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How Technologial Potentials are Undermined by Economic and Behavioural Responses

The Treatment Effect of Endogenous Energy Efficiency Measures

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Abstract

Governments worldwide spend increasing amounts of money on policy schemes to reduce energy consumption and related carbon emissions. We investigate the actual treatment effect of energy efficiency measures and therein compare actual demand responses to technological potentials. Based on a demand system analysis of household data and by approximating unobserved energy awareness, we find economic and behavioural responses that counteract expected savings from energy efficiency. Results show strong rebound and even backfiring effects but also suggest heterogeneity of the effectiveness driven by behavioural concepts, such as sunk cost fallacy or habit formation. Understanding these can contribute to target-oriented policy designs and increased effectiveness and efficiency of policies.

Keywords: Policy evaluation, household demand, unobserved heterogeneity, energy efficiency

JEL classification: C21, D12, Q58

1. Introduction

Different countries worldwide aim at minimizing the consumption of fossil fuels and hence, carbon emissions. Carbon taxes or cap-and-trade mechanisms are implemented to address negative environmental externalities of fossil fuel consumption. While these are mostly directed at large-scale consumers like the manufacturing industries, transaction costs tend to be disproportionately large within the residential, trade and commerce sectors. For these, second-best policies are implemented.

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Most of these policies aim at changing the stock of energy durable, energy consuming and converting goods as well as improving the thermodynamic characteristics of dwellings. Examples for these policies could be energy efficiency standards, such as the internationally known Energy Star label[1], or policies that reduce financial barriers for investment in energy efficiency, such as subsidies or loans. In recent years, governments have invested increasing amounts of money in such schemes. In 2013, the Obama Administration provided USD 250 million to the Energy Efficiency and Conservation Loan Program in the US Climate Action Plan (White House, 2013). In Germany, in 2015 renovations of buildings to improve energy efficiency are supported with EUR 686 million (BMWi, 2015). In the UK, in 2015 GBP 70 million are available for energy efficiency improvements in the residential sector (DECC, 2015).

A meaningful evaluation of these policies requires addressing effectiveness towards achievement of the programme objectives and cost-efficiency of the policy design. Cost-efficiency focusses on free-ridership as well as non-additionality and was recently discussed in Boomhower and Davis (2014). Whether or not energy consumption and carbon emissions were reduced by a policy is the focal point of effectiveness evaluation. Most evidence on this effectiveness is solely based on engineering calculations and often ignores economic effects. A well-known example is the study on energy efficiency by the McKinsey Company (Granade et al., 2009) which is entirely based on engineering calculations. The UK Government Energy Review Report 2006 (DTI, 2006) does not even mention economic responses to energy efficiency investments (Madlener and Alcott, 2009), either.

That is surprising, as fundamental economic responses have been discussed ever since Jevon (1865). But even in economic studies on energy efficiency investments, the reference level for the effectiveness is generally given by engineering calculations for potential technological efficiency improvements. The actual efficiency improvements, thus demand reductions, are related to these potential technological efficiency improvements. The difference in percentages is quoted as the *rebound effect* (e.g. Greening et al., 2000; Gillingham et al., 2013). The evaluation of effectiveness is therefore strongly linked to understanding the rebound effect. Within economics, demand theory provides arguments for the rebound effect. With reduced demand for energy services due to large-scale implementation of energy efficiency measures, the price for energy drops. Since point price elasticities of demand differ, demand adjustments can be of ambiguous directions and also increase the consumed quantity. At the household level, this direct effect is accompanied by an indirect effect. The additional income from reduced energy consumption can be spent on other goods as well as on further energy services increasing the energy consumption, again.

[1] `https://www.energystar.gov/`

However, next to price and income effects, insights from behavioural economics need to be considered. It needs to be investigated if behaviour counteracts energy savings and further rises the rebound effect. While income effects will have a substantial influence, short-term temptations towards energy consumption should do likewise. Firstly, while individuals will have developed habits in energy consumption prior to implementing an energy efficiency measure (Jessoe and Rapson, 2014), research shows that adaptation to new habits is limited (Neal et al., 2011). Persistence in habits and therefore energy consumption behaviour is likely. An example could be that individuals overheat their homes after an energy efficiency implementation.

Secondly, if we consider mental-accounting and self-licensing, these might also trigger additional demand, in the short term. Under self-licensing, investing in energy efficiency can be regarded as something (ecologically) *good*, due to its positive connotation to climate change. Hence, temptation to consume more energy in the present (which might be seen as something equivalently *bad*) might be permitted by having made the 'good' investment/purchase in the past (Mazar and Zhong, 2010). Further, mental-accounting might classify expected savings from energy efficiency measures as additional short-term disposable income or energy consumption, leading to an even higher energy demand (Thaler, 1990).

As a summary, the previous discussion illustrates two issues of great importance. Ignoring economic as well as behavioural responses in the evaluation of energy efficiency policies will overestimate the effectiveness of energy efficiency measures and the accompanied policies. However, an adequate evaluation of the effectiveness is not trivial, since engineering, economic, and behavioural drivers as well as their interactions need to be addressed.

So far, a large body of literature analysed the rebound effect. Valuable literature reviews are given in Greening et al. (2000), Sorrell et al. (2009) and most recently Gillingham et al. (2013) and Gillingham et al. (2015). Due to the up-to-dateness of the latter articles, we refrain from reviewing the literature once again and refer to Gillingham et al. (2015) for a sound presentation of the status of the academic debate.

Most of recent studies use either experimental (e.g. Davis et al., 2014) or econometric methods (e.g. Frondel and Vance, 2013b). A well known issue with the latter is that demand models used for identification are simplified for methodological practicability rather than microeconomic accuracy (Deaton and Muellbauer, 1980). Sometimes cross-product and income effects are completely ignored. That is suprising, as demand systems that were derived from the expenditure minimization problem of consumers were introduced by Deaton and Muellbauer (1980) and further developed up until Lewbel and Pendakur (2009). These allow among others for aggregation of preferences, seperability, budget-constraints as well as unobserved heterogenity. While energy demand has been explored in such demand modells (e.g. Baker and Blundell, 1991;

Labandeira et al., 2006), the evaluation of energy efficiency measures and thus, the rebound effect, has not been undertaken based on such modelling.

Given the engineering calculation[2] based findings (from such as Granade et al. (2009)) that it is cost-efficient to invest in energy efficiency technologies, actual adoption rates suggest that something drives a wedge between optimal and actual investments. Research on this so-called *energy efficiency gap* argues that this can be explained by heterogeneity among consumers, asymmetric information, and inattention (e.g. Allcott and Greenstone, 2012; Boomhower and Davis, 2014). The marginal individual who implements an energy efficiency measure is either better informed or more attentive to energy costs than extramarginal individuals. This gives rise to a selection problem in the evaluation of energy efficiency measures. If well-informed consumers that are more attentive to energy costs are marginal adopters of energy efficiency measures, they are also more likely to have differing energy consumption patterns (Jessoe and Rapson, 2014). Therefore, unobserved heterogeneity that drives investment and utilization decisions needs to be taken into account (e.g. Kahn, 2007; Kotchen and Moore, 2008, 2007). Within an adequate evaluation of energy efficiency effectiveness, this endogeneity issue needs to be resolved.

In this paper, we investigate the effectiveness of energy efficiency measures by identifying the treatment effect of these on energy demand. Therein, we incorporate economic and behavioural responses to address the rebound effect.

Our analysis makes three main contributions. First, we apply the implicit Marshallian demand system developed by Lewbel and Pendakur (2009) that combines Marshallian and Hicksian demands. To our knowledge, we are the first to evaluate the effectiveness of energy efficiency measures in such a multi-product demand system consistent with microeconomic theory. That is, we explore consumption of different fuel types within the overall household budget. By applying a multi-product approach, we evaluate direct as well as indirect effects on energy consumption simultaneously. Direct effects give consumption responses to the fuel demand that is directly addressed by an energy efficiency measure, while indirect effects also take into account interdependencies with consumption of other goods within the household budget. There has been extensive work on the direct effect (as reviewed by Gillingham et al., 2015), by means of evaluating the price elasticity of demand. However, our approach allows to address both effects at the same time and identify the semi-elasticity of demand with respect to the implementation of an energy efficiency measure.

Second, we rely on an approach from productivity analysis to resolve the selection issue within our demand model. We define unobserved heterogeneity that reflects unobserved energy cost attentiveness and

[2] Engineering calculations represent expected reductions in energy demand from implementation of an energy efficiency measure, considering only thermodynamic improvements and taking demand for the final energy service as fixed.

the information level regarding energy efficiency measures as *energy awareness*. Our analysis approximates energy awareness using the approach by Olley and Pakes (1996). The validity of our approximation approach is tested by investigating the impact of unobserved energy awareness on the decision to implement an energy efficiency measure. Further, we explore how the energy efficiency measures drive energy consumption. Hence, within our application of the Olley-Pakes-Approach, we map unobserved heterogeneity and obtain insights on how unobserved heterogeneity drives energy consumption and the treatment effect of energy efficiency measures.

Our third contribution lies in the identification of behavioural responses to energy efficiency measures. By evaluating and comparing the treatment effect of different energy efficiency measures, we explore whether or not behavioural responses do play a role in the rebound effect. This has not been addressed in the literature so far and our results show that behavioural effects impact significantly on the effectiveness of energy efficiency measures.

We use micro data of German households for 2006-2008. By analysing billing information, we estimate the actual effectiveness of energy efficiency measures, incorporating the rebound effect. Exploring a German dataset is suitable for our approach for several reasons given in Germany. Energy usage is an important topic within the political economy and public attention on energy issues is large. Also, several large-scale promotion schemes for energy efficiency measures are in place.

We find that unobserved heterogeneity is a significant driver of the decision to invest and of energy usage. These results regarding efficiency of policy schemes are overshadowed by the fact that economic and behavioural responses to energy efficiency measures counteract expectations based on technological potentials. Understanding these can contribute to target-oriented policy designs and increased effectiveness and efficiency of policies.

The next section presents the theoretical model followed by the econometric approaches. Data is described in section 3. Results follow in section 4, section 5 concludes.

2. Methodology

In this section, we first discuss our theoretical approach. We point out the resulting endogeneity issue and continue with the econometric application. We explain the methodology of incorporating energy awareness in our models.

2.1. Theoretical Framework

Our modelling reveals the underlying decision process with respect to the choice of energy efficiency measures and consumption of non-durable energy goods. The theoretical framework in Figure 1 presents the drivers of energy efficiency measures and of energy demand. Key policies aim at inducing a reduction in energy demand by supporting the implementation of energy efficiency measures. The implementation then impacts itself on energy demand, but is endogenous. Next to observable characteristics such as socio-economic and building characteristics, unobserved drivers, here energy awareness, determine whether or not a household implements an energy efficiency measure.

