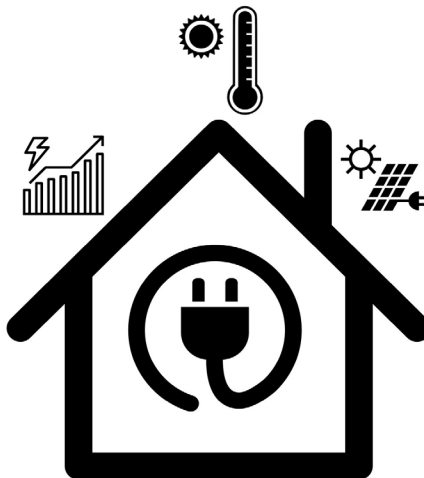


Energy Consumption Behavior of Private Households: Heterogeneity, Prosuming, and Rebound

Hendrik Schmitz

Institute for Future Energy Consumer Needs and Behavior



**Energy Consumption Behavior of Private Households:
Heterogeneity, Prosuming, and Rebound**

Von der Fakultät für Wirtschaftswissenschaften der Rheinisch-Westfälischen Technischen Hochschule Aachen zur Erlangung des akademischen Grades eines Doktors der Wirtschafts- und Sozialwissenschaften genehmigte Dissertation

vorgelegt von

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Hendrik Schmitz

March 3, 2020

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Chapter 1

Introduction

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1.1 Background and Motivation

In order to reach the ambitious climate goals set out by the global community, a fundamental transition of both energy production and consumption is inevitable. To this end, a multitude of energy and climate policy measures and regulations aim at curbing energy consumption, promoting energy efficiency, and de-carbonizing the economy in numerous countries worldwide. Private households are at the core of many of these measures. 25.7% of final energy consumption in the EU-28 in 2016 was consumed by households (Eurostat, 2018). In addition, a large portion of the energy consumed by the other two major sectors, i.e. transport (33.2%) and industry (25.0%), is also used for goods and services that either directly or indirectly serve private consumers. Therefore, a better understanding

of consumer energy demand is fundamental in assessing the effectiveness and economic efficiency of different policy measures that aim to influence this behavior. This dissertation uses a variety of econometric methods to derive insights into different aspects of household energy demand from consumer data.

Virtually any human activity either directly or indirectly consumes some form of energy, which makes analyzing energy consumption multifaceted and complex. This is further amplified by the fact that people usually do not consume energy directly, but rather use it as an input to provide an energy service, such as heating, cooling, transportation, or lighting. Furthermore, the same input fuel can provide different services, e.g. electricity can provide lighting, heating, dish washing, and other services. A particular service, such as heating, can also be provided by different fuels, e.g. gas, oil, or electricity. Therefore, the relationship between energy fuels and energy services may be opaque for consumers depending on the specific context of consumption, which also makes applied economic research more demanding (Chan and Gillingham, 2015; Borenstein, 2015).

This makes it challenging to generalize behavioral patterns in energy use, which means that any analysis of energy consumption behavior is highly context dependent. For example, the energy an individual consumes for heating may be determined by a multitude of factors, including her desired level of comfort, the level of insulation of the home, the choice of heating technology, the efficiency of the heating system, the price of heating fuels, climatic conditions, and others.

The goal of chapter 2 is to assess differences in energy consumption behavior between different socio-economic groups. To this end, I analyze space heating expenditures of private households in Germany, using panel data and utilizing different econometric methods in order to find new empirical evidence of heterogeneity between different groups, which would necessitate differentiated policy measures depending on the targeted group.

In chapter 3, we consider differences in consumption behavior between households who are themselves producing energy (also known as *prosumers*) and traditional consumers. If, for example, there is a prosumer rebound effect (Schill et al., 2017), this would lead to higher consumption as a result of the increasing prevalence of prosuming. The opposite might also be the case, as households may be more energy aware after becoming prosumers. Either way, any significant effect of prosuming on energy consumption would also have implications on the optimal level of subsidies that prosumers receive. This study is the first to provide empirical evidence on this issue.

In chapter 4, I assess the magnitude of direct and indirect rebound effects of household consumption in Germany. Compared to similar studies, which are limited to estimating rebound effects in energy fuels (Peters and McWhinnie, 2015), this analysis includes the embodied emissions of all goods and services consumed by German households. One result from this chapter is that large direct effects can be offset by small or negative indirect rebound effects and vice versa, which is consistent with theoretical discussions in Chan and Gillingham (2015) and Borenstein (2015).

To summarize, this dissertation aims at answering the following research questions:

- Do energy consumption patterns for space heating differ significantly between different socio-economic groups?
- Do prosumers exhibit different energy consumption behavior compared to consumers?
- What is the magnitude of direct and indirect energy rebound effects across all goods and services consumed by German households?

1.2 Scope

1.2.1 Heterogeneity of Energy Consumption

Energy consumption behavior is complex and can be influenced by a large number of factors depending on the context of usage. These factors include economic variables such as the cost of usage and income, as well as technical characteristics, for example living space and building age in the case of residential space heating, or powertrain technology and vehicle weight for car travel. Furthermore, socio-demographic factors such as age and gender and psychological factors such as risk attitudes can play a significant role in explaining energy consumption (Volland, 2017). Energy consumption by private households has significant implications for policy makers aiming to achieve the ambitious climate goals that are in place today in many jurisdictions around the world. Many of these goals can only be achieved with a substantial decrease in fossil energy consumption by private households. For this reason, a large number of regulations of different types are in place, such as energy taxes, minimum fuel standards, and building code regulations. However, in order to select and implement policies that can successfully induce energy savings, policy makers first need to know the factors that influence energy use.

In this context, one energy service of particular relevance is residential space heating. In 2018, some 83% of the energy consumed by German households was used for space heating (including hot water preparation, BMWi 2019). Furthermore, most of this energy originated from sources that are neither renewable nor CO₂neutral, in particular natural gas and heating oil. As a consequence, heating is a prime target for energy saving measures and has been examined by researchers before.

In the literature, there is a number of studies that focus on space heating using household level data for different regions. Schuler et al. (2000) model energy demand for space heating in (West) Germany, analyzing data from a household survey from 1988. The authors find that building characteristics are an important factor in determining energy consumption, while socio-economic factors can only explain a small part of the energy use of households in the sample. Rehdanz (2007) uses data from the German Socio-Economic Panel (SOEP) to investigate space heating and hot water preparation expenditures for German households for the years 1998 and 2003. The author finds a significant influence of a range of technical and socio-economic variables on households' expenditures for heating. Using the same data source, Braun (2010) analyzes the determinants of a household's type of space heating system using discrete choice methods.

Another relevant study that models heating expenditures, using panel data from Great Britain, is Meier and Rehdanz (2010). Similarly to Rehdanz (2007), the authors estimate the influence of socio-economic and technical characteristics on the expenditures for space heating. However, they do not look into possible heterogeneity in price responsiveness between different groups. More recently, researchers have also examined other possible explanatory factors, such as environmental habits and attitudes (Lange et al., 2014) or risk tolerance and trust (Volland, 2017).

For the Netherlands, Brounen et al. (2012) use cross-sectional data from 2007, focusing exclusively on owner-occupied dwellings to model gas and electricity consumption regardless of end use. While they do not investigate the influence of price changes on energy consumption, the authors find most of the socio-economic and technical variables included to be statistically significant. Most notably, these contain type, size and age of the dwelling as well as the number of household members, occupants' age, and income. Projecting their results into the future, they conclude that the aging of

the Dutch population alone could easily offset the energy savings of a possible home insulation program. This finding underlines the importance of socio-demographic factors in the analysis of energy demand.

None of these studies focuses on the heterogeneity between groups regarding the factors that determine energy consumption for heating. However, due to the complexity of energy usage behavior, the response to policy measures might be very heterogeneous between different socio-economic groups of consumers. For example, Druckman and Jackson (2008) find that patterns of energy consumption of private households in the UK differ substantially based on factors such as income, household composition, and type of dwelling. If there is significant heterogeneity regarding the determinants in energy use, this means that not all policy measures may be equally effective for all groups of consumers. For example, differences in the price elasticity would mean that price-based measures such as energy taxes would result in larger energy savings for some groups. This creates potential to develop interventions that target specific groups of households.

This leads to two relevant questions that can be addressed by empirical research, namely:

- What are the determinants of household energy consumption?
- Do energy consumption patterns differ significantly between different socio-economic groups?

Using panel data from Germany, chapter 2 of this dissertation provides empirical evidence regarding these questions for the case of residential space heating. While exploring heterogeneity in space heating is largely uncharted territory, there is a small amount of papers assessing heterogeneity between households for energy use in general, using quantile regression methods (Kaza, 2010; Valenzuela et al., 2014). Another related stream of literature aims at explaining the existence and magnitude of heterogeneity in gasoline demand, utilizing a variety of methods. Wadud et al. (2010) explore heterogeneity in gasoline demand using household level panel data for the US. The authors find significant heterogeneity by interacting both price and income with a number of demographic variables. Frondel et al. (2012) provide further evidence for heterogeneous reactions to price changes for private car travel in Germany. In attempting to explain heterogeneity in direct energy rebound effects, which is explained through price elasticities, the authors employ quantile regression on a rich set of panel data. They find significant differences in price responses of drivers in different quantiles. While the authors also interact fuel prices with different demographic variables, they do not find any of the interaction terms to be statistically significant, contradicting the findings from Wadud et al. (2010). Gillingham (2014) and Gillingham et al. (2015) derive estimates for vehicle-miles-traveled (VMT) in private transport with respect to gasoline prices in the US. The authors explore heterogeneity in demand response by using quantile regression, splitting the sample into subgroups, interacting the gasoline price variable with demographic factors, and conducting k-means clustering. Both studies find significant heterogeneity between groups regarding their price and income elasticities. Whether the mechanisms causing this heterogeneity in private transport translate to other energy services, such as space heating, remains an open question.

1.2.2 Energy Prosuming

Recently, the role of households in the energy market has shifted due to the emergence of distributed energy generation; after primarily being consumers for a long time, customers have started producing their own energy either for self-consumption or to feed it back into the grid, turning them into *prosumers* (a portmanteau of **pro**ducers and **con**sumers). In Germany, prosuming is supported

through federal subsidies as part of the effort to decarbonize the electricity supply. This can lead to a number of changes in the energy system, such as changing the load for distribution and transmission grids. Apart from technical effects of prosuming, there might be additional behavior effects that influence energy consumption of households who are becoming prosumers. These effects should be taken into account when evaluating the optimal subsidy scheme for prosuming.

Prosuming changes the relationship between the different actors in the energy market. Given that it presents a fundamental shift in the way households interact with energy, it may also change the relationship between households and energy as a good. These changes stemming from the diffusion of technological innovations such as PV systems and home batteries could significantly influence the way people perceive and utilize energy and energy services. Government policy should take these behavioral effects into account. For example, if prosumers become more aware of their energy use and therefore reduce energy consumption after starting to produce their own energy, this would be an additional benefit of subsidizing prosuming which should be taken into account. If, in contrast, prosumers were to consume more energy after transitioning from consumers to prosumers, public subsidies should be lower to take this additional consumption into account. Either way, prosuming would imply either a positive or negative externality which may justify additional government intervention.

Regarding energy use in general, there is some research on the role of behavioral mechanisms in energy decision making, such as exogenous and endogenous inattention or biased beliefs (see, e.g., Allcott 2016). These studies can show us some behavioral mechanisms that could influence the way private households use energy when they become prosumers. However, the analysis of behavioral responses specifically following the switch from consuming to prosuming is still in its infancy. Empirical work remains particularly scarce (Schill et al., 2017). Luthander et al. (2015) review the literature and conclude: “From these previous studies, it is not possible to draw any general conclusions on the responses to PV installations.”

