The Impact of Social Factors and Consumer Behavior on Carbon Dioxide Emissions in the United Kingdom

A Regression Based on Input–Output and Geodemographic Consumer Segmentation Data

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Summary

In this article we apply geodemographic consumer segmentation data in an input–output framework to understand the direct and indirect carbon dioxide (CO_2) emissions associated with consumer behavior of different lifestyles in the United Kingdom. In a subsequent regression analysis, we utilize the lifestyle segments contained in the dataset to control for aspects of behavioral differences related to lifestyles in an analysis of the impact of various socioeconomic variables on CO_2 emissions, such as individual aspirations and people's attitudes toward the environment, as well as the physical context in which people act.

This approach enables us to (1) test for the significance of lifestyles in determining CO_2 emissions, (2) quantify the importance of a variety of individual socioeconomic determinants, and (3) provide a visual representation of "where" the various factors exert the greatest impact, by exploiting the spatial information contained in the lifestyle data.

Our results indicate the importance of consumer behavior and lifestyles in understanding CO_2 emissions in the United Kingdom. Across lifestyle groups, CO_2 emissions can vary by a factor of between 2 and 3. Our regression results provide support for the idea that sociodemographic variables are important in explaining emissions. For instance, controlling for lifestyles and other determinants, we find that emissions are increasing with income and decreasing with education. Using the spatial information, we illustrate how the lifestyle mix of households in the United Kingdom affects the geographic distribution of environmental impacts.

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Introduction and Literature Review

Evidence increasingly suggests that the human-induced release of greenhouse gases into the atmosphere might cause serious, potentially irreversible changes to the global climate within the next decades (IPCC 2007). Although further warming is inevitable, the challenge has become checking human-induced increases in global mean temperature enough to avoid the most catastrophic consequences. This requires deep-rooted cuts in the global release of carbon dioxide (CO_2) emissions—particularly in industrialized countries, such as the United Kingdom.

In its climate change bill (OPSI 2008), the United Kingdom was the first country to commit to a set of legally binding reduction targets, including greenhouse gas emission reductions, through action in the United Kingdom and abroad, of at least 80% by 2050. In addition, the bill aims for CO_2 emission reductions of at least 26% by 2020, against a 1990 baseline. There is agreement in the sustainable consumption literature (Lintott 1998; Charkiewicz et al. 2001; Princen et al. 2002) and in the policy community (HM Government 2005, 2006; Sustainable Consumption Roundtable 2006) that this reduction will require substantial increases in the carbon efficiency of production processes and changes in the way people live and consume.

"Lifestyle analysis" provides a systemic view of the entire sociotechnological system that links consumption and induced production activities together in one analytical framework. Lifestyles themselves are usually seen to be reflected in the consumption patterns of societal groups with different socioeconomic characteristics, such as social identity, education, employment, or family status (Hertwich and Katzmayr 2004). Lifestyle-related emissions therefore include the carbon emissions consumers release directly from heating their homes and driving their cars but also all the indirect emissions released throughout the global supply chain from the production of the final goods and services purchased. Because lifestyle analysis accounts for both kinds of emissions, it can generate a comprehensive carbon output measure for a set of consumer behaviors attached to a particular lifestyle.

Environmental input–output models have been used most frequently for the assessment of the direct and indirect carbon emissions associated with different lifestyles (e.g., Symons et al. 1994; Duchin 1998; Labandeira and Labeaga 1999; Weber and Perrels 2000; Wier et al. 2001; Pachauri and Spreng 2002; Lenzen et al. 2004b; Bin and Dowlatabadi 2005; Cohen et al. 2005; Hertwich 2005; Hubacek and Sun 2005; Tukker et al. 2005; Tukker and Jansen 2006; Lenzen et al. 2008; Ornetzeder et al. 2008; Hubacek et al. 2009). This standard environmental input–output-based lifestyle approach can also be challenged on various grounds, however. Four lines of criticism are briefly summarized here.

The first line of criticism is directed toward the treatment of import-related CO_2 emissions in lifestyle-related studies. Because lifestyle analysis is interested in all CO_2 emissions associated with the consumption patterns of a particular group of households (e.g., within a country), studies conventionally compile emission inventories on the basis of the principle of consumer responsibility. These inventories include import-related and exclude export-related CO_2 emissions (see Munksgaard and Pedersen 2001; Munksgaard et al. 2009; Lenzen et al. 2007; Peters 2008). Due to limited data availability and the complexity of the task, however, most studies have assumed that the structure of the economy and the sectoral CO_2 intensities are the same abroad as at home (Weber and Perrels 2000; Lenzen et al. 2004a; Bin and Dowlatabadi 2005; Cohen et al. 2005; Druckman and Jackson 2008). Lenzen and colleagues (2004a) have shown that such a "single-region assumption" can lead to a significant estimation error (Munksgaard et al. 2005; Wiedmann et al. 2007; Wiedmann 2009). A proposed way forward is to base estimations on a multiregional input–output model (Lenzen et al. 2004a; Munksgaard et al. 2009; Peters and Hertwich 2008; Weber and Matthews 2008; Minx et al. 2009; Wiedmann et al. 2010).

The second line of criticism is directed toward the purely expenditure-based characterization of a lifestyle. Schipper and colleagues (1989) highlight the need for a redefinition of *lifestyle* in terms of human activity patterns, with a focus on what people do rather than on what they spend. In this context, time-use data have been proposed as a complement for operationalizing such a human-activity-based approach to lifestyle analysis (Minx and Baiocchi 2009). These considerations have been recently incorporated in the input—output literature (Brodersen 1990; Jalas 2002, 2005; Stahmer 2004; Schaffer and Stahmer 2005; Kondo and Takase 2007; Minx and Baiocchi 2009).

The third line of criticism addresses the way lifestyle groups are conventionally classified in input—output studies. Most frequently, lifestyle groups are identified on the basis of a small set of preselected variables. These variables are typically closely related to the occupation and associated socioeconomic status of individuals (Duchin 1998). The most important problem of such a top-down classification is that it fails to recognize spatial aspects associated with lifestyles and that it often includes only a very limited number of socioeconomic background variables for further analysis.

Marketing practitioners have long recognized these problems and have adopted a geodemographic approach in the classification of lifestyles to better understand consumer behaviors. Geodemographics might be best defined as the "analysis of people by where they live" (Harris et al. 2005, 2). The rationale behind geodemographics is that places and people are inextricably linked. Knowledge about the whereabouts of people reveals information about them. 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 literature (Schelling 1969; Harris et al. 2005; Pancs and Vriend 2007; Vickers and Rees 2007).

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. Lifestyle group names, such as "villages with wealthy commuters," "affluent urban professionals, large flats," or "single elderly people, high-rise flats," are a reflection of this. In the context of environmental research, such classifications seem superior to conventional "occupation-based" systems, as they account for important aspects of the immediate physical environment in which people operate, which have considerable impact on people's emission patterns. For example, people in rural areas can afford bigger houses—which often have greater heating requirements (Boardmann 2007). Access to public transport and to other private and public services, together with the distance to shops, the commuting requirement, or the age and the condition of the housing stock, are other important neighborhood-specific determinants of carbon emissions associated with a lifestyle. Regardless of the appeal, however, so far, only very few studies have started to explore the potential of geodemographic data for lifestyle analysis (e.g., Duchin 1998; Duchin and Hubacek 2003; Druckman and Jackson 2008; Druckman et al. 2008; Minx et al. 2009).

A final line of criticism can be directed toward the fact that most input—output-based lifestyle studies remain purely descriptive in their analysis of the results. Simply estimating the level of emissions associated with different consumption patterns across societal groups might provide important insights, but unless links can be established between emissions and different socioeconomic factors, such as education, income, or gender, it will be difficult to improve our understanding of the relationship between lifestyles and emissions. Even though researchers have made more and more attempts to further investigate this issue on the basis of univariate (e.g., Lenzen 1994; Vringer and Blok 1995; Cohen et al. 2005; Hertwich and Peters 2009) and multivariate regression models (e.g., Weber and Perrels 2000; Ferrer-i Carbonell and van den Bergh 2004; Lenzen et al. 2006; Weber and Matthews 2008), no study so far has established the importance of lifestyles in explaining emissions and accounted for them in its empirical investigations of emissions and their determinants.

