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A Household's Burden – The embodied resource use of household equipment in Germany

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Abstract

We use cluster analysis and material flow accounting to describe patterns of resource use in German households. Data on socio-demographic characteristics, and expenditures on fuel, electricity and household equipment allow for a differentiation of seven different household types. The corresponding resource use, expressed in Material Footprint per person and year, is calculated based on cradle-to-gate material flows of average household goods. Our results show that patterns of resource use are mainly driven by the use of fuel and electricity and the ownership of cars. The quantified Material Footprints correlate to higher social status and are also linked to city size, age and household size. Affluent, established and/or younger families living in rural areas typically show the highest amounts of durables and expenditures on non-durables, thus exhibiting the highest use of natural resources.

Keywords: Resource use patterns**,** Material Footprint, Carbon Footprint, Cluster Analysis, Households

1 Introduction

It is widely accepted nowadays that private households contribute greatly to the overall environmental impacts of nations (see Stocker et al., 2014, p. 59); Ferrara and Serret, 2008 and Hertwich, 2010, p. 48). Ivanova et al. (2015) for example show that in 2007, 65% of the global Carbon Footprint and 48% of the global raw material use (not accounting unused extraction) was directly associated with household consumption. Traditionally, studies analyzing household consumption use multiregional input-output (MRIO) models based on national statistics (see e.g. Hellweg and i Canals, 2014 and Hertwich, 2005). Miehe et al. (2016) for example, recently analysed greenhouse gas (GHG) emissions of German households in 2004 regarding spatial and financial influences. They found regional differences at federal-state level and particularly differences between urban cores and suburban areas.

However, MRIO models show a number of shortcomings, when it comes to the analysis of household consumption and its environmental impacts (see e.g. Kitzes, 2013 and Moran et al., 2016 on the limitations). While the national and global trade statistics used for MRIO models allow for numerous ways to evaluate global linkages between production and consumption, they are also highly aggregated and aggregated differently for different MRIO tables. The level of detail in sectoral aggregation for example, directly influences output multipliers for consumption-based environmental accounting (see Steen-Olsen et al., 2014). Further shortcomings stem from the underlying assumption of an arbitrary demand that passes throughout all sectors, because it is not necessarily a direct reflection of what households actually consume. In addition, household characteristics cannot be directly drawn from MRIO tables, which in turn would allow to differentiate between household types and their consumption patterns.

Some researchers tackle these problems by combining MRIO models with additional data sets to link environmental load factors to activities, groups or spatial distribution (see for example Jalas and Juntunen, 2015 or Lenzen and Peters, 2009). Nonetheless, the use of MRIO datasets is limited to current or past production recipes, while other methods such as Life Cycle Assessment, can also be used to quantify potentials for environmental improvement based on the technological development of household goods.

In terms of the socio-demographic characteristics, most studies conclude that income, household size and location are the main influencing factors for private consumption (see e.g. López et al., 2017; Tukker et al., 2010). Other than that, behavioural and cultural aspects also seem to play an important role (see Birch et al., 2004 for a collection of articles on driving forces of and barriers to sustainable consumption). Overall, we still miss studies considering the relation of lifestyles, their typical consumption patterns and the associated environmental burden.

In contrast to studies analyzing *ecological or Carbon Footprints* according to household characteristics (see for example Druckman and Jackson, 2009 and Chitnis et al., 2014), only a few studies have tried to elicit and differentiate the use of natural material resources or the *Material Footprint* of and among private households. While comparative research on the Material Footprint among *nations* has grown in the past decade (for example Wiedmann et al., 2015; Bringezu, 2015; Bringezu et al., 2004; Giljum et al., 2008), comparative empirical research on the Material Footprint among *private households* remains limited.

These research gaps – the use of endogenic production recipes as well as missing disaggregated data on household types, consumption patterns and corresponding use of natural resources – cannot be closed by usage of trade statistics and extended input-output (I-O) tables alone. Instead, the method described in the paper combines a different statistical basis with methods from the life cycle assessment (LCA) methodology to differentiate profiles of households and their natural resource use.

By doing so, we seek to find out, if there are typical consumption patterns of natural resource use related to household goods in Germany. The answer to this question depends on whether empirical (micro) data on household equipment and expenditure is sufficient to identify different representative household types and whether bottom-up accounting of natural resources enables us to equip these types with current and future resource profiles. If so, the method could provide beneficial input for existing holistic models or even used directly in future research to measure the success of policies towards sustainable consumption.

The starting point for our analysis is a recent study on behalf of the Federal Environmental Agency in Germany, which quantifies the limits of sustainability for the raw material demand of German households in 2050 (Ahlert et al., 2015). While the quantification in Ahlert et al. (2015) focused on prioritized raw materials, we extend the research methodology by quantifying all life cycle-wide material and energy flows of household goods.

2 State of research

There are a number of studies that combine input-output tables with other data sets to quantify different environmental impacts by households and link it to their consumption.

Ivanova et al. (2015) used the EXIOBASE database, which is already supplemented with additional environmental load intensities for different sectors (sourced from different databases). They calculated the direct and embodied Carbon Footprint (GWP 100a) and Material Footprint (Domestic Extraction) on a global and per capita scale of 43 countries. The United States for example "contribute to 4.9 times higher GHG emissions than the world average from a consumption perspective and to only 3.9 times higher emissions from a production perspective" (Ivanova et al., 2015, p. 528). On average, 80 % of the GHG emissions are embodied in purchases such as shelter or manufactured products. For Material Footprint, 40 % of the extracted materials can be linked to foreign trade. Both indicators show a high correlation with the national GDP.

In another study, Jalas and Juntunen (2015) combined a single I-O table of Finland with datasets of household expenditure and time use to analyse the changes in embedded and direct energy consumption over a period of 22 years (1987 to 2009). The researchers identified which changes in activity patterns, energy intensities and demographics lead to an increase in energy consumption. They showed that, "in the case of Finland, increases in energy consumption are mostly due to housing related consumption and to the intensity effect" (Jalas and Juntunen, 2015, p. 55) such as increase in living space or the increase in consumption of products and services for human activities. Further decomposition analyses revealed, that demographic changes cancelled each other out to some extent, because groups with high energy use (couples without children) and low energy use (elderly households) alike, have higher shares in the overall population in 2009 than 1987.

