Local drivers and global suppliers of GHG emissions from the city of Madrid, 2010-2021*

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Abstract

Urban economies bear a significant responsibility in climate change, but estimating scope-3 emissions of urban areas is challenging due to the lack of city-level input-output tables and air emissions accounts. These limitations have led to various bottom-up and top-down strategies to address the information gap, often relying on the adoption of stringent domestic input-output modeling assumptions that limit considerably the analytical scope and granularity of the results. This paper presents the most rigorous quantification of the 3-scope carbon footprint of the city of Madrid to date, a full 2010-2021 series with a 28-industry and 47-country breakdown. The methodology consists in, firstly, integrating municipal-level economic data with regional supply and use tables to construct a series of city-specific input-output tables and to incorporate them into the FIGARO global multiregional input-output framework; secondly, constructing the first air emissions account for the city of Madrid, including direct emissions by households; thirdly,deriving a final consumption expenditure vector from household surveys. Our analysis reveals that the city's carbon footprint in 2021 was 17,447 ktCO2e for GDP and 13,920 ktCO2e for households. Only 15% originated within the city limits, 34% from the rest of Spain, and 51% from the rest of the world. The analytical possibilities offered by these data are considerably broad. We find significant emissions inequality among residents, with the top 20% of the equivalized spending distribution emitting 4.8 times more than the bottom 20%. Structural decomposition analysis shows that while efficiency improvements and technological advancements contributed to emissions reduction, these gains were largely offset by increases in consumption demand. Notably, our simulations indicate that reshaping consumption patterns of higher-income households could potentially reduce emissions by up to 26%, which is similar to the potential emissions savings from a substantial shift modality in private transport. The study underscores the need for consumption-oriented mitigation strategies and highlights the importance of addressing emissions inequality in urban climate action plans.

Keywords: carbon footprint, input-output, cities, mitigation planning, scope 3.

1 Introduction

According to the IPCC Sixth Assessment Report, policy implementation will likely fall short of the carbon dioxide (CO_2) emissions targets implied in the Nationally Determined Contributions (NDCs) of the Paris Agreement announced ahead of the UN Climate Change Conference (COP26) (IPCC, 2022). Under the current scenario, limiting global warming to below 2°C will require a rapid acceleration of mitigation efforts in overall fossil fuel use after 2030. Such transformation will require drastic reductions in industry emissions for which sector-specific interventions may prove insufficient without substantial changes to consumption and mobility patterns (IPCC, 2023b). For this purpose, urban areas are uniquely positioned to contribute to this type of mitigation efforts. Cities are responsible for a significant proportion of CO_2e emissions (IPCC, 2023a; Wiedmann and Allen, 2021; Hoornweg et al., 2011) and, with global urban population at 56% and projected to host more than 70% in 2050 (UN, 2022), its weight on decarbonization responsabilities will only continue to grow.

In the European context, Madrid is the second-largest metropolitan area of the European Union with over 6 million people (Eurostat, 2024b). It is also one of the fastest-growing economic regions in Southern Europe (Eurostat, 2024a). At the center is the city of Madrid, which in 2022 had a population of 3.28 million inhabitants (6.9% of the country and 48% of the region), reached a GDP of €168 billion (12.7% of the Spanish GDP), and a per capita GDP of €51466 (AM, 2023a,b). The service sector dominates the local economy (88.3%), specially in industries such as professional business activities, tourism, and trade, and it hosts only a modest amount of manufacturing activity (7.4%) (AM, 2023a, 2013, 2022, 2023b). It has few sources of primary energy, with no fossil fuel reserves or energy transformation plants, but a substantial level of energy consumption (Pérez et al., 2019). The economic and demographic scale of the city make its firms and households fundamental drivers of direct and indirect CO_2e emissions in Spain.

The City Council has repeatedly stated its commitment to tackling climate change (AM, 2021). After several plans guiding mitigation and adaptation interventions, the City Council approved the *Roadmap towards Climate Neutrality for 2050* (the Roadmap, hereafter) (AM, 2022), which lays out a comprehensive plan to meet the objectives of the Paris Agreement and the EU Climate Agenda (Ciambra et al., 2022). In particular, the "Roadmap aims at reducing emissions in the city of Madrid by 65% by 2030, as compared to 1990, and to achieve climate neutrality by 2050" (AM, 2022, p.3). If direct emissions totaled 12954 ktCO_2e in 1990, this means that they should fall below 4534 ktCO_2e by 2030 (AM, 2022, 12). To monitor this evolution, the City Council produced the local *Air Pollutant Emissions Inventory* in addition to the *Energy Balance* of the municipality of Madrid. The Air Emissions Inventory (AEI) provides information for over two decades on "direct emissions (scope 1) and indirect emissions due to electricity consumption and distribution losses (scopes 2 and 3), broken down by sector of activity" (AM, 2022, p.6). This complex piece of information has been a crucial contribution to the quantification of the city's responsability in climate change, as well as an indispensable tool to evaluate the implementation of mitigation policies, specifically the Roadmap. According to the Council, these data indicate that Madrid seems on track to meet its mitigation goals within a conservative 'sustainable' scenario (Ciambra et al., 2022; AM, 2022).

Consequently, the construction of a city scale AEI have been an invaluable first step toward achieving *direct* CO_2e emissions reduction in Madrid. Nevertheless, we know that *indirect* emissions tend not only to be larger than direct emissions, but also grow in time as countries or cities transition towards a highly tertiarize economy. In the 2010s, coinciding with a growing number of cities setting net-zero emissions targets and producing CO_2e inventories using standard protocols, a literature studying the carbon footprint (CF) of cities started to quantify the extent of transboundary emissions (Wiedmann and Allen, 2021). These studies have shown time and again that direct emissions are but a fraction of the total CF of any urban area (Wiedmann et al., 2021; Wiedmann and Allen, 2021; C40 et al., 2019; EEA, 2013). Since cities have offshored most of its energy production and manufacturing activity, so it has the CO_2e emissions requirements embodied in those imports (Wiedmann et al., 2021). The notion of emissions scopes separates clearly the visible from the invisible part of any CF. If inventories account for scope-1 or direct emissions, scopes-2 and -3 reflect the full carbon responsability of economic and domestic choices. In particular, scope-3 or embedded emissions are the hardest to quantify, but they account for the lion's share of the contribution to climate change (Creutzig et al., 2022; Wiedmann and Allen, 2021; Chen et al., 2020; Moran et al., 2018; Ivanova et al., 2017; Wiedmann et al., 2016; Kennedy et al., 2014). According to C40 et al. (2019, p. 16), around 85% of the consumption-based GHG emissions of C40's 94 members are generated outside the city boundaries, which influeces close to 10% of global emissions. Thus, increasing our knowledge about the geographical distribution of outsourced emissions is crucial to properly quantify cities' indirect emissions (Wiedmann et al., 2021; EEA, 2013). Furthermore, by differentiating the geographical origin of emissions, we can identify possible international constraints on decarbonization ambitions (Remond-Tiedrez and Rueda-Cantuche, 2019).

City CFs show a particularly large discrepancy between production-based and consumption-based estimations (C40 et al., 2019). In addition to being substantially more open than countries to cross-boundary exchanges of material and financial flows, cities are richer on average (Wiedmann and Allen, 2021). The level of per capita consumption is closely correlated with total consumption-based emissions (Wiedmann et al., 2021; López et al., 2017; EEA, 2013). Inequality contributes to shape the urban emissions profile by introducing heterogeneity in demand (Chancel et al., 2023; López et al., 2017). A well-known stylized fact of consumption is that the weight of essentials on family budgets, such as the amount spent on food or heating, declines as a function of the level of real income (Browning, 2018; Kaus, 2013; Chai and Moneta, 2013). Hence, different levels of inequality will introduce non-linear variations in total emissions as real income grows (Levinson and O'Brien, 2015). Urban consumption patterns are not only heterogenous but also distinctive vis-à-vis rural areas (López et al., 2016; Wiedmann and Allen, 2021), which controlling for the level of spending tend to be less CO_2e intensive (Córcoles et al., 2024; López et al., 2016). This have been connected to household's private transport and heating/cooling use (Córcoles et al., 2024), which, given the economies of scale of urban transport systems, invites further scrutiny over private mobility choices. The combination of lifestyles, municipal regulation, agglomeration economies, and infraestructure limitations shape the peculiar structure of urban economies. Understanding the sources of heterogeneity of consumption demand and economic activity in urban areas are, thus, crucial to properly design mitigation and adaptation policies (IPCC, 2023a).

Although input-output analysis has been applied to cities for a long time, the lack of tables at city scale have drawn many researchers to use national coefficient tables and non-survey methods (Wiedmann et al., 2016; Fry et al., 2018; Wiedmann and Allen, 2021; Moran et al., 2018). The substantial differences in the carbon intensity of city products and activities often lead to overestimation of production-based CFs depending on the weight of industrial activity in the city or the institutional sectors included in the calculation (Fry et al., 2018). On the other hand, the lack of city-scale global multi-regional input-output tables (GMRIO) further distorts the interconnections of the city with the rest of the world, increasing the, often downward, bias in the estimation of consumption-based CFs. Similarly to the literature working on regional CFs, this bias often stems from the data quality compromises required to produce simultaneously thousands of city footprints (Moran et al., 2018; Caro et al., 2017; EEA, 2013; Ivanova et al., 2017). The ability to focus on a single case opens the possibility to treat sources more carefully, and bring external validation to more comprehensive studies. Despite the availability of studies presenting information for many cities including Madrid (Andrade et al., 2018; C40, 2018; Wiedmann et al., 2021), they either fail to exploit the full potential of available information to improve estimation precision, or lack continuity and timeliness by presenting out-of-date single-year estimations.

No coherent decarbonization target can be reached by offshoring the emissions we are responsible for. Ignoring the accounting gap is unacceptable given the committment displayed by the European Comission, e.g. the European Green Deal. Therefore, if local authorities are comitted to come to grips with their decarbonization targets, they need to quantify and factor the full scope of indirect emissions into their mitigation planning. If indirect emissions are not factored into decarbonization scenarios, we can be certain that a 65% reduction of emissions will not equal 4534 ktCO_2e in 2030, but a substantially higher figure that is incompatible with the carbon neutrality commitment by 2050. In this connection, the paper presents the most precise and complete estimation to date of the structure and evolution of Madrid's CF by looking at the supply and demand of CO_2e emissions along the entire global value chain. It aims to contribute to the growing literature on urban CFs by exemplifying the analytical potential of using city-augmented models in combination with household surveys to track the origin and characteristics of emissions generation from the supply and the demand side (Wiedmann and Allen, 2021; Chen et al., 2020; Moran et al., 2018; C40, 2018). It aims to estimate and characterize the 3-scope CF of the city and to break down its drivers and suppliers by geographical area, industry, consumption purpose, and socio-demographic grouping. To do this, we project a city industry-by-industry input-output table (IOT) exploiting the regional supply and use framework (SUT) and 28-industry macro data from the municipal economic accounts (AM, 2023a). We embed the city table within the GMRIO framework provided by the *Full International and Global Accounts for Research in input-Output analysis* (FIGARO) database (Remond-Tiedrez and Rueda-Cantuche, 2019) to obtain as much geographical and industry detail as possible. We obtain city-level emission factors by constructing an air emissions account (AEA) from the city's inventory data (AM, 2021) following Eurostat's methodology (Eurostat, 2015, 2013). Consumption spending and socio-demographic information about city residents come from the Spanish Household Budget Survey (ES-HBS), which we use to derive a city consumption vector following the steps explained by Cazcarro et al. (2022), as well as direct household emissions related to heat and transport activities as in Córcoles et al. (2024). Additionally, we impute individual-household CO_2e volumes by 3-digit consumption purpose using aggregate emissions intensity per unit of nominal spending, with which we are able to present a bird's-eye view of the socio-demographic composition of the city's CF. Finally, we illustrate the potential of trade vis-à-vis consumption for mitigation policy via several emission reduction simulation scenarios based on supply chain reconfiguration and household behavior.

The outline of the rest of the paper is as follows. Section 2 presents the sources and methods used to derive the city-augmented GMRIO framework. In section 2.1 we briefly explain the computation method for the total CF in line with the literature. Section 2.3 explains the information requirements and methodological choices involved in the derivation of a workable city final consumption vector using micro observations from the ES-HBS. In section 2.2 we document the process by which we construct a city input-output series from 2010 to 2021 to be then included coherently within FIGARO, which includes the derivation of the rest-of-the-nation and international requirement coefficients. Section 2.4 explains the construction of the city AEA. Last for section 2, 2.5 shows the methodology applied to obtain the structural decomposition of the city's CF into an intensity, a trade, a technology, and consumption level component, as well as how we are able to simulate changes to global supply chains parsimoniously. Section 3 presents the empirical results, which separates the perspective of the city's activity (GDP) in 3.1 from households' consumption in 3.2 and from the structural decomposition with the trade and consumption scenarios in 3.3. In sections 3.1 and 3.2 we emphasize the geographical and group-wise (industry or consumption purpose) distribution of embedded emissions, but it is in the latter that we go in more depth about the distributional drivers of total emissions from the perspective of household choices. We conclude with a section 4 discussing the main takeaways, implications, and limitations of the empirical results.

2 Methodology and sources

2.1 An GMRIO model for Scope-3 CF estimation

The methodology for estimating CFs by means of environmentally extended input-output models (EEIO) is well-supported by an extensive literature (Miller and Blair, 2022; Ivanova et al., 2017; Eurostat, 2015; EEA, 2013; Martinez et al., 2019). The use of GMRIOs to distribute emissions along the global value chain further expands out ability to pin down the geografical origin of locally triggered emissions (Wiedmann et al., 2021, 2016; Remond-Tiedrez and Rueda-Cantuche, 2019). Any CF can be calculated using the standard Leontief-inverse demand-pull input-output model shown in Equation 1.

$$\mathrm{CF}^{\mathrm{p}} = \hat{\mathbf{e}}(\mathbf{I}-\mathbf{A})^{-1}\hat{\mathbf{y}} \quad (1)$$

where $\hat{\mathbf{e}}$ is the diagonalized $1 \times \mathrm{n}$ vector of emission factors. The Leontief inverse $(\mathbf{I}-\mathbf{A})^{-1}$ is a $\mathrm{n} \times \mathrm{n}$ total requirements matrix indicating the amount of inputs from the n industries directly and indirectly required per unit of industry's j output. The vector $\hat{\mathbf{y}}$ is the $\mathrm{n} \times 1$ final demand vector, which can also be a diagonalized $(\mathrm{n} \times \mathrm{n})$ or simply spread by the different demand components $(\mathrm{n} \times \mathrm{d})$, such as households' final consumption or government spending. In the case of a GMRIO, the dimensions span m number of regions or countries, such that the Leontief inverse becomes an $\mathrm{mn} \times \mathrm{mn}$ matrix, and $\mathbf{e}^{\mathrm{t}}$ and $\mathbf{y}$ $\mathrm{mn} \times 1$ vectors. One advantage of diagonalizing a unique final demand vector $\hat{\mathbf{y}}$, regardless of it being final consumption or gross domestic product, is that it preserves the dimensions of the Leontief inverse and, thus, allows for a row-wise or column-wise perspective, depending on whether a supplier or driver approach is followed. The latter corresponds to the CF concept used henceforth.

