[Your Thesis Title]

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[Your Full Name]

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1 Introduction

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2 Literature Review

Climate change mitigation policies are heavily influenced by the development trajectories of nations and their respective stages of economic growth, as outlined in the fifth assessment report by the Intergovernmental Panel on Climate Change (IPCC, 2007). According to emission estimates for 2023 provided by the EDGAR database, global greenhouse gas (GHG) emissions increased by 1.9% compared to 2022, reaching 53.0 Gt CO2eq. The major contributors to global GHG emissions in 2023 were China, the United States, India, the European Union (EU27), Russia, and Brazil, which together accounted for 62.7% of the total global emissions. Carbon dioxide (CO2) produced by human activities remains the largest driver of global warming, with its concentration in the atmosphere having risen by 48% above pre-industrial levels (before 1750) by 2020. The primary sources of CO2 emissions include the combustion of coal, oil, and natural gas, deforestation, livestock farming, the release of fluorinated gases from industrial equipment, and the use of nitrogen-based fertilizers (Weber & Matthews, 2008). These activities have led to more frequent and severe weather events, including heatwaves and droughts, that are impacting regions around the world. In 2024, the United States experienced 27 weather and climate-related disaster events, each resulting in losses exceeding $1 billion (NOAA, n.d.). The growing acknowledgment of global warming as a significant threat has prompted international initiatives aimed at reducing greenhouse gas (GHG) emissions. These initiatives rely on accurate assessment and reporting of GHG emissions to inform climate policies (IPCC, 2007). Households account for 17% of total global carbon dioxide (CO2) emissions, underscoring their critical role in addressing climate change. Understanding and mitigating residential contributions to greenhouse gas (GHG) emissions require prioritizing the household carbon footprint, a vital measure of emissions stemming from residential consumption (Du & Zhong, 2024). Several methodologies are available for estimating GHG emissions, with the concept of carbon footprint gaining significant attention (Guinee, 2011). A carbon footprint is defined as the total GHG emissions caused directly and indirectly by an individual, organization, event, or product, traditionally calculated by summing emissions from every stage of a product or service's life cycle (Center for Sustainable Systems, 2024). Among the available methodologies, the GHG Protocol has emerged as a widely used framework for corporate GHG reporting, considering direct and indirect emissions resulting from household consumption. However, this method has limitations, such as double-counting and restricted adjustments for market dynamics (WBCSD, 2004).

Another widely used approach is the Input-Output Analysis (IOA) method, a top-down model that calculates carbon footprints by analyzing monetary transactions between activities and extending them to an environmental level through greenhouse gas (GHG) emissions. This approach, known as Environmentally Extended Input-Output Analysis (EEIO), provides a macro-level view of the environmental impacts of economic activities (Encyclopedia of Ecology, 2019). For instance, a study using EEIO to examine the carbon footprints of Australian equity investments and Socially Responsible Investments (SRI) demonstrated that applying SRI criteria significantly reduces the carbon footprint of equity portfolios. This highlights equity investments as a major driver of economic activity and a crucial lever in advancing a sustainable economy (Chard, 2024).

Another frequently used method for calculating carbon emissions is the Emission Factor (EF) method. According to the Intergovernmental Panel on Climate Change (IPCC, 2019), the formula for estimating GHG emissions is:

$$\text{GHG Emissions} = \text{Activity Data (AD)} \times \text{Emission Factor (EF)}$$

Here, Activity Data (AD) refers to the scale of production or consumption activities that result in GHG emissions, such as fossil fuel use or electricity consumption. The Emission Factor (EF) represents the amount of GHG emitted per unit of activity, such as the emissions per liter of fuel burned or per kilowatt-hour of electricity consumed. Life Cycle Assessment (LCA) is a highly sophisticated tool for examining the environmental impact of products and services. It offers a holistic evaluation, tracing environmental consequences across every stage of a product's existence, from the extraction of raw materials to its final disposal—often described as a 'cradle-to-grave' approach. By analyzing phases such as production, distribution, usage, and end-of-life processes, LCA quantifies resource use, greenhouse gas emissions, and pollution affecting air, water, and soil systems (Global Climate Initiatives, 2023). A study leveraging LCA and household survey data provided precise calculations of carbon footprints by capturing emissions associated with daily consumption, household production activities, and the supply chain of consumed goods (Peng, 2021).

The model by Hakenes and Schliephake (2024) offers a fresh perspective on carbon footprint estimation by addressing the shortcomings of traditional static models. This consequentialist approach integrates market behaviors and industry-specific responses to provide a more dynamic and realistic analysis of household emissions. It highlights the connection between individual consumer decisions and broader emission outcomes, accounting for variables such as price elasticity and interdependencies between industries in both product and financial markets. By separating direct emissions tied to household activities from spillover effects influencing other sectors, this model delivers a more detailed and actionable understanding of household contributions to carbon emissions, paving the way for tailored climate strategies.

3 Methodology

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4 The GHG Protocol

The Greenhouse Gas (GHG) Protocol is a globally recognized standard for accounting and reporting greenhouse gas emissions. Developed in the late 1990s through a collaboration between the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD), the GHG Protocol was officially launched in 2001 with the primary aim of providing a consistent and comprehensive framework for emissions accounting across corporate and public sectors. Over the years, its importance has grown significantly, with subsequent expansions such as the development of the GHG Protocol Scope 3 Standard in 2011, which broadened the accounting boundary to include indirect emissions across a company's or household's value chain. The historical motivation behind its creation was rooted in the need for greater transparency and comparability in emissions disclosures, especially as climate policy instruments and stakeholder expectations became increasingly sophisticated.

The GHG Protocol is structured around three main scopes of emissions, each delineating a distinct layer of responsibility and source attribution. Scope 1 covers direct emissions from sources that are owned or controlled by the reporting entity, such as the combustion of fuels in household-owned vehicles or heating systems. Scope 2 includes indirect emissions associated with the generation of purchased electricity, steam, heating, or cooling consumed by the household but produced off-site. Scope 3 is the broadest category, encompassing all other indirect emissions that occur as a consequence of the household's activities but are not directly controlled by it. These include emissions from the production and transport of goods and services consumed by the household, as well as those associated with financial investments and capital goods.

The principal reason for employing the GHG Protocol in household-level emissions analysis lies in its capacity to provide a standardized and granular approach to calculating emissions across different dimensions of behavior. It allows for a full inventory of climate impacts arising from everyday life—from fueling a car to investing in equity portfolios. Additionally, the protocol facilitates benchmarking across time and geography, making it possible to compare the carbon intensities of different households or regions. This is particularly valuable for policymaking, where a reliable basis for comparison is needed to design effective incentives, taxes, or subsidy programs aimed at reducing emissions.

Households may apply the GHG Protocol methodology when they aim to understand the full extent of their carbon footprint, either for personal environmental awareness or to comply with voluntary disclosure programs. It is also useful in academic and policy research, where household-level emissions data feed into broader simulations of national carbon inventories or help evaluate the effectiveness of climate policies. Moreover, with the rise of ESG (Environmental, Social, and Governance) investing, households are increasingly motivated to assess not only their consumption patterns but also the environmental implications of their financial choices. The GHG Protocol's inclusion of Scope 3 investment-related emissions is thus particularly timely and relevant.

The benefits of using the GHG Protocol are manifold. First, it ensures methodological consistency by offering a clearly defined structure and a set of standard emission factors that can be applied universally or tailored regionally. This consistency is crucial for the comparability of results and for building credible datasets over time. Second, the protocol is transparent and traceable. It encourages users to document the sources of their activity data and the emission factors applied, thus allowing for auditing, replication, and critical scrutiny. Third, its structure is flexible enough to accommodate varying levels of data availability and resolution. Households with access to detailed energy bills and expenditure data can achieve high-resolution footprints, while those with limited data can still generate reasonable estimates using average or proxy figures.

However, the protocol is not without its criticisms and limitations. One prominent challenge is the reliance on emission factors, which are often generalized and may not reflect specific production technologies or regional energy mixes. This can introduce inaccuracies, particularly in Scope 3 categories, where supply chains are long, complex, and globalized. Another issue is the risk of double counting. Since emissions are reported across both upstream and downstream actors, a single emission source may be attributed to multiple entities. Although the protocol offers guidance to mitigate this, ensuring strict boundary-setting remains an operational challenge. Additionally, the protocol does not inherently capture dynamic changes in market behavior or consumer preferences. It provides a static snapshot, which is useful for diagnostics but limited in predictive or behavioral modeling capabilities.

The mathematical formulation under the GHG Protocol for calculating a household's carbon footprint begins with the aggregation of emissions across all three scopes. The total carbon footprint of a household is expressed as:

$$CF_{\text{household}} = E_{\text{Scope 1}} + E_{\text{Scope 2}} + E_{\text{Scope 3}} \tag{1}$$

Each of these components is calculated based on the product of activity data and corresponding emission factors. For Scope 1, this includes the quantity of fuel combusted in household-controlled devices or vehicles, multiplied by the fuel-specific emission factor. Scope 2 emissions are determined by multiplying electricity or district heating usage by grid-specific emission factors. Scope 3 is more complex and can be further disaggregated into emissions from the consumption of goods and services, and emissions from household investments. For the consumption subcategory, expenditures are multiplied by lifecycle emission factors derived from environmentally extended input-output models or product-level lifecycle assessments. For investment-based emissions, the monetary value of investments is multiplied by portfolio-weighted emission intensities of the respective industries.

An illustrative example of this methodology can be found in the case of household consumption patterns in Spain for the year 2022. Using data from the Spanish National Statistics Institute (INE), we observe that the average household expenditure was approximately €31,568. This expenditure was spread across various COICOP categories such as housing, transport, food, communication, and leisure. Each category was assigned an appropriate emission factor derived from lifecycle assessment studies and national inventories. For example, food and beverage consumption had an emission factor of 0.50 kg CO_2e per euro, while housing-related expenditures including electricity and heating had a lower emission factor of 0.25 kg CO_2e per euro due to Spain's relatively cleaner energy grid.

