Carbon mitigation in domains of high consumer lock-in

Abstract

As climate policy needs to address all feasible ways to reduce carbon emissions, there is an increasing focus on demand-side solutions. Studies of household carbon footprints have allocated emissions during production to the consumption of the produced goods, and provided an understanding of what products and consumer actions cause significant emissions. Social scientists have investigated how attitudes, social norms, and structural factors shape salient behavior. Yet, there is often a disconnect as emission reductions through individual actions in the important domains of housing and mobility are challenging to attain due to lock-ins and structural constraints. Furthermore, most behavioral research focuses on actions that are easy to trace but of limited consequence as a share of total emissions. Here we study specific alternative consumption patterns seeking both to understand the behavioral and structural factors that determine those patterns and to quantify their effect on carbon footprints. We do so utilizing a survey on consumer behavioral, attitudinal, contextual and socio-demographic factors in four different regions in the EU. Some differences occur in terms of the driving forces behind behaviors and their carbon intensities. Based on observed differences in mobility carbon footprints across households, we find that the key determining element to reduced emissions is settlement density, while car ownership, rising income and long distances are associated with higher mobility footprints. For housing, our results indicate that changes in dwelling standards and larger household sizes may reduce energy needs and the reliance on fossil fuels. However, there remains a strong need for incentives to reduce the carbon intensity of heating and air travel. We discuss combined effects and the role of policy in overcoming structural barriers in domains where consumers as individuals have limited agency.

Keywords

Climate change mitigation, lock-in, consumer behavior, carbon intensity, determinants, policy measures

1. Introduction

Scientists and policy makers are increasingly calling for demand-side solutions for mitigating climate change (Creutzig et al., 2018; Wood et al., 2017). Shelter, transport, food, and manufactured products have been identified as high-impact consumption domains (Hertwich and Peters, 2009; Ivanova et al., 2016) and mitigation actions and targets have been suggested (Girod et al., 2014). However, targeting consumer behavior poses its own challenges (Barr et al., 2011; Dietz et al., 2009; Klöckner, 2015). Behavioral scientists have questioned the presumption of control consumers have over their consumption in the context of systematic barriers (Akenji, 2014; Sanne, 2002). Environmental footprints depend to a significant degree on external factors such as infrastructure and technology, institutions (e.g. social conventions, power structures, laws and regulations), and unsustainable habits, creating lock-ins (Jackson and Papathanasopoulou, 2008; Liu et al., 2015; Sanne, 2002; Seto et al., 2016). Such lock-ins reinforce existing social structures and may hinder a transition towards more sustainable systems (Geels, 2011), although opportunities for positive lock-ins have also been explored (Ürge-Vorsatz et al., 2018).

Here we explore the carbon footprints of mobility and housing, and the factors that may explain their variation. Mobility and shelter stand out among the highest contributors to the household carbon footprint (CF) in the EU (Ivanova et al., 2017, 2016), making their de-carbonization a high priority. While previous work has addressed some of these concerns in parts, this study integrates the investigation of attitudinal, structural and socio-economic factors of consumption choices and their CF in four EU regions, thereby enhancing policy relevance of the results.

The importance of context for behavior has been a longstanding theme in consumer behavior research, where studies have broadly explained behavior through individual and contextual factors (Ertz et al., 2016; Newton and Meyer, 2012; Stern, 2000). According to the low-cost hypothesis, attitudinal variables have less influence when a behavior is too difficult to perform (e.g. due to high structural barriers). Mobility and energy behaviors are identified as typical high-cost domains (Diekmann and Preisendörfer, 2003; Klöckner, 2015) as complex decisions, such as location of residence and vehicle ownership, define the use-patterns for a long time (Klöckner, 2015).

Most research effort on sustainable consumption focuses on either the physical dimension (technology, supply chains, urban form) or the social dimension (attitudes, behavior) (Banister, 2008; Thomsen et al., 2014). For example, studies on behavioral drivers generally do not introduce footprint controls and instead rely on measuring pro-environmental behavioral proxies. This may introduce a behavior-impact gap (Csutora, 2012) and lead to targeting the most visible, or easy, rather than the most environmentally relevant behaviors(Klöckner, 2015). In contrast, studies that focus only on the technical characteristics leave out important factors for consumption change, such as attitudes, habits, and behavioral plasticity (Dietz et al., 2009; Thøgersen, 2013). The importance of socio-economic effects such as expenditure and income (Ivanova et al., 2017; Minx et al., 2013; Wilson et al., 2013a), household size (Ala-Mantila et al., 2014; Minx et al., 2013; Wilson et al., 2013b), urban-rural typology (Ala-Mantila et al., 2014; Heinonen et al., 2013; Minx et al., 2013), demographics (Baiocchi et al., 2010) and car ownership (Minx et al., 2013; Ornetzeder et al., 2008) for the household carbon footprint has been widely discussed (see SI table 15). However, prior work differs in fundamental ways in terms of unit of analysis (Ivanova et al., 2017, 2016), consumption detail (Newton and Meyer, 2012), and geographical coverage (Heinonen et al., 2013; Minx et al., 2013).

Here we examine individual-level behavior and carbon intensity determinants separately, which is not a common practice; we do so to uncover potential differences in their driving forces. Determinants may also be significantly interrelated, e.g. with urban cores exhibiting different incomes and household types (Ottelin et al., 2015). Therefore, we explore combined effects and their footprint implications. Furthermore, we evaluate potential emission trade-offs from other consumption areas. Focusing on a single consumption domain may overlook substantial rebound effects, e.g. where lowering of emissions in one domain causes emission increases in another (Hertwich, 2005; Ornetzeder et al., 2008; Wiedenhofer et al., 2013). For an adequate mitigation of greenhouse gas (GHG) emissions from the consumption side, we argue that several main facets need to be considered:

- lifecycle emissions from various consumption domains
- technical and social dimensions of mitigation potential
- lock-in effects beyond the individual's control

Our study is the first one, to our knowledge, to combine these considerations in an analysis of carbon emissions that integrates consumption-based accounting with determinants studies in a policy-relevant framework.

2. Data and method

We examined consumption patterns through a survey on behavioral, attitudinal, contextual and socio-demographic factors in a survey sample of four European regions: Galicia (Spain), Lazio (Italy), Banat-Timis (Romania) and Saxony-Anhalt (Germany). The total sample included 1,617 respondents, of which 1,399 (85%) and 1,407 (87%) provided enough detail for mobility and shelter-specific calculations, respectively. Details about survey design, sampling and distribution can be found in the "Survey design" section of the Supplementary information.

Below we present the carbon footprint calculator used as an input to our statistical analysis. The design of the calculator was informed by prior product-level input-output assessments of household consumption (Ivanova et al., 2017, 2016) and mixed approaches to cover emissions and behavioral aspects (Birnik, 2013; West et al., 2016). We focus on the domains of mobility and shelter, with an additional estimation of food and clothing consumption, to capture most of the GHG emissions of European households and enable mitigation discussions in relevant low-agency domains. For survey background information, uncertainty and validation on footprint calculations, see the "Carbon footprint calculations" in the SI.

2.1 Mobility footprint calculations

We collected data on transport means and distance of regular return trips, including active transport (walk, bicycle, e-bicycle), private motorized transport (car, motorbike) and public transport (bus, tram, underground, train). Regular travel distance (bottom-up) was validated with the annual top-down estimate that car users provided. Additional adjustments were made in the cases of carpooling. We assumed regular travel of 35 weeks/year for work purposes and 40 weeks/year for private purposes. Observations with annual land travel above 80,000 passenger km (km)/year (or 220 km/day) were treated as outliers, conforming to the upper limit of the top-down car-travel range. Air travel was based on annual number of short- and long-haul return flights with assumed distance of 2,300 and 8,000 km/return trip, respectively. See SI "Carbon footprint calculations" for a detailed discussion of the distance assumptions. We treated observations with a number of return flights above 365 in a year as outliers.

The total carbon intensity of mobility results from dividing the mobility footprint by the total distance travelled. Lifecycle (indirect) emissions from cradle-to-gate and direct tailpipe emissions were based on lifecycle assessment (LCA) studies and the Ecoinvent database (GWP100 in kgCO_2eq/passenger km (pkm)) (Frischknecht et al., 2005). The emission intensity of electricity mix was considered where relevant (GWP100 in kgCO_2eq/kWh, Ecoinvent). We utilized car- and fuel-specific intensities where additional car and fuel data were available. We allocated emission factors for air depending on flight length (see Ross, 2009). Figure 1 visualizes our sample's mobility CF as a function of distance travelled (x-axis) and carbon intensity (y-axis).

The mean and median of annual land-based travel was about 9,500 km (26 km/day) and 4,900 km (13 km/day), respectively (table 1). About 13% of the land-based distance was travelled actively, with an average daily return trip of 6 km (for sub-sample estimates see SI figure 1). Our sample had active travel with annual emissions of 4 kgCO_2eq/cap. About 29% of distance on land was travelled by public transport, with an average trip of 19 km/return trip. Private motorized travel was 5,500 km/cap on average (or 22 km/daily return trip), with a footprint of 1.2 tCO_2eq/cap. About 36% of respondents owned a car and used it alone, while 51 % shared the car with other members of the household.