Although we have addressed the first two sets of criticisms elsewhere (e.g., Minx and Baiocchi 2009; Minx et al. 2009), this study adds to the last two strands of literature and attempts to make the following contributions: We use geodemographic consumer segmentation data provided by the ACORN database for our analysis of the CO_2 emissions associated with different lifestyles in the United Kingdom. This adds to the literature a very detailed carbon account for 56 lifestyle types and allows a general investigation of the environmental significance of lifestyles (see also Duchin 1998; Duchin and Hubacek 2003; Druckman and Jackson 2008; Druckman et al. 2008).

By applying a regression approach, we are able to exploit the unique geodemographic nature of the data to identify the impact of lifestyles on the relationship between emissions and a set of important socioeconomic determinants. By allowing for "lifestyle effects," we are able to control not only aspects of the immediate physical environment in which people operate that have considerable effect on their environmental impact but also for aspects of economic and social behavioral differences related to lifestyles, such as individual aspirations and people's attitudes toward the environment (e.g., toward consumption, education, housing, transport, and leisure activities). We finally provide a visual representation of where the various socioeconomic factors exert the greatest impact and discuss the applications of our approach to sustainable consumption policy.

In the next section, we describe the underlying input–output model and data, further explain the nature of the geodemographic lifestyle data used in this study, and discuss the results on emissions associated with different lifestyles. In the subsequent section, we describe and apply a panel data approach to determine the impact of socioeconomic factors on emissions. Conclusions are provided in a final section.

Carbon Emissions of Lifestyle Types in the United Kingdom

Input–Output Model

The total CO_2 emissions, $\boldsymbol{p}^{hh,tot}$, from household consumption of s different lifestyle groups can be expressed most generally as the sum of their direct ($\boldsymbol{p}^{hh,dir}$) and indirect emissions ($\boldsymbol{p}^{hh,ind}$),

$$\boldsymbol{p}^{hh,tot} = \boldsymbol{p}^{hh,dir} + \boldsymbol{p}^{hh,ind} \qquad (1)$$

The direct CO_2 emissions, $\boldsymbol{p}^{hh,dir}$, are associated with domestic energy consumption and private transport. We obtain lifestyle-group-specific estimates by assigning direct emissions of all households across each of the s lifestyle groups proportionally to their energy and transport expenditures.

We can calculate the indirect emissions by multiplying a vector of total CO_2 intensities, $\boldsymbol{\epsilon}^{ind}$, of n different production sectors with $\mathbf{Y}^{hh} = [y^{kl}]$, a matrix of detailed household consumption expenditures of the s different lifestyle groups in m functional spending categories—that is,

$$\boldsymbol{p}^{hh,ind} = (\boldsymbol{\epsilon}^{ind})'\mathbf{Y}^{hh} = (\boldsymbol{\epsilon}^{ind})'\mathbf{A}^{hh}\mathbf{Y}^{hh,soc} \qquad (2)$$

$\mathbf{A}^{hh} = [a_{ik}] = \frac{y_{ik}}{\sum_{j=1}^{n} y_{jk}}$ is an $n \times m$ matrix of direct coefficients indicating the proportion of final household demand for products provided by the n different sectors across the m different functional spending categories. $\mathbf{Y}^{hh,soc}$ is a matrix of household consumption expenditures of the s different socioeconomic groups in the m spending categories.

The vector of indirect CO_2 intensities, $\boldsymbol{\epsilon}^{ind}$, from the n different sectors is derived from a supply and use model (Miller and Blair 2009).[1] This vector can be estimated as follows:

$$\boldsymbol{\epsilon}^{ind} = \boldsymbol{r}'(\boldsymbol{I} - \boldsymbol{DB})^{-1}\boldsymbol{D} \qquad (3)$$

where $\boldsymbol{r}$ is a vector of sectoral direct CO_2 intensities indicating the amount of CO_2 emitted per unit of final output of the n different sectors, I_n is an identity matrix of order n, $\boldsymbol{D} = [d_{ji}] = \frac{v_{ji}}{q_i}$ is a coefficient matrix of size $n \times n$ based on an industry technology assumption indicating the supply v_{ji} of commodity i to industry j per unit of total supply q_i of commodity i, and $\boldsymbol{B} = [b_{ij}] = \frac{u_{ij}}{x_j}$ is a technical coefficient matrix of size $n \times n$ providing information about the use u_{ij} of commodity i by industry j per unit of output x_j of industry j. We used this method to estimate the direct and indirect CO_2 emissions from the different lifestyle groups as presented in the ACORN consumer segmentation database. The approach is described in detail by Wiedmann and colleagues (2006).

Input–Output and Geodemographic Data

Input–Output Data

For the input–output estimations, we used supply and use tables provided by the Office for National Statistics for 2000 (ONS 2003b), in combination with sectoral CO_2 data from the UK Environmental Accounts for 2000 (ONS 2005a). All calculations were carried out at the 76-sector aggregation level.

To use the published supply and use tables for a modeling application, we had to undertake a variety of steps, including price conversions, updating, and rebalancing procedures. The steps are described in detail by Wiedmann and colleagues (2006).[2] Furthermore, we used officially published statistics to break down the household consumption expenditure vector into 39 functional spending categories, following the Classification of Individual Consumption by Purpose (COICOP; ONS 2003b).

Geodemographic Data

Lifestyles are distinguished according to CACI's ACORN classification.[3] *ACORN* stands for "a classification of residential neighborhoods." The classification includes every street in the country and groups spatial areas according to socioeconomic profiles of the residents. The most recent ACORN classification distinguishes 17 household groups and 56 household types (see table 1).[4]

ACORN data are designed for companies to understand consumers and their wants. More than 400 variables were used to build ACORN in a cluster analysis procedure and help to describe the different ACORN types. More than 30% of the data used for this purpose were sourced from the 2001 census. These data are geographically coded down to the postal code level. The remainder were derived from CACI's consumer lifestyle databases, which cover all of the United Kingdom's 46 million adults in 23 million households and are built from other private and public survey data (CACI 2004; ONS 2005c).

Central to the estimations here is a functional consumer expenditure table, which provides weekly per-household spending estimates across 34 COICOP consumption categories for ACORN categories, groups, and types. This table has been built from the United Kingdom's Family Expenditure Survey for 2004. One can derive total expenditure figures by multiplying this functional spending table by the number of households in each ACORN category, group, and type. This table can then be linked with the input–output data.

To reconcile the ACORN functional spending with the input–output household final demand matrix, we needed to use imputation to fill the data gaps in the CACI data for COICOP categories "purchase of vehicles" (7.2), "accommodation services" (11.2), "social protection" (12.4), and "insurance" (12.5). In the absence of better information, we roughly grouped the 56 ACORN types into income deciles and used respective estimates from the United Kingdom's Family Expenditure Survey for gap-filling (ONS 2005b). This is likely to lead to some error, as the ACORN types are less homogenous in their income profile. All spending estimates were calibrated to the spending levels of 2000 in each COICOP category. Hence, the estimates reflect the spending levels of 2000 and the composition of consumption baskets of 2004. Finally, to derive a spatial picture of CO_2 emissions associated with lifestyles in different areas of the United Kingdom, we used the small-area household and population estimates from CACI's ACORN data set.[5]

Data Limitations

The major sources of uncertainty in the input–output data are associated with the required price conversions and updating procedures. A recent Monte Carlo experiment by Wiedmann and colleagues (2008) has shown that this is unlikely to heavily affect estimates at high aggregation levels, as errors tend to cancel out, even though estimates at the detailed sectoral level can show considerable uncertainties under certain circumstances.[6] Therefore, we do not perceive these sources of uncertainty to be a major obstacle for the current analysis, as all the input–output results reported in this study are highly aggregated.