Applying this methodology, we find that Scope 1 emissions, predominantly from petrol and gas use in private vehicles and heating, amounted to 1,114.83 kg CO_2e annually. Scope 2 emissions, arising from heating and cooling energy consumed, contributed an additional 829.70 kg CO_2e. In contrast, Scope 3 emissions, which include emissions from the production and delivery of consumed goods and services, accounted for the largest share—totaling 9,883.55 kg CO_2e. The aggregate household carbon footprint was therefore estimated to be 11,828.08 kg CO_2e per annum.

This case study illustrates not only the quantitative value of the GHG Protocol methodology but also its diagnostic power. It becomes evident that indirect emissions dominate the carbon footprint of Spanish households, a trend consistent with data from other high-income countries. Such insights can be pivotal for policy recommendations, such as encouraging low-carbon food choices, promoting public transport, or offering green investment options to households.

Despite the effectiveness of the GHG Protocol, further enhancements could be considered to address its limitations. One potential improvement is the integration of behavioral elasticities into Scope 3 modeling. This would account for changes in consumer behavior in response to price signals or information campaigns, thereby making emissions accounting more responsive and dynamic. Another avenue for advancement is the regionalization of emission factors. Instead of relying on national averages, more localized data—such as city-level electricity mixes or transport infrastructure—could significantly improve the granularity and relevance of household-level assessments.

Moreover, the GHG Protocol could be supplemented with time-series data to allow for temporal comparisons and trend analysis. This would enable users to track progress toward emissions reduction goals and to evaluate the impacts of policy interventions over time. Additionally, the inclusion of complementary environmental metrics, such as water use or material intensity, could broaden the perspective beyond carbon and offer a more holistic view of household sustainability.

In conclusion, the GHG Protocol remains one of the most robust, widely accepted, and adaptable frameworks for emissions accounting. Its application at the household level yields critical insights into the drivers of climate impact and serves as a foundational tool for behavioral and policy interventions. While not perfect, its continued evolution—particularly with respect to Scope 3 measurement accuracy and behavioral modeling—will be essential for deepening our understanding of the complex relationship between everyday choices and global climate outcomes.

4.1 Illustration: Application of the GHG Protocol to Spanish Household Consumption (2022)

To provide a concrete empirical demonstration of the GHG Protocol methodology, we apply the framework to Spanish household expenditure data for the year 2022. This case study not only operationalizes the theoretical components outlined above but also highlights the magnitude and distribution of household emissions when analyzed across Scopes 1, 2, and 3.

The data is sourced from the Spanish National Statistics Institute (INE), which reports average annual consumption expenditures per household disaggregated by COICOP classification. This dataset is especially suitable because it provides category-specific expenditure values and percentage structures, allowing us to assign appropriate emission factors to each type of consumption.

We begin with the total mean annual expenditure per household, reported to be €31,568. This expenditure is then categorized across essential consumption areas such as food and non-alcoholic beverages, housing and energy, transport, communication, and services like restaurants and recreation. The corresponding structure percentages indicate the relative share of each category in the total expenditure. For instance, housing and energy accounted for approximately 32.4% of the total, while food and beverages represented around 16.0%. Transport expenditures stood at 12.0%, with significant growth observed in service-oriented categories such as restaurants and hotels.

Table 1: Mean Consumption Expenditure per Household in Spain, 2022

Category	**Mean Expenditure (€)**	**Structure %**	**Annual Rate %**	**Annual Difference (€)**
Total	31,568	100.0	7.9	2,324
Food and non-alcoholic beverages	5,050	16.0	5.1	244
Alcoholic beverages and tobacco	481	1.5	-3.0	-15
Clothing and footwear	1,232	3.9	6.5	76
Housing, water, electricity, gas	10,243	32.4	3.5	350
Furnishings and maintenance	1,296	4.1	0.8	10
Health	1,228	3.9	2.1	25
Transport	3,794	12.0	17.5	564
Communications	925	2.9	-1.3	-12
Recreation and culture	1,534	4.9	18.0	241
Education	468	1.5	6.4	29
Restaurants and hotels	2,953	9.4	29.1	665
Miscellaneous goods and services	2,364	7.5	7.5	148

Next, we calculate Scope 1 emissions. These emissions arise from the direct combustion of fossil fuels by households, primarily through private vehicle use and home heating. We use energy consumption data expressed in gigajoules (GJ) per capita and apply appropriate emission factors. According to Spain's INE and international emission factor databases such as DEFRA and IPCC, petrol used for transport has an emission factor of 73.3 kg CO_2e/GJ, while natural gas used in heating has a slightly lower factor of 56.1 kg CO_2e/GJ.

Table 2: Direct Emissions from Household Energy and Transport (Scope 1)

Energy Source	**Consumption (GJ/hab)**	**Emission Factor (kg CO_2e/GJ)**	**Emissions (kg C**
Natural Gas (Transport)	0.04	56.1	2.24
Petrol (Transport)	14.44	73.3	1058.45
Natural Gas (Heating)	0.73	56.1	40.95
Petrol (Other)	0.18	73.3	13.19
Total			**1114.83**

We then proceed to Scope 2 emissions, which pertain to purchased energy—namely electricity and district heating—used within the household but generated off-site. The average household in Spain consumed approximately 8.96 GJ of heating and cooling energy. The national grid's emission factor for such energy consumption, based on 2022 data, is estimated at 92.6 kg CO_2e per GJ.

Table 3: Indirect Emissions from Heating and Cooling (Scope 2)

Energy Source	**Consumption (GJ/hab)**	**Emission Factor (kg CO_2e/GJ)**	**Emissions (kg C**
Heating/Cooling Energy	8.96	92.6	829.70
Total			**829.70**

The most complex and voluminous part of the analysis involves Scope 3 emissions. These emissions arise from the indirect impacts of household consumption decisions, including the carbon embedded in food, manufactured goods, services, and transportation infrastructure. Each expenditure category is multiplied by a category-specific emission factor derived from lifecycle assessment databases. For example, the food category carries an emission factor of 0.50 kg CO_2e per euro spent, reflecting emissions from agriculture, processing, and distribution. Clothing, by contrast, has a lower factor of 0.25 kg CO_2e/€, while restaurant services, due to their energy intensity, have a higher factor of 0.40 kg CO_2e/€.

Table 4: Consumption-Based Emissions (Scope 3)

Category	**Expenditure (€)**	**Emission Factor (kg CO_2e/€)**	**Emissions (kg CO_2e)**
Food and non-alcoholic beverages	5,050	0.50	2525.00
Alcoholic beverages and tobacco	481	0.30	144.30
Clothing and footwear	1,232	0.25	308.00
Housing and utilities	10,243	0.25	2560.75
Furnishings	1,296	0.30	388.80
Health	1,228	0.20	245.60
Transport services	3,794	0.30	1138.20
Communications	925	0.15	138.75
Recreation	1,534	0.35	536.90
Education	468	0.10	46.80
Restaurants and hotels	2,953	0.40	1181.20
Miscellaneous goods and services	2,364	0.30	709.20
Total			**9883.55**

Finally, by summing the results from all three scopes, we obtain the total household carbon footprint for a typical Spanish household in 2022. The emissions distribution clearly reveals that Scope 3 emissions dominate, comprising nearly 84% of the total. This insight aligns with broader research indicating that in high-income settings, the indirect emissions associated with consumption patterns far exceed direct household emissions.

Table 5: Total Household Carbon Footprint by Scope

Scope	**Emissions (kg CO_2e)**
Scope 1	1114.83
Scope 2	829.70
Scope 3	9883.55
Total	**11828.08**

This empirical illustration not only validates the functionality of the GHG Protocol when applied to real-world household data but also emphasizes the critical role of consumption behavior in shaping emissions outcomes. The findings suggest that while improvements in home energy efficiency and cleaner fuels are valuable, the most substantial reductions may be achieved through systemic shifts in consumption patterns, such as transitioning to plant-based diets, reducing air travel, or shifting investments away from carbon-intensive industries.

5 Life Cycle Assessment (LCA) Method

The LCA method calculates emissions throughout the entire life cycle of a product or service, from production to disposal. This model captures emissions from every stage of the supply chain and provides a comprehensive assessment of indirect emissions.

The carbon footprint for a single industry using the LCA approach is:

$$fp_h = q_h \cdot \mathrm{LCA}_j$$

where q_h is the quantity consumed by household h, and LCA_j represents the life cycle emissions per unit in industry j.

5.1 Methodology for Household Carbon Footprint Calculation based on LCA approach

The methodology developed by Peng et al. (2021) provides a comprehensive framework for calculating household carbon footprints by integrating life-cycle assessment (LCA) approaches. This framework accounts for both carbon emissions and sequestration from various household activities, including consumption and production, using survey data. It employs three primary LCA methods: (1) *Process LCA*, which evaluates emissions from agricultural and livestock-related processes, capturing material inputs like fertilizers and operational activities; (2) *Input–Output LCA*, applied to household consumption activities such as energy, food, housing, and transportation; and (3) *Hybrid LCA*, which combines process and input-output methods to assess afforestation activities and durable goods like clothing. The methodology categorizes household activities into specific domains, including direct energy consumption, living consumption (short-lived and durable goods), agricultural activities (emissions from material inputs and sequestration from biomass growth), afforestation (carbon sequestration from tree plantations such as citrus farming), and livestock raising (emissions from fodder preparation, livestock growth, and manure management). The total carbon footprint is expressed as the sum of emissions and sequestration across these domains, incorporating emission factors and material inputs derived from IPCC guidelines and regional data.

5.2 Overall Carbon Footprint

$$CF_i = \sum_n E_{in} + \sum_m S_{im} \tag{2}$$

where CF_i represents the Carbon footprint of household i, E_{in} is the annual carbon emissions of household i in category n and S_{im} is the annual carbon sequestration of household i in category m.

