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Creating Opportunities

Economics of Climate Change and Big Data

The Spanish Households' Carbon Footprint Inequality in High Definition & Real Time

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Takeaways

- We present the results of the Environmental Distributional Accounts for Greenhouse Gas Emissions (GHG) for Spanish Households combining a Standard Input-Output approach and a novel rich BigData database based on financial transactions.
- A notable inequality exists in CO2 emissions, which is closely aligned with consumption but tends to be lower compared to income. The primary contributor to emissions inequality is the higher consumption of transport among affluent individuals. In contrast, housing CO2 emissions by households (including shelter services and energy utilities) demonstrates a more balanced distribution, with relatively higher consumption and GHG emissions utilization observed in the lower percentiles of consumption.
- There is also inequality in CO2 emissions when examined through the lenses of age and gender. In general, emissions tend to exhibit an inverted "U" pattern with respect to age, with males exhibiting higher levels of pollution compared to females.
- The high granularity of the distributional emission data opens the door to the design of smarter policies (i.e addressed where more needed and/or more effective).
- The approach also delivers Consumption emissions in real time. The data from 2022 and 2023 shows that the adjustment effect by Covid-19 in 2020 is already over.
- There were important divergences during Covid-19: while CO2 emissions from activities affected by lockdowns (i.e transport) adjusted rapidly, other emissions as the ones coming from Food proved to be more resilient.

1. Motivation

The Earth's climate is changing faster as a result of human activities. The latest IPCC's report concludes (with high confidence) that emissions of greenhouse gases from human activities are responsible for 1.1°C of warming since 1850-1900, a human-caused climate change that “has led to widespread adverse impacts and related losses and damages to nature and people”. The best estimate of reaching 1.5°C in the near term will intensify multiple and concurrent hazards.

Consumption patterns are key for mitigating climate change. By making more sustainable consumption choices, individuals can help to reduce the negative impacts of their actions on the environment and support the transition to a more sustainable future. Household consumption is the largest component of demand, nearly 55% of Spain's GDP in 2022. Households' CO2 emissions, both directly and indirectly generated, represent between 60% and 70% of the total emissions (Hertwich and Peters, 2009, Hertwich et al., 2016a).

Consumption, inequality, GHG emissions and policies to tackle it. A defining feature of consumption is its very unequal distribution among individuals according to their disposable income and lifestyles. Also, environmental policies need to incorporate inequality considerations given their uneven impacts (see Climate Inequality Report 2023[1]). Furthermore, the multiple policy options to tackle environmental sustainability, with different political, economic and social implications within countries, call for having better and more granular measures of GHG emissions, especially for individuals.

2. Estimating the Direct & Indirect Greenhouse Gas Emissions (GHG) of Spanish Households[2]

We present a new hybrid approach to estimate Greenhouse Gas (GHG) Emissions generated by Spanish households through their consumption demand. This approach combines the emission intensity coefficients of the different Consumption by Purpose (COICOP) categories estimated through the Input-Output analysis (IO), and our novel BigData consumption database for the Spanish Economy (Buda et al.,2022) offering some advantages:

- **Macro Consistency:** Leveraging the standard Macro (IO) Approach, we are able to obtain coefficients with sectoral granularity that reveal the amount of GHG emissions required to meet one additional unit of (consumption) demand. These coefficients are then aggregated by COICOP categories and applied to proprietary Big Data household consumption values, which have been demonstrated to be consistent with the official household consumption data as shown in Buda et al. (2022).

- **Direct and Indirect Emissions:** Our methodology enables us to capture both Direct Emissions, which are emitted by individuals through activities such as private car use or energy utilities with combustion at home (provided by official statistics office), as well as Indirect Emissions, which are embedded in the consumption of goods and services by individuals and estimated through the IO methodology. These indirect emissions arise from various sources, such as the production of a T-shirt, food consumed in a restaurant, home cleaning products, electronic products, or the manufacturing process of a car, among others, and are ultimately the

1: Chancel, L., Bothe, P., Voituriez, T. (2023) Climate Inequality Report 2023, World Inequality Lab Study 2023
2: This Economic Watch is based on our forthcoming work Barrutiabengoa et al. (2023) Distributional Accounts of Households´s Carbon Footprint from Financial Transaction data (Mimeo).

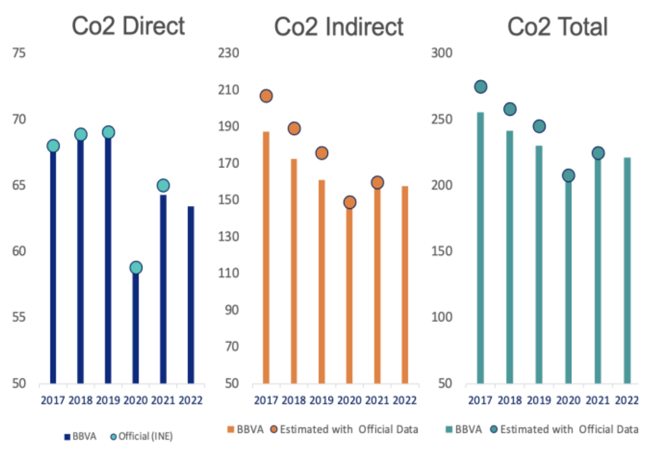
result of household consumption decisions[3]. To obtain the total emission footprint of household consumption, these indirect emissions need to be added to the direct emissions.

- **Distributional Emissions Accounts and GHG Emissions in Real Time:** The Big Data consumer expenditure database, updated in real time, provides a comprehensive distribution of consumption and its categories (COICOP) at various consumption levels. By multiplying these data with the GHG coefficients per COICOP, we are able to estimate emissions distributed according to different demographic characteristics, such as age, gender, etc[4]. This integrated approach allows for the estimation of GHG emissions in real time, with high granularity, providing a deeper understanding of how Spanish household consumption contributes to GHG emissions at different levels and moments.

2.1 Measuring the CO2 Footprint of Households: Aggregates and Categories

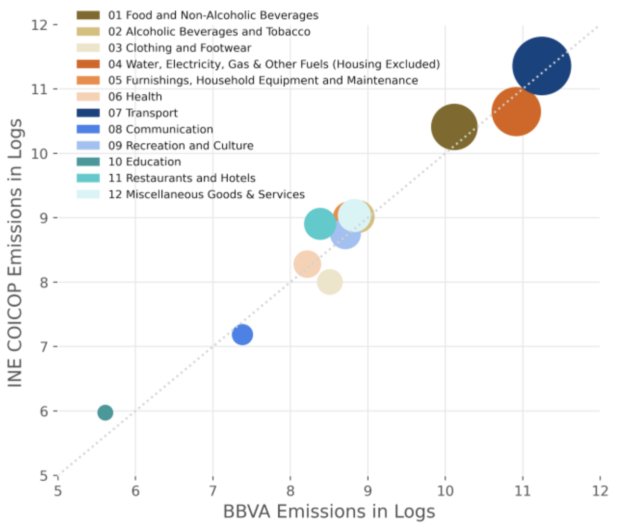
The following graphs illustrate several advantages of our methodology, including the close alignment of direct emissions between BBVA and Official data, the ability to estimate emissions for 2022 by incorporating indirect emissions (which account for 70% of the total), and the cross-consistency by categories.

Figure 1. **SPAIN: CO2 EMISSIONS, 2017-2022.** (EMISSION IN MILLION TNS.)



Source: BBVA Research based on Buda et al. (2022), BBVA Research and INE.

Figure 2. **EMISSIONS BY CATEGORY 2020** (BBVA VS INE) (LOGS OF MILLION TNS)



Source: BBVA Research based on Buda et al. (2022), BBVA Research and INE.

