Energy Policy 190 (2024) 114144

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Who brings emissions home? Comparing female and male breadwinner households by matching techniques

Francisca Toro [a,*], Esteban Fernández-Vázquez [b], Mònica Serrano [a]

[a] Department of Economics, Faculty of Economics and Business, University of Barcelona, Av. Diagonal 696, 08034, Barcelona, Spain
[b] Department of Applied Economics, Faculty of Economics and Business, University of Oviedo, Av. Del Cristo s/n, 33006, Oviedo, Spain

A R T I C L E I N F O

Keywords:
Household energy consumption
Female breadwinner
Gender
Greenhouse gases emissions
Matching estimator

A B S T R A C T

This paper tests the hypothesis that female and male breadwinner household present significant differences in the greenhouse gases (GHG) emissions patterns induced by consumption. We investigate this issue by studying a sample of consumption basket of Spanish households for 2008, 2014, and 2018, linking consumption levels with emissions by means of input-output analysis. Once a vector of GHG emissions have been calculated for each household sampled, we apply the Propensity Score Matching estimator to analyze the mean difference between households with female and male breadwinners, finding a significant negative effect of having female breadwinner households on the GHG emissions patterns derived by household energy consumption, mainly due to the larger use of private transport by male breadwinner households. These results contribute to the growing demand for studies linking environment and gender and to expose the role of women in sustainable energy production and consumption. Therefore, policies that encourage the inclusion of women in different economic activities are also likely to have climate related benefits.

1. Introduction

Female Breadwinner Households (FBH), a term used to refer to women being main supplier of income within the household (Kowalewska and Vitali, 2021), account for a significant proportion of households across developed countries nowadays (Winkler et al., 2005; Wang et al., 2014; Wooden and Hahn, 2014), being a relatively new phenomenon around the world that could differ from traditional gender roles and family dynamics.

The growing presence of FBH might be explained by different factors, being education one of the most relevant. In recent decades, women have increased their level of education more intensively than men, both in quantity and quality (Klesment and Van Bavel, 2017). This educational advancement among women is closely linked to an increase in employment rates and rising presence of women in human capital elite (Malinowski and Jabłońska-Porzuczek, 2020; Bühler et al., 2023), which, in turn, could be influencing the increase of FBH. However, little is known about the consequences that this structural change within households might entail, both at aggregated level as well as in terms of the internal organization of the households.

An increase in economic resources provided by women might lead to an increase in female bargaining power within the household (Antman, 2014) and, consequently, in the demand for certain goods and services and modifying the structure of the household consumption (Bourguignon et al., 1993), even when total household income is fixed (Duncan, 1990; Schultz, 1990). One example is the housing reform policy in China that transferred property rights of rented homes to individuals; when rights were given to women, the increased female bargaining power within the household lead to a reduction of household consumption of some goods preferred by men (Wang et al., 2014). Thus, policies designed to increase women's education, employments rates, economic resources, or reduce gender inequalities in accessing higher positions can indeed lead to a rise in the prevalence of FBH, thereby altering household consumption patterns.

Literature indicates that women tend to exhibit environmentally conscious behaviors such as recycling, minimise waste, buy organic food and eco-labeled products, engage in water and energy saving initiative, and have more knowledge and concern for environmental issues compared to men (Yaccato and Jaeger, 2003; Johnson-Latham, 2007; Kaenzig et al., 2013; Khan and Trivedi, 2015). The different environmental concern might influence a demand for different products and services, leading to different consumption patterns between women and

* Corresponding author.
E-mail addresses: fran.toro@ub.edu (F. Toro), evazquez@uniovi.es (E. Fernández-Vázquez), monica.serrano@ub.edu (M. Serrano).

https://doi.org/10.1016/j.enpol.2024.114144
Received 28 October 2023; Received in revised form 18 March 2024; Accepted 21 April 2024
Available online 2 May 2024
0301-4215/© 2024 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

men as recent studies evidenced. Women tend to be more engaged with brand and make more impulse purchases (Tifferet and Herstein, 2012). They are less likely to order large portions of food, prefer home -cooked meals, and eat more sweets, fruit, and vegetables; on the contrary, men consume higher quantities of fats, oils, beverages, and animal products (Bilouka and Utermohlen, 2000; Baker and Wardle, 2003; Liebman et al., 2003; Wansink et al., 2003; Greene-Finestone et al., 2005). In terms of transport, women are more likely to walk and, in most cities, to use public transport than men (Prati, 2018; Goel et al., 2023).

Household emissions contribute substantially to national greenhouse gases (GHG) −59% 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). These figures put the spotlight on the role of household consumption patterns as crucial element in global warming (Munksgaard et al., 2000; Long et al., 2021). Moreover, the rise in the number of FBH marks a significant trend with the potential to impact this dynamic. Vitali and Mendola (2014) shows how this shift is manifesting across some European countries. For instance, Ireland experienced a notable increase in FBH from 10% to 23.8% between 2004 and 2010. In Southern European countries, –including Greece and Spain– the share of FBH rise from 10% in 2004 to 18% in 2010, with Greece experiencing the most dramatic increase from 8% to 24%. These examples illustrate the profound structural changes underway. Therefore, the new role of women in defining household consumption patterns might have a significant impact in household emission level and so in national ones.

In this context, this paper answers the following research question: are the GHG emissions embedded in the consumption pattern of FBH and Male Breadwinner Households (MBH) significantly different due to gender[1] differences exclusively? If this is the case, the increasing participation of women as breadwinner of households would not only impact on socio-economic indicators but will also have environmental consequences.

To answer this question, we consider Spain as case of study, an economy that has experienced an important and intensive growing incorporation of women to labour market since the 1980s (Duarte et al., 2019). According to Spanish Ministry of Labor and Social Economy (2021), between 2007 and 2021, women aged 45–54 experienced a much higher increase in the labour force (59.2%) than men of the same age (28.4%). Additionally, women represented more than the half of employees with tertiary education (53.1%) with an upward trend. Female workers with the highest level of education have increased by 51.5%, compared to a smaller increase of male workers (28.3%). These changes reflect in the growing presence of FBHs, which have increased from less than 14% in the early 1980s to 36% in 2022 (Aldás and Solaz, 2017; INE, 2024). Additionally, Vitaly and Arpino (2016) research provides evidence that Spain exhibits the highest predicted probabilities of observing a female breadwinner when compared to other European countries.

This paper aims at studying the differences in emission between Spanish FBH and MBH by applying the so-called Propensity Score Matching (PSM) estimator, which quantifies average differences between two groups with identical characteristics excepting the classification (treatment) of interest: being the breadwinner a woman or a man. The analysis includes emissions derived from consumption baskets comprising 39 products —grouped into 12 COICOP[2] categories—. These commodities are produced by 62 industries that generate emissions of 6 GHGs aggregated in CO_2 equivalent units, including direct and indirect GHG emissions derived from households' consumption expenditure, and households' consumption of energy goods. In other words, this study incorporates the emissions derived from energy consumption from (*i*) domestic energy use (e.g., gas for cooking), (*ii*) private transport energy use (e.g., gasoline), and (*iii*) energy use derived from all production chain to produce any other product.