5.3 Carbon Emissions from Direct Energy Consumption

$$E_{id} = \sum_d (F_{id} \cdot EF_d) \tag{3}$$

$$EF_d = OX_d \cdot \left(C_{o,d} \cdot \frac{12}{44} + C_{h,d} \cdot \frac{12}{16} \right) \cdot H_d \cdot 10^{-9} \tag{4}$$

where E_{id} is the carbon emissions from direct fuel consumption, F_{id} is the fuel consumption of household i for fuel type d, EF_d is the emission factor of fuel d, OX_d is the oxygenation efficiency (assumed 100%), $C_{o,d}$ and $C_{h,d}$ are the CO_2 and CH_4 emission factors, and H_d is the net calorific value of the fuel.

5.4 Carbon Emissions from Living Consumption

$$E_{if} = \sum_f (EF_f \cdot C_{if}) \tag{5}$$

$$E_{ij} = \sum_j \frac{(EF_j \cdot C_{ij})}{L_j} \tag{6}$$

where: E_{if} and E_{ij} are the carbon emissions from short-lived and durable consumer products, C_{if} and C_{ij} are the amounts of consumed material, and L_j is the lifetime of durable consumer product j.

5.5 Carbon Footprint in Agricultural Activities

$$CF_{ia} = \sum_a (EF_a \cdot M_{ia}) + \sum_t (EF_t \cdot FS_{ia}) + \sum_v (B_v \cdot 0.475) \tag{7}$$

where: CF_{ia} is the carbon footprint from agricultural activities, EF_a and EF_t are the emission factors for materials and field operations, M_{ia} is the material input, FS_{ia} is the field size, and B_v is the biomass produced.

5.6 Carbon Sequestration from Afforestation

$$S_{iaf} = FS_{iaf} \cdot CS_{\text{citrus}} \tag{8}$$

where: S_{iaf} is the carbon sequestration from afforestation, FS_{iaf} is the field size for afforestation, and CS_{citrus} is the carbon stock of citrus trees.

5.6.1 Carbon Emissions from Livestock Raising

$$E_{il} = \sum_f (EF_{if} \cdot F_{if}) + \sum_l (EF_{il} \cdot N_{il}) \tag{9}$$

where: E_{il} is the carbon emissions from livestock raising, EF_{if} and EF_{il} are the emission factors for fodder and livestock, F_{if} is the fodder consumption, and N_{il} is the number of livestock.

5.7 Aggregate Formula for Household Carbon Footprint

The total carbon footprint (CF_{total}) of a household is the sum of emissions and sequestration from all relevant activities, including direct energy consumption, living consumption, agricultural activities, afforestation, and livestock raising:

$$\begin{aligned} CF_{\text{total}} = & \underbrace{\sum_d (F_{id} \cdot EF_d)}_{\text{Direct energy consumption}} \underbrace{+ \sum_f (EF_f \cdot C_{if}) + \sum_j \frac{(EF_j \cdot C_{ij})}{L_j}}_{\text{Living consumption}} \\ & \underbrace{+ \sum_a (EF_a \cdot M_{ia}) + \sum_t (EF_t \cdot FS_{ia}) + \sum_v (B_v \cdot 0.475)}_{\text{Agricultural activities}} \\ & \underbrace{- \sum_{iaf} (FS_{iaf} \cdot CS_{\text{citrus}})}_{\text{Afforestation}} \underbrace{+ \sum_f (EF_{if} \cdot F_{if}) + \sum_l (EF_{il} \cdot N_{il})}_{\text{Livestock raising}} \end{aligned} \tag{10}$$

The total household carbon footprint is denoted by CF_{total}. Fuel consumption for fuel type d is represented by F_{id}, and the emission factor of fuel d is denoted by EF_d. The amount of consumed materials for short-lived (f) and durable products (j) is represented by C_{if} and C_{ij}, respectively, with the lifetime of durable product j given by L_j. The emission factors for short-lived and durable products are represented by EF_f and EF_j, respectively. The material input for agricultural activity a is denoted by M_{ia}, while the emission factors for agricultural materials and field operations are given by EF_a and EF_t. The field size for agricultural activities is represented by FS_{ia}, and the biomass produced is denoted by B_v. The field size for afforestation is represented by FS_{iaf}, while the carbon stock of citrus trees is given by CS_{citrus}. Fodder consumption for livestock is denoted by F_{if}, and the number of livestock is represented by N_{il}. The emission factors for fodder and livestock are represented by EF_{if} and EF_{il}, respectively.

5.8 LCA Illustration

An integrated life cycle assessment (LCA) illustration highlights the relative contributions of household activities to carbon footprints by combining insights from Peng et al. (2021), Sala et al. (2014), and Matthews et al. (2008). Direct fuel use, including heating fuels and private vehicle fuels, accounts for approximately 20%–30% of total household greenhouse gas emissions. Living consumption, encompassing short-lived goods, services, and food, represents 50%–60% of total emissions. Within this category, the Mediterranean diet contributes approximately 2–3 tCO2e per capita annually, with red meat and dairy products responsible for over 60% of diet-related emissions despite contributing a smaller share of caloric intake. Cereals, fruits, and vegetables, staples of the Mediterranean diet, contribute a relatively minor portion of dietary greenhouse gas emissions. Durable goods, such as furniture and household appliances, contribute an additional 5%–10% of emissions over their service life. The combined evidence demonstrates that focusing solely on direct energy use or Tier 1 emissions substantially under-estimates the total carbon footprint of household consumption, as supply chain and embodied emissions account for the majority of impacts. This illustration is important because it emphasizes the need for comprehensive, activity-based accounting of household emissions to inform effective mitigation strategies and to enable comparison with input-output or equilibrium-based models.

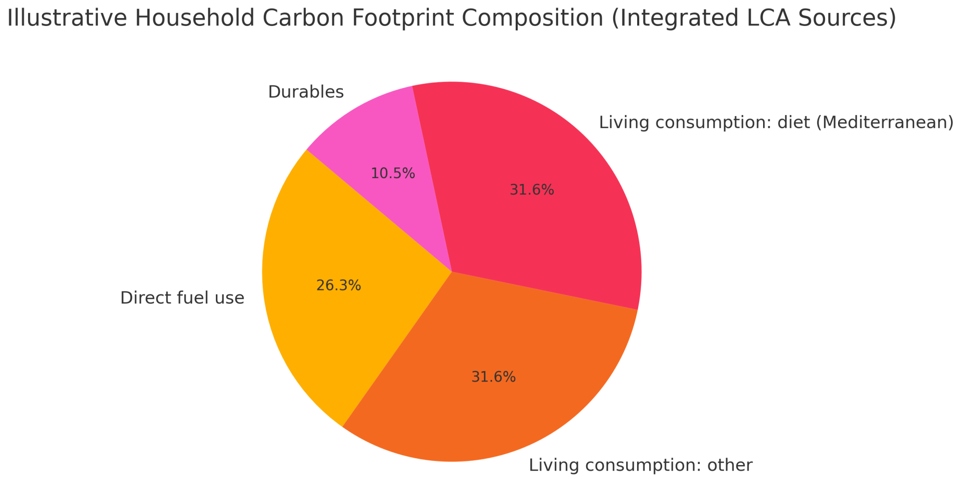

Figure 1: Relative contributions of household activities to carbon footprints

5.9 Illustration of LCA with Comparative Insights from EEIOA

Life cycle assessment (LCA) and environmentally extended input–output analysis (EEIOA) are two established methods for quantifying the carbon footprint of household consumption. While both approaches aim to capture direct and indirect greenhouse gas (GHG) emissions, they differ significantly in scope, resolution, and attribution of emissions. This section illustrates the application of LCA to household carbon footprints, integrating insights from Steubing et al. (2022), who compare LCA-based carbon footprints with those derived from EEIOA databases.

In the LCA approach, household carbon footprints are computed by summing emissions across all relevant activities and life cycle stages. The total household carbon footprint can be expressed as:

$$\mathrm{CF}_{\text{total}} = \sum_d (F_{id} \cdot EF_d) + \sum_f (C_{if} \cdot EF_f) + \sum_j \left(\frac{C_{ij} \cdot EF_j}{L_j} \right) + \sum_a (M_{ia} \cdot EF_a) - \sum_t (S_{it} \cdot CS_t) \tag{11}$$

where F_{id} is the fuel consumption for fuel type d, C_{if} is the consumption of short-lived goods f, C_{ij} is the consumption of durable goods j with lifespan L_j, M_{ia} is the material input for agricultural activity a, and S_{it} is the sequestration from afforestation activity t. EF and CS denote emission factors and carbon stock, respectively.

Steubing et al. (2022) highlight that LCA-based carbon footprints typically provide a detailed, process-specific view, often including the life cycle impacts of capital goods and infrastructure. In contrast, EEIOA provides a macroeconomic perspective, covering the entire supply chain through national accounting frameworks. A key finding is that, despite theoretical expectations that EEIOA would yield higher carbon footprints due to the avoidance of truncation errors, LCA-based estimates can be higher in certain sectors. This discrepancy arises because LCA more comprehensively accounts for capital goods and specific life cycle stages, whereas EEIOA often omits the impacts of capital formation, as represented mathematically by the exclusion of gross fixed capital formation from the supply chain matrix:

$$\mathrm{CF}_{\mathrm{EEIOA}} = R(I - A)^{-1}y \tag{12}$$

where R is the vector of emission intensities, A is the technology matrix, I is the identity matrix, and y is the final demand vector. In standard EEIOA practice, y excludes capital goods destined for production.

Comparative analysis reveals that LCA is particularly effective in capturing emissions from long-lived assets and infrastructure-intensive activities, such as renewable energy installations, whereas EEIOA better reflects the systemic supply chain emissions associated with everyday consumption. This has critical implications for household carbon footprint assessments: neglecting either method's strengths risks underrepresenting key components of emissions. For instance, Steubing et al. (2022) report that for electricity, fossil-fuel-based power shows good alignment between LCA and EEIOA results, while renewable energy systems exhibit larger discrepancies due to the treatment of construction impacts in LCA.

Illustrating household carbon footprints using LCA not only clarifies the sources of emissions by activity and material flow but also exposes the limitations of relying on purely economic or monetary input–output models. The integrated perspective is essential for designing mitigation strategies that address both immediate consumption patterns and the long-term impacts of infrastructure and capital goods.

