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Carbon footprint of American lifestyles: a geodemographic segmentation approach

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**Abstract**

In order to deliver substantial reductions of U.S. residential emissions, cost-effective responses to climate change will need to recognize changes in consumer behavior and lifestyles as important mechanisms to mitigate carbon dioxide emissions. Marketing experts have long recognized the usefulness of developing composite variables to target specific consumer lifestyles and have subsequently developed market segmentation approaches to express relationships between geodemographics and consumer behavior. This paper represents the first use of detailed segmentation data to look at US footprint at high spatial resolution. We employ market segmentation data to delineate lifestyles for approximately 70 000 census tracts in the US and develop a spatial framework to better conceptualize lifestyles as location specific typologies of emission drivers. We find that lifestyles are not only very useful in explaining variations in emissions but in fact are as important as income, typically recognized as the major determinant of consumption emissions. Results from our analysis link the differences between suburban and urban footprints directly to lifestyle patterns and illustrate the geographic distribution of emissions resulting from households' consumption. We find that statistical clustering and consumer classification methods provide a unique perspective for understanding how various CO₂ drivers interact and impact household emissions. Our proposed framework suggests that carbon mitigation strategies should move beyond a 'one-size-fits-all' approach centered on income and account for community specific lifestyle impacts related to consumer preferences and demographic characteristics at fine spatial scale.

1. Introduction

Household consumption in the United States is directly and indirectly responsible for nearly 20% of annual global greenhouse gas (GHG) emissions (Weber and Matthews 2008, Hertwich and Peters 2009) and despite slowing down in recent years, GHG emissions continue to rise (Olivier *et al* 2017). Explaining the spatially and socially explicit drivers for household related CO₂ emissions has become a focal point of a growing body of scientific literature (e.g. Baiocchi *et al* 2010, Jones and Kammen 2011, 2014, Minx *et al* 2013, Chen *et al* 2018, Jones

et al 2018, Kanemoto *et al* 2020, Long *et al* 2021). Also, drivers of the household carbon footprint have also been analyzed using datasets containing data from a large number (e.g. more than 1000) of households (e.g. Weber and Perrels 2000, Lenzen *et al* 2006, Weber and Matthews 2008, Ivanova *et al* 2016, Fremstad *et al* 2018, Shigetomi *et al* 2021) to understand the relevance of specific determinants in predicting household emissions. Estimating the CO₂ emissions associated with individual demographic variables can provide important insights into the linkages between consumers and the global environment. However, one of the major drawbacks of such an

approach is that it fails to recognize how the interlink of geographic, social, demographic, and behavioral dimensions of households jointly shape consumption patterns and lifestyles. The rationale behind an ‘analysis of people by where they live’ is that places and people are inextricably linked. Knowledge about the whereabouts of people reveals critical information pertaining to how people live and can be utilized to support place-specific mitigation strategies. Such an approach has been shown to work well, because people with similar lifestyles tend to cluster—a longstanding theoretical and empirical finding in the sociological, business and economics literature (Schelling 1969, Harris *et al* 2005, Pans and Vriend 2007, Clark 2009). Successful, cost-effective carbon mitigation strategies will need to embrace the role of consumer behavior and lifestyles to complement approaches focusing on infrastructure and technology (Meyer *et al* 2014, Creutzig *et al* 2016). Developing a framework for incorporating lifestyles and geodemographics in the context of household emissions is a necessary prerequisite for this endeavor. Operationally, lifestyles can be broadly conceptualized as patterns of household consumption influenced by context, choices and actions, including where people live, what they spend their money on and how they use goods and services. Specifically, ‘lifestyle analysis’ has been a popular tool in an effort to identify CO₂ mitigation opportunities through a consumer-oriented approach (Weber and Perrels 2000, Duchin and Hubacek 2003, Bin and Dowlatabadi 2005, Baiocchi *et al* 2010). However, despite the introduction of several frameworks that emphasize the importance of lifestyle analysis in carbon footprinting, the concept of lifestyle remains ambiguous in research and policy, often being proxied by individual demographic variables such as income or education level, both of which lack the explanatory power and practical relevance needed to develop informed policies (Wedel and Kamakura 2002). Marketing experts focused on identifying potential markets have long acknowledged this issue and have subsequently developed market segmentation approaches to target specific lifestyle characteristics related to values, beliefs, and shopping preferences (Dickson and Ginter 1987, Wedel and Kamakura 2002, Dolnicar 2003, Foedermayr and Diamantopoulos 2008). Such geodemographic lifestyle classifications are built in a bottom-up procedure based on a large set of spatially specific variables that cover characteristics of both people and places. This geographic component is equally important when investigating and predicting the CO₂ emissions of specific consumers.

Such datasets combining demographics with other location specific information can account for important aspects of the social and physical environment in which people operate. These aspects inevitably have a considerable impact on people’s

emission patterns. Two principles are at the base of the geodemographic segmentation approach of consumers. On the one hand, households living in the same neighborhood tend to have more similar characteristics than two randomly selected households. This principle, which amounts to a specific application of a major tenet in geography known as ‘Tobler’s first law of geography, taken to its logical extreme, would advocate for a one-to-one marketing strategy. On the other hand, differently located neighborhoods populated by similar households, can be included in the same segment, if their behavior is sufficiently close. For example, Baiocchi *et al* (2015) showed how local climate, economic conditions, age and condition of housing infrastructure, location in relationship to city centers, can lead to similar behavior when it comes to carbon footprint. At the extreme, if all households behaved in the same way, this would suggest a one-size-fits-all strategy. These opposite forces, determine a trade-off that requires pragmatic consideration such as economies of scale, quality of data, and convenience of interpretation for its resolution. By adopting market segmentation data for the purpose of calculating carbon footprints, we can interpret different categories (such as *Laptops and Lattes* or *Metro Renters*) as individual lifestyles and identify simple and coherent insights into carbon mitigation opportunities at the local level. Regardless of the appeal, however, only a handful of studies have examined the potential of utilizing geo-demographic data and consumer segmentation information for environmental analysis (Duchin and Hubacek 2003, Minx *et al* 2009, Baiocchi *et al* 2010). Particularly, no such approach has been used to look at carbon footprints in the US. Our study proposes a lifestyle segmentation based approach for analyzing the carbon emission impacts of household consumption behavior. By linking Esri’s georeferenced Tapestry Segmentation System (ESRI 2011) with the American Community Survey (ACS) (United States Census Bureau 2013) and an environmentally-extended input-output (EIO) model for the U.S. (Bureau of Economic Analysis 2007), we develop a spatially-explicit modeling framework that provides meaningful interpretation of lifestyle as a mitigation mechanism to complement policy options focusing on behavioral change. As environmental conditions, local infrastructure and consumer preferences vary widely, our analysis provides a unique perspective for understanding how various CO₂ drivers work together and impact household emissions. Results from our analysis add a detailed account of emissions resulting from specific lifestyles in the United States. We illustrate the importance of spatial heterogeneity and variation between lifestyle segments and control for critically important variables like income and household size to estimate the geographic distribution of CO₂ emissions resulting from lifestyle consumption choices.