3: GHG emissions can be understood as an economic input under the framework of origin and destination, sources and uses. The sum of the emissions generated directly by households, those produced by companies resident in a country and those incorporated in the imports of goods and services, are the resources (the origin) to meet the different demands (destinations) including public and private consumption, investment and exports. An extended households' carbon footprint should include not only direct emissions but also those emissions embodied in the different goods and services, produced in the country or imported, that households enjoy as consumers. The Input Output analysis, provides the amount of emissions needed to meet demand, for instance from Household Consumption.
4: Trendl et al (2023) find for the case of the UK that financial transactions offer a credible alternative to survey-based sources and, if made more widely accessible, could provide important advantages for profiling emissions. These include objective, micro-level data on consumption behaviors, larger sample sizes, and longitudinal, frequent data capture.

Figure 1 presents a comparison of annual CO_2 Direct Emissions, the indirect emissions, and the total emissions estimated using our methodology, alongside the official estimates based on Input-Output and COICOP consumption categories. All emissions are estimated using dynamic energy-intensive coefficients for the period from 2017 to 2020, with constant 2020 ratios used for 2020 onwards. In our case, we also provide estimations for 2022, as the official estimates for 2022 are not yet available.

- **The evolution of our CO_2 Direct emissions and the official emissions is remarkably similar. This is expected for the first four years** as we use the official emissions data and redistribute them to obtain the direct emission intensity ratios, which are then multiplied by consumption. However, our estimations for the subsequent year, 2021, also show an important similarity and we also provide an estimate for 2022 (not yet available officially). Our estimations reveal a post-COVID rebound of CO_2 emissions in 2021 (consistent with the official information), followed by a moderation in 2022[5].

- **More importantly, our estimates also include CO_2 Indirect emissions, which are highly relevant as they account for 70% of the total emissions.** These estimates are fairly accurate, especially during 2020 and 2021, with a near-perfect match (0.5% and 0.4% error, respectively). For the years 2017 to 2019, the error is slightly higher (around 8%). The accuracy of our estimates is further supported by the high and robust consistency across emission categories[6]. Figure 2 illustrates how closely the levels of emissions by consumption categories align between our estimations and the official ones. The relationship is nearly linear, with small differences in COICOP categories balancing out. For instance, a slight overvaluation in Energy utilities is compensated by a slight undervaluation in the food category. Moreover, important emission categories, such as transport, show close alignment between the alternative databases.

3. Spanish Emission Inequality: Household Emissions in High Definition

Since the seminal work of Piketty et al. (2018), the literature of “Inequality” has expanded rapidly from income to other issues including climate change and the GHG emissions footprint. Most of the GHG inequality literature, including the work by Chancel and Piketty (2012) has addressed the issue of inequality on Carbon Footprint through the analysis of the income distributional accounts. The key reason for this indirect approach -applying energy income elasticities rather than computing directly from consumption- is the lack of consumption distributional accounts and the fact that numerous country income tables have been already developed (see the WID and the recent GRID Project).

However, and as many of these authors have signaled, this strategy has some problems. First, the GHG emissions are not produced by income, but rather by production or consumption (directly or indirectly). Second, some uncertainty about estimates of these elasticities remain. The heterogeneity between countries, activities or different income groups could lead to important errors in the estimation without reliable elasticities[7].

5: The estimation for 2022 may be biased due to the fact that technical emission coefficients may have changed as a result of the war between Ukraine and Russia, especially in the utilities sector.
6: We extend the robustness analysis in appendix 2.
7: The pioneer work by Chancel and Piketty (2015) recognizes this and uses several elasticity values from 0.6 to 1.5 in order to account for different forms of the CO_2e-income relationship. Moreover, in the case of Chakravarty et al. (2009), for 17 countries and time periods, elasticities range from 0.4 to 1 for energy and from 0.6 to 1 for CO_2e, with most results in the 0.8-1 range. Nevertheless, as reminded by Lenzen et al. (2006) there is no “one fits all” value for elasticity, which varies from country to country and over time.

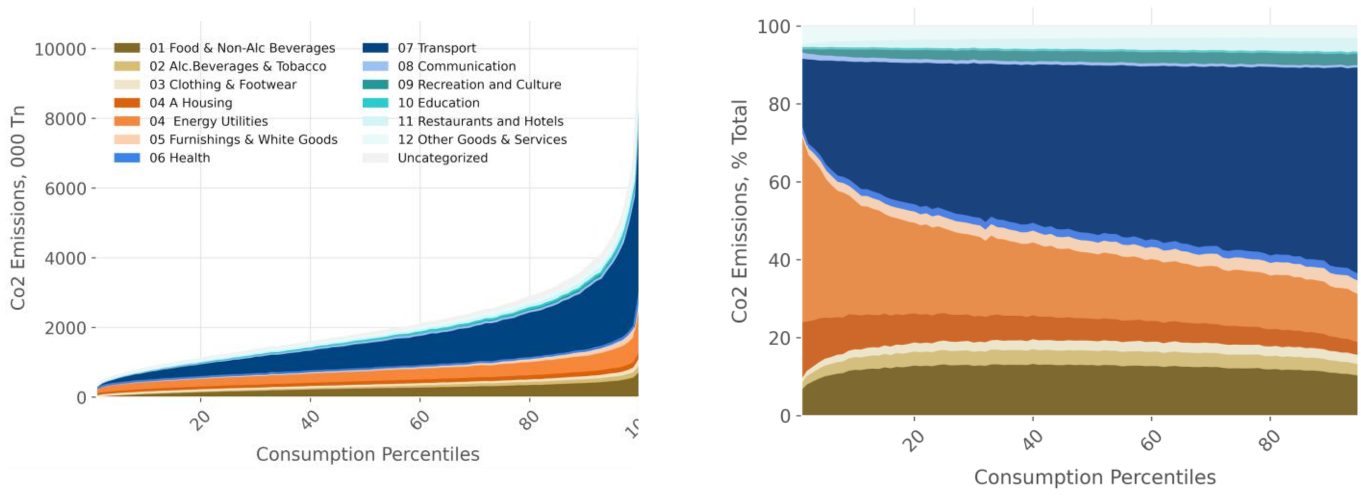
3.1 The Distributions Accounts of CO2 emissions

Fortunately, our novel approach of Distributional Consumption Accounts for Spanish Households (Buda et al., 2022) enables us to directly estimate emissions inequality by combining distributional consumption accounts with consumption-based GHG intensities calculated in the Input-Output framework. Figures 3 and 4, as well as Table 1, illustrate the distribution of CO2 emissions by consumption percentile, both in terms of CO2 tons and as a percentage of total CO2 emissions. Additionally, traditional inequality measures are calculated and presented in the results.

- **The analysis of CO2 emissions by categories and percentiles in 2021 highlights an unequal distribution.** The degree of inequality increases significantly from the 80th percentile onwards, with the top 10% of polluters being responsible for almost 24% of the CO2 emissions (as shown in Table 1), while the bottom 50% account for 29% of emissions.

- **The inequality in the Spanish Carbon Footprint is consistent with findings from existing literature[8] and reflects a global phenomenon.** The recent Climate Inequality Report[9] reveals that the top 10% of global carbon emitters generate nearly half (47%) of all greenhouse gas emissions, which aligns with the findings of the Oxfam report published in 2020. Furthermore, Chancel (2022) demonstrates that the top 10% of polluters are responsible for approximately 30% and 33% of emissions in Europe and North America, respectively.

Figure 3. **CO2 EMISSIONS: LEVELS & SHARE** (%)
CO2 EMISSIONS BY COICOP CATEGORY (IN %) AND CONSUMPTION PERCENTILES. 2021



Source: BBVA Research based on Buda et al. (2022), BBVA Research and INE.