The paper will present two different approaches as we select the city's GDP or households as our unit of analysis. On the one hand, we are interested in the bi-dimensional distribution of emissions by source industry and country of origin that the gross domestic product of the city of Madrid is responsible for. From this perspective, the unit of analysis is the domestic economic activity of the urban area, and it is bounded by the National Accounts rules determining what counts as economically meaningful activity (Lequiller and Blades, 2014; Eurostat, 2013). On the other, we also want to investigate the emissions produced by households. These do not only include the direct and indirect emissions driven by household final consumption expenditure, but also those originating in heating, cooling, transportation or other household activities, which fall outside of market-oriented production. In the case of households, the CF^{h} will be a combination of the emissions embedded in the goods and services purchased by households (CF^{p}) and those direct $\mathrm{CO_2e}$ emissions originated in their direct domestic activity (CF^{d}), which is divided in three different categories: transportation, heating/cooling, and other fugitive emissions.

$$\mathrm{CF}^{\mathrm{h}} = \mathrm{CF}^{\mathrm{d}} + \mathrm{CF}^{\mathrm{p}} \quad (2)$$

We choose to derive symmetric industry-by-industry input-output tables (IOTs) from the city-projected regional supply and use tables (RSUTs) (Remond-Tiedrez and Rueda-Cantuche, 2019), organized according to the second revision of the Statistical Classification of Economic Activities in the European Community (NACE). However, we will move from industry-by-industry to product-by-product according to the Statistical classification of Products by Activity (CPA) as required by the necessary transformations applied to consumption microdata (Miller and Blair, 2022; Cazcarro et al., 2022). Whereas for GDP-related emissions it suffices to match the classification matrix and the emissions factors, results for household consumption come only after additional steps.

2.2 A city-augmented FIGARO-GMRIO

For the GMRIO framework, we rely on the global multi-regional supply and use tables (GMSUTs) provided in the *Full International and Global Accounts for Research in input-Output analysis* (FIGARO) database (Remond-Tiedrez and Rueda-Cantuche, 2019), which is an official EU statistics produced jointly by Eurostat and the Joint Research Centre of the European Commission. In its current 2024 edition, FIGARO covers the whole time series from 2010 to 2022 for the 27 EU Member States, the United Kingdom, the United States and another 17 main EU partners, plus a "rest of the world" region.

Following a series of authors (e.g. Córcoles et al., 2024, and Wiedmann et al. (2021)), we understand how crucial is to balance practicality, granularity, and accuracy in the production of city CFs. In this regard, we go beyond using national tables and emission factors to approximate smaller territorial units, for which direct observations are lacking. At the same time, we retain the detailed information provided by the national database by embedding the new tables within global value chains. This paper expands the available FIGARO-GMRIO to include a symmetric input-output table of the city of Madrid, with the corresponding adjustment to the rest of the nation. Our approach takes inspiration from several contributions that propose innovative non-survey methods to derive city-scale IOTs or SUTs

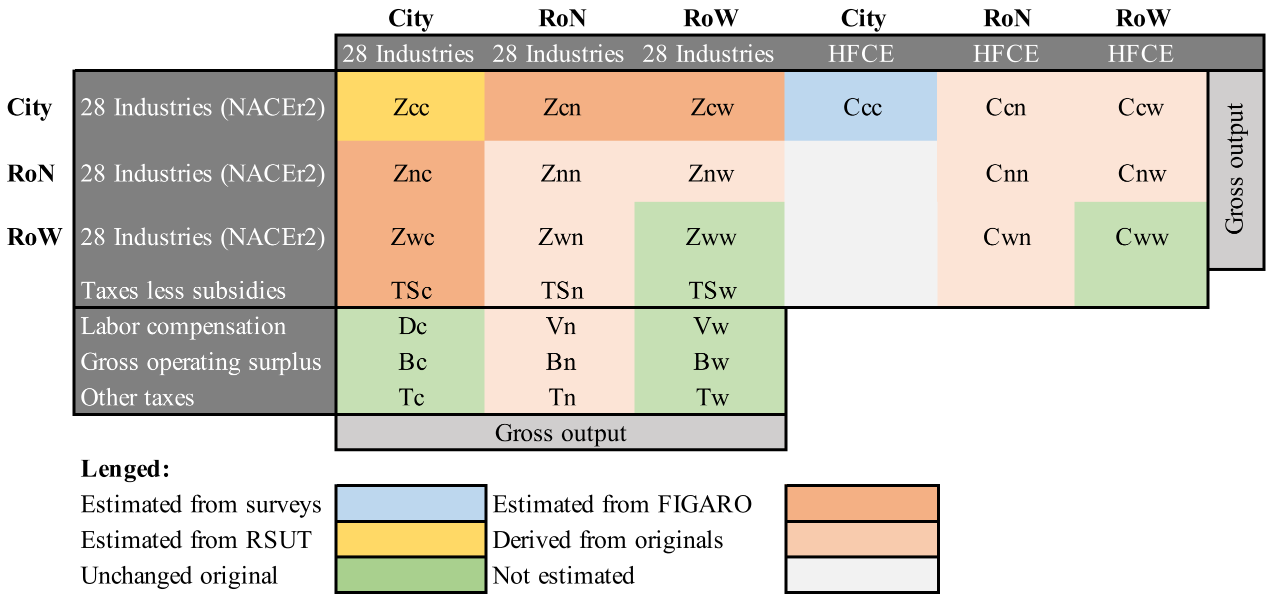

Figure 1: City-augmented GMRIO structure. Source: Authors' own elaboration.

(see Wiedmann et al., 2021; Moran et al., 2018; Zheng et al., 2022; Wiedmann et al., 2016). The three main data sources on which we produce our estimation are, first, FIGARO's GMRIO 2010-2022 series, second, the RSUTs from the region of Madrid covering the period from 2013 to 2019, and, third, the municipal accounts data running from 2010 to 2022. Figure 1 describes the different elements involved in the compilation of the city-augmented FIGARO-GMRIO database, where the c, n, w subscripts designate the city, the rest of the nation (RoN), and the rest of the world (RoW), respectively.

To arrive at this result, we initially apply the GRAS algorithm, a bi-proportional technique for updating IOTs with both positive and negative elements (Temurshoev et al., 2013; Lenzen et al., 2007; Junius and Oosterhaven, 2003), to the 2010-2021 series of RSUTs using as constraints the row and column sums derived from the value added, intermediate input, and total output vectors provided by the municipal industry accounts as shown in equations 3 and 4

$$\mathrm{b_i} = \mathrm{x_i} - \sum_{\mathrm{d}=1}^{\mathrm{k}} \mathrm{f_{i,d}} \tag{3}$$

$$\mathrm{b_j} = \mathrm{x_j} - \sum_{\mathrm{s}=1}^{\mathrm{r}} \mathrm{v_{s,j}} \tag{4}$$

where $\mathrm{f_{i,d}}$ are the k, $\mathrm{n} \times 1$ vectors of final demand components, $\mathrm{v_{s,j}}$ the r individual $1 \times \mathrm{n}$ vectors of value-added subcomponents, typically gross operating surplus, total labor compensation, and other taxes minus subsidies, $\mathrm{x_i}$ and $\mathrm{x_j}$ are the $\mathrm{n} \times 1$ and $1 \times \mathrm{n}$ vectors of final output, respectively, and $\mathrm{b_i}$ and and $\mathrm{b_j}$ are the $\mathrm{n} \times 1$ and $1 \times \mathrm{n}$ summation vectors of the $\mathrm{n} \times \mathrm{n}$ interindustry transactions matrix $\mathbf{Z} = [\mathrm{z_{ij}}]$. The vector of interindustry row sums $\mathrm{b_i}$ is provided by the municipal accounts (AM, 2023a), so only $\mathrm{b_j}$ has to be derived. Due to the lack of information about the city's final demand, we obtain the final demand vector $\mathrm{f_i}$ not by using equation 3, but by multiplying the row sums of the regional direct requirement coefficients times the municipal output vector. Furthermore, since the available RSUTs series is smaller than our target FIGARO series, we use the 2013 RSUT for years 2010 to 2012, and the 2019 RSUT for years 2020 onwards as templates for the missing coefficients.

As noted in the introduction, the region of Madrid is highly specialized toward the service sector, with negligible contributions from agriculture and only a modest one from manufacturing. Given this constraint, we find that approximating the city table by means of the regional table is almost certainly superior to using the national table. On the other hand, since the municipal accounts data follows a 28-industry NACE (rev.2) classification, we first aggregate the regional industry-by-industry symmetric table according to the municipal classification. Thanks to a many-to-one relationship between the regional and urban disaggregations, this poses no complication. Given that the regional matrix distinguishes between domestic and imported interindustry flows, we only need to aggregate both matrices to apply the GRAS algorithm so that later we can separate the two using the proportion of the original import flows to the corresponding domestic ones. This way we can estimate the $\mathrm{n} \times \mathrm{n}$ (n=28) interindustry city matrix, defined as $\mathbf{Z}_{\mathrm{cc}}$ in figure 1.

Secondly, we need to estimate matrices $\mathbf{Z}_{cn}$ and $\mathbf{Z}_{nc}$, which corresponds to the exports from the city to the rest of the nation and the imports to the city from the rest of the nation. From the import side, we have an interindustry import matrix that we can use to separate the demand from the nation $\mathbf{Z}_{nc}$ from that of the rest of the world $\mathbf{Z}_{wc}$. To be efficient, we assume that the same proportion of the national to the foreign value of each interindustry flow $z_{i,j}$ applies to the distribution of imports at the city level. This assumes that firms in Madrid have the same incentive to purchase inputs from the rest of the world as Spanish firms in general, which is akin to a gravity assumption about extra-urban trade. Following Miller and Blair (2022, p. 475), we can obtain the total value of imports from the rest of the nation $z^{nc}_{i,j}$ as follows:

$$z^{nc}_{i,j} = m^{c}_{i,j} - (m^{n}_{i,j}/z^{n}_{i,j}) = [1 - (m^{n}_{i,j}/z^{n}_{i,j})]m^{c}_{i,j} \tag{5}$$

where $m^{c}_{i,j}$ is the total city imports, $m^{n}_{i,j}$ the total national imports, and $z^{n}_{i,j}$ the total value of domestic flows from industry i to industry j, respectively.

From the export side, we face additional difficulties to derive matrix $\mathbf{Z}_{cw}$. Unlike in the case of imports, we lack a matrix of export coefficients from industry j in the city to industry i from the rest of the world. Furthermore, we have some concerns about the reported values in the regional tables, as unlike any other macro magnitude, they do not match the regional accounts provided by the regional and the national statistical offices. The only relevant pieces of information we preserve are the *aggregate* trade balance and the sectoral distribution of exports. We proceed, first, by adding up the *regional* trade balance to the city's import total to derive the aggregate level of exports. We then multiply this total by the industry export shares to apply the original distribution to the new level. This way we can have a $n \times 1$ vector of industry export totals as in equation 6,

$$e^{c}_{i} = (e^{r^*} - m^{r^*})(e^{r}_{i}/\sum_{i=1}^{n} e^{r}_{i}) \tag{6}$$

where e^{c}_{i} is the $n \times 1$ vector of city export totals by industry, e^{r}_{i} the equivalent vector from the regional table, and e^{r^*} and m^{r^*} are the aggregate magnitude of exports and imports at the regional level, respectively. Note that the regional table is first of all transformed into industry-by-industry IOTs and then aggregated to match the city industry classification.

At this point, we can apply the same procedure as in Equation 5 to split the total between the rest of the nation and the rest of the world. Basically, we multiply the level of exports computed in the previous step by the share of domestic and imported flows on total intermediate output from the Spanish national table. This way we find a distribution between the rest of the nation and the rest of the world assuming, again, that the pull from domestic intermediate supplies is proportional to the demand that the city makes from the rest of the nation. The full matrix of exports encompassing all countries and sectors is found by premultiplying the diagonalized vector of total industry exports to the rest of the world by the matrix of industry export shares from Spain to the rest of the world, where the normalizing constant is the total industry exports to the rest of the world from the country. Finally, we obtain the rest-of-the-nation matrix $\mathbf{Z}_{nn}$ by substracting matrices $\mathbf{Z}_{cc}$, $\mathbf{Z}_{cn}$, and $\mathbf{Z}_{nc}$ from the original Spanish national table, previously aggregated down to 28 industries to match the municipal accounts.

Once all these pieces are ready, we can append them to the world interindustry matrix. However, to produce fully-fledged IOTs, we include the value added components from the city accounts (B2A3G, D29X39, and D1, as per the SNA 2010 definition), adjusting the national vector accordingly. We derive the vector of taxes minus subsidies on products (D21X31, as per the SNA 2010 definition) by allocating proportionally the national vector to the share of the city to the Spanish intermediate flows total. Due to the limited information on final demand components available in the city accounts, we decided to include only gross domestic product (GDP), which for all countries can be derived from the information available in FIGARO, final consumption of the household sector (P3_S14, as per the SNA 2010 definition), and final demand as the sum of consumption and investment (P3AP5, as per the SNA 2010 definition). We perform several checks on the final matrix to make sure that the totals from the new and the old matrix match for each interindustry transaction total, value added subcomponent, gross domestic product, final consumption of households, final demand, and total output (recomputed as column and row sums) to the 10^6 decimal place.