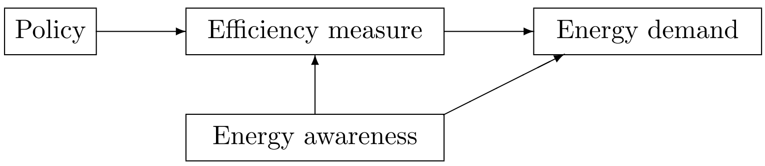

Figure 1: Energy awareness is unobserved but impacts on various causal paths

Energy aware individuals can be described by a larger attention to energy costs. They further possess more information on energy efficiency measures. Accordingly, individuals with a high level of energy awareness should be marginal adopters of energy efficiency measures and could demonstrate a different behaviour regarding energy good consumption. Not addressing energy awareness and neglecting this type of unobserved heterogeneity leads to selection and omitted variable biases and therewith, endogeneity.

We address this endogeneity problem using the approximation approach by Olley and Pakes (1996) and approximate unobserved energy awareness by observed automobile choices. With a given demand for automobile transportation[3], the decision to purchase a more efficient automobile, with lower fuel consumption and corresponding higher mileage[4], depends on the demand for automobile transportation and the awareness of future energy costs. Here, we use specific CO_2-emissions as an inverse equivalence for mileage[5]. Further, we approximate demand for automobile transportation by population density. We assume that in more densily populated areas private transportation demand is lower, given that alternative means of transportation increase in population density. Equation (1) reflects the above mentioned decision making process.

[3] Automobile transportation demand is assumed to be exogenous within our modelling framework. Thus, means of changing automobile demand, such as moving, as well as substitution options are unconsidered.

[4] In particular in the United States of America, mileage describes the automobile fuel economy by means of the ratio of distance traveled per unit of fuel. Often given in miles per gallon.

[5] Specific CO_2-emissions reflect grams of CO_2 emitted by driving one kilometer. Hence, larger specific CO_2-emissions correspond to lower mileage. Data on automobile fuel consumption is not available within the data set.

$$\text{Specific CO}_2\text{-emissions} = f(\text{energy awareness}, \text{population density}) \tag{1}$$

More energy aware individuals should always prefer an automobile with lower specific CO_2-emissions. However, transportation demand intensifies this effect. Meaning, with low population density and thus high demand for automobile transportation, the variable energy costs have a larger share in total automobile costs than with a low demand for automobile transportation. Therefore, consumers with large specific emissions and a high demand for automobile transportation can be considered as comparably energy unaware.

Under the assumption of strict monotonicity in the effect of energy awareness and population density on automobile specific CO_2-emissions, we can invert function f as follows:

$$\text{Energy awareness} = f^{-1}(\text{specific CO}_2\text{-emissions}, \text{population density}) \tag{2}$$

As the exact functional form of this relationship is unknown, we control for energy awareness allowing for semi-parametrical forms. We use a fourth-order Taylor polynomial with all interaction terms (as in Olley and Pakes, 1996). Hence, we construct a measure of the joint effect of unobserved energy awareness and observed population density. Decomposing the unobservables within the decision processes into the approximated energy awareness and the truly random error term resolves the selection and omitted variable biases[6].

We begin with modelling the decision to implement an energy efficiency measure using an ordered probit approach, taking into account observed characteristics and unobserved energy awareness. This way we get a better understanding of the underlying decision making process and show that energy awareness does have an effect within this decision. As a next step, we estimate a consumer demand system for non-durable energy goods to explore the treatment effect of energy efficiency measures. We resolve the endogeneity issue by accounting for energy awareness.

2.2. Model I - Ordered Probit Approach

Within the ordered probit approach, the dependent variable m is the implementation of one or more energy efficiency measures. Thus, we focus on the question of whether or not efficiency measures have been implemented rather than exploring them separately. m is a discrete, ranked and ordinal variable that incorporates the number of all energy efficiency measures implemented by each household since 2002. m

[6] An illustration can be found in Appendix C.

captures the following measures: roof or top storey ceiling insulation, basement ceiling insulation, outer walls insulation, replacement of windows as well as replacement of the heating system. The effectiveness of these measures is differing in practice. These differing effects however are excluded from our analysis and average energy efficiency effects alone are captured in m. Resulting coefficient estimates are interpreted correspondingly.

We derive a model that regresses observed and unobserved household characteristics on m. We denote exogenous observed and preference related characteristics, such as demographics and dwelling conditions, by vector $\vec{z}$. In addition to $\vec{z}$, we control for $\vec{a}$, the semi-paramteric approximation of unobserved energy awareness and observed population density. As discussed, we apply an approach similar to the Olley-Pakes methodology for unobserved energy awareness[7]. The error term ρ is assumed to be joint normally distributed (Train, 1986). We specify the following ordered probit estimation equation and estimate it via standard maximum likelihood[8].

$$m = \sum_{c=1}^{C} \alpha_c z_c + \sum_{d=1}^{D} \beta_d a_d + \rho \tag{3}$$

Equation (3) allows us to calculate the continuous predicted energy efficiency variable $\tilde{m}$ and cut points that enable us to derive probabilities for implementing specific numbers of energy efficiency measures. If a significant effect of $\vec{a}$ on the decision to implement an energy efficiency measure shows, the above mentioned endogeneity issue arises and needs to be resolved by controlling for unobserved heterogeneity.

So as to explore the effect of energy efficiency measures on household energy demand, we discuss the demand system analysis in the following section.

2.3. Model II - Demand System

Our demand system is based on standard assumptions regarding consumer preferences, including reflexiveness, completeness, and transitivity. Consumers maximize their utility following the properties of homogeneity of degree one in prices, being increasing in utility, non-decreasing, continuous, and concave in prices, and derivable (Edgerton, 1996). Given the nature of the problem as well as the available data, we apply a product space approach with multiple products and heterogeneous agents. To efficiently estimate a multi-product system requires simplifications. Methods of simplifications such as aggregation and assumptions regarding separability are commonly used in literature (e.g. Hausman et al., 1994). Assuming (weak)

[7]As a fourth-order polynomial with all interaction terms $D = 17$ in Equation (3).

[8]An overview about variable notations is given in Appendix A in Table A.1.

separability corresponds with partitioning goods into groups and restricting preferences within groups to be independent of quantities purchased within other groups (Deaton, 1980). Therewith, overall utility maximization under a budget constraint can be split into maximization of several subutility functions ν. In our particular applicaton this coincides with households distributing overall household income on different aggregated groups of goods (i.e. budgeting groups), such as housing, food and energy, in a first budgeting stage.

$$u = f(\nu_{housing}, \nu_{food}, \nu_{energy}, ...) \tag{4}$$

The resulting distribution of overall household income gives the subgroup expenditures, which restrict the maximization process for the subutility functions. For our analysis, we focus on the energy budgeting group and the related conditional demand function. That implies, the consumption of different energy goods is optimized taking individual prices and energy good subgroup expenditures (from the first budgeting stage) into account. In this multi-stage approach, separability of preferences is implicitly assumed. Hence, we assume that the consumptions of energy and other goods are separable but separability for consumption of different fuels is not assumed.

However, as Moschini et al. (1994) point out: "the convenience of an assumption [regarding separability] is no substitute for its truth". Therefore, several tests for separability were proposed in the past (e.g. Varian, 1983; Moschini et al., 1994). Unfortunately, data availability hinders us to test our separability assumptions. Therefore, we reason the assumption by intuition. Firstly, grouping non-durable energy goods into one budgeting group is plausible for several reasons: Energy goods can be transformed into different forms of energy and are used for different kinds of services, such as heating or cooking, and a general substitutability exists. Households also tend to be contracted to one single provider that supplies most of the non-durable energy goods used. This applies in particular to electricity and heating fuels. Joint billing thus creates a perceptional linkage between these energy goods that is also invigorated by public attention being given to energy as a whole rather than to individual fuels (e.g. regarding the German *Energiewende*). Further, non-durable energy goods can be regarded as contributing to housing comfort (e.g. in terms of heating, warm water, lighting, entertainment). Lastly, the assumption is consistent with comparable energy demand estimations, see among others Baker and Blundell (1991) or Labandeira et al. (2006).

Yet, we have to consider the energy efficiency investment as a durable energy good within our budgeting approach. The discrete decision to implement an energy efficiency measure indirectly contributes to the energy subgroup utility ν_{energy}. Indirectly by means of increasing the specific utility from consuming nondurable energy goods for heating. Therefore, we cannot assume intertemporal separability between the implementation of the energy efficiency measure and non-durable energy good consumption. Even though Deaton (1980) shows that durable goods can be easily expressed in a way similar to nondurable goods, the necessary assumptions of indivisibilities and perfect reselling of the durable good do not hold in our application. However, the highly individualised nature of energy efficiency measures, in particular in insulation applications, puts an absolute selling constraint on the durable energy efficiency measure. Hence, despite contributing to the subutility function, after the decision to invest[9] households stick with their choice. Expenditures associated with the investment[10] are predetermined and reduce subgroup expenditures without altering the subutility cost minimization problem dual to the subutility maximization problem. Thus, restricting our analysis on the residual subgroup expenditures is an appropriate approximation.

The implementation of the identification strategy requires the assumption that changes in durable energy goods that consume electricity are not correlated with the implementation of an energy efficiency measure. Such a correlation would be a likely scenario if energy efficiency measures are just a part of several investments when moving into a new house (e.g. larger kitchen space allows for larger/more kitchen appliances such as refrigerators). However, data suggests that energy efficiency measures are generally implemented after a change in occupation took place[11].

We use the Exact Affice Stone Index (EASI) implicit Marshallian demand system introduced by Lewbel and Pendakur (2009)[12]. In contrast to other product space approaches with multiple products and heterogeneous agents[13], the EASI demand system allows for almost unrestricted Engel curves, thus an unbounded relationship between product expenditure and household income, as well as unobserved preference heterogeneity.

The main trick of Lewbel and Pendakur (2009) is the combination of Marshallian and Hicksian demands. By expressing utility, u, by implicit utility, y, and replacing it in Hicksian budget share equations, they define implicit Marshallian demand equations described entirely by observable and approximable variables[14].

Households are considered as single consumers (based on the assumption of additivity of individual household member preference functions). As previously discussed, we assume a multi-stage budgeting approach.

[9]Because of expected utility returns.
[10]E.g. by means of credit payments.
[11]For an illustration refer to Figure A.1 in Appendix A.
[12]See Pendakur (2009) for a less technical introduction to the EASI demand systems and implicit Marshallian demands.
[13]Such as e.g. Deaton and Muellbauer (1980) and Banks et al. (1997).
[14]The approach used here as well as the estimation procedure are based on Pendakur (2009). A detailed description of the approach is given in Appendix B.

In a first budgeting stage, total income is distributed to subgroup expenditures, of which the energy group is in the focus of this study. Households receive utility, u, from consuming a bundle of some subset of J different goods within the energy group. They spend total nominal group expenditures, x, on that bundle, taking the vector of prices, $\vec{p}$, into account. The value of the chosen bundle can be described by $\vec{w}$, a vector of budget shares of length J. Observed and preference related characteristics, such as demographics and housing conditions are given by vector $\vec{z}$. We separate energy efficiency measures, $\vec{m}$, from $\vec{z}$[15]. Contrary to the ordered probit estimation, we now disaggregate $\vec{m}$ and explore individual dummy variables for each type of efficiency measures. This enables us to capture behavioural aspects linked to differing measures implemented.