More recently, Qiu et al. (2019) use hourly and daily electricity consumption and generation data for around 4,300 households in the US, of which 277 are solar prosumers. Using matching methods combined with panel data regressions, they estimate the rebound effect from residential solar electricity generation to be 18%.

1.2.3 Rebound Effects

Increasing energy efficiency is widely considered as an effective tool to decrease energy consumption and, in many jurisdictions, is part of the policy mix to reach climate goals. For example, the European Union set the goal of increasing energy efficiency by 32.5% until 2030, compared to a baseline scenario. In their most recent directive on energy efficiency, the EU explicitly assumes that this increase in efficiency would lead to a decrease in energy consumption by 32.5% as well (European Parliament, 2018), i.e. rebound is assumed to be zero.

However, an increase in efficiency reduces the price of the energy service that is consumed, as the same output (e.g., kilometers driven) can be achieved with lower input (e.g. liters of fuel consumed). As standard microeconomics would predict, this implicit price decrease usually leads to an increase in demand. This, in turn, means that less energy is saved compared to the technical calculations, which usually do not account for these behavioral changes. This phenomenon of reduced energy savings following an efficiency increase is known as the ‘Rebound Effect’. First discussed more than

150 years ago (Jevons, 1865), the rebound effect was revisited by Khazzoom (1980) and has received increasing attention since. While different definitions and classifications of rebound effects exist, the most commonly accepted definition separates rebound effects into three different mechanisms (Sorrell and Dimitropoulos, 2008). These are *direct effects*, *indirect effects*, and *economy-wide effects*.

Direct rebound effects are defined as the demand increase for a good or service following an efficiency increase for that same good. Following standard microeconomics, they can be divided into an income effect and a substitution effect. *Indirect rebound effects* occur when an efficiency increase related to one good or service increases the demand for other goods and services. For example, buying a more fuel-efficient car can cause a number of different reactions: driving more frequently and for longer distances in the new car is a direct energy rebound effect, whereas using some or all of the monetary savings to undertake more trips by airplane would be an indirect effect. The third category, which are *economy-wide effects*, describes macroeconomic adjustments that follow efficiency changes and lead to new equilibria regarding factor use in the economy, including the emergence of new products that only become feasible as a result of gains in efficiency (Fouquet and Pearson, 2012).

Formally, direct rebound can be explained as

$$\eta_{q_e, \varepsilon} = \frac{\delta \ln(q_e)}{\delta \ln(\varepsilon)} \quad (1.1)$$

where q_e is the amount of energy required to produce a quantity of an energy service q_s with efficiency $\varepsilon = \frac{q_s}{q_e}$ (Chitnis and Sorrell, 2015).

Measuring the magnitude of rebound effects empirically poses several challenges to researchers. Estimating rebound based on efficiency changes would require extensive amounts of data on appliance efficiency and purchasing behavior. Furthermore, the relationship between energy fuels and energy services is not always straightforward. For example, Electricity can provide a multitude of different energy services, such as lighting and cooking. At the same time, a specific service may be provided by different energy fuels, such as heating. This can lead to biased rebound estimates when these estimates are based on energy fuel price elasticities (Chan and Gillingham, 2015).

Even for the same good or service, rebound effects can occur across multiple dimensions. For example, buying a more fuel-efficient car might result in more kilometers being driven, but it could also lead to a less efficient style of driving (e.g. higher average speed) regardless of any changes in driving distance. Consumers might also opt for larger and heavier cars, which would also diminish the energy savings from higher efficiency.

Numerous studies have estimated rebound effects across different goods and services and for different countries¹. Many of those exploit the close relationship between price elasticities of energy demand and rebound effects. However, this identity relies on strong assumptions. Namely, energy prices need to be exogenous, energy efficiency needs to be constant, and energy service demand needs to be dependent on energy service prices only (Sorrell and Dimitropoulos, 2008; Chan and Gillingham, 2015). Since these assumptions are unlikely to hold in practice, Hunt and Ryan (2014) suggest explicitly incorporating energy efficiency in the estimations so that price elasticities can serve as unbiased estimates of a rebound effect. However, most studies so far have not addressed this issue. Furthermore, most empirical estimations of direct and indirect rebound effects only take into account

¹ For an extensive review of direct rebound estimates, see e.g. Sorrell et al. (2009); Azevedo (2014).

immediate energy use, omitting the embodied energy that is used in the production and shipping of all goods, including food or clothing (Chitnis and Sorrell, 2015).

1.3 Methodology

This section provides an overview of the different methods used in this dissertation to answer the research questions outlined above. In each chapter of the dissertation, the appropriate methodology has been chosen and applied, depending on the available data and the research question at hand. Many empirical studies in economics, including this dissertation, aim at establishing a causal relationship between variables, such as a change in prices causing a change in quantity demanded (Wooldridge, 2007). Whether a causal relationship can be credibly invoked in a given research scenario depends on the available data, the research design, and the research methodology used. If experimental data is not available, as is the case for the work performed in this dissertation, econometric methods need to be used to establish causality.

1.3.1 Heterogeneity of Energy Use

The most commonly used tool in empirical economics to establish correlation between variables of interest is linear regression. Depending on the context of the data and the specific identification strategy, linear regression models can be used to determine causality between the independent variables and the dependent variable (Wooldridge, 2007). In chapter 2, I use econometric methods to determine the factors explaining heating expenditures in German households, and to examine heterogeneity between socio-economic groups regarding these factors.

In line with the current literature, the model of heating expenditures takes the form

$$\ln(E_{i,t}) = \beta_P \ln(P_{i,t}) + \beta_T \mathbf{T}_{i,t} + \beta_D \mathbf{D}_{i,t} + \beta_S \mathbf{S}_{i,t} + \gamma_i + \varepsilon_{i,t} \quad (1.2)$$

with $E_{i,t}$ denoting the heating expenditures of household i at time t , $P_{i,t}$ the consumer gas price, $\mathbf{T}_{i,t}$ the building characteristics, $\mathbf{D}_{i,t}$ the socio-demographic and socio-economic variables, $\mathbf{S}_{i,t}$ the state dummies, γ_i the time-invariant household fixed effects, and $\varepsilon_{i,t}$ the error term. As is common in the literature, I use a log-linear model specification.

Using household fixed effects allows to control for unobserved heterogeneity, which separates the work done in chapter 2 from previous studies who either use cross-sectional data (Rehdanz, 2007; Brounen et al., 2012; Lange et al., 2014) or use household random effects (Meier and Rehdanz, 2010). Using fixed effects leads to more consistent estimations if unobserved variables exist that are correlated with the observed variables (Greene, 2003).

Analyzing heterogeneity in price responses between socio-economic groups requires the use of additional econometric methods. One of these methods employed in chapter 2 of this dissertation is quantile regression. While standard OLS regressions estimate the conditional mean of the distribution, quantile regression allows the researcher to derive coefficients at different quantiles of the distribution of the dependent variable (Koenker and Bassett Jr., 1978). This is relevant in many applications of empirical economic research. For example, the mean effect of some policy change on household income could be estimated by linear regression. Many economists as well as policy makers would, however, be more concerned with the effect on the income distribution, e.g. the effect that

this change has on households with particularly high or low incomes. A commonly used tool to model these effects is quantile regression (Angrist and Pischke, 2009).

Means clustering is another statistical technique to separate data into groups of similar observations (Forgy, 1965). Specifically, k-means clustering splits the n observations in the data set into k groups. The researcher chooses the number of groups and the variables on which to cluster. Initial group means are chosen at random. Then, observations are assigned to those groups in order to minimize the sum of squared differences between every observation and the nearest mean. Usually, the Euclidean distance is used as the measure for the sum of squares. Afterwards, new group means are chosen, if necessary. Observations are then reassigned to different clusters if it improves the solution. This process is iterated until a stable equilibrium is reached.

1.3.2 Propensity Score Matching

Matching, as applied in chapter 3, allows the researcher to create a quasi-experimental setting using non-experimental data. This is particularly useful when the implementation of a field or lab experiment is not possible, e.g. due to technical, financial, ethical, or legal limitations. Matching was first proposed by Rosenbaum and Rubin (1983) to derive causal effects from observational data. The fundamental challenge of estimating treatment effects for any kind of treatment is the fact that any observational unit can only be seen by the researcher either in its treated or untreated state, but not in both states at the same time. The average treatment effect can be denoted as

$$E(r_1) - E(r_0) \tag{1.3}$$

with E as the expected value in the population, r as the outcome, and $z_i = 1$ and $z_i = 0$ as treatment and non-treatment status, respectively (Rosenbaum and Rubin, 1983). Furthermore, let X_i be a vector of observed characteristics of observation i .

If the observations are taken from a random sample, e.g. as part of a randomized controlled trial, (1.3) is an unbiased estimator of the treatment effect since x_i does not differ systematically between the treatment and control groups (Rubin, 1974). However, without randomized treatment assignment, as is the case in most observational studies, the individual covariates X_i might be correlated with treatment status, which would bias the estimation of treatment effects (Pan and Bai, 2015). The goal of matching is to balance the distribution of covariates between the treatment and control groups, which, under certain assumptions, would greatly reduce this selection bias.

The first of these assumptions is that of strongly ignorable treatment assignment. This means that given the vector of covariates X_i , the assignment to treatment z_i is conditionally independent from the outcome r , or

$$(r_1, r_0) \perp z_i \mid X_i. \tag{1.4}$$

Matching has been employed in a number of different contexts, for example in labor economics (Heckman et al., 1997; Dehejia and Wahba, 1999; Lechner, 2002; Ichino et al., 2008) and environmental economics (Muehlenbachs et al., 2015; Woodward et al., 2016). In chapter 3 of this dissertation, I estimate a behavioral effect of using self-produced electricity on energy use. In this case, owning and operating a PV system is the treatment. Since we can assume that for this particular treat-

ment, selection is non-random for virtually all cases, selection bias is an issue that needs to be addressed.

1.3.3 Linearized Almost Ideal Demand System

In chapter 4, I derive direct and indirect rebound effects for all goods and services consumed by private households in the German economy, using a Linearized Almost Ideal Demand System (LAIDS) approach. The original Almost Ideal Demand System (AIDS) was first proposed by Deaton and Muellbauer (1980) and possesses a number of desirable characteristics that contribute to its long-lasting popularity and widespread use in analyzing consumer demand. Specifically, the AIDS allows perfect aggregation across consumers and can serve as a first-order approximation for any demand system (Holt and Goodwin, 2009).

The original AIDS model is defined by Deaton and Muellbauer (1980) as

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln(p_j) + \beta_i \ln\left(\frac{x}{P}\right) + \varepsilon_i, \quad (1.5)$$

where $i, j \in \{1, \dots, n\}$ indicate the commodity, w_i is the budget share for good i , p_j is the price of good j , x are expenditures, and α , β , and γ are coefficients to be estimated. This means that I estimate one α and one β , respectively, for each good, in addition to one γ for each pair of goods. The total number of coefficients is therefore $n + n + n^2$. Furthermore, ε is the error term, and P is a price index. In the original AIDS framework, the non-linear nature of this index makes its estimation computationally challenging. However, when prices are highly collinear, P can be approximated linearly, for example by using Stone's price index (Deaton and Muellbauer, 1980). While many empirical applications use this price index proposed by Stone (1954), it suffers from simultaneity bias since the expenditure shares appear on both sides of the equation to be estimated (Eales and Unnevehr, 1988). To avoid this issue, I use a simplified Laspeyres index as proposed by Moschini (1995), which is defined as

$$\ln(P_t) = \sum_k w_{k0} \ln(p_{kt}). \quad (1.6)$$

As (1.6) shows, the simplified Laspeyres index weights the prices of the different goods and services p_k by their respective initial budget shares w_{k0} .