5.10 Input-Output Matrix Model

Measurement of Carbon Footprint Using I-O Matrix

Household carbon footprints (HCF) are categorized into three tiers: *Tier 1* (direct fuel combustion), *Tier 2* (indirect emissions from purchased electricity and heating), and *Tier 3* (indirect emissions from goods and services). An Input-Output (I-O) framework is employed to estimate these emissions systematically. This methodology follows the approach outlined in Matthews et al. (2008) and Long et al. (2019).

Input-Output Framework

The total economic output required to satisfy final demand **F** in an economy is derived from the fundamental balance equation of input-output analysis:

$$\mathbf{X} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{F} \tag{13}$$

where $\mathbf{X}$ represents the total output vector across all sectors, $\mathbf{A}$ is the technology coefficient matrix that defines the interdependencies between industries, and $\mathbf{I}$ is the identity matrix. The term $(\mathbf{I}-\mathbf{A})^{-1}$ is known as the Leontief inverse, which accounts for both direct and indirect production effects required to meet final demand.

Tier 1: Direct Emissions

Tier 1 emissions result from the direct combustion of fuels by households, including natural gas, gasoline, and heating oil. These emissions are quantified using the emission coefficient matrix $\mathbf{R}$, which is a diagonal matrix where each element r_{ii} denotes the emission intensity per unit of fuel consumption. Household fuel consumption is represented as a vector $\mathbf{y}$, yielding direct emissions:

$$\mathbf{E}_1 = \mathbf{R}\mathbf{y} \tag{14}$$

where $\mathbf{E}_1$ captures emissions directly attributable to household fuel usage.

Tier 2: Indirect Energy Emissions

Indirect emissions arise from electricity and heating consumption, which are not directly combusted within households but contribute to emissions at the production stage. The calculation follows:

$$\mathbf{E}_2 = \mathbf{R}(\mathbf{I}+\mathbf{A}')\mathbf{y} \tag{15}$$

where $\mathbf{A}'$ is a subset of the input-output matrix specific to energy-producing industries. The emission intensity vector $\mathbf{R}$ in this case reflects the carbon footprint of electricity and heat generation.

Tier 3: Indirect Supply Chain Emissions

Traditional I-O models have been criticized, including by Matthews et al. (2008), for underestimating supply chain emissions due to the exclusion of imports and economic interactions beyond the primary production stage. To improve accuracy, we adopt an import-adjusted balance equation:

$$\mathbf{X} = [(\mathbf{I}-\mathbf{M})(\mathbf{I}-\mathbf{A})]^{-1}[(\mathbf{I}-\mathbf{M})\mathbf{F}+\mathbf{EX}] \tag{16}$$

where $\mathbf{M}$ is the import-adjustment matrix that removes non-domestic contributions, ensuring that emissions are calculated based solely on domestic production. The term $\mathbf{EX}$ represents exports, ensuring that emissions are assigned to domestic consumption rather than international trade.

Applying the emission intensity matrix $\mathbf{D}$, the total indirect supply chain emissions are given by:

$$\mathbf{E}_3 = \mathbf{D}[(\mathbf{I}-\mathbf{M})(\mathbf{I}-\mathbf{A})]^{-1}[(\mathbf{I}-\mathbf{M})\mathbf{F}+\mathbf{EX}] \tag{17}$$

This formulation captures emissions embedded in the entire production and distribution chain, offering a more comprehensive estimation of the household carbon footprint.

Total Household Carbon Footprint

The overall household carbon footprint integrates direct, indirect energy, and supply chain emissions:

$$\mathbf{E}_{\text{total}} = \mathbf{E}_1 + \mathbf{E}_2 + \mathbf{E}_3 \tag{18}$$

This formulation aligns with recent advances in environmentally extended input-output models, refining emission estimations by incorporating full economic feedback loops and import corrections. The inclusion of trade-adjusted emissions ensures a more realistic and policy-relevant estimation of household contributions to carbon emissions, as emphasized by Long et al. (2019).

5.11 Input-Output Matrix Model

Measurement of Carbon Footprint Using I-O Matrix

Household carbon footprints (HCF) are categorized into three tiers: *Tier 1* (direct fuel combustion), *Tier 2* (indirect emissions from purchased electricity and heating), and *Tier 3* (indirect emissions from goods and services). An Input-Output (I-O) framework is employed to estimate these emissions systematically. This methodology follows the approach outlined in Matthews et al. (2008) and Long et al. (2019).

Input-Output Framework

The total economic output required to satisfy final demand $\mathbf{F}$ in an economy is derived from the fundamental balance equation of input-output analysis:

$$\mathbf{X} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{F} \tag{19}$$

where $\mathbf{X}$ represents the total output vector across all sectors, $\mathbf{A}$ is the technology coefficient matrix that defines the interdependencies between industries, and $\mathbf{I}$ is the identity matrix. The term $(\mathbf{I} - \mathbf{A})^{-1}$ is known as the Leontief inverse, which accounts for both direct and indirect production effects required to meet final demand.

Tier 1: Direct Emissions

Tier 1 emissions result from the direct combustion of fuels by households, including natural gas, gasoline, and heating oil. These emissions are quantified using the emission coefficient matrix $\mathbf{R}$, which is a diagonal matrix where each element r_{ii} denotes the emission intensity per unit of fuel consumption. Household fuel consumption is represented as a vector $\mathbf{y}$, yielding direct emissions:

$$\mathbf{E}_1 = \mathbf{R}\mathbf{y} \tag{20}$$

where $\mathbf{E}_1$ captures emissions directly attributable to household fuel usage.

Tier 2: Indirect Energy Emissions

Indirect emissions arise from electricity and heating consumption, which are not directly combusted within households but contribute to emissions at the production stage. The calculation follows:

$$\mathbf{E}_2 = \mathbf{R}(\mathbf{I} + \mathbf{A}')\mathbf{y} \tag{21}$$

where $\mathbf{A}'$ is a subset of the input-output matrix specific to energy-producing industries. The emission intensity vector $\mathbf{R}$ in this case reflects the carbon footprint of electricity and heat generation.

Tier 3: Indirect Supply Chain Emissions

Traditional I-O models have been criticized, including by Matthews et al. (2008), for underestimating supply chain emissions due to the exclusion of imports and economic interactions beyond the primary production stage. To improve accuracy, we adopt an import-adjusted balance equation:

$$\mathbf{X} = [(\mathbf{I} - \mathbf{M})(\mathbf{I} - \mathbf{A})]^{-1}[(\mathbf{I} - \mathbf{M})\mathbf{F} + \mathbf{EX}] \tag{22}$$

where $\mathbf{M}$ is the import-adjustment matrix that removes non-domestic contributions, ensuring that emissions are calculated based solely on domestic production. The term $\mathbf{EX}$ represents exports, ensuring that emissions are assigned to domestic consumption rather than international trade.

Applying the emission intensity matrix $\mathbf{D}$, the total indirect supply chain emissions are given by:

$$\mathbf{E}_3 = \mathbf{D}[(\mathbf{I} - \mathbf{M})(\mathbf{I} - \mathbf{A})]^{-1}[(\mathbf{I} - \mathbf{M})\mathbf{F} + \mathbf{EX}] \tag{23}$$

This formulation captures emissions embedded in the entire production and distribution chain, offering a more comprehensive estimation of the household carbon footprint.

Total Household Carbon Footprint

The overall household carbon footprint integrates direct, indirect energy, and supply chain emissions:

$$\mathbf{E}_{\text{total}} = \mathbf{E}_1 + \mathbf{E}_2 + \mathbf{E}_3 \tag{24}$$

This formulation aligns with recent advances in environmentally extended input-output models, refining emission estimations by incorporating full economic feedback loops and import corrections. The inclusion of trade-adjusted emissions ensures a more realistic and policy-relevant estimation of household contributions to carbon emissions, as emphasized by Long et al. (2019).

5.12 Input-Output Matrix Model

Measurement of Carbon Footprint Using I-O Matrix

Household carbon footprints (HCF) are categorized into three tiers: *Tier 1* (direct fuel combustion), *Tier 2* (indirect emissions from purchased electricity and heating), and *Tier 3* (indirect emissions from goods and services). An Input-Output (I-O) framework is employed to estimate these emissions systematically. This methodology follows the approach outlined in Matthews et al. (2008) and Long et al. (2019).

Input-Output Framework

The total economic output required to satisfy final demand $\mathbf{F}$ in an economy is derived from the fundamental balance equation of input-output analysis:

$$\mathbf{X} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{F} \tag{25}$$

where $\mathbf{X}$ represents the total output vector across all sectors, $\mathbf{A}$ is the technology coefficient matrix that defines the interdependencies between industries, and $\mathbf{I}$ is the identity matrix. The term $(\mathbf{I} - \mathbf{A})^{-1}$ is known as the Leontief inverse, which accounts for both direct and indirect production effects required to meet final demand.

Tier 1: Direct Emissions

Tier 1 emissions result from the direct combustion of fuels by households, including natural gas, gasoline, and heating oil. These emissions are quantified using the emission coefficient matrix $\mathbf{R}$, which is a diagonal matrix where each element r_{ii} denotes the emission intensity per unit of fuel consumption. Household fuel consumption is represented as a vector $\mathbf{y}$, yielding direct emissions:

$$\mathbf{E}_1 = \mathbf{R}\mathbf{y} \tag{26}$$

where $\mathbf{E}_1$ captures emissions directly attributable to household fuel usage.

Tier 2: Indirect Energy Emissions

Indirect emissions arise from electricity and heating consumption, which are not directly combusted within households but contribute to emissions at the production stage. The calculation follows:

$$\mathbf{E}_2 = \mathbf{R}(\mathbf{I} + \mathbf{A}')\mathbf{y} \tag{27}$$

where $\mathbf{A}'$ is a subset of the input-output matrix specific to energy-producing industries. The emission intensity vector $\mathbf{R}$ in this case reflects the carbon footprint of electricity and heat generation.