We further control for two types of unobserved preference heterogeneity: energy awareness and random utility. In line with the notation of the ordered probit estimation, energy awareness is incorporated in $\vec{a}$. Random utility is denoted by $\vec{\varepsilon}$.

Our matter of interest is the effectiveness of energy efficiency measures, i.e. the change in demand for an energy good by implementing an energy efficiency measure ($\partial Q^j/\partial m$). With $w^j = p^j Q^j/x$ and exogenous prices, Equation (5) follows.

$$\frac{\partial Q^j}{\partial m} = \frac{\partial w^j}{\partial m}\frac{x}{p^j} + \frac{\partial x}{\partial m}\frac{w^j}{p} \tag{5}$$

For good j a change in purchased quantity, Q^j, is described by changes in the group budget share, w^j, and changes in group expenditures, x. Engineering calculations on the effect of an energy efficiency measure would give alterations in both w^j and x. With all considered energy efficiency measures aiming at reducing the demand for heating fuels, a reduced consumption of heating fuels due to an energy efficiency measure would decrease their budget share and related group expenditures.

The effectiveness of an energy efficiency measure, as follows from Equation (5), can be measured by changes in both the budget share of heating fuels and group expenditures. However, due to data limitations, the first budgeting stage (determining group expenditures) cannot be accounted for. Nevertheless, we can identify whether there is a positive[16] impact of implementing energy efficiency measures by considering energy group budget shares only and comparing these with engineering estimates.

For identification, we utilize the fact that the physical (i.e. thermodynamic) effect of energy efficiency measures affects heating fuels only. Consider three scenarios by which we illustrate that a positve treatment

[15]See Table A.2 in Appendix A for the distribution of energy efficiency measures within the data

[16]From a policy point of view, by means of reduced nondurable energy good consumption.

effect should always relate to $\partial w^j/\partial m < 0$. Firstly, assume the energy efficiency measure would lower group expenditures but keeps the budget shares unaltered (i.e. $\partial Q^j/\partial m < 0$). Hence, behavioural reductions in demand for other energy goods would compensate thermodynamic as well as behavioural induced reductions in heating fuel demand. Secondly, assume the energy efficiency measure would unalter group expenditures and budget shares (i.e. $\partial Q^j/\partial m = 0$). This would correspond to behavioural effects in heating fuels that counteract thermodynamic effects entirely. Hence, no demand reducing effect of energy efficiency measures is observable. Similar results follow if considering $\partial Q^j/\partial m > 0$. Hence, in combination with estimates from engineering calculations (Stolte et al., 2012) we can identify and quantify economic and behavioural responses to implementation of energy efficiency measures.

Consider the endogeneity issue resulting from energy aware households being marginal adopters of energy efficiency measures. We argue that energy aware households tend to have a higher share of heating fuels compared to other energy goods (i.e. mostly electricity). Observable characteristics such as dwelling, heating and other things equal, energy aware households should still have a more efficient stock of energy consuming durable goods. In addition, research shows that the lower bound for heating demand is restricted by individual comfort levels (e.g. Nicol and Humphreys, 2002), while such a lower bound for other energy services is currently unknown. Therefore, consumption restrictions induced by energy cost attentiveness should primarily occur in non-heating fuels and hence, increase the budget share for heating fuels. Consequential, endogeneity needs to be addressed when evaluating the second stage budgeting process.

The following estimation equation for the budget shares results from the EASI implicit Marshallian demand system [17]:

$$w^j = \sum_{e=1}^{E} \gamma_e^j \tilde{y}^e + \sum_{f=1}^{F} \delta_f^j z_f + \sum_{g=1}^{G} \tau_g^j m_g + \sum_{h=1}^{H} \psi_h^j a_h + \sum_{k=1}^{J} b^{jk}(\vec{z}, m, \vec{a}) \ln p^k + \varepsilon^j \tag{6}$$

In addition to the variables already specified, the linear approximation of the implicit utility $\tilde{y}$ and its powers are implemented in Equation (6). These variables give rise to another endogeneity problem: implicit utility y (and its powers) is simultaneously defined by exogenous variables $\ln x$, $\vec{z}$ and $\ln \vec{p}$ as well as the endogenous budget share $\vec{w}$. However, this is solved by the exogeneity of $\ln x$, $\vec{z}$ and $\ln \vec{p}$. By simply regressing the exogenous variables on y and its powers, this endogeneity problem can be resolved. We estimate Equation (6) using a Two-Stage-Least-Squares (2SLS) approach.

[17] Derivation of this equation based on Pendakur (2009) as well as an overview of variable notations (Table A.1) are given in Appendix A.

3. Data

Our study is based on the German Residential Energy Consumption Survey (GRECS[18]) 2006-2008. The survey is conducted triennialy based on a tendering by the German Federal Ministry of Economic Affairs and Energy[19]. So as to obtain information on the use of energy in private households, a representative sample of the German population is interviewed on their consumption of various fuels and corresponding characteristics. The dataset consists of cross-sectional information on socio-economic characteristics (income, residence, number of children etc.), housing conditions (year of construction, type of building, rent/ownership etc.), heating system (fuel used, type of heating, auxiliary systems etc.), hot-water supply and food preparation (fuel etc.), billing information for the individual fuels/energy services, potential renewable energy systems (year of construction, type etc.), data on the implementation of energy efficiency measures as well as automobile ownership and climate indicators (heating degree days) for the years 2006 to 2008. The survey aims at observing energy efficiency measures implemented since 2002. We thus assume persistence in the households' observed and unobserved characteristics that influence the investment decision since 2002.

Within the dataset information for some variables (billing information[20] for energy goods, heating degree days, number of energy efficiency measures and household size) is given on a yearly level for 2006 to 2008. For all other variables information is only given for one point in time. This particularly concerns the socio-economic characeristics[21]. However, under the assumption of permanence in the cross-sectional information of the survey, we expand the dataset for the years 2006-2008. Given the yearly variation of some of the variables, we handle it as a cross-sectional dataset but allow for more than one observation per household.

We further analyse the choice of automobiles to proxy unobserved energy awareness. We match the stated automobile manufacturer key number and type key number in the survey with specific CO_2-emissions of the ADAC automobile database (Allgemeiner Deutscher Automobilclub, 2014). Based on this information, we calculate household average CO_2-emissions per kilometer as the mean of the specific CO_2 emissions of all automobiles in each household. Population density is matched from German Federal Statistical Office and the Land Statistical Offices (2014) at the local authority level.

We subset the original dataset in various ways. We restrict our analysis to homeowners of detached and semi-detached houses. These households directly benefit from potential energy efficiency measures and we

[18]GRECS was used in energy demand related articles among others in Grösche and Vance (2009), Frondel and Vance (2013a) and Grösche and Schröder (2011).

[19]The report, including the questionnaire used to generate GRECS, is given in Frondel et al. (2011).

[20]Billing information includes individual price data for each household. We thus account for individual supply side characteristics within the data.

[21]The survey was conducted between February 22nd and April 15th in 2010.

Fuel combination	Frequency	Percent
Electricity and natural gas	393	32.37 %
Electricity, natural gas and wood	182	14.99 %
Electricity and heating oil	156	12.85 %
Electricity, heating oil and wood	122	10.05 %
Electricity and wood	56	4.61 %
Electricity, heating oil, wood and solar thermal energy	34	2.8 %
Electricity, natural gas and solar thermal energy	34	2.8 %
Electricity, natural gas, wood and solar thermal energy	33	2.72 %
Only electricity	29	2.39 %
Electricity, heating oil and solar thermal energy	24	1.98 %
Electricity, natural gas, wood and lignite	19	1.57 %
Electricity and liquified petroleum gas	15	1.24 %
Electricity and district heating	12	0.99 %
Electricity, heating oil, wood and lignite	12	0.99 %
Observations	1121	

Table 1: Distribution of energy goods utilization among households

can circumvent the tenant-landlord problematic. In order to minimize the measurement bias, households with heat cost allocators are excluded. Our sample only includes households with stated automobile ownership. Further, the lack of filing of energy bills leads to a missing data problem. We assume that missing variables are missing at random and thus, listwise deletion of the corresponding observations does not bias our results (Little and Rubin, 2002).

Table 1 gives an overview of the different combinations of energy goods used by households in the dataset[22]. It shows different energy good combinations. Even though all relevant data for the different combinations for estimating each combination individually are in principle available, two data problems make such an endeavour impossible. First, a low number of observations for some combinations would lead to inefficient estimates and second, for combinations including wood, prices at the household level are unavailable. Despite the fact that price indices for wood exist, the application of such energy indices (e.g. on federal state level) for households is inappropriate. With a vast number of different sources and thus, large differentiation in costs and prices, heterogeneity of wood prices on a regional level cannot be captured within the data. For these reasons, we will restrict our demand analysis on households that only utilize electricity and natural gas.

Summary statistics for the samples used are given in Table A.3, Table A.4, and Table A.5 in Appendix A.

[22]For reasons of clarity, fuel combinations with less than ten observations are omitted. The information is given for the data used in the ordered probit estimation.

4. Results

Prior to identification of the treatment effect of energy efficiency measures, we discuss whether unobserved heterogeneity, as approximated by energy awareness, impacts on the decision to implement an energy efficiency measure. Recall that if we find a statistically significant impact of the approximation of unobserved heterogeneity results on the investment decision, neglection of unobserved heterogeneity results in biased estimates within the demand model estimation. According to the model described in section 2.2, the ordered probit estimation results are presented in Table 2. Exogenous and observable characteristics $\vec{z}$ show the expected tendencies. For example, the probability of implementing energy efficiency measures is significantly higher for older buildings and lower for the lowest income group in our data.