2.3 Matching consumption microdata and the supply and use framework

In the input-output framework (Remond-Tiedrez and Rueda-Cantuche, 2019; UNDESA, 2018), household final consumption expenditure is aggregated into a single column vector containing final demand flows from each industry. With this vector $\mathbf{y}^{h}$, it is possible to compute the CF of household consumption by industry. However, it is well-known that this aggregation suppresses information on the heterogeneity of the household sector, in addition to presenting the information in a product classification that is very different from the one that consumers can relate to in their spending choices (Mongelli et al., 2010). As explained by Cazcarro et al. (2022), in the absence of information about aggregate household consumption or if we desire to match household microdata to SUTs, we need to transform the spending information from household surveys into the IOTs' price and industry classifications. Household expenditures are typically recorded at purchaser's prices and according to the Classification of Individual Consumption by Purpose (COICOP), whereas households' final consumption expenditure is presented at basic prices and according to the CPA classification. Purchaser's prices are equal to producer's prices plus taxes minus subsides on products, which, in turn, are equal to basic prices plus domestic transportation costs and trade margins (Remond-Tiedrez and Rueda-Cantuche, 2019). Each of these transformations require data that is often not reported for confidentiality reasons, which further complicates the estimation of the CF from the perspective of households' final consumption expenditure.

In this paper we are missing a city consumption vector. Following the CF regionalization literature, we exploit household-level data from the Spanish Household Budget Survey (ES-HBS) to derive it. To pin down which households are actual residents in the city of Madrid, we subset the ES-HBS by NUTS2 region and provincial capital, such that we can select all the available observations from residents. Notwithstanding this, it is an established fact that household surveys underestimate consumption totals by falling short of National Account's targets (Coli et al., 2022; Ivanova et al., 2016). To make up for these relevant constraints, we follow the four-step procedure described in Cazcarro et al. (2022). Firstly, we correct the survey weights to match the Spanish population total from Eurostat's Sector Accounts. Secondly, we proportionally distribute the gap between the survey and National Accounts' totals at each 3-digit COICOP heading as recommended by Coli et al. (2022). Thirdly, we transform the vector of COICOP macro totals into CPA by means of the estimated bridge matrix for Spain provided by Cazcarro et al. (2022) in their excellent online appendix. To update the table annually, we apply a GRAS algorithm to the appropriate consumption vectors at purchaser's prices in CPA and COICOP for each year (Temurshoev et al., 2013). Fourthly, we derive implicit transportation and tax margin rates and retrieve the vector of household consumption at basic prices, which matches the appropriate CPA vector in the SUTs. This step involves several intermediate operation and the use of the national SUTs to distribute taxes as well as trade and transportation margins. We first calculate transport and trade margins and derive implicit tax rates as a residual. Lastly, we apply the transformation matrix from the fixed sales structure model "D" to obtain the NACE industry vector with which we work to find footprint estimates (Miller and Blair, 2022, ch. 4). Conversely, when we present data on total emissions by consumption purpose in Section 3.2, we reverse the previous process by moving from NACE to COICOP classification using commodity-technology model "B" to revert back to CPA (Miller and Blair, 2022, p. 203) and then the same bridge matrix used in the first place. This procedure returns the same totals in both classifications. However, we do not undo completely the transformation from purchaser's to basic prices. Since taxes have no meaning in terms of emissions, we stop at producer's prices.

2.4 Challenges in the derivation of city emissions factors

Computing activity-related CFs requires data on CO_2e emissions matching the industry classification of the GMRIO tables. Eurostat provides GHG emission totals broken down by 64 industries (NACE) plus households, which are designed to be fully compatible with FIGARO tables. From these data it is straightforward to derive emissions factors relating GHG emitted by the entire national economy to specific macro aggregates, typically gross output (P1).[1] One relevant limitation of Eurostat's AEAs is that it only covers EU Member States, EFTA Countries, and Candidate Countries. FIGARO's intended reach is, however, the entire global economy. Fortunately, FIGARO includes an application module reporting the CFs of all countries. Following Córcoles et al. (2024), we reverse Equation 1 to retrive the national emissions total for each country in FIGARO, and then aggregate the resulting vectors to match the 28-industry city classification.

Since we operate with a city-augmented GMRIO model, we need a city AEA, which, unfortunately, does not exist. This imposes three main constraints on the derivation of emission factors for the city. First, inventories are based on the territorial principle, whereas emissions accounts follow the National Accounts convention of the residence principle (Eurostat, 2015). Second, the standard inventory classification follows a functional, not an economic distribution, and, thus, it is not directly compatible with the GMRIO's working classification. Third, we lack access to the source information on emissions used in the construction of the city CO_2e inventory to ground the derivation of the corresponding accounts, so we need to rely on an approximation.

To address these challenges, we start from the excellent city AEI released publically by the local administration for the period 1999-2021 (AM, 2021). The city's inventory reports all the kilotonnes of CO_2e emissions that occur within the limits of the city according to the Selected Nomenclature for Air Pollution (SNAP) sector classification, with the exception of SNAP 01 as no emissions of this type are found. It reports the same GHGs as Eurostat, with the exception of NF_3, for which there are no readings within the city limits. It follows the EMEP/CORINAIR methodology to estimate total atmospheric emissions, which causes small discrepancies with the IPCC methodology.

We address these issues by following an inventory-first approach based on imputation and secondary information (Eurostat, 2015; Córcoles et al., 2024; Sánchez Serrano, 2023). Firstly, we assume that changing from the territorial to the

[1] Eurostat's definition of GHG includes CO_2 in addition to N_2O, CH_4, HFC, PFC, NF_3, and SF_6 in CO_2e.

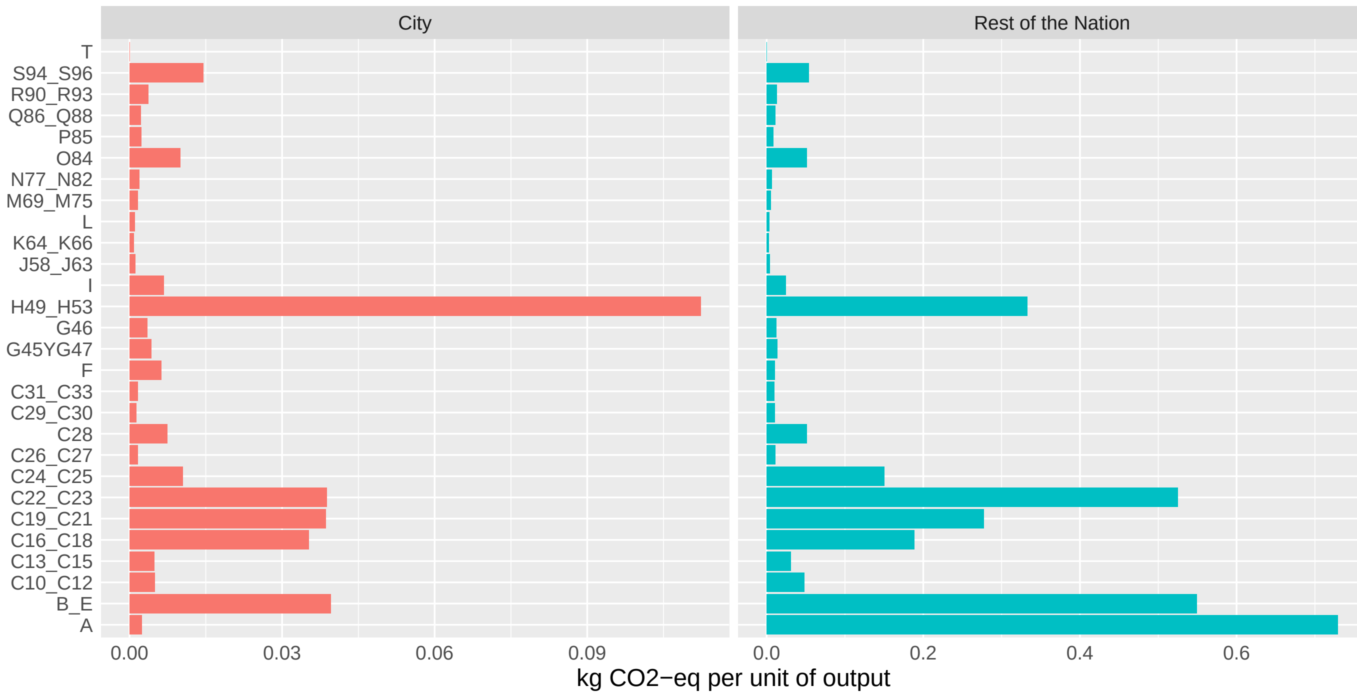

Figure 2: Emissions factors by industry (NACE rev.2) for the city and the rest of the nation, 2021. *Source*: Authors' calculations based on Eurostat's, FIGARO, and regional and city accounts data

residence principle is possible using the share of the national bridge items on the national inventory total provided by Eurostat for land and water transport. For air transport we rely on data from AENA (2023) on airport operations. We allocate the share of Madrid's Barajas Airport over the national emissions balance from air travel, 18% in 2021, to the sector of other transport (SNAP 08) in the city's inventory. Similarly, I assign 125.9% of the balance of land transport (a rather small quantity) to road transport (SNAP 07). Hence, changing from one to another classification upscales the GHG total, excluding households direct emissions, from 6356 ktCO_2e to 8001.7 ktCO_2e in 2021. Nevertheless, we regard this as a conservative estimation, since, from a National Accounts perspective, the emissions produced by many transport firms from the rest of the country should be considered part of the city's direct emissions. Due to lack of appropriate information, we do not pursue additional residence-principle adjustments.

Secondly, we exploit the information in Annex I of Eurostat's Manual for AEAs (Eurostat, 2015) to create a correspondence map between SNAP and NACE (rev.2). Unfortunately, it is not a one-to-one matching across classifications, so we rely on national data to derive a two-step bridge matrix to move from the 10-sector SNAP classification, in which the city inventory is presented, to the CRF/NFR classification used by national AEIs and, finally, to the 28-industry NACE classification to which the FIGARO GMRIO database has been aggregated to fit the estimated city IOTs. We construct two matrices $\mathbf{S}$ and $\mathbf{N}$ to achieve this transformation. The first one attaches to the CRF/NFR classification the corresponding national GHG totals from Eurostat's AEIs by source sector. Since there is a many-to-many relationship between the two classifications we distribute each AEI sector's total as a proportion on the SNAP row-sums total. In other words, we distribute each CRF/NFR total *proportionally* to the share of each total on the SNAP cross-CRF/NFR total. This way, we proxy the missing distributional information by the relative weight of each CRF/NFR code falling within individual SNAP categories. The resulting $\mathrm{s} \times \mathrm{m}$ matrix $\mathbf{S}$, where s is the number of SNAP codes and m the corresponding CFR/NFR codes, is normalized by the SNAP row sum totals. The second matrix follows a similar procedure in which Eurostat's national industry totals from the AEA are proportionally distributed across CRF/NFR codes. We exclude households (HH_TRA, HH_HEAT, HH_OTH) from the list of NACE industries considered. The $\mathrm{m} \times \mathrm{n}$ matrix $\mathbf{N}^{\mathrm{t}}$ is normalized by the row totals of the corresponding CRF/NFR sectors. Using the city's inventory $\mathrm{e}_{\mathrm{c}}^{\mathrm{S}}$, we derive the 28 NACE (rev.2) activities comprissing the city CO_2e emissions accounts $\mathrm{e}_{\mathrm{c}}^{\mathrm{N}}$ as follows,

$$\mathbf{e}^{\mathrm{N}} = \mathbf{e}^{\mathrm{S}}\mathbf{S}\mathbf{N}^{\mathrm{t}} \tag{7}$$

Thirdly, we introduce a series of modifications to $\mathbf{S}\mathbf{N}^{\mathrm{t}}$ to accommodate the peculiarities of the city's economy. We redistribute 30% the use of solvents and other products (SNAP 06) to other direct emissions by households (HH_OTH), downscale Agriculture (A01-A03) to 10% of the national proportion for each SNAP sector, and eliminate all mining activity (B) altogether on the premise that it does not exist or it is negligible. Most importantly, we apply a reduction of 95% in the amounts produced by the electricity, gas, steam and air conditioning supply industry (D35), which together with mining (B), water collection, treatment and supply (E37) and sewerage, waste management, and remediation activities (E37-E39) make up the total of the composite industry of mining and supplies (B_E). After these modifications, we allocate proportionally the gap across the remaining industries to match the aggregate constraints.

The resulting city accounts match the corrected inventory totals by construction. We apply one additional correction to the intensities to upscale (downscale) those sectors which are underrepresented (overrepresented) in the city vis-à-vis the country by applying the ratio of the city to the rest of the nation's output shares. This causes some redistribution from manufacturing to services, which we deem reasonable given the service orientation of the city economy (AM, 2023b). Figure 2 compares the emissions factors for the city of Madrid and the rest of Spain. We can see that the two economies present some differences in both the distribution and the magnitude of the emissions per unit of output. Regarding the later, the emissions intensity for the whole economy was in 2021 of 0.112 and 0.015 kg of CO_2e per unit of output for the rest of the nation and the city, respectively, which shows that the differences in magnitude are well within the general difference between the two economies. On the other hand, we observe a rather low intensity of transportation (H49_H53) and public administration (O85), and within tiny proportions for other services. Finaly, we subtract the city vector from the national one to derive the rest of the nation's CO_2e industry emission quantities. At this point, computing the emission intensity-ratios is trivially done by dividing industry CO_2e emissions by the corresponding gross output value (P1). Table 1 shows the totals broken down by direct emissions component, industries and the original inventory total.

A full AEA, however, must include direct emissions produced by household activities. Eurostat divides them into three categories: heating and cooling activities (HH_HEAT), transport activities (HH_TRA), and other emissions-producing activities (HH_OTH). The first two can be derived bottom-up from ES-HBS micro data. We estimate emissions from heating and transport activities by combining total quantities of different energy products with the appropriate emissions factors provided by MITECO (2023). There is no information to derive cooling-related emissions, and we exclude electricity as it represents scope-2 emissions that are included in the corresponding energy producing industry. An additional issue is that total direct transport emissions by households are larger than all the transport emissions reported in the city inventory. Besides the unlikely possibility that households build fuel stocks, this is likely due to household members driving to work outside the city limits. Since the latter uses direct measurements from road transport, we decide to exclude 30% of households direct transport emissions in order to substract households' road transport emissions from those made by firms and recorded in the inventory (SNAP 07). This, again, produces some redistribution before applying Equation 1. However, since the residence principle rules the construction of the accounts, this missing 30% from households direct emissions is kept for the purpose of reporting direct transport emissions by households; we found no reasonable criterion to substract the emissions from non-residents. Lastly, we reallocate 30% of total solvents and other products emissions (SNAP 06) from the city's inventory to other direct emissions by households. Table 1 shows the CO_2e total derived by household activities (heating/cooling, transport, other) and by economic activity across industries; we include the original AEI total reported by the City Council for reference.