Using similar types of data sets, Barrett et al. (2013) analyze whether "[...] people in lower socio-economic groups have lower environmental impacts [...] " and how "[...] changes in the distribution of socio-economic groups impact resource consumption[...]" (Barrett et al., 2013, p. 248). The researchers combine the environmental accounts of the Office of National Statistics (ONS) with socio-economic data on the UK using ACORN (A Classification of Residential Neighbourhoods) and COICOP (Classification of Individual Consumption According to Purpose) classifications. One of their preliminary results is that the ecological footprint from car and van use is up to three and a half times higher in the highest socio-economic group compared to the lowest group. The authors also acknowledge the fact, that money spent on products is not necessarily proportional to physical flows of materials, as certain products might be more expensive in order to consume less material and energy.

There are also empirical studies on the subject of resource use in private households and relevant socioeconomic factors in this regard.

Lähteenoja et al. (2008) compared the Material Footprint of 27 Finnish households and Kotakorpi et al. (2008) provided an in-depth analysis of these results in terms of levels and distribution of Material Footprints and some analysis of socioeconomic factors of the households involved. According to Kotakorpi et al. (2008), household goods (excluding their energy use and excluding mobility products) represent 7.5 % of the Material Footprint for an "average Finn" and ranges from 3 to 14 % of the overall households' Material Footprints (0.6 to 5.9 metric tons per person in a year).

Greiff et al. (2017), applying a similar methodology, analyzed the material and Carbon Footprints of 16 different households in Bottrop, Germany. For small and large electronic devices, the researchers calculated a Material Footprint between 0.3 and 4.3 tons per person and year, ranging from 2 to 10 % of the overall Material Footprint. In comparison, Carbon Footprints for the same devices ranged from less than 1 % to 4 % of the overall Carbon Footprints.

In a transition experiment study, Laakso & Lettenmeier (2015) described the Material Footprints of five Finnish households and reported on the experiments of these households in order to reduce their footprints. For household goods, the reduction in Material Footprints ranged from zero to 37 % of the respective Material Footprint for household goods.

Although the share of household goods in the overall expenditure (also see Wiedmann et al., 2006) and overall environmental impact is relatively low, this category appears relevant due to high amounts of stored resources and critical raw materials. As the use of household goods causes the main electricity and fuel use of households, there is also a direct link to the fields of mobility and housing. In terms of the environmental burden of household good production, especially electrical and electronic goods are characterized by fast changing supply chains, rapid technological development, falling prices and high rate of exchanges for new technologies before the old ones fail as a subject of fashion (Reichel et al., 2014, p. 77).

While studies relying on small samples can provide a deeper insight and understanding of consumption patterns and the resource use (Material Footprint) of individual households, they do not yet estimate more general consumption patterns of certain population groups. Those can only be derived by studying larger samples of households and their statistical distributions.

Buhl (2014), for example, shows the resource use of private households for food, housing and mobility broken down among deciles of net household income from representative data for Germany. On average, overall resource use rises as income rises. When splitting the sample based on average net household income, higher incomes show a resource use 1.5 times higher than that of lower incomes. Focusing in even more, the lowest decile shows an average total material requirement of a total of 22.1 tons, whereas the highest decile shows an average total material requirement of 57.2 tons. Thus, the highest decile shows a resource use that is 2.6 times higher than the lowest decile.

Buhl & Acosta-Fernandez (2015) differentiate the resource use of private households further by providing resource intensities of consumption (in terms of kg/€) and time use (in terms of kg/h) of private households in Germany as well as their marginal propensities to consume and to time use with respect not only to income, but also gender, age and education of the head of the household (main income earner) and household composition. Again, higher income correlates with higher consumption in all consumption categories according to COICOP (Classification of Individual Consumption per Purpose). However, a higher level of education, for instance, correlates to higher consumption in housing, but not in food or transportation. Older and male heads of household as well as bigger households show higher expenditures for food and housing, but lower expenditures for mobility. Gender is a highly significant predictor for expenditures and time use alike.

Additionally, Kalmykova et al. (2015) compared the domestic material consumption (DMC) via Material Flow Analysis (MFA) on national (Sweden) and urban levels (Gothenburg, Stockholm) with respect to income, education, household area and car ownership. These authors also found that increasing resource consumption correlates to income and probably as a function of income to education. In addition, "[consumption of] electronics and textiles [in Stockholm] are growing exponentially, even when normalized by population. This is a consequence of a number of factors, such as continual increases in income, residential floor area and technology development in consumer electronics" (Kalmykova et al., 2015, p. 11). Interestingly, Kalmykova et al. (2015) also show that the domestic material consumption (DMC) per capita in the cities of Stockholm and Gothenburg on average is 43 % lower than in Sweden overall.

In light of this research, we still miss empirical research that identifies types of resource use in private households. We further argue that linking representative microdata on household equipment, expenditure and socio-economics with bottom-up accounting of its embodied resource use, might reveal typical environmental profiles in private households. Methods and data for this purpose are described in Sections 3. Results are shown and discussed in section 4 and section 5, while section 6 provides an outlook for further research and data requirements.

3 Methods and data

We integrate a cluster analysis of household equipment on relevant durable goods and their usage into a corresponding analysis of the Material Footprint in order to identify types of resource use in German households. The upstream material and energy flows of household goods are totaled and allocated to the different types of household equipment. Within the methods section, we present representative micro data for Germany on households' equipment and expenditures as well as life cycle inventories (LCI) of such equipment.

3.1 Cluster analysis

Cluster analysis allows to identify *types* of household equipment and its usage and thus helps to address those patterns directly by tailoring more pattern or type specific consumer policies. As such, cluster analysis became a staple in various disciplines as well as an unsupervised learning method for large data sets (see Hastie et al., 2009).

A clustering strategy sorts information on how close, distant or similar two or more individuals or groups are to each other. According to Scheibler and Schneider (1985), Ward´s method yields most robust clustering results based on Euclidean distance measures, when the number of clusters in the underlying population is unknown (unlabeled information), but its full coverage is requested (robust to outliers). We choose to make use of Ward´s hierarchical, agglomerative clustering procedure as we do not know which types of household equipment and usage may be found in Germany.

According to Ward Jr (1963), the "loss of information" by treating two individuals as a single group (e.g. by calculating its mean) can be expressed by the error sum of squares (ESS); more simply, this means the variance that is not explained by the mean. Accordingly, Ward's method to cluster individuals in groups is also called the minimum variance method. The error sum of squares is defined as

$$ESS = \sum_{i=1}^{n} x_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)^2 = \sum_{i=1}^{n}(x_i - \bar{x})^2$$

where x represents the variable's value (e.g. the amount of a particular durable good in the household) of the i-th individual (i.e. household) in an n-sized sample.

This is what Ward calls an objective function for "loss of information" that the grouping procedure desires to minimize. A cluster analysis tries to minimize the sum of the error squares of the clustered individuals until all n are eventually paired to a single group (i.e. hierarchical agglomerative clustering). At each clustering stage, the total ESS is minimized with $ESS_{total} = ESS_j + ESS_k + \cdots + ESS_n$, where j and k represent merged clusters. We make use of the stopping criterion by Duda et al. (2001) in order to find the number of clusters that compromises optimally between generalization and differentiation.