Dependent Variable: Number of energy efficiency measures		
Exogeneous and observable characteristics ($\vec{z}$)		
Dwelling completion:		
before 1918	1.933***	(0.261)
1919 - 1948	1.710***	(0.260)
1949 - 1957	1.912***	(0.269)
1958 - 1968	2.042***	(0.254)
1969 - 1977	1.786***	(0.253)
1977 - 1983	1.426***	(0.243)
1984 - 1994	0.890***	(0.246)
1995 - 2001	0.222	(0.245)
2002 - 2008	(ref.)	
Dwelling characteristics:		
Living space (sq m)	-0.000710	(0.000740)
Year of heating system completion	0.0233***	(0.00367)
Semi-detached house	(ref.)	
Detached house	0.0327	(0.0850)
Monthly income:		
below 500 EUR/month	-5.385***	(0.286)
500 - 1000 EUR/month	0.181	(0.317)
1000 - 1500 EUR/month	-0.0768	(0.190)
1500 - 2000 EUR/month	-0.0866	(0.154)
2000 - 2500 EUR/month	-0.137	(0.125)
2500 - 3000 EUR/month	-0.189+	(0.127)
3000 - 3500 EUR/month	-0.107	(0.125)
3500 - 4000 EUR/month	-0.0931	(0.119)
above 4000 EUR/month	(ref.)	
Age:		
18-29 years (ref.)		
30-49 years	-0.119	(0.308)
above 50 years	-0.190	(0.305)
Energy awareness ($\vec{a}$)		
Automobile specific CO^2 emissions (SCE)	-0.0296+	(0.0202)
SCE^2	0.000129+	(0.0000848)
SCE^3	-0.000000212+	(0.000000142)
SCE^4	9.96e-11	(7.89e-11)
Population density (PD)	-0.0106**	(0.00437)
PD^2	0.00000923***	(0.00000320)
PD^3	-1.81e-09***	(6.08e-10)
PD^4	5.18e-14**	(2.24e-14)
SCE $\times$ PD	0.000115**	(0.0000468)

Continued on next page

Table 2: Ordered probit estimation results

Continued from previous page

$SCE^2 \times PD^2$	3.40e-10***	(1.18e-10)
$SCE^3 \times PD^3$	6.51e-17***	(2.39e-17)
$SCE^2 \times PD$	-0.000000412***	(0.000000151)
$SCE \times PD^2$	-9.52e-08***	(3.48e-08)
$SCE^3 \times PD$	4.57e-10***	(1.50e-10)
$SCE \times PD^3$	1.61e-11**	(6.32e-12)
$SCE^2 \times PD^3$	-5.79e-14***	(2.19e-14)
$SCE^3 \times PD^2$	-3.80e-13***	(1.26e-13)
Cut-off point 1	45.14***	(7.583)
Cut-off point 2	46.02***	(7.587)
Cut-off point 3	46.60***	(7.589)
Cut-off point 4	47.25***	(7.597)
Cut-off point 5	47.89***	(7.590)
Observations	1026	

Standard errors in parentheses
$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered by household

Table 2: Ordered probit estimation results

Coming to the coefficients for the proxy of unobserved energy awareness as well as population density, $\vec{a}$, our findings show that the polynomials of specific CO_2-emissions and population density as well as their interactions are statistically significant in their impact on the implementation of energy efficiency measures. To illustrate the relationship between the proposed functional form for energy awareness and the implementation of energy efficiency measures, we map the estimated coefficients for $\vec{a}$ graphically in Figure 2.

The figure shows that households that are by assumption less energy aware, and thus own a higher emitting automobile, tend to have a lower probability to implement an energy efficiency measure. Further, this result suggests that the first derivative with respect to specific automobile carbon emissions is negative along the entire range[23]. We further observe a slight population density effect. A larger number of efficiency measures is more likely to be implemented in less densely populated areas. This could be explained by lower social norm effects due to an increased anonymity in densily populated areas. Here, monumental protection and stricter building regulations are also more likely, restricting the potential for implementation of energy efficiency measures.

The estimation results support our hypothesis that unobserved energy awareness impacts on the decision to implement an energy efficiency measure. The validity of our approximation approach is thus confirmed and disregard leads to biased estimates.

[23]Figure A.2 and Figure A.3 in Appendix A visualize the first derivatives with respect to specific automobile carbon emissions and population density.

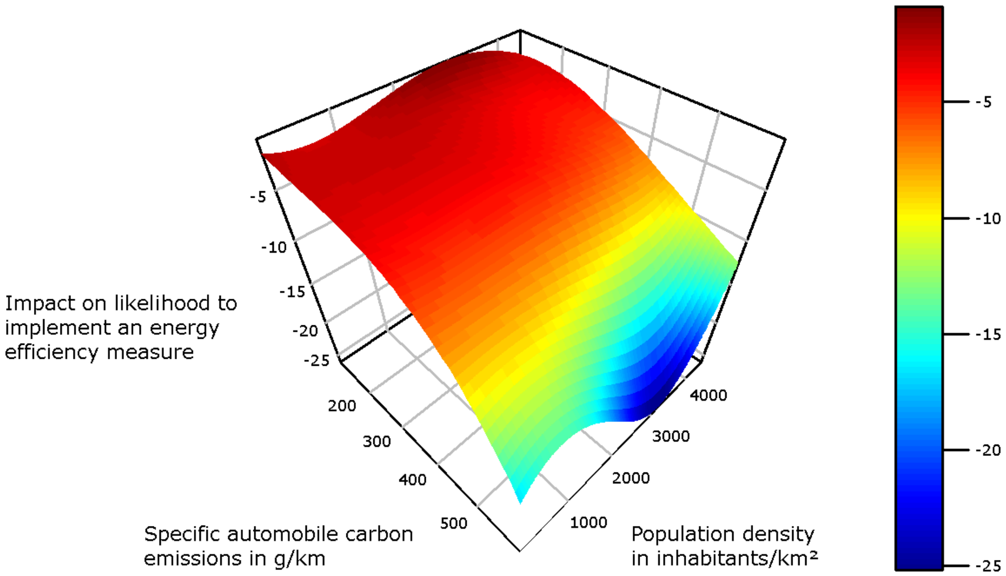

Figure 2: Joint impact of energy awareness and population density on the likelihood to implement an energy efficiency measure

Turning to the treatment effect of energy efficiency measures, the results of the demand system estimation are given in Table 3. Estimated coefficients represent semi-elasticities within the energy budget group, as illustrated in Equation (6). With these, the treatment effect is identified from Equation (5). As the budget shares in the budgeting group for energy goods sum up to unity, one budget share equation is dropped within the estimation process. With only electricity and natural gas under consideration, we estimate the system once with the electricity budet share and once with the natural gas budget share only. Coefficients do not express direct effects on energy demand, but distributional effects among energy goods within the energy budget group. For the exogenous and observable characteristics $\vec{z}$, we find among others the budget share for natural gas is increasing in dwelling age and the budget share for electricity is rising in the number of household members.

Semi-elasticities of budget shares	Electricity		Natural Gas	
Normalized price of energy good (ln)	0.0735***	(0.0224)	0.0735***	(0.0224)
Implicit utility/log real expenditures:				
Linear	0.501	(0.411)	-0.497	(0.415)
Squared	-0.0306+	(0.0205)	0.0304+	(0.0207)
Exogeneous and observable characteristics ($\vec{z}$)				
Dwelling completion:				
before 1918	-0.0333	(0.0332)	0.0330	(0.0333)
1919 - 1948	-0.0494+	(0.0331)	0.0498+	(0.0331)
1949 - 1957	-0.0406	(0.0358)	0.0424	(0.0359)
1958 - 1968	-0.00571	(0.0338)	0.00644	(0.0337)
1969 - 1977	0.00667	(0.0308)	-0.00632	(0.0308)
1977 - 1983	-0.0428+	(0.0292)	0.0435+	(0.0293)
1984 - 1994	0.0118	(0.0273)	-0.0110	(0.0273)

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Table 3: Demand system estimation results

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Semi-elasticities of budget shares	Electricity		Natural Gas	
1995 - 2001	0.0164	(0.0266)	-0.0162	(0.0267)
2002 - 2008	(ref.)			
Dwelling characteristics:				
Year of heating system completion	-0.000732	(0.000534)	0.000745	(0.000533)
Living space	0.000184	(0.000190)	-0.000187	(0.000190)
Detached house	-0.000524	(0.0107)	0.000625	(0.0107)
Semi-detached house	(ref.)			
Climate characteristics:				
Heating degree days	-0.00000674	(0.0000146)	0.00000647	(0.0000146)
Year	-0.000582	(0.00122)	0.00108	(0.00123)
Monthly income:				
below 500 EUR/month	0	(.)	0	(.)
500 - 1000 EUR/month	0	(.)	0	(.)
1000 - 1500 EUR/month	-0.00853	(0.0342)	0.00935	(0.0341)
1500 - 2000 EUR/month	0.0324	(0.0285)	-0.0322	(0.0284)
2000 - 2500 EUR/month	-0.0182	(0.0178)	0.0184	(0.0178)
2500 - 3000 EUR/month	-0.00252	(0.0165)	0.00278	(0.0164)
3000 - 3500 EUR/month	-0.00377	(0.0180)	0.00367	(0.0180)
3500 - 4000 EUR/month	-0.0152	(0.0203)	0.0151	(0.0202)
above 4000 EUR/month	(ref.)			
Head of household characteristics:				
Age: 18-29 years				
Age: 30-49 years	0.0159	(0.0364)	-0.0159	(0.0365)
Age: above 50 years	0.0148	(0.0353)	-0.0152	(0.0353)
Education: High-School and above	0.00963	(0.0112)	-0.00906	(0.0112)
Number of household members	0.0297***	(0.00552)	-0.0298***	(0.00554)
Energy efficiency measures ($\vec{m}$)				
Type of energy efficiency measure implemented:				
Roof or top storey ceiling	-0.0378*	(0.0195)	0.0378*	(0.0195)
Basement ceiling insulation	0.0379+	(0.0259)	-0.0392+	(0.0257)
Outer walls insulation	0.0594**	(0.0241)	-0.0598**	(0.0241)
Window replacement	0.0118	(0.0220)	-0.0120	(0.0220)
Heating system replacement	0.00897	(0.0158)	-0.00974	(0.0158)
Energy awareness ($\vec{a}$)				
Automobile specific CO^2 emissions (SCE)	0.0115**	(0.00474)	-0.0119**	(0.00478)
SCE^2	-0.0000513**	(0.0000246)	0.0000521**	(0.0000246)
SCE^3	9.88e-08*	(5.59e-08)	-9.72e-08*	(5.57e-08)
SCE^4	-7.21e-11+	(4.82e-11)	6.80e-11	(4.80e-11)
Population density (PD)	0.00310***	(0.000780)	-0.00337***	(0.000845)
PD^2	-0.00000274***	(0.000000613)	0.00000293***	(0.000000658)
PD^3	5.07e-10***	(1.18e-10)	-5.41e-10***	(1.26e-10)
PD^4	4.08e-15	(3.29e-15)	-4.15e-15	(3.30e-15)
$SCE \times PD$	-0.0000340***	(0.00000920)	0.0000373***	(0.0000100)
$SCE^2 \times PD^2$	-1.01e-10***	(2.41e-11)	1.09e-10***	(2.64e-11)
$SCE^3 \times PD^3$	-1.90e-17***	(4.50e-18)	2.06e-17***	(4.94e-18)
$SCE^2 \times PD$	0.000000105***	(3.36e-08)	-0.000000117***	(3.67e-08)
$SCE \times PD^2$	3.12e-08***	(6.92e-09)	-3.36e-08***	(7.51e-09)
$SCE^3 \times PD$	-9.55e-11**	(3.82e-11)	1.09e-10***	(4.15e-11)
$SCE \times PD^3$	-6.03e-12***	(1.26e-12)	6.44e-12***	(1.36e-12)
$SCE^2 \times PD^3$	9.65e-14***	(2.59e-14)	-1.06e-13***	(2.84e-14)
$SCE^3 \times PD^2$	1.96e-14***	(4.31e-15)	-2.11e-14***	(4.69e-15)
Observations	387		387	