2. Lifestyle segmentation and emissions

We use the Community Tapestry™ Segmentation of consumer markets in the United States from the Environmental Systems Research Institute (Esri®), as our source of US lifestyle data that include consumer profiles and spending patterns. Esri is a well known global leader and supplier of geographic information system (GIS) software, application and geodatabase management systems used in academia, federal institutes, and businesses, etc (ESRI 1998). Other available commercial segmentation data for the US include Psyte® from MapInfo® and Prizm® from Claritas/NDS®, Experian® and Consumer Styles from MB International provide global data. Geodemographic segmentation data has been used before to look at footprint of UK cities (Baiocchi *et al* 2010, Minx *et al* 2013) using Experian's segmentation and, to some extent, to global cities (Moran *et al* 2018) using MB International, however this is the first use of detailed segmentation data to look at US footprint at high spatial resolution. The next section discuss the methodology used in producing consumer segments and the advantages and limitations of using proprietary segmentation sources.

2.1. Tapestry segmentation methodology

Geodemographic classifications have developed from manual classifications of urban areas in specialized literature (see, e.g. Park *et al* 1925) to complex computational commercial products used in both the public and private sectors. Throughout this process, variables used for the classification expanded to include other proprietary and expensive datasets. The Tapestry Segmentation is a commercial US consumer marketing segmentation product designed to target different types of consumers with distinctive consumer expenditure patterns, socioeconomic, housing characteristics, attitudes based on integrating various big data sources. While Tapestry segments are designed to address consumer marketing needs, it is intuitively clear that they are relevant to understand consumer lifestyle footprints. For example, each segment is scored along a race and ethnicity diversity index, income and net worth, age by sex distributions, and neighborhood and socioeconomic traits. All known important determinants of footprints. The methodology and data used to construct the segments uses cluster analysis and data mining and is updated annually by Esri. This makes inter-year comparisons very difficult but could provide a cross-section of consumption behavior that, because of the costs and effort needed, proprietary data, etc, is out-of-reach to researchers. Though there have been attempts to produce open source segments, where all steps are documented and code and data are made available, currently they have a much more limited scope. Data sources used to construct Esri's Tapestry include the 2010 United States Census and the ACS,

both freely available from the U.S. Census Bureau, Esri's in-house demographic updates, and, among others, consumer surveys such as the Survey of the American Consumer from research company GfK MRI (Growth from Knowledge, Mediamark Research & Intelligence)⁴ and the Experian's ConsumerViewSM database, that includes information on attitudinal and behavioral data such as interests, hobbies and brand preferences⁵ ESRI (2014).

2.2. Segmentation validation and limitations

Although the exact formulation of the Esri Tapestry segments is proprietary, the basic procedure used to create these kind of typologies is standard and uses well understood methods from multivariate statistics (Harris *et al* 2005, Dan and Phil 2007) to select a set of variables useful for classification using dimension reduction statistical approaches such as principal component analysis, a clustering algorithm such as *k*-means, applied iteratively for computational tractability, and a form of validating the final classification using additional information from various sources. Esri has recently expanded the set of tools used to create the Tapestry Segmentation also by adding the 'latest data mining techniques to provide a robust and compelling segmentation of US neighborhoods' (ESRI 2014). The classification algorithms typically use heuristic search approaches that go through the space of possible solutions in stages with no backtracking to change any of its previous decisions. Because of this, heuristic algorithms solve a problem by making locally optimal choice at each stage and do not guarantee finding a global optimum. Typical solution to avoid being trapped in a local optima include randomizing starting conditions and repeat the search to look for better solutions. Moreover, the final solution is dependent on the definition of cluster implicit in the method chosen and other parametrizations, such as the similarity function used, the number of clusters, etc the results need to be validated. These clustering algorithms also belong to the unsupervised learning methods. Whereas the performance of supervised learning methods can be assessed based on, e.g. their cross-validation error, there is no clear guidance in the literature on the best approach to evaluate the performance clustering methods. Validation in the segmentation an application to a small to moderate number of real datasets. The quality of the classification critically hinges upon the quality of data and methodology used but also on its intended purpose. New consumer profiles can be introduced if there is enough detailed information and if the new profiles add distinctive consumption pattern useful to understand and predict consumer attitudes and

⁴ <https://mri.gfk.com/solutions/the-survey-of-the-american-consumerr/the-survey-of-the-american-consumerr/>.

⁵ www.experian.com/marketing-services/targeting/data-driven-marketing/consumer-view-data.html.

behavior that can be monetized. It is relevant for us as the dataset is designed to ‘Understand customers’ lifestyle choices, what they buy, and how they spend their free time’⁶.

Esri’s segmentation has been found useful by the Census Bureau researchers to inform coverage research and to plan for the 2020 Census. For example, the US Census Bureau used Esri Tapestry segmentation analysis to identify neighborhoods that are likely to underreport young children (Griffin and Konicki 2017). Also, researchers affiliated to US Census Bureau used Esri lifestyle segments to understand hard-to-survey populations in terms of their response behavior and interactions with social marketing communications, in order to prepare for the introduction the Internet as a mode of self-response for the first time in the 2020 Census (Mulry *et al* 2020).

2.3. Tapestry’s consumer segments

Our analysis is dependent on the consumption and demographic characteristics of the segmentation system used, which has been developed to enable businesses and marketing firms to understand lifestyles and consumer choices. In this study, lifestyles are distinguished by Esri’s Tapestry Segmentation System and are organized in a cross-sectional data set in which every census tract in the country is classified into one of 65 segments according to the dominant socioeconomic variables of local consumers (e.g. income, household size, housing location, population density, housing type, commuting information, education level and race). Lifestyle classification names, such as *Metropolitans* or *Inner City Tenants*, are reflection of these composite variables and convey consumer commonalities across space. Each lifestyle in each locale provides detailed information about the potential emission drivers and context useful for understanding potential policies better. Most descriptors of Esri lifestyles have an aspiring component and transiency that might off-set partially its potentially negative connotations. For example, ‘city commons’ are described in the Tapestry Reference Guide as the Tapestry Segmentation’s youngest segments with a very low median household income. It is generally expected that income will increase, and they will outgrow this status. Esri explicitly refers to the segments in terms of lifestyle and lifestage (ESRI 2014).