Even though about 47% of respondents only travelled to short-haul destinations, air travel was still the largest contributor to mobility emissions (Figure 1). Air transport brought about an annual CF of 2.4 tCO_2eq/cap on average, compared to 1.5 tCO_2eq/cap for land-based travel (table 1). These estimates seem higher than prior MRIO assessments, which may be due to the lack of consistency in reporting standards for air transport calculation (Usubiaga and Acosta-Fernández, 2015).

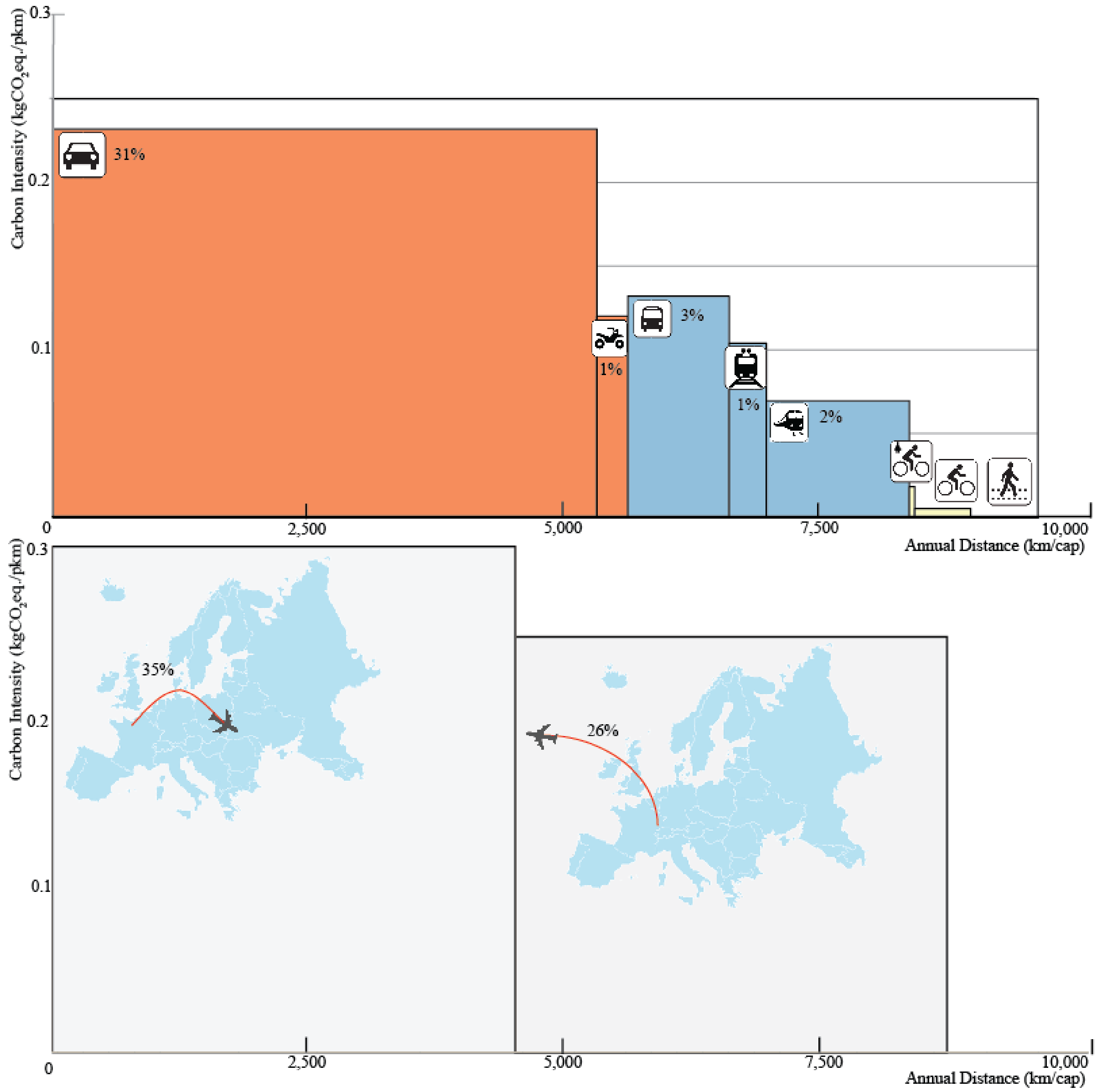

Figure 1: Land and air mobility carbon footprint (CF) by travel mode showing carbon intensities (in $kgCO_2eq$/pkm) and distance (in km). The area of each rectangular depicts the CF of that transport mode and the %s - the footprint share from total mobility (all summing to 100%). The top graph displays land-based travel by car and motorbike (private motorized transport), bus, tram/underground and train (public transport), electric bike, bike and walking (active transport) (from left to right); the bottom graph displays air-based travel by short- and long-haul flights (from left to right).

2.2 Shelter footprint calculations

Energy use covers use of electricity (ELEC), space heating (SH) and water heating (WH). Annual electricity consumption was derived from reported monthly payments in winter and summers, discounting any space and water heating powered by electricity to avoid double-counting. Physical energy demand for space and water heating was modelled using the TABULA methodology based on Europe-representative dwelling sample (IWU, 2013). Regression coefficients were estimated for the effects of dwelling type, period of construction, refurbishment level and climate zone on typical energy demand per square meter (R^2 = 0.48). The total theoretical energy demand per square meter was then scaled up by living space and divided by the number of inhabitants in the household. Thus, our analysis excludes emissions embodied in construction materials, which have been quantified to vary widely, e.g. with shares between 2-38% for conventional buildings (Sartori and Hestnes, 2007). Embodied emission in construction materials gain more relevance for low-energy buildings, where they can account for up to 50% of total emissions (Blengini and Di Carlo, 2010; Dahlstrøm et al., 2012; Sartori and Hestnes, 2007). We also excluded private and communal energy costs embodied in housing management fees (Heinonen and Junnila, 2014). A prior assessment of communal electricity (studying housing companies) quantified it at about 5% of energy use and CO_2 emissions from energy consumption in multi-family apartment buildings (Kyrö et al., 2011). The carbon intensity of space and water heating was calculated based on the lifecycle emissions by heating source (in $kgCO_2eq/kWh$, Ecoinvent). We adopted region-specific carbon intensities of the electricity mix.

Figure 2 depicts the shelter CF as a function of the carbon intensity of energy and energy use. Our sample had a mean annual energy use of 6,200 kWh (17 kWh/day) and a median of 4,700 kWh (13 kWh/day). Electricity comprised about 25% of average energy use and 42% of the shelter-related CF. Region-specific electricity mix had carbon intensity between 0.52 and 0.75 $kgCO_2eq/kWh$. About 47% of the shelter CF and 63% of energy use was associated with space heating. The mean and median of daily energy use for space heating was estimated to be 11 and 7 kWh/cap, respectively. Water heating contributed to about 10% and 12% of annual shelter CF and energy use, respectively. Water heating is more relevant in low-energy buildings, where energy use for heating is drastically reduced (Roux et al., 2016).

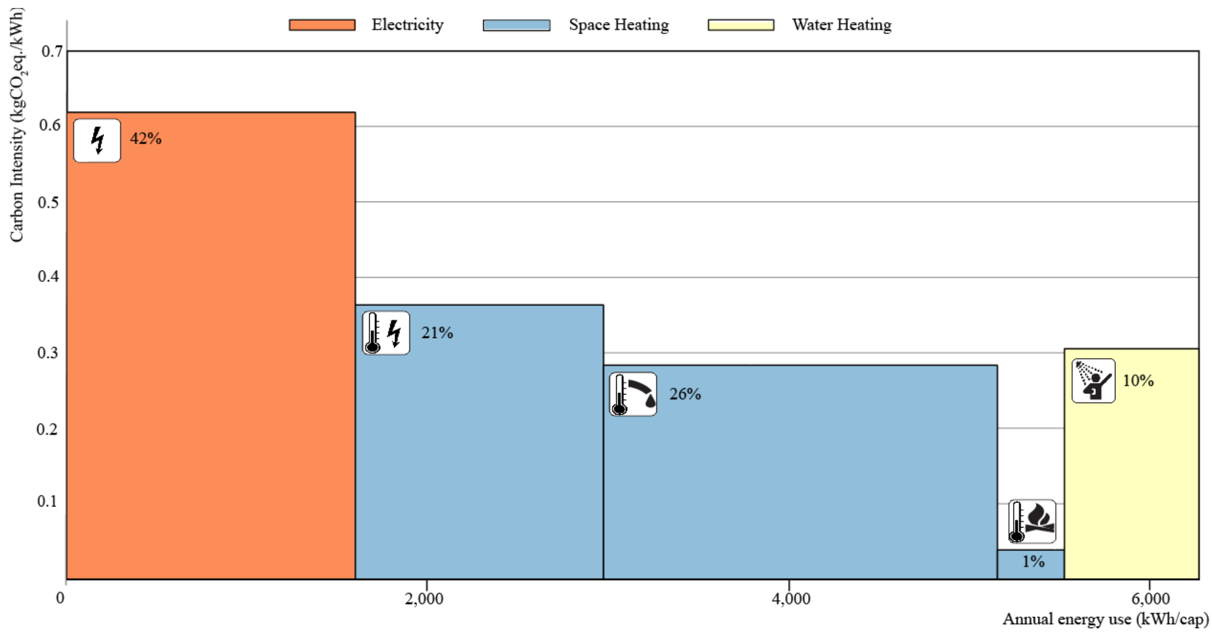

Figure 2: Electricity, space heating and water heating showing carbon intensities (in $kgCO_2eq/kWh$) and energy use (in kWh). The area of each rectangular depicts the CF and the %s - the footprint share of shelter CF (all summing to 100%). Space heating by electricity and district heating, by oil and gas, and by renewables (pellets/firewood or solar-thermal heater) and heat pump (from left to right).