As is common in the literature for estimating consumer demand, a number of restrictions is imposed on the parameters. Firstly, the sum of expenditures on each good has to sum up to total expenditures, which is known as the *adding-up* restriction. This implies that the budget shares w_i have to sum up to unity. Secondly, the demand system has to be homogeneous of degree zero, meaning that the quantity demanded remains constant when prices and total expenditures change by an equal proportion. This is the *homogeneity* restriction, which implies the absence of the so-called 'money illusion' (Shafir et al., 1997). Thirdly, the Slutsky matrix has to be symmetric (the *symmetry* condition). In addition to ensuring consistency with consumer demand theory, these restrictions reduce the number of parameters that need to be estimated in the demand system.

Additionally, researchers frequently use multi-stage budgeting, which was first introduced by Edgerton (1997). With this approach, goods are first split into broad categories which are then

further divided into subcategories. This allows the estimation of each category separately, which increases the total number of (sub-)categories that can be used without having to estimate too many coefficients. The use of multi-stage budgeting implies the assumption of weakly separable preferences. This means that the distribution of spending within a category is not influenced by the total spending in other categories. Consequently, the categories need to be chosen carefully for this condition to hold.

1.4 Structure and Contribution of the Dissertation

This dissertation contributes to this field of research in several ways:

- Chapter 2 presents empirical evidence on the heterogeneity of energy demand for space heating across different social groups in Germany.
- Chapter 3 analyzes behavioral aspects of prosuming and assesses whether prosumers exhibit energy consumption patterns that are different from those of regular consumers.
- Chapter 4 estimates direct and indirect rebound effects across all goods and services consumed by German households.

This dissertation consists of three research articles that empirically analyze different aspects of household energy behavior. The three articles have been presented at various international conferences and workshops. Specifically, these are:

Article 1: Heterogeneity in Price Responsiveness for Residential Space Heating in Germany (jointly with Reinhard Madlener)

- 20th Spring Meeting of Young Economists, May 21–23, 2015, Ghent, Belgium
- 9th RGS Doctoral Conference in Economics, February 23–25, 2016, Bochum, Germany
- 21st GEE Student Chapter Workshop, August 26, 2016, Aachen, Germany

Article 2: Are Prosumer Households That Much Different? Evidence from Stated Residential Energy Consumption in Germany (jointly with Christian Oberst and Reinhard Madlener)

- 39th IAEE International Conference, June 19–22, 2016, Bergen, Norway
- 19th INFER Annual Conference, June 7–9, 2017, Bordeaux, France

Article 3: Direct and Indirect Rebound Effects in German Households: A Linearized Almost Ideal Demand System Approach (jointly with Reinhard Madlener)

- Energy Economics Iberian Conference 2016, February 4–5, 2016, Lisbon, Portugal
- 19th INFER Annual Conference, June 7–9, 2017, Bordeaux, France
- 11th RGS Doctoral Conference in Economics, February 21–22, 2018, Essen, Germany

The following sections briefly outline the research questions, methodology, and results of the respective articles. The full articles can be found in sections 2, 3, and 4 of this dissertation, respectively.

1.4.1 Heterogeneity in Price Responsiveness for Residential Space Heating in Germany

More than 80% of the energy expenditures of private households in Germany are spent on space heating and hot water preparation. This creates opportunities for policy makers trying to influence energy consumer behavior. However, for these measures to be effective and efficient, the factors that determine energy usage need to be known. In this paper, we identify the determinants of heating and hot water consumption expenditures for German households, using a panel dataset derived from yearly residential household surveys covering the years 1996–2014. Furthermore, we examine heterogeneity between households using different methods. For the full sample, we find an own-price demand elasticity of heating expenditures ranging from 0.573 to 0.690. A large number of technical and socio-demographic factors are significant determinants of energy use. Additionally, we discover significant heterogeneity in price elasticity between different socio-economic groups. Our findings have implications for evaluating the effectiveness of policy measures that target influencing energy use across different groups of consumers.

1.4.2 Are Prosumer Households That Much Different? Evidence from Stated Residential Energy Consumption in Germany

This paper discusses the effect of residential energy prosuming on households' energy consumption behavior with the objective of finding evidence of a prosumer rebound effect on energy consumption. Prosuming is the partial self-consumption of distributed energy production. We hypothesize that prosumer households are systematically different from consumer households regarding their housing situation and socio-economic characteristics. We ensure an appropriate quasi-randomized comparison by using propensity score matching as our identification strategy. We employ data from a nationwide online survey among homeowners in Germany. While the data show a correlation between lower energy consumption and prosumer households, we find no statistically significant difference in energy consumption behavior between prosumers and non-prosumers after matching on socio-economic and housing characteristics. Instead, the lower energy consumption of prosumer households is attributed to more energy-efficient technical equipment and thus to purchasing behavior. Our results do not show evidence of either negative or positive externalities of prosuming on residential energy consumption behavior, and therefore we conclude that there is no need for additional governmental measures, e.g. in the form of taxation or subsidies, to address behavioral changes in energy prosuming.

1.4.3 Direct and Indirect Rebound Effects in German Households: A Linearized Almost Ideal Demand System Approach

I estimate direct and indirect energy rebound effects for a wide variety of goods and services in Germany. To this end, I employ a linearized approximation of the popular Almost Ideal Demand System (AIDS) approach suggested by Deaton and Muellbauer (1980). Excluding measures of energy efficiency when estimating rebound can lead to biased results. I compensate for this shortcoming of previous research by explicitly accounting for energy efficiency in the estimations. Using data for Germany from 1970 to 2017, I find moderate direct and significant indirect rebound effects for different energy carriers across four model specifications. Income rebound effects are outweighed by significant negative substitution effects, which in some cases even leads to negative overall rebound estimates.

1.5 Limitations and Shortcomings

The research in this dissertation is subject to some limitations that should be discussed. In chapter 2, I estimate an econometric model to analyze the determinants of space heating expenditures of German households using a long running panel. A limitation of the data is that the use of heating energy is not measured in kWh consumed, but instead in expenditures for heating, measured in €. This means that the model used is not estimating price elasticities, but expenditure elasticities. However, using a simple transformation, these elasticities can be used interchangeably. Another drawback of the data used is that it does not contain information on the heating technology used by the households. I use the natural gas price as a proxy for the price of heating, since natural gas is the most relevant energy carrier for heating in Germany and the prices for all heating sources are strongly correlated, with correlation coefficients between 0.87 and 0.98. In an alternative specification, I also use a price index for energy instead of consumer gas prices in Euro-cents as the price variable, which does not significantly affect the results.

In chapter 3, I use a cross-sectional study to assess possible differences in energy consumption between prosumers and consumers. In this analysis, the sample size is relatively small and there is no information on how much electricity prosumers feed into the grid or if and how much they self-consume. To ensure comparability between consumers and producers and avoid endogeneity issues, I therefore use heating expenditures as the dependent variable instead of electricity expenditures. The use of expenditures instead of consumption is necessitated by the fact that the consumption stated by the respondents is significantly less reliable compared to the self stated expenditures. Conducting a similar study with a larger sample would potentially increase the statistical significance of the results. However, the main finding of the chapter is that the differences in energy consumption between prosumers and consumers shrink significantly after matching, which arguably does not depend on the sample size used.

In chapter 4, the number of explaining variables that can be included is limited by the relatively small number of observations due to the use of yearly time series data. This is a common limitation when using time series data as opposed to panel data. However, this analysis focuses on prices as the most important explaining variables, which means that including additional variables is purely optional and may not help much in answering the research questions. Additionally, panel data was not available for the time frame in question.

Another limitation in this chapter, which can also be found in similar studies, is that the results are sensitive to the base year used for the expenditure shares. The methodology used includes the expenditure shares of the goods in question when calculating rebound effects. Since these shares fluctuate significantly over time, the resulting rebound estimates can also differ significantly depending on the expenditure shares that are used for their calculation. Based on the methodology, there is no obvious way to handle this (Chitnis and Sorrell, 2015). I therefore use the expenditure shares for 2017 in the main estimations and also include calculations using the expenditure shares for each year in the data set to show the variation that occurs when using different base years.

1.6 Future Research

The findings of this dissertation open several avenues for future research. Regarding energy use for space heating, which I analyze in chapter 2, including the heating technology used by the individual

household into the model would yield additional insights into energy consumption choices and behavior. If such data were available, a discrete-continuous choice model could be used to analyze how decisions regarding heating technology and energy usage are interlinked (Bakaloglou and Charlier, 2019). The analysis of residential heating behavior can also be a starting point towards estimating direct rebound effects for space heating. If this avenue were to be pursued, additional data on the efficiency of the heating systems used would be required, since rebound estimates based on price elasticities that ignore efficiency are biased (Hunt and Ryan, 2014).

Another way to analyze the existence and magnitude of rebound effects as a result of becoming a prosumer, which is the focus of chapter 3, would be through a long term field study of a sufficiently large number of households who are in the process of transitioning from consumers to prosumers. This would allow credible identification, for example via a difference-in-differences approach. Using this approach, researchers could also identify not just the magnitude of behavioral effects resulting from prosuming, but also the underlying mechanisms that cause these effects. The changes in regulation regarding PV prosuming in Germany could also be used as a natural experiment: feed in tariffs for prosumers are regularly reduced, which means that prosumers face different incentives based on the month in which their system was installed. This could be exploited if more detailed data on prosumer installations were available.

The estimation of direct and indirect rebound effects, as performed in chapter 4, could be extended by using household level panel data, similarly to Peters and McWhinnie (2015). This would allow researchers to include more socio-economic variables in the demand estimations. Additionally, modeling energy services instead of energy fuels could help in obtaining unbiased estimates of the rebound effect (Chan and Gillingham, 2015). Another option is to explore different ways to model efficiency, such as stochastic trends. A number of recent papers examines the role of stochastic trends and seasonal effects in energy demand modeling (Hunt et al., 2003; Dimitropoulos et al., 2005; Sa'ad, 2011; Hunt and Ryan, 2015; Atalla and Hunt, 2016). Reconciling this stream of literature with rebound modeling could prove fruitful in obtaining more precise rebound estimates.

1.7 Author's Contribution to the Individual Chapters

Chapter 2

The work contained in chapter 2 was originally published in:

Schmitz H., Madlener R. (2020). Heterogeneity in Price Responsiveness for Residential Space Heating in Germany. *Empirical Economics* (accepted, published online August 27, 2019).

The author's contribution to this work can be summarized as follows:

- Contribution to formulation of research questions
- Data collection and processing
- Formulation of econometric models
- Analysis and evaluation of the obtained results
- Writing of the manuscript

Chapter 3

The work contained in chapter 3 was originally published in:

Oberst C.A., Schmitz H., Madlener R. (2019). Are Prosumer Households That Much Different? Evidence from Stated Residential Energy Consumption in Germany. *Ecological Economics*, 158: 101-115.

The author's contribution to this work can be summarized as follows:

- Contribution to formulation of research questions
- Formulating and conducting propensity score matching
- Contribution to analysis and evaluation of the obtained results

Chapter 4

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The author's contribution to this work can be summarized as follows:

- Formulation of research questions
- Data collection and processing
- Formulation of econometric models
- Analysis and evaluation of the obtained results
- Writing of the manuscript

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Chapter 2

Heterogeneity in Price Responsiveness for Residential Space Heating in Germany

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2.1 Introduction

Space heating and hot water preparation accounted for 83.2% of household energy demand in Germany in 2015, making them the two foremost drivers of residential energy consumption. This far outweighs all other domestic applications such as cooking, information and communications technology (ICT), lighting, or cooling (BMWi, 2016). Therefore, space heating has a significant impact on overall energy consumption and, in light of the still dominating fossil fuel technologies used for heating, also on greenhouse gas emissions. Consequently, understanding the determinants of residential energy consumption for heating is highly relevant for the design and evaluation of policy measures aimed at curbing energy use. This is especially true when considering the ambitious energy policy goals set by the German Federal Government. Among these is the commitment to cut primary energy consumption by 20% until 2020 and by 50% until 2050, compared to the base year 2008 (BMWi, 2015).