The information about household equipment and its usage relies on the national survey of household income and expenditure (EVS) for Germany in 2008 provided by the German Federal Statistical Office (Destatis). The EVS is a representative sample of Germany's income, expenditures and household equipment comprising 44,088 households for 2008. The EVS is the only dataset available that offers a representative picture of equipment and consumption patterns along socioeconomic characteristics of German households.

We cluster the surveyed households according to their household equipment and usage, taking into consideration 14 consumer durables in terms of household equipment (i.e. the number of each durable present in households) representing transportation; recreation; information and communication; housing and routine household maintenance; and two corresponding consumer non-durables (electricity and fuel in terms of expenditures) accounting for the usage of the durables. Table 1 gives an overview of the variables entered in the cluster analysis (durables and non-durables)

With respect to non-durables, we give households' average expenditures in 2008. The expenditures on the non-durables electricity and fuels are used as proxies for the usage of household appliances and transportation vehicles. We assume this is justifiable, since electricity and fuels are rather homogenous goods in Germany that do not differ much with respect to price.

Table 1: Description of household durables and non-durables

Variable	Obs	Mean	Std. dev.	Min	Max
Equipment (no.)					
Car	11022	0.4450191	0.6072619	0	6
Car, used	11022	0.6810016	0.7490975	0	5
Motorcycle	11022	0.1516059	0.449386	0	7
Bicycle	11022	2.087824	1.56506	0	9
DVD player	11022	1.210488	1.122061	0	9
TV	11022	1.596806	0.9273691	0	8
PC, desktop	11022	0.9096353	0.8559212	0	9
PC, mobile	11022	0.4570858	0.6586551	0	5
Game console	11022	0.3117402	0.7790504	0	9
Refrigerator combo	11022	1.254128	0.5314863	0	8
Freezer	11022	0.6546906	0.6156882	0	4
Dishwasher	11022	0.725186	0.4717391	0	3
Microwave	11022	0.7411541	0.4894785	0	4
Mobile phone	11022	1.699873	1.119937	0	9
Usage (in €)					
Motor fuels	11022	1377.716	1228.506	0	13376
Electricity	11022	750.8293	589.4499	0	11620

Note: Equipment is given in terms of the number of each durable (Car, car used, etc.) present in households. Usage is given in terms of the households' yearly expenditures on motor fuels and electricity.

Data: 2008 National Survey on Income and Expenditure for Germany

3.2 Material Flow Accounting – the Material Footprint

The resource use or Material Footprint of the household clusters was calculated using the MIPS method. MIPS (Material Input per Service) is a Material Flow Accounting (MFA) method, which accounts for all natural material resources from nature on a life-cycle scale. It was developed in the late 1990s (Schmidt-Bleek, 1998; Schmidt-Bleek and Wuppertal Institut für Klima, Umwelt, Energie, 1998) as a rough measure for the overall environmental burden a product carries (the "environmental backpack"). Since then, it has been employed for extensive studies on the resource efficiency and productivity of different sectors, companies and processes, as well as the activities of households (see Liedtke et al., 2014 for examples). MIPS can be calculated using LCA software and linked to LCI databases such as ecoinvent (see also Wiesen et al., 2014; Wiesen and Wirges, 2017).

Natural resources in MIPS are inputs from nature, which are extracted over the life cycle to fulfill a certain purpose or service in the technosphere (similar to the functional unit of an ISO 14040/44 LCA). These resources are classified in up to five categories: abiotic resources, biotic resources, water, air and soil erosion. In contrast to LCA methods in general and to abiotic depletion indicators in particular, MIPS also accounts for material flows which have not been put to a direct economic purpose, such as overburden, by-catch or crop waste on site.

We used the OpenLCA software (Ciroth, 2007), the ecoinvent database in the versions 2.2 and 3.1 (see Frischknecht et al., 2005) for framework) and the aggregated resource use indicator Material Footprint (MF_{ab+bi}) (Liedtke et al., 2014, p. 550) for modeling and quantification purposes. The Material Footprint aggregates the use of abiotic and biotic resources from nature over the defined scope of the life cycle. As the intended purpose of this study is to link household equipment to the corresponding resource use, a cradle-to-gate analysis was conducted: extraction of raw materials for production (including material losses and energy demand), transportation to production site, pre-forming of finished materials, and assembly. Use phase, End-of-Life (EoL), other transportation and packaging were excluded. The latter was omitted because packaging data was not available for all products. For spatial system boundaries, European data was preferred wherever possible, but provision of individual materials could also be global (e.g. extraction of gold for electronics) or national. The timeline is one year within the estimated lifetime of products. The MF_{ab+bi} therefore amounts to kg of abiotic and biotic resources per cluster or household type (HH) and year [kg/(HH*a)] by

$$MF_{HH} = \sum_{i}^{n} MF_i$$

$$MF_i = \frac{N_i \times \left(MF_{composition_i} + MF_{material\ losses_i} + MF_{preforming_i} + MF_{assembly_i}\right)}{LT_i}$$

where MF is the Material Footprint of product i, N_i the number of these products in a household and LT_i the estimated lifetime of the product.

For calculation, data on material type and composition had to be matched to ecoinvent processes for European, global, German or other production sites (in this order of preference). For some materials, either no corresponding process could be found or the original data source did not specify the material type in such a manner that it could be matched to a certain process in ecoinvent. For both cases, substitutional processes were selected, representing bulk materials (e.g. mass plastics) or materials with similar functions. While the assembly of electronic products, if not otherwise specified in the source, was assumed to be similar to the assembly of an LCD display, preforming was often based on assumptions. In general, consistency went before accuracy, meaning that the same assumptions for different products were made if a lack of data prevented a more accurate calculation. The preforming of bulk plastics, for example, was usually assumed to be a mix of 50% injection molding and 50% extrusion.

The appendix lists all primary data sources and assumptions made (appendix B). It also includes an example for a material inventory (appendix C). In addition, some materials and processing steps were cut off, due to lack of data or very low impact to the results (see appendix A).

Primary data sources included final ecoinvent processes for cradle-to-gate products (which were deemed to have the best available data); this was followed by literature on life cycle-wide material and energy flows of average European products such as the EuP preparatory studies mandated by the European Commission.[1] All sources are publicly available, but do not necessarily represent current products on the market, as some sources date back to the 2000s.