Tier 3: Indirect Supply Chain Emissions

Traditional I-O models have been criticized, including by Matthews et al. (2008), for underestimating supply chain emissions due to the exclusion of imports and economic interactions beyond the primary production stage. To improve accuracy, we adopt an import-adjusted balance equation:

$$\mathbf{X} = [(\mathbf{I} - \mathbf{M})(\mathbf{I} - \mathbf{A})]^{-1}[(\mathbf{I} - \mathbf{M})\mathbf{F} + \mathbf{EX}] \tag{28}$$

where $\mathbf{M}$ is the import-adjustment matrix that removes non-domestic contributions, ensuring that emissions are calculated based solely on domestic production. The term $\mathbf{EX}$ represents exports, ensuring that emissions are assigned to domestic consumption rather than international trade.

Applying the emission intensity matrix $\mathbf{D}$, the total indirect supply chain emissions are given by:

$$\mathbf{E}_3 = \mathbf{D}[(\mathbf{I} - \mathbf{M})(\mathbf{I} - \mathbf{A})]^{-1}[(\mathbf{I} - \mathbf{M})\mathbf{F} + \mathbf{EX}] \tag{29}$$

This formulation captures emissions embedded in the entire production and distribution chain, offering a more comprehensive estimation of the household carbon footprint.

Total Household Carbon Footprint

The overall household carbon footprint integrates direct, indirect energy, and supply chain emissions:

$$\mathbf{E}_{\text{total}} = \mathbf{E}_1 + \mathbf{E}_2 + \mathbf{E}_3 \tag{30}$$

This formulation aligns with recent advances in environmentally extended input-output models, refining emission estimations by incorporating full economic feedback loops and import corrections. The inclusion of trade-adjusted emissions ensures a more realistic and policy-relevant estimation of household contributions to carbon emissions, as emphasized by Long et al. (2019).

6 Illustrative Application of the Input-Output Model

Following the formal derivation of the environmentally extended input-output (EEIO) model, this section presents an illustrative application of the framework to household carbon footprint estimation. The aim is to operationalize the Leontief-based formulation:

$$\mathbf{E} = \mathbf{C}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{F}$$

where $\mathbf{F}$ denotes the final demand vector, here represented by annual household consumption expenditure by category; $(\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse, capturing direct and indirect production requirements to satisfy $\mathbf{F}$; $\mathbf{C}$ is the vector of direct emission intensities (kg CO_2e per unit output).

In this illustration, pre-calculated environmentally extended emission intensities (kg CO_2e per euro spent) are applied to household consumption data for France, Spain, and Germany for

2021. These intensities represent the aggregated effect of $\mathbf{C}(\mathbf{I} - \mathbf{A})^{-1}$ and are derived from the EXIOBASE multi-regional input-output (MRIO) model, as accessed via Climatiq.io. The method aligns with the tier-3 comprehensive accounting approach discussed in Matthews et al. (2008), Long et al. (2019), and Sheng et al. (2024).

6.1 Data and Methodology

Household final consumption expenditure data were obtained from Eurostat and supplementary sources, converted to euros at the 2021 average exchange rate (1 USD = 0.85 EUR). Table 6 summarizes the emission intensities applied.

Table 6: Spend-Based Emission Factors (EXIOBASE via Climatiq.io)

Category	**Emission Factor (kgCO_2e/€)**
Housing, water, electricity, gas	0.30
Food and non-alcoholic beverages	0.48
Transport	0.40
Other goods and services	0.18
Recreation and culture	0.20
Restaurants and hotels	0.45
Furnishings and household equipment	0.25
Health	0.20
Alcoholic beverages and tobacco	0.42
Clothing and footwear	0.25
Communications	0.15
Education	0.15

For each country c, and for each category i, the household carbon footprint is calculated as:

$$E_{i,c} = F_{i,c} \cdot EF_i$$

where:

- $F_{i,c}$ is the household expenditure in euros for category i in country c;
- EF_i is the spend-based emission factor for category i;
- $E_{i,c}$ is the resulting emissions (kg CO_2e).

6.2 Explicit Calculation Example

For France, the household expenditure on food and non-alcoholic beverages is:

$$F_{\text{food,FR}} = 1.322 \times 10^9 \cdot 0.139 = 183.8 \times 10^9 \text{ EUR}$$

The corresponding emissions are:

$$E_{\text{food,FR}} = 183.8 \times 10^9 \cdot 0.48 = 88.2 \times 10^6 \text{ tonnes } CO_2e$$

Analogously, calculations are performed for all categories and countries.

6.3 Results

Table 7: Estimated Household Carbon Footprints by Category (Million Tonnes CO_2e)

Category	**France**	**Spain**	**Germany**
Housing, water, electricity, gas	109.5	50.4	137.3
Food and non-alcoholic beverages	88.2	47.1	100.7
Transport	66.6	30.4	94.1
Other goods and services	29.8	12.8	42.3
Recreation and culture	20.4	9.1	34.1
Restaurants and hotels	37.3	37.3	32.3
Furnishings and household equipment	16.2	8.5	31.4
Health	11.1	6.1	20.1
Alcoholic beverages and tobacco	22.8	12.8	27.1
Clothing and footwear	10.9	6.0	17.1
Communications	5.0	2.8	6.2
Education	1.0	1.5	2.2
Total	**419.0**	**223.0**	**544.9**

6.4 Discussion

This illustration demonstrates how the IO model framework, when combined with spend-based emission intensities, yields a comprehensive household carbon footprint that captures both direct and indirect emissions. The method is widely applied due to its ability to integrate complex supply chain interactions, incorporate international trade adjustments (Long et al. 2019), and support policy-relevant analyses of consumption-based emissions (Matthews et al. 2008; Sheng et al. 2024).

7 Bibliometric Analysis of Household Carbon Footprint Studies Using Input-Output Models

7.1 Methodology

This bibliometric analysis follows the methodological approach used by Sheng et al. (2024). Publications were retrieved from Scopus, using search terms related to household carbon footprint, input-output, EEIO, and environmentally extended, comprising 208 unique publications

Table 8: Household Expenditure Share by Category (% of Total, 2021)

Category	France	Spain	Germany
Housing, water, electricity, gas	27.6	24.3	25.5
Food and non-alcoholic beverages	13.9	14.2	11.7
Transport	12.6	11.0	13.1
Other goods and services	12.5	10.3	13.1
Recreation and culture	7.7	6.6	9.5
Restaurants and hotels	6.2	12.0	4.0
Furnishings, household equipment	4.9	4.9	7.0
Health	4.2	4.4	5.6
Alcoholic beverages, tobacco	4.1	4.4	3.6
Clothing and footwear	3.3	3.5	3.8
Communications	2.5	2.7	2.3
Education	0.5	1.4	0.8

on household carbon footprint estimation using input-output (IO) models, including environmentally extended input-output (EEIO) and multi-regional input-output (MRIO) frameworks. The dataset covers publications from 2008 to 2025. Duplicate records were removed using DOI and EID identifiers. Python (pandas and matplotlib) was used for data cleaning and visualization. Metrics examined include temporal publication trends, lead author contributions, co-authorship patterns, and source journals with their publishing countries.

7.2 Results

7.2.1 Temporal Publication Trends

The annual distribution of publications (Figure 2) shows steady growth in the field since 2010, with notable peaks in 2020 (27 publications), 2021 (26 publications), and sustained activity through 2024 (23 publications). This trend is consistent with findings reported by Sheng et al. (2024).

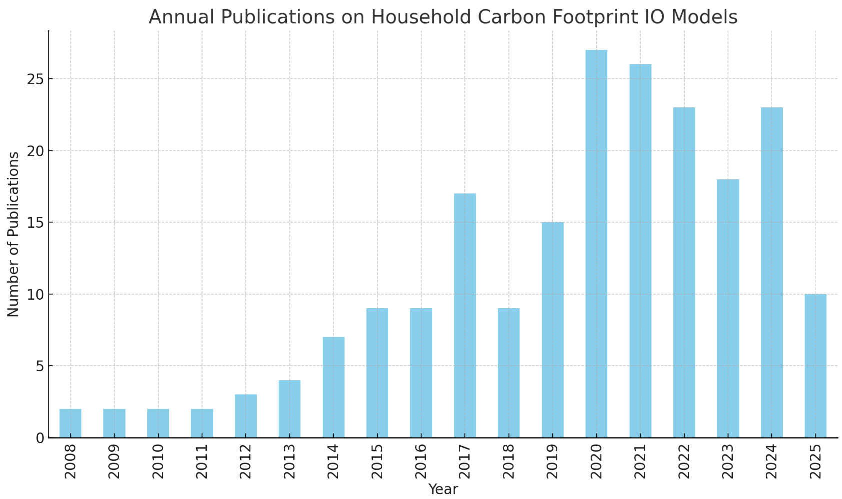

Figure 2: Annual publications on household carbon footprint using input-output models (2008–2025)

7.2.2 Lead Author Contributions

The analysis of lead authorship indicates that a small number of researchers have contributed repeatedly as lead authors in this field (Table **??**).

Table 9: Top lead authors, number of publications, and affiliations.