In this paper, we provide micro-econometric evidence on the factors that drive the demand for space heating of different socioeconomic groups. Specifically, we explore the heterogeneity in consumer response between groups using several different approaches. In addition to fixed effects regressions, we interact our price variable with demographic variables to find differences in price reactions between

groups. Furthermore, we utilize quantile regression to gauge differences between households across the distribution of heating expenditures. Finally, we use a k -means clustering algorithm to group similar households according to demographic characteristics and evaluate how they differ in their heating behavior. To our knowledge, this paper is the first to investigate heterogeneity for the case of space heating in such detail.

There are a number of studies that focus on space heating using household level data for different regions. Typically, both technical and socio-demographic variables are found to be significant predictors of heating energy consumption (Schuler et al., 2000; Brounen et al., 2012). Rehdanz (2007) uses data from the German Socio-Economic Panel (SOEP) to investigate space heating and hot water preparation expenditures of German households for the years 1998 and 2003. The author finds a significant influence of a range of technical and socioeconomic variables on households' expenditures for heating. Another relevant study models heating expenditures using panel data for Great Britain (Meier and Rehdanz, 2010). However, they do not look into possible heterogeneity between groups. More recently, researchers have also examined other possible explaining factors, such as environmental habits and attitudes (Lange et al., 2014) or risk tolerance and trust (Volland, 2017).

The vast majority of studies estimating price and income elasticities in the context of consumer energy demand focus on obtaining the mean elasticity across all households. However, this ignores the possibility of heterogeneity between different groups of households that cannot be captured by simply estimating a mean effect over the entire sample. For example, low-income households might have significantly different price elasticities compared to more affluent ones due to several factors such as energy demand satiation of high-income households or the lack of access to energy substitutes of low-income households. Exploring the heterogeneity in energy demand by means of econometric modeling can help to better understand the underlying economic mechanisms that determine energy behavior, enhance policy efficiency, and design better targeted and thus more effective energy-saving policies.

While exploring heterogeneity in space heating with econometric models is largely uncharted territory, there are a small amount of papers assessing heterogeneity between households for energy use in general, using quantile regression methods (Kaza, 2010; Valenzuela et al., 2014). Another related stream of the literature explores heterogeneity in gasoline demand, utilizing a variety of methods such as interaction terms between prices and demographic variables (Wadud et al., 2010; Frondel, 2012; Gillingham, 2014), quantile regression (Frondel, 2012; Gillingham, 2014; Gillingham et al., 2015), and k -means clustering (Gillingham, 2014). These studies find strong evidence for heterogeneity between groups regarding their price and income elasticities. Whether the mechanisms causing this heterogeneity in private transport translate to other energy services, such as space heating, remains an open question.

Our research goal is twofold. Firstly, we want to examine what determines household expenditures for space heating, including technical factors as well as social characteristics and attitudes. Fixed effects modeling at the household level allows for more credible inference compared to previous studies that rely on cross-sectional data. Secondly, we investigate possible heterogeneity in price elasticities and other factors between different groups of consumers. We draw on annual data for Germany from 1996 to 2014 comprising more than 30,000 households in total. For the full sample, we find a price elasticity of expenditures for heating ranging from 0.573 to 0.690 across specifications, which is equivalent to a price elasticity of demand between -0.310 and -0.427 . We find evidence for heterogeneity in price responsiveness due to socioeconomic factors such as income and age. In contrast,

technical variables such as building age and type do not lead to significantly different price elasticities across groups. Still, these technical factors explain a substantial portion of the variation in heating expenditures for the sample as a whole.

The remainder of this article has the following structure. Section 2.2 presents the methodology employed for our estimations and the dataset used, which we compile from a variety of sources. Section 2.3 discusses the results obtained in light of our primary research questions. Firstly, we present the results for our main regressions on the full sample, which helps to explain the drivers of residential heating expenditures. Secondly, we investigate the heterogeneity of price responsiveness between household groups applying several distinct methods. Section 2.4 concludes and suggests some avenues for future research.

2.2 Data and Model

2.2.1 Data

We utilize data from a variety of sources. Our main data source is the German Socio-Economic Panel (SOEP), a panel survey conducted yearly by the German Institute for Economic Research (DIW Berlin). Initiated in 1984, this survey uses questionnaires to gather representative micro-level data on German households regarding their economic, social, and demographic situation.¹

Each individual in the sample who is at least 17 years old is questioned to assess individual characteristics, including level of education, detailed job history, and political preferences. Furthermore, the household head fills out an additional questionnaire with questions regarding household-specific characteristics such as the size of the dwelling, appliance stock, or the total household income. A separate set of survey questions is answered by the household head for each child living in the household.

Since one of the goals of the survey is to allow for long-term observations, the same participants are interviewed every year. To mitigate attrition caused by interviewees opting out or passing away, and in order to maintain the representative nature of the survey, additional samples are drawn irregularly, usually every 3-5 years. At the same time, people moving out of a sample household (e.g. due to divorce or children leaving their parents' home) remain in the sample as a new household. Non-sample people who move into a SOEP household are also included in all subsequent iterations of the survey.²

For our study, we combine personal and household data, clustered at the household level. Since not all of the variables of interest have been gathered since the beginning of the survey in 1986, we only investigate data from the period between 1996 and 2014. People residing in institutions such as retirement homes or student dormitories typically have no influence on how the heating system is operated. We therefore exclude these observations, which results in a main sample of 163,168 observations from 30,033 households in an unbalanced panel.

As the fuel type used for heating can only be observed for the waves of 1998 and 2003 of the sample, we do not include this variable in our estimations. Furthermore, the survey only monitors the expenditures of households for heating and hot water, but not their actual consumption or the prices they face. As a proxy for the price of space heating, we use the real consumer gas price, taken

¹ Similar panels from other countries include the PSID (US), BHPS (UK), SLID (Canada), and HILDA (Australia).

² For a more thorough description of the SOEP panel, see Wagner et al. (2007).

from BMWi (2016).³ As of 2010, nearly half of all households in Germany use natural gas for heating (Federal Statistical Office, 2012). Table 2.1 shows the relative shares of heating sources for German households in different years.

Table 2.1: Heating sources in German households, in %

Year	Natural gas ^a	Heating oil	District heating	Electricity	Renewables	Other
1998	43.25	33.97	13.10	4.62	1.13	3.94
2002	47.69	31.82	13.68	4.10	0.99	1.73
2006	48.56	30.15	13.24	4.04	2.98	1.02
2010	48.61	28.12	13.13	3.96	4.35	1.82

^a Shares based on number of households using a particular source. For households using multiple heating sources, only the primary source is counted.

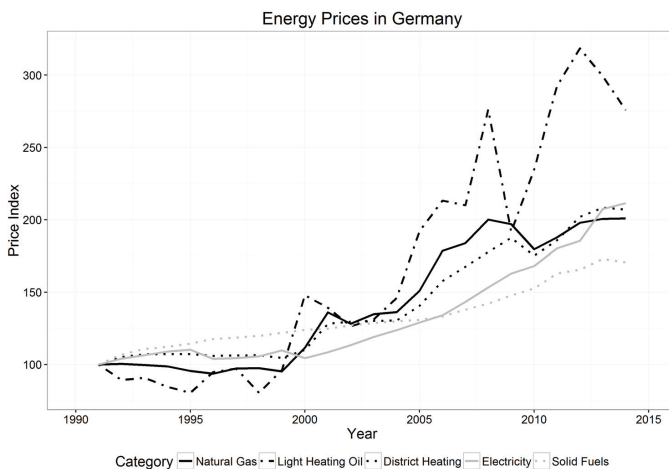


Figure 2.1: Consumer fuel prices in Germany (1991 = 100)

Figure 2.1 shows the price development of the most common residential heating fuels in Germany. After a period of stability between 1991 and 1999, heating fuel prices for consumers increased sharply across energy carriers since 2000. Visual inspection indicates that prices are highly correlated. Expanding on this, Table 2.2 shows the correlation coefficients between the prices of the five main energy carriers used for heating in Germany for the years 1991 to 2013, with coefficients between 0.87 and 0.98. Accordingly, we are confident in using consumer gas prices as our main variable for explaining the price of space heating. In an alternative specification, we also use a price index for energy instead of consumer gas prices in Eurocents as the price variable, which turns out to not significantly affect the results.

We account for regional price variation in two ways: Firstly, we calculate the deviation (in percent)

³ This approach has also been employed by Dieckhöner (2012), among others.

of state-level prices from the federal level for the years 2012-2014.⁴ Due to the lack of state-level data for the rest of our observation period, we assume the differences between states in terms of price during these years to be constant and add or subtract the previously calculated corresponding deviation for the individual states. Secondly, we include state dummies to account for any other variation in prices or other factors between the sixteen federal states in Germany, such as differences in regulatory schemes.

Table 2.2: Correlation matrix of heating fuel prices

Variable	Natural gas	Light heating oil	District heating	Electricity	Wood
Natural gas	1	0.944	0.982	0.887	0.872
Light heating oil	0.944	1	0.957	0.916	0.906
District heating	0.982	0.957	1	0.947	0.923
Electricity	0.887	0.916	0.947	1	0.896
Solid fuels	0.872	0.906	0.923	0.896	1

For most households, the survey is conducted in the first quarter of the year, and some of the questions relate to the year before.⁵ Therefore, we add the consumer gas price from the previous year to our dataset (in 2010 terms). Table 2.3 presents an overview of the selection of variables that we use for our empirical analysis.

2.2.2 Descriptive Statistics

The relevant descriptive statistics of our socio-demographic and technical variables can be seen in Tables 2.4 and 2.5, respectively. For the person-related variables, we compute the mean of all adult members of the household. An alternative specification would be to only use the data for the household head. However, we assume that heating consumption decisions are usually not only made by the head of the household, but by all (adult) household members.⁶

We include the variables on occupation ('Fulltime', 'Parttime', 'Unemployed', and 'Retired') to assess whether they also influence expenditures. Some of these groups are likely to spend more hours at home, such as unemployed people (Longhi, 2015). We use the share of all adult members in the household falling into that category, meaning that for any given household, values can range between 0 and 1. People can also fall into multiple categories if they occupied more than one role over the course of a given year. To account for differences in climate between federal states and years, we include the number of heating degree days at the state level of the previous year, measured in $^{\circ}\text{C} \cdot \text{d}$ with base temperature 15°C . For the 'Education' variable, we take the average of the highest educational degree of each adult household member converted into years. The values in our sample range from 7 years (no household member has a degree) to 18 years (all household members have a university degree). For the price, expenditure, income, and dwelling size variables, we take the logarithm of the respective values to be able to interpret these changes as percentages.

Figure 2.2 depicts the distribution of heating expenditures in 2010 terms among households. The mean value for yearly real expenditures in our sample is € 1,228.96, with a median of € 1,082.74.

⁴ Regional price data are taken from Bukold (2015).

⁵ Specifically, renters are asked what their average monthly cost of heating is, whereas homeowners are asked what their cost of heating was in the preceding calendar year.

⁶ We also estimate our models using only household head data, which leads to results that are virtually identical both in terms of model fit and coefficient estimates. Full model results can be found in the appendix.