4 Results

4.1 Types of household equipment and usage

Theoretically, an integrative lifestyle typology for Germany suggests differentiating among nine lifestyles in Germany (Otte, 2005). For the sake of an appropriate typology in our case, interpreting more than nine groups is not supported by theory and is not viable. Statistically, we rely on the stopping criterion by Duda et al. (2001) as described in the methods section. The results of Ward's (1963) clustering procedure suggest differentiating among seven groups of household equipment and its usage in Germany according to the Duda-Hart stopping rule (see appendix D in the supplementary material for results on the Duda-Hart stopping criterion and optimal cluster solution).

Table 2 summarizes the results from the cluster analysis. As can be seen, Groups 1 and 2 are closest to the overall mean in terms of the household equipment as well as socio-economics characteristics– they are the mainstream groups. Group 2 is clearly the younger group of the both. They are not very distinct in terms of household equipment, but they are in terms of expenditures on non-durables. Group 1 shows higher expenditures for electricity than Group 2, but lower expenditures for motor fuels.

Group 5, a disadvantaged group in terms of socio-economic characteristics, shows the lowest average total of household durables. It shows the lowest amount of durables and the lowest expenditures for non-durables. Main income earners in this group are relatively young, female and jobless, and live in bigger cities. Households in this group show the lowest levels of income, dwelling size and household size, indicating a rather disadvantaged situation. In contrast, Groups 6 and 7 show large numbers of household equipment and high expenditures for electricity and motor fuels. Group 6 turns out to be the wealthiest group. Households in Group 7 show similar characteristics, but on a lower level with lower income, size of household and dwelling. Group 4 can be described by having more expenditures for electricity than motor fuels, which is remarkable among the seven clusters and clearly distinguishes this group from the others. Main income earners in Group 4 are relatively old, with a great deal of living space in relation to household size, which points to empty nests in this case. Group 3 seems to be placed between the reference mainstream in Groups 1 and 2 and the high equipment and expenditure Groups 6 and 7. Group 3 are younger and households include more members, which suggests families rather than empty nests.

Our cluster analysis suggests that similar patterns appear in pairs. Levels of equipment in Groups 6 and 7 are highest, followed by Groups 3 and 4, and Groups 1 and 2. The latter represent average patterns and levels of equipment in a German household. Those help to interpret findings by referring to those as reference points. Group 5 shows a

[1] See http://www.eup-network.de/product-groups/preparatory-studies/

significant drop in equipment levels, a relatively high share of TVs and microwaves, but a relatively low share of bicycles[2].

We interpret the household types as following: Group 1 is the older mainstream. Group 2 is the younger mainstream. Group 3 is a well-equipped, established group. Group 4 is the electricity consumer. Group 5 is the disadvantaged low-level consumer. While group 7 is a fuel consumer, group 6 is the wealthiest group in terms of socio-economic characteristics and amount of durables in the households.

[2] In order to find a small but distinctive number of groups, it is also possible to use a graphic representation – a dendrogram. The dendrogram is the decision tree of the clustering procedure (see Figure 1 in Supplementary Material 1 for the dendrogram). The dendrogram shows that Groups 1 and 5 are the largest groups; Groups 6 and 7 are the smallest groups. In subsequent cluster steps, the first two groups would have been merged with each other as well as the third and fourth, and Groups 6 and 7, since they show the lowest dissimilarity to each other. This suggests that those pairs of groups may show similarities, whereas Group 5 represents rather exclusive patterns of equipment and expenditures. Groups 1 and 2 constitute the largest groups. We assume that those groups represent the modus of household equipment or reference to all other groups.

Table 2: Cluster means of household durables and non-durables

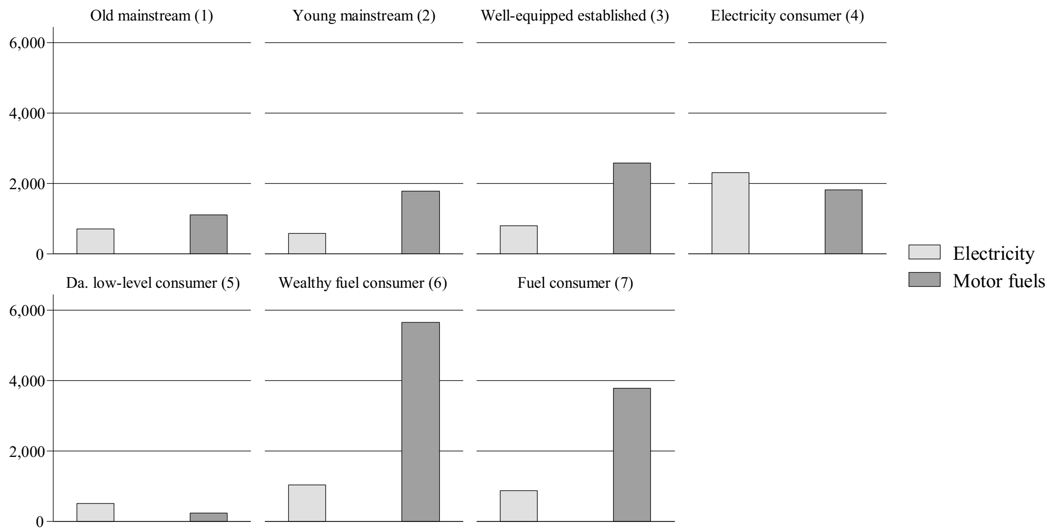
Cluster	1	2	3	4	5	6	7	total
Household type	Older mainstream	Younger mainstream	Well-Equipped Established	Electricity consumer	Disadvantaged low-level consumer	Wealthy fuel consumer	Fuel consumer	
Equipment								
Car	0.50	0.49	0.57	0.59	0.26	0.69	0.63	0.45
Car, used	0.67	0.78	1.03	0.93	0.33	1.46	1.26	0.68
Motor cycle	0.14	0.17	0.24	0.23	0.06	0.34	0.33	0.15
Bicycle	2.16	2.27	2.75	2.84	1.38	3.03	2.87	2.09
TV	1.63	1.60	1.85	2.04	1.28	2.14	2.07	1.60
DVD player	1.19	1.38	1.63	1.60	0.79	1.92	1.77	1.21
PC, desktop	0.91	0.94	1.22	1.35	0.60	1.49	1.29	0.91
PC, mobile	0.43	0.53	0.56	0.57	0.32	0.94	0.71	0.46
Game console	0.27	0.32	0.52	0.52	0.18	0.59	0.49	0.31
Mobile phone	1.68	1.84	2.24	2.21	1.16	2.83	2.53	1.70
Refrigerator combo	1.27	1.23	1.36	1.55	1.12	1.52	1.43	1.25
Freezer	0.71	0.63	0.77	1.00	0.47	0.90	0.82	0.65
Dishwasher	0.79	0.79	0.90	0.93	0.50	0.94	0.90	0.73
Microwave	0.76	0.77	0.83	0.88	0.63	0.93	0.85	0.74
Total	13.12	13.73	16.47	17.24	9.07	19.72	17.93	12.93
Usage								
Electricity	706.62	591.12	796.90	2309.19	521.27	1038.09	881.66	750.83
Motor fuels	1111.06	1776.31	2584.71	1821.64	238.29	5657.06	3788.55	1377.72
Socioeconomics								
Sex	1.32	1.31	1.22	1.23	1.51	1.25	1.25	1.36
Age	53.18	48.47	47.56	52.96	55.99	46.65	46.62	52.27
Education	2.49	2.65	2.72	2.53	2.37	2.85	2.72	2.52
Employed	0.62	0.78	0.87	0.72	0.40	0.97	0.90	0.63
City size	2.86	2.80	2.53	2.47	3.30	2.07	2.39	2.89
Dwelling owner	0.60	0.55	0.70	0.83	0.34	0.79	0.70	0.54
Dwelling size	102.88	101.40	120.65	136.43	77.92	133.39	120.61	100.26
Household size	2.26	2.37	2.85	2.96	1.62	3.14	2.99	2.24
Net household income	10216	10833	13804	13993	6769	17069	14703	10223