2.3 Regression model

We conducted linear multivariate regression analyses with behavior and carbon intensity of behavior as dependent variables (individual level). For mobility, we explored explanatory factors behind the carbon intensity of land and air travel (in $grCO_2eq/pkm$), and travel distance (in km/day). For shelter, we examined the factors behind energy use (in kWh/day) and its carbon intensity (in $grCO_2eq/kWh$). Intensities were set to zero for the zero-footprint cases. Distance and energy use enter the model in linear terms (instead of logarithmic) in order to keep the zero observations (e.g. those who do not fly).

We further explored the choice of transport mode and heating source, which had direct implications for the carbon intensity of mobility and shelter. We performed a pooled multinomial logit model (MLOGIT) to assess the likelihood (probability) of opting for a specific transport or heating mode. MLOGIT is suitable when the dependent variable is categorical and cannot be ordered (Fan et al., 2007; Pforr, 2014). We performed MLOGIT on a trip rather than individual level (long format) for mobility as individuals generally reported multiple regular trips. We further fit a MLOGIT with fixed effects (FE) accounting for the unobserved heterogeneity where individuals reported the regular use of several transport modes (SI table 17). We reported marginal effects (table 3 and table 5) depicting the predicted probabilities of belonging to one of the dependent variable outcomes and the predicted changes in probabilities resulting from changes in the independent variables.

The regression approach allows for the investigation of effects in isolation. However, the change in one factor important for the CF may be associated with a change in other factors as well. For example, the carbon savings achieved from urbanization may be reduced or even removed altogether in the case of higher income levels or smaller household sizes (e.g. see Ottelin et al., 2015). We used the marginal effects results to explore combined effects of selected highly correlated factors (table 2) on the CF (table 4 and table 6), setting all other factors to mean levels. For odds ratios of pooled and FE MLOGIT, as well as food- and clothing-specific footprint determinant analysis, see “Results” in the SI.

Variable selection was informed by prior literature and survey design. In the mobility-specific regressions, we controlled for travel distance, purpose of travel (work/private), car ownership, and attitudes and use of ride sharing and car sharing initiatives and platforms. In shelter-specific regressions, we controlled for energy use, dwelling characteristics, attitudes and use of energy cooperatives. As we incorporated a large number of independent variables, we additionally performed tests for multicollinearity, or the potential for instability of the coefficients and their “inflated” variance (Belsley et al., 1980; Chen et al., 2003). We reported variance inflation factor (VIF) and tolerance values in SI table 16, which pointed to no strong evidence for multicollinearity.

		Definition and Unit	Total		Galicia (ES)		Banat-Timis (RO)		Lazio (IT)		Saxony-Anhalt (DE)	
Sample size		*No. respondents*	*1,617*		*488*		*292*		*458*		*379*	
Land-mob footprint	LMOB_FP	Annual carbon footprint from land travel, tCO_2eq/cap	1.5	(2.2)	1.4	(1.9)	1.1	(2.0)	1.5	(2.1)	2.0	(2.5)
Air-mob footprint	AMOB_FP	Annual carbon footprint from air travel, tCO_2eq/cap	2.4	(6.8)	2.3	(4.5)	2.6	(7.7)	2.6	(5.9)	2.0	(9.0)
Electricity footprint	ELEC_FP	Annual carbon footprint from electricity use at home, tCO_2eq/cap	1.0	(1.4)	0.9	(0.9)	0.3	(0.5)	1.5	(2.2)	1.0	(0.9)
Space heating footprint	SH_FP	Annual carbon footprint from space heating, tCO_2eq/cap	1.1	(1.9)	0.8	(0.9)	1.0	(1.6)	0.7	(0.9)	1.9	(3.2)
Water heating footprint	WH_FP	Annual carbon footprint from water heating, tCO_2eq/cap	0.2	(0.1)	0.2	(0.1)	0.2	(0.1)	0.2	(0.1)	0.3	(0.1)
Land-mob distance	LMOB_DIS	Daily distance travelled by land, km/day	26.0	(34.7)	24.5	(34.3)	20.6	(33.7)	25.8	(30.6)	32.4	(39.7)
Short flights	AMOB_SHORT	Annual N short flights	1.96	(7.0)	2.27	(3.7)	1.98	(9.4)	2.11	(3.6)	1.30	(10.5)
Long flights	AMOB_LONG	Annual N long flights	0.51	(2.0)	0.39	(1.6)	0.58	(1.7)	0.57	(2.2)	0.54	(2.4)
One-user car	CAR_ONE	Share of respondents who own a car and use it alone	0.36	(0.48)	0.28	(0.45)	0.29	(0.45)	0.43	(0.50)	0.45	(0.50)
Many-user car	CAR_MANY	Share of respondents who own a car and share it with other household members	0.51	(0.50)	0.59	(0.49)	0.46	(0.50)	0.48	(0.50)	0.46	(0.50)
Attitude mob initiative	MINI_ATT	Attitude towards ride/car sharing initiatives/platforms, 7-point scale: 1. Very negative, 7. Very positive	5.2	(1.7)	5.6	(1.5)	4.4	(1.9)	5.3	(1.7)	5.3	(1.6)
Use mob initiative	MINI_USE	Use of ride/car sharing initiatives/platforms, 7-point scale: 1. Very negative, 7. Very positive	2.3	(1.9)	2.4	(2.0)	2.7	(2.0)	2.3	(1.8)	2.2	(1.7)
Electricity use	ELEC_USE	Daily electricity use, kWh/day	4.3	(6.0)	4.7	(4.6)	1.2	(2.0)	6.2	(9.1)	4.2	(3.6)
Space heating use	SH_USE	Daily space heating energy use, kWh/day	10.7	(19.0)	8.1	(9.1)	9.5	(14.7)	7.6	(7.4)	18.2	(33.0)
Water heating use	WH_USE	Daily water heating energy use, kWh/day	2.0	(0.5)	2.0	(0.5)	2.0	(0.5)	2.0	(0.4)	2.2	(0.5)
Dwelling size	DSIZE	Surface in m^2	113.9	(146.4)	115.9	(100.7)	109.7	(120.4)	96.3	(50.9)	135.2	(247.7)
Dwelling type	DTYPE	1. Single family house, 2. Terraced house, 3. Multi-family house, 4. Apartment block (> 10 dwellings)	2.4	(1.4)	2.7	(1.4)	2.6	(1.5)	2.5	(1.3)	1.7	(1.1)
Period of construction	CONSTR	1. Before 1900, 2. 1900-1945, 3. 1945-1970, 4. 1970-1990, 5. 1990-2000, 6. After 2000	4.2	(1.3)	4.6	(1.1)	4.4	(1.1)	4.2	(1.2)	3.5	(1.6)
Electricity production	EPROD	Share of electricity produced (and consumed) by the household	0.04	(0.19)	0.02	(0.14)	0.02	(0.13)	0.04	(0.19)	0.07	(0.26)
Refurbishment	REFURB	Quality of thermal insulation, 7-point scale: 1. Very bad, 7. Very good	4.6	(1.7)	4.3	(1.8)	5.1	(1.6)	4.1	(1.8)	5.1	(1.5)
Attitude energy initiative	EINI_ATT	Attitude towards energy cooperatives, 7-point scale: 1. Very negative, 7. Very positive	5.1	(1.6)	5.6	(1.4)	4.9	(1.6)	5.1	(1.6)	4.8	(1.7)
Use energy initiative	EINI_USE	Use of energy cooperatives, 7-point scale: 1. Very negative, 7. Very positive	2.1	(1.8)	2.1	(1.8)	3.0	(1.9)	1.9	(1.6)	1.8	(1.5)
Urban-rural	RURAL	1. Urban, 2. Sub-urban, 3. Rural	1.61	(0.80)	1.57	(0.77)	1.49	(0.81)	1.42	(0.65)	2.00	(0.87)
Household size	HHSIZE	No. household members	2.93	(1.91)	3.28	(2.82)	3.03	(1.59)	3.03	(1.20)	2.28	(1.07)
Female	FEMALE	Share of female respondents	0.62	(0.49)	0.70	(0.46)	0.60	(0.49)	0.60	(0.49)	0.55	(0.50)
Age	AGE	No. years	40.1	(15.6)	34.9	(13.4)	31.5	(12.2)	40.1	(13.6)	53.3	(14.3)
Education	EDUC	1. No education, 2. Primary school, 3. Secondary school, 4. High school, 5. Vocational school, 6. University degree	5.07	(1.14)	5.42	(0.90)	4.87	(0.98)	5.21	(1.00)	4.63	(1.46)
Married	MARRIED	Share of married respondents (relationship status)	0.52	(0.50)	0.37	(0.48)	0.44	(0.50)	0.59	(0.49)	0.69	(0.46)
Income	INCOME	Monthly net household income: 1. < 600€, 2. 601-1500€, 3. 1501-3000€, 4. 3001-4500€, 5. 4501-6000 €, 6. >6000€.	3.10	(1.09)	2.99	(0.93)	3.41	(1.36)	2.95	(1.01)	3.21	(1.08)
		RO sample: 1. < 176€, 2. 177-330€, 3. 331-552€, 4. 553-882€, 5. 883-1214€, 6. >1214€										
Working time	WHRS	1. <20 hrs./week, 2. 20-40 hrs./week, 3. 40-60 hrs./week, 4. >60 hrs./week	2.94	(1.06)	3.05	(1.06)	3.10	(1.05)	2.67	(1.07)	3.00	(0.99)

Table 1: Descriptive statistics. Means and standard deviations (in parenthesis) reported for the total sample and across the regional sub-samples. Descriptive statistics are reported for individuals as units of analysis. See SI "Descriptive Statistics" for additional variables.