Standard errors in parentheses
$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered by household

Table 3: Demand system estimation results

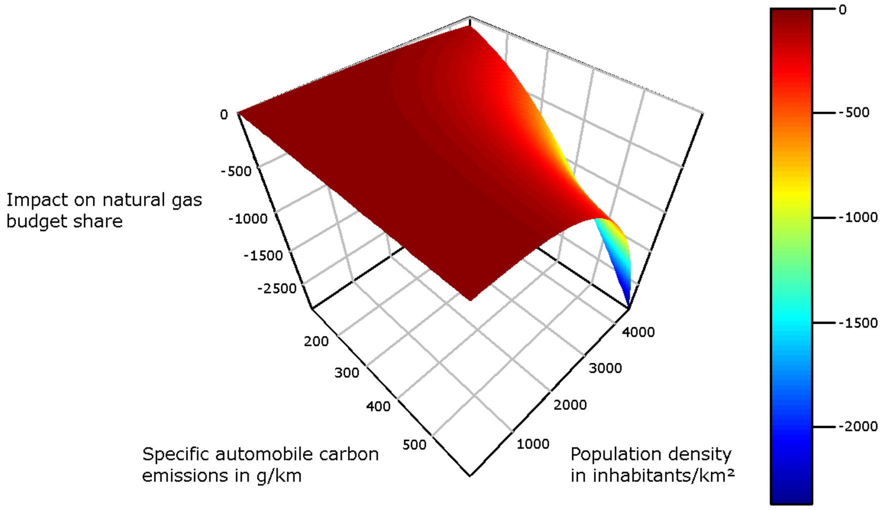

Figure 3: Joint impact of energy awareness and population density on budget share of natural gas

The estimation results for the joint impact of energy awareness and population density, $\vec{a}$, as presented in Figure 3[24] illustrate two results. First, energy aware individuals have a higher (lower) share of natural gas (electricity) consumption compared to less energy aware households. This confirms our hypothesis that energy aware households are not only marginal adopters of energy efficiency measures, but in addition show different consumption patterns. This is a reasonable result, as it is to be expected that these households also utilize more efficient durable goods that consume electricity, hence, bolstering budget shares for natural gas. The related endogeneity problem should result in an underevaluation of the effectiveness of energy efficiency measures. Additionally, a population density effect becomes apparent: With an increase in population density, the budget share for natural gas decreases which can be explained by the urban heat island effect.

The most important results, that is the treatment effect of energy efficiency measures on natural gas budget shares, are given by the coefficients for $\vec{m}$. Prior to discussing these, let us summarize what engineering calculations would suggest. All measures considered aim at reducing the consumption of heating fuels only. Therefore, expenditures on natural gas should decrease after implementation. Assuming that direct and indirect rebound effects within energy consumption are absent, the additional income from savings in heating fuel expenditures will be spent on other goods, for instance food. Within our specification of the demand system, this translates to a reduction in energy budget group expenditures ($\partial x/\partial m < 0$) and thus, increasing budget share for electricity ($\partial w^{\text{electricity}}/\partial m > 0$) and decreasing budget share for natural gas ($\partial w^{\text{natural gas}}/\partial m > 0$). Lack of appropriate data hinders us to evaluate the first budgeting stage, necessary to quantify $\partial x/\partial m$. Hence, in our discussion we focus on the semi-elasticities of budget shares with respect

[24]First derivatives are given in Figure A.4 and Figure A.5 in Appendix A.

to implementation of energy efficiency measures. In this respect, we would expect statistically significant reductions in budget shares for natural gas. Nevertheless, one has to keep in mind that statistically insignificant results do not show that there is no demand reducing effect whatsoever. A small effect might still exist.

We find statistically significant results with expected signs for the implementation of basement ceiling and outer wall insulation. Implementation of either of these reduces the budget share of the heating fuel, i.e. natural gas. Further, no statistically significant impact of either window or heating system replacement shows. As for roof or top storey ceiling insulation, we also find statistically significant changes in budget shares. These however are counterintuitive: implementation corresponds with an increasing budget share for natural gas. Assuming constant spending on electricity, these results indicate an increase in natural gas spending, which can probably be explained by strong *backfiring effects*[25].

As a first summary, we find that only two out of five energy efficiency measures give estimation results which signs are in line with expectations from engineering calculations. Thus, two conclusions follow: first, rebound effects are likely to counteract demand reductions from energy efficiency measures. These effects might completely counteract efficiency gains and even result in backfiring. Second, results suggest a large heterogeneity within the rebound effect for the different efficiency measures.

In order to evaluate and make these conclusions more plausible, we compare our budget share semi-elasticities with engineering calculations within examplary model calculations. For reference, we consider a detached house, built between 1969 and 1977, with living space of 144 m^2. Further, the overall heating demand prior to implementation of the insulation is assumed to be at 237 kWh/m^2a and electricity demand is assumed to be 3500 kWh/a. Electricity (0.2526 EUR/kWh) and natural gas (0.0675 EUR/kWh) prices for 2011 are taken from BNetzA and BKartA (2012)[26]. Engineering calculations for energy savings from different energy efficiency measures are taken from Stolte et al. (2012). Using this information, we can calculate expected changes in budget shares and compare these to our results.

Table 4 illustrates the expenditures for electricity and natural gas as well as related budget shares from engineering calculations in Stolte et al. (2012). Further, it compares these to our estimation results. We find that economic and behavioural responses increase the budget share for natural gas from roof or top storey ceiling insulation by 6.0 pp, from window replacement by 2.2 pp and from heating system replacement by 5.4 pp. These results relate to a direct rebound effect that is on the one hand of expected sign and on

[25] If rebound effects counteract efficiency gains from energy efficiency measures in its entirety and even overshoots these, this effect is called backfiring.

[26] We restrict our analysis to one example setting due to lack of available data.

	Annual expenditures in EUR (Stolte et al., 2012)		Budget shares in % (Stolte et al., 2012)		Changes in budget shares of natural gas in pp		
	Electricity	Natural gas	Electricity	Natural gas	Engineering expectation	Our estimation results	Δ
Without efficiency measure	884	2304	27.7%	72.3%	-	-	-
Roof or top storey ceiling insulation	884	2069	29.9%	70.1%	-2.2pp	3.8pp	+6.0pp
Basement ceiling insulation	884	2134	29.3%	70.7%	-1.6pp	-3.9pp	-2.3pp
Outer walls insulation	884	1758	33.5%	66.5%	-5.7pp	-6.0pp	-0.3pp
Window replacement	884	2065	30.0%	70.0%	-2.2pp	0.0pp	+2.2pp
Heating system replacement	884	1782	33.2%	66.8%	-5.4pp	0.0pp	+5.4pp

Table 4: Comparison of expectations from engineering calculations and estimation results

the other hand heterogeneous with respect to energy efficiency measure. These results suggest, that the rebound effect significantly counteracts technological efficiency gains. Assuming that households maximize their utility, these results could still imply a higher level of utility. For roof and top storey insulation, results suggest that even backfiring (i.e., $\partial Q^{\text{natural gas}}/\partial m > 0$) is likely.

The results for outer walls insulation closely resemble engineering expectations. Hence, there are either hardly any such effects, or cross-product effects (i.e., indirect effects reducing consumption of electricity) counteract reductions in natural gas budget shares. As the absence of rebound effects is rather unlikely, this result allows us to calculate the cross-product, i.e., indirect, rebound effect.

Given that additional consumption of natural gas from the direct rebound effect requires additional consumption of electricity to keep budget shares similar to engineering calculations, we can calculate additional spending on electricity in relation to additional spending on natural gas. This results in further 0.38 EUR spent on electricity for each 1 EUR spent on natural gas due to the direct rebound effect.

Contrary, we find additional budget share reductions originating from economic and behavioural effects by 2.3 pp from implementation of basement ceiling insulation. This result suggests behavioural responses that either further reduce natural gas demand or increase electricity demand. Hence, an *inverse* rebound effect shows. However, as for low numbers of observations for this energy efficiency type[27] focus on this result should be restricted.

[27]See Table A.2 in Appendix A.

Yet, these results are not an unimpeachable evidence as we can only control for the second budgeting stage. This implies that regarding Equation (5), we can identify $\partial w^j/\partial m$ only and have no information on $\partial x/\partial m$. By showing necessary changes in electricity consumption that would allow for the joint realization of the estimation results and the demand reduction from engineering calculations, we illustrate the plausibility of our results. Further, assume no behavioural effects in heating fuels (i.e. no rebound effect[28]). By this approach, we want to illustrate how improbable these scenarios are and hence, qualify our results by contradiction.

	Annual expenditures in EUR (Stolte et al., 2012)		Budget shares in %		Additional spending on electricity	
	Electricity	Natural gas	Natural gas (Stolte et al., 2012)	Natural gas (our estimation)	in EUR	in %
Without efficiency measure	884	2304	72.3%	-	-	-
Roof or top storey ceiling insulation	884	2069	70.1%	76.0%	-231.9	-26.2%
Basement ceiling insulation	884	2134	70.7%	68.4%	104.2	+11.8%
Outer walls insulation	884	1758	66.5%	66.3%	8.8	+1.0%
Window replacement	884	2065	70.0%	72.3%	-94.2	-10.7%
Heating system replacement	884	1782	66.8%	72.3%	-200.0	-22.6%

Table 5: Necessary changes in electricity spending for the joint realization of savings from engineering calculations and our estimation results

The necessary changes in electricity demand that would explain a joint realization of the engineering calculations and our estimation results are presented in Table 5. The results suggest that large reductions in electricity consumption from -10.7% to -26.2% would be required for window, heating system replacement and roof or top ceiling insulation. As no plausible driver for such reductions exists, we can conclude that significant economic and behavioural rebound effects exist for these measures. As for outer walls insulation, only 1% additional spending on electricity were required.

Taken all together, comparing our results to engineering calculations confirms our prior conclusions. Rebound effects are likely to counteract demand reductions in particular for roof or top storey insulation and window and heating system replacements. For outer wall insulation, we find that our results are either in line with engineering calculations or suggest existence of indirect rebound effects of considerable magnitude. Therefore, heterogeneity in the rebound effect manifests.

[28]Behavioural responses in heating fuels by means of a positive rebound effect would require opposed behavioural responses in electricity and heating fuels.

This heterogeneity allows for the following classification. On the one hand, we have measures leading to moderate or high direct rebound effects and on the other hand, outer wall insulation showing either no direct effect or a combination of direct and indirect effects. As previously discussed, rebound effects as in the first group were to be expected. The differing effect for outer wall insulation needs to be explained in the context of other factors. Expected savings of this measure are high, but this is also the case for other measures, such as heating system replacement. Looking at the investment costs and disutility resulting from construction for outer wall insulation, these are comparatively high. That is, this measure is linked to high costs that need to be amortized over a longer period of time. In addition, the high visibility of this measure leads to a repeated priming of these costs and suggesting altogether *sunk cost fallacy*. For outer wall insulation, we thus propose the strongest impact on habit formation within the group of energy efficiency measures that we explore.