Note: Note: Sex (1 = male) and age of the household's head, education from [1] no educational degree to [4] university degree; monthly net household income in classes from [1] lower than €300 to [8] more than €5,000, city size from [1] below 5,000 inhabitants to [5] half a million inhabitants. Electricity, motor fuels, net household income in euros per year

Data: 2008 National Survey on Income and Expenditure for Germany

The amount of durable goods in the specific clusters shows no highly variable distribution of household durables across the seven groups. All groups show a low variation of patterns of household equipment. Differences occur when the levels of household equipment are taken into consideration. By far a more distinct picture emerges if one looks at expenditures for electricity and fuels (see Figure 1). Group 1 differs from Group 2 by showing a lower level of fuel consumption. Importantly, Group 4 differs from Group 3 by showing relatively higher expenditures for electricity than for fuels. This is remarkable because the marginal consumer costs of fuels are considerably higher than for electricity. It indicates the highest consumption of electricity across groups. Groups 6 and 7 show the highest consumption of fuels. The levels of household equipment correspond to a large extent with levels of usage. A low level of household equipment suggests a low level of energy consumption with respect to fuels and electricity. However, this does not necessarily hold true throughout the groups, as the usage pattern in Group 4 shows.

Figure 1: Yearly expenditures for motor fuels and electricity per household in Germany



Note: "Da." stands for Disadvantaged

Data: 2008 National Survey on Income and Expenditure for Germany

The next section examines if the different types of household equipment and usage in terms of the amount of household durables, and expenditures on electricity and fuels, mirrors the typical resource use of those households. Do we find different types of resource use in German households, and if so, how do they manifest themselves and what are the reasons for this?

4.2 Material Footprints of household equipment and usage

Table 3 shows the final MF results for each product per item and per year of lifetime. The highest MFs were calculated for cars and desktop PCs (more than 1 ton per year); the lowest for smartphones and DVD players (less than 50 kg per year). Most other products range from 200 to 450 kg per year. The values for estimated lifetime (average duration of use in household) are drawn from a recent survey conducted in the course of the “Globally Sustainable Material Prosperity Standards” project on behalf of the German Federal Environment Agency (UBA) (Ahlert et al., 2015).

The resource use of fuel and electricity was also modeled in OpenLCA and is based on the ecoinvent database. The conversion from expenses into amounts is based on average

German prices for electricity (Bundesnetzagentur, 2014) and fuel (Statistisches Bundesamt et al., 2015) and a fuel mix for German households based on mileage, density and average fuel consumption in Ahlert et al. (2015).

For reasons of comparison, the Carbon Footprint[3] of all products was calculated in addition. Its calculation is based on the same LCIs and assumptions, and therefore correlates closely to the MF results (r = 0.988), with the highest deviations for game consoles, microwaves, desktop PCs and laptops. These deviations can be attributed to precious metals in the electronic components and nickel in the stainless steel, because these materials require relatively high amounts of abiotic resources during the extraction phase compared to iron or copper, for example. If CF and MF values for fuel (gasoline, diesel) and electricity are included, Pearson correlation remains high ($r = 0.987$).

Table 3: MF and CF results for analyzed products

Product	Lifetime	MF per item	CF per item	MF per year	CF per year
Car	10.7 a	57,723 kg/item	8,095 kg CO2-eq./item	5,395 kg/a	757 kg CO2-eq./ a
Motor scooter	13.0 a	2,649 kg/item	448 kg CO2-eq./item	204 kg/ a	34 kg CO2-eq./ a
Bicycle	14.0 a	761 kg/item	156 kg CO2-eq./item	54 kg/ a	11 kg CO2-eq./ a
Television	9.4 a	7,195 kg/item	640 kg CO2-eq./item	765 kg/ a	68 kg CO2-eq./ a
DVD player	9.0 a	447 kg/item	43 kg CO2-eq./item	49 kg/ a	5 kg CO2-eq./ a
PC, desktop	7.2 a	7,758 kg/item	572 kg CO2-eq./item	1,078 kg/ a	79 kg CO2-eq./ a
PC, laptop	6.3 a	2,244 kg/item	141 kg CO2-eq./item	356 kg/ a	22 kg CO2-eq./ a
Game console	9.0 a	3,031 kg/item	158 kg CO2-eq./item	337 kg/ a	18 kg CO2-eq./ a
Smartphone / Mobile phone	4.5 a	220 kg/item	33 kg CO2-eq./item	49 kg/ a	7 kg CO2-eq./ a
Refrigerator / freezer combination	12.6 a	5,578 kg/item	491 kg CO2-eq./item	443 kg/ a	39 kg CO2-eq./ a
Freezer	13.6 a	5,308 kg/item	455 kg CO2-eq./item	391 kg/ a	34 kg CO2-eq./ a
Dishwasher	12.3 a	3,089 kg/item	329 kg CO2-eq./item	251 kg/ a	27 kg CO2-eq./ a
Microwave	12.1 a	4,098 kg/item	228 kg CO2-eq./item	338 kg/ a	19 kg CO2-eq./ a