Esri has combined these segments into 12 ‘Life-Mode’ Summary Groups based on *life-style* and *life-stage* composition (Esri.com/Tapestry, 2014). For example *Solo Acts*, including five segments of consumers described as young and singles that prefer the city starting out in more densely populated U.S. neighborhoods without child-rearing nor home ownership responsibilities, such as *Laptops and Lattes* and

Metro Renters or *Senior Styles* encompassing nine segments of a rapidly expanding market of aging households such as *The Elders* and the *Prosperous Empty Nesters*.

Esri has also classified the US into 11 Urbanization Groups ranging from the urban canyons of the largest cities to the rural lanes of villages or farms. These summary groups are based on geographic and physical features along with socio-economic characteristics (ESRI 2014). Esri formed the urbanization summary groups based upon population density, existence and size of population center, and location relative to a metropolitan area. The 11 groups included more (I) and less (II) affluent categories of each of four urban forms—‘principal urban centers,’ ‘metro cities,’ ‘urban outskirts,’ ‘suburban periphery’—and three categories that represent rural areas – ‘small towns,’ ‘rural I,’ and ‘rural II.’ Places were categorized across these 11 groups for a wide range of geographic units (e.g. state, county, zip code). The Lifestyles belonging to each urban group are shown in figure 3.

Segments provide more differentiating power than summary groups. However, if the user wants to summarize or analyze a smaller number of markets, summary groups are appropriate. Choosing between the two ways of grouping segments depends on the application at hand. For certain products or services, Urbanization Groups may more effectively distinguish the consumption pattern than LifeMode Groups; for example, going to the movies. But for certain life-style or life-stage-related behavior, such as domestic travel, grouping by LifeMode may be more effective (ESRI 2014).

2.4. Linking lifestyles to emissions

To accurately represent the CO₂ emissions linked with each lifestyle classification, it is essential to capture the emissions associated with direct household energy use (Min *et al* 2010) (e.g. travel, utilities) as well as the emissions associated with the production of household consumption items (such as electronics, cars, toys, food, and furniture) along the supply chains (also referred to as embodied emissions). In order to calculate both types of emissions we use environmentally EIO analysis. This approach has been widely adopted to estimate national energy and GHG embodiments in goods and services (Lenzen 1998, Druckman and Jackson 2008) and to develop consumer-oriented carbon mitigation policies (Bin and Dowlatabadi 2005, Baiocchi *et al* 2010, Min *et al* 2010). By extending the latest BEA Input-Output Benchmark comprising of 389 sectors, we georeference each carbon footprint to their corresponding census tract’s demographic profile through the ACS 2007–2011 five year composite. Using the per capita emissions for every census tract in the country as our primary unit of observation, we can characterize the relationships between potential determinants

⁶ www.esri.com/en-us/arcgis/products/tapestry-segmentation/overview.

and household related CO₂ emissions (supplementary figure 1, tables 1 and 2 (available online at stacks.iop.org/ERL/17/064018/mmedia)). Additional details on the IO data and our empirical modeling approach are provided in section 6.

3. Results

Overall, the average household contributes approximately 40 tons of carbon per year (supplementary table 3). By linking emission estimates with spatially explicit consumer spending data, we can express the CO₂ emissions associated with each lifestyle segment for nearly 70 000 census tracts. In absolute terms, three of the four most populous lifestyles, *Green Acres*, *Boomburbs*, and *Up and Coming Families* emit the most CO₂ (.6 Gt CO₂); representing nearly 12% of national emissions (supplementary table 4). However, when we express the total emissions of each segment in per capita terms, we find lifestyles rank very differently. Figure 1 illustrates the average per capita emissions for each of the 65 lifestyle against their income, population density and household size. categories. The graph shows that *Top Rung*, a suburban lifestyle, has the largest per capita income as well as the largest CO₂ footprint. In this manner, we can compare consumer profiles against each other and examine why these differences occur.

To see if the lifestyle classification provides useful information about footprints, we need to determine whether the computed lifestyle footprints were significantly different from each other both statistically and quantitatively. A multiple comparison test was performed using Tukey's honestly significant difference criterion. Tukey's test compares the mean emissions of every lifestyle to the means of every other lifestyle, in this case 2080 comparisons. More importantly, as opposed to pairwise *t*-tests, the Tukey's procedure corrects the *p*-values for multiple testing in order to control the family-wise error rate (supporting table 11). We found that almost 90% of the 2080 possible differences were statistically significant. The quantitative difference were also found to be relevant. As an example, *Top Rung* has about 30 t per capita of CO₂ emission more than lifestyles such as *Las Casas*, *City Commons*, *NeWest Residents*, and *High Rise Renters*. For *City Commons* and *Las Casas* the difference and significance are low. *Las Casas* and *NeWest* have a high proportion of Hispanic households.

In general, we find that lifestyle carbon footprints vary considerably with income, household location, and household size. Unsurprisingly, high-income lifestyles are ranked among the top emitters (e.g. *Silver* and *Gold*, *Connoisseurs*, *Suburban Splendor*, *Urban Chic*). In per capita terms, the two highest earning segments, *Top Rung* and *Laptops and Lattes*, contribute the highest impacts out of all 65 lifestyles. While we find a gradual growth in

emissions as per capita income increases significantly (Druckman and Jackson 2008, Weber and Matthews 2008, Jones and Kammen 2011), figure 1 shows also that there is a significant heterogeneity in lifestyle emission footprints, even among those with similar income levels. For example, some low-income lifestyles display emission levels that are similar to middle income segments (e.g. *Modest Income Homes*, *Metro City Edge*, *Rural Bypasses*) (supplementary table 5).

Interestingly, the age of residential infrastructure and the associated household energy efficiencies becomes apparent in this context. For example, *Metro City Edge* presented one of the highest carbon intensities of direct emissions (.05 kg US\$⁻¹) among low income lifestyles (below \$30 000), with nearly 70% of consumers of this category living in single-family housing stock built before 1970. This is a critical observation when examining the potential emissions resulting from poor housing conditions. By ranking each lifestyle by carbon intensity (supplementary table 4), we can evaluate which lifestyle segments could be prioritized with retrofitting strategies. Like income, housing conditions tend to cluster. Low-income segments, such as *City Dimensions*, *Modest Income Homes* and *Metro City Edge* all inhabit areas with relatively older housing conditions and are located in the urban periphery of major U.S. cities. This effect is captured by the segmentation process and is the result of underlying CO₂ drivers blending together differently in each location (Baiocchi et al 2015).