Year	Heating	Transport	Other	Industries	Inventory
2010	1335.7	4139.2	375.4	5825.7	8899
2011	1385.5	3981.7	369.4	5295.4	8261
2012	2139.5	3426.1	364.3	4676.1	8043
2013	1357.4	3152.5	362.7	5386.0	7802
2014	1279.9	2951.3	360.8	5395.2	7441
2015	1529.2	3069.0	211.2	5157.4	7187
2016	1190.8	2930.1	208.2	5879.9	7429
2017	1301.3	2925.9	166.4	5645.3	7219
2018	2025.1	2986.1	128.7	5222.1	7501
2019	1424.3	3045.6	126.3	5720.3	7230
2020	1779.6	1820.5	108.0	3470.3	5880
2021	1593.9	2312.2	109.3	3986.2	6356

Table 1: Breakdown of household direct emissions by type of activity, city industry emissions total, and the original city GHG inventory total, expressed in ktCO_2e. *Source*: Authors' own calculations.

2.5 Structural decomposition as a base for simulating trade shocks on total emissions growth

In Section 3.3, we use structural decomposition analysis (SDA) to disentangle the contribution by changes in emissions intensity, trade, technology, and final demand to the variation in industry-level emissions for the input-output model in equation 1. SDA methodology uses the main elements of the standard input-output model, such as the Leontief inverse and the final demand vector, to decompose the change in one variable into the changes of its constituent parts (Arto and Dietzenbacher, 2014). The application of SDA to the quantification of the underlying sources of changes in CO_2e emissions has grown considerably in the last decade from Dietzenbacher and Los' seminal paper (1998). More recently, papers by Hoekstra et al. (2016), Arto and Dietzenbacher (2014), and Xu and Dietzenbacher (2014) have expanded on the original model to include additional decompositions to the the Leontief inverse and final demand vector to capture specific effects, such as separating trade and technology contributions, or distinguishing between the level and composition impacts of final demand. In this paper, SDA will allow us to break down the evolution of Madrid's consumption-based CF into the contribution of emissions intensities, consumption, trade, and technology. It must be noted that due to data limitations, the decomposition uses flows at current prices.

For this purpose, we introduce a few modifications to the canonical threefold decomposition in Miller and Blair (2022, sec. 13.1.5) or Dietzenbacher and Los (1998). We start by defining $\Delta\varepsilon$ as the growth in the volume of CO_2e emissions between two periods, with superscripts 0 and 1 for the two different years, which in this case are 2010 and 2021. By definition, $\Delta\varepsilon$ is the result of our standard model in the two periods as follows,

$$\Delta\varepsilon = \varepsilon^1 - \varepsilon^0 = \mathbf{e}^1\mathbf{L}^1\hat{\mathbf{y}}^1 - \mathbf{e}^0\mathbf{L}^0\hat{\mathbf{y}}^0 \tag{8}$$

where $\mathbf{e}$, $\mathbf{L}$, $\hat{\mathbf{y}}$ are the $1 \times \mathrm{n}$ CO_2e emissions intensity vector, the Leontief inverse, and the $\mathrm{n}\times\mathrm{n}$ diagonalized vector of final household consumption, respectively. From equation 8 we can follow the standard SDA methodology (Dietzenbacher and Los, 1998; Miller and Blair, 2022, sec. 13.1.1 to 13.1.5) to expand and rearrange the definition of $\Delta\varepsilon$ and break it down into the three components of the basic additive decomposition. As noted by Dietzenbacher and Los (1998, p. 310), structural decompositions are non-unique, but taking the average of the two polar decompositions provides a sufficient approximation to the average of all possible approaches. Equation 9 presents the threefold decomposition described by Miller and Blair (2022, 13.1.5), which presents separately the effects of changes in emissions intensity, the technique of production, and final consumption demand, which add up to $\Delta\varepsilon$ by construction.

$$\begin{aligned}\Delta\varepsilon = &\frac{1}{2}\underbrace{(\Delta\hat{\mathbf{e}})(\mathbf{L}^0\hat{\mathbf{y}}^0 + \mathbf{L}^1\hat{\mathbf{y}}^1)}_{\text{emissions intensity change}}\\ &+ \frac{1}{2}\underbrace{[\hat{\mathbf{e}}^0(\Delta\mathbf{L})\hat{\mathbf{y}}^1 + \hat{\mathbf{e}}^1(\Delta\mathbf{L})\hat{\mathbf{y}}^0]}_{\text{technological change}}\\ &+ \frac{1}{2}\underbrace{(\hat{\mathbf{e}}^0\mathbf{L}^0 + \hat{\mathbf{e}}^1\mathbf{L}^1)(\Delta\hat{\mathbf{y}})}_{\text{final consumption change}}\end{aligned} \tag{9}$$

However, the Leontief inverse captures and, thus, blurs differences in trade and technology. To tell the contributions from trade and technology apart, we draw from the decomposition within a multiregional framework of the $\mathbf{A}$ matrix into the Hadamard product of two component matrices, $\mathbf{C} \otimes \mathbf{H}$, as described in detail in Xu and Dietzenbacher (2014), Arto and Dietzenbacher (2014), and Hoekstra et al. (2016). In this setting, matrix $\mathbf{H}$ contains the total intermediate input requirements irrespective of the source country, such that $\mathrm{z}^{\mathrm{s}}_{\mathrm{ij}} = \sum_{\mathrm{r}} \mathrm{z}^{\mathrm{rs}}_{\mathrm{ij}}$, as described in Hoekstra et al. (2016). Conversely, matrix $\mathbf{C}$ contains the share of all inputs of good i from country s coming from country r, where the corresponding elements are derived as $\mathrm{c}_{\mathrm{ij}} = \mathrm{a}^{\mathrm{sr}}_{\mathrm{ij}}/\mathrm{h}^{\mathrm{r}}_{\mathrm{ij}}$.

Starting from $\mathbf{L} = (\mathrm{I} - \mathbf{C} \otimes \mathbf{H})^{-1}$, Miller and Blair (2022, p. 607) show that $\Delta\mathbf{L} = \mathbf{L}^1(\Delta\mathbf{CH})\mathbf{L}^0$, where $\Delta\mathbf{CH}$ can be itself divided into the specific $\Delta\mathbf{C}$ and $\Delta\mathbf{H}$ effects,

$$\Delta\mathbf{CH} = \frac{1}{2}(\Delta\mathbf{C})(\mathbf{H}^0 + \mathbf{H}^1) + \frac{1}{2}(\mathbf{C}^0 + \mathbf{C}^1)(\Delta\mathbf{H})$$

Using this useful decomposition, we we can piece all previous elements together and split the technological change effect from 9 into a trade and pure technique of production contribution, so that we can rewrite the decomposition formula and reach our final expression as follows

$$\begin{aligned}\Delta\varepsilon = &\frac{1}{2}\underbrace{(\Delta\hat{\mathbf{e}})(\mathbf{L}^0\hat{\mathbf{y}}^0 + \mathbf{L}^1\hat{\mathbf{y}}^1)}_{\text{emissions intensity change}}\\ &+ \frac{1}{4}\underbrace{\{\hat{\mathbf{e}}^0\mathbf{L}^0[\Delta\mathbf{C} \otimes (\mathbf{H}^0 + \mathbf{H}^1)]\mathbf{L}^1\hat{\mathbf{y}}^1\}}_{\text{trade structure change}}\\ &+ \frac{1}{4}\underbrace{\{\hat{\mathbf{e}}^0\mathbf{L}^0[(\mathbf{C}^0 + \mathbf{C}^1) \otimes \Delta\mathbf{H}]\mathbf{L}^1\hat{\mathbf{y}}^1\}}_{\text{technological change}}\\ &+ \frac{1}{2}\underbrace{(\hat{\mathbf{e}}^0\mathbf{L}^0 + \hat{\mathbf{e}}^1\mathbf{L}^1)(\Delta\hat{\mathbf{y}})}_{\text{final demand change}}\end{aligned} \tag{10}$$

Splitting $\mathbf{A}$ into the element-wise product of matrices $\mathbf{C}\otimes\mathbf{H}$ presents us with the opportunity to simulate changes in trade patterns on the assumption that the technique of production remains unaffected. In section 3.3, after presenting the structural decomposition results, we introduce a series of simulation results to illustrate the potential effect of blunt decoupling or global supply chain restructuring on total consumption emissions. The premise is that substituting one supplier from another, even though these systemic transformations are very hard to come by in practice, may have a potentially beneficial or adverse contribution to decarbonization efforts. Furthermore, by providing a transparent quantification of this potential contribution we expect to facilitate the discussion about prioritizing local drivers or global suppliers in implementing decarbonization policies.

The overall approach consists in downscaling the participation of decoupling countries on the global supply of inputs to industry j and, conversely, upscaling the input coefficient of the remaining industries by proportionally allocating the total amount of input value that is no longer coming from decoupling countries. We introduce this changes in matrix $\mathbf{C}$, which we then use to retrieve matrix $\mathbf{A}$ and $\mathbf{L}$, such that

$$\mathbf{A}^{\text{new}} = \mathbf{C}^{\text{new}} \otimes \mathbf{H}^{\text{old}}$$

From this point we simply follow the standard approach from section 2 to derive the new emissions level and distribution.

3 Results

3.1 Industry drivers and suppliers of the city's GDP CF

We estimate the total CF of the city's gross domestic product (GDP) in 2021 to be in the order of 17447 $ktCO_2e$, from which 2699 $ktCO_2e$ are direct CO_2e emissions generated within the city limits. This is 62.4% of the emissions estimated for 2010, when the total CF of domestic activity was 27963 $ktCO_2e$, of which 3567 $ktCO_2e$ resulted from direct emissions. In 2021, 15% of emissions came from the city, whereas the rest of the nation and the rest of the world contributed by 33% and 51%, respectively. Conversely, in 2010, the rest of the world accounted for 47% and the rest of the nation for 40% of total emissions. We observe a decline in total emissions but an increased relevance of the global supply, as the rest of the world captures a substantially larger share of scope-3 emissions.

Figure 3 shows the time series of emissions volume by source area from 2010 to 2021. To zoom in on the underlying trends, the European Union, the United States, and China have been separated from the rest of the world's total. In general we observe a decline for all source areas in accordance with a declining total. Nevertheless, across the period we observe a redistribution of emissions from China to the United States after a period reversal from 2014 to 2018. The ratio of total emissions coming from China to those from the United States went down from 2.68 to 2.07, which amounts to 338.6 $ktCO_2e$. This concentrates on mining and energy supply (B_E), whose emissions declined for China but shot up for the United States. The same tendency can also be observed for other sectors such as manufacturing of chemicals, coke and petroleum products (C19_C21), manufacture of other machinery and equipment (C_28) or wholesale and retail trade (G45YG47). In the case of mining and energy supply, imports from China fell slightly whereas those of the United States went up from 22.17 to 86.35 million euros. Nonetheless, looking at emissions factors, we can observe that there are similar improvements in efficiency in China versus the US for mining and energy supply, whereas for other equipment or trade the efficiency gains almost double the ones realized in the US or Germany. Hence, even with expanding demand for manufactures, the relative and absolute decline is noticeable in the time series.

In the same way that upstream emissions come predomintly from energy and transportation industries, learning about

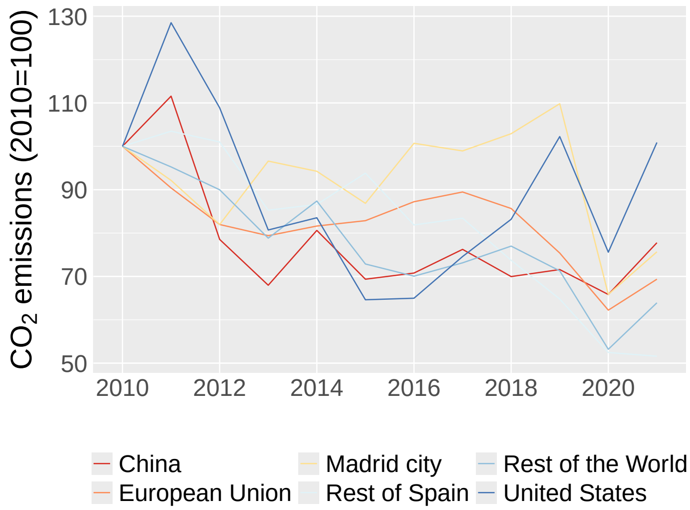

Figure 3: Decomposition of $ktCO_2e$ emissions growth by main geographical area, 2010-2021 (2010=100). *Source*: Authors' own calculations

the sectors driving indirect emissions presents the responsibilities in a clear way. Incidentaly, this enhences the ability to target the correct industries for environmental policies at city scale. Figure 4 aggregates the contribution of 2-digit industries as suppliers and drivers of emissions by aggregating the row or column totals from the CF matrix in equation 1, respectively. The first bar indicates that three sectors: mining and energy products (B_E), manufacturing (C), and transportation and storage (H), account for more than 90% of total emissions embedded on goods and services imported by domestic expenditures. Conversely, from the standpoint of the city's final demand, we see that sector responsibility is more balanced, even if the same sectors together with wholesale and retail trade (G) trigger 50% of total city emissions.

Looking at the driver industries of the city's CF, figure 6 shows the two-dimensional distribution of the total CF of the city broken down by industry and main source area. The first thing to notice is the strong discrepancy between direct and indirect emissions, but also how the gap behaves across industries. As noted in figure 4, the largest contributor is the composite sector of mining and energy supply (B, E), which accounts for 3477 $ktCO_2e$. They come predominantly from the city, but in 2021 1142 $ktCO_2e$ were imported from the rest of Spain and 1789 $ktCO_2e$ from the rest of the world. The situation changes for other industries. The second largest driver is the wholesale and retail industry (G), in which the rest of Spain dominates with 50% of the total. An even larger 71% share is obtained for transportation and storage, but the picture holds for most sectors. This highlights how urban economies are crucially integrated within larger metropolitan or country-spanning economic agglomerations.