Data: Own calculations

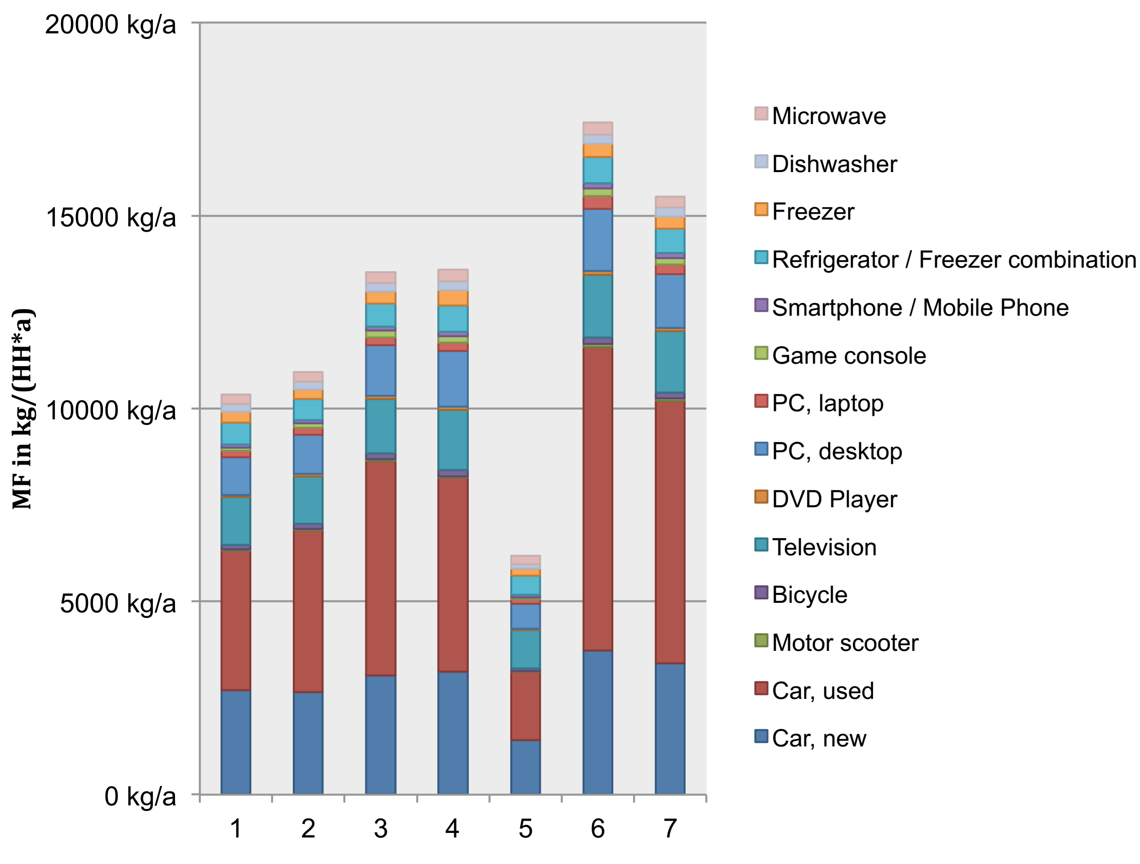
[3] The GWP 100a factors in the 4th IPCC report were used (Qin et al., 2007).

We distinguish between Material Footprints for household equipment and their usage, because the calculated overall electricity consumption in the clusters is caused by more than the captured electric devices in this paper.

Figure 2 shows the results on the embodied resource use for the equipment of the household types. As expected, the car dominates the MF in all seven types. Comparably high MFs can be attributed to televisions, desktop PCs, and refrigerators and freezers.

The "Wealthy fuel consumer "(Group 6) exhibits the highest MF with 17.4 and the "Disadvantage low-level consumer" (Group 5) the lowest with 6.2 tons per year. "Well-equipped established" (Groups 3) and "Electricity consumer" (Group 4) require similar amounts of resources for their equipment; this is also true for "Old mainstream" (Group 1) and "Young Mainstream" (Group 2), which corroborates the findings of the cluster analysis. While the two mainstream groups 1 and 2 show differences in the resource use for cars, "Well-equipped established" (Group 3) and "Electricity consumer" (Group 4) also differ in their MF for electronics.

Figure 2: Material Footprint of seven groups according to household equipment



Group 1: Old mainstream; Group 2: Young mainstream; Group 3: Well-equipped established; Group 4: Electricity consumer; Group 5: Disadvantage low-level consumer; Group 6: Wealthy fuel consumer; Group 7: Fuel consumer

Data: own compilation

The differences in resource consumption observed here are not necessarily an indicator of high and low resource consumption or comparable resource-intensive equipment. In general, resource use per person differs to a lower degree and is nearly negligible for the quantified electronic equipment. In this case, the resource use of a "Wealthy fuel consumer" (Group 6) exceeds that of a "Disadvantage low-level consumer" (Group 5) only by a factor of 1.5, which is about half of the difference among households. In addition, Groups 1 to 4 do not exhibit any major differences overall, even if vehicles are included in the MF. On the other hand, large households (more people sharing the same products) do not necessarily require fewer resources per person due to economies of scale[4].

Since the MFs of all inventoried items and groups are very much alike on a per person scale, with the exception of the car, it is feasible to compare them against the more heterogeneous consumption of electricity and fuel.

For all groups, the MF of the vehicles is higher than the resource use for fuels, but to a different extent. The "Disadvantage low-level consumer" Group 5, for example, exhibits a MF for its vehicles that is about ten times higher than the MF for its fuel consumption, while the MF for vehicles in the "Wealthy fuel consumer" Group 6 exceeds the MF for its fuel by a factor of only 1.5[5].

With the exception of Group 5, all CFs for vehicles are lower than CF results for fuel (factors of 0.21 to 1.39). This is to be expected, as the greenhouse gas emissions for the usage of a vehicle over its lifetime (in terms of fuel combustion) are usually higher than for its production and end-of-life.

Since the original statistics include only a limited number of non-vehicles, one cannot add up the resource requirements of electronics to the MF results of the yearly electricity consumption in a consistent manner. Nonetheless, electricity seems to change the relations among the seven household clusters. With the exception of "Electricity consumer" (Group 4), all groups exhibit a very similar resource use for electricity. MF results range from 5.8 to 7.6 tons per year. In contrast to other resource requirements, Group 5 (lowest MF in goods and fuel) now exceeds most of the other groups and its difference to Group 6 (highest MF in goods and in fuel) in this area is very low. Group 4, with a nearly average Material Footprint of goods and fuel, consumes the most electricity per capita. Its corresponding resource use for electricity exceeds all other groups by factors of 2.4 to 3.1.