Estimations are made for the decade 2008–2018, taking 2008, 2014 and 2018 as relevant milestones characterized by significant economic events for the Spanish economy. The more male-dominated sectors —manufacturing and construction— suffered the first and most direct effect of the financial crisis started in 2008, leading a reduction of gender employment gap and the subsequent increasing of FBH. However, when the first wave of the crisis began to wane, the gender employment gap stopped decreasing and levelled off, partly due to the mid and long-term consequences of the crisis in the more feminised services sectors, such as health and social work or education. The recovery from 2014 onwards lasted until the COVID-19 crisis in 2020, with the year 2018 serving as a pre-COVID reference point (Serrano et al., 2020).

Studies relating households' consumption and environmental impacts have been increasing since the pioneering work of Herendeen and Tanaka (1976), who found that households consume more energy indirectly thought the purchase of goods and services than directly though the consumption of energy itself. Household income has been identified as one of the main factors that impact the environment (Duarte et al., 2021), being 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; Jiang et al., 2020). Household demographic characteristics —including changes in population size, urbanisation, and the size, age, and sex households' composition— also have a great influence in household energy consumption and therefore environmental footprint (O' Neil et al., 2001; Zhou and Yang, 2016; Dubois et al., 2019; Yu et al., 2022).

However, the potential effect of the feminisation on GHG emissions have not been fully studied yet. Exceptions are Räty and Carlsson-Kanyama (2010) and Toro et al. (2019). Räty and Carlsson-Kanyama (2010) estimate energy use derived from consumption of female and male one-person households for Germany, Norway, Greece, and Sweden to analyze differences between both groups. Results show differences in Greece and Sweden, where in general men living alone use more energy than their female counterparts. 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. These results were confirmed by Toro et al. (2019), who analyze the carbon footprint of female and male one-person household in Spain from 2008 to 2013, employing econometric methods to capture the differences. These two studies were the first to report gender differences in environmental responsibility derived from consumption of energy use and carbon footprint.

This paper, however, goes further, by (*i*) measuring differences in environmental impact based on the gender of the main breadwinner of the household, encompassing all type of households rather than focusing only on one-person households to consider the diversity of Spanish household structure and to capture a more accurate representation of Spanish society, and (*ii*) analysing the differences in GHG emissions between FBH and MBH by using statistics techniques that control for household characteristics other than gender. This strategy is particularly

[1] Databases used in this study only allow us to know the "sex" of individuals, a term primarily associated with biological attributes. Although "gender" is not explicitly present in the data, we use this term in this paper as it represents better issues related with socialization (Rippon, 2019), particularly in the context of the purchase of goods and services under the shadow of "feminine" and "masculine."

[2] COICOP is the acronym of "classification of individual consumption by purpose".

relevant, since FBH have different characteristics than MBH: female breadwinner[3] has higher level of education and higher labour force participation rates (Raley et al., 2006; Vitali and Mendola, 2014), are older (Bloemen and Stancanelli, 2015), and live in smaller household (Bianchi et al., 1999) than male breadwinner.

The rest of the paper is organized as follows. Section 2 describes the database and the required data processing to produce our estimates. Section 3 describes the methodologies employed to attribute GHG emissions to consumptions and to estimate the average effect of gender. Finally, Section 4 presents the main results, and Section 5 summarizes the conclusions of the study.

2. Databases

The Spanish Statistical Office (INE) compiles the official and publicly available data required to estimate the GHG footprint of Spanish FBH and MBH. This section describes the three statistical data sources used in our study: the Spanish Input-Output Tables (IOT) estimated from Supply and Use Tables (SUT, INE, 2019a), the Environmental Accounts (INE, 2019b), and the Household Budget Survey (HBS, INE, 2019c). Additionally, these datasets are combined with supplementary information that allows to link sectorial indicators in the IOT with HBS microdata, the so-called bridge matrix (Denmark Statistik, 2019).

The Spanish INE compiles a national input-output framework by producing SUTs on a yearly basis, which allows for estimating IOTs from SUTs at different levels of aggregation for the years 2008, 2014 and 2018. Some analytical steps are necessary to compile these IOTs. For the transformation of SUT into IOT, some assumptions must be made, and adjustments are required. The format of an IOT can either be made based on an industry-by-industry (NACE[4]) or product-by-product (CPA[5]) 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. While the data in SUT are given in purchase and basic prices, the resulting IOT must 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 (Stone, 1962; Bacharach, 1970; Golan et al., 1994).

The atmospheric emissions accounts, that are organized annually from 1995 to 2019, 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. For the purposes of this study, we 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), all gases are aggregated in equivalent CO_2 units generated by each economic activity and households as final consumers. One of the characteristics of the atmospheric emissions account is that are classified by industry, while IOT estimates are product-by-product. Therefore, a method to transform the atmospheric information from industries to products is required. As in previous sections and following Eurostat (2008, p.347), we applied the product-by-product classification under the industry technology assumption (Model B),[6] assuming each industry has its own specific way of producing atmospheric emissions independently of its product mix. We obtain the GHG related gases of Spain of 2008, 2014 and 2018 from the different economic sectors and households as final consumers consistent with the NACE/CPA classifications.

The HBSs are national surveys that focus primarily on household consumption expenditures of goods and services. They provide information on the nature and destination of consumption expenditures, as well as various household characteristics and of its members such as education level, age, and sex of the main breadwinner.[7] Consumption figures are classified according to the COICOP European classification, which structures consumption in 12 large products categories comprising 39 different products (see Annex A for more details). Expenditures in HBS are represented under COICOP classification at purchase prices, while IOT and GHG emissions are estimated under NACE/CPA classification at basic prices. The bridge matrix allows for solving this problem. The bridge matrix connects macroeconomic data classified according to the NACE/CPA classification with microeconomic data following the COICOP classification. Therefore, it is necessary to estimate an annual series of bridge matrices that homogenises the different classifications and principles. Given a lack of an officially estimated Spanish bridge matrix publicly available, we take as priori the annual Danish bridge matrix (Denmark Statistik, 2019) corresponding to each year and we have adjusted to the observed totals of the Spanish economy by applying the RAS method.[8]

3. Methodologies

3.1. Estimating GHG emissions embedded in household consumption

Analyzing the difference of environmental impacts derived from consumption patterns of FBH and MBH requires, first, to estimate GHG emissions embedded for each consumption basket of each household. Quantifying environmental footprints in our analysis implies the estimation of all GHG generated direct and indirectly by any unit of goods or services consumed. In other words, we consider the emissions produced directly when the combustion of any energy products —i.e., driving a car— takes place, as well as all emissions embedded in the whole production chain of the production of each product consumed; this implies to consider the emissions of a product and the emissions of the inputs needed to produce such product and so on.

Following Roca and Serrano (2007) and Eriksson et al. (2021), direct and indirect emissions of each household are defined as a function of h different GHG gases and p different COICOP products as[9]

$$\mathrm{HE} = \mathbf{FLB}\hat{\mathbf{c}} + \mathbf{E}\hat{\mathbf{c}} = \mathbf{M}\hat{\mathbf{c}} + \mathbf{E}\hat{\mathbf{c}} \quad (1)$$

[3] It is worthy to explain the difference between "female (male) breadwinner" and "female (male) breadwinner household". We use "female (male) breadwinner" when we refer to individual characteristics of the main breadwinner, such as age and educational level. In contrast, we use "female (male) breadwinner household" when we refer to the attributes of the entire household.