3. Results

Table 1 outlines descriptive statistics and definitions of all variables which enter the regression models. An analysis of the pairwise correlation coefficients and their significance between the explanatory variables is presented in table 2. The correlation table highlights where more caution is needed to interpret regression coefficients. It can also be useful for profiling, e.g. classifying respondents who use mobility- and energy- initiatives.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
CAR_ONE	1	1.00																		
CAR_MANY	2	**-0.75**	1.00																	
MINI_ATT	3	-0.03	-0.02	1.00																
MINI_USE	4	**-0.07**	**0.08**	**0.28**	1.00															
DSIZE	5	0.02	0.04	-0.03	-0.01	1.00														
DTYPE	6	**-0.10**	-0.00	0.03	0.03	**-0.22**	1.00													
CONSTR	7	0.02	0.01	-0.05	**-0.08**	**-0.07**	**0.07**	1.00												
EPROD	8	-0.00	0.04	-0.04	-0.02	**0.09**	**-0.10**	0.03	1.00											
REFURB	9	0.04	0.01	**-0.09**	-0.05	*0.06*	-0.04	*0.05*	0.05	1.00										
EINI_ATT	10	**-0.09**	0.04	**0.51**	**0.17**	-0.01	*0.05*	0.01	-0.01	-0.05	1.00									
EINI_USE	11	**-0.07**	-0.00	0.03	**0.46**	0.04	0.03	-0.01	0.05	*0.05*	**0.20**	1.00								
RURAL	12	*0.06*	*0.05*	*-0.06*	**-0.06**	**0.21**	**-0.51**	-0.04	**0.11**	*0.05*	**-0.07**	-0.01	1.00							
HHSIZE	13	**-0.17**	**0.20**	0.01	0.04	**0.09**	**-0.08**	**0.07**	0.01	-0.04	*0.05*	0.05	**0.07**	1.00						
FEMALE	14	**-0.13**	**0.09**	*0.06*	0.02	-0.02	0.03	0.04	0.01	-0.01	0.04	0.01	0.01	*0.05*	1.00					
AGE	15	**0.18**	-0.03	**-0.07**	**-0.19**	0.03	**-0.10**	**-0.22**	**0.07**	**0.15**	**-0.11**	**-0.13**	**0.10**	**-0.26**	**-0.17**	1.00				
EDUC	16	**0.09**	-0.02	**0.12**	-0.00	*-0.06*	**0.12**	0.05	-0.02	-0.04	**0.13**	**-0.07**	**-0.16**	-0.03	-0.04	0.01	1.00			
MARRIED	17	0.03	**0.13**	-0.09	-0.15	*0.06*	**-0.10**	*-0.05*	**0.07**	**0.16**	**-0.10**	**-0.08**	**0.10**	0.03	**-0.11**	**0.44**	0.01	1.00		
INCOME	18	**0.08**	0.05	-0.02	**-0.10**	**0.13**	**-0.08**	0.01	*0.06*	**0.19**	0.01	-0.04	0.04	**0.12**	**-0.09**	**0.15**	**0.19**	**0.27**	1.00	
WHRS	19	**-0.17**	0.04	-0.04	**0.07**	0.04	-0.04	0.00	0.02	0.03	0.00	**0.08**	**0.08**	*0.06*	0.02	**-0.17**	**-0.23**	**-0.21**	**-0.17**	1.00

Table 2: Pair-wise correlation coefficients of explanatory variables. Bold values indicate 99% significance, italic values indicate 95% significance, and rest are insignificant.

3.1 Mobility

The total carbon intensity model has high values of adjusted R-squared, 0.28. The distance models have lower Adjusted R^2, between 0.03 and 0.04 (table 3). The pooled MLOGIT model reported a Pseudo R^2 of 0.17.

3.1.1 Distance and travel characteristics

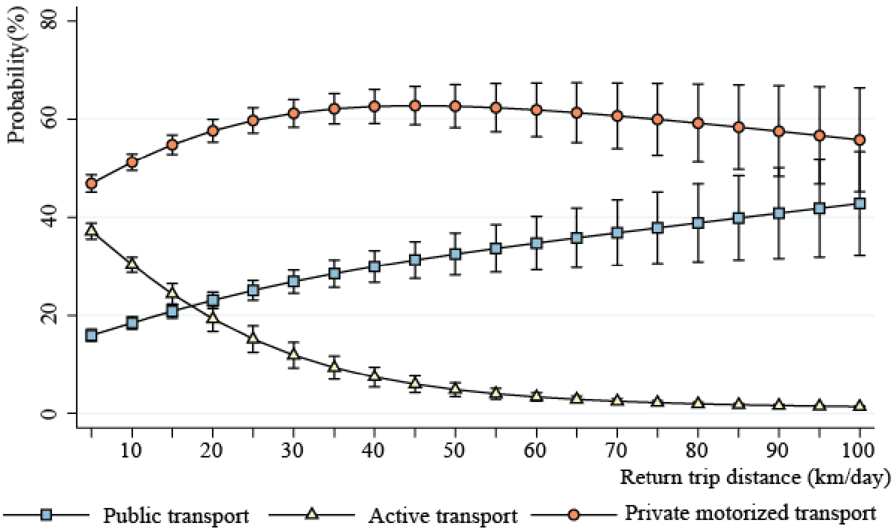

Figure 3: Predictive Margins with 95% CIs calculated for the daily km predictor of the pooled MLOGIT. Y axis (probability %) and x axis (return trip distance km/day).

Mobility	**Distance**			**Carbon intensity**	**Land-travel marginal effects**		
	Total	Land	Air	Total	Active	Public	Private motorized
LMOB_DIS (km/day)				**-0.609*** **	***-0.012****	***0.005****	***0.008****
				(0.13)	***(0.001)***	***(0.001)***	***(0.001)***
LMOB_DIS sq.				0.001	***0.000****	***-0.000****	***-0.000****
				(0.00)	***(0.000)***	***(0.000)***	***(0.000)***
AMOB_SHORT				**8.390*** **			
				(1.03)			
WORK					*0.023**	***0.063****	***-0.086****
					(0.014)	***(0.012)***	***(0.016)***
CAR_ONE	1.040	2.217	-1.526	**63.636*** **	**-0.209*** **	**-0.284*** **	**0.493*** **
	(5.35)	(3.22)	(4.30)	**(6.76)**	**(0.026)**	**(0.021)**	**(0.034)**
CAR_MANY	-0.104	1.845	-2.415	**34.219*** **	**-0.150*** **	**-0.162*** **	**0.311*** **
	(5.26)	(3.12)	(4.20)	**(6.78)**	**(0.026)**	**(0.020)**	**(0.036)**
MINI_ATT	0.012	-0.569	0.594	-0.572	0.007	0.007*	**-0.014*** **
	(0.89)	(0.58)	(0.62)	(1.13)	(0.005)	(0.004)	**(0.005)**
MINI_USE	**3.251** **	**1.345** **	1.891*	0.504	0.004	-0.007*	0.002
	(1.34)	**(0.62)**	(1.10)	(1.01)	(0.004)	(0.004)	(0.005)
RURAL	3.641*	**5.029*** **	-1.418	**11.256*** **	**-0.037*** **	**-0.027*** **	**0.063*** **
	(1.89)	**(1.32)**	(1.30)	**(2.36)**	**(0.009)**	**(0.009)**	**(0.010)**
HHSIZE	-1.709	-0.614	-1.081*	-0.844	**0.006** **	-0.002	-0.004
	(1.07)	(0.74)	(0.63)	(0.91)	**(0.003)**	(0.003)	(0.004)
FEMALE	**-12.200*** **	**-6.440*** **	-5.792*	-0.842	-0.022	**0.044*** **	-0.022
	(3.79)	**(2.00)**	(3.02)	(3.63)	(0.014)	**(0.014)**	(0.017)
AGE	-0.179	-0.128*	-0.050	-0.179	0.001	**-0.002** **	0.001
	(0.12)	(0.08)	(0.09)	(0.15)	(0.001)	**(0.001)**	(0.001)
EDUC	**4.350** **	0.646	**3.794*** **	-0.854	**0.026*** **	**-0.013** **	-0.014*
	(1.73)	(0.98)	**(1.37)**	(1.73)	**(0.007)**	**(0.006)**	(0.008)
MARRIED	-2.756	-1.210	-1.381	**13.644*** **	**-0.032** **	-0.053*	**0.082** **
	(4.32)	(2.19)	(3.54)	**(3.87)**	**(0.016)**	(0.028)	**(0.019)**
INCOME	**6.630*** **	**2.720*** **	**3.865*** **	**5.869*** **	-0.011*	0.001	0.010
	(1.77)	**(1.05)**	**(1.33)**	**(1.88)**	(0.007)	(0.006)	(0.009)
WHRS	-2.161	-1.224	-0.900	**-4.053** **	0.011*	0.013*	**-0.025*** **
	(1.54)	(0.93)	(1.17)	**(1.79)**	(0.007)	(0.007)	**(0.008)**
Adjusted (Pseudo) R^2	0.035	0.040	0.026	**0.282**	**(0.172)**		
N individuals (N trips)	**1399**	**1409**	**1399**	**1399**	**1,394 (4,393)**		

Table 3: Multiple linear regressions (b/se) with total carbon intensity (in grCO_2eq/pkm) and daily travel distance (in km). Marginal effects from pooled MLOGIT with land-based transport mode as dependent variable. Independent variables measured per return trip (for variables in italic) and individual (for other variables). WORK is a binary variable with a value of 1 for work and 0 for private trips. Regional controls and robust standard errors included. *p< .1, ** p < .05, *** p < .01.