We find substantial evidence suggesting that differences in emission profiles are explained by spatial variances in population density, housing choice and the segregation of different consumer groups. The largest differences in carbon responsibility, i.e. total carbon emissions attributed to a particular lifestyle category, occur between suburban segments (e.g. *Suburban Splendor*, *Wealthy Seaboard Suburbs*) and city lifestyles (e.g. *Young and Restless*, *City Lights*). For example, despite making up only 2.77% of the U.S. population, *Boomburbs* is responsible for 4.13% of U.S. household emissions. In comparison, *City Lights*, falling in a similar income category as *Boomburbs*, has less influence on the national carbon footprint, making up 1.12% of the U.S. population and responsible for 1.15% of total emissions. Our findings are consistent with similar studies showing that consumers in densely populated areas with increased access to nearby employment, higher costs of living and demand for smaller living spaces have smaller footprints (Karathodorou et al 2010, Jones and Kammen 2011), while suburban populations have larger carbon footprints due to income effects, larger homes and longer commuting distances (Jones and Kammen 2011).

The impact of household size becomes apparent through the visualization of per capita emissions, especially in the context of segments with

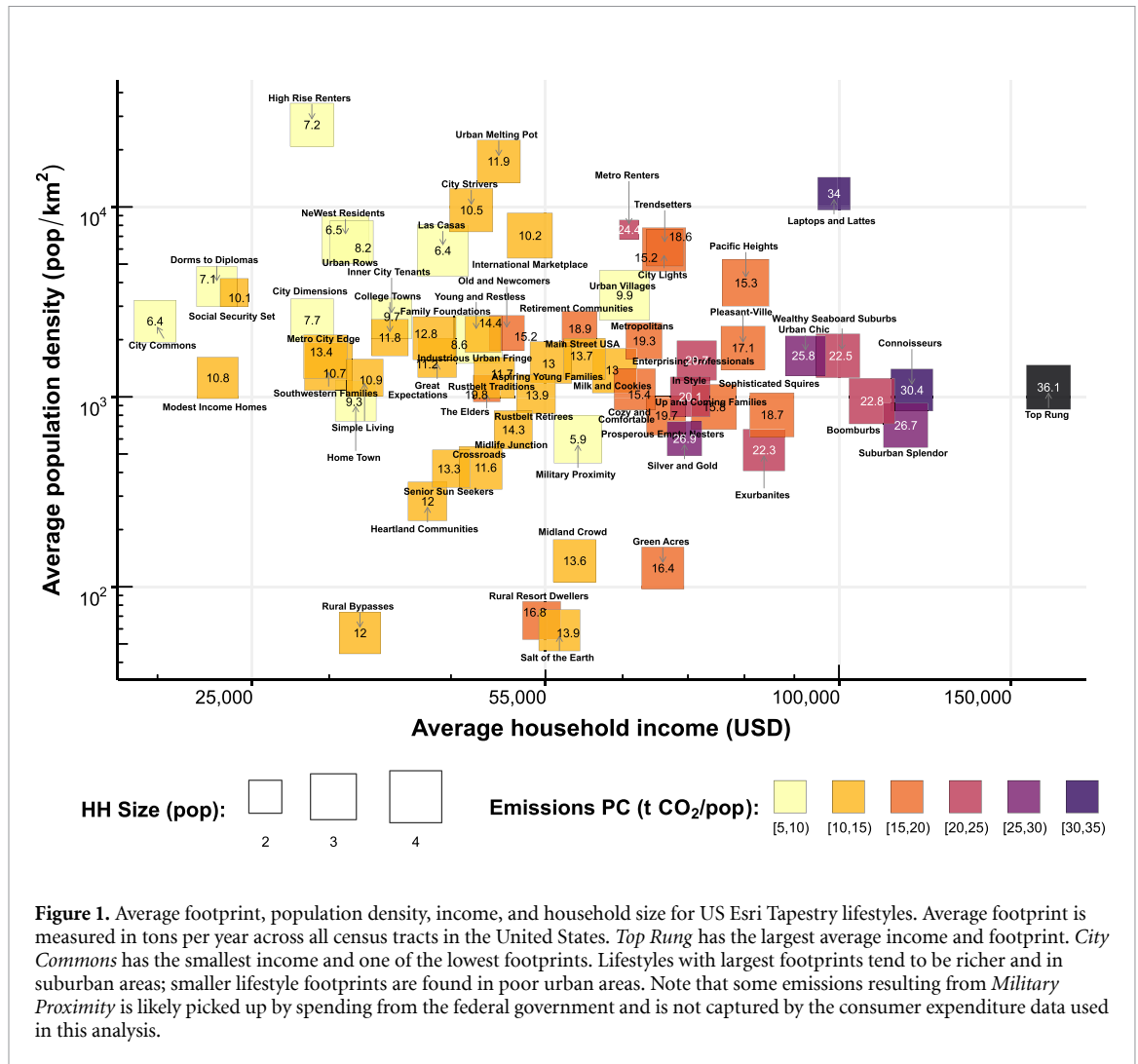


Figure 1. Average footprint, population density, income, and household size for US Esri Tapestry lifestyles. Average footprint is measured in tons per year across all census tracts in the United States. *Top Rung* has the largest average income and footprint. *City Commons* has the smallest income and one of the lowest footprints. Lifestyles with largest footprints tend to be richer and in suburban areas; smaller lifestyle footprints are found in poor urban areas. Note that some emissions resulting from *Military Proximity* is likely picked up by spending from the federal government and is not captured by the consumer expenditure data used in this analysis.

more children (e.g. *Las Casas*, *Urban Villages*). In general, per-capita carbon dioxide emissions decline with increases in household size, indicating the sharing of consumption items like household heating, appliances and transportation is critical in identifying mitigation prospects (supplementary table 1). For example, despite nearly having identical household incomes, *Metro Renters* (1.75 people per household) is responsible for nearly 10 more tons of CO₂ emissions (per capita) compared to *Cozy and Comfortable* (2.59 people per household).