Lastly, we compare the number of items in a household and the corresponding Material Footprint with the mean of each item of all clusters, allowing for a differentiation in resource use based solely on the piece of household equipment. As shown in Figure 3, the two mainstream households, Groups 1 and 2, are slightly below, and Groups 3 and 4 slightly above average, both in item quantity and its resource use. The high income Groups 6 and 7 exceed all other clusters in both categories, while Group 5 shows the lowest quantity of items and resource use. In all cases except for "Electricity consumer" (Group 4), the deviation for resource use is higher than the deviation for quantity. This can mainly be attributed to the number of resource-intensive cars each group owns on average.

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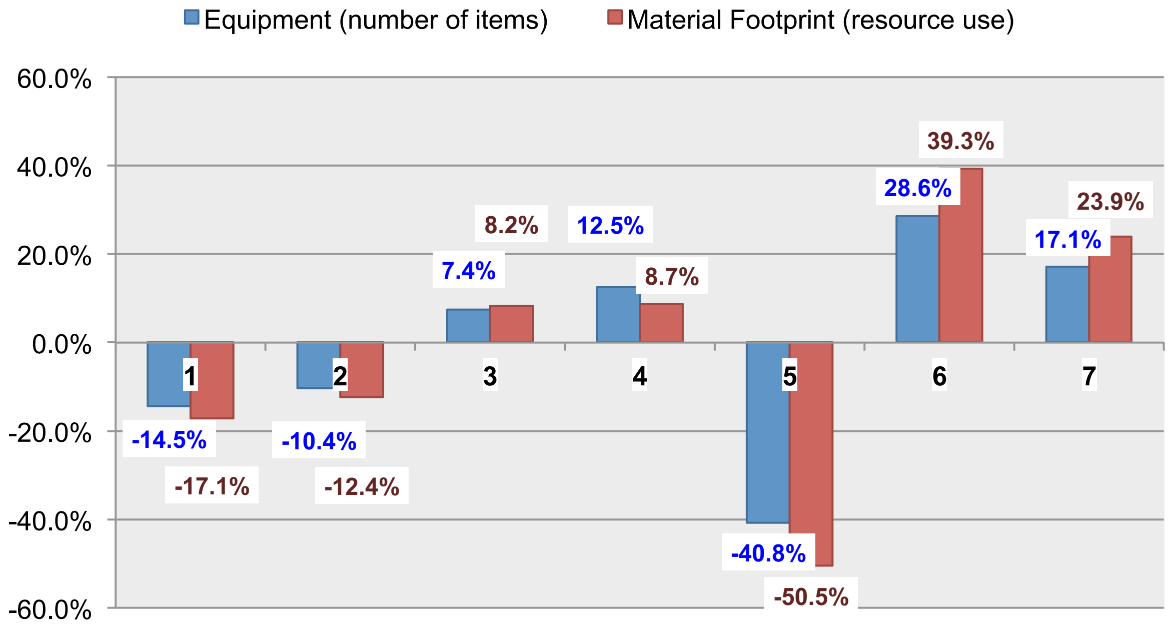
[4] It is important to note, however, that the calculation of MFs is based on the same products and the same lifetimes for every product. Households may differ with respect to the cost, material composition and lifetime of the goods in their household equipment.

[5] This discrepancy cannot be explained by the available data alone (number of cars and expenses on fuel). In addition to comparably low amounts of mileage, certain households might drive in a more environmentally friendly way or own more fuel-efficient cars.

Figure 3: **Deviation of clusters from the average of each item group**



Group 1: Old mainstream; Group 2: Young mainstream; Group 3: Well-equipped established;
Group 4: Electricity consumer; Group 5: Disadvantage low-level consumer;
Group 6: Wealthy fuel consumer; Group 7: Fuel consumer

Data: own compilation

5 Discussion

In regard to our research question, linking representative microdata consisting of differentiated information on expenditures, equipment as well as socio-economics of private households with respective bottom-up accounting of its natural resource use enabled us to describe seven different German household types and their corresponding profiles of natural resource use. The differences among these seven groups are closely linked to the environmental burden of household equipment and it use in terms of embodied natural resources.

By comparison, the results on the Material and Carbon Footprint of the 16 German households analyzed by Greiff et al. (2017) are in close proximity to the results of the study at hand. They are based on comparable calculation methods for the footprints of goods, but focus on a small sample of 16 households in the German city of Bottrop and include other areas of household consumption. The Carbon Footprint of fuel combustion in Greiff et al. (2017) for example ranges from 730 to 8,900 kg/a (CO_2 equivalents per household and year), while we calculated a range of 330 to 8,000 kg/a. We calculated a CF for fuel combustion of 2,000 kg/a if using the total sample and a mean value of 3,400 kg/a among the seven groups. The mean CF for fuel combustion in Greiff et al. (2017) is at 3,100 kg/a.

For the CF of vehicle ownership, Greiff et al (2017) calculated a range from 280 to 2,400 kg/a with a mean of 620 kg/a. Our method resulted in ranges from 460 to 1,700 kg/a with 700 kg/a on average (total sample).

For electric appliances Greiff et al. calculated a CF range of 203 to 480 kg/a with a mean (households) of 367 kg/a. The CF of electric and electronic devices in this study ranges from 240 to 460 kg/a with an average (total sample) of 319 kg/a.

As stated in the introduction, there are a number of studies which calculate annual greenhouse gas emissions for households in a certain region (see e.g. Druckman and Jackson, 2009) for the UK or Jones and Kammen, 2011 for the USA). They usually apply direct and embodied emission factors based on regional input-output tables and focus on the distribution of these emissions between different sectors or countries. As such, results in those studies cannot be directly compared to our findings. However, the average household values in these studies for e.g. vehicle manufacturing, fuel combustion, electricity use and production of appliances are within the range of the life-cycle wide emissions in our study.

Regardless of these differences, the main result of the described assessment is that information on household equipment allows for a description of typical resource profiles of households. It can be used to quantify the environmental burden by all or only parts of the household goods and can be compared to other areas of household consumption such as housing.

Still, the identified research gaps could only be closed partially. Since the socio-economic dataset on household equipment did not include detailed technical information on the types of goods purchased and used by German households, we could not test whether technological trends such as the electrification of mobility or the *internet of things* would influence our results. Despite that, one can argue the case that current LCA methods are advanced enough to quantify these effects in future research. Dewi (2016) for example showed that LCA methods can be combined with models for technological foresight and Onat et al. (2016) successfully integrated LCA models for vehicles into a dynamic ex-ante assessment of sustainability including Life Cycle Costing (LCC) and Social Life Cycle Assessment (SLCA).

Additional socio-economic characteristics as well as data on the use of fuel and electricity were required to generate an appropriate typology of household groups beforehand. Household consumption cannot significantly be differentiated by the ownership of household goods but rather by the use of them and thus by electricity and fuel consumption. We conclude that the behavioral aspects are deciding factor for differentiating household consumption. This corroborates the findings of other studies on the environmental burden of households (Barrett et al., 2013; Birch et al., 2004b; Ivanova et al., 2015; Tukker et al., 2010).

