	2,829.56	3,388.50
Castilla La Mancha			
1	5,447.76	2,037.39	3,410.37
2	5,507.54	2,130.90	3,376.64
3	5,335.44	2,262.30	3,073.14
4	5,550.89	2,390.58	3,160.31
5	5,824.53	2,579.95	3,244.58
Cataluña			
1	4,906.11	1,453.01	3,453.10
2	6,562.81	2,435.09	4,127.72
3	5,967.69	2,284.98	3,682.70
4	6,143.79	2,413.19	3,730.60
5	6,927.94	2,940.38	3,987.56
Comunitat Valenciana			
1	4,643.92	1,483.50	3,160.43
2	4,444.02	1,615.14	2,828.89
3	4,994.55	1,909.82	3,084.73
4	5,379.17	2,166.43	3,212.74
5	4,986.05	1,955.17	3,030.88
Extremadura			
1	5,279.87	2,221.08	3,058.79
2	5,670.91	2,261.53	3,409.38
3	4,920.70	1,952.23	2,968.47
4	5,021.53	1,900.23	3,121.30
5	4,666.97	1,939.32	2,727.65
Galicia			
1	4,777.22	1,568.33	3,208.89

2	6,189.79	2,301.20	3,888.59
3	5,779.54	2,475.83	3,303.70
4	5,442.38	2,210.84	3,231.55
5	6,006.36	2,699.62	3,306.74
Comunidad de Madrid			
1	6,284.37	2,345.24	3,939.13
2	7,421.11	3,196.20	4,224.91
3	7,012.12	2,763.30	4,248.82
4	9,076.67	4,376.66	4,700.02
5	7,457.77	3,451.24	4,006.53
Murcia			
1	5,114.07	1,927.67	3,186.41
2	5,648.47	2,310.56	3,337.91
3	5,154.96	2,122.10	3,032.86
4	5,492.96	2,636.86	2,856.10
5	5,947.74	3,010.93	2,936.81
Navarra			
1	6,389.55	2,330.67	4,058.88
3	5,835.01	1,942.42	3,892.59
4	6,883.46	2,940.07	3,943.39
5	7,242.67	3,398.75	3,843.93
País Vasco			
1	5,697.30	1,842.19	3,855.11
2	6,153.43	2,137.67	4,015.77
3	5,191.98	1,655.66	3,536.32
4	5,954.87	2,078.65	3,876.22
5	6,620.34	2,591.39	4,028.95
La Rioja			
1	5,703.16	2,194.58	3,508.58
3	6,354.80	2,772.45	3,582.35
4	4,780.90	1,966.64	2,814.25
5	6,461.26	2,710.54	3,750.72

Note: municipality size is measured in a scale from 1 to 5 (1 100,000 inhabitants or more; 2 between 50,000 and 100,000 inhabitants; 3 between 20,000 and 50,000 inhabitants; 4 between 10,000 and 20,000 inhabitants; 5 less than 10,000 inhabitants

Source: Own elaboration

ANNEX A4.5

Table A4.4: Average total, direct, and indirect greenhouse gases (GHG) emissions (kgs of eq CO_2) by municipality. Spain 2011. Top 50th

Autonomous Community	Municipality	Total GHG emissions	Direct GHG emissions	Indirect GHG emissions
Comunidad de Madrid	Boadilla del Monte	12,024	5,208	7,194
Comunidad de Madrid	Pozuelo de Alarcón	12,017	5,172	7,230
Comunidad de Madrid	Tres Cantos	12,005	5,161	7,195
Comunidad de Madrid	Torrelodones	12,004	5,190	7,203
Comunidad de Madrid	Villaviciosa de Odón	11,977	5,087	7,203
Comunidad de Madrid	Majadahonda	11,918	5,121	7,157
Navarra	Barañain	11,913	4,899	6,923
Comunidad de Madrid	Rozas de Madrid (Las)	11,901	5,137	7,099
Comunidad de Madrid	Galapagar	11,879	5,071	7,107
Comunidad de Madrid	Algete	11,831	5,113	7,068
Comunidad de Madrid	Rivas-Vaciamadrid	11,813	5,136	7,000
Comunidad de Madrid	San Fernando de Henares	11,714	4,982	7,008
Comunidad de Madrid	Coslada	11,705	5,034	7,001
Comunidad de Madrid	Collado Villalba	11,701	4,998	6,981
Comunidad de Madrid	Colmenar Viejo	11,695	4,998	6,997
Navarra	Pamplona/Iruña	11,674	4,769	6,836
Comunidad de Madrid	Alcobendas	11,645	4,645	6,944
Comunidad de Madrid	Mejorada del Campo	11,619	5,019	6,910
Comunidad de Madrid	Aranjuez	11,614	4,951	6,959
Navarra	Tudela	11,604	4,719	6,757
Comunidad de Madrid	San Sebastián de los Reyes	11,602	4,962	6,914
Comunidad de Madrid	Madrid	11,585	4,483	6,973
Comunidad de Madrid	Alcalá de Henares	11,577	4,604	6,906
Comunidad de Madrid	Getafe	11,574	4,576	6,922
Comunidad de Madrid	Leganés	11,572	4,556	6,923
Comunidad de Madrid	Alcorcón	11,562	4,536	6,908
Comunidad de Madrid	Fuenlabrada	11,549	4,672	6,840
Comunidad de Madrid	Pinto	11,536	4,904	6,873