8: A general result of the literature is that the CO2 Emissions by households are highly unequal. This is result is share either by works using a functional relationship between income and aggregate national consumption emissions (Chancel & Piketty, 2015; Otto et al., 2019; Wiedenhofer et al., 2016) or similar Input-Output models relying on Consumer Surveys (Ivanova and Wood (2020), rather than Consumption BigData.
9: See Climate Inequality Report (2023) and the Oxfam (2020) 'Confronting Carbon Inequality (Chancel 2023) report.

- **The inequality in Spanish household CO_2 emissions is found to be in line with household consumption, but significantly lower than income**[10]. The Gini coefficient for households' CO_2 emissions is 0.32, which indicates a less unequal distribution compared to income (Gini coefficient of 0.42) but slightly higher than household private consumption (Gini coefficient of 0.30). However, despite this, a significant level of CO_2 emissions inequality still persists. The top 10% of CO_2 polluters are responsible for approximately 25%[11] of the CO_2 emissions, while the lowest 50% of emitters account for less than a third of the emissions. Moreover, the CO_2 footprint of households in the top 10% of the emission distribution is more than seven times that of households in the bottom decile, underscoring the substantial disparity in emissions among different consumption groups.

- **The primary source of household CO_2 emissions inequality in Spain stems from transportation.** These emissions, depicted in dark blue on the graph, are highly concentrated in the upper part of the distribution and exhibit a sharp increase as we move towards higher percentiles. The top 10 percentile of emitters is responsible for nearly 30% of the total transport CO_2 emissions, and the p90/10 ratio, which measures the ratio between the emissions of the top 90% and the bottom 10%, reaches 16.6, indicating a significant disparity. Transport-related CO_2 emissions constitute a substantial share of the total households' emissions (nearly 40%) and exhibit a high level of inequality, as indicated by a Gini coefficient of 0.39, as shown in Figure 4. Previous research has well-documented the contribution of individuals with higher socioeconomic status to this inequality, with a significant portion of it associated with different modes of transportation. For instance, while the top 10% of consumers are responsible for almost 30% of transport emissions, this share can increase notably in certain means of transportation such as air travel, further exacerbating the inequality in CO_2 emissions from transportation[12].

- **The distribution of CO_2 emissions from housing and energy utilities is relatively balanced,** with emissions from shelter (accounting for nearly 25% of total households' CO_2 emissions) such as housing exhibiting a Gini coefficient of 0.13, and emissions from energy utilities like water, gas, and electricity showing a Gini coefficient of 0.17. These emissions are evenly spread across consumption percentiles, with the bottom 50% of emitters responsible for nearly 40% of the total emissions, and the ratio of p90/p10 falling between two and three, indicating a relatively moderate level of inequality in this category.

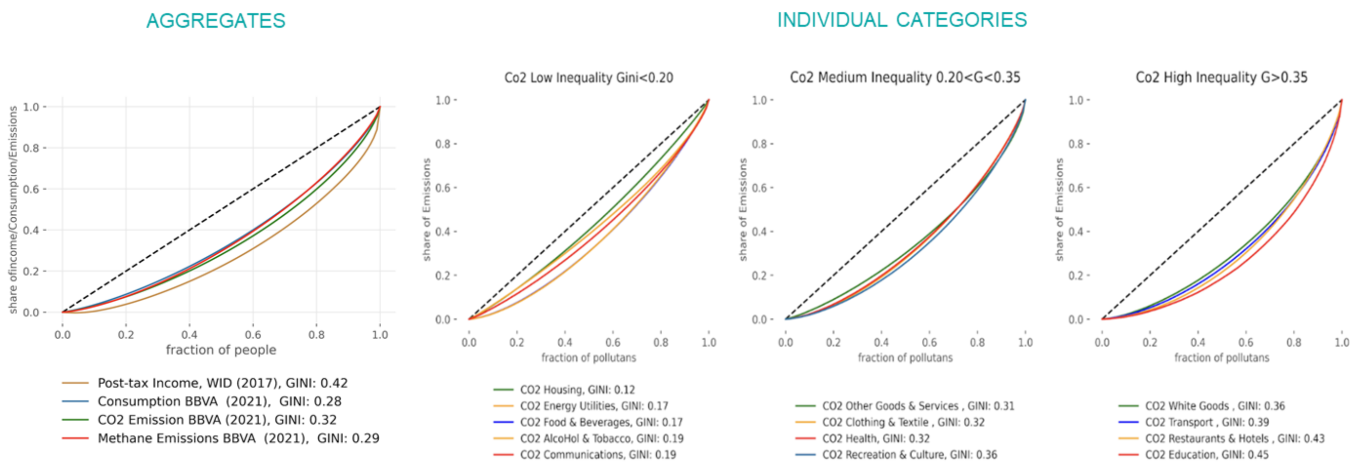
- **The contrasting pattern of CO_2 emissions between transport and housing-related consumption has significant implications for designing policies for transitioning to a more sustainable economy.** Reducing transport emissions is likely to involve higher costs for the higher percentiles of consumption-pollution, as emissions in this category are concentrated in the upper part of the distribution. On the other hand, reducing emissions from housing and energy utilities will primarily impact the lower percentiles of consumption, potentially resulting in a higher relative cost for the poorer segments of the population. This disparity in cost distribution underscores the importance of considering equity and social implications in policy measures aimed at addressing emissions and promoting sustainability.

- **The inequality of indirect emissions is slightly lower than that of direct emissions.** It is notable that some emission categories, such as Food & Beverage (Gini: 0.27), Alcohol & Tobacco (Gini: 0.27), and Communications (Gini: 0.21), exhibit relatively egalitarian distribution patterns. In contrast, emissions

10: Note that only private consumption is taken into account, which can be relevant in Education or Health, where public consumption has also an important weight.
11: This result is in line for those from Ummel (2014) for the US and GHG emissions: Who Pollutes? A Household-Level Database of America's Greenhouse Gas Footprint.
12: There is a huge divergence in terms of energy intensity and emissions and its inequality by transport means and even between means. According to the intensity coefficients the air transport remains the most pollutant transport by far, followed by car, train and ferries. Moreover, it is important to distinguish the type of cars or even the class of the air trip We explore this issue in our forthcoming working paper (Barrutiabengoa et al., 2023).

associated with durable goods like furnishing (i.e., white goods) and maintenance (Gini: 0.36) and other goods and services, such as insurance and financial services (Gini: 0.30), tend to be more unequally distributed. Additionally, there are sectors characterized by higher levels of emissions inequality, particularly in luxury services like recreation and culture (Gini: 0.35) and Restaurants and Hotels (Gini: 0.41). These findings highlight the varying degrees of inequality across different emission categories, suggesting the need for targeted policies and interventions that take into account the specific characteristics of each sector to address emissions disparities effectively.

Figure 4. **CO2 EMISSIONS, 2021: LORENZ CURVES AND GINI COEFFICIENTS** (%)



Source: BBVA Research based on Buda et al. (2022), BBVA Research and INE.