Table 2.3: Variable definitions

Variable	Description
log(Exp_Space)	Log of yearly real heating expenditures per square meter, in Euros
log(Exp_Capita)	Log of yearly real heating expenditures per inhabitant, in Euros
log(Gasprice)	Log of real gas price, in Eurocents per kWh
log(EPI)	Energy price index, 2010 = 100
log(Income_Capita)	Log of yearly real net household income per inhabitant, in Euros
log(Space)	Log of size of dwelling, in square meters ($1 \text{ m}^2 = 10.76 \text{ ft}^2$)
Condition	Condition of home (in good condition, partial renovation, major renovation, ready for demolition), 1 or 0
New_Windows	1 if new windows were installed in the previous year, 0 otherwise
New_Heating	1 if new heating system was installed in the previous year, 0 otherwise
Type	Type of building (farm house, single or double house, row/terrace house or duplex, building containing 3 to 4 dwellings, building containing 5 to 8 dwellings, building containing 9 or more dwellings, high rise building, other), 1 or 0
Year	Vintage class of building (before 1919, 1919–1948, 1949–1971, 1972–1980, 1981–1990, 1991–2000, 2001–2010, 2011 or later), 1 or 0
Central_Heat	1 if household has a central heating system, 0 otherwise
Adults	Number of adults (age 17 or older) in household
Children	Number of children (age 16 or younger) in household
Owner	Owner or tenant of dwelling, 1 or 0
Gender	Share of male household members (adults only)
Age	Mean age of adult household members
Greens	Share of adult household members who support the Green Party
Education	Mean education level of adult household members, in years
Fulltime	Share of adult household members working full time
Parttime	Share of adult household members working part time
Unemployed	Share of adult household members registered unemployed
Retired	Share of adult household members in retirement
HDD	Heating degree days (measured at federal state level), in $^{\circ}\text{C} \cdot \text{d}$
State	Federal State (Schleswig-Holstein, Hamburg, Lower Saxony, Bremen, North Rhine-Westphalia, Hesse, Rhineland-Palatinate, Baden-Wuerttemberg, Bavaria, Saarland, Berlin, Brandenburg, Mecklenburg-Western Pomerania, Saxony, Saxony-Anhalt, Thuringia), 1 or 0

Table 2.4: Summary statistics, economic and socio-demographic variables

Variable	Mean	St. Dev.	Min	Max
Income_Capita	14,854.620	11,942.900	45.200	1,170,731
Gasprice	5.844	1.057	3.923	7.540
Exp_Space	12.587	6.940	0.005	169.583
Exp_Capita	581.795	441.195	0.167	9,414.025
Adults	1.991	0.811	1	10
Children	0.589	0.971	0	11
Owner	0.516	0.500	0	1
Gender	0.477	0.268	0	1
Age	49.016	15.891	18	100
Age_sq	2,655.057	1,700.534	324	10,000
Greens	0.051	0.197	0	1
Education	12.193	2.477	7	18
Fulltime	0.426	0.393	0	1
Parttime	0.146	0.274	0	1
Unemployed	0.090	0.243	0	1
Retired	0.271	0.417	0	1
HDD	3,062.76	283.67	2,428.51	4,063.74

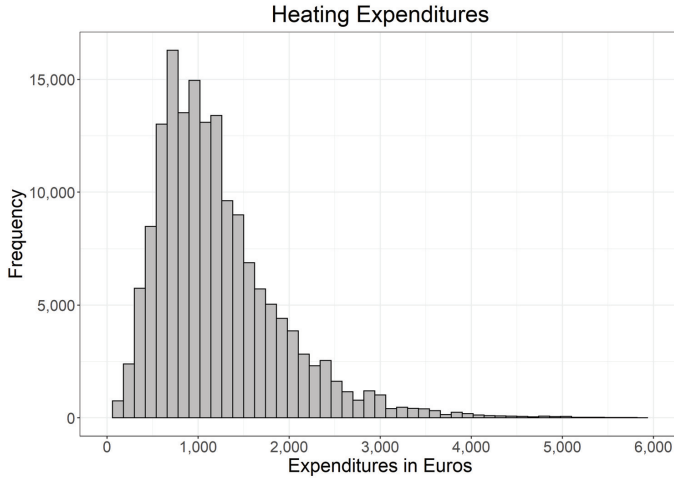


Figure 2.2: Distribution of heating expenditures per year

Table 2.5: Summary statistics, technical variables

Variable	Mean	St. Dev.
Space	104.529	45.635
New_Heating	0.021	0.144
NEW_Windows	0.044	0.205
Central_Heat	0.948	0.221
Condition_1 (In Good Condition)	0.701	0.458
Condition_2 (Partial Renovation)	0.271	0.445
Condition_3 (Major Renovation)	0.027	0.163
Condition_4 (Ready For Demolition)	0.001	0.032
Type_1 (Farm House)	0.028	0.166
Type_2 (1-2 Fam. House)	0.367	0.482
Type_3 (1-2 Fam. Rowhouse)	0.181	0.385
Type_4 (Apt. In 3-4 Unit Bldg.)	0.102	0.303
Type_5 (Apt. In 5-8 Unit Bldg.)	0.180	0.384
Type_6 (Apt. In 9+ Unit Bldg.)	0.129	0.335
Type_7 (High Rise)	0.012	0.110
Type_8 (Other)	0.001	0.027
Built before 1919	0.148	0.355
Built 1919-1948	0.152	0.359
Built 1949-1971	0.285	0.451
Built 1972-1980	0.145	0.352
Built 1981-1990	0.104	0.305
Built 1991-2000	0.123	0.329
Built 2001 or later	0.044	0.205

2.2.3 Model Specification

We assume that households maximize their utility from heating and choose the amount of space heating consumed accordingly. Until 1998, the supply of gas to end consumers in Germany was organized in regional monopolies. Even after liberalization, the option to switch providers appears severely limited. In 2005, consumers who changed providers accounted for only 0.01% of total gas consumption.⁷ In 2007, 0.8% of private gas consumers decided to switch their provider; in 2014, this ratio was 8.4% (BNetzA, 2015). We therefore assume consumers to be price takers and prices to be exogenous. Given that expenditures are defined as a function of price and consumption, information on consumption choices can be derived by comparing changes in expenditures and prices.

In line with related recent literature (Meier and Rehdanz, 2010; Lange et al., 2014), our model of heating expenditures takes the form

$$\ln(E_{i,t}) = \beta_P \ln(P_{i,t}) + \beta_T \mathbf{T}_{i,t} + \beta_D \mathbf{D}_{i,t} + \beta_S \mathbf{S}_{i,t} + \gamma_i + \epsilon_{i,t} \quad (2.1)$$

with $E_{i,t}$ denoting the heating expenditures of household i at time t , $P_{i,t}$ the consumer gas price, $T_{i,t}$ the building characteristics, $D_{i,t}$ the socio-demographic and socio-economic variables, $S_{i,t}$ the state dummies, γ_i the time-invariant household fixed effects, and $\epsilon_{i,t}$ the error term. Prices, incomes, and expenditures are in 2010 terms. As is common in the literature, we use a log-linear model specification.

Conducting a Hausman test rejects the hypothesis that errors are uncorrelated with the regressors (Hausman, 1978). Therefore, we employ fixed effects at the household level rather than random effects. Using the average for all adult members of the household for variables such as education and gender, instead of only considering the household head, results in sufficient year-to-year variation in our sample due to individuals leaving or joining the household in question, rendering a fixed effects approach feasible. The same is true for the technical characteristics of the home such as the construction year of the building: since the observational unit is the household and not the home itself, the variables describing the home change everytime a household moves. The large sample size, coupled with the long time horizon of the data, allows for sufficient variation in the data for these variables. Whereas previous studies either used cross-sectional data or employed random effects models, the use of household fixed effects allows for more consistent estimations. In line with related studies (Baker et al., 1989; Meier and Rehdanz, 2010; Brounen et al., 2012; Lange et al., 2014), we model conditional demand, meaning that we neither observe nor account for possible changes in the appliance stock of the individual household. Instead, we analyze energy behavior given the current equipment stock of the households.

2.3 Results

2.3.1 Regression Results

In the first step of our analysis, we aim at finding determinants of energy expenditures among the technical, economic, and demographic variables at our disposal. Table 2.6 shows the results of our regression for four model specifications that differ in the dependent variable and in the price variable included. As our dependent variables, we use expenditures per square meter and expenditures per

⁷ In the category households and small businesses consuming 300 MWh/a or less. Data from BNetzA (2006).

capita, respectively. We do not equalize per capita expenditures, meaning that we do not use weights to distinguish between different household members such as adults and children. To represent the price of heating, we utilize the consumer gas price in model specifications (i) and (iii) and an energy price index in specifications (ii) and (iv).⁸

Table 2.6: Regression results

	Heating expenditures per m ²		Heating expenditures per capita	
	(i)	(ii)	(iii)	(iv)
log(Gasprice)	0.638*** (0.013)		0.690*** (0.014)	
log(EPI)		0.571*** (0.014)		0.639*** (0.015)
log(Income_Capita)	0.026*** (0.006)	0.026*** (0.006)	0.091*** (0.007)	0.092*** (0.007)
log(Space)	-0.700*** (0.012)	-0.711*** (0.012)	0.251*** (0.012)	0.237*** (0.012)
In Good Condition		(base)	(base)	(base)
Partial Renovation	0.026*** (0.004)	0.023*** (0.004)	0.026*** (0.004)	0.022*** (0.004)
Major Renovation	0.054*** (0.011)	0.050*** (0.011)	0.056*** (0.011)	0.051*** (0.011)
Ready For Demolition	0.107** (0.049)	0.100** (0.050)	0.109** (0.049)	0.102** (0.049)
New_Windows	-0.004 (0.006)	-0.008 (0.006)	-0.007 (0.006)	-0.011* (0.006)
New_Heating	-0.020** (0.010)	-0.022** (0.010)	-0.021** (0.010)	-0.023** (0.010)
Farm House		(base)	(base)	(base)
1-2 Fam. House	0.040 (0.040)	0.041 (0.040)	0.038 (0.039)	0.040 (0.039)
1-2 Fam. Rowhouse	0.005 (0.041)	0.006 (0.041)	0.002 (0.041)	0.003 (0.040)
Apt. In 3-4 Unit Bldg.	-0.020 (0.041)	-0.017 (0.041)	-0.017 (0.040)	-0.014 (0.040)
Apt. In 5-8 Unit Bldg.	-0.032 (0.041)	-0.029 (0.040)	-0.030 (0.040)	-0.026 (0.040)
Apt. In 9+ Unit Bldg.	-0.080* (0.042)	-0.078* (0.042)	-0.071* (0.041)	-0.069* (0.041)
High Rise	-0.019 (0.055)	-0.027 (0.055)	-0.020 (0.054)	-0.028 (0.054)
Other	0.060 (0.055)	0.062 (0.055)	0.026 (0.041)	0.028 (0.041)
Built before 1919		(base)	(base)	(base)
Built 1919-1948	0.007 (0.015)	0.008 (0.015)	0.005 (0.016)	0.006 (0.016)
Built 1949-1971	-0.033** (0.015)	-0.036** (0.016)	-0.037** (0.016)	-0.040** (0.016)
Built 1972-1980	-0.052*** (0.018)	-0.054*** (0.018)	-0.057*** (0.018)	-0.060*** (0.018)
Built 1981-1990	-0.063*** (0.021)	-0.067*** (0.021)	-0.069*** (0.021)	-0.074*** (0.021)
Built 1991-2000	-0.117*** (0.019)	-0.116*** (0.019)	-0.122*** (0.019)	-0.122*** (0.019)
Built 2001 or later	-0.299*** (0.023)	-0.317*** (0.024)	-0.295*** (0.023)	-0.317*** (0.024)
Central_Heat	0.040*** (0.010)	0.048*** (0.010)	0.039*** (0.010)	0.049*** (0.010)
Adults	0.076*** (0.005)	0.055*** (0.005)	-0.322*** (0.005)	-0.347*** (0.006)
Children	0.032*** (0.004)	0.044*** (0.005)	-0.297*** (0.005)	-0.282*** (0.005)
Owner	0.014*** (0.007)	0.022*** (0.007)	0.023*** (0.007)	0.031*** (0.007)
Gender	-0.049*** (0.014)	-0.038*** (0.014)	-0.067*** (0.017)	-0.054*** (0.017)
Age	0.008*** (0.002)	0.005*** (0.002)	-0.005*** (0.002)	-0.008*** (0.002)
Age_sq	-0.00004*** (0.000)	-0.00006*** (0.000)	0.0001*** (0.000)	0.0001*** (0.000)
Greens	-0.017* (0.009)	-0.022** (0.010)	-0.017* (0.010)	-0.022** (0.010)
Education	0.001 (0.003)	-0.001 (0.003)	0.002 (0.003)	-0.005* (0.003)
Fulltime	-0.006 (0.007)	-0.005 (0.007)	0.016** (0.007)	0.014** (0.007)
Parttime	-0.021*** (0.007)	-0.024*** (0.007)	-0.033*** (0.007)	-0.036*** (0.007)
Unemployed	0.012 (0.007)	0.016** (0.007)	0.015** (0.008)	0.021 (0.008)
Retired	-0.022** (0.009)	-0.024*** (0.009)	-0.022** (0.009)	-0.025*** (0.009)
HDD	0.00005*** (0.000)	0.00002*** (0.000)	0.00005*** (0.000)	0.00002*** (0.000)
Federal state dummies	Yes	Yes	Yes	Yes
<i>N</i>	163,168	163,168	163,168	163,168
<i>R</i> ²	0.140	0.137	0.273	0.272
Adjusted <i>R</i> ²	-0.055	-0.058	0.108	0.108
<i>F</i> Statistic (<i>df</i> = 50; 30032)	172.045***	160.287***	368.758***	360.141***

Notes:***,**, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Clustered robust standard errors in parentheses.