[4] NACE come from the French *Nomenclature statistique des activités économiques dans la Communauté européenne* and refers to the "statistical classification of economic activities in the European Community."

[5] CPA is the acronym of "classification of products by activity."

[6] The main reason to apply this strategy was the difficulty to solve the negative values with the RAS technique 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.

[7] Definition used by Household Budget Survey to determine the main breadwinner of a household is the "household member 16 years old or older, whose regular (not occasional) contribution to the common budget is used to cover household expenses to a larger extent than the contributions of each of the other members" (INE, 2019c).

[8] A proper comparison was conducted between the estimated 2010 Spanish bridge matrix based on the published by Cazcarro et al. (2020) and the based on the Danish bridge matrix, revealing no significant disparities.

[9] Matrices are indicated by bold, upright capital letters; vectors by bold, upright lower-case letters; and scalars by italicized lower case letters. By definition vectors are columns, 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.

Direct emissions from households are represented by $\mathbf{E}\hat{\mathbf{c}}$, being $\mathbf{E}$ the intensity matrix of direct household emissions, whose elements represent the direct emissions of pollutant h associated with each monetary unit spent on a consumption purpose p, and $\hat{\mathbf{c}}$ the expenditure on each of the p COICOP products on the household consumption basket. Under COICOP classification, direct household emissions derive from the consumption of 4.5: "Electricity, gas, and other fuels" and 7.2: "Operation of personal transport equipment," specifically 7.2.2: "Fuels and lubricants for personal transport equipment."

Indirect GHG emissions from households' consumption are represented by $\mathbf{M}\hat{\mathbf{c}}$, where $\mathbf{M}$ ($\mathbf{M} = \mathbf{FLB}$) is the multiplier matrix that expresses emissions produced in industry n generated by a monetary unit spent on each p COICOP product in the consumption basket of each household. In this expression, $\mathbf{F}$ is the emission coefficient matrix that represents the amount of each h atmospheric pollutants generated by one unit of product of industry n, whose element $f_{hj}=\delta_{hi}/x_j$ is defined as the total amount of each atmospheric gas measured in physical units (δ_{hi}), per unit of each industry product (x_j).

Matrix $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse, being $\mathbf{I}$ the identity matrix of appropriate dimension and $\mathbf{A}$ the matrix of total technical coefficients. The Leontief inverse gathers all the sectoral interdependencies in the economy and its typical element l_{ij} shows the total output from sector i required to satisfy an extra unit of final demand from sector j.

$\mathbf{B}$ is a matrix of aggregated commodity of consumption that relates n products under CPA with p COICOP products. Matrix $\mathbf{B}$, the 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 $\mathbf{L}$ and $\mathbf{F}$— with data classified by consumption purposes —such as the information from microeconomic databases from vector $\mathbf{c}$, that represents the expenditure on each of the p COICOP products. Due to matrix $\mathbf{B}$ characteristics, GHG emissions embedded in consumption are calculated at the two-digit COICOP detail. Afterwards results are aggregated at one-digit COICOP level for illustration purposes. Because of this aggregation, the outcomes not only depend on the expenditure on each product at two-digit COICOP level, but also on the expenditure distribution on each product within the group at one-digit COICOP level.

Finally, $\mathbf{HE}$ is the matrix containing the emissions embedded in each consumption basket of each household.

3.2. *Quantifying female and male breadwinner household's differences in GHG emissions patterns by means of Propensity Score Matching estimator*

Once the GHG emissions have been estimated for each one of the households included in the HBS, we could identify that the total household GHG emissions in 2008, 2014, and 20,218 account for approximately 47% of the national total GHG emissions (see Annex B). Specifically, FBH –without adjustment– contribute to 10–13% of the national total GHG, while MBH make up 33–38%. Moreover, this section aims to investigate if there are significant differences in the GHG levels that can be attributed just to gender. This research questions lies in the field of identifying the effect of a treatment (having a female breadwinner) between an effectively treated group (the FBH) and a control group (the MBH).

Identifying FBH in the HBS samples is straightforward, since the household files details the characteristics of every household member and identify the main breadwinner for each household sampled. Following this criterion, those households on which the main breadwinner is a female will be categorized in our study as FBH. With this classification in mind, we have studied the HBS samples of households for each year considered, which after some data cleaning (e.g., eliminating households not reporting monetary consumption or other variable of interest), leaves us with a sample size of a total of 64,538 households (approximately 21,500 per year), of which approximately 30% corresponds to cases for which the breadwinner is a female individual.

Table 1 shows summary statistics of the household characteristics distinguishing between FBH and MBH calculated using the type of households at population level with the equivalent household size correction reported in the HBS to facilitate more accurate comparisons between types of households. Corresponding standard deviations are provided in parentheses below each statistic for clarity.

Total GHG emissions have been estimating through equation (1); results show that MBH contribute to 69–75% of Spain's total household emissions in the studied period. Additionally, in terms of consumption patterns (kilograms of CO_2 equivalent per €1000 spent), FBH exhibit 5–10% higher emissions than MBH on average, due to the disparity of the ratio between emissions and expenditures of FBH and MBH.

Spanish FBH differ from MBH in several aspects. Regarding expenditure level, MBH outspend FBH by about 240–630 euros. On average, FBH lived in smaller families and reside in denser areas. The size of household can affect emission footprints, with evidence suggesting that smaller families may produce higher emissions due to less efficient sharing of resources that emit carbon, indicating an economy of scale for larger families. Conversely, living in urban settings is often linked with lower GHG emissions compared to rural areas (Ala-Mantila et al., 2014). Furthermore, female breadwinners tend to be older, and considering the findings of studies such as Chancel (2014), it is observed that generation such "baby boomers" have a stronger tendency to emit more CO_2 than

Table 1
Descriptive statistics of household characteristics of female and male breadwinner households. Spain 2008, 2014, and 2018.

	2008	2014	2018
Total (number of households)			
FBH	4,642,774	6,064,084	6,265,044
MBH	12,257,274	12,115,457	12,236,506
Total greenhouse emissions (tons of equivalent CO_2)			
FBH	27,580,304	27,888,991	30,360,711
MBH	84,373,166	63,470,750	67,564,621
Mean household emissions per thousand € (kilograms of equivalent CO_2/ thousand €)			
FBH	248.14	206.89	200.36
	(-1.91)	(-1.42)	(-1.57)
MBH	222.62	196.13	188.99
	(-1.08)	(-1.05)	(-1.1)
Mean annual household expenditure (€)			
FBH	18,128.53	16,147.56	17,898.21
	(-223.17)	(-147.12)	(-146.54)
MBH	18,372.06	16,675.21	18,529.16
	(-110.05)	(-99.81)	(-117.45)
Mean age of main breadwinner (years)			
FBH	55.35	55.07	56.76
	(-0.32)	(-0.27)	(-0.27)
MBH	50.86	53.14	54.25
	(-0.16)	(-0.16)	(-0.16)
Mean household size (number of persons)			
FBH	2	2.13	2.07
	(-0.02)	(-0.02)	(-0.02)
MBH	2.87	2.67	2.66
	(-0.01)	(-0.01)	(-0.01)
Mean education level of main breadwinner			
FBH	1.71	1.86	1.91
	(-0.01)	(-0.01)	(-0.01)
MBH	1.67	1.78	1.85
	(-0.01)	(-0.01)	(-0.01)
Mean degree of urbanization			
FBH	1.64	1.66	1.67
	(-0.01)	(-0.01)	(-0.01)
MBH	1.77	1.78	1.79
	(-0.01)	(-0.01)	(-0.01)