Table 1. **CO2 EMISSIONS, 2021: INEQUALITY RATIOS**

	CO2	Methane	CO_Direct	CO_Indirect	Coicop 1	Coicop 2	Coicop 3	Coicop 4	Coicop 5	Coicop 6	Coicop 7	Coicop 8	Coicop 9	Coicop 10	Coicop 11	Coicop 12	Coicop 13
Emissions (000Tn)	215401	32430	66311	149089	23243	6761	4955	10104	33043	6577	3896	94744	1547	6471	323	6199	7176
Average per Household (kg)	114.9	17.29	35	79	12.4	3.6	2.6	5.4	17.6	3.5	2.1	50.5	0.8	3.5	0.2	3.3	3.8
Average Per person (kg)	45.5	6.9	14	31	4.9	1.4	1.0	2.1	7.0	1.4	0.8	20.0	0.3	1.4	0.1	1.3	1.5
% Total Emissions of Gas	100.0%	100.0%	30.8%	69.2%	10.8%	3.1%	2.3%	4.7%	15.3%	3.1%	1.8%	44.0%	0.7%	3.0%	0.1%	2.9%	3.3%
Gini Coefficient	0.32	0.29	0.34	0.31	0.27	0.27	0.32	0.13	0.17	0.36	0.31	0.39	0.21	0.35	0.47	0.41	0.30
Top 1%	4.8%	3.8%	5.3%	4.6%	3.0%	2.8%	4.0%	1.7%	3.6%	5.8%	4.1%	5.8%	3.5%	5.1%	7.6%	5.2%	5.9%
Top 5%	15.4%	12.9%	16.9%	14.8%	11.3%	10.9%	13.6%	7.5%	11.2%	17.6%	13.8%	18.5%	11.6%	15.5%	22.4%	17.0%	16.4%
Top 10%	25.0%	22.0%	26.9%	24.2%	20.0%	19.5%	23.0%	14.2%	18.7%	27.8%	23.3%	29.2%	19.6%	25.3%	34.2%	28.2%	25.5%
Mid 40%	46.9%	48.3%	46.4%	47.1%	49.3%	49.8%	49.4%	45.1%	42.6%	46.9%	48.5%	47.5%	44.8%	48.9%	47.2%	50.4%	44.4%
Bottom 50%	28.0%	29.7%	26.6%	28.7%	30.8%	30.7%	27.6%	40.6%	38.7%	25.3%	28.2%	23.3%	35.7%	25.7%	18.6%	21.5%	30.1%
p90/p10	8.53	7.78	9.68	8.06	7.62	7.73	10.56	2.24	2.87	13.12	9.92	16.56	3.80	12.68	30.73	21.60	6.74
p90/p50	0.89	0.74	1.01	0.84	0.65	0.64	0.83	0.35	0.48	1.10	0.83	1.25	0.55	0.99	1.84	1.31	0.85
p10/50	0.10	0.09	0.10	0.10	0.09	0.08	0.08	0.16	0.17	0.08	0.08	0.08	0.14	0.08	0.06	0.06	0.13
p75/25	5.22	5.35	5.32	5.18	5.50	5.64	6.00	3.75	3.55	5.85	5.69	6.47	4.05	6.22	7.80	7.67	4.54

Coicop1: Food & Beverages. Coicop2: Alcohol and Tobacco. Coicop3: Textile & FootWear.Coicop4: Housing. Coicop5: Housing Energy Utilities. Coicop6: Furnishing & Maintenance. Coicop7: Health. Coicop8: Transport. Coicop9: Communications. Coicop 10:Recreation and Culture. Coicop11:Education. Coicop 12: Restaurant & Hotels Coicop13: Other good and services

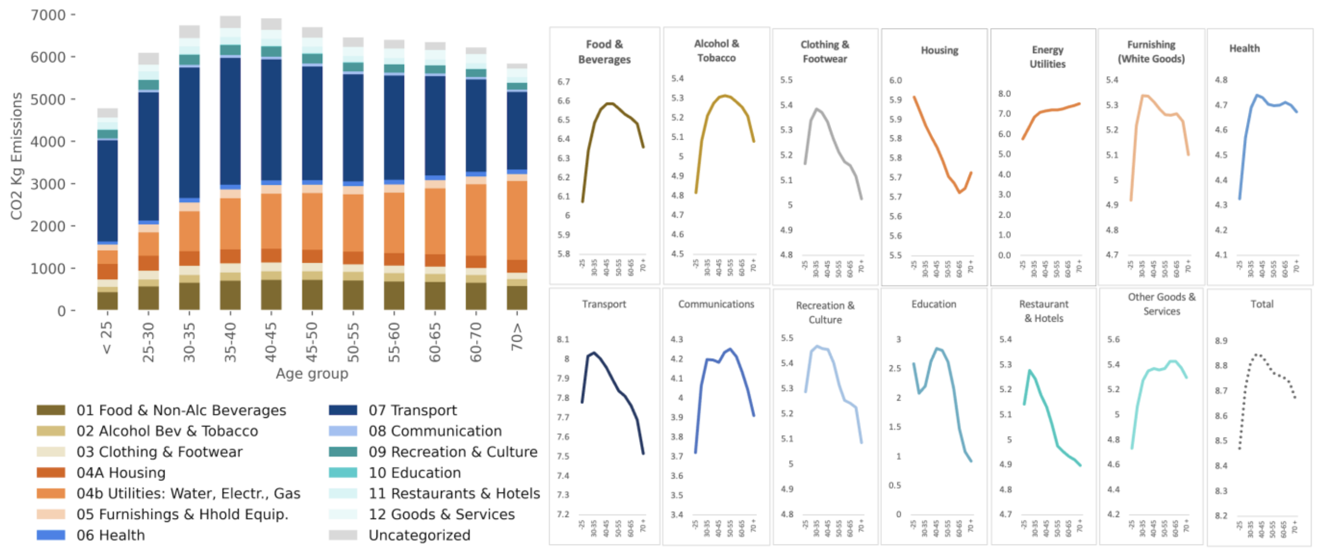
Source: BBVA Research based on Buda et al. (2022), BBVA Research and INE.

3.2 The Distribution of the Carbon Footprint through the Life Cycle

The highly detailed Distributional CO2 Emissions accounts provide us with a unique opportunity to examine two crucial trends simultaneously: climate change and population aging. While existing literature on the relationship between age structure and emissions often shows an aggregate inverted U-shaped pattern for emissions across different age cohorts (Wilson et al., 2013; Lenglart et al., 2010; Zagueni, 2011), these interactions are complex and influenced by various factors such as lifestyles and consumption patterns. In this regard, our findings can shed light on the evolution of the carbon footprint across the different age groups of Spanish households and offer deeper insights into the individual emission patterns within various consumption categories. The key stylized facts from our analysis are as follows (refer to Figure 5 for details):

- **The distribution of CO2 emissions among different age cohorts and consumption categories follows a familiar hump-shaped pattern that aligns with Spanish household consumption trends.**[13] On average, adults in the 35-40 years age group emit 6.855 Tns of CO2, which is 10% more than the average emissions of adults in Spain during the same year. However, emissions decrease rapidly by nearly 27% among individuals in the 70 years and older age group, compared to the peak emissions observed in the 35-40 years age group. In contrast, younger individuals (under 25) emit 10% and 18% less CO2 emissions than the average and the highest emitting group (35-40), respectively. In summary, we observe a 22% increase in CO2 emissions over the life cycle from young adulthood to middle age, followed by a similarly sized decline in consumption in old age.[14]

Figure 5. **AVERAGE CO2 EMISSIONS BY CATEGORY AND AGE GROUP: GROUPED LEVELS OF EMISSIONS & INDIVIDUAL CATEGORY** (CO2 EMISSIONS IN 2017 IN KG IN THE FIRST GRAPH. INDIVIDUAL CO2 EMISSIONS BY INDIVIDUAL CONSUMPTION CATEGORIES IN LOGS IN THE SECOND)



Source: BBVA Research based on Buda et al. (2022), BBVA Research and INE.