Further uncertainties are introduced by the single-region technology assumption applied in the estimation of the CO_2 emissions embodied in imported goods and services. We adjusted

Table 1 ACORN consumer classification

ACORN group	*ACORN type*	*ACORN group*	*ACORN type*
1 – Wealthy executives	1 – Wealthy mature professionals, large houses 2 – Wealthy working families with mortgages 3 – Villages with wealthy commuters 4 – Well-off managers, large houses	9 – Settled suburbia	32 – Retired homeowners 33 – Middle income, older couples 34 – Lower income, older couples, semis
2 – Affluent grays	5 – Older affluent professionals 6 – Farming communities 7 – Old people, detached houses 8 – Mature couples, smaller detached homes	10 – Prudent pensioners	35 – Elderly singles, purpose-built flats 36 – Older people, flats
3 – Flourishing families	9 – Older families, prosperous suburbs 10 – Well-off working families with mortgages 11 – Well-off mangers, detached houses 12 – Large families and houses in rural areas	11 – Asian communities[a]	37 – Crowded Asian terraces 38 – Low-income Asian families
4 – Prosperous professionals	13 – Well-off professionals, larger houses 14 – Older professionals in suburban houses	12 – Postindustrial families	39 – Skilled older families, terraces 40 – Young working families
5 – Educated urbanites	15 – Affluent urban professionals, flats 16 – Prosperous young professionals, flats 17 – Young educated workers, flats 18 – Multiethnic young, converted flats 19 – Suburban privately renting professionals	13 – Blue-collar roots	41 – Skilled workers, semis and terraces 42 – Home-owning families, terraces 43 – Older people, rented terraces
6 – Aspiring singles	20 – Student flats and cosmopolitan sharers 21 – Singles and sharers, multiethnic areas 22 – Low-income singles, small rented flats 23 – Student terraces	14 – Struggling families	44 – Low income larger families, semis 45 – Low income older people, smaller semis 46 – Low income, routine jobs, terraces and flats 47 – Low income families, terraced estates 48 – Families and single parents, semis and terraces 49 – Large families and single parents, many children
7 – Starting out	24 – Young couples, flats and terraces 25 – White-collar singles and sharers, terraces	15 – Burdened singles	50 – Single elderly people, council flats 51 – Single parents and pensioners, council terraces 52 – Families and single parents, council flats

Continued.

Table 1 Continued

ACORN *group*	ACORN *type*	ACORN *group*	ACORN *type*
8 – Secure families	26 – Younger white-collar couples with mortgage 27 – Middle-income, home-owning areas 28 – Working families with mortgages 29 – Mature families in suburban semis 30 – Established home-owning workers 31 – Home-owning Asian families[a]	16 – High-rise hardship	53 – Old people, many high-rise flats 54 – Singles and single parents, high-rise estates
		17 – Inner city adversity	55 – Multiethnic purpose-built estates 56 – Multiethnic, crowded flats

Note: Flats are apartments, *semis* are semidetatched houses, and *terraces* are row housing.
[a]Although ACORN classification uses the ethnic label *Asian* to help describe Group 11 and a portion of Group 8, we want to note that the term is very broad and does not define a person's lifestyle, nor does it predict one's lifestyle-related CO_2 emissions. Although the ACORN classification indicates that individuals who fall into the noted groupings tend to be Asian, one's being Asian does not necessarily mean inclusion in these particular named ACORN groupings.

sectoral direct CO_2 intensities to reflect global averages for imported goods and services, however, as explained by Wiedmann and colleagues (2006). The resulting estimates are very close to the ones derived in a recent UK analysis that used a multiregional input—output model (see Wiedmann et al. 2010). Other sources of uncertainties that are typical for this kind of input—output estimation are discussed in work by Suh and colleagues (2004).

Uncertainties in the ACORN data are associated with the imputation of missing information. However, imputation was only necessary in 4 of the 39 functional spending categories (mainly services and transport equipment), and is not expected to affect the results in a way that would alter the main conclusions of the article. Other sources of uncertainties are difficult to quantify, as this type of commercial information is not as well documented as official government statistics. This is certainly an important limitation of commercial geodemographic data (Harris et al. 2005). Still, expenditure estimates should be of reasonable quality, as the Office for National Statistics appended ACORN codes to each individual observation of the UK Family Expenditure Survey, making use of the best available information.[7]

For spatial emission estimates, we need to assume that there is no regional or local variation in the expenditure profiles. Households belonging to the same type are presumed to have the same spending patterns no matter where they are located in the territory. This is bound to be a crude but, we hope, useful approximation of reality. Minx and colleagues (2009) explain how this assumption can be overcome through the inclusion of regional and local data.

Results

Table 2 shows that in 2000, all final demand activities in the United Kingdom were responsible for 681 million tonnes of CO_2 emissions globally.[8] This is very close to the 682 million tonnes reported by Wiedmann and colleagues (2010) and is approximately 11% higher than territorial emissions in the United Kingdom, as reported in the Environmental Accounts (ONS 2005a). Seventy-five percent, or 505 of the 681 million tonnes of CO_2 emissions from UK consumption, is directly or indirectly related to private households. This explains much of the attention this issue has received in the literature. Of this amount, 70%, or 358 million tonnes, occurs in the global supply chains of products consumed in the United Kingdom, whereas the remaining 30%, or 147 million tonnes, is directly emitted by households: 86 million tonnes of CO_2 through domestic energy use, and 61 million tonnes for fueling private vehicles.

In table 3, we provide a more detailed overview of how carbon emissions from household consumption of 17 ACORN groups break down into basic emission components. We distinguish direct, indirect, and total CO_2 emissions and express these emission figures in absolute, per household, and per capita terms. The sociodemographic characteristics are taken from the ACORN user guide (CACI 2004). Each characteristic is expressed as an index, where 100 represents the UK average.[9] As one moves from the left to the right in table 3, ACORN groups tend to become less wealthy and live in more urban areas.

In absolute terms, the most CO_2 is produced by Group 8, "secure families." This is also the largest ACORN group, however; it comprises 3.64 million households. When we express results from the input—output model in per household terms, Group 11, "Asian communities," is identified as living the most CO_2-intensive lifestyle. This is somewhat surprising, as this ACORN group comprises households with comparatively moderate means (see the income index in table 3), but the finding is explained by the group's higher transport emission component, which stems from a high demand for transport.[10] Other high-impact households tend to come from wealthier backgrounds and live in bigger houses in rural areas, such as ACORN Group 1, "wealthy executives," which is also the richest group in the sample, or ACORN Group 3, "flourishing families."

Table 2 Total consumer emissions in million tonnes (megatons, or Mt) of carbon dioxide (CO_2) by final demand (FD)

FD category	*Emissions (in Mt)*
Domestic energy consumption (household direct)	86.2
Private transport (household direct)	61.3
Household consumption (household indirect)	357.9
Government	61.9
Capital investment	109.2
Other final demand	4.7
Total	**681.3**

Once we express the total CO_2 emissions of each lifestyle group in per capita terms, the picture changes again, as the number of household members tends to be higher in rural areas than in urban areas. The large household size also partially explains the high per household emissions of Asian communities, which have the largest households in the sample, with 3.27 members on average. Even though their per capita CO_2 impact still remains high, some wealthier groups have higher impacts, such as Group 4, "prosperous professionals," or Group 5, "educated urbanites."

The variation in CO_2 emissions from consumption across ACORN groups is substantial. In per capita terms, the difference between the highest (Group 5, "educated urbanites") and lowest (Group 14, "struggling families") emitting group is almost a factor of 2, and on a per household basis it is even a factor of 3 (Group 11, Asian communities, and Group 16, "high-rise hardship").[11] Among the 12 functional spending categories, we find that transportation and housing have the largest impacts. This is in agreement with evidence from other input—output studies (e.g., Tukker et al. 2005; Tukker and Jansen 2006).