Lead Author	Publications	Affiliation
Long Y.	9	Beijing Institute of Technology, China
Shigetomi Y.	5	Kyushu University, Japan
Ivanova D.	4	Norwegian University of Science and Technology, Norway
Ala-Mantila S.	4	Aalto University, Finland
Druckman A.	3	University of Surrey, UK
Liu X.	3	Chinese Academy of Sciences, China
Owen A.	2	University of Leeds, UK
Zhong H.	2	Chinese Academy of Sciences, China
Chen G.	2	Norwegian University of Science and Technology, Norway
Christis M.	2	University of Antwerp, Belgium

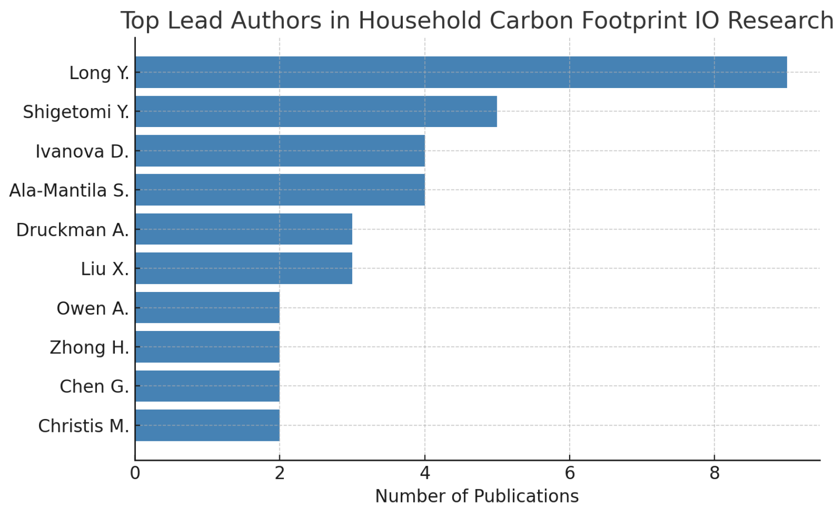

Figure 3: Top lead authors in household carbon footprint IO research

7.2.3 Co-authorship Patterns

The distribution of co-authorship (Figure 4) demonstrates the collaborative nature of the field, with most publications involving multiple authors.

7.2.4 Top Source Journals

Table 10 presents the top journals in terms of publication count, along with their publishing countries. The results highlight a strong presence of journals published in the Netherlands (Elsevier) and the USA.

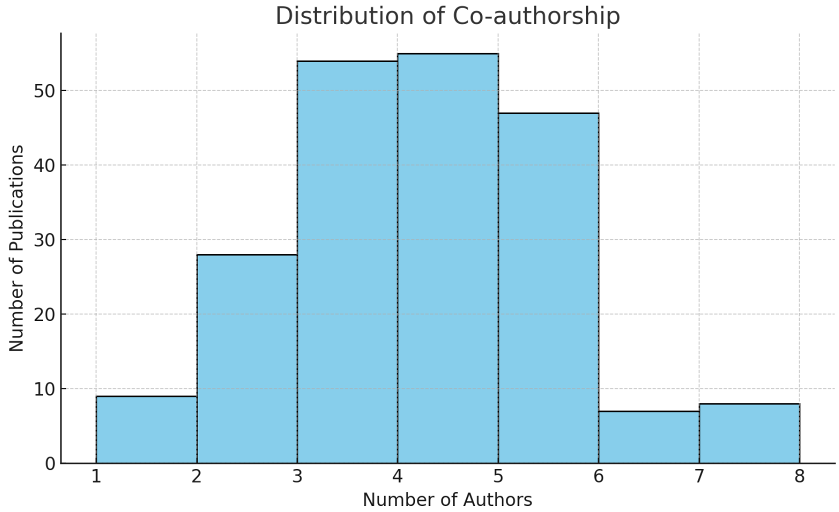

Figure 4: Distribution of co-authorship in household carbon footprint IO publications

Table 10: Top Source Journals, Number of Publications, and Publishing Countries

Journal	**Publications**	**Country**
Journal of Cleaner Production	24	UK / Netherlands
Ecological Economics	16	Netherlands
Environmental Research Letters	14	UK
Journal of Industrial Ecology	11	USA
Resources, Conservation and Recycling	11	Netherlands
Science of the Total Environment	11	Netherlands
Energy Policy	9	Netherlands
Sustainability (Switzerland)	8	Switzerland
Journal of Environmental Management	8	Netherlands
Environmental Science and Technology	5	USA

7.3 Discussion

The analysis reveals the significant growth of input-output based household carbon footprint studies, particularly after 2010. A small group of researchers, such as Long Y. and Shigetomi Y., have been especially productive. The field shows a strong collaborative character, as evidenced by the prevalence of multi-authored publications. The majority of research outputs are concentrated in leading journals published in the Netherlands, the USA, and the UK, reflecting the central role of these countries in disseminating knowledge on this topic.

The Hakenes & Schliephake Model

Traditional methods for estimating household carbon footprints attribute emissions based on direct consumption or financial ownership in emitting industries. However, they often ignore the market feedback loops triggered by individual decisions — such as how a household reducing demand might simply shift that demand to other consumers or investors.

The model developed by Hakenes and Schliephake (2024) addresses this issue through a general equilibrium framework. By embedding both product and financial markets, the model assigns carbon footprints based not only on what households consume or invest in, but also on the spillover effects of those choices across the economy. This consequentialist approach attempts to capture the true marginal impact of household behavior on aggregate emissions.

8 Deriving the Household Footprint in a One-Industry Economy

We consider a simplified version of the model developed by Hakenes and Schliephake (2024), focusing on an economy with a single industry. A representative good is produced using capital as the only input. Firms operate under constant returns to scale, with a marginal cost of production c. Let Q denote the aggregate quantity produced and consumed, and I the total capital invested. Given the linear technology, we have:

$$I = cQ.$$

Each unit of the good generates emissions x, which aggregates both production-related and consumption-related emissions. Thus, total emissions in the economy are given by:

$$X = xQ.$$

Firms and Capital Market

Firms raise capital I from households and produce output Q. After selling the output at price P, they repay investors using the liquidation value λ and a noise term ε, which follows a normal distribution with zero mean and variance σ^2. The return on investment is:

$$r = \frac{P}{c} + \lambda + \varepsilon.$$

Profits are distributed to investors in proportion to their capital contributions. Firms operate competitively, so expected profits are zero in equilibrium.

Household Optimization Problem

Household h is endowed with wealth w and allocates it between investment i_h and consumption q_h. The portion not invested yields a risk-free return r_f. The budget constraint is:

$$m_h = ri_h + r_f(w - i_h) - Pq_h,$$

where m_h is the leftover wealth after investment and consumption. The household derives utility from consumption and terminal wealth. The expected utility function is given by:

$$U_h = \mathbb{E}\left[-e^{-\alpha\left(aq_h - \frac{b}{2}q_h^2 + m_h - xQ\right)}\right],$$

where a represents the marginal utility of the first unit of the good, $b > 0$ captures diminishing marginal utility, α is the coefficient of absolute risk aversion, and xQ reflects the disutility from global emissions.

Substituting m_h into the utility function and linearizing expectations due to the exponential-normal structure, we obtain:

$$\mathbb{E}[U_h] = -\exp\left\{-\alpha\left[(a-P)q_h - \frac{b}{2}q_h^2 + r_f w + \left(\frac{P}{c} + \lambda - r_f\right)i_h - \frac{\alpha}{2}\sigma^2 i_h^2 - xQ\right]\right\}.$$

Market Equilibrium and Footprint Derivation

To calculate the household's consequentialist footprint, we compare the equilibrium outcome with and without household h. In equilibrium, the market clears:

$$Q = q_h + (n-1)q_{-h}, \quad I = i_h + (n-1)i_{-h}, \quad I = cQ.$$

Other households maximize the same utility, taking P as given. Their optimal demand and investment are derived from the first-order conditions:

$$q_{-h} = \frac{a - x - P}{b}, \quad i_{-h} = \frac{1}{\alpha\sigma^2}\left(\frac{P}{c} + \lambda - r_f\right).$$

Substituting these into the equilibrium conditions and solving, we obtain the aggregate quantity:

$$Q = \phi q_h + (1-\phi)\frac{i_h}{c} + (\text{terms independent of } h),$$

where the weighting parameter ϕ is defined as:

$$\phi = \frac{b}{b + c^2\alpha\sigma^2}.$$

This weight determines how the household's choices affect equilibrium quantities and, consequently, emissions. The consequentialist footprint of household h is defined as the marginal impact of their participation on total emissions:

$$fp_h = x\left(Q(q_h, i_h) - Q(0,0)\right) = x\left(\phi q_h + (1-\phi)\frac{i_h}{c}\right).$$

The parameter ϕ captures the relative influence of consumption and investment. When the financial asset is risk-free ($\sigma^2 = 0$), we obtain $\phi = 1$, and the entire footprint is attributed to consumption. Conversely, if consumption utility is linear ($b = 0$), then $\phi = 0$, and the footprint depends entirely on investment. This formulation ensures full accounting of emissions across households:

$$\sum_h f p_h = xQ = X.$$

9 Derivation of the Weighting Parameter ϕ

To derive the footprint weighting parameter ϕ, we begin with the assumption that aggregate output Q is produced by a linear technology using capital I with constant marginal cost c. Hence,

$$Q = \frac{I}{c}.$$

The total capital in the market is supplied by n households. We distinguish a representative household h from the remaining $n-1$ households, and denote their investment and consumption decisions by (i_h, q_h) and (i_{-h}, q_{-h}), respectively.

In equilibrium, market clearing implies:

$$Q = q_h + (n-1)q_{-h}, \quad I = i_h + (n-1)i_{-h}, \quad I = cQ.$$

Substituting into the identity $I = cQ$, we obtain:

$$i_h + (n-1)i_{-h} = c\left(q_h + (n-1)q_{-h}\right).$$

Now consider how the quantity Q changes when household h changes its behavior. Holding the other households' behavior fixed, the marginal effect of h's consumption and investment on output is given by the total differential:

$$\frac{\partial Q}{\partial q_h} = 1, \quad \frac{\partial Q}{\partial i_h} = \frac{1}{c}.$$

However, these effects are attenuated by the endogenous reactions of other households. If household h increases consumption q_h, market price P rises. Other households respond by lowering their own consumption q_{-h} and adjusting their investment i_{-h} to the new return. Conversely, if h increases investment i_h, the capital supply rises, which reduces price and affects others' choices.

We now derive the explicit behavioral responses.