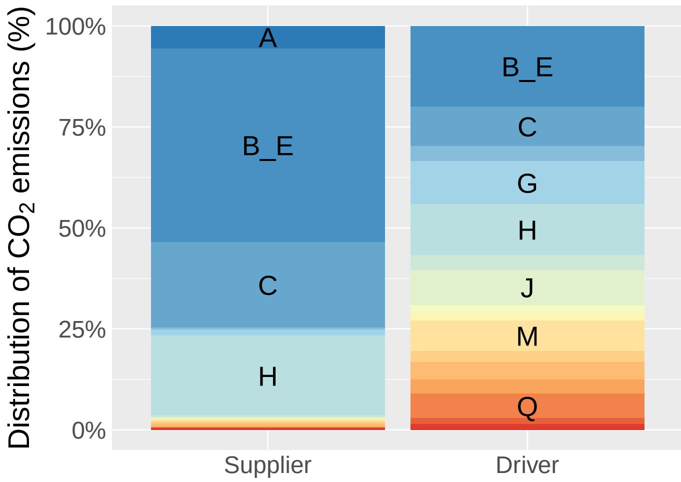

Figure 4: Distribution of $ktCO_2e$ emissions by supplier and driver sector, 2021. *Note*: only sectors contributing in more than 5% are labeled in the plot. *Source*: Authors' own calculations

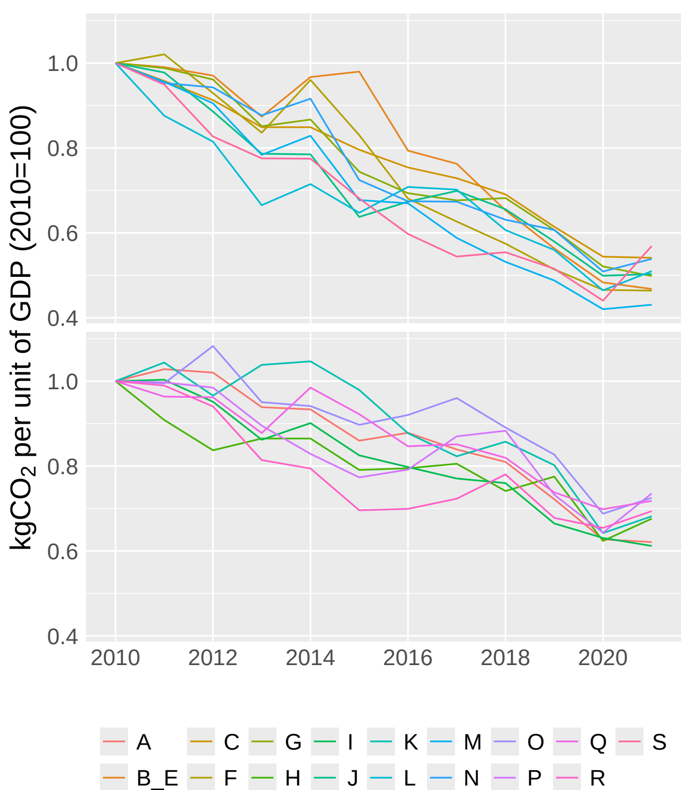

Figure 5: Evolution of total $kgCO_2e$ per unit of city GDP, 2010-2021 (2010=100). *Source*: Authors' own calculations

Interestingly for Madrid, the industry of ICT activities (J), which is one of the main growth engines and vectors of specialization of the city economy, has a relatively large scope-3 CF. This works as a cautionary tale about the need to include upstream emissions to properly evaluate the environmental standing of service-driven growth. If the domestic footprint of the industry reaches a relatively modest 94 $ktCO_2e$, the direct plus indirect emissions total reaches 1507 $ktCO_2e$. The same can be said of other economic bulwarks such as business and scientific activities (M) or hotels and restaurants (I).

In terms of $kgCO_2e$ per unit of gross domestic product, the highest intensity 0.736 in 2021 was in education (P), while the lowest 0.431 corresponds to business and scientific activities (M). Below 0.8 we find construction (F), real state (L), administration (N), and ICT activities (J), with mining and energy supply (B_E) at 0.468. Despite the almost negligible contribution to GDP, agriculture (A) has a medium-high intensity of 0.621, and hotels and restaurants (I), transportation and storage (H), and recreation activities (R) show the highest intensity ratios after education with 0.612, 0.676, and 0.694, respectively. Manufacturing, on the other hand, has a mid-tier intensity of 0.541, very similar to other services (S) 0.569. Whereas we can expect high $ktCO_2e$ services, e.g. industries catering to recreational demand or business activities, to be driven mostly by robust final demand, the reality is that they are among the most CO_2e intensive as well.

As per their evolution across the period, Figure 5 shows the evolution of the direct plus indirect carbon intensity of all 2-digit industries. We can separate the ones displaying a stronger from a weaker downward trend in CO_2e intensity. Despite accounting for the majority of upstream emissions, the total intensity of mining and energy supply (B_E) and trade (G) have declined by -53.2% and -50.2%, respectively. Business and scientific activities (M) show the best progress, with a total -56.9% fall in their CO_2e intensity, whereas manufacturing indicates a more internally heterogeneous evolution that renders a comparatively weaker -45.9%. At a more granular 3-digit level, we observe the lowest efficiency gains in food manufacturing (C10_C12) at -41.5% and the highest in plastic and non-metallic manufacturing with -53.8%. Conversely, the worst performing 2-digit industries are education (P) and recreation activities (R) with a -26.4% and a -30.6% reduction, respectively. A relevant case is transport and storage (H), which accounts for 13% of total emissions but whose CO_2e intensity has declined comparatively less by a -32.4%. Overall, the tendency seems to have stalled across the board in 2020, even reversing slightly for some industries, but we would need to include more recent years to fully grasp any persistent change.

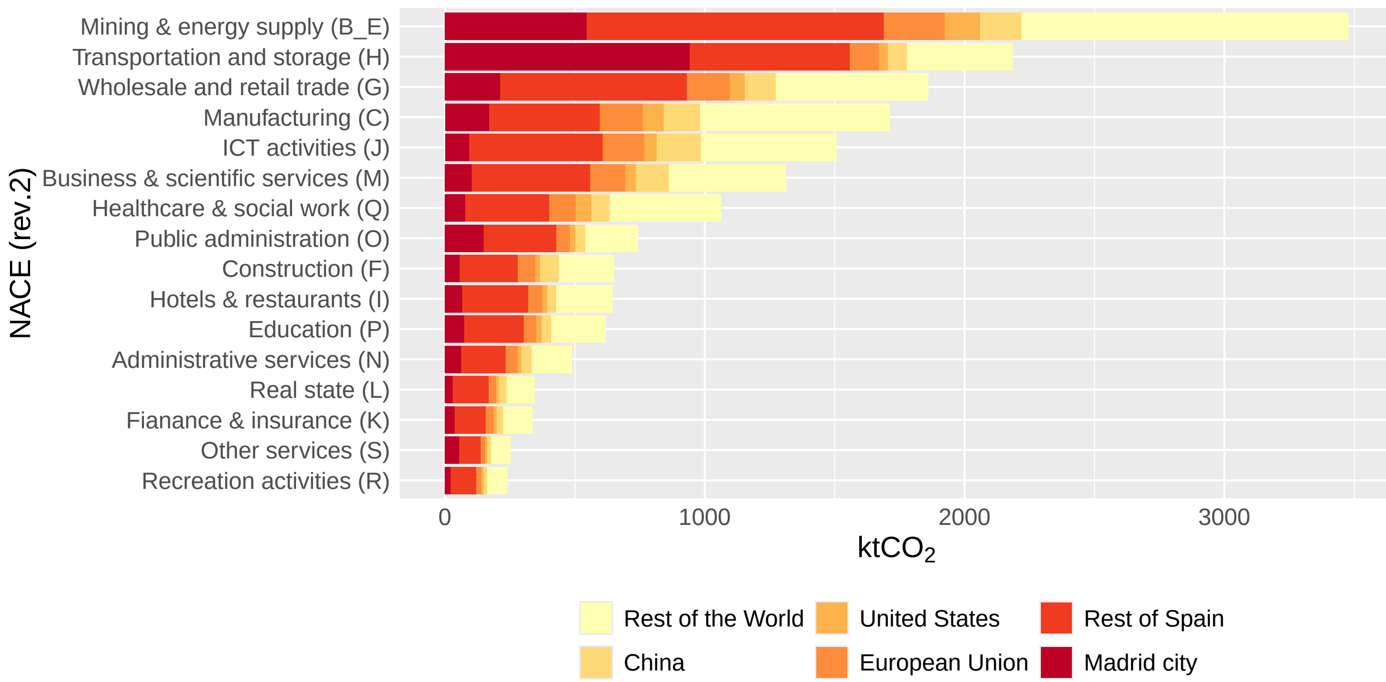

Figure 6: Total embedded GDP-linked emissions from Madrid by sector and geographical origin, 2021. *Note*: Agriculture (A) and Household activities (T) are excluded due to very low amounts. *Source*: Authors' own calculations

3.2 Households' contribution to total CO_2e emissions from Madrid

Despite a variety of challenges (Macekura, 2020; Stiglitz et al., 2009), gross domestic product remains the go-to indicator of economic activity. As such, it has allowed us to derive the total emissions which the city's final demand is responsible for. This includes government spending, net exports, and investment in addition to final consumption. However, if we are interested in the environmental impact of material well-being, we are forced to focus on households' final consumption expenditure (Sala et al., 2019). In 2021, we estimate that the CF of households in the city of Madrid totaled 13921 ktCO_2e, coming slightly down from 19424 ktCO_2e in 2010. From these, 4015 ktCO_2e or 28.8% correspond to direct emissions by households in 2021. Final consumption expenditure explains the other 9905 ktCO_2e, which is equal to 0.163 kgCO_2e per unit of nominal spending, which is in the low end of the urban density distribution (Córcoles et al., 2024; Ivanova et al., 2017). In per capita terms, the average resident emitted 4194 kgCO_2e in 2021 and 5908 kgCO_2e in 2010. As stated in equation 2, these figures combine the emissions required from firms along the entire international supply chain to cater to households' consumption needs and the emissions that result from households' direct activities, primarily home temperature regulation and private road transport.

Figure 7 shows the magnitude and geographical distribution of the total emissions requirements for meeting nominal consumption demand by main COICOP group in 2021. As noted in section 2.3, once we derive the vector of industry CO_2e totals according to equation 1, we revert the procedure to go back from the industry-based classification to COICOP and producer's prices so that we can report industry totals by consumption purpose. Note, however, that this totals *exclude* direct emissions by households-qua-producers, so that transportation CO_2e volumes belong exclusively to services purchased by households and does not include, for instance, the use of private cars. The first thing to notice in the chart is that transportation is, in fact, at the top with 1972 ktCO_2e. Food products and housing and utilities follow closely at 1876 ktCO_2e and 1118 ktCO_2e, respectively. Accomodation, caterings, and restaurants, which represent an important driver of economic activity in the city, stand high on the raking at 1149 ktCO_2e. These four categories make up 61.7% of total consumption-linked emissions in Madrid. Education, clothing and footwear, and communications generate the least emissions. Fron the standpoint of the geographical distribution of emissions, the city's weight is highest for transport, whereas the rest of Spain dominates in restaurants, food products, and housing supplies. The rest of the world is most important for transportation services, and very similar for food and restaurants and hotels. Proportionally, its largest share is in healthcare, although the emissions total is relatively low compared with the top consumption groups.

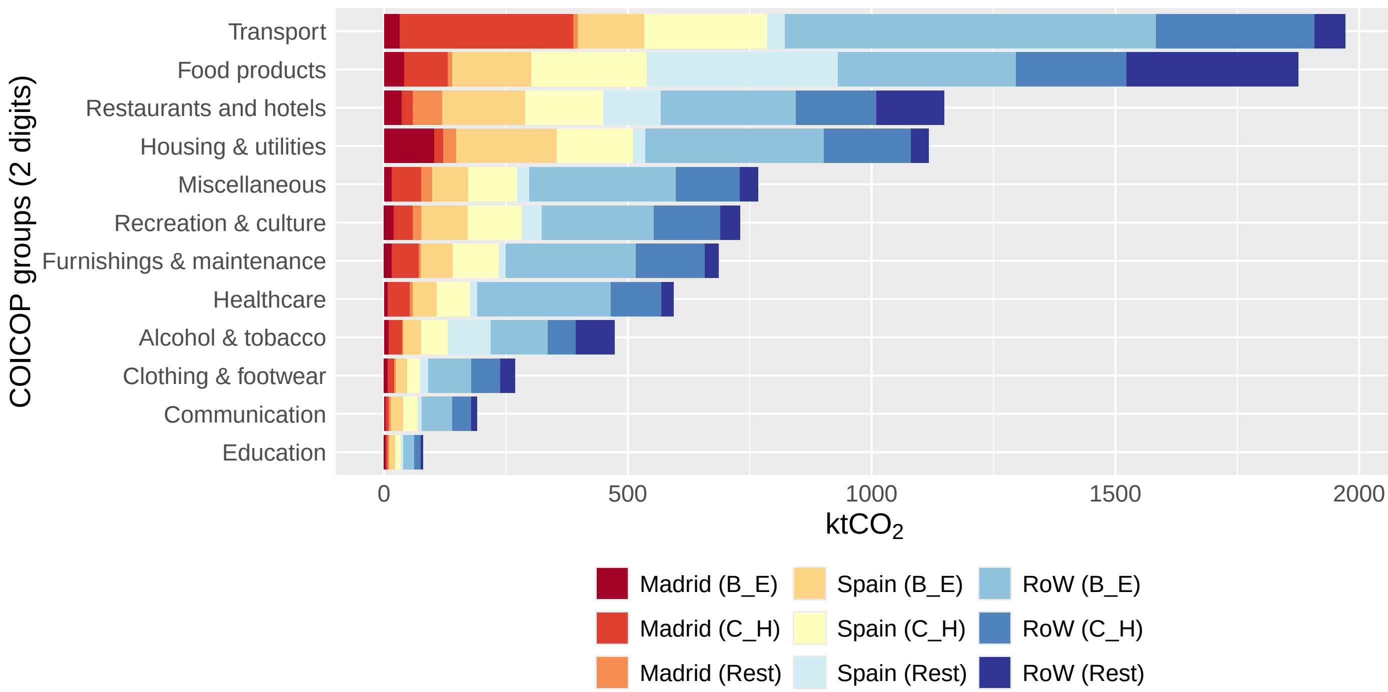

Figure 7: Total embedded household consumption-linked emissions from Madrid by driver consumption purpose and supplier sector and geographical area, 2021. *Note*: Agriculture (A) and Household activities (T) are excluded due to very low amounts. Whenever we make reference to (the rest of) Spain, we exclude emissions and spending from Madrid. *Source*: Authors' own calculations

Additionally, Figure 7 breaks down emissions by three main composite supplying sectors: mining and energy supply (B_E), manufacturing and transport (C_H), and all remaining industries (Rest), such as agriculture, recreational services or construction. In the same way that Figure 4 showed that the first two sectors dominate the upstream supply of CO_2e emissions, Figure 7 synthesizes the supply and driver perspective by accounting for the geographical-sectoral supply distribution of CO_2e requirements by consumption purpose. It indicates, for instance, that approximately a third of the transport services' footprint comes from the domestic transport industry, with a strong contribution from the rest of the world and the rest of Spain. Food products have a substantial component of embedded emissions from manufacturing and transportation, and in general from the rest of the world, which accounts for more than 50% of the total. The same holds for accommodation and restaurants, although the contribution from the rest of Spain is in this case the most relevant. Recreation and culture has a considerable indirect CF that is masked by its low direct emissions volume. More importantly, this indirect footprint relies on a relatively large upstream contribution by foreign manufacturing and transportation. As indicated above, the largest contribution from the rest of the world is in healthcare services and products, but we can see now that this is mostly due to mining and energy supply. For clothing and footwear the proportion of the foreign contribution is similar but the weight of manufacturing is on a level with energy supply.