5. Conclusion and discussion

While governments worldwide spend increasing amounts of money on policy schemes to reduce energy consumption and related carbon emissions, economic and behavioural responses undermine their effectiveness. In this paper, we investigate the actual treatment effect of energy efficiency measures and therein compare actual demand responses to technological potentials. This is crucial as evaluation of measures to increase energy efficiency relies mostly on engineering based calculations.

Based on German household survey data for the period 2006-2008, we find that unobserved energy awareness does impact on the decision to implement an energy efficiency measure. Controlling for energy awareness approximated by the automobile choice and population density shows, that more energy aware households are more likely to invest. This has implications not only for the effectiveness and efficiency of policy schemes, but further gives rise to a selection problem in evaluation.

Target-oriented policy measures should thus either increase the number of energy aware households by for example information campaigns or address particularly households that are energy aware. This would increase the adaption and hence, reduce the energy efficiency gap. Further, targeting policy schemes to marginal adopters increases the efficiency of respective policies.

Additionally, our demand system estimation illustrates two important findings. First, economic and behavioural responses counteract demand reductions from energy efficiency measures. Second, our results confirm heterogeneity in these responses for different energy efficiency measures. Even if energy awareness is taken account of, technological potentials are not fully realized due to economic and behavioural responses to the measures. Our results suggest that rebounding effects might actually increase energy demand and hence, fail policy target levels. The effectiveness of policies thus falls short of its expectations, but must not be negative per se. Individual utility will still be maximized and it might be that households reach a higher level of utility due to the implementation.

Our results further show response heterogeneity of the different energy efficiency measures. This suggests that behavioural aspects are linked to the measures themselves. These seem to be relevant in particular for high cost and visible investments, such as outer wall insulation. Habit formation, priming, and the sunk cost fallacy seem to be likely drivers of the effectivness of energy efficiency measures. However, further research is required to fully understand these behavioural effects and their policy implications.

To conclude, understanding the economic and behavioural responses of such measures will contribute to a better policy design and public discussion. Thus, it will promote the effectiveness of policy schemes and the achievement of the overarching goal to reduce carbon emissions and mitigate climate change.

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Appendix A. Data

Abbreviation	Explanation	Coefficient	Length
$\vec{a}$	Semi-parametric approximation for energy awareness and population density	$\vec{\beta}^{(1)}$, $\vec{\psi}^{(2)}$	$D^{(1)}$, $H^{(2)}$
$\boldsymbol{b}$	Slutsky coefficients	-	$J \times J$
C	Cost function	-	-
$m^{(1)}$,$\vec{m}^{(2)}$	Number of implemented energy efficiency measures	$\tau^{(2)}$	$1^{(1)}$, $G^{(2)}$
n	Hicksian budget share function	-	J
$\vec{p}$	Prices of energy goods	$b^{(2)}$	J
u	Utility	-	-
$\vec{v}$	Hicksian budget share	-	J
$\vec{w}$	Budget share	-	J
x	Total (group) expenditures	-	-
y	Implicit utility	$\gamma^{(2)}$	$E^{(2)}$
$\vec{z}$	Exogenous, observed characteristics	$\alpha^{(1)}$, $\delta^{(2)}$	$C^{(1)}$, $F^{(2)}$
ρ	Ordered probit error term	-	-
ε	EASI random utility	-	J
nu	Budgeting group subutility	-	-

(1) Econometric Model I: Ordered Probit, (2) Econometric Model II: EASI

Table A.1: Notation

Type of energy efficiency measure	Frequency	Percent
Roof or top storey ceiling insulation	72	19%
Basement ceiling insulation	8	2%
Outer walls insulation	36	9%
Window replacement	66	17%
Heating system replacement	88	23%
Observations	387	100%

Table A.2: Distribution of energy efficiency types among households

	Mean	Standard deviation	Min	Max
Dependent Variable: Number of energy efficiency measures	.8421053	1.118545	0	5
Exogeneous and observable characteristics ($\vec{z}$)				
Dwelling completion:				
before 1918	.0896686	.2858457	0	1
1919 - 1948	.0935673	.2913677	0	1
1949 - 1957	.0662768	.2488866	0	1
1958 - 1968	.0984405	.2980547	0	1
1969 - 1977	.128655	.334981	0	1
1977 - 1983	.1364522	.3434356	0	1
1984 - 1994	.1315789	.3381973	0	1
1995 - 2001	.1666667	.3728597	0	1
2002 - 2008	.0877193	.2830242	0	1
Dwelling characteristics:				
Living space (sq m)	137.0575	43.38398	40	772
Year of heating system completion	1993.896	11.02201	1924	2009
Detached house	.6929825	.4614817	0	1
Semi-detached house	.3070175	.4614817	0	1
Monthly income:				
below 500 EUR/month	.0009747	.0312195	0	1
500 - 1000 EUR/month	.0155945	.123961	0	1
1000 - 1500 EUR/month	.0526316	.2234058	0	1
1500 - 2000 EUR/month	.1130604	.3168211	0	1
2000 - 2500 EUR/month	.1578947	.3648201	0	1
2500 - 3000 EUR/month	.1510721	.3582938	0	1
3000 - 3500 EUR/month	.1374269	.3444654	0	1
3500 - 4000 EUR/month	.1159844	.3203624	0	1
4000 - 4500 EUR/month	.1023392	.3032417	0	1
above 4500 EUR/month	.1530214	.3601837	0	1
Age:				
18-29 years	.0175439	.1313503	0	1
30-49 years	.3489279	.4768636	0	1
above 50 years	.6335283	.4820754	0	1
Energy awareness ($\vec{a}$)				
Automobile specific CO^2 emissions (SCE)	229.4425	98.22171	90	828
SCE^2	62281.96	61222.64	8100	685584
SCE^3	2.01e+07	3.49e+07	729000	5.68e+08
SCE^4	7.62e+09	2.18e+10	6.56e+07	4.70e+11
Population density (PD)	612.0979	894.262	14	4592
PD^2	1173589	3377958	196	2.11e+07
PD^3	3.56e+09	1.38e+10	2744	9.68e+10
PD^4	1.28e+13	5.90e+13	38416	4.45e+14
$SCE \times PD$	141736.3	239259.4	2156	2459488
$SCE^2 \times PD^2$	7.73e+10	3.35e+11	4648336	6.05e+12
$SCE^3 \times PD^3$	8.16e+16	6.25e+17	1.00e+10	1.49e+19
$SCE^2 \times PD$	3.86e+07	8.99e+07	332024	1.49e+09
$SCE \times PD^2$	2.77e+08	9.02e+08	30184	1.00e+10
$SCE^3 \times PD$	1.23e+10	4.11e+10	5.08e+07	8.97e+11
$SCE \times PD^3$	8.54e+11	3.69e+12	422576	4.20e+13
$SCE^2 \times PD^3$	2.43e+14	1.37e+15	6.51e+07	2.46e+16
$SCE^3 \times PD^2$	2.54e+13	1.54e+14	7.16e+08	3.65e+15
Observations	1026			

Table A.3: Ordered probit estimation - summary statistics

	Mean	Standard deviation	Min	Max
Budget share of energy good	.3784045	.1075553	.0590275	.7483409
Implicit utility/log real expenditures:				
Linear	10.00476	.3889487	8.65094	11.07085
Squared	100.2462	7.750888	74.83876	122.5638
Normalized price of energy good (ln)	1.082285	.2263139	-1.077474	2.337301
Exogeneous and observable characteristics ($\vec{z}$)				
Dwelling completion:				
before 1918	.0801034	.2718045	0	1
1919 - 1948	.0956072	.2944325	0	1
1949 - 1957	.0697674	.2550845	0	1
1958 - 1968	.0878553	.2834508	0	1
1969 - 1977	.118863	.3240462	0	1
1977 - 1983	.0878553	.2834508	0	1
1984 - 1994	.1524548	.3599265	0	1
1995 - 2001	.255814	.4368826	0	1
2002 - 2008	.0516796	.2216659	0	1
Dwelling characteristics:				
Year of heating system completion	1995.196	9.550123	1963	2009
Living space	128.5736	33.54599	60	250
Detached house	.4806202	.500271	0	1
Semi-detached house	.5193798	.500271	0	1
Climate characteristics:				
Heating degree days	3324.92	343.0874	2537.892	4560.433
Year	2006.863	.7406439	2006	2008
Monthly income:				
below 500 EUR/month	0	0	0	0
500 - 1000 EUR/month	0	0	0	0
1000 - 1500 EUR/month	.0465116	.210863	0	1
1500 - 2000 EUR/month	.0620155	.2414959	0	1
2000 - 2500 EUR/month	.1808786	.3854158	0	1
2500 - 3000 EUR/month	.1963824	.3977753	0	1
3000 - 3500 EUR/month	.1447028	.3522564	0	1
3500 - 4000 EUR/month	.0904393	.2871813	0	1
4000 - 4500 EUR/month	.121447	.3270689	0	1
above 4500 EUR/month	.1576227	.3648586	0	1
Age: 18-29 years	.0077519	.0878167	0	1
Head of household characteristics:				
Age: 30-49 years	.3100775	.4631238	0	1
Age: above 50 years	.6821705	.4662355	0	1
Education: High-School and above	.5193798	.500271	0	1
Number of household members	2.821705	1.051396	1	8
Energy efficiency measures ($\vec{m}$)				
Type of energy efficiency measure implemented:				
Roof or top storey ceiling	.1317829	.3386925	0	1
Basement ceiling insulation	.0155039	.1237055	0	1
Outer walls insulation	.0594315	.2367366	0	1
Window replacement	.0775194	.2677599	0	1
Heating system replacement	.1111111	.3146765	0	1
Energy awareness ($\vec{a}$)				
Automobile specific CO^2 emissions (SCE)	217.6331	96.0457	109	604
SCE^2	56565.1	57856.37	11881	364816
SCE^3	1.77e+07	3.02e+07	1295029	2.20e+08
SCE^4	6.54e+09	1.58e+10	1.41e+08	1.33e+11
Population density (PD)	746.5672	986.9007	14	4592
PD^2	1528819	3535677	196	2.11e+07
PD^3	4.44e+09	1.36e+10	2744	9.68e+10
PD^4	1.48e+13	5.50e+13	38416	4.45e+14
SCE $\times$ PD	177846.5	306968.3	2156	2459488
$SCE^2 \times PD^2$	1.26e+11	5.22e+11	4648336	6.05e+12
$SCE^3 \times PD^3$	1.64e+17	1.13e+18	1.00e+10	1.49e+19
$SCE^2 \times PD$	5.18e+07	1.39e+08	332024	1.49e+09

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Table A.4: Demand system estimation electricity - summary statistics

Continued from previous page

	Mean	Standard deviation	Min	Max
SCE × PD^2	3.93e+08	1.12e+09	30184	1.00e+10
SCE^3 × PD	1.84e+10	7.41e+10	5.11e+07	8.97e+11
SCE × PD^3	1.19e+12	4.25e+12	422576	4.08e+13
SCE^2 × PD^3	4.89e+13	2.85e+14	7.16e+08	3.65e+15
SCE^3 × PD^2	4.00e+14	2.03e+15	6.51e+07	2.46e+16
Observations	387			