Across lifestyle groups, the share of transport-related emissions seems to decrease when one moves from the wealthier, rural lifestyles on the left to the poorer, urban lifestyles on the right in table 3, with the exception of Group 11, "Asian communities." On the one hand, people in urban environments have less need for long-distance travel.[12] On the other hand, poorer lifestyle groups simply might not be able to afford a car or long recreational trips by plane. The opposite trend is found for housing-related emissions: Housing-related CO_2 emissions are

Table 3 Summary statistics for ACORN groups

		ACORN group																
		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*
Emission component	Indirect[a]	36.5	28.0	31.9	9.9	22.8	14.5	9.2	51.8	19	9.6	6.9	14.5	23.7	37.3	12.6	4.9	7.5
	Domestic energy[a]	8.2	7.6	7.7	2.2	5.1	4.1	2.3	12.4	5.1	2.6	2.2	3.7	6.7	9.5	3.2	1.2	2.3
	Private transport	6.9[a]	5.9	6.2	1.7	3.2	2.2	1.7	10.0	3.9	1.8	0.7	2.7	4.4	6.5	2.0	0.7	0.8
	Total CO_2[a]	51.6	41.4	45.9	13.7	31.1	20.8	13.2	74.2	28.0	14.0	9.9	20.9	34.9	53.4	17.8	6.8	10.6
COICOP group (% of total)	1 – Food and non-alcoholic drinks	4.2	4.4	4.5	4.0	3.5	4.1	4.3	4.7	4.9	4.4	3.2	4.9	4.9	5.4	5.3	5.0	4.3
	2 – Alcoholic drinks, tobacco and narcotics	0.8	0.8	0.9	0.8	0.8	0.9	0.9	0.9	0.9	0.9	0.4	0.9	0.9	1.0	1.1	1.1	0.7
	3 – Clothing and footwear	1.4	1.4	1.5	1.4	1.4	1.4	1.5	1.6	1.5	1.4	1.3	1.6	1.6	1.7	1.6	1.6	1.6
	4 – Housing (net), fuel and power	32.1	36.6	34.1	33.3	34.4	40.7	35.8	34.3	37.1	37.6	44.2	36.4	39.8	39.3	40.4	40.6	46.9
	5 – Household goods and services	5.4	5.7	5.7	5.1	5.1	5.3	5.8	6.0	6.3	5.8	3.6	6.4	6.5	7.1	7.3	7.3	5.0
	6 – Health	0.7	0.8	0.7	0.8	0.6	0.7	0.7	0.7	0.7	0.7	0.4	0.7	0.6	0.6	0.6	0.5	0.5
	7 – Transport	32	30.2	30.7	31.8	30.7	27.2	30.1	30.2	28.3	29.1	34.9	28.3	26.1	25.4	25	25.6	22.8
	8 – Communication	0.7	0.8	0.8	0.8	0.8	0.9	0.9	0.9	0.9	0.9	0.7	0.9	0.9	1.0	1.0	1.0	1.0
	9 – Recreation and culture	6.6	6.6	6.8	5.9	5.1	5.9	6.4	7.1	7.1	6.2	3.9	7.1	6.8	7.3	7.1	6.6	5.1
	10 – Education	1.0	0.6	0.7	0.9	1.0	0.9	0.6	0.7	0.5	0.6	0.4	0.6	0.5	0.4	0.4	0.4	0.7
	11 – Restaurants & hotels	5.6	4.7	5.4	5.8	6.1	4.9	5.2	5.3	5.1	5.0	3.2	5.3	5.1	5.1	5.0	4.9	4.8
	12 – Miscellaneous	9.5	7.3	8.2	9.4	10.4	7.1	7.8	7.7	6.8	7.6	3.8	6.9	6.4	5.7	5.2	5.4	6.7
Households[b]		1,945	1,978	1,986	566	1,471	1,033	726	3,644	1,637	800	294	1,086	2,129	3,383	1,358	615	566
t of CO_2 per household		26.5	21.0	23.1	24.3	21.2	20.2	18.2	20.4	17.1	17.5	33.5	19.3	16.4	15.8	13.1	11.1	18.7
Population[b]		5,170	4,574	5,271	1,339	2,802	2,363	1,480	9,219	3,569	1,553	963	2,846	4,713	8,322	2,691	949	1,291
CO_2 per capita[c]		10.0	9.1	8.7	10.3	11.1	8.8	8.9	8.0	7.9	9.0	10.2	7.4	7.4	6.4	6.6	7.2	8.2
Income[d]		165	112	133	155	144	97	107	108	85	98	73	92	74	61	53	49	82
Education[d]		166	116	116	225	241	116	138	89	69	119	71	65	58	36	38	48	114
Unemployment[d]		47	57	57	64	117	140	79	70	65	82	192	95	116	158	181	236	226

Continued.

Table 3 Continued

	ACORN group																
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*
Large dwelling[d]	304	178	192	183	53	61	53	96	75	82	77	66	50	37	22	12	19
Small dwelling[d]	18	28	21	90	394	231	127	33	37	166	131	33	72	63	167	369	403
Social housing[d]	11	21	18	23	83	99	32	33	42	74	104	73	77	239	307	363	341
Sharing[d]	61	62	64	153	297	270	154	75	51	80	200	98	85	73	62	65	192
National Trust[d]	187	184	141	170	90	61	95	106	114	155	30	83	65	49	44	45	38

Note: For ACORN groups, see table 1.
[a] 10^6 tonnes (t) CO_2.
[b] Thousands.
[c] tonnes (t) CO_2/capita.
[d] UK average = 100.

more prominent in the consumption patterns of poorer groups. This is closely related to the issue of *fuel poverty*, which has been high on the political agenda in the United Kingdom (Dresner and Ekins 2005).

The descriptive analysis as presented above has clear limits in revealing the influence of individual factors underlying people's lifestyles unambiguously. In the next section, we therefore further analyze the results of our lifestyle analysis in a regression approach.

Lifestyles and the Impact of Socioeconomic Factors on Emissions

Regression Approach

In this section, we outline the methodology used to estimate the relationship between household CO_2 emissions by ACORN type, obtained in the previous section, and several socioeconomic factors that characterize these households. In the *Income Elasticity and Spatial Data* subsection, we will illustrate how the estimated relationship, jointly with the additional geographical information available about the location of household types, can be used to provide a visually clear representation of where the various socioeconomic factors exert the greatest impact on the map. This analysis hinges on the specific nature of the geodemographic lifestyle data used, which have been designed to enable firms to understand people's preferences and consumption activities in the context of their everyday life.[13] The ACORN data are arranged in a cross-sectional data set in which each household *type* observation belongs to a well-defined *group* (refer back to the *Input–Output and Geodemographic Data* subsection for details). Due to the specific way the data are constructed, we can interpret the different ACORN groups, such as wealthy executives or educated urbanites (see table 1), as *lifestyles*. Although in principle we can analyze these data using ordinary regression, we want to emphasize the data's special features for making use of the additional information content that is specific to the geodemographic lifestyle classification. We can treat the ACORN data, for the purpose of analysis, as a panel or longitudinal data set[14] (for simplicity, referred to as *panel* here), in that lifestyle groups are observed repeatedly. We can exploit the variation of types within lifestyle groups to improve on the standard regression approach. The general form of the panel data model that incorporates heterogeneity among household types is given by

$$\ln E_{it} = \alpha_i + \sum_{j=1}^{p} \beta_j (\ln X_{0_{it}})^j + \sum_{j=1}^{k-p} \beta_{j+p} \ln X_{j_{it}} + \varepsilon_{it} \tag{4}$$

with $i = 1,..., N$ and $t = 1,..., T_i$ representing groups and types, respectively. Here, E_{it} is a measure of household CO_2 emissions, $X_{0_{it}}$ is income, and $X_{j_{it}}$, for $j = 1,..., k-p$, denote the other sociodemographic control variables from the ACORN database that correspond to additional determinants of emissions. p is the order of the polynomial in the log of income, k is the total number of regressors, and ε_{it} is the classical error term.

From a statistical viewpoint, incorporating heterogeneity can mitigate the problem of *omitted variable bias*, which occurs when relevant regressors are excluded from the model (see, e.g., Verbeek 2008, 358–359). Allowing for group- or lifestyle-specific parameters α_i provides a way to “control” for heterogeneity among households, including economic and social behavioral differences related to lifestyles, such as individual aspirations and people’s attitudes toward the environment. Also, if all other things are equal, panel data methods yield more efficient estimators (see, e.g., Diggle et al. 2002, 24–26). In particular, the higher the positive correlation between observations is, the more efficient the estimator is. Because geodemographic classification is based on the principle of (positive) spatial autocorrelation (i.e., residents of the same neighborhood are taken to share several common socioeconomic and behavioral characteristics), the gains in efficiency from the use of a panel method can be substantial.