The price variable has a highly significant influence on expenditures, with values between 0.573 and 0.690. Since our dependent variable is heating expenditures and not heating energy consumption, a value of 1 would correspond to a situation of perfectly inelastic demand, whereas a value of 0 would mean that demand is perfectly elastic. Two other studies that are directly comparable, given that they also use heating expenditures as their dependent variable, find values between 0.33 and 0.65 for Germany (Rehdanz, 2007) and between 0.36 and 0.83 for Great Britain (Meier and Rehdanz, 2010) across different fuel types and model specifications. When we use a price index for energy instead of the gas price (specifications (ii) and (iv), denoted as EPI), the estimates for the price coefficient are slightly lower, while most of the other coefficient estimates are similar.

Let E denote expenditures for heating, C is heating consumption, and p describes the price of heating. Given

⁸ Specifically, we use the price index for CC045 (electricity, gas and other fuels) in the COICOP classification scheme, which is a weighted combination of the price indices for electricity, gas, liquid fuels, solid fuels, and other fuels (including district heating). Data taken from Federal Statistical Office (2016).

$$E = Cp \quad (2.2)$$

and

$$\ln(E) = \ln(C) + \ln(p), \quad (2.3)$$

the elasticity with respect to expenditures can easily be approximated as a standard price elasticity using the following transformation:

$$\frac{\partial \ln(E)}{\partial \ln(p)} = \frac{\partial \ln(C)}{\partial \ln(p)} + \frac{\partial \ln(p)}{\partial \ln(p)} \Leftrightarrow \frac{\partial \ln(E)}{\partial \ln(p)} - 1 = \frac{\partial \ln(C)}{\partial \ln(p)} \quad (2.4)$$

Accordingly, the corresponding price elasticity of heating demand in our estimations ranges from -0.31 to -0.43.

We find that the income elasticity varies from 0.026 to 0.092 across models when using per capita household income, which is largely consistent with comparable studies. Comparable values from the literature include 0.055 for the Netherlands (Brounen et al., 2012), 0.009 to 0.037 for Great Britain (Meier and Rehdanz, 2010), and 0.010 to 0.095 for Germany (Rehdanz, 2007). Negative values are uncommon, but not unheard of (see e.g. Berkhout et al. 2004). Since we model conditional demand only, the results should be considered as short-term elasticities. In contrast, medium- and long-term income elasticities tend to be higher. Households with increased income are likely to move into larger homes over the medium term, which would increase their heating expenditures as well (Nesbakken, 1999).

Given that in Germany access to sufficient heating is available to virtually anyone due to social assistance programs, it is not surprising that expenditures do not vary much with income. It appears likely that even low-income households are able to fulfill their heating needs to a large extent. Furthermore, high-income households presumably have access to better insulation and more efficient heating systems. This means that even if these households were to seek a significantly higher level of thermal comfort, their energy consumption (and therefore expenditures) would not necessarily increase much. Since we cannot control for measures of efficiency directly, we expect that part of this effect is captured by the income variable, which might have slightly higher coefficients otherwise. We observe the self-assessed condition of the home, which we assume to be at least partially correlated with thermal efficiency. We find the mean household income of people living in a home with the highest condition rating (in good condition) to be 84% higher than for people living in a dwelling with the lowest level (ready for demolition). This appears to confirm our hypothesis that high income households have access to more energy-efficient heating services. Furthermore, our results indicate that heating is a necessity, rather than a luxury service.

Moving on to other technical characteristics of the home, we find expenditures to significantly increase with building age. In Germany, the Energy Savings Ordinance (EnEV), which was first introduced in 2001 and most recently amended in 2015, requires that all newly constructed buildings fulfill strict efficiency standards (EnEV, 2013). Our results provide evidence for the strong effect of these rules. Other significant drivers of heating expenditures are living space, building condition, and the existence of a central heating system.

A number of socio-demographic variables also significantly influence heating expenditures. Namely, the number of inhabitants has a positive influence on expenditures per square meter. The negative coefficients for models (iii) and (iv) imply significant economies of scale. The average age of occupants also has a small positive influence on expenditures. Other studies find the relationship between age and energy use to be nonlinear: energy consumption generally increases with age, before declining again after a certain age threshold (Baker et al. 1989; Meier and Rehdanz 2010). We include age squared in the model to test for this possibility.

Some other socio-demographic characteristics have previously received little attention in modeling heating demand. For instance, we observe that a larger share of female adults in the household increases expenditures for space heating. According to specifications (i) and (ii), the difference in magnitude between an all-male and an all-female household is roughly equivalent to an additional person living in the household. While few comparable studies exist, there is some evidence that female-dominated households use more energy than male-dominated ones (Elnakat and Gomez, 2015). As a proxy for environmental consciousness, we use the variable ‘Greens’: it indicates the share of adult household members who state that they support the German Green Party. As our results show, the variable has a significant negative influence on energy expenditures for all four model specifications. While there is some evidence for a negative influence of high environmental consciousness and energy consumption (Sapci and Considine, 2014), others find no significant correlation between expenditures and eco-friendly attitudes and beliefs (Lange et al., 2014).

Regional climatic variation in Germany is relatively low compared to other countries. The mean number of yearly Heating Degree Days between 1995 and 2015 was 3075.62 across the sixteen German federal states, with a standard deviation of 290.58. Still, climatic conditions are an important factor in heating demand, and a higher average temperature results in lower heating expenditures in our estimations. Additionally, we include dummies for each state to account for further heterogeneity between federal states in terms of climate, prices, and other factors. However, given the lack of statistical significance for the majority of coefficients, these differences appear to be already captured by other variables in our models. The relatively low values for R^2 indicate that a large part of the variation in expenditures cannot be explained by the variables in our model and are therefore caused by unobserved or unobservable factors. This is further emphasized by the large coefficients of the household fixed effects. In model (i), the mean effect is 3.74 with a standard deviation of 0.42.

2.3.2 Evidence for Heterogeneity between Groups

In order to quantify the heterogeneity of the determinants of heating demand between different groups of consumers, we employ three distinct methods. Each of these allows us to uncover different facets of heterogeneity in our data: firstly, we utilize interaction terms between the log of the real gas price and seven other explanatory variables to reveal differences in price responsiveness between different groups of consumers. Furthermore, we employ quantile regression to obtain information about the relationship between heating expenditures and fuel price at different quantiles of the distribution. Finally, we split the sample into groups of similar households across a number of characteristics using k -means clustering. Based on model fit, but also for the sake of clarity and comparability with other studies in the literature, we focus on the log of heating expenditures per capita (specification (iii) from Table 2.6) as our dependent variable from now on.

2.3.2.1 Interaction terms

Table 2.7 shows the results for a model specification that includes seven interaction terms. All the explanatory variables from Table 2.6 are still included in the specification, but not all of them are shown in this table for the sake of brevity. To allow for easier interpretation, all variables that are involved in interactions are mean-centered, with the exception of ‘Owner’, which is a categorical variable. We choose these particular interactions to investigate differences in price responsiveness between different socio-demographic groups.

Table 2.7: Regression results including interaction terms

Heating expenditures per capita, in Euros		
	(i)	(ii)
log(Gasprice)	-0.127 (0.217)	0.690*** (0.014)
log(Income_Capita)	-0.051 (0.038)	0.091*** (0.007)
log(Space)	0.246*** (0.012)	0.251*** (0.012)
New_Windows	-0.009 (0.006)	-0.007 (0.006)
New_Heating	-0.023** (0.010)	-0.021** (0.010)
Central_Heat	0.048*** (0.010)	0.038 (0.039)
Adults	-0.331*** (0.026)	-0.322*** (0.005)
Children	-0.420*** (0.025)	-0.297*** (0.005)
Owner	0.318*** (0.034)	0.023** (0.007)
Gender	-0.051 (0.072)	-0.067*** (0.017)
Age	-0.005*** (0.002)	-0.005 (0.002)***
Age_sq	0.0001*** (0.000)	0.0001*** (0.000)
Greens	-0.016 (0.080)	-0.017* (0.010)
Education	-0.001 (0.003)	0.002 (0.003)
Fulltime	-0.015** (0.007)	0.016** (0.007)
Parttime	-0.034*** (0.007)	-0.033*** (0.007)
Unemployed	0.014* (0.008)	0.015 (0.008)**
Retired	-0.022** (0.009)	-0.022** (0.009)
HDD	-0.00004*** (0.000)	-0.00005*** (0.000)
log(Gasprice) * log(Income)	0.082*** (0.021)	
log(Gasprice) * Adults	0.004 (0.015)	
log(Gasprice) * Children	0.074*** (0.014)	
log(Gasprice) * Owner	0.207*** (0.021)	
log(Gasprice) * Gender	-0.012 (0.040)	
log(Gasprice) * Age	-0.002** (0.001)	
log(Gasprice) * Greens	-0.002 (0.045)	
Building type effects	Yes	Yes
Building condition effects	Yes	Yes
Building age effects	Yes	Yes
Federal state dummies	Yes	Yes
N	163,168	163,168
R ²	0.275	0.273
Adjusted R ²	0.111	0.108
F Statistic	457.004***	160.287***
	(df = 42; 30032)	(df = 50; 30032)

Notes:***,**, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Clustered robust standard errors in parentheses. Column (ii) reproduces column (iii) from Table 2.6 for comparison.

The results show that higher income is associated with higher elasticity of heating expenditures, which corresponds to lower price elasticities in magnitude. Since this paper is the first to investigate

this issue for space heating expenditures, comparisons with previous research are challenging. One comparable study is Madlener and Hauertmann (2011); the authors find similar results investigating the heterogeneity of rebound effects in residential space heating in Germany by income and ownership. For driving, evidence is mixed: Gillingham (2014) finds that wealthier households react more strongly to price increases, which is the exact opposite of what we find for heating. This can be explained by two factors: firstly, richer households may have more discretionary driving that can easily be avoided when facing higher prices. Secondly, wealthy households are more likely to own multiple vehicles, which allows them to switch to the more fuel-efficient one when prices increase (Gillingham, 2014). In space heating, these two phenomena seem less relevant. The potential for fuel switching is low, especially in the short term, due to the significant costs of installing a new heating system (Michelsen and Madlener, 2016). Discretionary consumption also appears to be less of an issue in heating than in driving: taking into account that the price of heating is relatively low compared to overall income especially for high-income consumers, it appears likely that these households simply consume as much heating as they desire, with little regard to costs. Since heating costs represent a more significant share of expenditures for low-income households, it seems reasonable to conclude that they pay more attention to price increases for heating, and react more strongly to those increases as a consequence.