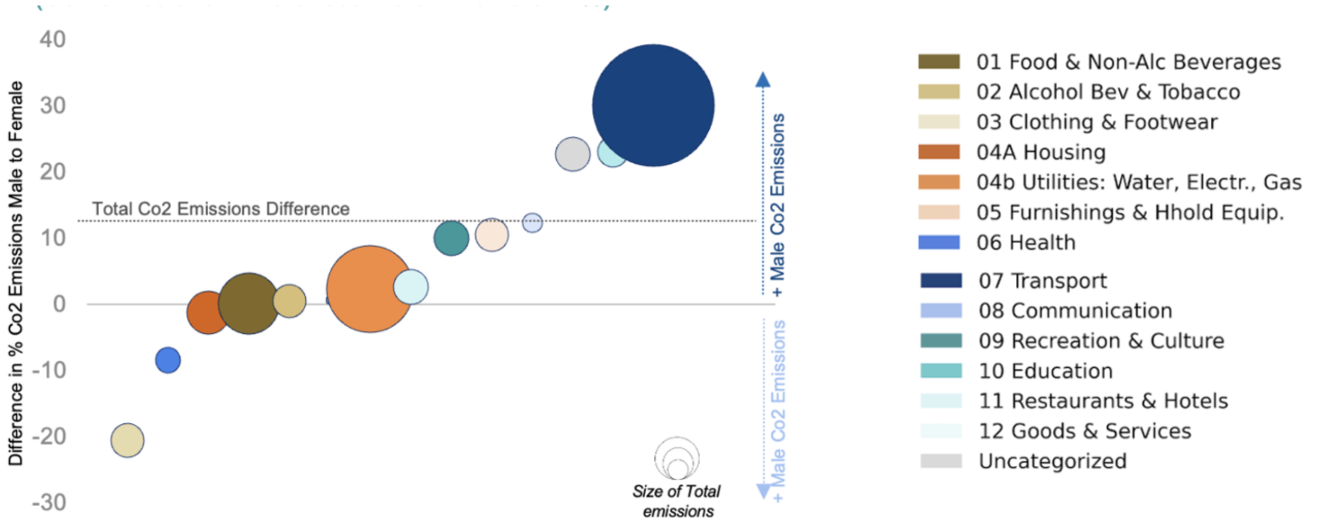
13: This is consistent with results obtained by Buda et al (2021) for Spain and Aguiar and Hurst (2013) and Fernandez-Villaverde and Krueger (2007) for the US case, showing that adult consumption grows throughout the 20s and 30s, peaks in middle age and declines smoothly thereafter.
14: The CO2 emissions general inverted U-turn pattern is consistent with Zagheni, E. The Leverage of Demographic Dynamics on Carbon Dioxide Emissions: Does Age Structure Matter?. Demography 48, 371–399 (2011).

- **While the hump-shaped pattern of CO2 emissions is generally consistent across age cohorts, there are variations in terms of adjustments throughout the life cycle:**
  - **The inverted U-shaped pattern is smoother in the case of basic needs goods** and some basic service emissions, such as Food and Beverage, Alcohol & Tobacco, health, and other goods and services.
  - **The correction in emissions throughout the life cycle is most pronounced in the case of luxury goods,** such as Transport, where there is a significant 50% adjustment from the peak use at 30-35 years to the older group of 70 years or more. Similarly, luxury services, such as communications, recreation & culture, education, and restaurants and hotels, also show a notable adjustment throughout the life cycle.
  - **Housing and utilities emissions present a different pattern.** Housing emissions show a continuous downward trend throughout the life cycle, except towards the end[15]. In contrast, CO2 emissions from energy utilities exhibit an upward trend throughout the life cycle[16].

3.3 Addressing Gender Disparity in the Carbon Footprint

The distributional accounts of CO2 emissions have been found to be a valuable tool for analyzing gender inequality with regards to CO2 emissions. As illustrated in Figure 6, **CO2 emissions are approximately 12% higher for males than females.** This disparity can be attributed to a variety of factors, such as income inequality and differing lifestyle choices. Furthermore, the gender inequality in emissions is predominantly linked to the increased consumption of more polluting activities by males.

Figure 6. **CO2 EMISSIONS. GENDER INEQUALITY IN 2017: MALES VS FEMALES IN** (%). THE SIZE OF THE BUBBLE REPRESENTS THE WEIGHT OF THE COICOP CATEGORY IN TOTAL CO2 EMISSIONS



Source: BBVA Research based on Buda et al. (2022), BBVA Research and INE.

15: A similar result can be found in the official survey of consumer spending (INE).
16: Zagheni (2011) found a similar pattern for the US Energy utilities as Gas and Electricity.

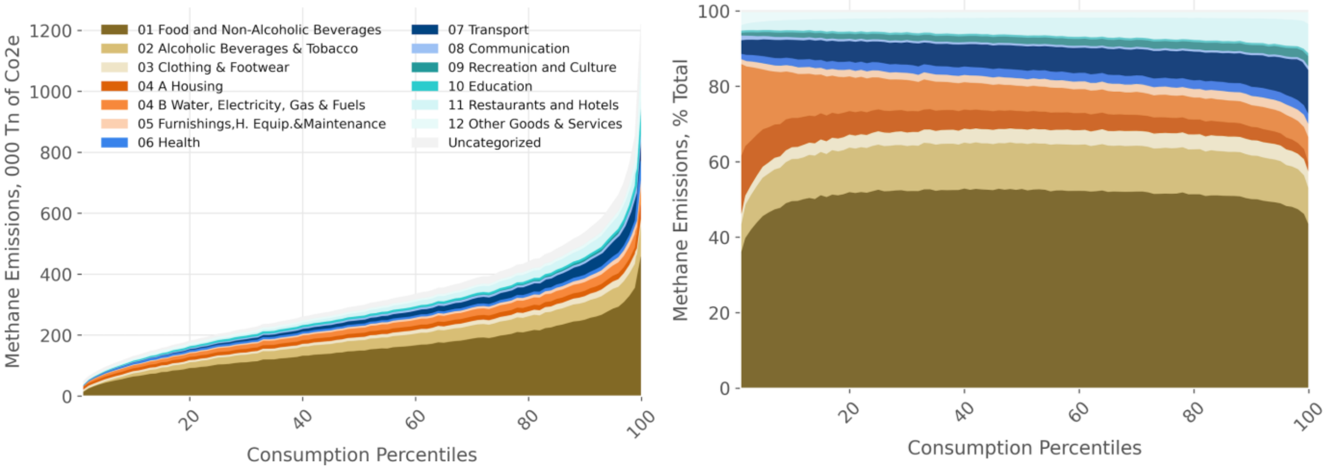
There are several important factors that contribute to the inequality in CO_2 emissions, and one key factor is the disparity in consumption patterns, particularly in categories such as luxury goods and transportation, which are associated with high CO_2 emissions intensity.[17] In fact, the transportation sector alone accounts for nearly 40.5% of total CO_2 emissions. What's noteworthy is that males tend to have emissions levels that are approximately 30% higher than their female counterparts in the transportation sector. Additionally, there is a considerable difference in CO_2 emissions between males and females in the consumption of services related to restaurants and hotels, with male emissions surpassing female emissions by 20.5%. However, it's important to note that the overall contribution of this sector to total emissions is relatively low, at just 2.5%.

On the other hand, when it comes to basic goods such as energy utilities, food and beverages, and housing, no significant gender differences in CO_2 emissions are detected. Interestingly, there are a few sectors where female emissions are higher than male emissions, specifically in the health and clothing and textile industries.