Note: Female breadwinner household (FBH). Male breadwinner household (MBH). Figures in parentheses indicate standard deviations. Level of education is measured in a scale from 1 to 3 (1 first cycle or less; 2 secondary; 3 university). The degree of urbanization is a categorical variable in a scale from 1 (densely populated) to 3 (sparsely populated).
Source: Own elaboration

former and later generations. Research by Toro et al. (2019) analyze the interplay of age and gender suggests that aging has a less pronounced effect on emissions among men than women, pointing to varying behavioral patterns across gender as they age. Additionally, Table 1 shows that female breadwinners had slightly higher levels of education compared to their male counterparts, potentially contributing to lower CO_2 emission considering that education could foster environmental awareness and sustainable practices (Zaman, et al., 2021).[10] Therefore, it is challenging to isolate the influence of the main breadwinner's gender on households' emissions levels without being influenced by other characteristics.

In other words, Table 1 reveals that, irrespectively of the year considered, FBH have higher polluting patterns for euro spent than MBH on average. But part of that difference could be attributed to other household characteristics apart from the gender of their main breadwinner. For example, it is expected that the size of the household or the household income affects the consumption basket making the GHG emissions to vary, and FBH present differences on these characteristics when compared to MBH —as Table 1 suggests. This should be accounted as an effect of these characteristics and not should be attributed as an effect of gender.

Therefore, a "treatment effect" problem is faced, which refer to the causal effect of a binary variable (female breadwinner and male breadwinner) on an outcome (emission patterns). 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 (Frölich and Sperlich, 2019).

One straightforward way of quantifying the effect of gender on emissions is through regression analysis, on which our variable of emissions is regressed on several observable characteristics –covariates–, including a dummy for the gender of the main breadwinner. The estimate of the coefficient on this dummy would be taken as the "gender effect". This approach can be problematic in our context, since regression analysis typically assumes that covariates are not correlated with the residual. However, if selection effects are present, the residual in the regression can be correlated with the independent variables, including our dummy for gender, producing an endogeneity problem.

In particular, a potential problem of selection bias could be present in our analysis, given that households with female breadwinners are not purely randomly observed, which produces results that not only show the effect of the female breadwinner itself, but also the effect of variables affecting the probability of being a breadwinner. In other words, a classical regression analysis is problematic in such a case.

The strategy proposed by Rosenbaum and Rubin (1983) suggesting the use of a propensity score (PS) is a natural way to address the problem. The application of this strategy to our problem allows for controlling both for differences in characteristics and selection bias by, roughly speaking, comparing FBH and MBH with identical observable characteristics. More technically, we rely on a nonexperimental evaluation method known as Propensity-Score Matching (PSM), which in recent years has become one of the preferred methods for estimating intervention impacts using comparison group data and has gradually replaced more traditional strategies as estimating regression equations. PSM, originally proposed in Rosenbaum and Rubin (1983), is a particular variant of the matching techniques that aim at matching individuals belonging to each one of the comparison groups, given they have similar observables. More specifically, PSM uses information from a pool of units that do not present the characteristic of interest —i.e., MBH— to identify what would have happened to the units that do present that characteristic —i.e., FBH— in the absence of it (Abadie and Imbens, 2006; Cattaneo, 2010; Abadie and Cattaneo, 2018).

The intuition of PSM is being as close as possible to a case on which randomized trials are the basis for evaluating the effect of certain treatment: when experimental designs are not possible, the assignment to treatment is usually non-random, since the units that receive it and those that do not receive it may differ also in other characteristics that affect both participation and the outcome of interest. Matching methods try to avoid the bias that this could generate by finding a nontreated unit as similar as possible to a participating unit, estimating the effect of interest as the difference in outcome between both units. Averaging across all the sampled units, these procedures produce estimates of the mean effect.[11]

The basic PSM formulation can be expressed as follows:

$$p(X) = Pr(W = 1 \mid X) = E(W \mid X) \tag{2}$$

where $W = \{0, 1\}$ is a binary indicator reflecting exposure to treatment and X is the multidimensional vector of characteristics. In our study, X is given by the logarithm of the annual household expenditure measured in euros, the household size expressed as the sum of all its members, the number of children living in the household, the age of the main breadwinner (and its square), the level of education of the main breadwinner (as a categorical variable that takes value 1 for primary education or less, 2 for secondary education, 3 for university education). To better classify between treatment and control groups, we have interacted the variables of education and household size with the log of household expenditure as well. Additionally, contextual variables that describe the environment on which the household lives are considered, in the form of regional dummies and a categorical variable that reflect the degree of urbanization of the municipality of residence (1 for high, 2 for medium and 3 for low population density).[12]

Two conditions are needed too properly apply PSM: (*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 available data provide a suitable problem to solve with a treatment effect considering the own characteristics of the database, where the results would make it possible to observe the differences in GHG emissions between households without biasing the results (see Annex C for more details).

4. Results and discussion

This section studies the differences in GHG emissions estimated applying the PSM estimator. GHG emissions —measured in kilograms of

[10] Given data limitations, an exhaustive analysis of emissions in recent periods is not possible. The 2022 HBS, nonetheless, corroborates the trends identified in Table 1 regarding household demographics characteristics. However, it reveals an interesting shift: in 2022, FBH on average spent approximately €97 more than MBH. Our analytical methodology should neutralize the influence of this differential in expenditure by matching households on several key characteristics, including spending levels, thus ensuring the comparison remains unaffected by the increased spending observed among households. (See Annex D for more details).

[11] In this section we have applied the psmatch command of Stata 16 software.

[12] Culture, religion, ethnicity, and other societal practices might have in shaping consumption patterns and their potential impact on our research outcomes. However, Spanish HBS does not encompass such information. This limitation is partially mitigated in the study by considering dummies to capture geographical (NUTS dummies) and rural-urban differences, which indirectly reflect aspects of culture and practice. On the other hand, HBS provides valuable insights into actual purchases made by different households. Purchasing decisions are influenced by a multitude of factors, including but not limited to religion, culture, ethnicity, and societal norms. Therefore, in a certain sense, the differences arising from these cultural and practice-related factors are already reflected in the observed purchasing patterns within the HBS data.

equivalent CO_2 per €1000 spent— include direct and indirect emissions embedded in households' consumption generated in 2008, 2014, and 2018.

Our analysis is implemented in two stages: first, we estimate the average effect of receiving the treatment of having a female breadwinner for each one of the years studied, to later apply the same PSM estimator to 12 COICOP categories, also including the detail for products related to direct household emissions derived from domestic energy use and private transport energy use 4.5: "Electricity, gas and other fuels" and 7.2: "Electricity, gas and other fuels."

Following this organization, Table 2 shows the results of the effect of FBH on total GHG emissions per €1000 embodied in consumption.