The other households' optimal consumption satisfies:

$$\frac{\partial \mathbb{E}[U_{-h}]}{\partial q_{-h}} = 0 \quad \Rightarrow \quad a - x - bq_{-h} - P = 0,$$

which yields:

$$q_{-h} = \frac{a - x - P}{b}.$$

Their optimal investment satisfies:

$$\frac{\partial \mathbb{E}[U_{-h}]}{\partial i_{-h}} = 0 \quad \Rightarrow \quad \frac{P}{c} + \lambda - r_f - \alpha\sigma^2 i_{-h} = 0,$$

so that:

$$i_{-h} = \frac{1}{\alpha\sigma^2}\left(\frac{P}{c} + \lambda - r_f\right).$$

Now insert these behavioral responses into the aggregate equilibrium conditions:

$$Q = q_h + (n-1)\left(\frac{a-x-P}{b}\right), \quad I = i_h + (n-1)\left(\frac{1}{\alpha\sigma^2}\left(\frac{P}{c} + \lambda - r_f\right)\right).$$

Combining these with $Q = \frac{I}{c}$, we solve for the dependence of Q on q_h and i_h. Define the partial footprint of household h as the difference in total output caused by its activity:

$$fp_h = x\left(Q(q_h, i_h) - Q(0,0)\right).$$

Linearizing Q in q_h and i_h, and denoting the resulting coefficients as footprint weights, we obtain:

$$fp_h = x\left(\phi q_h + (1-\phi)\frac{i_h}{c}\right),$$

where

$$\phi = \frac{b}{b + c^2\alpha\sigma^2}.$$

This expression reflects how much of the household's carbon footprint is attributed to consumption versus investment. It arises from the equilibrium interactions between price responses and household behavioral elasticities in both the product and capital markets.

10 Comparative Statics of the Weighting Parameter ϕ

We now investigate how the footprint weighting parameter ϕ, defined as

$$\phi = \frac{b}{b + c^2\alpha\sigma^2},$$

responds to changes in the underlying structural parameters of the model.

Differentiating ϕ with respect to the coefficient of absolute risk aversion α, we obtain

$$\frac{\partial \phi}{\partial \alpha} = -\frac{bc^2\sigma^2}{(b + c^2\alpha\sigma^2)^2} < 0.$$

This implies that as households become more risk-averse, the footprint share attributed to consumption declines, while the relative importance of investment decisions increases.

With respect to the volatility of financial returns, captured by σ^2, we find

$$\frac{\partial \phi}{\partial \sigma^2} = -\frac{bc^2\alpha}{(b + c^2\alpha\sigma^2)^2} < 0.$$

An increase in financial risk similarly reduces ϕ, shifting the footprint burden from consumption to investment channels.

Finally, consider the effect of changing the curvature of the utility function through the parameter b. Differentiation yields

$$\frac{\partial \phi}{\partial b} = \frac{c^2\alpha\sigma^2}{(b + c^2\alpha\sigma^2)^2} > 0.$$

A higher value of b, indicating stronger diminishing marginal utility from consumption, increases the share of the footprint attributed to consumption activities.

In sum, the weighting parameter ϕ is decreasing in both risk aversion and return volatility, and increasing in the concavity of consumption preferences. These results highlight how the relative responsibility of consumption and investment for carbon emissions is endogenous to household behavior and financial risk, making the model responsive to empirical variation across households or economies.

11 Empirical Illustration: Application of the Single-Industry Model

Here, the simplified version of the Hakenes and Schliephake (2024) model is applied to the U.S. wheat market, using USDA data from 2010 to 2016. Production volumes serve as a proxy for quantity supplied, while total domestic use approximates quantity demanded. Farm prices are taken as observed average annual prices.

To estimate supply behavior, an ordinary least squares (OLS) regression of price is fitted on observed production, yielding the empirical supply curve. In the empirical illustration, the demand curve is specified as linear and downward sloping. Its slope is calibrated using average values from the dataset, consistent with observed market behavior in the U.S. wheat sector. While the curve is not estimated directly via regression (due to data limitations on price responsiveness), it reflects a stylized elasticity based on domain knowledge. This contrasts with the supply curve, which is estimated using OLS on observed price and production data. We simulate the 2016–2017 wheat supply shock, during which production declined by 15.6%. The intersection of the two curves provide the empirical equilibrium quantities and prices before and after the 2016–2017 supply shock. This is modeled by proportionally shifting the supply curve upward. Equilibrium price and quantity before and after the shock are obtained by solving the intersection between the demand curve and the respective supply curves.

Carbon Footprint Estimation under Empirical Supply Curve

We compute the carbon footprint associated with each equilibrium using an emission factor of 10.88 kg CO_2e per bushel (based on FAO and USDA estimates).

Scenario USDA data	**Quantity (million bushels)**	**Price (USD)**	**Carbon Footprint (million kg CO_2e)**
Before Shock	2100.71	5.58	22859.68
After Shock	2068.38	5.82	22500.32
Change	—	—	**-359.36**

Table 11: Carbon footprint before and after the supply shock using real market data.

Carbon Footprint Estimation under Theoretical Supply Curve

To simulate the same supply shock within the Hakenes and Schliephake (2024) framework, the demand curve from the empirical estimation was retained. However, instead of using a supply curve estimated via ordinary least squares, a theoretically derived supply curve was constructed based on model assumptions. In this approach, firms were assumed to raise capital from households, who in turn optimally allocate their investments under risk.

The equilibrium supply curve in this setup is derived from the market-clearing condition and the household's optimal investment response under uncertainty, and takes the form:

$$P(Q) = c(r_f - \lambda) + \frac{c^2\alpha\sigma^2}{n-1}Q,$$

where c denotes the marginal cost of production, r_f the risk-free rate, λ the liquidation value of capital, α the coefficient of absolute risk aversion, σ^2 the variance of investment returns, and n the total number of households.

This expression yields a linear and upward-sloping supply curve. The theoretical supply curve applied in this illustration was constructed using parameter values selected to reflect realistic conditions in the U.S. wheat and financial markets during the study period. The marginal cost of production was assumed to be $c = 4$, which is consistent with per-bushel production costs observed in U.S. wheat farming and allows the resulting equilibrium prices to align with historical market levels. The risk-free rate was set to $r_f = 0.05$, corresponding to the average yield on 10-year U.S. Treasury bonds between 2010 and 2016. The liquidation value of capital was taken as $\lambda = 0.01$, reflecting the reduced resale value of farm-specific capital such as machinery or equipment. The coefficient of absolute risk aversion was assumed to be $\alpha = 0.5$, a value that captures moderate household risk sensitivity consistent with empirical estimates from investment literature. The volatility of investment returns was specified as $\sigma = 0.4$, implying a variance of $\sigma^2 = 0.16$, which falls within the range typically observed for U.S. agricultural investments and related financial instruments. Finally, the number of households was assumed to be $n = 100{,}000$, representing an approximation of the number of wheat-producing farms in the

United States during the relevant years. These parameter values were used to generate a supply curve that reflects theoretical investment behavior under risk, providing a basis for comparison with the empirically estimated curve, and the intercept reflects the opportunity cost of capital. The new equilibrium values were obtained by solving the intersection of this supply curve with the demand curve used previously.

By solving the intersection of this supply curve with the same demand curve used in the empirical case, equilibrium values for price and quantity were obtained both before and after the simulated shock. The corresponding carbon footprints were then computed using the same emissions factor of 10.88 kg CO_2e per bushel.

Scenario Theory	**Quantity (million bushels)**	**Price (USD)**	**Carbon Footprint (million kg CO_2e)**
Before Shock	2112.36	5.69	22983.46
After Shock	2095.13	5.85	22808.35
Change	—	—	**-175.11**

Table 12: Model-based carbon footprint before and after the supply shock.

Structural Sources of Difference in Emissions Outcomes

Although the same demand curve was used in both the empirical and theoretical approaches, the estimated reduction in carbon footprint differed considerably. The empirical estimation yielded a reduction of 359.36 million kg CO_2e, while the theoretical model predicted a more modest reduction of 175.11 million kg CO_2e.

This difference can be attributed entirely to the way supply was modeled. In the empirical estimation, the supply curve was estimated via OLS using observed data on price and quantity. This approach captured market behavior as it appeared in the historical record but did not account for underlying decision-making under uncertainty or equilibrium responses. In contrast, the theoretical supply curve was derived from the model's structural assumptions, incorporating risk preferences, investment volatility, and optimal capital allocation. It reflected how households would respond to market changes under forward-looking behavior, leading to a more muted response in output and, correspondingly, in emissions.

Additionally, the theoretical model introduced a consequentialist perspective by assigning carbon responsibility based on the marginal impact of a household's consumption or investment. In doing so, it internalized substitution effects and capital reallocation, which were not accounted for in the empirical estimation. As a result, while the same emissions formula was applied in both cases, the theoretical model predicted a smaller footprint change due to the buffering effects of equilibrium adjustments. This difference underscores the importance of integrating behavioral dynamics into footprint assessment, particularly when evaluating the impact of shocks or policy interventions.

12 Responsibility for Household Carbon Emissions

12.1 Rethinking Responsibility

Households are often portrayed as central actors in climate mitigation—urged to fly less, retrofit their homes, shift their diets, or reduce electricity use. Yet, the basis on which such responsibility is assigned remains contested. What does it mean to hold a household responsible for climate change, and how do we ensure that this responsibility is fair, actionable, and grounded in reality?

Existing carbon accounting methods offer different answers. Some emphasize direct control over emissions, others focus on consumption or supply chains, and still others ask whether a household's actions actually reduce emissions. These differences reflect deeper questions about agency, influence, and obligation.

This chapter rethinks household responsibility by comparing the attribution logics embedded in four key models—production-based (GHG Protocol), product-based (LCA), demand-based (EEIO), and marginal impact models (Hakenes and Schliephake) [1]. Our aim is to evaluate not only how these methods measure emissions, but also how they construct the idea of responsibility itself and with what consequences for policy, fairness, and climate action.

12.2 Attribution Principles

12.2.1 Attribution Based on Operational Control

Control-based attribution allocates emissions to the actor who directly controls the physical source of greenhouse gas release. Emissions are assigned based on *operational responsibility*,that is, who manages the combustion process or industrial activity rather than on who benefits from or demands the resulting goods and services. In this framework, emissions from electricity generation are attributed to power plants, and those from food or goods production are attributed to manufacturing firms, not to the households that consume the outputs.