4. Emissions resulting from lifestyle consumption choices

Strategies for decreasing household CO₂ emissions across lifestyles requires an understanding of the consumer choices lifestyle groups make. Doing so, allows us to gauge which census tracts have the largest potential for mitigation and investigate how the lifestyle mix of households in the United States impacts the spatial distribution of CO₂ emissions. However, as consumer choice is a partial reflection of how consumers maximize the limitations of their household

expenditures, it is necessary to equalize all lifestyles' access to income to accurately gauge which households emit more (Abel 1991, Abel and Cockerham 1993). To standardize the relationship between lifestyle consumer choices and household conditions that constrain these choices. We decompose the contribution to emissions into two separate components: contributions due to differences in income and household size and the ones due to more short-time consumption choices. To achieve this we estimate the best model linking emissions to its determinants for each lifestyle and use these relationships to predict emissions that would prevail if households in each lifestyle were brought to the same level of income and household size. This approach allows us to address the hypothetical question (counterfactual) of what would happen to emissions if households adopted different lifestyles within a given location and assuming the same income and family size. This way we estimate new emissions that exclude the limitations of lifestyle expenditures. In essence, by controlling for these variables, we 'standardize' (Glaeser and Kahn 2010) consumers' accessibility to resources, allowing us to evaluate the carbon implications of consumer

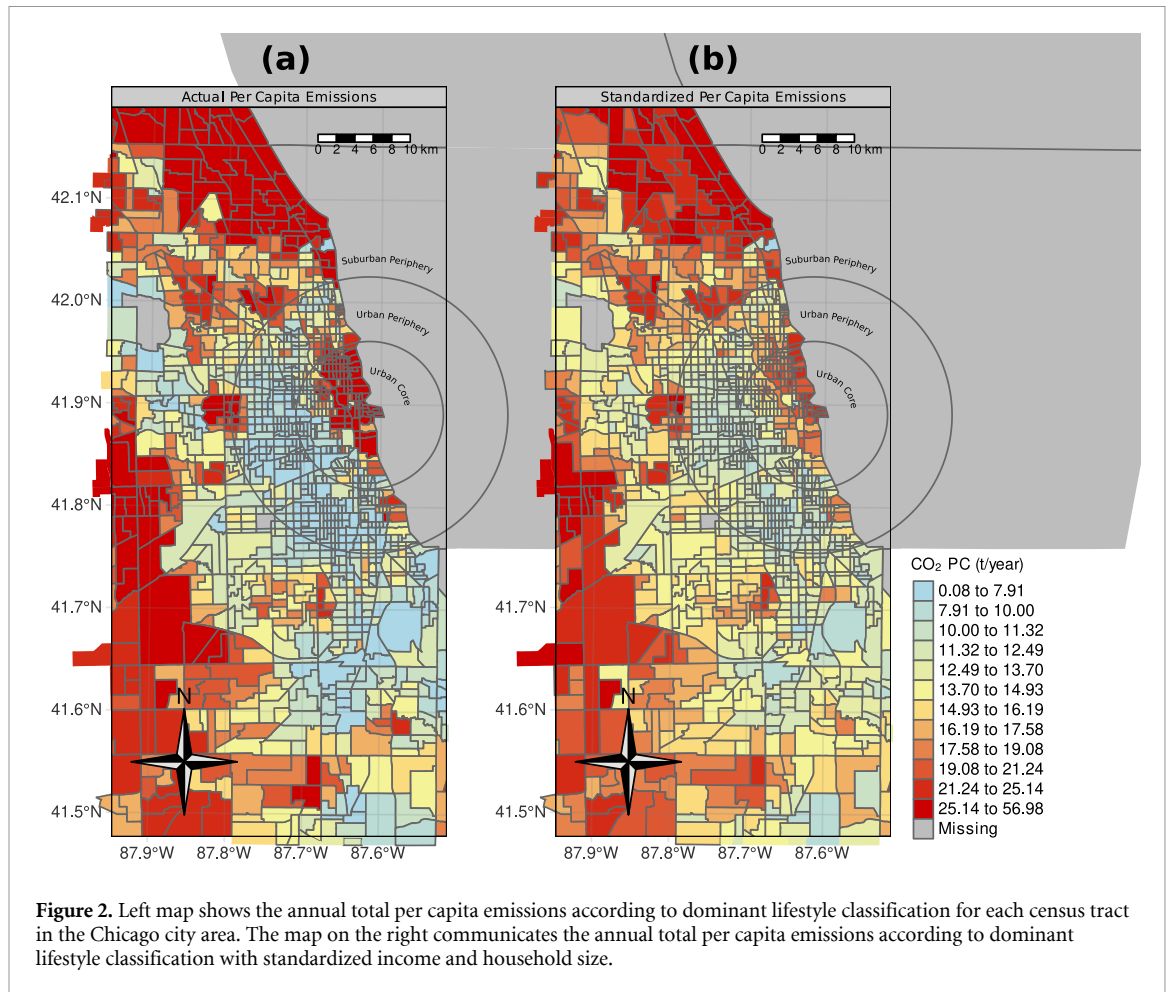
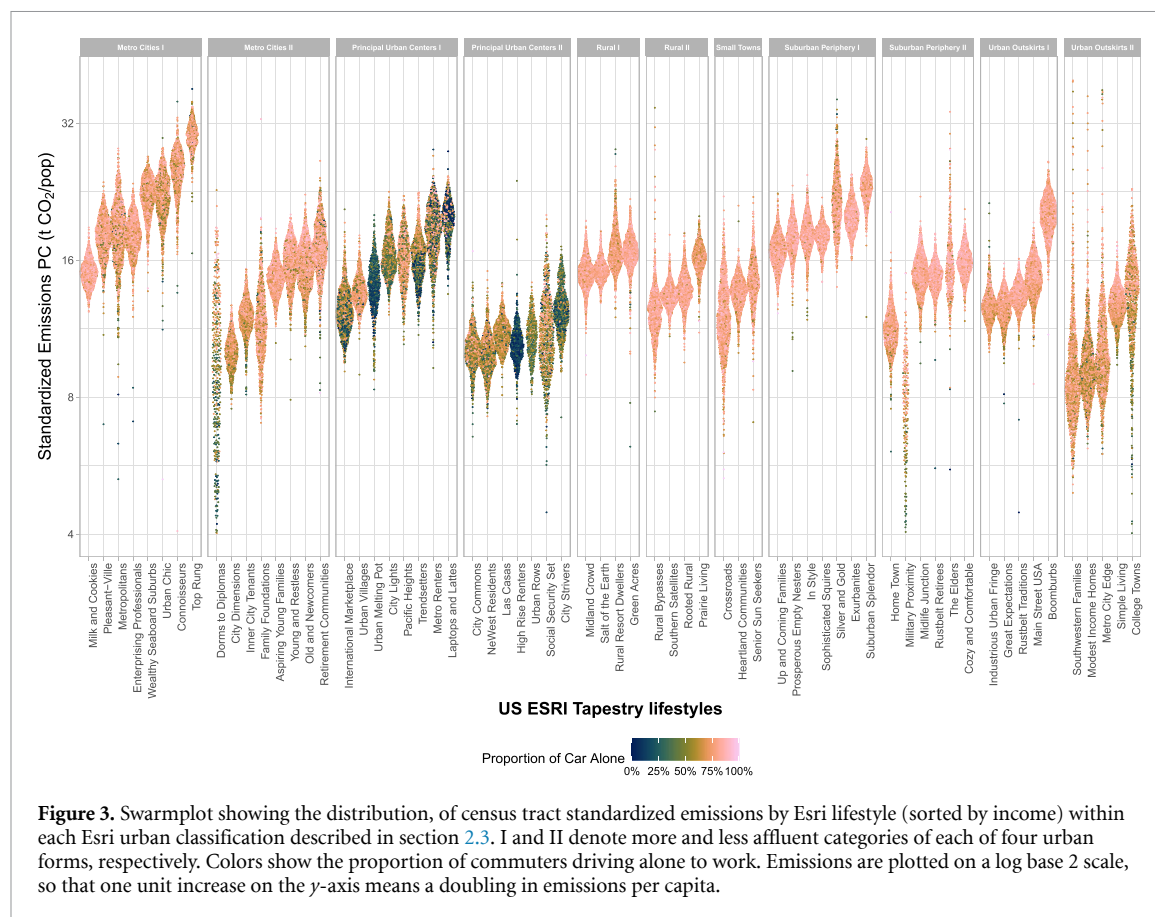