These results show the presence of a significant negative effect of FBH on GHG emissions patterns. Taking the average of 2008, 2014, and 2018, FBH emit approximately 12.5 kg less GHG for each €1000 spent than an "identical" MBH: when households with the same characteristics (expenditure level, education, age, number of adult members, number of children members, density, and region) are compared, FBH are significantly less emitters than MBH over the years.[13]

One natural question that might arise from these results is if the average treatment effects estimated for the emissions are distributed uniformly across products or if there is some heterogeneity. To answer this question, the previous analysis applying the PSM estimator is replicated for each one of the 12 COICOP categories, also considering products related to direct household emissions in 2008, 2014, and 2018.

Table 3 shows the results for the 12 COICOP categories with the disaggregation of the products related with emissions derived from domestic energy use and private transport energy use. The category 04: "Housing, gas, and other fuels" does not present significant differences between FBH and MBH, specifically the one related with domestic energy use 4.5: "Electricity, gas, and other fuels." Moreover, the category 7: "Transport" provides the largest differences and shows a significant negative average treatment effect for FBH. In other words, FBH emits on average across the three years studied, 13 kgs of equivalent CO_2 per €1000 spent in 07: "Transport" less than an equivalent MBH. Similar figures correspond to the category 7.2: "Operation of personal transport", being the product directly related with private transport energy use.

These findings align with reach by Räty and Carlsson-Kanyama (2010) and Toro et al. (2019), which identifies those predominant differences in energy consumption and emissions levels between individual women and men –measured considering one-person households– are produced by the consumption of private car use by male one-person households. However, in the category "Other transport," that includes 7.1: "Purchase of vehicles" and 7.3: "Transport services", we found an average treatment effect with a reverse sign, where FBH emit on average 2 kgs of equivalent CO_2 per €1000 spent more than MBH. This results, particular under the umbrella of 7.3: "Transport services", which includes emissions associated to the use of public transport services, such results are not surprising and in line with existing studies indicating a higher propensity for public transport usage among women (Prati, 2018; Goel et al., 2023).

Table 2
Estimate of the average treatment effect on greenhouse gas emissions patterns (in kilograms of equivalent CO_2 per €1000) of female breadwinner households. Spain 2008, 2014, 2018.

Average treatment effect of female breadwinner	Coefficient
2008	−13.808***
2014	−8366***
2018	−15,264***

Note: Propensity Score are estimated by means of a probit model.
Legend. *p < 0.1. **p < 0.05. **p < 0.01.
Source: Own elaboration

Table 3
Estimate of the average treatment effect on greenhouse gas emissions patterns (in kgs of equivalent CO_2 per €1000) of female breadwinner households by products categories. Spain 2008 , 2014, 2018.

Products categories	Average treatment effect of female breadwinner		
	2008	2014	2018
Food and non-alcoholic beverages	−1.785**	−0.366	−0.662
Alcoholic beverages and tobacco	−0.335***	−0.219***	−0.068***
Clothing and footwear	1.436***	0.563***	0.286***
Housing, gas, and other fuels	−0.252	1.046	1.033
Other households' maintenance	0.496*	0.289	0.428**
Electricity, gas, and other fuels	−0.748	0.757	0.605
Furniture, household equipment, etc.	0.139	0.144	0.109
Health	0.445***	0.183*	0.207**
Transport	−13.483***	−9.518***	−16.601***
Other transport	2.389***	1.777***	2.301***
Operation of personal transport equipment	−15.872***	−11.294***	−18.902***
Communications	0.335***	0.236***	0.172***
Recreation and culture	−0.123	−0.003	0.240
Education	0.060**	0.078***	0.072***
Restaurants and hotels	−2.161***	−1.373***	−1.876***
Miscellaneous goods and services	1.917***	0.862***	1.824***

Legend. *p < 0.1. **p < 0.05. ***p < 0.01.
Source: Own elaboration

Similar outcomes are found for emissions throughout the production chain to produce any other product such as in category 11: "Restaurant and hotels", which presents a significant negative average treatment effect for FBH when compared to equivalent MBH counterpart: FBHs emit on average along the years studied 1.8 kgs of equivalent CO_2 per €1000 spent in 11: "Restaurant and hotels" less than similar MBHs. These results corroborate existing research, which suggests that women are more likely to eat at home, while men eat out (Liebman et al., 2003). Finally, in categories such as 03: "Clothing and footwear", 12: "Miscellaneous goods and services", and 08: "Communications", FBHs produce significantly more emissions per €1000 than equivalent MBHs.

To better see changes across years, Fig. 1 complements results of Table 3 by facilitating a more comprehensive comparison. In Fig. 1, COICOP categories below the zero threshold (negative values) indicates that female breadwinner households tend to produce lower greenhouse gas emissions per 1000 euros spent, thereby suggesting less-polluting behaviors relative to their male counterparts. Conversely, categories above the zero threshold (positive values) imply that female breadwinner households are related with higher emission patterns than male breadwinner households.

Hence, the findings illustrate a distinct connection between individual preferences and household consumption patterns, depending on whether the household is led by a female or a male. Essentially, the emission levels of a household are significantly influenced by the gender of its primary earner.

5. Conclusions and policy implications

The results presented in the paper enrich the dialogue on the potential outcomes of increasing female participation in various domains, including workforce. Our results suggest that greater female participation also carries significant environmental implications. Expanding opportunities for women increase the proportion of FBH, which would affect different aspects of societies, including the adoption of household consumption patterns that are less GHG-intensive. This study

[13] The results were also verified using the Blinder-Oaxaca decomposition method, which yielded consistent findings with the main conclusions. The details of this supplementary analysis are available upon request.