The functional specification is inspired by the literature on the environmental Kuznets curve (EKC; Grossman and Krueger 1993). The EKC hypothesis envisages an inverted-U-shaped relationship between income and environmental degradation. EKC models have been estimated in either logarithmic, quadratic, or cubic polynomial functional form specifications between pollutant concentration and per capita income (for a survey, see, e.g., Panayotou 2000; Stern 2004). Although the method is usually applied in cross-country studies, it is used here for the provision of an intrasocietal perspective on the relationship between CO_2 emissions and income. By using this approach, we acknowledge the particular importance of income in the determination of CO_2 from households (e.g., Ferrer-i Carbonell and van den Bergh 2004; Lenzen et al. 2006) in the model specification while also controlling for a wide range of other sociodemographic determinants.

Regressions that incorporate heterogeneity are typically estimated with *fixed-effects* (FE) and *random-effects* (RE) models. The FE model treats the α_i as regression parameters, whereas the RE model considers them components of random error. To decide between fixed and random approaches, one can use the Hausman statistic, which tests the hypothesis that the regressors are correlated with the individual effect. If the individual effects, α_i, are correlated with the regressors, the RE estimator is inconsistent (for further details on panel methods, see, e.g., Verbeek 2008).

Emission Determinants

Socioeconomic variables that can affect CO_2 emissions in the United Kingdom were obtained from the ACORN data set. The variables included in the final regression were selected from a larger set of possible determinants belonging to the wider categories of *housing* (one to two rooms, seven or more rooms, etc.), *families* (couple with children, single parent, etc.), *education* (degree or equivalent, no qualifications, etc.), *work* (self-employed, looking for work, etc.), *finance* (average family income, have mortgage, etc.), and so on,[15] through the widely used backward elimination statistical procedure, as described in standard applied regression references, such as the work of Draper and Smith (1998, 339–340) or Weisberg (2005, 222), and theoretical considerations.[16]

Table 4 Description and summary statistics of regression variables

Variable name	Label	Unit	Mean	Standard Deviation	Minimum	Maximum	UK average
Total CO_2 per household	CO	t/hh	20.30	5.81	10.58	44.58	19.36 t/hh[a]
No. individuals	HHSIZE	Count	2.37	0.46	1.40	3.93	2.36
Average family income	INC	Index[b]	102.11	37.9	47	188	£447[c]
Degree or equivalent	EDU	Index[b]	108.50	66.4	27	302	20%[f]
Large houses (7+ rooms)	BHO	Index[b]	138.20	111.9	16	451	20%[f]
Families with children	FWC	Index[b]	98.12	44.46	13	225	21%[f]
Pensioners	PENS	Index[b]	94.59	45.20	28	225	23%[f]
Single nonpensioner	SING	Index[b]	109.66	62.6	37	320	16%[f]
Use Internet for e-mail	INTER	Index[b]	106.16	39.53	32	199	55%[df]
Social housing	SOCH	Index[b]	106.86	114.55	5	370	20%[f]
National Trust member	NTRUST	Index[b]	97.70	55.20	21	240	0.013%[ef]

[a]From table 3.
[b]UK average = 100.
[c]Average weekly disposable income from UK Expenditure and Food Survey (ONS 2005b).
[d]From UK households with access to the Internet (ONS 2008).
[e]Derived from membership of selected environmental organizations (ONS 2003a).
[f]Percentage of UK households represented by each category.

The most important criticism of any selection strategy of this kind, which one should keep in mind when interpreting the regression findings, is that it can overstate the significance of the results, as multiple testing is performed with the same body of data. This problem is mostly referred to as "data mining" in statistical literature (see, e.g., Lovell 1983). Wilkinson and Dallal (1981) showed with Monte Carlo that final regressions obtained by stepwise selection, said to be significant at the 0.1% level, were in fact only significant at the 5% level.

There is no generally accepted simple solution to this problem. The recommended approach of splitting the available data into a subset for exploratory analysis and another for testing may only increase the chance of selecting a wrong model if too few observations are available (Lovell 1983). We address this concern by testing the resulting model for several specification problems. The importance of specification testing to recover the correct model has been highlighted in a Monte Carlo study by Hoover and Perez (1999). Also, our final model includes variables that are significant at the 0.1% level.

The variables used in this study, together with descriptive statistics for the sample, are reported in table 4. The final sample consists of 56 observations, determined by the maximum number of household types distinguished in the data set; the observations fall (unevenly) into the 17 household groups (see table 1) and are restricted to the year 2000.[17]

A correlation matrix between determinants of emissions is presented as a scatterplot matrix in figure 1. The figure clearly illustrates the importance of using a regression approach. We find that emissions are positively correlated with household size, having children, Internet use, income, and education and negatively correlated with being a pensioner and being single. It is important to stress, however, that these are only *marginal relationships*—that is, they do not take into account the influence of other variables. For instance, education and the use of the Internet are highly correlated with each other and with income; therefore, we need to "control" for income to determine the variables' direct impact on emissions to avoid biased estimates.

Regression Estimation Results

Table 5 presents the results of our estimation of equation (4) with "pooled" ordinary least

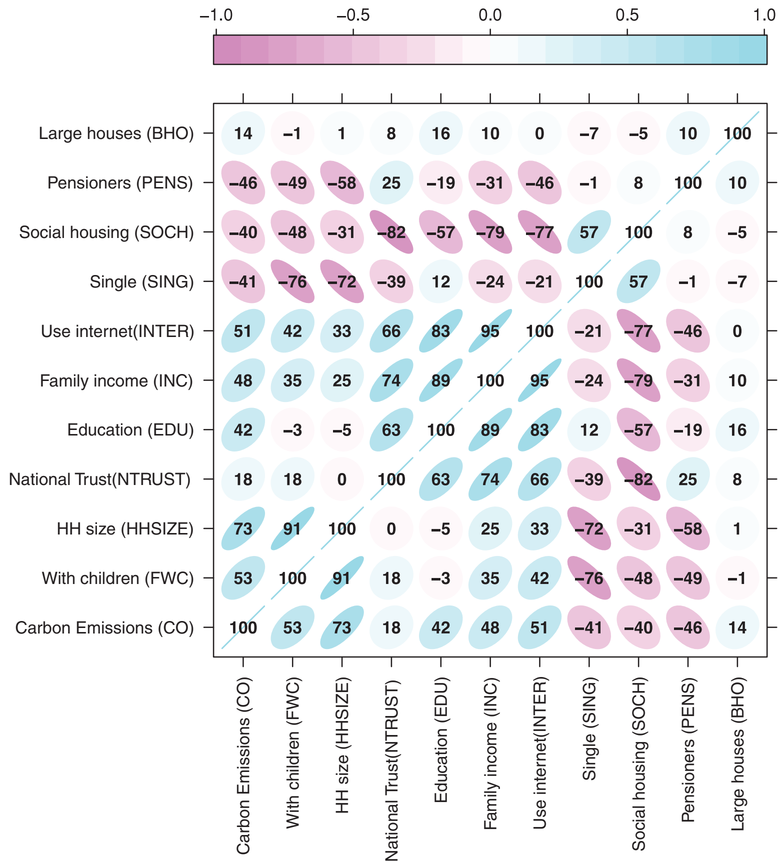

Figure 1 Pairwise correlation between regression variables (correlation times 100). Variables are transformed in natural logs. Ellipses are added to the scatterplot matrix to visually display both the sign and the magnitude of the correlation. The online version of this article uses blue for positive values and pink for negative values; either way, intensity increases uniformly as the correlation value moves away from 0.

squares (OLS) and two-panel estimation methods. Figures in parentheses below coefficients are *t* statistics.[18]

The observed *F* statistic for the joint significance of the 17 household group effects is significant at any conventional level. We can conclude that lifestyles are considerably important and that panel methods are necessary to determine the impact of socioeconomic factors on the emissions. The statistically significant Hausman statistic implies that only the FE model can be usefully interpreted.