Figure 2. Left map shows the annual total per capita emissions according to dominant lifestyle classification for each census tract in the Chicago city area. The map on the right communicates the annual total per capita emissions according to dominant lifestyle classification with standardized income and household size.

choices between lifestyle groups. The final product communicates 65 unique values for all census tracts and allows us to compare and rank lifestyle carbon footprints. Spatially, these results offer evidence for the areas of the country that provide the most potential for mitigation focused on lifestyle consumption choices (rather than income).

The results of this approach are best represented in the spatial context of a major U.S. city. For example, figure 2(a) reflects the average emissions of the dominant lifestyle classifications for every census tract in Chicago. In this perspective, we can observe the CO₂ emissions of the high-income segments in the urban core and in the surrounding suburban population (represented in red). In contrast, lower and moderate income lifestyles are located in the urban periphery surrounding the urban core. Figure 2(b) represents the residential emission impacts once income and household size are controlled for. Generally, we find a major drop in 'lifestyle choice' emissions and ranking among the lifestyle classifications located in the urban core of Chicago (*Laptops and Lattes*, *Metro Renters*, *Trendsetters*). In comparison, the suburban lifestyle segments located in the periphery of Chicago maintain relatively high levels of emissions (above 30 CO₂ tons per capita per year).

Our results from the counterfactual analysis illustrate the spatial clustering of consumer choices between lifestyle types and enables the targeting of specific households based upon emission profiles. We can rank lifestyles based on their carbon emissions and evaluate the changes in emissions when controlling for income and household size (supplementary table 6). For example, in terms of actual emissions, *Laptops and Lattes* ranks as the second highest emitter among all lifestyles. However, after income and household size are controlled for, *Laptops and Lattes* becomes one of the most efficient consumers among the top income segments, decreasing per capita emissions by nearly 50%. Overall, we find that consumer choices in suburban lifestyles are responsible for the most emissions. In the context of per capita emissions, we see an increase of ranking of suburban lifestyles like *Suburban Splendor*, *Wealthy Seaboard Suburbs*, *Exurbanites* and *Pleasant-Ville* towards the top rankings. These lifestyles reflect the distinctive mode of living a traditional CO₂ intensive suburban consumer who tends to demand larger homes, possess multiple cars and tends to commute alone to work. In comparison, we find a drop in ranking for urban lifestyles, in densely populated areas, like *Laptops and Lattes*, *Metro Renters*, *Trendsetters*,



and *Enterprising Professionals*. While some of these lifestyles have relatively high household incomes, these segments display consumer choices that are less impactful, usually living in smaller living spaces in areas with higher population densities.

The counterfactual approach highlights the differential impact of lifestyles once main controls like income are fixed. Using our approach, it is possible to show which features could be responsible for the differences in footprint within and between similar lifestyles and should be further investigated as potential levers to reduce emissions and tailor policies to specific lifestyles. As an example, the swarmplot in figure 3 shows the distribution of census tract standardized emissions by Esri lifestyle (sorted by income) within each Esri urban classification. Colors show the proportion of commuters driving alone to work (supporting figure 2 shows the impact of age). It is clear that *Urban Melting Pot* and *High Rise Renters*, with residents of mixed race living in dense urban areas according to the Tapestry Segmentation Reference Guide (ESRI 2011), are the least likely to drive alone to work and have low emissions within their residential type. It is also possible to see that for several lifestyles such as *Trendsetters* and *Dorms to Diplomas*, the means of transportation seems to make a substantial impact on emissions and potentially contribute to its spread. These Lifestyles tend to be young employed and college students

living in urban areas that rent an apartment or live in dormitories. Lifestyles' impacts depend on the complex interaction between soft (i.e. norms, habits, and behavioral framing) and hard infrastructure (i.e. building size, walkable neighborhoods, public transit systems, etc).

The fact that income still plays an important role in the counterfactual emission ranking highlights the high interdependence between income, values, preferences, opportunities, choice of residential location, employment location, daily mobility, education centers, etc that end up defining lifestyles. Once households have adopted a specific high-carbon lifestyle, the opportunity for reductions might be more limited.

5. Discussion

In this paper, we present a geodemographic framework to model the impacts of lifestyle consumption patterns in the context of household emissions. Environmental conditions, local infrastructure and consumer activities vary widely across the United States, and there is no reason to assume that emission drivers related to these characteristics are uniformly the same (Baiocchi et al 2015). Instead, our conceptualization of lifestyle analysis suggests emissions drivers work together in different ways dependent on the socio-economic, geographic and infrastructural

context and can only be appreciated in their respective context. Marketing experts focused on identifying specific consumer behaviors have long acknowledged the importance of place-specific composite variables (Harris *et al* 2005) to predict consumer behavior and have subsequently developed data products that convey consumer lifestyles and consumption practices at high-spatial resolution. This geographic context is equally important when identifying carbon intensive consumers.