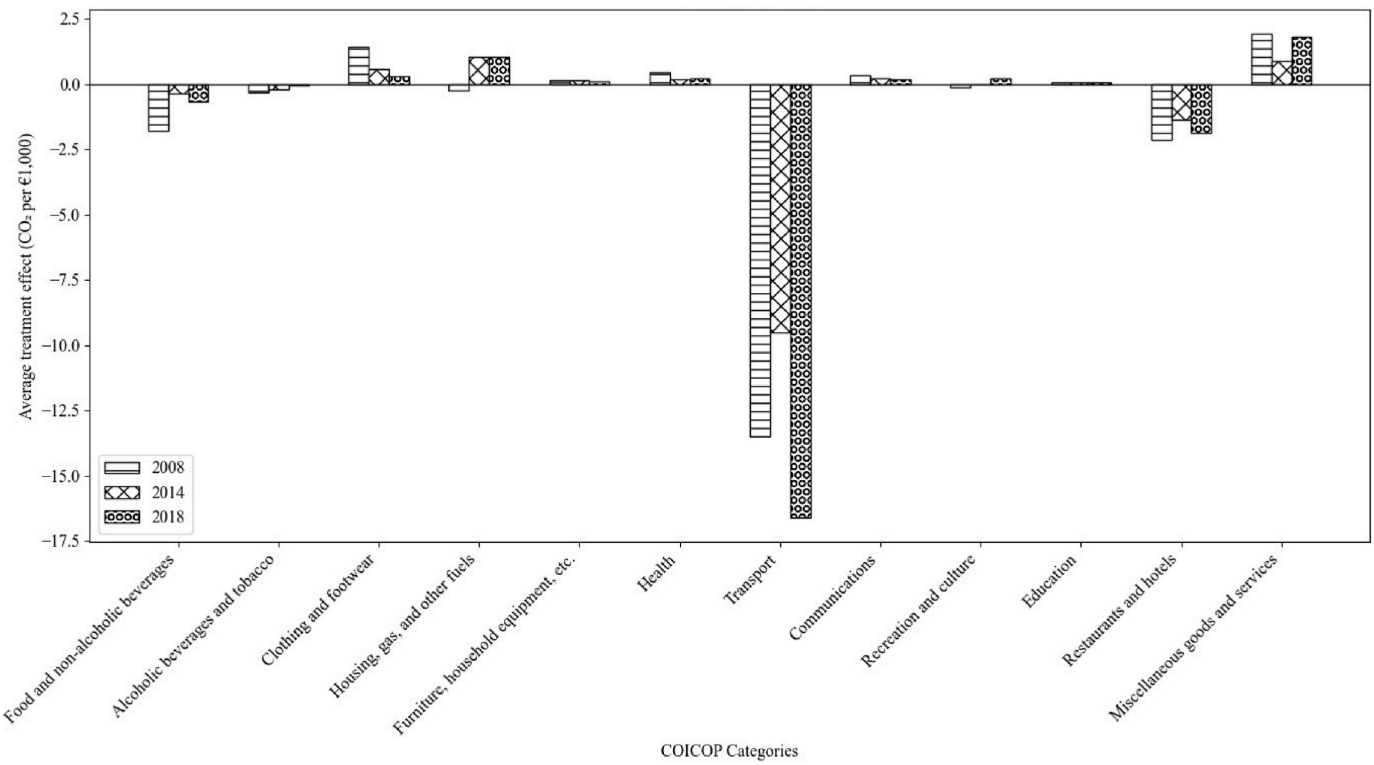

Fig. 1. Average treatment effect on greenhouse gas emissions patterns (in kgs of equivalent CO_2 per €1000) of female breadwinner households by products categories. Spain 2008, 2014, 2018.
Source: Own elaboration

contributes to the existing literature by collecting data and providing empirical evidence on the environmental effects produced by women's economic advancement, achieved through higher education and better job opportunities, impact household dynamics. This shift increases the prevalence of FBH, altering consumption behaviors and emissions.

Under this context, this work aims to answer the research question: are the GHG emissions embedded in the consumption pattern of FBH and MBH significantly different due to gender differences exclusively? The application of a PSM estimator combined with emissions dataset derived from 6 GHGs generated by consumption over the years 2008, 2014, and 2018 indicates that, averaging along the years, FBH produce 12 kgs of GHG emissions per €1000 less than MBH, being this difference directly attributed to gender issues. The analysis by product categories shows that (*i*) emission derived from domestic energy use do not exhibit significant difference between FBH and MBH, (*ii*) emission derived from private transport energy use are the main source of significant differences between FBH and MBH, aligning with previous studies (Räty and Carlsson-Kanyama, 2010; Toro et al., 2019), and (*iii*) emission derived from energy use vary across the production chain to produce any other products. For example, it is worth highlights that FBH contribute higher emissions per €1000 spent in certain categories such as "Clothing and footwear.". These findings reveal how gender socialization influences the environmental impact of family purchasing behaviors.

The findings presented hold significant policy implications in the context of current environmental and gender-focused initiatives such as the Sustainable Development Goals (SDGs) (UN, 2015). This works underscores the need of gender-disaggregated data on energy consumption and GHG emission to identify the specific needs, preferences, and behaviours of different groups of consumers. Such data is crucial for monitoring the effectiveness and social impact of policy measures. Looking at differences by product categories, the differences estimated between FBH and MBH provides valuable guidance to design effective environmental policies aimed at modifying certain consumption behaviors, such as public service announcements, health warnings and/or advertising aimed at encouraging more sustainable consumption patterns. Furthermore, in the context of fiscal instruments designed to influence consumer behaviour through pricing adjustment, understanding the demographic and economic implications is important for devising equitable strategies as fair as possible.

CRediT authorship contribution statement

Francisca Toro: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Esteban Fernández-Vázquez:** Writing – review & editing, Validation, Supervision, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Mònica Serrano:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by the Spanish Ministry of Science, Innovation, and Universities [RTI 2018-095484-B-I00; PID 2021-123129NB-C41; PID 2021-126295OB-I00].

We would like to express our sincere gratitude specially to the editor and the two anonymous reviewers, whose insightful comments and suggestions have significantly improved the quality and clarity of this research.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2024.114144.

References

Abadie, A., Imbens, G., 2006. Large sample properties of matching estimators for average treatment effects. Econometrica 74 (1), 235–267. https://doi.org/10.1111/j.1468-0262.2006.00655.x.

Abadie, A., Cattaneo, M., 2018. Econometric methods for program evaluation. Annual Review of Economics 10, 465–503. https://doi.org/10.1146/annurev-economics-080217-053402.

Ala-Mantila, S., Heinonen, J., Junnila, S., 2014. Relationship between urbanization, direct and indirect greenhouse gas emissions, and expenditure: a multivariate analysis. Ecol. Econ. 104, 129–139. https://doi.org/10.1016/j.ecolecon.2014.04.019.

Aldás, J., Solaz, M., 2017. Patrones de consumo de los hogares españoles: Evolución histórica [1973-2017] e impacto de la crisis de 2007. Fundación Ramón Areces, Madrid, España. https://www.ivie.es/es_ES/ptproyecto/patrones-consumo-los-hogares-espanoles-diferencias-sociodemograficas-e-impacto-la-crisis/.

Antman, F., 2014. Spousal employment and intra-households bargaining power. Appl. Econ. Lett. 21 (8), 560–563. https://doi.org/10.1080/13504851.2013.875101.

Bacharach, M., 1970. Biproportional Matrices in Input-Output Change. Cambridge University Press, p. 170. https://doi.org/10.2307/2343675.

Baiocchi, G., Minx, J., Hubacek, K., 2010. The impact of social factors and consumer behavior on carbon dioxide emissions in the United Kingdom. J. Ind. Ecol. 14, 50–72. https://doi.org/10.1111/j.1530-9290.2009.00216.x.

Baker, A., Wardle, J., 2003. Sex differences in fruit and vegetables intake in older adults. Appetite 40, 269–275. https://doi.org/10.1016/S0195-6663(03)00014-X.

Bianchi, S., Casper, L., Peltola, P., 1999. A cross-national look at married women's earnings dependency. Gend. Issues 17, 3–33. https://doi.org/10.1007/s12147-999-0001-0.

Bilouka, O., Utermohlen, V., 2000. Correlates of food consumption and perceptions of foods in and educated urban population in Ukraine. Food Qual. Prefer. 11, 475–485. https://doi.org/10.1016/S0950-3293(00)00020-3.

Bin, S., Dowlatabadi, H., 2005. Consumer lifestyle approach to US energy use and the related CO2 emissions. Energy Pol. 33 (2), 197–208. https://doi.org/10.1016/s0301-4215(03)00210-6.

Bloemen, H., Stancanelli, E., 2015. Toyboys or supergirls? An analysis of partners' employment outcomes when she outearns him. Rev. Econ. Househ. 13, 501–530. https://doi.org/10.1007/s11150-013-9212-y.

Bourguignon, F., Browning, M., Chiappori, P., Lechene, V., 1993. Intra household allocation of consumption: a model and some evidence from French data. Ann. Econ. Stat. 29, 137–156. https://doi.org/10.2307/20075899.