Interpreting individual coefficients reveals interesting insights into the links between socioeconomic factors and CO_2 emissions in the UK economy and might provide important insights for the formation of demand-side policies for facing the climate change challenge. Due to the reasons outlined above, we limit the discussion to the results of the FE model. To conserve space, we limit the more detailed analysis to a few findings.[19]

Results for Income

The results show that the income variables (LINC, $LINC^2$, and $LINC^3$) are all highly significant. We are unable to find an environmental Kuznets curve, as emissions monotonically increase, with decreasing rates up to the sample mean income and increasing rates afterward. Our findings seem to agree with a growing body of theoretical and empirical evidence that has cast doubt on the previous conjecture that the demand for environmental quality

Table 5 Results from panel regressions

Model	*OLS*	*FE*	*RE*
Constant	−50.28**** (−3.66)		−60.17**** (−7.22)
LINC	33.45**** (3.68)	37.00**** (6.35)	39.54**** (7.22)
$LINC^2$	−7.23**** (−3.62)	−7.86**** (−6.13)	−8.45**** (−6.28)
$LINC^3$	0·53**** (3.60)	0.56**** (6.05)	0.61**** (6.20)
LEDU	−0.05 (−0.64)	−0.16*** (−3.47)	−0.12** (−2.52)
LFWC	−0.38**** (−6.41)	−0.31**** (−8·47)	−0.31**** (−8.14)
LHHSIZE	2.45*** (11.86)	1.96**** (16·62)	2.06**** (16.40)
LSING	0.30*** (4.90)	0.20**** (6·15)	0.23**** (6.39)
LPENS	0.08* (1.85)	0.06** (2.62)	0.06** (2.56)
LBHO	0.02* (1.98)	0.04**** (4.64)	0.03**** (4.65)
LSOCH	−0.07**** (−4.46)	−0.03*** (−3.17)	−0.04*** (−3.63)
LINTER	−0.18** (−2.13)	−0.17*** (−3·60)	−0.16*** (−3.31)
LNTRUST	0.08** (2.12)	0.10**** (5.81)	0.09**** (5.05)

Note: Robust t statistics are reported in parentheses. The symbols *, **, ***, and ****, denote significance levels, α, of 10%, 5%, 1%, and 0.1% respectively. Figures in parentheses beside coefficients are t statistics. The F statistic for the joint significance of the 17 household group effects is 14.3****. The Hausman statistic is 21.7**. OLS = ordinary least squares; FE = panel fixed effect estimator; RE = panel random effects estimator; LINC = natural-log-transformed average family income; LEDU = natural-log-transformed education; LFWC = natural-log-transformed families with children; LHHSIZE = natural-log-transformed household size; LSING = natural-log-transformed single nonpensioners; LPENS = natural-log-transformed pensioners; LBHO = natural-log-transformed large houses; LSOCH = natural-log-transformed social housing; LINTER = natural-log-transformed use of Internet for e-mail; LNTRUST = natural-log-transformed National Trust member.

increases more than proportionally with income, so that emissions may rise at first with economic growth but eventually fall as income continues to rise (see, e.g., Flores and Carson 1997; McConnell 1997; Hökby and Söderqvist 2003). A look at the description of ACORN's wealthiest households, such as wealthy executives, suggests that perhaps their demand for improved environmental quality is expressed through demand for luxury homes in high-status suburban or rural neighborhoods, regular holidays in relatively pollution-free locations, and engagement in golf and gardening—that is, these households adopt a carbon-intensive lifestyle. Further analysis is required to verify this hypothesis, however.

Coefficients from a regression model in which the dependent and independent variable of interest are in *natural log* form and linearly related to each other can be conveniently interpreted as the average percentage change in the dependent variable, corresponding to a percentage change in the independent variable (see, e.g., Verbeek 2008, 55). In economics, such coefficients are known as *elasticities*. In general, for nonlinearly related log-transformed variables, one can obtain the "impact" in terms of elasticity of a variable of interest on the dependent variable by taking the differential of the regression equation, holding all independent variables constant except the relevant regressor. It can be shown that the emission elasticity of income, the average percentage change in emissions resulting from a percentage change in income, ceteris paribus, is a U-shaped function of income.[20] At the national average income level of GBP £447 per week, a 10% increase in income determines a rise of about 6% in CO_2 emissions. For the same 10% increase in income, at the highest household-type income level (about twice the national average, for the type "wealthy executives"), the increase in CO_2 emissions is about 12%; at the lowest household-type income, (about half the national average, for the "old people, many high-rise flats" type), it is about 16%.

Results for Other Determinants

Keeping in mind that a regression approach on its own is not sufficient to establish a causal relationship among variables, we find that household types with large homes (LBHO) or large family sizes (LHHSIZE) and those that consist of single nonpensioners (LSING), of pensioners (LPENS), or of members of the National Trust (LNTRUST) are associated with higher emissions. The factors of education (LEDU), social housing (LSOCH), Internet usage (LINTER), and families with children (LFWC) seem to reduce emissions.

Some of the variables can be interpreted in light of general sociodemographic trends in the United Kingdom. For instance, households composed of pensioners tend to increase emissions due to older adults' greater requirements for warmth and the fact that they tend to spend a much larger portion of the day at home. As the UK population ages, this could become an issue of concern. Haq and colleagues (2007) provided a detailed analysis of what determines the carbon emissions of older people's lifestyles, how this relates to the United Kingdom's demographic patterns, and what the implications for environmental policies might be.

The result for education could be seen to support the green consumerism argument (e.g., Pettit and Sheppard 1992) and could be used in justification of information campaigns and environmental education of the general public, as, for example, undertaken in the UK Climate Change Communication Programme (DEFRA 2007). Our findings are also consistent with the idea that Internet use substitutes other, more CO_2-intensive activities, as suggested, for example, by Wilsdon (2002). Further research is needed to verify these interpretations, however.

Other variables are more difficult to explain. For instance, household types with National Trust memberships tend to have higher CO_2 emissions. This might be counterintuitive at first, as we interpret membership in this environmental organization as an indicator of a positive attitude toward the environment. National Trust membership is culturally very segregated, however, in that predominantly middle-income and high-income households are enrolled, so the variable seems to act as a proxy for wealth, another important determinant of consumption. This is also shown by the high correlation with income in figure 1.[21] The same argument can be used to explain the negative correlation for social housing. Social housing has, in fact, the highest negative correlation with income.

Income Elasticity and Spatial Data

Using the panel-fixed-effect estimation results, we can illustrate how the spatial information content of our geodemographic data set can be used to link lifestyle-related CO_2 emissions to specific locations within the United Kingdom.

For simplicity of notation, we assume that all variables are in logs and that $T_i = T$, with $i = 1, \ldots, N$. We can obtain predicted emissions for household types by computing

$$\hat{\boldsymbol{E}} = [\boldsymbol{Z}_\alpha, \boldsymbol{X}]\,(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}})', \tag{5}$$

where $\boldsymbol{E}$ is the $NT \times 1$ vector of emissions, $\boldsymbol{X}$ is the $NT \times k$ matrix of data, that is, $\boldsymbol{X} = [\boldsymbol{X}_0, \boldsymbol{X}_0^2, \boldsymbol{X}_0^3, \boldsymbol{X}_1, \ldots, \boldsymbol{X}_{p-k}]$, $\alpha' = (\alpha_1, \ldots, \alpha_N)$, and $\boldsymbol{\beta}' = (\beta_1, \ldots, \beta_k)$. $\boldsymbol{Z}_\alpha = \boldsymbol{I}_N \otimes \boldsymbol{\iota}_T$, where $\boldsymbol{I}_N$ is an identity matrix of order N, $\boldsymbol{\iota}_T$ is a vector of 1s of dimension T, and $\otimes$ denotes the Kronecker matrix product. Note that $\boldsymbol{Z}_\alpha$ is the matrix of group dummies included in the regression to estimate the α_i when they are assumed to be fixed.

ACORN data provide detailed spatial information on households classified by lifestyle groups. In particular, the data provide the number of households of each ACORN lifestyle type living in every local authority area in England and Wales.[22] For details on the methods involved in producing this kind of data, see the work of Webber (1998, 2007) and Harris and colleagues (2005). We arrange the data on the number of 56 different ACORN household types living in each of the 410 local authority areas in England and Wales in a matrix $\boldsymbol{T}$ of size 410×56. Hence, each of the 410 rows of $\boldsymbol{T}$ contains the number of households belonging to each one of the 56 household types for one specific local authority area. $\boldsymbol{T}$ can be used to map CO_2 emissions by household types, $\hat{\boldsymbol{E}}$, to map emissions by UK local authority areas, $\hat{\boldsymbol{E}}_{LA}$.