3.4 Are all GHG Emissions alike?: The case of Methane

While CO_2 emissions constitute the largest share of greenhouse gas emissions at 79.2%, it's important to note that **there are other gasses that are also relevant to the challenge of climate change**. Methane (CH_4) is a potent greenhouse gas with global warming effects, primarily associated with agricultural production and certain energy production practices. With the availability of information in the National Environmental Accounts, we can also estimate Consumption-based Methane Emissions using our highly granular consumption database. An initial analysis of the level and distribution of Methane Emissions by consumption categories reveals **both similarities and significant differences compared to CO_2 emissions, as highlighted in Figure 7.**

Figure 7. **METHANE EMISSIONS: LEVELS & SHARE (%)**
CH4 EMISSIONS BY COICOP CATEGORY (IN %) AND CONSUMPTION PERCENTILES. 2021



Source: BBVA Research based on Buda et al. (2022), BBVA Research and INE.

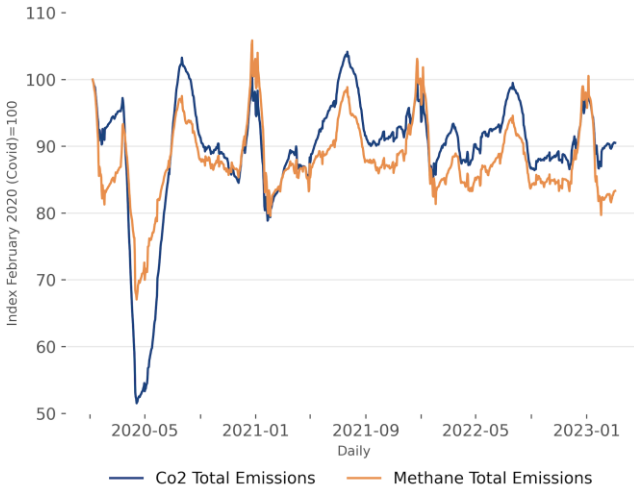
17: A similar result can be found for other European countries in Räty, A. Carlsson-Kanyama (2010) Energy consumption by gender in some European countries.Energy Policy,Volume 38, Issue 1, 2010.

- While there is a positive relationship between the level of Methane (CH4) emissions and consumption, **the inequality of Methane Emissions is slightly lower than the one of CO2 emissions (Gini Coefficient of 0.28 for Methane and 0.30 for CO2).** Moreover, the 10% of higher polluters were responsible for 21.5% of the total CH4 emissions.
- **The relatively more egalitarian distribution of Methane emissions can be attributed, in part, to the higher relevance of basic needs consumption categories.** For instance, the Food and Beverage category accounts for nearly 40% of Methane emissions across different percentiles, indicating its significant contribution. Additionally, other consumption categories associated with agricultural products, such as Alcohol and Tobacco, Textile and Footwear, contribute another 20%. **In contrast, the categories of Transport and Housing have relatively lower importance in terms of Methane emissions.**
- **Policies to reduce Methane emissions face a more balanced distribution among most of the Emissions Categories.**

4. The Spanish Household GHG Emissions in real time

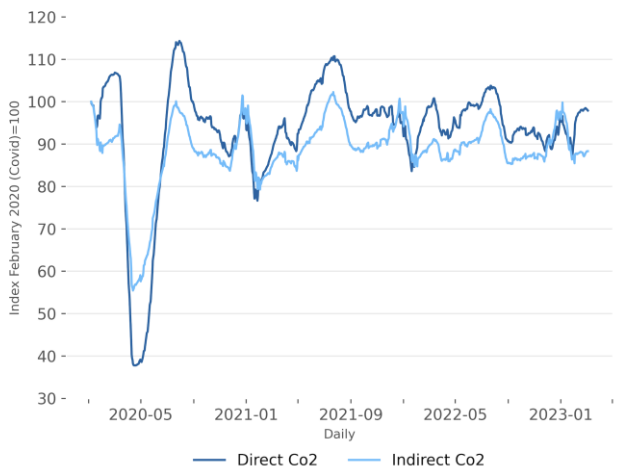
In the preceding sections, we have demonstrated how our hybrid methodology enables a detailed distributional analysis of the Carbon Footprint, providing valuable insights. Furthermore, our approach can also be utilized for real-time monitoring of households' greenhouse gas (GHG) emissions, including both direct and indirect CO2 emissions, as well as other gasses such as Methane. Real-time indicators have proven to be a powerful and useful tool for the timely assessment of the impacts of various policies and shocks, particularly during recent events such as the Covid-19 pandemic. Applying these indicators to GHG emissions can provide relevant information for policy-making and tracking the effectiveness of mitigation measures.

Figure 8. **SPAIN: CO2 AND METHANE EMISSIONS** (INDEX 100=1/1/2020)



Source: BBVA Research.

Figure 9. **SPAIN: CO2 EMISSIONS: DIRECT VS INDIRECT** (INDEX 100=1/1/2020)



Source: BBVA Research.

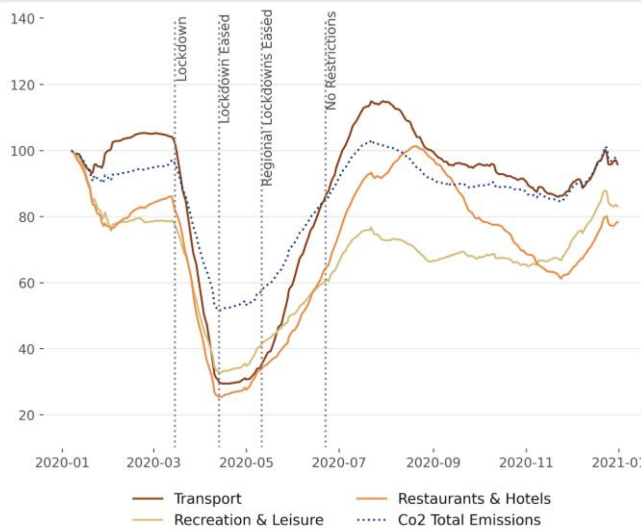
Figure 8 depicts the real-time (daily basis) evolution of CO2 and Methane emissions in Spain, revealing some noteworthy insights. Firstly, it highlights the differential impact of Covid-19 lockdowns. CO2 emissions, which are heavily influenced by the transport sector, experienced a sharp decline during the initial lockdown but rebounded quickly as mobility restrictions eased in mid-2020. On the other hand, Methane emissions, which are linked to food consumption, exhibited higher resilience during the crisis and displayed a more stable performance in recent years. As the recovery accelerated, the gap between CO2 and Methane emissions widened, particularly since 2023, with increased emissions from the transport sector being observed.

Figure 9 presents the contrasting performance of direct and indirect CO2 emissions over time. Direct emissions, primarily stemming from the transport sector (as well as utilities), decreased more significantly during the Covid-19 lockdown and rapidly recovered during the summer of 2020. In contrast, indirect emissions, where the food sector holds higher relevance, displayed a pattern of evolution more akin to that of Methane emissions.

4.1 How did CO2 emissions by sectors change during the Covid-19 pandemic?

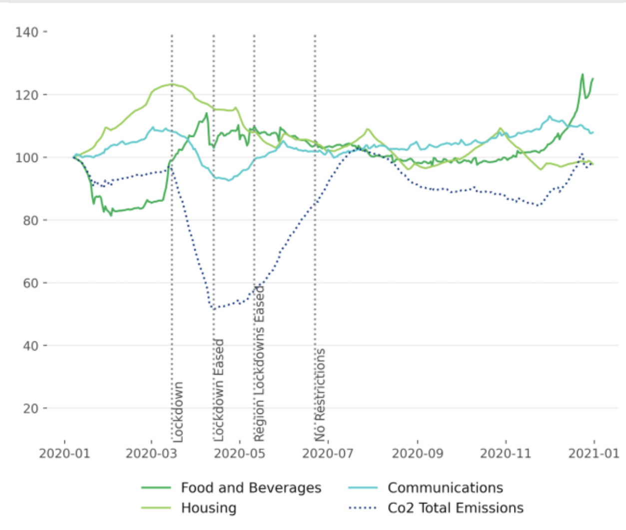
The high-frequency data can also be disaggregated by COICOP category, as shown in Figures 10 and 11. The sectoral disaggregation allows us to understand how shocks propagate among different consumption categories. In fact, the Covid-19 crisis, and particularly the lockdowns implemented to fight it, revealed a significant heterogeneity in the performance of different consumption categories in terms of CO2 emissions. Some sectors were highly affected, while others benefited from it. Sectors related to mobility, luxury goods, and services associated with recreation and leisure experienced a sharp decline in CO2 emissions during the lockdown, while sectors related to food and housing consumption, such as utilities payments, increased their emissions during the same period.