The demographic interactions are not statistically significant, indicating that price elasticities do not vary substantially with gender, environmental consciousness, and number of household members. While our analysis in section 2.3.1 shows that male-dominated households spend less on heating than those with more female inhabitants, there is no significant difference between men and women regarding their price elasticity. In contrast, the interaction between price and home ownership is statistically significant and relatively large in magnitude. Specifically, homeowners react less strongly to price changes than renters. This effect, which also confirms previous findings by Madlener and Hauertmann (2011), might be driven at least partially by the fact that homeowners usually have higher incomes than tenants.

2.3.2.2 Quantile Regression

While standard OLS regressions estimate the conditional mean of the distribution, quantile regression allows us to derive coefficients at different quantiles of the distribution of the dependent variable (Koenker and Bassett Jr., 1978). Therefore, we can discover whether households who spend more on heating react differently to changes in prices and other variables compared to those who consume less. This is especially relevant in this context since households with high consumption levels are a particular valuable target for policy measures when the goal is to reduce consumption. If significant differences between quantiles exist, policy measures aimed at the average household might be ineffective for other groups of consumers. Table 2.8 shows the results for the quantile regression at the 0.1, 0.3, 0.5, 0.7, and 0.9 quantiles of logged heating expenditures per capita.

While most of our coefficients are highly statistically significant, they are also relatively stable between quantiles. Conducting F -tests reveals statistically significant differences between coefficients for the different quantiles for some of the variables. Notably, the price variable has significantly different effects for some of the quantiles, as Table 2.9 shows. On the other hand, the effect of additional income does not vary significantly between quantiles.⁹

When comparing the price elasticities at the different quantiles, the price response is slightly

⁹ Additional F -test results for the variables 'Income_Capita', 'Space', and 'Owner' can be found in the appendix.

Table 2.8: Quantile regression results, full sample

Variable	Q10 (i)	Q30 (ii)	Q50 (iii)	Q70 (iv)	Q90 (v)
log(Gasprice)	0.667*** (0.011)	0.656*** (0.007)	0.639*** (0.007)	0.634*** (0.008)	0.647*** (0.011)
log(Income_Capita)	0.076*** (0.076)	0.074*** (0.004)	0.076*** (0.003)	0.074*** (0.004)	0.080*** (0.005)
log(Space)	-0.521*** (0.007)	-0.517*** (0.006)	-0.523*** (0.006)	-0.541*** (0.005)	-0.579*** (0.008)
New_Windows	-0.028** (0.015)	-0.012* (0.009)	0.006 (0.006)	0.022*** (0.007)	0.013 (0.009)
New_Heating	-0.048** (0.017)	-0.016 (0.010)	0.064 (0.011)	0.013 (0.009)	0.037*** (0.014)
Central_Heat	0.251*** (0.015)	0.152*** (0.001)	0.108*** (0.007)	0.090*** (0.007)	0.071*** (0.011)
Adults	0.105*** (0.003)	0.091*** (0.002)	0.087*** (0.002)	0.083*** (0.002)	0.079*** (0.003)
Children	0.039*** (0.004)	0.037*** (0.002)	0.037*** (0.002)	0.040*** (0.002)	0.045*** (0.003)
Owner	-0.101*** (0.006)	-0.055*** (0.004)	-0.044*** (0.004)	-0.033*** (0.004)	-0.030*** (0.005)
Gender	-0.088*** (0.008)	-0.055*** (0.006)	-0.030*** (0.006)	-0.020*** (0.005)	-0.014 (0.007)
Age	0.013*** (0.001)	0.008* (0.001)	0.006*** (0.001)	0.005* (0.001)	0.003*** (0.001)
Age_aq	-0.0001*** (0.000)	-0.00004*** (0.000)	-0.00001** (0.000)	-0.000002 (0.000)	0.0000004 (0.000)
Greens	-0.070*** (0.013)	-0.079*** (0.007)	-0.069*** (0.007)	-0.061*** (0.008)	-0.072*** (0.010)
Education	0.003 (0.001)	0.002 (0.001)	0.002* (0.001)	0.003*** (0.001)	0.002 (0.001)
Fulltime	-0.050*** (0.008)	-0.033*** (0.006)	-0.022*** (0.005)	-0.013* (0.006)	-0.002 (0.007)
Parttime	-0.028*** (0.009)	-0.029*** (0.006)	-0.037*** (0.005)	-0.027*** (0.006)	-0.013* (0.009)
Unemployed	0.046*** (0.010)	0.046*** (0.007)	0.039*** (0.007)	0.037*** (0.006)	0.040*** (0.008)
Retired	-0.055*** (0.011)	-0.038*** (0.009)	-0.031*** (0.008)	-0.025*** (0.007)	-0.012 (0.010)
HDD	0.00004*** (0.000)	0.00004*** (0.000)	0.00004*** (0.000)	0.00004*** (0.000)	-0.00003 (0.000)
Constant	1.351*** (0.076)	2.026*** (0.054)	2.394*** (0.044)	2.824*** (0.048)	3.385*** (0.057)
Building type effects	Yes	Yes	Yes	Yes	Yes
Building condition effects	Yes	Yes	Yes	Yes	Yes
Building age effects	Yes	Yes	Yes	Yes	Yes
Federal state dummies	Yes	Yes	Yes	Yes	Yes
N	163,168	163,168	163,168	163,168	163,168
Pseudo R ²	0.1095	0.1134	0.1104	0.1073	0.1110

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Clustered robust standard errors are in parentheses, calculated via bootstrap methods.

Table 2.9: F-Test results for differences between quantiles, gas price

Quantiles	10%	30%	50%	70%	90%
10%	-	-	-	-	-
30%	1.12	-	-	-	-
50%	5.66**	8.42***	-	-	-
70%	6.69***	6.85***	0.55	-	-
90%	1.66	0.58	0.63	1.77	-

Notes:***, **, and * indicate significant differences between the respective quantiles at the 0.01, 0.05, and 0.10 levels, respectively.

weaker for households in the middle of the distribution (Q_{50} and Q_{70}) compared to the other groups. A similar U-shaped pattern for the price reaction is reported by Kaza (2010), who considers total household energy consumption, including heating, cooling, and electricity, for households in the US. Our results show that many of the coefficients are smaller in magnitude at the higher end of the distribution, with some of them becoming statistically insignificant as well. This is compensated by a larger intercept for the higher quantiles. Our finding suggests that households at higher quantiles spend more due to unobserved factors, which are then captured by higher coefficients for the fixed effects at the household level. In contrast with our previous results, we find that homeowners spend less on heating in this specification, compared to renters.

2.3.2.3 Means Clustering

Means clustering is a statistical technique to separate data into groups of similar observations (Forgy, 1965). Specifically, k -means clustering splits the n observations in the data set into k groups. The researcher chooses the number of groups and the variables on which to cluster. Initial group means are chosen at random. Then, observations are assigned to those groups in order to minimize the sum of squared differences between every observation and the nearest mean. Usually, the Euclidean distance is used as the measure for the sum of squares. Afterwards, new group means are chosen, if necessary. Observations are then reassigned to different clusters if it improves the solution. This process is iterated until a stable equilibrium is reached.

In principle, any combination of variables can be used to cluster. Here, our goal for the clustering is to identify groups of archetypical households and investigate whether they exhibit significant differences in their behavior, which would allow policymakers to implement more specific measures that target heating behavior. For this analysis, we utilize age and income as two of the main indicators by which households are often classified into socioeconomic groups. Before clustering, we z-standardize both variables. Since the clustering uses the Euclidean distance between observations, variables with higher variation have a stronger impact on group composition. In our case, the clustering would be almost entirely driven by variation in income if we did not standardize the variables. Generally, a higher number of groups allows for more exact clustering as it reduces the sum of squared differences in the sample. On the other hand, having too many groups can result in group sizes that are too small for meaningful estimations. As a compromise between these factors, we use four groups. After assigning each observation to a group, we proceed using the non-standardized values for income and age for clarity and comparability. The summary statistics for the groups are reported in Table 2.10. All groups are sufficiently large for further analysis. Table 2.11 shows the results for our preferred specification, estimated separately for the four subgroups.

Groups 1 and 2 are similar in age, but differ substantially in income per capita. The estimated coefficient for the price variable ranges from 0.584 to 0.737 across the four groups, which corresponds to price elasticities between -0.263 and -0.416 . This is in line with the results reported in Table 2.7, where the interaction between price and income shows that higher income households exhibit a weaker price reaction.

Most of the other variables have the expected signs, but differ in magnitude and significance. A notable exception is ‘Owner’, which is positive for groups 1 and 3, negative for group 2, and insignificant for group 4. Generally, the principal-agent problem between landlords and tenants would suggest that renters spend more on heating than homeowners (Allcott and Greenstone, 2012;

Table 2.10: Group means

Statistic	Mean	St. Dev.	N
Group 1: young, low income			
Age	36.81	7.57	60,355
Income	7,202.44	1,857.21	60,355
Group 2: young, medium income			
Age	37.72	7.37	59,684
Income	15,849.14	4,586.99	59,684
Group 3: high age, medium income			
Age	69.21	8.70	53,472
Income	12,892.42	3,807.48	53,472
Group 4: medium age, high income			
Age	57.00	10.88	27,641
Income	31,731.22	21,895.36	27,641

Table 2.11: Regression results for clustered groups

	Group 1	Group 2	Group 3	Group 4
log(Gasprice)	0.601*** (0.027)	0.639*** (0.025)	0.584*** (0.028)	0.737*** (0.035)
log(Income)	0.048*** (0.048)	0.072*** (0.017)	0.068*** (0.017)	0.035* (0.018)
log(Space)	0.191*** (0.022)	0.243*** (0.021)	0.199*** (0.023)	0.329*** (0.038)
New_Windows	-0.009 (0.014)	-0.028** (0.012)	0.003*** (0.011)	0.011 (0.013)
New_Heating	-0.024** (0.021)	-0.043** (0.019)	0.017 (0.018)	-0.004 (0.023)
Central_Heat	0.055*** (0.018)	0.029 (0.019)	0.040** (0.017)	-0.011 (0.025)
Adults	-0.210*** (0.009)	-0.310*** (0.009)	-0.517*** (0.014)	-0.492*** (0.019)
Children	-0.247*** (0.007)	-0.330*** (0.009)	-0.259*** (0.052)	-0.407*** (0.026)
Owner	0.032** (0.014)	-0.039*** (0.014)	0.068*** (0.015)	0.021 (0.021)
Gender	-0.079* (0.042)	-0.114 (0.031)	-0.089*** (0.032)	-0.080* (0.046)
Age	0.013*** (0.006)	0.016** (0.007)	-0.016** (0.008)	-0.027*** (0.007)
Age_sq	-0.0001 (0.0001)	-0.0002* (0.0001)	0.0001*** (0.0001)	0.0002*** (0.0001)
Greens	-0.005 (0.019)	-0.017 (0.016)	-0.006 (0.023)	-0.030 (0.021)
Education	-0.001 (0.005)	0.0005 (0.005)	-0.003 (0.007)	-0.003 (0.007)
Fulltime	-0.026** (0.011)	-0.047*** (0.013)	0.017 (0.017)	0.004 (0.019)
Parttime	-0.020* (0.011)	-0.041*** (0.013)	-0.037** (0.017)	-0.001* (0.020)
Unemployed	0.028** (0.011)	-0.008 (0.016)	0.004 (0.017)	0.011 (0.032)
Retired	0.002 (0.033)	-0.026 (0.033)	-0.017 (0.014)	-0.002 (0.019)
HDD	0.0001*** (0.00001)	0.00002** (0.00001)	0.0001*** (0.00001)	-0.00004*** (0.00001)
Building type effects	Yes	Yes	Yes	Yes
Building condition effects	Yes	Yes	Yes	Yes
Building age effects	Yes	Yes	Yes	Yes
Federal state dummies	Yes	Yes	Yes	No
N	47,915	47,442	43,558	24,253
R ²	0.163	0.189	0.232	0.217
Adjusted R ²	-0.185	-0.123	0.041	-0.037
F Statistic	63.964***	85.262***	87.324***	70.372***
	(df = 49; 14033)	(df = 49; 13158)	(df = 50; 8640)	(df = 34; 5916)

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Clustered robust standard errors in parentheses. State dummies excluded for Group 4 due to multicollinearity issues.