Expenditure category	$kgCO_2e/€$	$ktCO_2e$	€M	Growth
01 Food products	0.272	18.9	11.3	-0.9
02 Alcohol & tobacco	0.287	4.8	2.7	0.3
03 Clothing & footwear	0.132	2.7	3.4	-3.5
04 Housing & utilities	0.066	11.3	27.7	-5.8
05 Furnishings	0.195	6.9	5.8	-5.8
06 Healthcare	0.213	6.0	4.6	-1.3
07 Transport	0.308	19.9	10.5	-1.6
08 Communication	0.123	1.9	2.6	-4.6
09 Recreation & culture	0.172	7.4	7.0	-1.8
10 Education	0.087	0.8	1.5	-5.8
11 Restaurants & Hotels	0.137	11.6	13.8	-3.5
12 Miscellaneous	0.139	7.7	9.1	-3.9

Table 2: $kgCO_2e$ per unit of nominal household spending ratios and descriptives in 2021. *Note*: $ktCO_2e$ emissions and €M spending figures are presented in shares, whereas the last column shows the 2010-2021 period compound growth rate of the emissions ratios by expenditure category. *Source*: Authors' own calculations.

From Figure 7 we can learn that consumption spending drives an extremely large volume of indirect emissions. However, this depends on two parameters: the level of final demand and the carbon intensity of each consumption purpose. To understand this difference, we need to derive in-

Emissions group	Q1	Q2	Q3	Q4	Q5	15-34	35-54	55-70	+71	Total
Equivalized income €	17116	21784	25373	29045	36428	23057	25514	26633	27265	25931
Equivalized kgCO_2e	2318	3940	5246	7570	11234	5774	6333	6503	5046	6053
01 Food products	269	408	446	543	597	318	438	495	507	456
02 Alcohol & tobacco	61	149	221	225	333	140	186	265	165	200
03 Clothing & footwear	39	50	73	105	148	98	90	81	76	86
04 Housing & utilities	112	144	144	161	220	126	141	174	181	157
05 Furnishings	32	46	83	153	249	100	89	129	190	118
06 Healthcare	58	102	150	198	381	145	135	239	237	185
07 Transport	140	280	463	716	1087	623	626	569	392	577
08 Communication	41	55	58	64	70	52	54	62	68	58
09 Recreation & culture	35	57	86	128	274	95	132	139	87	124
10 Education	16	29	59	76	193	19	108	79	46	95
11 Restaurants & hotels	81	168	332	448	984	375	493	461	329	450
12 Miscellaneous	53	70	94	128	284	158	117	119	166	131
Heating/cooling	675	881	821	908	984	702	791	844	1070	859
Transport	414	1147	1590	2430	2461	2397	1677	1744	1097	1682
Other	19	29	40	56	96	43	50	51	44	48

Table 3: Breakdown of households' average kgCO_2e footprint of 2-digit consumption purposes and domestic activities by spending quintile and age group in Madrid, 2021. *Source*: Authors' own calculations.

tensity ratios by 2-digit COICOP groups. Table 2 shows the emissions intensity per unit of nominal household spending (kgCO_2e€) of main expenditure groups, followed by the shares of each category on total embedded emissions and consumption spending. The last column reports the 2010-2021 compound growth rate of the intensity ratios. We can see that spending on transportation and storage is the most CO_2e intense in the city, whereas housing and utilities is in the opposite situation. The outstanding contribution of transport spending is explained by its 10.5% share on total household spending and an intensity of 0.308 kgCO_2e€, which explains its leading position in figure 7. Similarly, housing and utilities is less carbon intense, but tops the ranking with 27.7% of total expenditure. Lastly, it is worth noting that all groups' intensity ratios are declining, with the exception of alcohol and tobacco, albeit at different speeds. While the housing and utilities group has reduced its emissions intensity by -5.8% per year, food products and transport have realized much smaller efficiency gains at -0.9% and -1.6%, respectively.

At a more granular level (3-digit COICOP), the picture is validated with a few exceptions. For food products, for instance, we see that the emission intensity is driven down by food (011), with an average compound growth of -0.9% and an average factor of 0.3. For alcoholic beverages (021) we see a moderate -1% decline, where the emission intensity of tobacco (022) grew by 1.7%, both with high ratios similar to food and non-alcoholic beverages. Clothing (031) and footware (032), on the other had, have low intensities that are also underwent a robust process of decline. For instance, clothing reduced its intensity by a an average -3.7% from an already low 0.202 intesity in 2010. The largest reductions are, basides actual and imputed rentals (041-042), in other services (127: -5%), postal services (081: -15%), insurance (125: -4.1%), and housing tools and equipement (055: -10.6%). Communications equipment (082: -7.5%), household utensils (054: -10.5%) and textiles (052: -4.6%) have also strongly reduced their CO_2e intensity. On the oposite end, medical products and equipment (061: 1%) and other recreational goods and services (092: 3%) stand out as growing more carbon intensive.

We noted in section 2.3 that it is possible to retrieve household-level CFs. After deriving 3-digit intensity ratios, we impute the estimated total CF per consumption purpose to each household reported in ES-HBS (INE, 2024), whose aggregation matches the figures reported before by construction. Using information on energy products (measured in physical units) and on emissions factors from MITECO (MITECO, 2023), we can also impute the estimated *direct* CF of household activity (Córcoles et al., 2024). The resulting micro data creates a distributional perspective into the volume of emissions triggered by household decisions. This is crucial to understand the drivers of a city's footprint and, most importantly, to act on them without disregard for the economic inequalities that could compromise mitigation strategies. For instance, the average equivalized household income after taxes and transfers was €25931 in 2021, but this glosses over substantial distributional differences that can go from €17116 on average for the bottom 20% to €36428 for the corresponding top 20% of the equivalized spending distribution.[2] Each spending quintile represents aproximatedly 288006 households, but an unequal number of people ranging from 698865 (Q1) to 655229 (Q5). This translates into quite different emissions profiles and overall levels of inequality in each group's contribution to climate change.

Table 3 presents the breakdown of households' average annual equivalized $kgCO_2e$ emissions by spending quintile and four age groups (15-34, 35-54, 55-65, +71). It also separates the contribution of 2-digit COICOP groups and direct CO_2e emissions. We include the aggregate figures for comparison. Unless stated otherwise, all values are equivalized and refer to 2021. Overall, we see a strong correlation between income and emissions levels. For instance, the bottom 20% of the spending distribution emitted an average of 2299 $kgCO_2e$ in 2021, whereas the top 20% contributed with 4.8 times as much $kgCO_2e$. However, this distributional gap is due not only to level but compositional changes. On the one hand, $kgCO_2e$ for all consumption purposes and domestic activities increases with households' equivalized disposable income. While education and restaurants & hotels are the emissions groups with the largest quintile gap, housing & utilities and communication are the ones with the lowest. In accordance with the environmental expression of Engel's Law (Browning, 2018; Levinson and O'Brien, 2015), we tend to see essentials on the lower end of the gap distribution. Food purchases are 51.8% higher for the second than the first quantile, but they only grow by 46.4% from the second to the fifth quantile, indicating the marginally decreasing growth in expenditure and emissions as a function of income levels. Hence, to observe such a large distributional gap, other consumption purposes need to reverse the relationship between expenditure and income that obtains for essentials. This is especially the case of restaurants and hotels. Equivalized emissions grow by 1113.4% from the bottom to the top quintile. Similarly, for transport, recreation and cultural activities, and miscellanea we find gaps of 678.5%, 688.2%, 434.9%, respectively. Education is an interesting case, since related emissions are comparatively low, but due to the remarkable spending gap, we are left with a 1106.2% increase across the quintile distribution. The aggregate picture is, therefore, a mixture of opposing tendencies. It seems clear that any policy targetting consumption needs to reckon with this radical difference between essentials and other expenditure groups in designing mitigation plan.

Comparing emissions from expenditure and activities, we can calculate that while the top quintile represents 35.3% of total emissions, or 4881.7 $ktCO_2e$, the bottom quintile generates only 8%. This amounts to a gap of no less than 3778.6 $ktCO_2e$. The gap in emissions derived from expenditure is 3043.8 $ktCO_2e$ and in emissions-generating activities 734.8 $ktCO_2e$. The ratio of the last to the first quantile is 5.1 for the former and 3.1 for the latter. Emissions inequality is higher in consumption than in direct activities, but in transport activities the ratio is 6.2. Differences in heating/cooling emissions are minor (1.6), indicating that they are comparatively much more income-inelastic. In terms of equivalized emissions, differences are stronger in heating/cooling and as much in transport activities and other emissions.

Subsetting by socio-demographic groups, as shown in Tables 3 and 4, we find a different reading. Looking across age groups for the household reference person we find some differences, particularly in terms of average equivalized $kgCO_2e$ and for the cases of transport expenditure and activity. The central age groups (35-54, 55-70) have higher equivalized income, expenditure, and $kgCO_2e$, than the young (15-34) and the old (+71), but only to a limited extent. In equivalized terms, households whose reference person is female or male show only small variations, with the exception of transport, recreation activities, and hotels and restaurants, as well as heating/cooling emissions, where the former is responsable for a larger $kgCO_2e$ volume. The opposite is true in the case of direct transport activity, where male reference person households generate more $kgCO_2e$. As for the highest education level achieved by the reference person, the overlap with income is visible, and we have a strong jump from primary to secondary and, then, to tertiary in terms of income but more than proportionally in terms of $kgCO_2e$, growing by 109%. By education level, we can observe the largest differences in recreation & culture, restaurants & hotels, and transport activity. As per tenure status, the sharpest variation obtains between partial owner and renteer, in large part seemingly due to the substantial income difference between the two demographics.

We can illustrate the relative importance of the expenditure *structure* in addition to the expenditure level. While moderation of expenditure levels have a straightforward implications for households' CF, variation in the spending composition as a function of per capita spending can have a less obvious but sizeable impact (Levinson and O'Brien, 2015). A possible implication of Engel's Law is the non-linear growth in total emissions (Browning, 2018; Levinson and O'Brien, 2015). As we have seen, essentials, such as food or transport, are relatively more carbon intensive than other products. If we imposed a poorer consumption structure, hence a higer share of spending on essentials, on the the upper segment of the spending distribution, we might increase, rather than reduce, the total amount of consumption-related $ktCO_2e$ if consumption levels remained the same for the whole distribution. However, the opposite seems true. Imposing the median consumption structure above the 50^{th} percentile would amount to a reduction of 3688.2 $ktCO_2e$ (26.7%) in 2021.

[2] Household equivalized income accounts for differences in a household's size and composition to make individual incomes comparable across household types. It adjusts total household income using the modified OECD equivalence scale, where the first adult counts as 1, but the second and each subsequent person aged 14 and over only 0.5, 0.3 to each child aged under 14 (Deaton, 1997)

Emissions group	Female	Male	Primary	Secondary	Tertiary	Full	Partial	Renteer	Free user
Equivalized income €	24692	26792	18382	22082	30975	28351	29118	19010	26530
Equivalized kgCO_2e	5655	6330	3370	5577	7038	6055	7061	5145	5961
01 Food products	452	458	407	455	466	504	470	370	428
02 Alcohol & tobacco	188	207	216	215	184	220	196	165	249
03 Clothing & footwear	95	81	45	71	105	80	96	76	152
04 Housing & utilities	175	145	135	157	162	182	144	128	147
05 Furnishings	120	117	104	95	139	154	118	58	116
06 Healthcare	213	167	143	192	188	249	161	110	145
07 Transport	584	573	241	551	640	540	616	607	440
08 Communication	61	56	49	58	60	62	53	56	74
09 Recreation & culture	142	114	44	113	142	123	147	93	203
10 Education	89	98	150	40	123	54	88	161	37
11 Restaurants & hotels	391	482	165	388	531	382	570	368	776
12 Miscellaneous	155	116	85	108	160	143	102	139	146
Heating/cooling	980	777	769	862	875	944	835	757	632
Transport	1594	1722	610	1555	1926	1680	1786	1538	1842
Other	47	49	29	43	57	48	53	42	53

Table 4: Breakdown of households' average kgCO_2e footprint of 2-digit consumption purposes and domestic activities by gender, main education level, and tenure status in Madrid, 2021. *Source*: Authors' own calculations.

For comparison, total CO_2e emissions caused by food spending will slightly increase by 14.8%, whereas for housing and utilities they would remain at the same level. On the other hand, emissions from transport services, hotels and restaurants , and recreation and culture will decline noticeably by 15.8%, 13.6%, and 15.6%, respectively. By looking at the rest of consumption purposes we can see that furnishings and home maintenance, healthcare, and miscellanea are more important as we move up in the spending distribution, but nowhere near the case of education, whose emissions would be almost negligible compared to the rest of consumption groups.

Conversely, we can also evaluate the potential of mobility policies vis-à-vis expenditure policies by simulating the impact on total CO_2e that interventions targeting either a substantial limitation of private emissions-generating road transport or the increasing adoption of electric vehicles could potentially have. Table 3 highlighted the outstanding contribution of private mobility choices to the average household's CF in Madrid. In this sense, reductions in private transport outweight any reasonable intervention on consumption demand. To exemplify this point, Figure 8 reports how many ktCO_2e would the city save if households reduced 50% of their use of private vehicles cummulatively from the richest to the poorest of the target bottom decile of the intervention. In orther words, by simulating a 50% adoption of carbon-neutral transport activities by households in the ninth, or from the ninth to the eighth, and so on, decile, we can illustrate the total ktCO_2e savings.Within the top 10%, 20%, 30%, and down to 80% we randomly sample with probability 1/2 a series of households from the set of those with positive fuel spending records. We then eliminate completely their transport emissions and derive the new totals. This assumes that all household members either switch to other means of transportation (public transit, cycling or walking) or turn to electric vehicles (EVs) to meet their mobility needs.