Bühler, M., Vullmer, L., Wimmer, J., 2023. Female education and social change. J. Econ. Growth. https://doi.org/10.1007/s10887-023-09232-w.

Cattaneo, M., 2010. Efficient semiparametric estimation of multi-valued treatment effects under ignorability. J. Econom. 155, 138–154. https://doi.org/10.1016/j.jeconom.2009.09.023.

Cazcarro, I., Amores, A., Arto, I., Kratena, K., 2020. Linking multisectoral economics models and consumption surveys for the European Union. Econ. Syst. Res. 34 (1), 22–40. https://doi.org/10.1080/09535314.2020.1856044.

Chancel, L., 2014. Are younger generations higher carbon emitters than their elders?: inequalities, generations and CO_2 emissions in France and in the USA. Ecol. Econ. 100, 195–207. https://doi.org/10.1016/j.ecolecon.2014.02.009.

Denmark Statistik, 2019. Input-output. Date accessed: July 2019) Available: https://www.dst.dk/en/Statistik/emner/oekonomi/nationalregnskab/input-output. .

Duarte, R., Sarasa, C., Serrano, M., 2019. Structural change and female participation in recent economic growth: a multisectoral analysis for the Spanish economy. Econ. Syst. Res. 31 (4), 574–593. https://doi.org/10.1080/09535314.2019.1589425.

Duarte, R., Miranda-Buetas, S., Sarasa, C., 2021. Household consumption patterns and income inequality in EU countries: Scenario analysis for a fair transition towards low-carbon economies. Energy Econ. 104, 105614 https://doi.org/10.1016/j.eneco.2021.105614.

Dubois, G., Sovacool, B., Aall, C., Nilsson, M., Barbier, C., Herrmann, A., Bruyère, S., Andersson, C., Skold, B., Nadaud, F., Dorner, F., Richardsen Moberg, K., Ceron, J.P., Fischer, H., Amelung, D., Baltruszewicz, M., Fischer, J., Benevise, F., Louis, V., Sauerborn, R., 2019. It starts at home? Climate policies targeting household consumption and behavioral decisions are key to low-carbon futures. Energy Res. Social Sci. 52, 144–158. https://doi.org/10.1016/j.erss.2019.02.001.

Duncan, T., 1990. Intra household resources allocation: an inferential approach. J. Hum. Resour. 25 (4), 635–664. https://doi.org/10.2307/145670.

Eriksson, F.A., Owen, A., Malhi, Y., 2021. Net national metabolism as a fine-scale metric of energetic biophysical size in an industrialised country. The Anthropocene Review 00 (0), 1–21. https://doi.org/10.1177/20530196211038658.

Eurostat, 1996. European System of Accounts: ESA 1995. Publications Office of the European Union, Luxembourg. Available: https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ca-15-96-001.

Eurostat, 2008. Manual of Supply, Use and Input-Output Tables. Publications Office of the European Union, Luxembourg. Available: https://ec.europa.eu/eurostat/documents/3859598/5902113/KS-RA-07-013-EN.PDF/b0b3d71e-3930-4442-94be-70b36cea9b39.

Frölich, M., Sperlich, S., 2019. Impact Evaluation: Treatment Effect and Causal Analysis. Cambridge University Press, New York, USA. www.cambridge.org/9781107042469.

Greene-Finestone, L., Campbell, M.K., Gutmanis, I., Evers, S., 2005. Dietary intake among young adolescents in Ontario: Associations with vegetarian status and attitude toward health. Prev. Med. 40 (1), 105–111. https://doi.org/10.1016/j.ypmed.2004.05.009.

Goel, R., Oyebode, O., Foley, L., Tatah, L., Millet, C., Woodcock, J., 2023. Gender differences in active travel in major cities across the world. Transportation 50, 733–749. https://doi.org/10.1007/s11116-021-10259-4.

Golan, A., Judge, G., Robinson, S., 1994. Recovering information from incomplete or partial multisectoral economic data. Rev. Econ. Stat. 76 (3), 541–549. https://doi.org/10.2307/2109978.

Herendeen, R., Tanaka, J., 1976. Energy cost of living. Energy 1, 165–178. https://doi.org/10.1016/0360-5442(76)90015-3.

INE, Instituto Nacional de Estadística, 2019a. Contabilidad nacional anual de España: Tablas de Origen y Destino. https://ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177059&menu=resultados&idp=1254735576581.

INE, Instituto Nacional de Estadística, 2019b. Cuentas ambientales: Cuentas de emisiones a la atmósfera. https://ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176941&menu=ultiDatos&idp=1254735976603.

INE, Instituto Nacional de Estadística, 2019c. Nivel y condiciones de vida: Encuesta de presupuestos familiares. https://ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176806&menu=ultiDatos&idp=1254735976608.

INE, Instituto Nacional de Estadística, 2024. Distribución según sexo y edad del sustentador principal. https://www.ine.es/jaxiT3/Tabla.htm?t=24982&L=0.

Jiang, L., Yu, L., Xue, B., Chen, X., Mi, Z., 2020. Who is energy poor? Evidence from the least developed regions in China. Energy Pol. 137, 111122 https://doi.org/10.1016/j.enpol.2019.111122.

Johnson-Latham, G., 2007. A Study on Gender Equality as a Prerequisite for Sustainable Development. Report to the Environmental Advisory Council. Swedish. https://api.semanticscholar.org/CorpusID:132460829.

Jones, C., Kammen, D., 2011. Quantifying carbon footprint reduction opportunities for U.S households and communities. Environmental Science & Technology 45 (9), 4088–4095. https://doi.org/10.1021/es102221h.

Kaenzig, J., Heinzle, S.L., Wüstenhagen, R., 2013. Whatever the customer wants, the customer gets? Exploring the gap between consumer preferences and default electricity products in Germany. Energy Pol. 53, 311–322. https://doi.org/10.1016/j.enpol.2012.10.061.

Khan, N., Trivedi, P., 2015. Gender differences and sustainable consumption behavior. British Journal of Marketing Studies 3 (3), 29–35. https://www.eajournals.org/wp-content/uploads/Gender-Differences-and-Sustainable-Consumption-Behavior.pdf.

Klesment, M., Van Bavel, J., 2017. The reversal of the gender gap in education, motherhood, and women as main earners in Europe. Eur. Socio Rev. 33 (3), 465–481. https://doi.org/10.1093/esr/jcw063.

Kowalewska, H., Vitali, A., 2021. Breadwinning or on the breadline? Female breadwinners' economic characteristics across 20 welfare states. J. Eur. Soc. Pol. 31 (2), 125–142. https://doi.org/10.1177/0958928720971094.

Lenzen, M., Wier, M., Cohen, C., Hayami, H., Pachauri, S., Schaeffer, R., 2006. A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan. Energy 31, 181–207. https://doi.org/10.1016/j.energy.2005.01.009.

Liebman, M., Propst, K., Moore, S., Pelican, S., Holmes, B., Wardlaw, M., Melcher, L., Harker, J., Denne, P., Dunnagan, T., 2003. Gender differences in selected dietary intakes and eating behaviors in rural communities in Wyoming, Montana, and Idaho. Nutr. Res. 23, 991–1002. https://doi.org/10.1016/S0271-5317(03)00080-0.