Comunidad de Madrid	Móstoles	11,528	4,575	6,875
Comunidad de Madrid	Valdemoro	11,513	4,979	6,803
Comunidad de Madrid	Ciempozuelos	11,512	4,909	6,850
Comunidad de Madrid	Arganda del Rey	11,488	4,953	6,825
Comunidad de Madrid	Navalcarnero	11,454	4,912	6,820
Comunidad de Madrid	Torrejón de Ardoz	11,448	4,569	6,798
Comunidad de Madrid	Arroyomolinos	11,325	4,924	6,660
Comunidad de Madrid	Parla	11,306	4,551	6,667
Galicia	Ferrol	10,582	4,327	6,205
Cantabria	Camargo	10,575	4,674	5,989
Cantabria	Santander	10,553	4,381	6,037
Galicia	Estrada (A)	10,511	4,450	6,154
Cantabria	Castro-Urdiales	10,492	4,609	5,890
Cantabria	Piélagos	10,462	4,653	5,890
Cantabria	Torrelavega	10,451	4,372	5,977
Galicia	Ourense	10,446	4,234	6,093
Galicia	Oleiros	10,414	4,397	6,034
Galicia	Pontevedra	10,392	4,348	6,048
Galicia	Coruña (A)	10,385	4,192	6,038
Galicia	Lugo	10,352	4,275	6,022
Galicia	Santiago de Compostela	10,294	4,290	5,974
Galicia	Vigo	10,292	4,227	5,966

Source: Own elaboration

CONCLUDING REMARKS

Main findings

The general objective of this thesis is to analyze the carbon footprint generated by private consumption in Spain under the temporal, spatial and gender perspectives. By using an input-output framework, the greenhouse gases emissions embedded in household's consumption between 1998 and 2018 are estimated. Moreover, different econometric strategies are applied to understand gender differences and specific geographical patterns. This work is structured with four separate chapters, each of them with specific but partially interrelated research questions.

After the introductory chapter, chapter 1 presents the methodologies associated with the input-output framework and all the techniques necessary to estimate the carbon footprint, specifically the greenhouse gases derived from consumption. The close integration between the theoretical model and the database is one of the pillars of this approach. Considering the characteristics of national accounting, the environmental extensions introduced in the input-output framework are described with the ramifications for the estimates of the emissions derived from each household consumption. Information is available on six greenhouse gases: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulfur hexafluoride (SF_6), hydrofluorocarbons (HFCs) and perfluorocarbons (PFCs). Therefore, by exploiting a public data base, the greenhouse gases derived from the Spanish household's consumption between 1998 and 2018 are estimated and some results throughout time, age, and educational and expenditure levels are presented and described in this chapter.

One of the first research questions addressed in this doctoral thesis was if emissions from consumption were different between women and men and to quantify the amount of this potential gender gap in emissions. Chapter 2 aims to address this issue. Given the lack of data on consumption at the individual level within households, the differences in emissions by gender only for the one-person-households between 1998-2004 and 2006-2018 are studied. By applying Blinder-Oaxaca decompositions and Propensity Score Matching estimators, it is found that male one-person households have significantly higher emitters patterns than corresponding female one-person households. One of the drivers of these differences is the emissions associated with transport consumption, especially those associated with the use of private cars, where male one-person-households are the main consumers and therefore the main emitters. However, although on a smaller scale, female-one-person households have higher emissions patterns from within household consumption, such as gas and food.