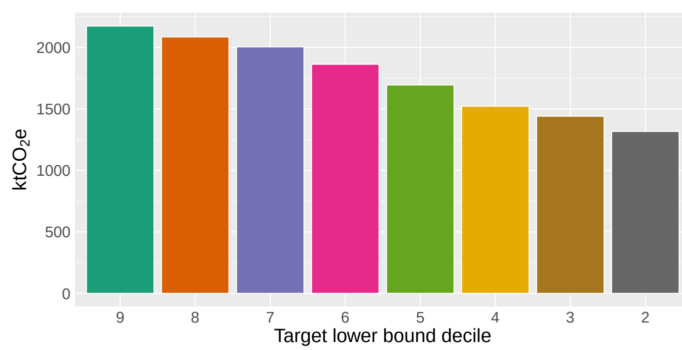

Figure 8: Simulated direct transport emissions levels resulting from a 50% addoption rate of carbon-free transport activities by households from the top down to the corresponding bottom spending decile of the intervention range, 2021. *Source*: Authors' own calculation.

Figure 8 shows that the mitigation potential of changes to private transport are considerable. Depending on the penetration rate of (close to) carbon neutral means transportation across the spending distribution, we obtain different CO_2e savings. If we limit this transformation to the top 10%, we find that direct transport emissions by households go down from 2312.2 ktCO_2e to 2174.1 ktCO_2e, which is a 6% reduction. Alternatively, if one in every two households implement this drastic change, we would end up with 1694.9 ktCO_2e, which represents 26.7% or 1694.9 ktCO_2e fewer direct transport emissions. If this process reaches half of the household population, but excluding the bottom 10%, we would talk of approximately 43% lower direct transport emissions by households in 2021. By changing the probability of adoption, we obtain very different emissions reduction totals. With one out of every twenty households in the top 50% following suit, we get as little as a 3.4% reduction. Conversely, if the likelihood of adoption increases to 80% among the top three deciles, we could see direct transport emissions falling to 1702.8 ktCO_2e, which is 26.4% less. These scenarios highlight the enormous potential for CO_2e emissions reduction that could derive from a strong commitment to fostering the adoption of electric vehicles, public transportation, or cycling.

3.3 Breaking down the drivers of the carbon footptint's growth path

Sections 3.1 and 3.2 have reported the level, composition, and evolution of 3-scope CO_2e emissions driven by the city's gross domestic product and final household consumption. Using structural decomposition analysis (SDA) we can now delve into the underlying factors determining emissions generation. As presented in section 2.5, we break total emissions down by the contribution of intensity, trade structure, technology, and final household consumption. Figure 9 presents the breakdown of total CO_2e emissions by 28-NACE activities into this four factors for the period from 2010 to 2021. Starting with the aggregate economy, it experienced a decline in total emissions of -1440.3 ktCO_2e or -13.3%. This result is driven by a 1487.5 ktCO_2e push by final consumption, 13.8% increase, and a -9.4%, -9.2%, and -8.5% fall in emissions driven by efficiency, trade, and technology, respectively. While the smallest contribution comes from changes to the technique of production, the larger emissions savings are realized thanks to efficiency gains.

Figure 10 shows the full country results using data from FIGARO. Across countries, we see that regardless of emissions growing or shrinking, the contribution by the CO_2e intensity of the aggregate economic activity is negative and considerable with very few exceptions, such as Norway, Cyprus, Argentina, Brazil, Russia, and Turkey. Trade, on the other hand, tends to add to total emissions for the majority of countries, most notably export-oriented economies, such as India, Ireland, Canada, and Norway, ordered by the proportion of their contribution. Technology tends to substract from emissions growth, but there are some examples of the opposite, such as Russia, Cyprus, Lithuania, and Norway. Consumption demand, however, adds considerably to total emissions, and is in most cases solely responsible for countries failing to reduce their emissions despite gains in efficiency, trade or technology. Countries with negative growth of consumption demand are Argentina, Russia, Turkey, Australia, Greece, and Brazil. Spain excluding Madrid city displays a very common pattern: negative contributions by intensity and technology, but positive by consumption and trade, albeit small in the latter case. There are 13 countries in this situation that have seen their emissions declined, most importantly Estonia, Germany, United Kingdom, Denmark, France, Sweden, Slovenia, and the rest of Spain, and 7 countries with rising emissions, among which we can highlight India, the rest of the world, South Korea, Canada, and South Africa. A majority of medium to large EU countries share the same pattern as Spain. In addition to this pattern, the city of Madrid benefits also from trade, and only consumption demand is pushing emissions higher, compensating most of the emission saved by the other three factors. Even if comparing a capital city with other countries is unreasonable, it still shows that it is not on the emissions-intensive end of the country and their neighbours.

If we compare this results with individual industries, we observe a large degree of heterogeneity that makes aggregate results not representative of the underlying drivers. The three industries that have increased their emissions the most in absolute terms are transport and storage, clothing and foorwear, and culture and recreation, with 210.9, 124.3, and 57.3 ktCO_2e, respectively. Conversely, public administration, construction, and administrative services realized the largest fall in emissions, -11.3, -8.5, and -2.8 ktCO_2e. In percentage terms, clothing and foorwear, wood and paper, and electronics showed the largest increases, and construction, administrative services, and food and beverages the largest declines. By component, we find no industry where the contribution of emissions intensity was positive. Nevertheless, variance in the extent of the reduction is considerable. From -180.6 ktCO_2e in hotels and restaurants to -1.8 ktCO_2e in public administration. For the most part, the negative contribution of trade to emissions growth is smaller than intensity, but still significant. In particular, professional services, construction, and clothing and foorwear show a larger contribution to emissions reduction from trade than intensity. On the other hand, the effect of technology is modest and mixed, with some sectors adding and other substracting from total emissions. Noteworthy sectors are education, culture and recreation, and transport and storage, where technology outweights intensity and trade. Finally, the contribution of final consumption is robust and inequivocally positive, with the exception of education, public administration, and retail and motor repair, where it declines. Overall, these results indicate that CO_2e emissions have continued to grow due to the strong pull by consumption demand despite the generalized gains in efficiency, trade, and technology across a majority of industries along the entire global value chain supplying to the city's economy.

Figure 9: Structural decomposition of total $MtCO_2$ growth in Madrid into emissions intensity, trade, technology, and consumption demand contributions for the city of Madrid. *Source*: Author's own calculations using FIGARO, ES-HBS, and municipal accounts.

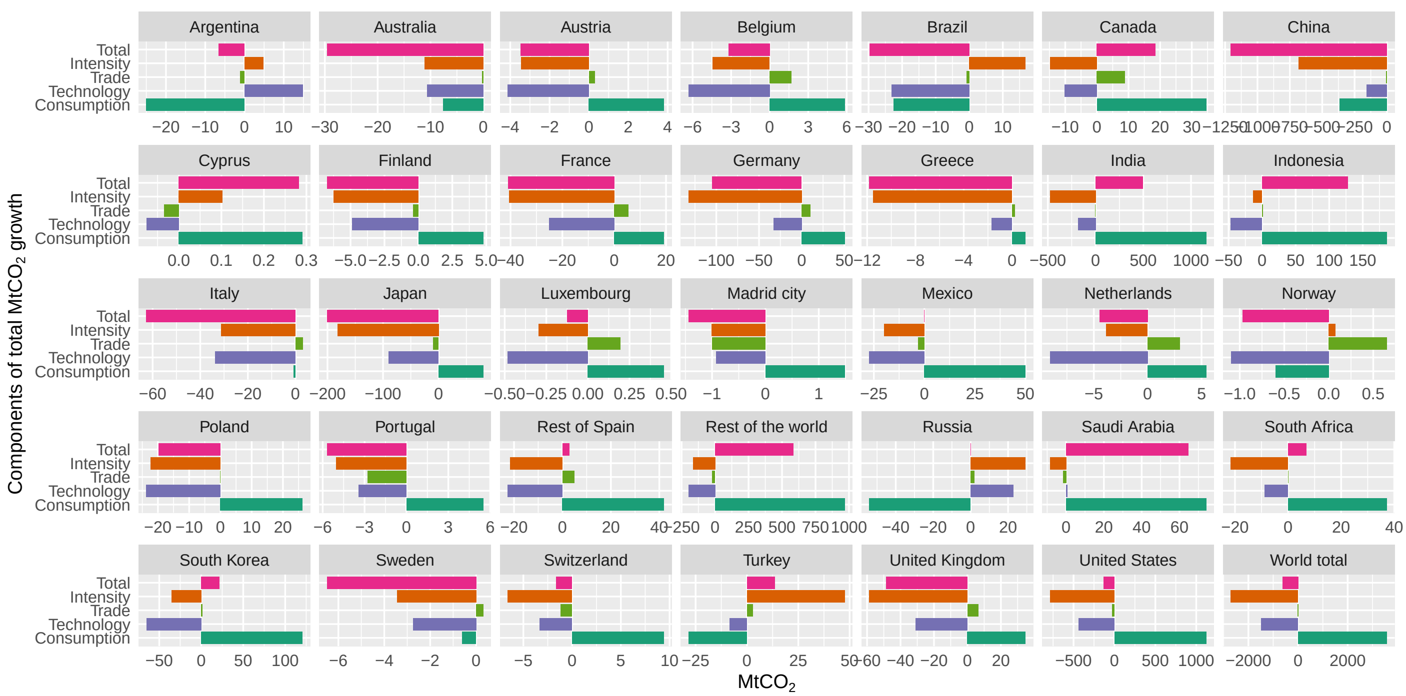

Figure 10: Structural decomposition of total $MtCO_2$ growth for selected countries into emissions intensity, trade, technology, and consumption demand contributions for all countries in the sample. *Source*: Author's own calculations.

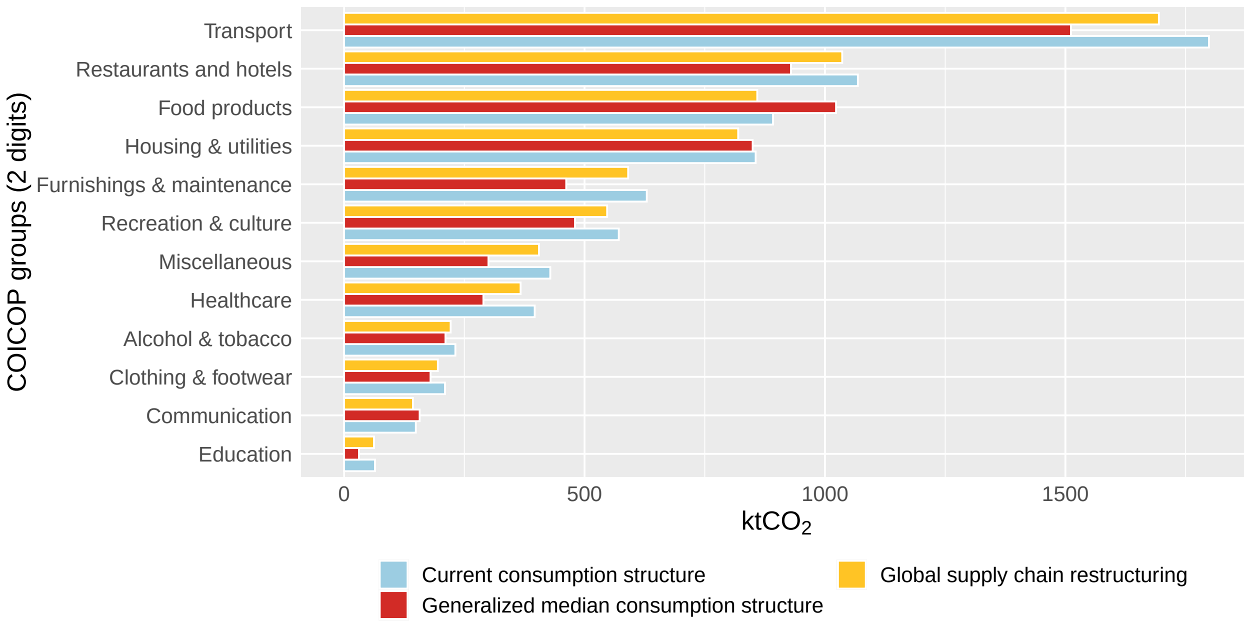

Figure 11: Total embedded household consumption-linked emissions from Madrid by consumption purpose before and after the hypothetical projection of the median consumption structure, 2019. *Source*: Author's own calculations

We have observed that consumption strongly constraints or even reverses the push by efficiency, technology, and trade towards emissions reduction. By the same token, we can highlight that the contribution by the trade structure is only modest. An important hypothesis in the literature, and a environmental talking point, is that supply chain offshoring had been used as means for pollution evasion by advanced economies (Levinson and Taylor, 2008), which would indirectly benefit from shifts in the trade structure towards more efficient countries. This argument has been challenged in the past (Arto and Dietzenbacher, 2014), and our results agree with a relatively modest, and sometimes contradictory, emissions reduction potential from supply chain restructuring. Consumption demand clearly shapes the slow pace of decarbonization. Likewise, an important policy concern is the the potential of re-shoring to enhance mitigation efforts. To further assess the potential for emissions abatement and as a way to indirectly highlight the weight of domestic policies, we simulate three scenarios. From a methodological perspective, this is implemented, as explained in section 2.5, by simulating a trade shock to matrix $\mathbf{C}$, from which we derive a modified matrix $\mathbf{A}$ to calculate consumption-driven emissions following the Equation 1. In the first scenario, we explore the consequences of trade decoupling from non-Western suppliers by simulating a series of shocks on 10-point increment intervals to the input supplied by non-Western to Western countries, which are then substituted by intra-block Western supplies. For instance, we reduce the supplies of energy products from Saudi Arabia to France and, at the same time, we proportionally increase the supply from other Western countries to meet up the trade gap left by Saudi Arabia. This reallocation of input supplies follows the existing procurement proportions from other countries in the block, and assumes, somewhat unrealistically, that firms in Western countries are fully able to close the import gap in quality, quantity, and price. In addition to the current 28 EU countries, we include Canada, the United Kingdom, Japan, and the United States within the Western block. Secondly, we replicate the same exercise but this time restricting the domestic block to EU countries, with the purpose of illustrating harsh EU import restrictions that might be motivated by the desire to avoid carbon leakage. Finally, we produce an additional simulation in which EU countries switch from Chinese to US supplies, without affecting any other intermediate flow in the system. These three simulation scenarios are inspired by the recent implementation of tariffs and other trade barriers between the US, the EU, and China, and seeks to explore the extent to which, if feasible to swap suppliers, emissions will grow or fall as a result. These scenarios, which affect multiple countries, illustrate possible reconfigurations of trade that can potentially impact Madrid's scope-3 emissions.