Our findings also show that low amounts of durables in households do indeed correspond to low usage in terms of electricity and fuel use in total. The patterns of electricity and fuel use differ in Germany to a relevant extent though. We found general patterns that revealed higher expenditures for electricity than for fuels. That is remarkable, given the high differences in marginal costs for electricity and fuels. However, the differences in use patterns stem mainly from the high variation in fuel use among the groups. This suggests that typical patterns of household equipment and its usage are related to mobility patterns in terms of cars and motor fuels. For instance, the "Electricity consumer" may represent empty nests of seniors, which also suggests old and inefficient equipment of electronics and appliances. Additionally, the very high expenditures for motor fuels of the "Wealthy fuel consumer" may be explained by the fact that these households are younger families living in more rural areas often requiring a car due to the lack of public transportation infrastructure. Both, the

“Electricity consumer” as well as the “Wealthy fuel consumer” represent typical consumption patterns in Germany. Whereas the first type is best described by age of household members at respective age of equipment and appliances, the latter is best described by fuel consumption, family status and living area. Specific consumer policies, either addressing more resource efficient consumption of electronics or more resource efficient mobility may take into consideration the specifics of the typical electricity (age) and fuel consumption (family status and living area) accordingly.

In accordance with the literature (see e.g. Tukker et al., 2010), we found that higher amounts of household durables and higher expenditures on electricity and fuels are closely linked to higher social status in terms of net household income, employment status, and home ownership. Moreover, our clustering results suggest that differences may also be linked to city size, age and household size. We conclude that affluent, established or younger families living in more rural areas typically exhibit the highest amounts of durables in their households and the highest expenditures on non-durables, especially on fuels. In contrast, a rather precarious milieu of young, female and jobless people living in cities shows the lowest amounts of durables and lowest expenditure on non-durables. These findings coincide with results from Miehe et al. (2016).

When it comes to typical patterns of resource use, results show at first glance that there is a high correlation between the equipment level of household groups and the corresponding Material and Carbon Footprints. The major differences are attributed to car ownership (highest environmental burden per item), while electronics seem to be of less importance.

The importance of car ownership for the overall environmental burden of households is also emphasised in other studies. Ornetzeder et al. (2008) compared the carbon intensities of a car-free household in Vienna to a household with similar characteristics in close proximity without the car-free feature. As a result, the car-free household shows a lower environmental burden in terms for energy use and ground transportation, but higher burdens in the areas of air transport, nutrition and other consumption areas[6].

The results also show, that consumer electronics and their resource use are evenly spread among the household groups on a per person scale. It seems that the main contributors to electricity use in households (heterogeneous distribution among household groups) are by themselves not a relevant factor for different types of resource use.

The calculated environmental impact for the production of household equipment is considerably lower than for its use. Our findings suggest that policies on sustainable consumption and sustainable use of natural resources (and carbon emissions) could focus on typical patterns of usage rather than the resources embodied in products themselves. Policies on eco-efficient design could concentrate on the design of the sustainable use or consumption of products rather than the sustainable use of materials for production.

[6] While the extent of these indirect rebound effects might lessen with the use of an electric vehicle, it is important to note, that electric cars can show higher Material Footprints per mileage than conventional cars, if incorporated into a non-renewable energy system (see also Frieske et al., 2015).

6 Outlook

The approach in this paper focuses on the ownership and use of goods in different types of private households. The clustering of representative survey data on expenditures on homogenous goods and information on most relevant durable goods is sufficient to describe types of resource use in private households appropriately. Future research could, however, combine cluster analysis with regression analysis in order to test our findings on statistical significance with regard to socio-economic predictors of the expected patterns. Moreover the data used and method developed do not yet sufficiently reflect the dynamics of the way households actually live. This would require a complex allocation model, which incorporates a more accurate description of lifestyles in private households. A model based on time use data rather than expenditure may be suitable for such an undertaking (see Buhl and Acosta-Fernandez, 2015 for such an approach).

Apart from the limitations of the descriptive clustering procedure, a number of data gaps were identified. From the point of household statistics, a more detailed and comprehensive list of household expenditures and equipment is necessary. For example, the statistics for 2008 do not include environmentally relevant goods such as ovens and washing machines. This also weakens the relationship between the products analyzed in this paper and the overall electricity use of households.

In addition, the aim should be to not only quantify product groups (e.g. car), but also product types (e.g. low, middle, high class car). Whether product types with higher levels of performance or higher than average prices lead to different results is up to future research. Further information on the prices paid for the durable goods under study could provide valuable information on the quality of those products. Additionally, the prices paid in combination with information on expenditures would enable researchers to account for the amount of goods consumed. This data extension might affect the results, in particular for resource-intensive products such as cars, desktop PCs and laptops.

The overall data availability for Material Flow Accounting is good, but could still be improved. LCI databases have grown to become a helpful tool for quantifying the material and energy flows in the life cycles of products. The ecoinvent database is frequently updated and includes the majority of bulk materials and common material compositions. The method can be adapted to other LCA impact categories and other statistics or empirical data on household equipment. In terms of literature on the material flows of household goods, the EuP preparatory studies have proven to be reliable sources. However, there is currently no information on average smartphones and other modern ICT products, which have become more and more important in people's everyday lives. There is also still a need for additional data regarding material losses and energy demand during assembly, including pre-assembly of finished materials. By its nature, the method described in this paper would be extendable to other goods or even product-service systems (SPSS[7]). Depending on the availability of data on household and life cycle inventories (LCI) of equipment, it could also be used to differentiate among product types and product applications in different households.

[7] According to Mont (2002, p. 239), SPSS is "a system of products, services, supporting networks and infrastructure designed to be competitive, satisfy customer needs and have lower environmental impact than traditional business models."

The two environmental indicators, Material Footprint for natural resource consumption and Carbon Footprint for greenhouse gas emissions, complemented each other. While correlation is high for the main contributors to the environmental burden (electricity and fuel), differences in the trend emerge if goods are analyzed in detail. Since the Material Footprint is highly sensitive to the amount of precious metals in electronics, it helps to identify environmental hotspots, which would otherwise be neglected.

In order to validate these findings, future research should focus on advancing the methodology by considering different types of products including consumables such as food and incorporating not only the possession of goods but also possible differences in usage and technological development. Such an extension to the model and its data could also be beneficial to research on household consumption with the help of MRIO tables. By matching the outputs of our research to the inputs and coefficients of MRIO analysis, a *consumption module* could be generated and incorporated.

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