After studying the differences given purely by gender, additional related issues began to emerge. In a society that has increased the participation of its female labour force and the female education levels, which today even surpass those of men, a new structure is being created within households, with a considerable increase in the number of female breadwinners around the world. Different studies confirm that the purchasing power of household members directly affects their bargaining and decision-making power within the household. Therefore, an increase in female breadwinners should have an impact on consumption decisions and thus on associated emissions. Chapter 3 studies under Blinder-Oaxaca decomposition and Propensity Score Matching estimator the differences in the production of greenhouse gases between households of female and male breadwinners in 1998, 2008, 2014 and 2018 independently. Generally, female breadwinners' households have, on average, less emitter patterns than male breadwinners' households being equal the rest of covariates. In other words, the presence of more female breadwinner produces, all other things being equal, a more eco-friendly consumption. Although these differences are explained by a high level of emissions associated with the use of private car by male breadwinner's households, in contrast to conclusions reached in chapter 2, the differences in emissions associated with household energy use and food had no significant differences.

As a last chapter, the estimates of emissions derived from the consumption of each Spanish household were extended to a detailed geographical level. By using a variant of a Generalized Maximum Entropy estimator, chapter 4 estimates mean levels of greenhouse gases embedded in households' consumption by municipality in Spain corresponding to 2011. The estimates produced in this chapter allows for quantifying and studying potential differences within regions, for example between cities located in the same region with similar populations. It is concluded that the emissions of large cities, such as Madrid and Barcelona, are not as high as those of their neighbouring municipalities, especially those surrounding the metropolitan areas. Since the results are presented distinguishing between direct (from energy good consumption) and indirect emissions (from goods and services consumption independently), the estimates indicate that direct embedded emissions from households near Madrid are the most polluting in Spain. Similar patterns are found in municipalities close to large cities as Barcelona or Zaragoza, where the capital cities themselves are comparatively lower direct emitters, but they seem to exert some influence on the surrounding municipalities, probably by the use of private cars. While major municipal efforts are being made to improve the emission performance of large urban areas, investment in environmental policies for their neighbours appears to be insufficient. From indirect emissions embedded from goods and services consumption, large cities are in the middle ground, while municipalities related with high income level appear to be producing high levels of emissions per capita.

Policy implications and future research lines

One of the main contributions of this work is the estimate first longitudinal series of emissions derived from each Spanish household's consumption through 20 years, offering relevant elements to explain the relationship between global warming and consumption. Each chapter throughout this work brings together its corresponding and specific conclusions, however, jointly contribute to presents how households consumption affect the environment. Studies that relate consumer characteristics and their emissions patterns generally focus on income and/or expenditure levels, leaving open issues such as place of residence, gender, ageing, among others, which this thesis attempts to address. Chapter 2 and chapter 3 shows that the presence of women lead to an eco-friendlier emissions pattern, making visible the importance of women in environmental issues and how social stereotypes have led to men with more polluting emission patterns given their higher demand on private car use and catering services independently of other characteristics such as income. Chapter 4, besides presenting a methodology for connecting two databases and achieving consistency between their large aggregates, shows the environmental impact of large urbanisations, especially those related to their neighbouring localities.

Throughout this thesis, the importance of environmental policies aimed at the consumer is highlighted. This study provided elements for a correct planning and approach to environmental policies aimed at the consumer in an attempt to reduce greenhouse gases derived from consumption. Information on household's characteristics and their contribution to global warming will allow policy makers to apply different economic instrument to modify the composition of the consumption basket towards more environmentally responsible products. On the one hand, our results are relevant to the debate on the social effect of environmental taxes, where an increase in taxes related to private transport or households gas use would affect women and men differently, and mismanagement of these policies could lead to a regressive effect. On the other hand, solutions such as information campaigns, social awareness and/or green programs, which encourage households to change their consumption patterns are needed, since a correct customization this type of instrument is key to obtain a maximum impact.

This doctoral thesis also aims at opening avenues for future research topics. Although this work is closed in this document, the possible research ramifications leave much work to be done. Examples are the estimation of a series of Spanish bridge matrices that allow to connect industrial information derived from the input-output tables with private consumption, without having to rely on information from other countries. Moreover, it would be interesting to expand the geographical scope of the estimated database to Europe and integrate it in a multi-regional input-output framework. This would allow for estimating environmental impacts derived from consumption across countries within the continent and the analysis of these impacts with a temporal, regional and gender perspective, among other characteristics such as age or educational level. The production of the database also leads to other research questions, such as the analysis of demographic and preference changes in households over the years and how these changes affect the production of greenhouse gases, which could be extended to other pollutants. Generating forecast of emissions is also possible, thus having an overview of both the past and the evolution of emissions in the coming years. Finally, from a geographical point of view and given the forthcoming release of the detailed microdata corresponding to the Spanish population census 2021, studies on the environmental impact of different public policies would be appropriate, or even analyse the effect of depopulation and overpopulation on emissions.