Figure 10. **SPAIN CO2 EMISSIONS: MOST AFFECTED SECTORS BY COVID-19 IN 2020**
(INDEX 100=1/1/2020)



Source: BBVA Research.

Figure 11. **SPAIN CO2 EMISSIONS: LESS AFFECTED SECTORS BY COVID-19 IN 2020**
(INDEX 100=1/1/2020)



Source: BBVA Research.

The recovery from the Covid-19 pandemic has also been unbalanced. Sectors such as transport, recreation and leisure, and restaurants, which have a high embedded CO2 footprint, were among the most affected by the pandemic. While the initial and sharp decline in emissions was similar among these sectors, their recovery patterns differed after the lockdown (as shown in Figure 10). Transport emissions recovered rapidly as mobility restrictions eased by region starting in May 2020. However, CO2 emissions associated with restaurants and, especially, recreation and culture experienced a more persistent impact, not returning to pre-pandemic levels during 2020.

On a different note (as shown in Figure 11), CO2 emissions related to housing utilities, as well as communication expenditures (mainly related to internet and mobile payments), along with food and non-alcoholic beverages, were even positively impacted by the pandemic. With people spending more time at home, there was an increase in energy and food consumption at home, leading to a significant change in their CO2 footprint in line with their consumption patterns. However, there is no clear common path observed among these sectors. The sector with the highest increase in CO2 emissions during the pandemic was food and non-alcoholic beverages, as consumers substituted restaurants with home-cooked meals. In the case of housing utilities, there was an initial positive effect, but it started to correct with the easing of mobility restrictions in May 2020. On the other hand, the communications sector did not experience a positive impact at the beginning of the pandemic, but its emissions increased throughout 2020.

5. Conclusions

In this note, we present a novel integrated hybrid approach for developing distributional accounts for Carbon Footprint Emissions by Spanish Households. Our methodology combines standard methods for calculating direct and indirect emissions of greenhouse gasses (GHG) with high-granularity information extracted from a novel distributional consumption database derived from financial transactions. This innovative approach offers several advantages, including the elimination of uncertain elasticities and the ability to calculate emissions directly from transactions, eliminating the reliance on surveys.

The findings reveal a significant level of inequality in GHG emissions, with the top 10% of polluters accounting for nearly 30% of the total emissions. This inequality pattern aligns with consumption patterns, although it is comparatively lower than income inequality. The transport sector emerges as the primary source of this inequality, with emissions from transportation dominating the upper percentiles of the distribution, indicating that a small portion of the population is responsible for a large share of emissions. On the other hand, emissions associated with housing dominate the lowest percentiles of emissions and consumption distributions, showcasing a different pattern.

The analysis reveals that CO2 emissions exhibit an Inverted U-shaped pattern across most, though not all, emissions categories throughout the life cycle. Notably, emissions from energy utilities among older individuals tend to increase with age. In addition, there is gender inequality in the emissions of Spanish individuals. Male generate 12% more emissions, which can be explained by a more intensive use of transportation among the male population.

These findings highlight the significance of considering consumption and age differences when formulating policies related to transport or energy utilities, as the impacts of such policies can vary considerably depending on these factors. A deeper understanding of the distributional characteristics of GHG emissions can inform the design of effective and targeted transition policies, as the effects of such policies may differ significantly among consumption groups. This underscores the importance of taking a nuanced approach to policy-making, considering the diverse implications for different segments of the population.

In addition to the detailed analysis of the carbon footprint, our study offers a significant advantage: the ability to measure the direct and indirect emissions of various greenhouse gasses (GHG) in real-time. This represents a powerful and valuable tool that enables timely assessment of the impacts of different policies and shocks.

Appendix I. Estimations of the GHG Emissions by the Spanish Households: A Hybrid Approach

Our approach combines the standard Input-Output methodology for estimating emissions with a unique Big Data consumption database of the Spanish Economy (referred to as Buda et al. (2022)). By integrating different data sources and methodologies, our work aims to enhance the estimates of GHG emissions, contributing to a more informed understanding of the environmental impacts of consumption patterns in the country.

To calculate the indirect emissions embedded in the production process, we use the Leontief inverse matrix, which provides information on the inter-industry requirements of each sector to deliver one unit of output of final demand, as outlined by Miller and Blair in 2009. It is important to note that Input-Output (IO) modeling is a widely used tool in assessing carbon footprints, as it captures the indirect emissions generated throughout the upstream supply chain until the product is ready for use. Thus, the indirect household carbon intensity ratios ($e_{indirect}$) can be calculated as:

$$e_{Indirect} = g * (I\text{-}A)^{-1} \quad (1.a)$$

where g is the sectoral, production-based, emission intensity vector (1x63), and $(I\text{-}A)^{-1}$ is the Leontief inverse matrix (63x63). So, the product $g*(I\text{-}A)^{-1}$ yields a vector (1x63) of indirect emission coefficients by economic activity (NACE), that account for the total emissions (kg) needed in the economy (in the 63 sectors) to satisfy each unit (€) of final demand in each of the COICOP categories.[18]

To convert households' sectoral indirect emission intensity ratios into consumption by purpose (COICOP) ratios, we rely on the bridging matrices developed by Cai and Vandyck (2020), with dimensions of 63x13. These matrices are essential for converting the 63 NACE households' indirect emission ratios into 13 COICOP ratios. Note that bridging matrix tables enable data conversion between consumption- and production-based statistics, facilitating research that integrates macroeconomics, multi-sectoral international trade, and heterogeneous agents in household-level expenditure micro-data.

To obtain COICOP intensity ratios from CPA intensity ratios (1x63), a weighted average of the CPA ratios is employed as a conversion method. The weights are dependent on the composition of the corresponding COICOP category, which is determined through the use of bridging matrices (63x13). Specifically, the weights assigned to each ratio correspond to the share of consumption for the COICOP category in question that comes from each relevant CPA component. For example, if the FOOD COICOP category derives 95% of its household consumption from agricultural products and 5% from fisheries, then the ratio for the Food COICOP would be calculated as follows: 0.95 multiplied by the indirect intensity ratio for agricultural products, plus 0.05 multiplied by the indirect intensity ratio for fisheries. To accomplish this, the bridging matrix weights are computed first, followed by a matrix multiplication operation. The resulting values represent the indirect intensity ratios for the desired COICOP categories ($ec_{indirect}$) with dimensions of (1x13).

$$ec_{Indirect} = e_{Indirect} * BM \ (1.b)$$

where $e_{indirect}$ is the indirect emission intensity vector calculated in the previous step *(1x63)*, and *BM* is the bridging matrix mentioned in the above paragraph *(63x13)*. Note that our analysis assumes, due to data constraints, a constant percentage structure linking the CPA and COICOP categories over time.

18: To estimate the indirect CO2 emissions for households, the INE Input-Output Table and Environmental Extended Accounts are used. The sectoral emission intensities are calculated using production-based emissions.