Long, Y., Jiang, Y., Chen, P., Yoshida, Y., Sharifi, A., Gasparatos, A., Wu, Y., Kanemoto, K., Shigetomi, Y., Guan, D., 2021. Monthly direct and indirect greenhouse gases emissions from household consumption in the major Japanese cities. Sci. Data 8 (1). https://doi.org/10.1038/s41597-021-01086-4, 301-01.

Malinowski, M., Jabłońska-Porzuczek, L., 2020. Female activity and education levels in selected European Union Countries. Res. Econ. 74 (2), 153–173. https://doi.org/10.1016/j.rie.2020.04.002.

Maraseni, T.N., Qu, J., Zeng, J., 2015. A comparison of trends and magnitudes of households carbon emissions between China, Canada and UK. Environmental Development 15, 103–119. https://doi.org/10.1016/j.envdev.2015.04.001.

Munksgaard, J., Alsted Pedersen, K., Wien, M., 2000. Impact of household consumption on CO_2 emissions. Energy Econ. 22 (4), 423–440. https://doi.org/10.1016/s0140-9883(99)00033-x.

O'Neil, B., MacKellar, L., Lutz, W., 2001. Population and Climate Change. Cambridge University Press, Cambridge, UK, pp. 137–139. ECSP Report (9). https://assets.cambridge.org/97805210/18029/frontmatter/9780521018029_frontmatter.pdf.

Pachauri, S., Spreng, D., 2002. Direct and indirect energy requirements of households in India. Energy Pol. 30 (6), 511–523. https://doi.org/10.1016/s0301-4215(01)00119-7.

Prati, G., 2018. Gender equality and women's participation in transport cycling. J. Transport Geogr. 66, 369–375. https://doi.org/10.1016/j.jtrangeo.2017.11.003.

Raley, S., Mattingly, M., Bianchi, S., 2006. How dual are dual-income couples? Documenting change from 1970 to 2001. J. Marriage Fam. 68, 11–28. https://doi.org/10.1111/j.1741-3737.2006.00230.x.

Räty, R., Carlsson-Kanyama, A., 2010. Energy consumption by gender in some European countries. Energy Pol. 38, 646–649. https://doi.org/10.1016/j.enpol.2009.08.010.

Reinders, A.H.M.E., Vringer, K., Blok, K., 2003. The direct and indirect energy requirement of households in the European Union. Energy Pol. 31 (2), 139–153. https://doi.org/10.1016/s0301-4215(02)00019-8.

Rippon, G., 2019. Gender and Our Brains: How New Neuroscience Explode the Myths of the Male and Female Minds. Vintage, New York, US.

Roca, J., Serrano, M., 2007. Income growth and atmospheric pollution in Spain: an input-output approach. Ecol. Econ. 63, 230–242. https://doi.org/10.1016/j.ecolecon.2006.11.012.

Rosenbaum, P., Rubin, D., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70 (1), 41–55. https://doi.org/10.1093/biomet/70.1.41.

Schultz, P., 1990. Testing the neoclassical model of family labor supply and fertility. J. Hum. Resour. 25 (4), 599–634. https://doi.org/10.2307/145669.

Serrano, M., Duarte, R., Sarasa, C., 2020. More female employment than ever, but the gender gap persists. The Social Observatory. la Caixa" Foundation. https://elobservatoriosocial.fundacionlacaixa.org/en/-/more-female-employment-than-ever-but-the-gender-gap-persists.

Spanish Ministry of Labor and Social Economy, 2021. La situación de las mujeres en el mercado de trabajo 2021. Gobierno de España. Ministerio de trabajo y economía social. Date accessed: July 2022) Available: https://www.mites.gob.es/ficheros/ministerio/sec_trabajo/analisis_mercado_trabajo/situacion-mujeres/Mujeres-y-Mercado-de-Trabajo-2021.pdf.

Stone, R., 1962. Multiple classifications in social accounting. Bulletin de l'Institut International de Statistique. 39, 215–233.

Tifferet, S., Herstein, R., 2012. Gender differences in brand commitment, impulse buyin, and hedonic consumption. J. Prod. Brand Manag. 21 (3), 176–182. https://doi.org/10.1108/10610421211228793.

Toro, F., Serrano, M., Guillem, M., 2019. Who pollutes more? Gender differences in consumptions patterns. In: Research Institute of Applied Economics. Working Paper 2019/06, IR19/06. 48 Pp. University of Barcelona. http://hdl.handle.net/2445/131971.

United Nations, 1999. Handbook of Input-Output Table Compilation and Analysis. United Nations Publication, New York, USA. https://digitallibrary.un.org/record/370160?ln=en.

Vitaly and Arpino, 2016. Who brings home the bacon? The influence of context on partners' contribution to the household income. Demogr. Res. 35 (41), 1213–1244. https://doi.org/10.4054/DemRes.2016.35.41.

Vitali, A., Mendola, D., 2014. Women as main earners in Europe. SSRN Electron. J. https://doi.org/10.2139/ssrn.2555172.

Vringer, K., Blok, K., 1995. The direct and indirect energy requirements of households in The Netherlands. Energy Pol. 23 (10), 893–905. https://doi.org/10.1016/0301-4215(95)00072-q.

Wang, W., Parker, K., Taylor, P., 2014. Breadwinner Moms. Pew Research Center, Washington, D.C. https://www.pewresearch.org/social-trends/2013/05/29/breadwinner-moms/.

Wansink, B., Cheney, M., Chan, N., 2003. Exploring comfort food preferences across age and gender. Physiol. Behav. 79, 739–747. https://doi.org/10.1016/S0031-9384(03)00203-8.

Winkler, A., McBride, T., Andrews, C., 2005. Wives who outearn their husbands: a transitory or persistent phenomenon for couples? Demography 42 (3), 523–535. https://doi.org/10.1353/dem.2005.0028.

Wooden, M., Hahn, M., 2014. Female breadwinner families. Families, Incomes and Jobs 9 (57), 57–60. http://www.ncsehe.edu.au/wp-content/uploads/2014/06/Families-Incomes-and-Jobs-Vol-9.pdf#page=66.

Yaccato, J., Jaeger, J., 2003. The 80% Minority Reaching the Real World of Women Consumers. Viking Canada, Toronto, Canada. https://books.google.es/books?id=8foJAQAAMAAJ.

Yu, L., Wu, S., Jiang, L., Ding, B., Shi, X., 2022. Do more efficient buildings lead to lower household energy consumption for cooling? Evidence from Guangzhou, China. Energy Pol. 168, 113119 https://doi.org/10.1016/j.enpol.2022.113119.

Zaman, Q., Wang, Z., Zaman, S., Rasool, S.F., 2021. Investigating the nexus between education expenditure, female employers, renewable energy consumption and CO2 emission: evidence from China. J. Clean. Prod. 312, 127824 https://doi.org/10.1016/j.jclepro.2021.127824.

Zhou, K., Yang, S., 2016. Understanding household energy consumption behaviour: the contribution of energy big data analytics. Renewable and Sustainable Energy Review 56, 810–819. https://doi.org/10.1016/j.rser.2015.12.001.

Further reading

Busso, M., DiNardo, J., McCrary, J., 2014. New evidence on the finite sample properties of propensity score reweighting and matching estimators. Rev. Econ. Stat. 96 (5), 885–897. https://doi.org/10.1162/REST_a_00431.