The longer the distance, the less likely the travel is active. A one-kilometer increase in the distance of the daily trip decreases the probability of walking or biking by 1.2% on average. The percentage change decreases with rising distance non-linearly (figure 3), where an increase from 5 to 10 km per return trip reduces active travel by 6.8%, from 10 to 15 km by only 5.9%, and so on. Thus, lowering distances widens the travel mode choice (see also Chapman et al., 2016; Pucher and Buehler, 2006; Quinn et al., 2016). There is a slight increase in the likelihood of opting for public transport (0.5%) with one-km distance rise, though public travel is less susceptible to changing distance (table 3). Work trips (or regular commuting) are associated with a 6% higher probability of occurring via public transport (table 3), at 16.7% and 23.2% for private and work respectively. We do not control for potential explanatory factors such as time of travel (e.g. rush hours and traffic), opportunity for ride-sharing, or the role of affective and instrumental factors for trips (e.g. see Anable and Gatersleben (2005)).

Car owners have higher carbon intensity of travel, 64 and 34 grCO_2eq/pkm for single- and multi-users, respectively (table 3). On average, sole users of cars are 49.3% more likely to drive compared to those who do not own a car (table 3), with a high probability of driving even for short trips. The likelihood of driving for daily return trips at 5 km is 46.9% (figure 3). Car ownership is not associated with changes in travel distance. While car ownership has influenced travel distances and urban planning historically (e.g. the Marchetti Constant (Newman and Kenworthy, 2006)), the effect may be less important in a cross-sectional study controlling for urban-rural typology. We also find car ownership and use increase the likelihood of having car trips for both work and private (SI table 18). For the sub-sample with positive number of car trips, the selected variables have much lower power to explain variations in car trips. Particularly, being a single- and multi-user is associated with an increase in the annual number of car private trips by 89 and 72, respectively, but had no effect on the number of work trips.

Naturally, flying is associated with higher total carbon intensity (table 3), where an increase by one return short flight annually is associated with a rise of 8 grCO_2eq/pkm. Car owners show no difference in flying. Previously, car-free households have been shown to have somewhat higher air transport emissions, reflecting higher income levels (Ornetzeder et al., 2008; Ottelin et al., 2017).

3.1.2 Attitudes and use of initiatives

Table 3 provides no clear evidence that use of car- and ride-sharing initiatives translate into lower mobility behavior and footprint. Instead, we find a positive coefficient for land distance. It should be noted, however, that this is the effect keeping car ownership and urban-rural typology constant. Table 2 points to a negative correlations with car ownership (-0.07) and rural context (-0.06), both of which significant at the 99%. This is in support of prior findings that car-sharing facilities enable a reduction in vehicle ownership (Schanes et al., 2016).

More favorable attitudes towards ride- and car-sharing initiatives are associated with a decrease in the carbon intensity of land travel and likelihood of driving (table 3). Nevertheless, attitudes are of little relevance for the distance travelled by air and land (in line with Alcock et al., 2017). From a psychological perspective, the result can be interpreted by the autonomy of motivations that stimulate a certain behavior (Hartig et al., 2001; Ryan and Deci, 2000).

3.1.3 Urban-rural typology and household size

The likelihood of active travel rises with population density, on average 30.6% for urban and 23.2% for rural context (in line with Pucher and Buehler, 2006; Quinn et al., 2016). A similar decrease is noted for public transport, an average of 2.7% (table 3). Similarly, prior studies have noted that population growth in low-density suburban areas results in more commuting via passenger vehicles (Dodman, 2009; Jones and Kammen, 2014; Rosa and Dietz, 2012). Furthermore, the shift to rural living is associated with an increase in the travel distance by land (β=5.03, $p < .01$).

Household size is insignificant in determining the travel intensity and distance (see also Ivanova et al., 2017). This points to the lack of household economies of scale for land- and air-based travel, e.g. due to differences in travel routines and preferences within the household.

3.1.4 Socio-demographics

Females and younger respondents are more likely to opt for public transport (table 3). Furthermore, females note 12 km/day lower travel distance, on average. Prior studies have pointed to the gender- and age-unequal distributions of time use, patterns of expenditure, and employment (Caeiro et al., 2012; Chancel, 2014; Pullinger, 2012; Quinn et al., 2016). Relationship status has a limited effect in explaining the CF of travel, although married respondents were 8.2% more likely to drive on average. The relationship status has implications for time use, working schedules and children dependency (Pullinger, 2012).

Individuals with higher education are more likely to travel actively and by air, and less likely to use public transport. Differences may be partially attributed to socioeconomic status, place of residence (Pucher et al., 2011; Whitfield et al., 2015), or higher awareness about co-benefits (e.g. health).

3.1.5 Income and working Time

Income is an important determinant of distance travelled by both land and air, where a rise in income by one level brings about an increase in the average daily travel by 7 km/day. Our analysis confirms the mobility domain (and particularly air mobility) as income-elastic (Creutzig et al., 2015; Ivanova et al., 2017; Rosa and Dietz, 2012). The effect of working hours (in isolation of the income effect) is insignificant in most mobility models (table 3). This has implications for policies that aim to reduce working hours, while keeping the same level of disposable income. Furthermore, longer working hours (>60 hours/week) are associated with a decrease in carbon intensity, which is in line with prior hypothesis that very high work load may reduce participation in leisure and family travel (Czepkiewicz et al., 2018).

3.1.6 Combined effects

Table 4 explores the combined effect of urbanity, trip distance, car ownership, and mobility initiative use on the choice of transport mode and land-travel CF overall. Limiting the daily travel distance through compact urban environment may produce substantial footprint savings. For example, a 5-km average return trip (Case 1) is associated with an annual land-travel carbon footprint close to ten times lower than our sample's average. However, in order to realize the full benefit from urbanization and reduced distance, there needs to be proportionate changes in car use and ownership (e.g. Case 2-3, Case 4-5).

Land travel (mobility)	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**	**Case 6**
Urban/rural	Urban	Urban	Urban	Urban	Rural	Rural
LMOB_DIS (km/return trip)	5	10	10	20	20	30
CAR_ONE	No	No	Yes	Yes	No	No
CAR_MANY	No	No	No	No	Yes	Yes
MINI_USE	Always	Always	Never	Never	Never	Never
Active transport share	0.51	0.43	0.18	0.08	0.12	0.08
Carbon intensity ($kgCO_2eq/pkm$)	0.09	0.10	0.12	0.20	0.18	0.19
Annual carbon footprint (tCO_2eq/cap)	0.2	0.4	0.7	1.5	1.3	2.1

Table 4: Land trip characteristics based by case. The table is based on the marginal effects regression (table 3). The annual carbon footprint is calculated assuming trip distance is travelled daily. The reported values have assumed the

mean level for the rest of significant regressors. In white we present the fixated levels for the regressors, and in grey – the estimated values for choice of transport, carbon intensity and footprint.

Furthermore, there is a strong negative correlation between the car ownership and use of mobility initiative variables (table 2). The more frequent use of mobility initiatives may increase travel distance, holding car ownership constant (table 3); however, the use of such initiatives may also reduce car ownership rates. Table 4 signals for the substantial difference in emissions and active travel that may occur through the use of car sharing initiatives (e.g. Case 2-3).

3.2 Shelter

The regression models on the total energy use have a high adjusted R-squared, 0.77 (table 5), with varying model fit for daily electricity, space and water heating use models, 0.10, 0.84 and 0.57, respectively. The total carbon intensity model has an adjusted R-squared of 0.27. The choice of space heating, particularly, is explored through the marginal effects model with a Pseudo R-squared of 0.24. The choice of water heating sources is much less explained through our model with a Pseudo R-squared of 0.13 (see SI table 19).

3.2.1 Energy use and dwelling characteristics

An increase of electricity use by 1 kWh/day raises the likelihood of electricity-powered space heating by an average of 0.6%, explaining the noted increase in the total carbon intensity of energy use (table 5). Own electricity production (EPROD) is insignificant for energy use suggesting that producing own electricity does not necessarily increase its use.

Space heating needs play a significant role for the choice of heating source. Particularly, a rise in the daily space heating by 1 kWh raises the probability of heating by fossil fuel with 0.8% on average and reduces the probability of heating by district heating by the same amount. The effect on renewables is only partially significant. While lowering space heating needs may reduce reliance on fossil fuels, such efforts should be coupled with strong incentives for a transition to renewable heating sources and efforts to utilize local energy sources such as waste heat and energy-from-waste technologies (Lausselet et al., 2016; UNEP, 2015). Water heating needs have little relevance for the choice of space and water heating source.