While indirect emissions are a crucial factor to consider, it is important to note that IO (input-output) modeling does not account for direct emissions generated by households. These direct emissions result from activities such as burning fossil fuels for transportation or household energy needs, including gasoline for vehicles or gas for cooking.

To ensure a comprehensive analysis, it is necessary to include these direct emissions in our calculations. To address this, we incorporate data from the OECD's Air Emission Accounts, which provides a detailed breakdown of households' direct emissions in categories such as transport, heating, and cooking. We obtain corresponding data on the total direct household emissions from the Spanish Official Statistical Institute. Subsequently, transport direct emissions are allocated to the Transport COICOP category, while direct emissions from heating and cooking are included in the Electricity and Gas (Utilities) COICOP category. Once the emissions are assigned, we can determine the direct emission intensity ratios, denoted as $ec_{direct,i}$, by dividing the assigned emission quantities by the in-house household consumption (*cc*)'. It's worth noting that ec_{direct} is a 1x13 vector with values greater than zero only in the Transport and Electricity and Gas COICOP categories, as direct emissions are exclusively allocated to these two categories.

$$ec_{direct} = e_{direct} / cc' \quad (2)$$

Therefore, to calculate the total emission intensity ratios for each COICOP category, we sum the direct and indirect ratios, with ec_{direct} being only higher than zero in the Transport and Electricity and gas COICOP categories:

$$ec_{total,i} = ec_{direct,i} + ec_{indirect,i} \quad (3)$$

Finally, to obtain the emission quantities (*eq*) and the distributional accounts, the intensity ratios by COICOP categories (1x13) were applied to Buda et al.'s (2022) newly developed real-time and high-definition consumption vector (cc), with dimension 13x1. This approach offers several advantages, as it ensures macro consistency with the National Accounts and COICOP categories, provides real-time availability of CO2 emissions on a daily basis, and allows for application to a comprehensive distributional consumption database. Accurate consumption data is essential for calculating emission footprints correctly, as recognized by numerous authors in their efforts to explore the relationship between consumption-based greenhouse gas (GHG) emissions and income distribution.[19]

$$eq_{total,i} = ec_{total,i} * cc \quad (4)$$

It is worth emphasizing that the intensity ratios are computed annually to account for variations in the energy mix, technological advancements, and consumption patterns that may arise from year to year. This dynamic approach ensures that the most current and relevant information regarding emissions is captured and reflected in the calculations, enhancing the accuracy and utility of the approach for decision-making purposes. By recalculating the ratios each year, the approach remains up-to-date and adaptable to changing circumstances, making it well-suited for accurately assessing emissions and supporting informed decision making.

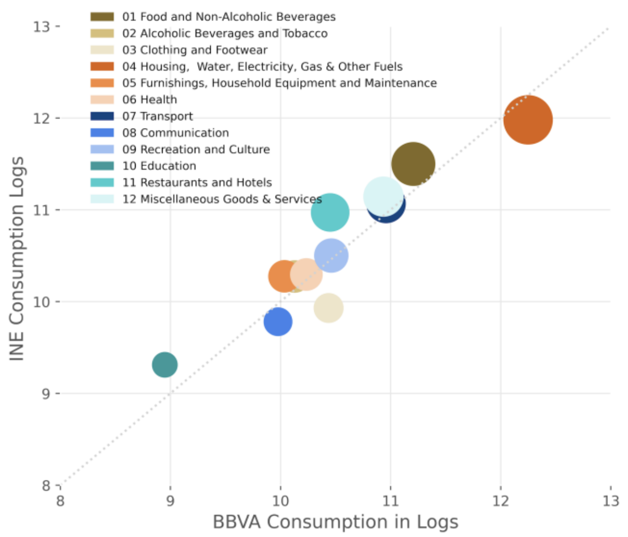
Appendix II. Strengthening Findings: Examining the Robustness of Consumption and CO2 Data Using Official Statistics

19: However, these investigations are not without limitations. One method involves linking emissions to income distribution using consumption-to-income elasticities, as illustrated by Piketty and Yucel (2015). This method is vulnerable to uncertainties associated with the accurate value of consumption-to-income elasticities. Another method involves integrating data on energy emissions with household characteristics obtained from surveys, as demonstrated by Baltruszewicz et al. (2023). However, this method is susceptible to biases that are typically present in survey data, such as underrepresentation of the upper percentiles of the income distribution.

In Buda et al. (2022) we identified discrepancies between BBVA Research and INE's consumption data, which could have a non-negligible impact on CO2 footprint estimations. To address this issue, we compare their COICOP-specific consumption measures with INE's national accounts COICOP values for the year 2020. Furthermore, we also evaluate the impact of these differences on households' footprint estimations.

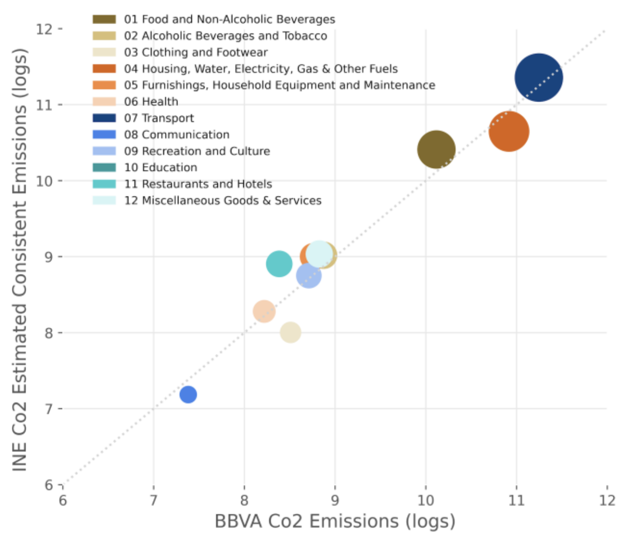
One of the issues encountered by the authors was non-categorized consumption, which led to a generic downward bias for all consumption categories in BBVA Research's estimates. Cash was found to be the largest contributor to non-categorized consumption. To address this, Buda et al.'s (2022) approach was to distribute cash across COICOP categories in proportion to offline card spending on those categories, as cash and offline card spending are typically spent on related items. After categorizing cash, 93% of total consumption was assigned a COICOP, resulting in a coverage ratio of 93% for classified categories.

Figure 12. **DISTRIBUTION OF CONSUMER SPENDING ACROSS COICOP CATEGORIES** (LN LEVEL). 2020



Source: BBVA Research.

Figure 13. **DISTRIBUTION OF CO2 EMISSIONS ACROSS COICOP CATEGORIES** (LN LEVEL). 2020



Source: BBVA Research.

Figure 12 above illustrates the level of category-specific 2020 consumption according to INE's and BBVA Research's values. Despite the inherent downward bias arising from non-classified consumption, there is a strong correlation between the two measures across categories, with significant similarities in consumption levels. However, differences are visible in some COICOP groups such as Housing, or Education. For a more detailed analysis of the differences, please refer to Buda et al. (2022).

The estimation of CO2 distributional accounts relies on multiplying emission intensity ratios by consumption data. However, the use of different sources for consumption data can result in disparities in CO2 estimations. To highlight this point, we present in Figure 13 the differences that would arise if consumption values from the Spanish Statistical Institute's official categories (COICOP) were used. Although the INE's data provides consumption values for only 12 COICOP categories and does not offer disaggregation by age or percentiles, it offers an opportunity to observe how the aggregate results would change with COICOP values from official sources. The figures demonstrate the variations in total emissions (direct and indirect) that would occur. While there may be some noticeable differences between the CO2 emissions estimates from INE and BBVA Research, the overall similarities between the two datasets (as seen in Figures 12 and 13) enhance the consistency and robustness of our findings.

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