For the first scenario, we obtain an -7.48% decline in emissions when applying a 50% shock to supplies from non Western countries, from 8655.8 ktCO_2e to 8008.5 ktCO_2e. The main industries contributing to this decline are food and beverages, mining and energy, hotels and restaurants, and chemical industry, with a -4.3%, -7.6%, -5.6%, and -14.4%. For the second scenario, total emissions fall down to 7937.4 ktCO_2e, which is 99.1% of the first scenario. We find the same sectors driving the reduction in emissions, with a -4.4%, -8.4%, -6%, and -18.6%, respectively. Lastly, we find that a 50% shock to trade from China filled in by the United States has almost no effect with a -0.02% decline down to 8654.5 ktCO_2e. There is no difference at the sectoral level to highlight. In general, the simulation exercises suggest that the ability of trade policy to have a meaningful impact on total emissions, even when drastic measures are taken, is very limited. Notwithstanding this, trade compounds with the evolution of technology and efficiency in the exporter countries, so it is possible that this may change in the future.

For the purpose of this simulation using data from 2021, the results underscore the overwhelming importance of consumption in determining the slow pace of emissions reduction despite the outstanding gains in efficiency. In this sense, Figure 11 shows how many ktCO_2e would the city save if we impose the median consumption structure on the top 50% of the equivalized spending distribution. To compare this result with the impact from trade restructuring, we also include one additional simulation scenario in which we reduce by 50% the supplies from all non-EU countries to Madrid and, conversely, fill the gap with imports from the EU alone.

4 Discussion and implications

By projecting urban-level SUTs and deriving an AEA out of the local inventory we have verified that the speed of the reduction in direct CO_2e emissions in the city of Madrid has remained unmatched by the evolution of scope-3 emissions during the period 2010-2021. Under the assumption that the regional proportion of imports plus the national distribution of international demand constitute a reasonable approximation to the economic relationship of the city with the outside world, this paper has quantified the city's consumption-based CF in the order of 17447 ktCO_2e for the city's GDP, from which 2699 ktCO_2e are direct emissions. We have also estimated the CF from the perspective of the residents' total expenditure and direct activities at 13920.9 ktCO_2e. In per capita terms, the average city resident emitted 4193.8 kgCO_2e in 2021.

These magnitudes differ from but fall in line with the very few available estimations. Andrade et al. (2018), using the PAS2070-DPSC methodology, estimated Madrid's total CO_2e emissions in 2010 at 28160 ktCO_2e and 8610 kgCO_2e per capita. Whereas direct emissions amount to 7330 ktCO_2e, Scope-2 and -3 add up to 4740 ktCO_2e and 16080 ktCO_2e, respectively. For 2010, using our approach, we find wery similar estimations: 27963 ktCO_2e for the city's GDP. On the other hand, C40 Cities quantified the total consumption-based greenhouse gas emissions for Madrid in 2011 at 47230 ktCO_2e and 14770 kgCO_2e per capita. However, in this case we find a substantially lower estimation of 19424.2 ktCO_2e driven by household final consumption expenditure. Nonetheless, at a more disaggregated level distributions are similar. Andrade et al. (2018) find that all combined transport industries emit the most at 11440 ktCO_2e, but they include also direct emissions by private transport. The industry of food and drinks is estimated at 3550 ktCO_2e and construction similarly at 3380 ktCO_2e. Instead of looking at industries, C40 provides information by consumption purpose. The ranking of sectors is very similar at 2 digits, but the values are twice as large on average. The available estimations are few, but, more importantly, considerably outdated. Comparatively, this paper presents a whole series groing from 2010 to 2021, in addition to an improved methodology benefitting from more up to date methodology, an GMRIO framework, and a formal process of conversion of the local AEI into a fully-fledged AEA.

Hence, we argue that our estimation improves not only the timeliness but the precision of previous contributions. First, the development of FIGARO's GMRIO database (Remond-Tiedrez and Rueda-Cantuche, 2019) and the methodological progress made in the literature (Cazcarro et al., 2022; Wiedmann et al., 2016; Córcoles et al., 2024) have refined the estimation method and reduced several sources of bias, such as the more rigorous derivation of the final consumption vector or international demand from several regions of the world. Crucially, by parting with the national technology assumption, we have reduced the weight of some overrepresented carbon-intensive industries, such as manufacturing, from direct and indirect emissions (EEA, 2013). Second, the construction of an AEA for Madrid have fine-tuned our quantification of consumption-based emissions and improved our understanding of emissions derived from household activities. Third, our ability to compute more consistent results for Madrid creates the opportunity for improving the coherence, granularity, and precision of the estimates such that they may enhance local mitigation planning. We consider these improvements a definite step closer to a state of the art CF estimation of the city of Madrid, which should contribute to the design of credible and effective decarbonization commitments by the City Council.

In this regard, we derive three main conclusions from Sections 3.1 and 3.2. First, the geographical distribution of emission sources problematizes the national assumption used in previous estimations. In 2021, only 15% of emissions came from within the city, while the rest of the nation and the rest of the world contributed 33.1% and 51.4%, respectively. The distribution has shifted slightly since 2010, with the rest of the world increasing its share from 47.2% to 51.4% at the expense of the rest of the nation, which accounted for 40.1% of all emissions in 2010. Furthermore, the ability to break indirect emissions down by industries and countries reveals both supply chain reconfiguration dynamics, such as a potentially problematic substitution of imports from China to the United States, and mitigation bottlenecks in the strong dependence from certain country's industrial production.

Second, our analysis reveals significant emissions inequality among Madrid's residents, with age, gender, and income quintile playing crucial roles. The top 20% of the spending distribution emitted on average 11138.2 equivalized $kgCO_2e$ in 2021, which is 4.8 times as much as the 2299 $kgCO_2e$ emitted by the bottom 20%. This distributional gap is due to both level and composition changes in consumption patterns across income groups. While healthcare and miscellaneous items show the largest quintile gap, food products and heating have the lowest. In general, we don't find strong differences by demographics, with the exception of the education level and partially the age group of the reference person of the household. Those groupings that overlap with income differentials tend to display larger variation. For the most part, emissions inequality is strongly correlated with income and expenditure inequality. These findings highlight the need for climate policies that remain sensitive to socioeconomic inequalities, gender differences, and age-shapped consumption patterns.

Third, as shown by our two simulation scenarios for consumption expenditure and direct household transport emissions, there is a substantial margin to shrink Madrid's CF by addressing the consumption and mobility choices of high-income households. Instead of focusing on the emissions intensity of foreing-supplied goods, our analysis has highlighted the outstanding potential of domestic policies without targetting consumption *levels*. For instance, we showed that by fixing the median consumption structure above the 50^{th} percentile would produce a total emissions savings of 3688.2 $ktCO_2e$ in 2021. This is due to the counter-intuitive result that high-income groups spend way more on recreational and personal services that poorer households, which have a considerble indirect emissions footprint. At the same time, we considered the potential of direct mobility policies for emissions curbing. If one in every two households in the top five deciles suppresed their use of private motor vehicles in exchange for carbon-neutral options for travel, we would save 617 $ktCO_2e$ (-26.7%). In the extreme and, unfortunately, unrealistic case that this two policies come to fruition simultaneously, the city's CF will decline from 13921 $ktCO_2e$ to 8538 $ktCO_2e$, or by 38.7%.

Third, our structural decomposition analysis underscores that consumption is the primary driver of emissions growth, offsetting gains made through efficiency improvements and technological advancements. Between 2013 and 2019, Madrid experienced a decline in total emissions of -1440.3 $ktCO_2e$. This result is driven by a 1487.5 $ktCO_2e$ increase of final consumption, offset by decreases of -9.4%, -9.2%, and -8.5%, which are driven by efficiency improvements, changes in trade structure, and technological advancements, respectively. While the smallest contribution comes from changes to the technique of production, the larger emissions savings are realized thanks to efficiency gains. However, these gains are being largely offset by increases in consumption, particularly among higher-income groups. This underscores the need for policies that do not only promote technological progress and efficiency gains but also address consumption patterns. Our simulation exercises further support this, showing that imposing the median consumption structure on the top 50% of the equivalized spending distribution would amount to a reduction of 3688.2 $ktCO_2e$ (26.7%) in 2019, with the largest reductions in transport services, hotels and restaurants, and recreation and culture.

We find that these conclusions bear two main policy implications for city decarbonization plans. On the one hand, the global nature of Madrid's CF, whose trans-bordering emissions reached 85% in 2021, highlights the need to consider the constraints imposed by global supply chains on emissions curbing plans. Policymakers should promote sustainable procurement practices by encouraging decarbonization efforts of key suppliers, even if the ability to enforce regulation on foreign firms might prove limited and the emissions savings low to moderate. Conversely, the observed shift in emissions from China to the United States between 2010 and 2021, coupled with the outstanding fall in Chinese emission factors, calls into question any long-term plans that do not monitor decarbonization strategies across the world. Particularly if it tries to make virtue out of necessity from emerging geopolitical rivalries between blocks. For the most part, any serious attempt at targeted mitigation policy needs to weigh in on the complicated balance between carbon intensity and growth-pulling industries in highly tertiarized economies. Hotels and restaurants is a case in point.

On the other, we emphasize the need to prioritize consumption in Madrid's mitigation efforts, with a particular focus on high-income households. Our analysis reveals that these groups generate significantly more emissions, especially due to their intense use of private transportation and recreational spending. Targeted policies aimed at reducing emissions from private vehicle use among these high-emitting groups could yield substantial reductions. This could involve a combination of incentives for electric vehicle adoption, improvements in public transport infrastructure, and measures to discourage private car use in urban centers. Additionally, policies addressing consumption patterns of high-income households could lead to significant emissions reductions. Our simulation shows that imposing the median consumption structure on the top 50% of households could reduce emissions by 11.9%, which illustrates the potential impact of such targeted interventions. Furthermore, the city's ability to enforce and implement these policies is crucial. Given the significant emissions inequalities observed, policies should be designed with social equity in mind. Measures that disproportionately burden low-income groups or fail to address the outsized contributions of high-income groups are likely to be both less effective and less socially acceptable. This calls for a nuanced approach that could involved a combination of awareness campaigns, education programs, and fiscal policies to discourage carbon-intensive consumption choices, particularly among high-income groups. While our analysis shows that efficiency improvements and technological advancements are contributing to emissions reductions, these gains are being largely offset by increases in consumption. Our main recommendation for Madrid's mitigation policies is to go beyond traditional supply-side measures and actively address household consumption patterns, which seem to stirr in the opposite direction of decarbonization.

5 Conclusions

This paper has presented the most rigorous quantification of the 3-scope CF of the city of Madrid to date, which is a crucial input to mitigation planning that has been missing. Additionally, it lays down relevant implications for specific policy designs. We provide sectoral data and household distributional information that opens the space for targeted and more sensitive interventions. The empirical results developed in the paper showed the importance of global supply chain constraints and possible trade shocks in monitoring progress of climate change mitigation. Nonetheless, the evidence collected leads to the recommendation to focus on consumption demand and, from the perspective of households' direct emissions, on private mobility. The latter can be seen to yield a disproportionate amount of emissions reduction, but consumption demand interventions emerge also as a potentially fruitful policy avenue. In this sense, a primary target for maximum emission savings should be high-emitting groups, which are strongly correlated with high-income households. Most importantly, our methodology and data compilation process lend themselves easily to periodic updates of the main estimates as new information becomes available, potentially becoming part of a timely monitoring dashboard for interested stakeholders.

These results show four main limitations, which create several research opportunities. Firstly, the regional series is limited to a six-year period from 2013 to 2019, which we extend using non-survey techniques to a longer series (2010-2021), mostly limited by the availability of the local emissions inventory. While RSUTs are published with a four-year gap, FIGARO is released with a narrower two-year one. Although coefficient projections add uncertainty, extending the time seires aligns with the recent emphasis on timeliness in statistical production (OECD, 2024, p. 190). Secondly, urban economies have a few distinct structural characteristics whose further study could improve the projections made to derive the AEA and IOTs. Specifically, properly representing a highly tertiarized economy, with minimal agricultural production, may benefit from the inclusion of additional information and estimation techniques (Zheng et al., 2022). Thirdly, more research is needed to understand the possibilities to exploit the distributional carbon gaps identified in Section 3.2 for mitigation policy. Consumption was identified as a more relevant driver of total emissions than the trade structure, but carbon inequality and transportation are not only the two most important mitigation vectors, but probably the two least difficult to enforce. Lastly, uncertainty evaluation has remained mostly unaddressed in the literature and the official estimations made by the designated statistical agencies (EEA, 2013). Although challenging, additional sensitivity analysis and uncertainty calculations could increase the reliability of the results presented in this paper, which we seek to continue developing.

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Appendix

NACE (rev.2)	Industry definition
A	Primary activities
B_E	Mining and energy
C10_C12	Manufacturing of food and beverages
C13_C15	Manufacturing of clothing and foorwear
C16_C18	Manufacturing of wood and paper
C19_C21	Manufacturing of chemical industry
C22_C23	Manufacturing of plastics & non-metallics
C24_C25	Manufacturing of metal and machinery
C26_C27	Manufacturing of electronics
C28	Manufacturing of other machinery
C29_C30	Manufacturing of transport equipement
C31_C33	Manufacturing of furniture and repairs
F	Construction
G46	Wholesale
G45YG47	Retail and motor repair
H49_H53	Transport and storage
I	Hotels and restaurants
J58_J63	ICT activities
K64_K66	Finance
L	Real state
M69_M75	Professional services
N77_N82	Administrative services
O84	Public administration
P85	Education
Q86_Q88	Healthcare
R90_R93	Culture and recreation
S94_S96	Other services
T	Domestic services

Table 5: Industry classification adapted to city aggregation (NACE rev.2).

Code	Heading	Unit	Factor
04521	Gas (main dwelling)	m^3	1.919
04522	Gas (other dwellings)	m^3	1.919
04523	Liquefied gas (main dwelling)	kg	2.966
04524	Liquefied gas (other dwellings)	kg	2.966
04531	Liquid fuel (main dwelling)	l	2.855
04532	Liquid fuel (other dwellings)	l	2.855
04541	Coal (main dwelling)	kg	2.239
04542	Coal (other dwellings)	kg	2.239
04548	Other solid fuels (main dwelling)	kg	3.109
04549	Other solid fuels (other dwellings)	kg	3.109
07221	Diesel	l	2.520
07222	Gasoline	l	2.249
07223	Other fuels	l	2.213

Table 6: Direct emissions factors in $kgCO_2$ per unit of energy good generated by household activities (5-digit ECOICOP). *Source*: Direct emissions factors and conversion of m^3 into kWh obtained from MITECO (2023).