The emissions for 410 local authority areas in England and Wales can be computed as

$$\hat{\boldsymbol{E}}_{LA} = \boldsymbol{T}\ \exp(\hat{\boldsymbol{E}}) \tag{6}$$

where *exp* denotes the vector-valued exponential function.

Equations (5) and (6), estimated for the available sample, can serve as a benchmark against which to measure the effect of counterfactual scenarios. Using these equations, we can evaluate

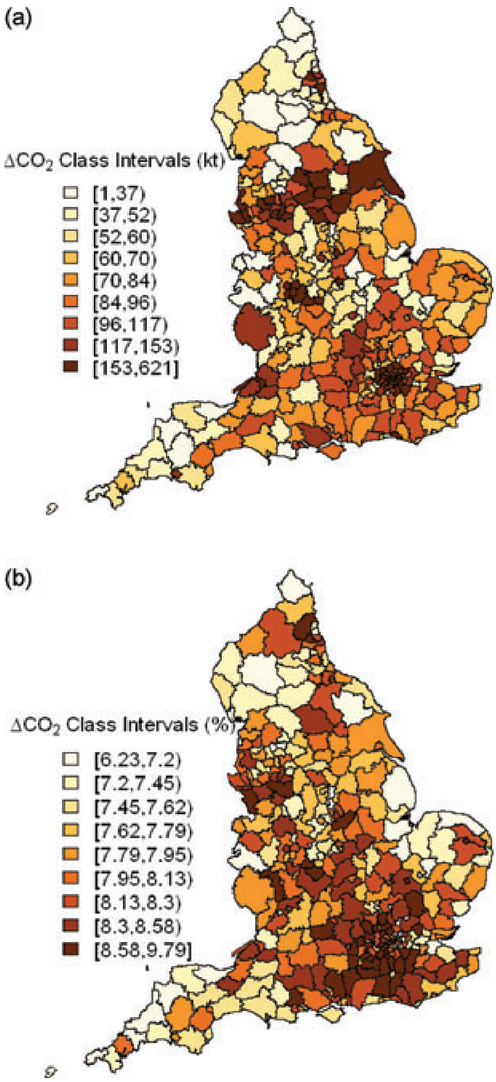

Figure 2 Maps showing the impact of income increases on direct and indirect carbon dioxide (CO_2) emissions attributable to consumers' lifestyle types, by local authority area in England. Class intervals are based on sample quantile breaks. Note that "(a,b)" denotes the set of values x, such as $a \leq x < b$. (**a**) Map of absolute changes from a 10% increase in household income, with all other variables fixed at their sample values, in direct and indirect CO_2 emissions from the 56 lifestyle types of consumers living in 390 unitary authority and local authority areas in England, $\hat{\boldsymbol{E}}_{LA}$. One kiloton (kt) = 10^3 tonnes (t) $\approx 1.102 \times 10^3$ short tons. (**b**) Map of relative changes from a 10% increase in household income, with all other variables fixed at their sample values, in direct and indirect CO_2 emissions from the 56 lifestyle types of consumers living in 390 unitary and local authority areas in England, $\frac{\Delta \hat{E}_{LA}}{\hat{E}_{LA}}$.

the impact of a suitable change ΔX_j on emissions, $\Delta\hat{\boldsymbol{E}}_{LA}$.

Using equation (6), we can map changes in emissions for household types into changes for local authority areas. We find that a 10% increase in income determines a rise of 7% in total CO_2 emissions, if we keep all other variables constant at their sample values. The impact for specific local authority areas depends on the lifestyle mix of households living in those areas. Figure 2 presents the distribution of CO_2 emission changes over 390 local authority areas for England.[23]

It is not surprising that if more households of any lifestyle inhabit a particular area, the environmental consequences are greater. The map in figure 2(a) shows that the local areas with larger absolute impact of income on CO_2 emissions correspond closely to densely populated areas in England, including the urban West Midlands, northern cities, and Greater London.

Figure 2(b) presents a map of the relative changes in CO_2 emissions for England determined by income increases, ceteris paribus. Large visual impacts of relative changes reflect the importance of households' lifestyle for the environment. The highest percentage changes occur in local areas that have the highest concentration of households with highly polluting lifestyles, such as those from the wealthiest types (ACORN Group 1) and from the poorest types (ACORN Types 51 through 54). Figure 3 shows maps of the number of the richer and poorer households, with large estimated emission elasticities of income. With the aid of these maps, we can see that in figure 2(b), the large visual impacts for the northern areas are mostly due to the large number of poorer families, such as single parents and pensioners, council flats (ACORN Type 51); old people, many high-rise flats (Type 53);[24] and "singles and single parents, high-rise estates" (Type 54; see figure 3b). Similarly, the large visual impact for the south can be explained by the large concentration of the wealthiest, more polluting lifestyles, including "wealthy mature professionals, large houses" (ACORN Type 1), "wealthy working families with mortgages" (Type 2), "villages with wealthy commuters" (Type 3), and "well-off managers, large houses" (Type 4; see figure 3b).

Conclusion

Climate change is a key issue on the UK policy agenda. It has been acknowledged that changes in both production technology and lifestyle are required to achieve the government's ambitious CO_2 emission reduction targets. In this article, we have explored the potential of geo-demographic marketing data for analyzing CO_2 emissions associated with lifestyles in the United Kingdom.

In a first step, we have applied geodemographic segmentation data in an input–output model to assess the direct and indirect CO_2 emissions associated with the consumption patterns of different lifestyle groups in the United Kingdom. In a second step, we have used a regression approach to estimate the relationship between household CO_2 emissions and several socioeconomic factors characterizing these households. We have also illustrated how the estimated relationship, together with the additional geographical information available about the location of household types, can be used to provide a visual representation of where the various socioeconomic factors cause the greatest emissions on the map.

Our results demonstrate the value of applying rich geodemographic data sets, with

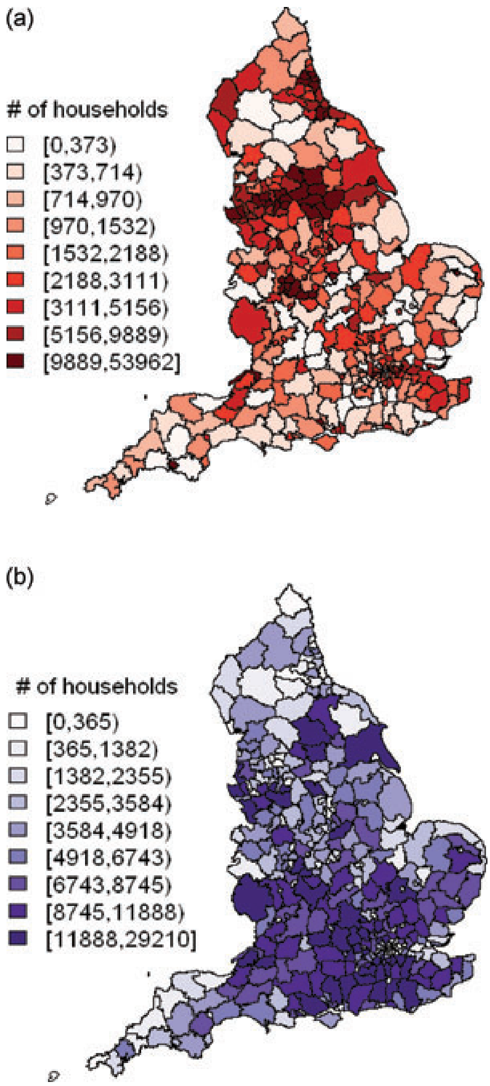

Figure 3 Maps of the number of household types with large emission elasticity of income, by local authority area in England. (**a**) Map of the number of poorest households, belonging to Groups 15 and 16 (see tables 1 and 3 for reference) with large emission elasticity of income, by 390 local authority areas in England. The types include "single parents and pensioners, council terraces" (ACORN Lifestyle Type 51), "old people, many high-rise flats" (Type 53), and "singles and single parents, high-rise estates" (Type 54). In some of the northern cities, such as Manchester, Middlesborough, Newcastle upon Tyne, and Sunderland, more than 20% of households belong to these types. (**b**) Map of the number of richest households, belonging to Group 1 (see tables 1 and 3 for reference), with large emission elasticity of income by 390 local authority areas in England. The types include "wealthy mature professionals, large houses" (ACORN Lifestyle Type 1), "wealthy working families with mortgages" (Type 2), "villages with wealthy commuters" (Type 3), and "well-off managers, large houses" (Type 4). Some of the rural, semirural, and suburban southern areas, including Chiltern, Mole Valley, Rushcliffe, and Waverley, have more than 40% households of these types.

information about people's attitudes, their behaviors, and the neighborhoods they live in, to the analysis of CO_2 emissions associated with different lifestyles. We find that lifestyles are important for determining CO_2 emissions associated with UK consumption. Seventy-five percent of the United Kingdom's consumer CO_2 emissions are associated with people's consumption choices. Differences in consumption choices lead to variations in CO_2 across lifestyle groups by a factor of 2 to 3 (on a per household or per capita basis), with transport- and housing-related expenditures accounting for the largest shares.