Larger dwellings use more energy for space heating. An increase in the dwelling size by 1m^2 brings about a rise in space heating needs by 0.1 kWh/day (or 41 kWh/year). However, larger dwelling have also lower carbon intensity (a reduction of 0.15 grCO_2/kWh per m^2), being more likely to be heated by renewables or district heating (table 5). District heating is in general a cost-competitive and cheap option to provide heat. Yet, district heating - and renewable electricity production - have high capital expenditure and relative low operating cost (UNEP, 2015), making them more suitable for larger dwellings.

Apartments are associated with lower energy use (negative 3.1 kWh/day compared to single family home), particularly electricity and space heating (keeping dwelling size constant). However, apartment blocks have higher carbon intensity per kWh, 62 grCO_2eq/kWh more compared to single family home. This increase in intensity is due to changes in heating source (less renewables/heat pump, more district heating) with the effect being highly significant for both space and water heating. District heating is not well suited for single-building options with its cost structure (UNEP, 2015). Dwelling type and urban-rural typology are highly correlated (-0.51), with houses being more likely located in rural areas, and apartments in urban areas.

Newer dwellings have lower space heating needs, but higher electricity consumption and, hence, higher carbon intensity per unit of energy use. Prior assessments of new constructions have found that energy savings per m^2 are generally offset by changes in user heating habits and the amount of energy appliances (EEA, 2016; Sandberg et al., 2016b). We find a strong pairwise correlation between age of dwelling and inhabitants (-0.22) pointing to younger inhabitants opting for newer dwellings (table 2); that is, the effect of electricity use may be explained variation in consumption patterns among age cohorts. The construction decade has no significant effect on the choice of space or water heating.

	Energy use				**Carbon intensity**	**SH marginal effects**				
	Total	**ELEC**	**SH**	**WH**	**Total**	**Electricity**	**District heating**	**Oil/gas**	**Renewables/heat pump**	**Not Heating**
ELEC (kWh/day)					**5.993***	**0.006***	-0.002	-0.000	-0.000	-0.003*
					(1.31)	**(0.001)**	(0.004)	(0.004)	(0.002)	(0.002)
SH (kWh/day)					0.372	0.002	**-0.009***	**0.008***	-0.002*	0.001
					(0.43)	(0.002)	**(0.003)**	**(0.003)**	(0.001)	(0.001)
WH (kWh/day)					-16.357*	0.005	0.050	-0.091*	0.019	0.018
					(9.90)	(0.028)	(0.031)	(0.053)	(0.035)	(0.013)
DSIZE	**0.112***	0.001	**0.112***	-0.000*	**-0.150**	-0.001	**0.001***	-0.000	**0.000***	0.000
	(0.01)	(0.00)	**(0.01)**	(0.00)	**(0.06)**	(0.000)	**(0.000)**	(0.000)	**(0.000)**	(0.000)
DTYPE	**-1.029***	**-0.353**	**-0.673***	-0.002	**19.103***	-0.006	**0.036***	-0.007	**-0.032***	**0.008**
	(0.26)	**(0.14)**	**(0.20)**	(0.01)	**(2.33)**	(0.007)	**(0.009)**	(0.012)	**(0.008)**	**(0.004)**
CONSTR	**-1.834***	**0.219**	**-2.052***	-0.001	**9.958***	-0.000	-0.010	0.007	-0.001	0.004
	(0.23)	(0.10)	(0.20)	(0.01)	**(2.25)**	(0.008)	(0.008)	(0.012)	(0.007)	(0.004)
EPROD	1.079	0.682	0.398	-0.001	-20.669	0.077	-0.080	0.201*	0.087	**-0.284***
	(1.37)	(0.79)	(0.99)	(0.03)	(14.70)	(0.063)	(0.103)	(0.109)	(0.047)*	**(0.048)**
REFURB	**-1.792***	-0.044	**-1.752***	0.004	**8.258***	-0.005	-0.009	**0.020**	-0.010	0.002
	(0.17)	(0.13)	**(0.10)**	(0.01)	**(1.68)**	(0.006)	(0.007)	**(0.009)**	(0.005)*	(0.003)
EINI_ATT	-0.280	-0.244*	-0.038	0.001	-0.005	-0.000	-0.010	0.004	0.004	0.002
	(0.20)	(0.14)	(0.13)	(0.01)	(1.68)	(0.006)	(0.006)	(0.009)	(0.005)	(0.003)
EINI_USE	0.051	-0.041	0.091	0.001	2.491	0.000	0.009	-0.005	0.001	**-0.006**
	(0.15)	(0.06)	(0.12)	(0.00)	(1.59)	(0.005)	(0.005)*	(0.008)	(0.004)	**(0.003)**
RURAL	-0.139	0.062	-0.177	-0.024*	**-16.62***	-0.016	0.011	**-0.048**	**0.063***	-0.011
	(0.44)	(0.18)	(0.38)	(0.01)	**(3.95)**	(0.014)	(0.015)	**(0.020)**	**(0.010)**	(0.009)
HHSIZE	**-2.825***	**-0.475***	**-2.186***	**-0.164***	-0.196	0.004	0.013	-0.023	0.005	0.000
	(1.00)	**(0.16)**	**(0.80)**	**(0.06)**	(1.99)	(0.007)	(0.007)*	(0.016)	(0.006)	(0.003)
FEMALE	0.978*	0.000	**0.982**	-0.005	2.843	-0.017	-0.021	0.045*	-0.019	0.011
	(0.58)	(0.35)	**(0.44)**	(0.02)	(5.38)	(0.018)	(0.019)	(0.027)	(0.016)	(0.011)
AGE	**0.105***	**0.036***	**0.061**	**0.007***	0.119	-0.001	0.001	0.002	-0.001	-0.001
	(0.04)	**(0.01)**	**(0.03)**	**(0.00)**	(0.22)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EDUC	-0.259	-0.010	-0.269	**0.020***	-1.002	-0.007	-0.004	0.008	0.005	-0.003
	(0.28)	(0.20)	(0.18)	**(0.01)**	(2.43)	(0.009)	(0.008)	(0.012)	(0.008)	(0.004)
MARRIED	**-3.035***	**-0.789**	**-1.936***	**-0.310***	-7.299	-0.005	**-0.064***	**0.085***	-0.008	-0.008
	(0.92)	**(0.34)**	**(0.72)**	**(0.05)**	(6.67)	(0.022)	**(0.025)**	**(0.032)**	(0.019)	(0.014)
INCOME	-0.206	0.177	-0.361	-0.022*	0.997	0.003	0.004	0.027*	-0.016*	**-0.017***
	(0.30)	(0.12)	(0.24)	(0.01)	(3.15)	(0.011)	(0.010)	(0.014)	(0.009)	**(0.006)**
WHRS	-0.360	-0.081	-0.257	**-0.022***	-2.569	-0.002	-0.015	0.008	0.009	0.000
	(0.23)	(0.14)	(0.17)	**(0.01)**	(2.54)	(0.009)	(0.009)	(0.014)	(0.008)	(0.005)
Adjusted (Pseudo) R^2	**0.766**	**0.104**	**0.844**	**0.565**	**0.269**			**(0.237)**		
N individuals	**1407**	**1407**	**1407**	**1407**	**1407**			**1,133**		

Table 5: Multiple linear regressions (b/se) with total carbon intensity (in grCO_2eq/kWh) and daily energy use (in kWh) as dependent variables. Marginal effects from the pooled MLOGIT with space heating source as dependent variables with unit of analysis – an individual. We only perform marginal effects for those that have selected a single heating source (81%). Regional controls and robust errors included in all models. *p< .1, ** p < .05, *** p < .01.

Similarly, higher level of refurbishment reduces space heating needs; the shift in the quality of thermal insulation from "very bad" to "very good" is associated with a drop in space heating consumption by 11 kWh/day (or 4 MWh/year). Energy reductions potentials are directly linked to refurbishment rates (IWU, 2013), with refurbishment rates across 11 European countries varying between 0.6-1.6% (Sandberg et al., 2016a). At the same time, better thermal insulation is associated with a higher likelihood of opting for oil or gas space heating and, hence, higher carbon intensity; particularly the shift from "very bad" to "very good" increases the likelihood of heating by fossil fuels by 12%.

3.2.2 Attitudes and Use of Initiatives

Finally, attitudes and use of energy cooperative initiatives are of no significance for the annual energy needs (see Diekmann and Preisendörfer, 2003). The use of energy cooperatives is associated with lower likelihood of not heating (table 5). Those who frequently use energy cooperative initiatives ("Always") are 6% more likely to heat water by electricity, suggesting a possible moral licensing effect (Tiefenbeck et al., 2013), and 13.8% less likely to heat by fossil fuels, than those who never use such initiatives.

3.2.3 Urban-Rural Typology and Household size

We find the effect of rural typology to be insignificant for energy use. This effect is likely influenced by the high correlation between urban-rural typology and dwelling type in European context (table 2). Furthermore, rural dwellings are more likely to be heated by renewables. The use of firewood is more common to rural areas due to the close supply (Euroheat and Power, 2006). Common heating solutions in urban areas have a line-based network energy supply as natural gas and district heating, requiring a certain heat demand density to justify investment (Euroheat and Power, 2006).