Table A.4: Demand system estimation electricity - summary statistics

	Mean	Standard deviation	Min	Max
Budget share of energy good	.6215955	.1075553	.2516591	.9409724
Implicit utility/log real expenditures:				
Linear	10.0048	.3889485	8.651021	11.07089
Squared	100.2469	7.750915	74.84016	122.5646
Normalized price of energy good (ln)	-1.082285	.2263139	-2.337301	1.077474
Exogeneous and observable characteristics ($\vec{z}$)				
Dwelling completion:				
before 1918	.0801034	.2718045	0	1
1919 - 1948	.0956072	.2944325	0	1
1949 - 1957	.0697674	.2550845	0	1
1958 - 1968	.0878553	.2834508	0	1
1969 - 1977	.118863	.3240462	0	1
1977 - 1983	.0878553	.2834508	0	1
1984 - 1994	.1524548	.3599265	0	1
1995 - 2001	.255814	.4368826	0	1
2002 - 2008	.0516796	.2216659	0	1
Dwelling characteristics:				
Year of heating system completion	1995.196	9.550123	1963	2009
Living space	128.5736	33.54599	60	250
Detached house	.4806202	.500271	0	1
Semi-detached house	.5193798	.500271	0	1
Climate characteristics:				
Heating degree days	3324.92	343.0874	2537.892	4560.433
Year	2006.863	.7406439	2006	2008
Monthly income:				
below 500 EUR/month	0	0	0	0
500 - 1000 EUR/month	0	0	0	0
1000 - 1500 EUR/month	.0465116	.210863	0	1
1500 - 2000 EUR/month	.0620155	.2414959	0	1
2000 - 2500 EUR/month	.1808786	.3854158	0	1
2500 - 3000 EUR/month	.1963824	.3977753	0	1
3000 - 3500 EUR/month	.1447028	.3522564	0	1
3500 - 4000 EUR/month	.0904393	.2871813	0	1
4000 - 4500 EUR/month	.121447	.3270689	0	1
above 4500 EUR/month	.1576227	.3648586	0	1
Age: 18-29 years	.0077519	.0878167	0	1
Head of household characteristics:				
Age: 30-49 years	.3100775	.4631238	0	1
Age: above 50 years	.6821705	.4662355	0	1
Education: High-School and above	.5193798	.500271	0	1
Number of household members	2.821705	1.051396	1	8
Energy efficiency measures ($\vec{m}$)				
Type of energy efficiency measure implemented:				

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Table A.5: Demand system estimation natural gas - summary statistics

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	Mean	Standard deviation	Min	Max
Roof or top storey ceiling	.1317829	.3386925	0	1
Basement ceiling insulation	.0155039	.1237055	0	1
Outer walls insulation	.0594315	.2367366	0	1
Window replacement	.0775194	.2677599	0	1
Heating system replacement	.1111111	.3146765	0	1
Energy awareness ($\vec{a}$)				
Automobile specific CO^2 emissions (SCE)	217.6331	96.0457	109	604
SCE^2	56565.1	57856.37	11881	364816
SCE^3	1.77e+07	3.02e+07	1295029	2.20e+08
SCE^4	6.54e+09	1.58e+10	1.41e+08	1.33e+11
Population density (PD)	746.5672	986.9007	14	4592
PD^2	1528819	3535677	196	2.11e+07
PD^3	4.44e+09	1.36e+10	2744	9.68e+10
PD^4	1.48e+13	5.50e+13	38416	4.45e+14
$SCE \times PD$	177846.5	306968.3	2156	2459488
$SCE^2 \times PD^2$	1.26e+11	5.22e+11	4648336	6.05e+12
$SCE^3 \times PD^3$	1.64e+17	1.13e+18	1.00e+10	1.49e+19
$SCE^2 \times PD$	5.18e+07	1.39e+08	332024	1.49e+09
$SCE \times PD^2$	3.93e+08	1.12e+09	30184	1.00e+10
$SCE^3 \times PD$	1.84e+10	7.41e+10	5.11e+07	8.97e+11
$SCE \times PD^3$	1.19e+12	4.25e+12	422576	4.08e+13
$SCE^2 \times PD^3$	4.89e+13	2.85e+14	7.16e+08	3.65e+15
$SCE^3 \times PD^2$	4.00e+14	2.03e+15	6.51e+07	2.46e+16
Observations	387			

Table A.5: Demand system estimation natural gas - summary statistics

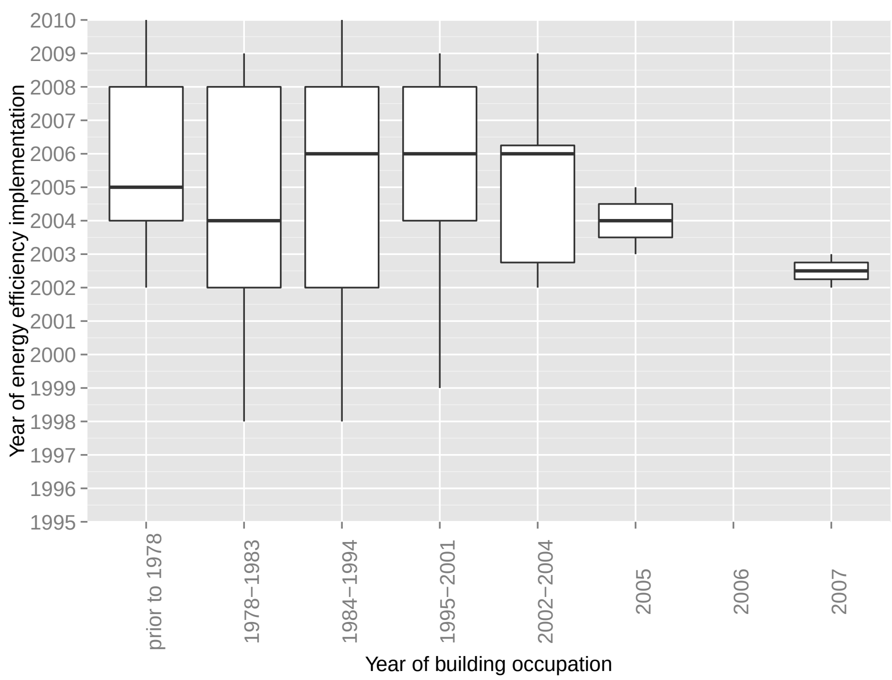

Figure A.1: Distribution of energy efficiency implementation years and years of building occupation

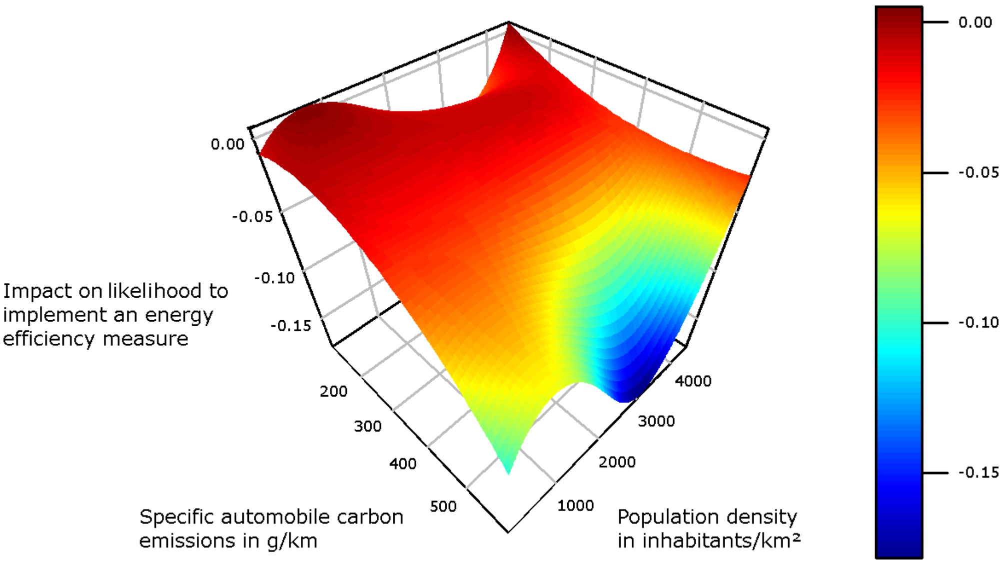

Figure A.2: First derivatives of the joint impact on the likelihood to implement an energy efficiency measure with respect to specific automobile carbon emissions

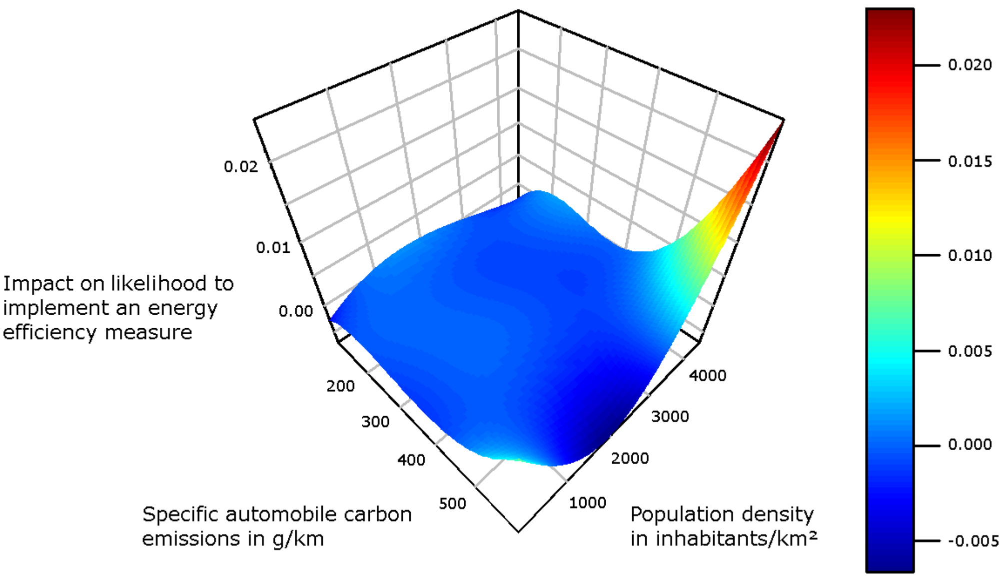

Figure A.3: First derivatives of the joint impact on the likelihood to implement an energy efficiency measure with respect population density