Our approach is unique in its application of market segmentation data and allows us to control for the complex interactions between geodemographic, infrastructural and environmental drivers of CO₂ emissions. Through a multivariate regression approach and relative importance analysis, we demonstrate how combinations of CO₂ drivers are best contextualized through clustering methods and that market segmentations are successful in explaining emissions compared to individual demographic variables. And while we find evidence that income is the dominant driver of household CO₂ emissions, lifestyles account for other correlated variables and better describe how income is consumed through lifestyle choices. This in turn has direct implications for the spatial resolution of climate mitigation policies. As traditional characterizations of household CO₂ emissions have largely depended on individual demographic variables to inform mitigation strategies, market segmentation data provides rich detail at the fine spatial scale and at the same time comprehensively covering the whole U.S. While our approach enables a deeper contextualization of household emissions, it alone is not enough to solely inform sound policy recommendations. However, some recommendations can be made, even in the context of our initial framework. For example, our results imply that low-income lifestyle carbon footprints are impacted by the age of residential infrastructure and associated level of energy consumption (*Metro City Edge, Modest Income Homes*). Carbon policies focused on utility emissions would need to provide tailored energy reduction recommendations specific to the composition and context of these communities. As lower income neighborhoods are likely to have higher energy consumption per square foot of living space due to less energy efficient homes and older appliances, having the necessary information of people's living situations and constraints on consumption choices is a critical precondition for designing a carbon policies considering the socio-economic and geographic context of consumers.

Additionally, the counterfactual analysis demonstrates how lifestyle segmentation data can be utilized to estimate CO₂ emissions related to lifestyle consumption choices at high spatial resolution. Our approach highlights where carbon-intensive lifestyles cluster and illustrates emission impacts resulting

from the spatial heterogeneity and variation of lifestyle segments. After standardizing income and household size between lifestyle segments, we find that the largest potential for CO₂ mitigation related consumer choices exist in the suburban periphery of major U.S. cities. The spatial resolution of our results could provide important information explaining municipal emissions patterns associated with different lifestyles.

Identifying the spatial uniformities and variations of lifestyle consumption choices is a prerequisite for tailoring carbon mitigation strategies at the sub-city level. As individual demographic variables lack the explanatory power needed to inform holistic policy recommendations, our application of spatially explicit market segmentation data takes an initial step toward the systematic use of composite variables to represent the spatial and demographic heterogeneity of residential consumers in carbon footprinting.

We can illustrate with a few examples how policy makers can target the more impactful consumers we have identified using the rich consumer segment data. As an example, according to the Tapestry Segmentation Reference Guide (ESRI 2011), *Pleasant-Ville* household residents work in a variety of occupations in diverse industry sectors, mirroring the US distributions. Many of these occupations have been found to make more limited use of teleworking, particularly when compared to management and professional jobs of the higher income lifestyles neighborhoods such as *Suburban Splendor, Boomburbs*, and *Wealthy Seaboard Suburbs* (Crisuolo *et al* 2021). Since, according to the reference guide, many employed in this lifestyle commute an hour or more to work, policies supporting remote working, such as the provision of close to home child care, and access to fast, reliable, and safe internet services, could help mitigate the impact of these suburban lifestyles (Crisuolo *et al* 2021). As another example of potential uses of geodemographic segmentations for targeting specific environmentally impactful lifestyles, *Boomburbs* is the 'top market to own big-screen TVs, DVD players, digital camcorders, video game systems, and scanners'. Based on this profile, a strategy based on web-based gamified platforms or mobile apps to induce positive environmental behavioral change could be promising for this group (Khanna *et al* 2021). Such lifestyle mitigation options can reduce emissions substantially and slowly shift preferences and nudging consumers toward more sustainable behaviors (Creutzig *et al* 2016). It is important to emphasize that these options have to be complemented by broader strategies aimed at increasing the solution space by reshaping the urban and suburban form offering built infrastructure options for more ambitious mitigation goals. Further research would be needed to assess the feasibility and effectiveness of both lifestyle solutions and broader more transformational strategies.

6. Methods

6.1. Environmental input-output model

The total CO₂ emissions $\mathbf{p}^{hh,tot}$ from household consumption of s different lifestyle groups can be expressed most generally as the sum of their direct $\mathbf{p}^{hh,dir}$ and indirect emissions $\mathbf{p}^{hh,ind}$,

$$\mathbf{p}^{hh,tot} = \mathbf{p}^{hh,dir} + \mathbf{p}^{hh,ind}. \quad (1)$$

The direct CO₂ emissions $\mathbf{p}^{hh,dir}$ are associated with domestic energy consumption and private transport. Indirect emissions are generated through intermediate production in the economy needed to meet the lifestyles' demands of good and services. We will standard matrix notation and algebra to describe the model. Matrices and vectors are denote in bold. Operations between matrices are standard matrix algebra operations. Operations between matrices are standard matrix operations. For more details see as standard input-output reference such as Miller and Blair (2009). Lifestyle group specific estimates are obtained by assigning direct emissions of all households across the s lifestyle groups proportionally to their energy and transport expenditures. The indirect emissions can be calculated by multiplying a vector of total CO₂ intensities ε^{ind} of n different production sector with a detailed matrix of household consumption expenditures of the s different socio-economic groups in m functional spending categories, that is

$$\mathbf{p}^{hh,ind} = \varepsilon^{ind} \mathbf{A}^{hh} \mathbf{Y}^{hh,soc}, \quad (2)$$

with $\mathbf{A}_{n \times m}^{hh} = [a_{ik}] = y_{ik} / \sum_{i=1}^n y_{ik}$, with indices $i = 1, \dots, n$ and $k = 1, \dots, m$, being a matrix of direct coefficients indicating the proportion of final household demands for products provided by the n different sectors across the m different functional spending categories and $\mathbf{Y}^{hh,soc}$ being a matrix of household consumption expenditures of the s different socio-economic groups in the m spending categories. The vector of indirect CO₂ intensities ε^{ind} from the n different sectors is derived from a standard input-output model (Miller and Blair 2009)⁷. This vector can be estimated as follows,

$$\varepsilon^{ind} = \mathbf{rL}, \quad (3)$$

where \mathbf{r} is a vector of sectoral direct CO₂ intensities indicating the amount of CO₂ emitted per unit of total output of the n different sectors and \mathbf{L} is the total requirement coefficients matrix (industry by industry of size $n \times n$) which indicates total inputs by industry required (directly and indirectly) in order to deliver

one dollar of industry output to final users derived from the BEA Input-Output table (Miller and Blair 2009). We used this method to estimate the direct and indirect CO₂ emissions from the different lifestyle groups as presented in the Esri consumer segmentation database. The approach is described in detail in Wiedmann *et al* (2006).