The household scale effect is substantial for energy needs. A rise in the household size of one member is associated with a drop of individual electricity, space and water heating needs by 0.5, 2.2 and 0.2 kWh/day (or about 170, 800 and 60 kWh/year), respectively (table 5). This effect is driven by shared consumption of heating, cooling and light, as well as common use of electrical appliances (Liu et al., 2003; Rosa and Dietz, 2012). The co-housing model emerges as a cost-competitive social innovation that that may further inspire a restructuring of the social institution of housing and technological innovations (Seyfang and Smith, 2007).

3.2.4 Socio-demographics

Females have 360 kWh/cap higher annual space heating needs, although the effect is only partially significant for total energy use. Age has a positive effect on energy needs, ceteris paribus. An additional year brings about an increase in the annual electricity, space heating and water heating needs by 13, 22 and 3 kWh/cap, respectively. Education is of no significance for the total energy needs or heating source.

Married people have substantially lower energy needs, about 3 kWh/day (or 1,095 kWh/year). A possible explanation is the effect of household composition beyond the household size, e.g. having children. Married respondents were 8.5% more likely to opt for fossil fuels and 6.4% less likely to heat by district heating. Being married was noted to be highly positively correlated with age (0.44), income (0.27) and refurbishment level (0.16), and negatively correlated with working hours (-0.21).

3.2.5 Income and working time

We find energy use to be income inelastic (table 5); this effect is in line with prior findings, similar to other basic needs (see Ivanova et al., 2017). That being said, higher income is associated with a lower likelihood of not heating. This suggests that financial savings may be a primary reason for not heating, calling attention to the potential of energy poverty-related cold housing rising with energy prices (Ürge-Vorsatz et al., 2014). Differences in the working time are of little relevance for the shelter footprint.

3.2.6 Combined effects

According to table 5, rural dwellings are more likely to be heated by renewables compared to urban dwellings and are, thus, less carbon intensive. Rural dwellings are also generally associated with larger sizes and single family house-types (higher heating needs), and larger household sizes (lower heating needs). There is a significant potential for carbon savings with the shift to urban and compact environment, e.g. 24% difference in the space heating footprint between Case 8 and Case 11 (table 6). Nevertheless, dwelling characteristics and household size should also be considered to realize the potential benefits, in both urban (e.g. Case 8-9) and rural (e.g. Case 10-12) context.

Space heating (shelter)	**Case 7**	**Case 8**	**Case 9**	**Case 10**	**Case 11**	**Case 12**
Urban/rural	Urban	Urban	Urban	Rural	Rural	Rural
SH (kWh/day)	11	11	17	26	19	22
DSIZE	60	100	100	160	100	90
DTYPE	Apartment block	Apartment block	Single family home	Single family home	Single family home	Single family home
HHSIZE	2	4	2	4	4	2
Oil and gas share	0.67	0.62	0.71	0.59	0.57	0.65
Carbon intensity (kgCO_2eq/kWh)	0.33	0.33	0.31	0.24	0.26	0.27
Annual carbon footprint (tCO_2eq/cap)	1.3	1.3	2.0	2.2	1.7	2.1

Table 6: Space heating characteristics by case. The table is based on the marginal effects regressions (table 5). The reported values have assumed the mean level for the rest of significant regressors. In white we present the fixated levels for the regressors, and in grey – the estimated values for choice of heating mode, carbon intensity and footprint.

3.3 Other consumption

No major increases in other consumption are noted on domain level according to the food- and clothing-specific regression results with regards to the effects discussed above. Instead, we find pro-environmental behaviors to be consistent across domains, with food- and clothing-related emission decreases associated with pro-environmental action in the shelter or mobility domains. The models have adjusted R-squared values of 0.28 and 0.20, respectively (SI table 20).

The shift from individualized motor transport to active or public transport does not relate to emission increases in other consumption domains. On the contrary, a 10% rise in active transport share is associated with a 1% drop in food-related emissions, which may be related to overall health awareness or concern. Car ownership and air travel are also associated with higher emissions in other consumption.

The use of electricity and space heating is positively related to food and clothing footprints. Own electricity production is associated with a drop in other consumption. The effect of construction decade is more ambiguous with newer dwellings having lower heating needs and higher food CF, which may be due to socio-economic differences among inhabitants. The shift to urban living has no significant effect on other consumption, while lower income and more favorable attitudes towards energy cooperatives bring about drops in food and clothing footprints.

3.4 Limitations

We discuss uncertainty with regards to some of the assumptions made for footprint calculations and validate our estimates and assumptions with prior studies and uncertainty ranges (see SI "Footprint uncertainty and validation").

Prior studies discuss the importance of under-reporting in consumption and expenditure surveys of irregular and small purchases (Bee et al., 2012; Ivanova et al., 2017) and more specifically of fuel consumption (Ottelin et al., 2017). Studies emphasize the error and uncertainty in the data collected in travel surveys and provide evidence for under-reporting, e.g. 10-15% and up to 50% for certain types of trips (Clarke et al., 1981). Particularly, off-peak trips and trips for non-work purposes seem to be associated with higher measurement error and incomplete recall and reporting of travel (Clarke et al., 1981; Giesbrecht, 2004; Minnen et al., 2015). Minnen and colleagues (2015) find an average day-to-day variability of travel (as a % of total variability) of 60%, varying between 46.7% for work and 75.7 for leisure, family- and friends-related travel, suggesting that travel is not very stable across weekdays. Furthermore, our survey covers only regular land-based travel and systematically disregards impacts embodied in irregular travel. The link to our survey was distributed between the winter months of December 2015 and February 2016, which may have contributed to some season-specific travel recording. Jara-Díaz and Rosales-Salas (2015) discuss measurement issues with survey responses recorded in a single day. To evaluate the accuracy of our estimates, we validated the bottom-up car trip data with annual mileages where available. We found that 40% of our bottom-up estimates were within the annual mileage range provided by respondents. About 16% of car-users had bottom-up car travel distance that was more than 5000 km longer than their annual mileage.

In terms of sample selection, our sample may suffer from self-selection. We discuss representativeness of the geographic samples with regards to observed socio-demographics; however, we could not control for other potentially important indicators for survey response, e.g. environmental concern. Hence, the point of our analysis is not to establish causal relationships, but rather to explore the role of technical and social factors hypothesized by prior literature (see SI "Model background") in explaining observed differences in emission variance and choice of transport and heating.

Our regression analysis focuses on factors that vary within geographic regions that have been previously suggested as important for mobility and shelter impacts. We expect that there are additional macro-level factors (e.g. as suggested by Ivanova and colleagues (2017)) that our model disregards, such as geographical factors, resource availability, social and cultural norms and market prices. While we cannot measure the isolated effect of these factors on mobility and shelter, we include regional fixed effects to account for their combined effect. There may, however, be other relevant factors that vary within regions (e.g. neighborhood location, infrastructure and connectivity) that we do not consider due to survey design limitations.

Furthermore, we explore the choice of heating and travel mode as explained by energy use and distance. Nevertheless, it could be that the effect runs in the opposite direction as well. For example, one could use more electricity if it is also the heating source. Or, the level of thermal insulation could be decided post the choice of heating mode. Mutual causality was beyond the scope of our statistical considerations.

We include attitudinal indicators related to mobility- and shelter- initiatives in order to contribute to the limited literature (Moser and Kleinhückelkotten, 2017) exploring the role of psychological variables from impact-oriented perspective. However, our attitudinal questions do not cover broader and relevant consumer attitudes on energy, transportation, consumption, environment and environmental issues etc., and, thus, should not be interpreted as capturing the relevance of consumer attitudes for mobility and shelter carbon impacts overall. While we control for use of sustainability-focused initiatives, we do not look specifically into initiative membership, which may have wider implications for sustainability transformations (Akenji, 2014; O'Brien, 2015).

Finally, while we observe effects on a broad domain level of other consumption in the context of rebound concerns. This is done to provide a wider perspective on the observed effects in terms of various consumption. Nevertheless, our analysis as a snapshot of behaviors and impacts is limited in capturing income rebound resulting from monetary savings and system-wide effects (Druckman et al., 2011; Wood et al., 2017). For example, while we can compare other consumption impacts of car-free and car-using households, we cannot confirm that the potential emission differences result from monetary savings. The design of such analysis would require additional considerations, e.g. experimental setting and omitted selection threats to validity (Ottelin et al., 2017), specific abatement intervention (Chitnis et al., 2013; Druckman et al., 2011), consumption coverage detail (Ottelin et al., 2017), temporal dimension (Ottelin et al., 2018), consideration of direct rebound (Chitnis et al., 2013), differences in emission intensities (Chitnis et al., 2013; Druckman et al., 2011; Wood et al., 2017), re-spending, savings and economy-wide effects (Chitnis et al., 2013; Druckman et al., 2011; Hertwich, 2005; Wood et al., 2017).

4. Policy implications

Some differences occur in terms of the driving forces behind behaviors (consumption patterns) and their carbon intensities. Particularly, distance is influenced by socio-demographics and use of energy cooperatives, while the carbon intensity of travel by distance and car ownership. Both are influenced by the context (urban-rural typology) and income. Factors such as household size, age, and relationship status are important for energy use, while the amount of electricity used and income are important for the carbon intensity of shelter. Dwelling characteristics are important for both. We find the parallel analysis of determinants to uncover potentially offsetting effects, e.g. where attempts to lower the energy use in the dwelling may also impact the choice of heating.