Our results provide support for the idea that sociodemographic variables are important in explaining emissions. For instance, emissions are increasing with income, but at increasing rates for richer households. This finding contributes to a growing body of literature that has cast doubts on the previously widely held conjecture that the demand for environmental quality increases with income, so that emissions may rise at first with economic growth but eventually fall as income continues to rise. This view was often used to support the environmental Kuznets curve hypothesis, which posits an inverted-U-shaped relationship between environmental degradation and income. Having found a similar relationship using a completely different data set (see Minx et al. 2009), we are reasonably confident about this general finding.

Apart from the fact that transport emissions are particularly high for wealthier households, however, our analysis does not provide deeper insights into why this might be the case. One possible explanation, suggested by the descriptors of lifestyles, is that the demand for improved environmental quality from the wealthiest households is expressed through a surrogate demand for luxury homes in high-status suburban and rural neighborhoods, regular holidays in relatively pollution-free locations, membership in country clubs, and so on.

As another example, our analysis finds that higher levels of education are associated with reduced emissions. This could be seen as evidence in favor of the "green consumerism" argument. Although further evidence is required to confirm this finding, it could give support to the United Kingdom's government's climate change communication program, which focuses on providing information about potential ways to reduce carbon emissions to particularly ill-informed groups of society (DEFRA 2007).

Finally, we also demonstrate how geodemographic data can help in estimating lifestyle-related emissions at smaller spatial scales and therefore in determining where households with carbon-intensive lifestyles can seem to cluster. Such information has direct application to policy, as government might want to work with high-emission households in a targeted approach to reduce the carbon emissions associated with their lifestyle. Equally, our findings could provide important information in explaining emission patterns attached to a particular lifestyle. The physical infrastructure of a particular neighborhood could be one key determinant of lifestyle-related emission that could also act as a barrier to lifestyle change. Such potential infrastructure bottlenecks to emission reductions are still relatively little understood and are one important avenue of research where geodemographic data could play an important role in the future. Recent activities of the IPCC as well as the fast-growing city-level climate change mitigation research underline the urgency of this issue (VandeWehge and Kennedy 2007; IPCC 2009; Kennedy et al. 2010). We hope that our initial findings will stimulate further much-needed research in geodemographic-based lifestyle analysis, making use of better data and improved methods.

Acknowledgements

We thank the editors and three anonymous referees for helpful comments and suggestions.

Notes

1. Note that energy use at work is part of the indirect emission component. The energy use from work-related activities is embedded in the goods and services households buy and is assigned to them on the basis of the type and quantity of products they choose.
2. The price conversion was undertaken by Cambridge Econometrics.
3. CACI is a commercial marketing data firm headquartered in London (see www.caci.co.uk). CACI and its ACORN data are approved data suppliers

of the Office for National Statistics in the United Kingdom and meet "the agreed standards of data analysis and dissemination" (ONS, 2005c, 1).

4. A complete listing of all household types can be found at www.caci.co.uk/acorn.
5. We are prepared to supply specific data on request, except when the data are only commercially available.
6. In fact, uncertainties are greatest for sectors with very small outputs and sectors that are heavily involved in international trade.
7. The main information deficit concerns the assumption made during the construction of the ACORN classifications.
8. This includes imported goods and services consumed in the United Kingdom and excludes all exports from the United Kingdom. One million tonnes = 1 megaton (Mt) = 10^6 tonnes (t) = one teragram (Tg, SI) ≈ 1.102 × 10^6 short tons.
9. These variables were derived by CACI, mainly from census data (see www.neighbourhood.statistics.gov.uk).
10. The "Asian communities" group seemed to be an outlier. Discussion with the ACORN data provider, CACI, revealed that these higher travel demands are a particular feature of this group.
11. Keep in mind that we are talking about averages of rather large segments of society, and substantial in-group variations still exist (see Weber and Matthews 2008).
12. We have reconfirmed this finding in a detailed spatial analysis elsewhere (SEI 2008).
13. As highlighted previously, this also includes the immediate physical environment in which people live.
14. The term *panel data* is more in use among economists (see, e.g., Wooldridge 2002), whereas other social scientists and statisticians prefer the the expression *longitudinal data* (see, e.g., Diggle et al. 2002).
15. For details, see the ACORN user guide (CACI 2004).
16. This model selection procedure is known as the "general-to-specific approach" in econometrics. The procedure followed in this study starts with a large number of variables and sequentially reduces them by removing the least significant variable, one at the time, if its p value is above a chosen threshold, reestimating the model each time with the remaining variables. The initial selection criterion used was p value greater than .2 to remove. Once the procedure stops, because all variables are significant at the .2 level, the selection criterion is gradually made more stringent until the predetermined final level of significance is obtained for the remaining subset of variables. In this first stage, only linear terms are considered. Nonlinear terms (cross-products and squares) were tried and tested in a second stage.
17. To be precise, we note that the ACORN data are from 2004 and the input—output and environmental account data are from 2000, as outlined in the *Input—Output and Geodemographic Data* subsection of this article. Further note that a suitable time series of data was not available due to a reclassification of the ACORN data between 2003 and 2004 as well as their limited availability for previous years.
18. We calculated the t statistics using a covariance matrix estimator, which is robust to heteroskedasticity and serial correlation of unknown form, which is known to have good properties in "short" panels (see, e.g., Wooldridge 2002). As emissions are a function of consumption, it is important to allow for heteroskedastic and autocorrelated errors for valid statistical inference. In fact, because consumption above subsistence levels is more likely to be discretionary, we would expect a greater variability in consumption and, therefore emissions as income increases.
19. We can provide additional results and data on request.
20. If we take the differential of equation (4) as a function of income, X_0, in its cubic form ($p = 3$), after rearranging we get $\varepsilon_{E,X_0} = \beta_1 + 2\beta_2 \ln(X_0) + 3\beta_3(\ln X_0)^2$, where $\varepsilon_{E,X_0} = \frac{dE}{dX_0}\frac{X_0}{E} \approx \frac{\%\Delta E}{\%\Delta X_0}$ is the elasticity of emissions with respect to income. As $\hat{\beta}_3 > 0$, the elasticity is a U-shaped curve.
21. Economic theory posits ("permanent-income hypothesis" and "life-cycle hypothesis") that consumption decisions are based not only on the level of currently disposable income but also on lifetime income and wealth.
22. For information about local authority areas in the United Kingdom, see the work of the Local Government Association (2005).
23. These maps are based on vector-based spatial data (administrative boundary) provided through EDINA Digimap, an online service to Ordnance Survey digital map data (http://edina.ac.uk/digimap), with the support of the ESRC and JISC, and uses boundary material that is copyrighted by the Crown. We used R release 2.8.1, the standard Win32 release available at the time we wrote this article, together with the routines for manipulating and reading geographic data provided by the maptools R package, version 0.7–23, developed by Nicholas J. Lewin-Koh and Roger Bivand.
24. The type "families and single parents, council flats" (ACORN Type 52) is found in significant numbers only in Scotland.

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