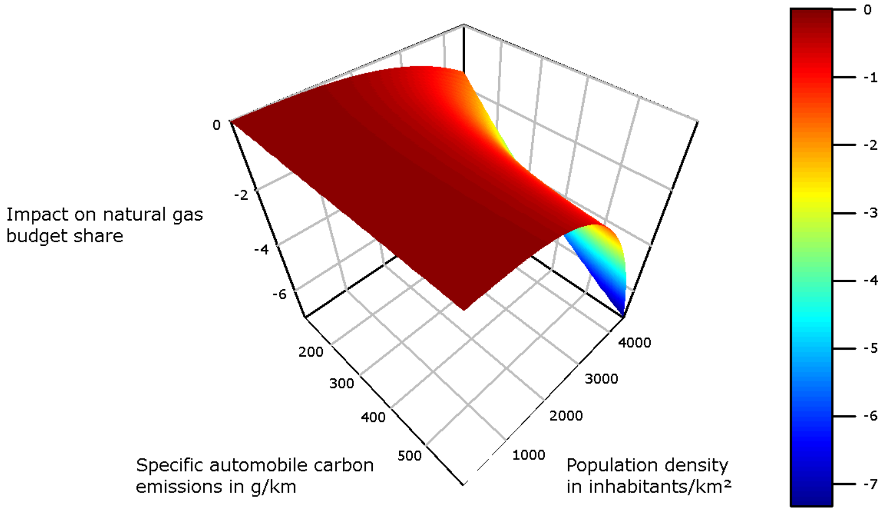

Figure A.4: First derivatives of the joint impact on budget share of natural gas with respect to specific automobile carbon emissions

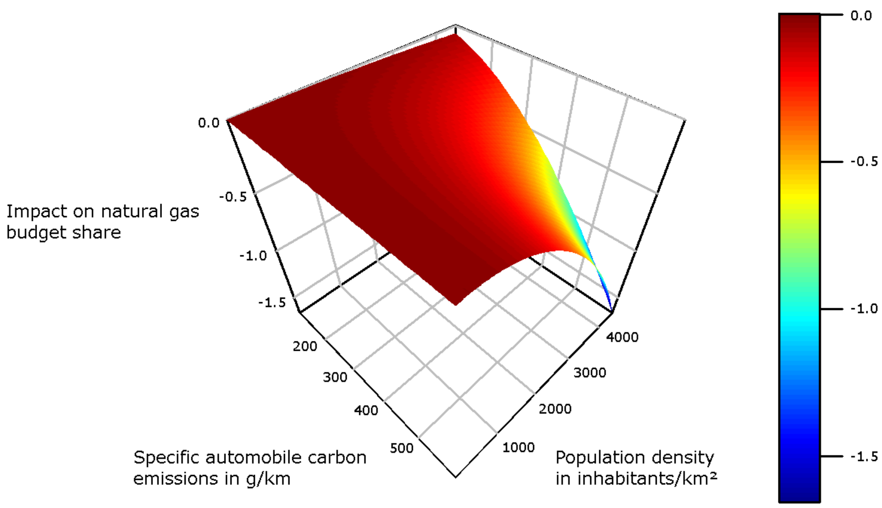

Figure A.5: First derivatives of the joint impact on budget share of natural gas with respect to population density

Appendix B. Derivation of the demand system estimation equation

By assuming a quadratic form in logarithmized prices, the minimal log expenditure for households with the observed and unobserved characteristics (as specified in section 2.3), prices $\vec{p}$ and utility level u are given by the EASI cost function:

$$\ln C(\vec{p}, u, \vec{z}, m, \vec{a}, \vec{\varepsilon}) = u + \sum_{j=1}^{J} n^j(u, \vec{z}, m, \vec{a}) \ln p^j + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} b^{jk}(\vec{z}, m, \vec{a}) \ln p^j \ln p^k + \sum_{j=1}^{J} \varepsilon^j \ln p^j \qquad \text{(B.1)}$$

with $n^j(u, \vec{z}, m, \vec{a})$ representing the J-vector Hicksian budget share function and $b^{jk}(\vec{z}, m, \vec{a})$ being the Slutsky coefficients. Using Shepard's Lemma, we can derive Hicksian budget shares, by $\partial \ln C / \partial \ln p^j$. Denoting the Hicksian budget share by $\vec{v}$ it follows:

$$v^j(\vec{p}, u, \vec{z}, m, \vec{a}, \vec{\varepsilon}) = n^j(u, \vec{z}, m, \vec{a}) + \sum_{k=1}^{J} b^{jk}(\vec{z}, m, \vec{a}) \ln p^k + \varepsilon^j \qquad \text{(B.2)}$$

From Equation (B.2) and due to the fact that the budget shares are observable in the data, it follows:

$$\sum_{j=1}^{J} w^j \ln p^j = \sum_{j=1}^{J} n^j(u, \vec{z}, m, \vec{a}) \ln p^j + \sum_{j=1}^{J} \sum_{k=1}^{J} b^{jk}(\vec{z}, m, \vec{a}) \ln p^j \ln p^k + \sum_{j=1}^{J} \varepsilon^j \ln p^j \qquad \text{(B.3)}$$

Manipulating Equation (B.3) for $\sum_{j=1}^{J} n^j(u, \vec{z}, m, \vec{a}) \ln p^j$, replacing it in Equation (B.1), replacing $\ln C$ by $\ln x$ and rearranging the resulting equation for u gives the implicit utility function, y:

$$y = u = \ln x - \sum_{j=1}^{J} w^j \ln p^j + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} b^{jk}(\vec{z}, m, \vec{a}) \ln p^j \ln p^k \qquad \text{(B.4)}$$

Thus, substituting Equation (B.4) into Equation (B.2) results in the implicit Marshallian budget shares:

$$w^j = n^j(y, \vec{z}, m, \vec{a}) + \sum_{k=1}^{J} b^{jk}(\vec{z}, m, \vec{a}) \ln p^k + \varepsilon^j \qquad \text{(B.5)}$$

From Equation (B.5) the first difficulty of the EASI demand system becomes obvious. Due to a possible non-linear dependency of n^j from y and the fact that y depends on $\vec{w}$, $\vec{p}$, $\vec{z}$, $\vec{m}$ and $\vec{a}$[29]. Therefore, we approximate Equation (B.4) in line with Lewbel and Pendakur (2009) by:

[29] Lewbel and Pendakur (2009) provide some evidence that the nonlinearity is of relatively small relevance.

$$\tilde{y} = \ln x - \sum_{j=1}^{J} w^j \ln p^j \tag{B.6}$$

Under the assumption that $n^j(\tilde{y}, \vec{z}, m, \vec{a})$ is additively separable in $\tilde{y}$, $\vec{z}$, $\vec{m}$ and $\vec{a}$, the following linear specification for n^j results in:

$$n^j(\tilde{y}, \vec{z}, m, \vec{a}) = \sum_{e=1}^{E} \gamma_e^j \tilde{y}^r + \sum_{f=1}^{F} \delta_f^j z_f + \sum_{g=1}^{G} \tau_g^j m_g + \sum_{h=1}^{H} \psi_h^j a_h \tag{B.7}$$

Inserting Equation (B.7) and Equation (B.6) into Equation (B.5), the budget share equation to be estimated is as follows:

$$w^j = \sum_{e=1}^{E} \gamma_e^j \tilde{y}^r + \sum_{f=1}^{F} \delta_f^j z_f + \sum_{g=1}^{G} \tau^g m_g + \sum_{h=1}^{H} \psi_h^j a_h + \sum_{k=1}^{J} b^{jk}(\vec{z}, m, \vec{a}) \ln p^k + \varepsilon^j \tag{B.8}$$

Appendix C. Endogeneity

The selection bias follows from the self-selection of households to implement an energy efficiency measure. Thus, the treatment (implementation of an energy efficiency measure, $\vec{m}$) cannot be considered to be randomly assigned. If we do not control for the unobserved heterogeneity, as incorporated in $\vec{a}$, our estimation approach would suffer from endogeneity. When omitting the unobserved heterogeneity ($\sum_{h=1}^{H} \psi_h^j a_h + \varepsilon^j = \eta^j$) following the conditional expectation function (CEF) of Equation (6) results.

$$\mathbb{E}(w^j \mid \vec{z}, m) = \sum_{e=1}^{E} \gamma_e^j \tilde{y}^e + \sum_{f=1}^{F} \delta_f^j z_f + \sum_{g=1}^{G} \tau_g^j m_g + \sum_{k=1}^{J} b^{jk}(\vec{z}, \vec{m}) \ln p^k + \mathbb{E}(\eta^j \mid \vec{z}, \vec{m}) \tag{C.1}$$

We are interested in the difference in outcomes for those households that implement one or several energy efficiency measures and those who do not. For simplification, assume we are only interested in the treatment effect of implemting one efficiency measure, i.e. $m = \{0, 1\}$. The CEF of households that choose to implement one energy efficiency measure is:

$$\mathbb{E}(w^j \mid \vec{z}, m = 1) = \sum_{e=1}^{E} \gamma_e^j \tilde{y}^e + \sum_{f=1}^{F} \delta_f^j z_f + \tau_1^j + \sum_{k=1}^{J} b^{jk}(\vec{z}, m) \ln p^k + \mathbb{E}(\eta^j \mid \vec{z}, m = 1) \tag{C.2}$$

For households that did not implement any energy efficiency measure m, following CEF results:

$$\mathbb{E}(w^j \mid \vec{z}, m = 0) = \sum_{e=1}^{E} \gamma_e^j \tilde{y}^e + \sum_{f=1}^{F} \delta_f^j z_f + \sum_{k=1}^{J} b^{jk}(\vec{z}, m) \ln p^k + \mathbb{E}(\eta^j \mid \vec{z}, m = 0) \tag{C.3}$$

Of our interest is the treatment effect, i.e. the difference between both outcomes. Hence, it follows

$$\mathbb{E}(w^j \mid \vec{z}, m = 1) - \mathbb{E}(w^j \mid \vec{z}, m = 0) = \tau_1^j + \underbrace{\mathbb{E}(\eta^j \mid \vec{z}, m = 1) - \mathbb{E}(\eta^j \mid \vec{z}, m = 0)}_{\text{Selection bias}} \tag{C.4}$$

Following the ordered probit estimation results, the decision to implement an energy efficiency measure crucially depends on $\vec{a}$ that is omitted as an individual variable and hence, included in η^j. Therefore the selection bias in this problem does not resolve to zero. However, with the introduction of $\vec{a}$ as control variables, i.e. proxy for the unobserved heterogeneity environmental awareness, the endogeneity problem can be resolved:

$$\mathbb{E}(w^j \mid \vec{z}, \vec{a}, m=1) - \mathbb{E}(w^j \mid \vec{z}, \vec{a}, m=0) = \tau_1^j + \underbrace{\mathbb{E}(\varepsilon^j \mid \vec{z}, \vec{a}, m=1) - \mathbb{E}(\varepsilon^j \mid \vec{z}, \vec{a}, m=0)}_{\text{Selection bias}} \tag{C.5}$$

With the unobserved heterogeneity excluded from the error term, the selection bias ($\mathbb{E}(\varepsilon^j \mid \vec{z}, \vec{a}, m = 1) - \mathbb{E}(\varepsilon^j \mid \vec{z}, \vec{a}, m = 0)$) is zero, as the decision to implement an efficiency measure should not be correlated to the error term. Thus, the incorporation of $\vec{a}$ as a proxy for the unobserved heterogeneity resolves the endogeneity issue.

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