The GHG Protocol is the principal framework that operationalizes this logic. In household-level applications, it typically attributes emissions only from direct fuel use (e.g., home heating, personal vehicles) and from purchased electricity or heat (Scopes 1 and 2). Emissions embedded in goods, services, or infrastructure (commonly classified as Scope 3) are excluded unless separately modeled. As a result, household responsibility appears significantly lower than in consumption-based frameworks. For instance, while households in developed economies are responsible for an estimated 60–70% of emissions under a consumption-based approach, control-based inventories typically attribute only 10–20% to them.[2]

This method reflects a production-based understanding of responsibility: households are

[1] The Hakenes and Schliephake model can be understood as a general equilibrium carbon footprint model, as it determines household responsibility based on the marginal change in total emissions across interconnected markets resulting from a behavioral shift, accounting for substitution, spillovers, and price effects.

[2] See Hertwich and Peters (2009). Consumption-based GHG emissions. *Environmental Science & Technology*.

held accountable for emissions they physically generate or for energy they purchase, but not for upstream emissions embodied in their consumption. Although narrower in scope, this attribution style serves a clear regulatory function. Its operational clarity makes it particularly suitable for emissions inventories, carbon pricing schemes, and supply-side decarbonization policies that target industrial emitters rather than individuals. The GHG Protocol underpins most national reporting systems and corporate disclosures, and is explicitly aligned with policy instruments such as emissions caps, sectoral mitigation targets, and producer-level carbon accounting.[3] By tracing emissions to producers rather than consumers, control-based attribution enables system-level mitigation efforts without requiring detailed behavioral data at the household level.

12.2.2 Consumption-Based Attribution

Consumption-based attribution assigns responsibility for emissions to end users, based on the idea that consumer demand drives production and, ultimately, greenhouse gas emissions. Unlike control-based methods that assign emissions to producers, consumption-based frameworks trace emissions along the supply chain and allocate them to the final household that purchases or uses the good or service.

Among the methods reviewed in this paper, two approaches operationalize consumption-based attribution: life cycle assessment (LCA) and environmentally extended input–output (EEIO) models. Both assign emissions to households for the upstream impacts of their consumption, but they differ in analytical resolution and system boundaries. LCA focuses on product-level analysis by quantifying emissions over a product's entire life cycle—from raw material extraction through use and disposal.[4] This method enables fine-grained comparisons of consumption choices (e.g., meat versus plant-based diets) and supports interventions like eco-labeling and sustainable procurement.

EEIO models, by contrast, estimate emissions based on monetary flows across sectors and are designed to capture systemic effects across entire economies. They link household expenditure data with environmental accounts using national input–output tables, assigning emissions in proportion to spending across categories such as food, transport, and housing.[5] While LCA relies on detailed process-level data, EEIO models are structured around macroeconomic datasets, making them suitable for national-scale analysis and policy evaluation.

Both approaches consistently attribute a large share of global emissions to households, typically between 60% and 70% in high-income countries, by including indirect emissions embedded in consumption.[6] This high attribution has made consumption-based methods influential

[3]See World Resources Institute and WBCSD (2004). *The Greenhouse Gas Protocol: A Corporate Accounting and Reporting Standard*. Also see den Elzen et al. (2020), *Nature Climate Change*, on policy alignment of production-based accounting.

[4]Curran, M. A. (2015). Life Cycle Assessment: Principles and Practice. EPA.

[5]Wiedmann, T. (2009). A review of recent multi-region input–output models used for consumption-based emission accounting. *Ecological Economics*.

[6]Ivanova, D. et al. (2016). Environmental impact assessment of household consumption. *Journal of Industrial Ecology*.

in shaping narratives around individual climate responsibility and has informed the design of tools such as carbon footprint calculators, dietary guidelines, and voluntary offsetting schemes. However, these methods also risk overstating household agency by abstracting from structural constraints, supply-side inertia, and the availability of low-carbon alternatives.

Despite these limitations, consumption-based attribution provides valuable insights for policymaking. It highlights carbon-intensive lifestyle domains, supports the development of behavioral nudges and fiscal instruments (e.g., carbon taxes or subsidies), and enables differentiated climate strategies across income groups. In this way, it complements production-based models by identifying downstream leverage points for demand-side mitigation.

12.2.3 Consequentialist Attribution

The general equilibrium structure and derivation of the Hakenes and Schliephake (2024) model are presented in Chapter 7. Here, we focus specifically on how the model attributes responsibility for emissions—offering a fundamentally different logic from control- or consumption-based methods.

Consequentialist attribution links household responsibility to the actual change in total emissions resulting from marginal economic decisions. In contrast to attribution by operational control or average consumption, this approach estimates how much aggregate emissions would differ if a household were absent from the economy. The household's carbon footprint is thus defined as the causal marginal impact of its consumption and investment choices on total emissions.

Within the Hakenes–Schliephake framework, emissions are attributed through a counterfactual comparison: the general equilibrium of the full economy versus the equilibrium that would occur if a given household did not participate. Because the model includes both product and financial markets, the resulting footprint incorporates not only direct effects but also indirect spillovers through price mechanisms, risk-adjusted investments, and inter-household substitution. The marginal impact of a household's behavior is calculated using a weighting parameter, φ, which determines the relative attribution of emissions between consumption and investment.[7]

This weighting is sensitive to structural characteristics of the economy: greater risk aversion or financial volatility shifts responsibility toward consumption, while higher substitutability across sectors amplifies the spillover effect through investment. As a result, households are only held responsible for emissions they can meaningfully influence. If consumption is perfectly substitutable or investment flows are fully absorbed by other agents, the attributed footprint may approach zero—even if the household's nominal expenditure is large.

By assigning responsibility based on marginal system-wide impact, the model avoids double-counting and mitigates the over-attribution seen in static frameworks. It also aligns well with policy approaches that emphasize structural levers, such as green financial regulation or carbon-intensity weighting of investment portfolios. While less intuitive and more data-intensive than

[7] Hakenes, H. & Schliephake, E. (2024). Your Carbon Footprint, Including Investments. SSRN 4710536. See also Section 7.1.4 in this thesis for derivation of φ.

other methods, this attribution logic provides a refined lens for distinguishing symbolic from substantive household climate action.

12.3 Comparative Synthesis of Attribution Frameworks

Attribution methods differ not only in analytical structure but in how they frame responsibility—what they assign to households, what they assume about agency, and what they ignore. As visualized in Figure 5, these differences create meaningful trade-offs that shape both interpretation and policy relevance.

Control-based attribution (GHG Protocol) limits household responsibility to direct actions, minimizing the risk of over-attribution but offering little behavioral or structural insight. Consumption-based approaches (LCA and EEIO) invert this: they assign large shares of emissions to households, enabling lifestyle-oriented analysis but often abstracting from real-world constraints, rebound effects, or structural inertia. They perform well descriptively but struggle to differentiate between symbolic and effective action.

Only the Hakenes and Schliephake model formally incorporates systemic feedbacks. Its consequentialist logic reframes attribution as marginal influence, not average burden. This avoids double-counting and grounds responsibility in causal agency, but at the cost of complexity, abstraction, and limited communicability.

Figure 5 illustrates this spectrum: methods differ in how much they reveal about behavioral influence, how they treat economic structure, and how carefully they delimit the scope of household responsibility. Choosing an attribution framework is therefore not just a technical exercise—it reflects underlying assumptions about fairness, tractability, and what forms of action are worth encouraging.

This synthesis sets the stage for the next chapter, where we assess how different attribution logics align with climate policy instruments and what this implies for equitable mitigation strategies.

13 Results

14 Discussion

15 Conclusion

References

Statement of authorship

I hereby confirm that the work presented has been performed and interpreted solely by myself except for where I explicitly identified the contrary.

Date: ________________________

Signature: ________________________

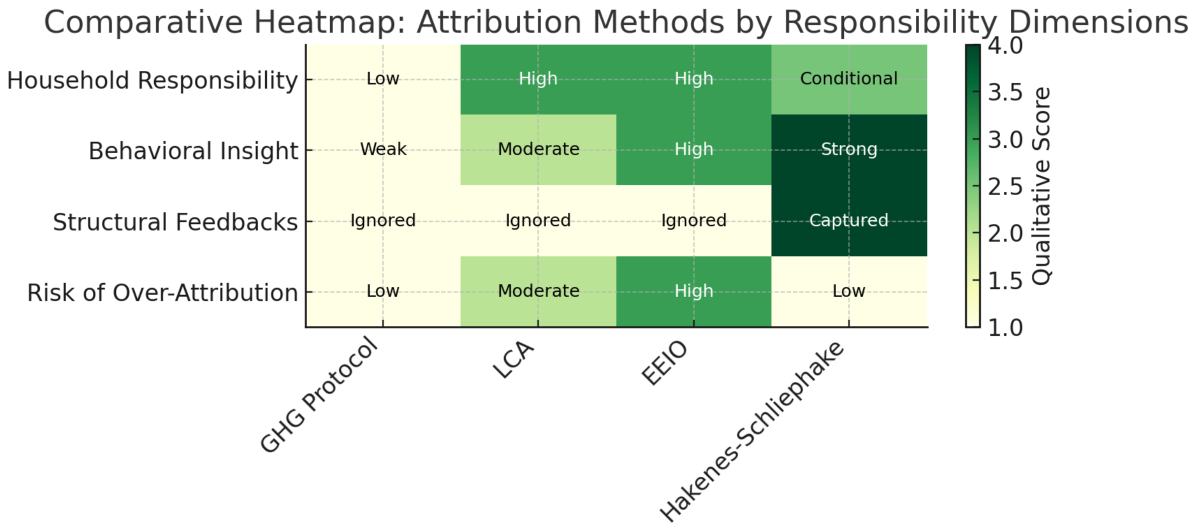

Figure 5: Comparative heatmap of attribution frameworks across key responsibility dimensions. Higher scores indicate greater behavioral relevance, structural sensitivity, or risk of over-attribution. Source: Author's own analysis based on Hertwich and Peters (2009), Ivanova et al. (2016), Hakenes and Schliephake (2024), and Capstick et al. (2019).