6.2. Empirical modeling

Investigating emissions associated with consumption patterns using standard empirical modeling approaches can provide some policy insights into carbon mitigation strategies. However, unless the relationship between residential carbon emissions and geodemographic composite factors can be established, it will be difficult to understand lifestyle consumption choices. We want to stress the additional value gained by using market segmentation data. By incorporating census tract lifestyle classifications from the segmentation system into a panel regression approach, we exploit the variation of dominant lifestyle types between census tracts and improve upon the ordinary least squares (OLS) using a fixed-effects regression (supporting tables 1 and 2). By applying a relative importance analysis to the fixed effects model, we can evaluate the proportion of explained variance between individual predictors (Johnson 2004, Tonidandel and LeBreton 2011) and show that lifestyle segmentations are successful in predicting emissions compared to individual demographic variables (supporting tables 7(a) and (b)).

We examine the determinants of CO₂ emissions through two estimation methods: First, we employ the use of a pooled OLS estimation to determine the impact of socioeconomic factors without the presence of a heterogenic market segmentation variable. Second, we use fixed effects estimation to determine the impact of socioeconomic variables in the presence of our lifestyle segmentation variable as dummy variables. The lifestyle segmentations provided by the Esri Tapestry System are arranged in a cross-sectional data-set and are geographically linked to emissions and socioeconomic information by census tract. We treat the lifestyle segmentations as factor panel data and are observed hundreds of times in various census tracts across the United States. Fixed-effect regressions are commonly used in regression with large degrees of heterogeneity. The empirical model in equation (4) estimates the total per capita emissions with lifestyles and various socioeconomic and infrastructural factors as primary predictors:

$$\ln E_i = \alpha_i + \sum_{s=1}^k \beta_s \ln X_{si} + \varepsilon_i, \quad (4)$$

where E_i is the per capita measure of CO₂ emissions, $i = 1, \dots, N$ represents the 65 unique lifestyles classifications that are detailed in the Esri Tapestry System. X_{si} where $s = 1, \dots, k$, denotes the total number

⁷ Note that energy use at work is part of the indirect emission component. The energy use from work related activities are embedded in the goods and services households buy and assigned to them depending on the type and quantity of products they choose.

of socioeconomic and environmental variables contained in the dataset. k denotes the total number of regressors and ε_i represents the standard idiosyncratic error term. α_i is treated as a regression parameter and is described as the unobserved lifestyle specific heterogeneity. Results for the OLS and FE regressions are presented in supporting information section.

To measure the relative importance for each regression predictor, we employ the Lindemann Merenda and Gold (LMG) algorithm popularized by Grömping's 'relaimpo' package (Groemping 2006). The origin of algorithm was originally developed by Lindeman *et al* (1980) and later expanded upon by Kruskal (1987). The LMG algorithm excels at decomposing the non-negative contributed percentage of variance explained by each regression variable. Because the order of predictors can have a considerable impact on the relative importance of determinants, the LMG algorithm controls for ordering bias by averaging over all possible orderings. While there are some limitations about using relative importance measurements, the LMG method is among the most widely used (see, e.g. Johnson 2004, Johnson and Lebreton 2004). Because of the computational requirements of so many variables used in the analysis, we provide two sets of results, both provided in our supporting materials (supporting table 7). Either way, the results of the analysis conclude that income and lifestyles are important in predicting consumer emissions. Further diagnostics checks on multicollinearity are presented in the supplementary information (supporting tables 8(a) and (b)).

7. Data sources

The data set used for the environmental input-output analysis was taken from the BEA's Input-Output Account of the U.S. economy for 2007 (Bureau of Economic Analysis 2007). The table provides a comprehensive account of U.S. production relationships among 389 economic sectors and commodities. We georeferenced emission accounts from Esri's U.S. Consumer Spending data (ESRI 2011) which is based on a combination of the latest Consumer Expenditure Surveys (CEX) from the Bureau of Labor Statistics. The regression analysis relies on a subset of the U.S. Census Bureau ACS 2007–2011 (United States Census Bureau 2013) five year composite; a cross sectional dataset in which each of the approximate 72 000 observations represents a U.S. census tract communicating average household information for determinants such as income, household size, geographic location, density, housing type, commuting information, education level and race. Household consumption data was obtained from the Esri Tapestry system; a marketing segmentation product which divides U.S. census tracts into 65 distinct lifestyle groups based

up geographic location. The Esri Tapestry system also provide detailed household consumption (400+ consumption items) data for each lifestyle groups. We assigned and aggregated the consumption items to the BEA IO sectors. The ESRI Tapestry Consumption Expenditures—BEA Input-Output sectors concordances are shown in supporting table 10. Additionally, information on fuel prices for each state was taken from the Energy Information Administration (EIA 2011). Heating and cooling degree information was taken from NOAA weather stations (NOAA 2003) and geographically assigned by proximity to census tracts using a GIS.

8. Limitations and further research

We have used a combination of national surveys and marketing datasets to predict consumption for approximately 70 000 census tracts for the United States. The results of the analysis should be understood in the context of some uncertainty and the methods used to derive expenditure at a high spatial resolution. Firstly, the expenditure breakdown of economic sectors for all census tracts is dependent on Esri's Consumer Spending data and is reported by product or services and includes total expenditures, average spending per household and a Spending Potential Index. These expenditures are considered sectoral percentage benchmarks and based on the Bureau of Labor Statistics Consumer Expenditure Survey. Model results presented in this study are an estimation consumption and lack emission details pertaining to certain economic sectors. For this reason, we restrict our analysis to only examining direct and indirect emissions.

In this paper we assumed a fixed technology assumption at the US level to focus on the impact of lifestyles consumption. One limitation of using a single region IO approach is that it is incapable of accounting of regional technological and supply chain differences in the calculation of the footprints. Following an approach analogous to Shigetomi *et al* (2021), more spatially relevant footprints could be calculated by linking lifestyles' to a more detailed representation of economic activities and flows along the supply chain using US based multi-regional input-output (MRIO) approach based on monetary flows between industrial sectors and US regions and a global MRIO through imports (Miller and Blair 2009). US-MRIO models have been recently developed and used (see, e.g. Faturay *et al* 2020, as an example). The usefulness of such an approach in determining the impact of lifestyles, given the added uncertainty from the construction of regional tables and from matching expenditure categories, is a matter for further research and beyond the scope of this paper.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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