We summarize the effects and list some policy-relevant considerations for carbon impact mitigation associated with these effects (table 7). Table 7 should be interpreted as pointing to the places to intervene, rather than ranking potential interventions in terms of their effectiveness and upscaling potential. Different disciplines have proposed various interventions and policy instruments, and assessing their effectiveness for impact mitigation is beyond the scope of our study (e.g see Abrahamse et al., 2005; Creutzig et al., 2018). Considering additional co-benefits of proposed measures should also be regarded in the motivation of carbon mitigation policies (see SI "Co-benefits").

Highly populated areas can substantially reduce emissions at a low cost through more compact, connected and efficient design of housing and transport infrastructure. Particularly, we find that urban living is associated with lower travel by land and a higher active and public transport share, as well as smaller dwelling sizes and a larger share of apartment blocks. The "economies" of scale, proximity, and connectivity of urban areas enable the provision of infrastructure for active and public transport and the use policy instruments for environmental management (Dodman, 2009; Wiedenhofer et al., 2013). Our results underline the importance of shortening the travel distance for reducing transport emissions (directly and indirectly through the intensity of travel). Compact development and reductions in distance would be most enabling for active travel in the presence of proportionate reductions in travel time (e.g. Newman and Kenworthy, 2006). Furthermore, changes in car ownership and use of mobility sharing initiatives are needed to reap the full benefits from reduced distance.

Urbanization may reduce shelter impacts through smaller dwelling sizes, high density living and energy saving refurbishment measures. Nevertheless, policies that encourage a shift to compact urban living should also aim for de-carbonization of heating sources typical for urban context. Urban and apartment-block dwellers are found to more likely use oil and gas for heating (directly) and, and less likely use renewables and heat pumps for heating, highlighting the need for top-down incentives for low-carbon heating in urban environment. Our analysis shows that lowering heating needs may reduce the reliance on fossil fuels, but strong incentives are needed for a transition to renewable heating sources. Prior studies have shown that district heating competes with natural gas and other fossil-based energy supply in high heat density urban area (Euroheat and Power, 2006), pointing to the de-carbonization of district heating as another priority in urban context. Furthermore, our sample suggests that household sizes tend to be smaller in urban areas (in line with Ottelin et al., 2015), suggesting the need to further enable household economies of scale in urban context. Although not investigated here, our results suggest that multi-household living could reduce shelter impacts, and options like co-housing have been proposed for their benefits (Williams, 2008). Finally, cities can be particularly vulnerable to climate change with high-density areas exposed to, for example, heat waves or coastal flooding (Dora et al., 2015).

With higher income levels, there are also expected increases in the carbon footprint, particularly associated with air travel and other consumption. Our findings confirm the relevance of income for mobility, food and clothing domains (Ivanova et al., 2017; Pullinger, 2012; Sommer and Kratena, 2016). A reduction in working hours without proportionate decreases in income would likely be of little relevance for emissions. Yet, longer working hours are associated with lower carbon intensity of travel, in line with the hypothesis that leisure travel is not only constrained by money but also time (Czepkiewicz et al., 2018).

Furthermore, we find the primary reasons for not heating to be financial, with higher income levels significantly reducing the likelihood of not heating. Importantly, green industrial policies may result in rising electricity prices for consumers, with the financial burden unequally distributed across social groups (Meckling et al., 2017; Wiedenhofer et al., 2013). Therefore, the transition to renewables should consider the potential for energy poverty and cold-housing related social hazards (Ürge-Vorsatz et al., 2014).

While our analysis confirms the importance of air travel in terms of climate impact (in line with Aamaas et al. (2013); Aamaas and Peters (2017)), the power of selected factors to explain observed variation in air-travelled distance is rather limited. We find that higher income and education are associated with a higher likelihood of air travel, which confirms (international) travel as highly income-elastic and carbon-intensive (Lenzen et al., 2018).

Car ownership is a significant carbon lock-in for our sample. This is in line with prior analysis pointing to conventional passenger vehicles as the highest carbon lock-in due to established subsidies, social norms, and supporting infrastructure (Seto et al., 2016). Nevertheless, there needs to be a behavioral alternative (e.g. public transport, manageable distance) for a change in car travel to occur. Directing public funds towards infrastructural development with significant social (inclusiveness, equality) and environmental (enabling active and public transport) consideration is key. Furthermore, upscaling of car- and ride-sharing initiatives may widen the choice of transport mode and enable carpooling, thus, significantly reducing mobility emissions. We also find low relevance of attitudes and use of energy initiatives for the shelter footprint, although benefits may occur beyond the domain of initiative activity.

Drivers	Effects on Mobility Footprint	Effects on Shelter Footprint	Effects on Other Consumption	Policy-relevant considerations
Mobility- and shelter-specific drivers: distance, travel characteristics, energy use and dwelling characteristics	• Longer distance reduces active travel (less so for public transport) • Car ownership is a carbon lock-in with high likelihood of driving (even at short distances) • No voluntary substitution between short flights and public land travel • Work trips more likely to be done via public transport	• Higher electricity use increases the likelihood that electricity is used as a heating source Larger dwelling size more likely to be heated by renewables/ heat pump (and by district heating); larger dwelling have also higher space heating needs • Apartments have lower energy needs and are less likely to heat by renewables and more likely to heat by district heating • Newer dwellings/better thermal insulation associated with lower heating needs (potentially higher electricity consumption)	• Active travel associated with lower food and clothing footprint • Air travel and car ownership associated with higher food- and clothing footprint • Higher energy use is associated with higher food-and clothing-footprint • Respondents living in newer dwellings associated with higher food footprint • Own electricity production associated with lower clothing footprint	• Reduce travel distance (e.g. urban connectivity, telecommuting) • Reduce carbon intensity of travel – encourage active/public travel (e.g., urban connectivity, infrastructure, financial incentives, bans and regulations), carpooling, tackle car ownership lock-in (e.g. incentives to change habits, parking and zoning restriction, vehicle and fuel tax), fuel decarbonization and efficiency gains • Reduce long distance travel and intensity (e.g. infrastructure, telecommuting, efficiency improvements, capacity constraints, carbon taxes or trading schemes) • Reduce energy use (e.g. efficiency improvements, dwelling standards, taxes) • Reduce carbon intensity of energy (e.g. regulations, financial incentives)
Attitudes and Use of Initiatives (ride sharing, energy coops)	• More favorable mobility-initiative attitudes are associated with a reduction in the land-traveled intensity (lower likelihood of driving) and a rise in air-based carbon intensity • Use of initiatives rise land-travel distance (holding car ownership constant)	• Energy-initiative attitudes insignificant for shelter impacts • No relevance of initiative use on total energy use; users of energy cooperatives less likely to "not heat"; more likely to heat water by electricity	• More favorable attitudes associated with lower food/clothing footprint	• Evaluate the holistic effect of initiatives (e.g. spillover effect, reduction in car ownership) • Low relevance of domain-specific attitudes for emissions • Account for potential rebound with use of initiatives
Urban-rural context, household size	• Urban context associated with lower travel distance by land, more active and public transport • Limited household economies of scale (e.g. due to differences in travel routines)	• No direct effect of rural context on energy use, though important urban-rural differences in dwelling characteristics • Household economies of scale for energy needs. No significance for carbon intensity	• No significant household economies of scale • No relevance of urban-rural typology (keeping income constant)	• High-density infrastructural development, incentives for compact multi-household living (e.g. sprawl taxes) considering other trends (e.g. income, household size) • Incentives for mitigating the carbon intensity of shelter particularly in urban environment
Socio-demographics	• Females travel lower distances both by land and air, and are more likely to opt for public transport • Well-educated travel more actively on the ground and by air • Married more likely to drive	• Limited relevance for the choice of heating source • Married and younger associated with lower energy needs; females associated with higher space heating needs	Limited relevance: • Females and more educated with lower food footprint	• Differences in time use and expenditure patterns of various groups should be considered (e.g. flexible working schemes, living situation) • Raising awareness about other benefits of active travel (e.g. health)
Income, working hours	• Air travel is very income elastic (intensity, distance) • Rising income increases land-travel distance • Limited relevance for transport mode and car ownership (own vehicle not a luxury) • Higher working hours may actually reduce the carbon intensity of travel	• Income and working hours are of limited relevance for shelter. • Higher income classes are less likely to not heat	• Rising income increases footprints in both food and clothing domains with clothing being the most income-elastic	• Reduction in the average paid working time are expected to produce emission decreases in most categories. • Schemes targeting only working hours (keeping income constant) would likely not produce significant footprint changes • Fuel poverty needs to be addressed (especially in the case of rising energy prices) with financial saving potentially being a significant driver to not heat.

Table 7: Summary of effects and related policy-relevant considerations.

This study points to key factors that shape energy demand and GHG emissions in high structural carbon-intensive consumption domains, which have important implications for policy design and climate mitigation. Increasing settlement density, while reducing travel distance, income, and car ownership rates, holds potential for significant emission reductions in the mobility domain. Key considerations for carbon mitigation in the shelter domain include dwelling characteristics, such as size, type, time of construction, refurbishment level, as well as income, energy use and household trends. Furthermore, we highlight the strong need to tackle car ownership, air travel and heating. Our study makes a key contribution towards the design of adequate policies to enable a successful transition to sustainability.

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