Davis, 2012; Gillingham et al., 2012; Levinson and Niemann, 2004).¹⁰ In contrast, other studies find that homeowners use more energy for heating (Meier and Rehdanz, 2010; Longhi, 2015). Our results suggest that the relationship between home ownership and energy consumption for heating is complex and could be influenced by a variety of other factors. Note that we still include age and income as independent variables after using them for clustering. This allows us to assess within group effects of age and income on heating expenditures, since there is still variation within the subgroups after clustering.

When comparing the coefficient estimates, we also need to check whether they are statistically significantly different across groups.¹¹ For this, we run a regression on the full sample, including cluster membership as a factor variable and interacting the cluster variable with the other variables. If an interaction is statistically significant, this points at significant differences between groups for that particular variable. Table 2.12 shows the statistical significance of the interactions between the cluster membership variable and the other explaining variables of the model.¹²

Table 2.12: Significance of interactions

Statistically Significant	Not Statistically Significant
log(Gasprice)***	New_Windows
log(Income_Capita)*	Adults
log(Space)***	Gender
New_Heating*	Fulltime
Central_Heat**	Parttime
Children*	Unemployed
Owner***	
Age***	
Age_sq***	
HDD***	
<i>Notes:</i> ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively for at least one interaction between a cluster level and that variable.	

From Table 2.12, we can conclude that for the majority of variables, statistically significant differences between groups exist, which underlines the heterogeneity of consumers in terms of heating expenditures and their determining factors.

2.4 Conclusions and Outlook

In this study, we investigate possible determinants of space heating expenditures for households via a fixed effects framework. Our analysis yields evidence that in addition to price and income, technical

¹⁰The landlord usually has to pay for energy-saving renovations like better insulation or a new, modern heating system, but the tenant then reaps the rewards through a lower heating bill, giving the landlord little incentive to undertake those renovations in the first place.

¹¹We thank an anonymous referee for this suggestion.

¹²Note that since the cluster variable has four levels (one for each group), there are four interaction terms for each variable that we interact the cluster variable with. The table shows the significance level for which at least one interaction between that variable and a cluster level is significant.

variables, most notably building age and dwelling size, as well as socio-demographic aspects, especially age and gender, are important factors for explaining household expenditures for heating.

In addition, our analysis provides empirical evidence for the existence of heterogeneity between socioeconomic groups, which has not been investigated before in the context of space heating. For example, wealthier occupants react less strongly to price changes than those with lower incomes. Similarly, homeowners show weaker price reactions compared to renters. For other demographic variables such as gender and number of household members, we find no evidence for differences in price responsiveness. The quantile regression approach shows that the absolute differences in magnitude, while statistically significant, are relatively low between groups across the distribution for almost all of the influencing variables that we considered.

Our results have implications for policy makers who attempt to target consumer behavior more effectively. The data indicate that consumer reactions to certain policy measures, such as mandatory efficiency standards or subsidies for retrofitting homes, would create divergent results for different groups of consumers. Subsequently, tailoring programs to specific groups might be a better choice than uniform legislation for the entire population. For example, the effectiveness of price-based measures, such as Pigouvian taxation of energy use, critically depends on the magnitude of the price response, which our results show to vary significantly between groups.

Across all investigated groups, we find that newer buildings are associated with lower heating expenditures. This suggests that stricter energy efficiency standards for new buildings have a significant negative impact on heating expenditures, which appears to make this a very effective measure. However, we do not observe the counterfactual scenario of having no building standards, since the additional savings might also stem from endogenous technological progress. Furthermore, newly constructed homes are usually larger, which takes back some of the savings.

While some effects are hard to influence by policy alone, they should still be taken into account when projecting future residential energy demand. For instance, we find that there are sizable economies of scale in terms of the number of inhabitants of a dwelling. This means that the rising number of single-person households could result in an unexpected increase in overall energy consumption if those effects are not explicitly taken into account. The average household size in Germany is projected to decrease from 2.0 in 2015 to 1.9 in 2035 (Federal Statistical Office, 2017). *Ceteris paribus*, this implies an increase in per capita energy use for heating by 3-3.6%. While policy measures that coerce people into living in multi-person households seem hardly feasible, this phenomenon should nevertheless be considered when projecting future energy use. Our analysis also shows that single-person households exhibit the strongest price reactions, which would increase the effectiveness of price-based measures for this particular group. Generally, our results show the complex nature of both the determinants of space heating consumption itself as well as the interaction between price responsiveness and other factors.

There are several avenues for future research that arise from this work. Utilizing actual energy consumption data as well as observing the fuel type and heating system used by households would likely yield additional insights and facilitate comparisons of our results with other studies that investigate household demand for energy. Another possible extension would be the estimation of welfare effects for price changes as well as different policy measures that directly or indirectly influence energy prices. Furthermore, additional research on the relationship between homeownership and energy use can prove valuable, given some of the ambiguous results reported here and elsewhere. More detailed data regarding the insulation of homes as well as the efficiency of the heating systems used could also

be valuable, for example in trying to estimate direct rebound effects in space heating.

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2.A Appendix

As discussed in section 2.2.3, we derive household characteristics such as age or education from the mean values of all adult household members. An alternative specification would be to only use the characteristics of the household head (Wadud et al., 2010; Gillingham, 2014). To verify the robustness of our results, we compare model (iii) from Table 6 in the main paper with an alternative specification using only household head data. The results are reported in Table A.1. As can be seen, the results are similar between the two models. We find that several of the socio-demographic characteristics, such as ‘Greens’ and ‘Fulltime’, are not statistically significant when using only the household head. This might be due to the lower variation in these regressors when only the household head is used.

In section 2.3.2.2 of the paper, we perform quantile regression to find heterogeneity between quantiles in the explanatory variables. We use F -tests to check whether the estimated coefficients are significantly different between the five quantiles. Tables A.2 to A.4 show the results of F -tests conducted for the ‘Income_Capita’, ‘Space’, and ‘Owner’ variables, respectively.

Table A.1: Regression results, alternative specification

	All Adults	Household Head Only
	(i)	(ii)
log(Gasprice)	0.690*** (0.010)	0.593*** (0.011)
log(Income)	0.091*** (0.005)	0.081*** (0.005)
log(Space)	0.251*** (0.007)	0.240*** (0.007)
New_Windows	−0.007 (0.005)	−0.006 (0.005)
New_Heating	−0.021*** (0.008)	−0.020*** (0.008)
Central_Heat	0.040*** (0.007)	0.039*** (0.007)
Adults	−0.322*** (0.003)	−0.331*** (0.003)
Children	−0.297*** (0.003)	−0.293*** (0.003)
Owner	0.023*** (0.005)	0.013*** (0.005)
Gender	−0.067*** (0.010)	−0.114*** (0.008)
Age	−0.005*** (0.001)	0.009*** (0.001)
Age_sq	0.0001*** (0.000)	−0.00001*** (0.000)
Greens	−0.017** (0.008)	−0.008 (0.007)
Education	−0.002 (0.002)	−0.0001 (0.002)
Fulltime	−0.016*** (0.006)	−0.001 (0.005)
Parttime	−0.033*** (0.006)	−0.016*** (0.005)
Unemployed	0.015** (0.006)	0.011** (0.005)
Retired	−0.022* (0.007)	−0.021*** (0.006)
HDD	0.00005*** (0.000)	0.00004*** (0.000)
Building type effects	Yes	Yes
Building condition effects	Yes	Yes
Building age effects	Yes	Yes
Federal state dummies	Yes	Yes
<i>N</i>	163,168	161,405
<i>R</i> ²	0.273	0.275
Adjusted <i>R</i> ²	0.108	0.111
F Statistic	998.555***	996.760***
	(df = 50; 133,085)	(df = 50; 131,620)

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Clustered robust standard errors in parentheses. Column (i) reproduces column (iii) from Table 2.6 of the main paper for comparison.

Table A.2: *F*-Tests for differences between quantiles, income

Quantiles	10%	30%	50%	70%	90%
10%	-	-	-	-	-
30%	0.10	-	-	-	-
50%	0.00	0.24	-	-	-
70%	0.13	0.02	0.66	-	-
90%	0.22	1.09	0.73	1.99	-

*Notes:****, **, and * indicate significant differences between the respective quantiles at the 0.01, 0.05, and 0.10 levels, respectively.

Table A.3: *F*-Tests for differences between quantiles, space

Quantiles	10%	30%	50%	70%	90%
10%	-	-	-	-	-
30%	0.33	-	-	-	-
50%	0.08	1.54	-	-	-
70%	7.54***	21.49***	19.59***	-	-
90%	32.91***	56.35***	49.84***	32.73***	-

*Notes:****, **, and * indicate significant differences between the respective quantiles at the 0.01, 0.05, and 0.10 levels, respectively.

Table A.4: *F*-Tests for differences between quantiles, owner

Quantiles	10%	30%	50%	70%	90%
10%	-	-	-	-	-
30%	110.24***	-	-	-	-
50%	119.40***	11.36***	-	-	-
70%	127.99***	28.46***	10.30***	-	-
90%	98.09***	18.12***	8.27***	0.29	-

*Notes:****, **, and * indicate significant differences between the respective quantiles at the 0.01, 0.05, and 0.10 levels, respectively.

Chapter 3

Are Prosumer Households That Much Different? Evidence from Stated Residential Energy Consumption in Germany

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3.1 Introduction

The main objectives of the energy transition in Germany are: to increase energy efficiency, to deploy renewable energy, and most importantly to reduce greenhouse gas (GHG) emissions. For the promotion of a more decentralized sustainable energy system, prosumer households can play a key role as investors in renewable energy technologies by partially or completely self-supplying themselves with renewable energies from distributed micro-generation technologies (MGTs). The term ‘prosumer’ (first introduced by Toffler 1981) is used in the debate on the energy transition to discuss the new dual role of private households as consumers and producers in the energy market (see, for example, IEA 2014; Flaute et al. 2017; May and Neuhoff 2016). The main reason for the rapidly increasing importance of prosumer households, and prosuming potential in general, is the successful market diffusion of MGTs for producing and storing electricity and heat. Since energy prosumer households are a relatively recent phenomenon, there is no universally accepted definition and there are no official statistics for them yet. In the strictest sense, prosumers fulfil parts of their energy needs through self-produced energy. The crucial variable for defining prosuming in the narrow sense is the degree of self-supplied energy, which can be increased through installing a storage device, implementing advanced energy management measures, and changes in consumption behavior. More broadly, any household producing electricity in their own home with an MGT might be considered to be a prosumer household, regardless of how and by whom that electricity is ultimately used. This broad

definition of prosumer households comprises all three types of prosumers as defined by IEA (2014)¹: (a) prosumers commercially selling “a large share of the power generated into the grid, while continuing to purchase electricity from the utility as well”, (b) prosumers self-consuming, by continuing “to purchase power from the grid, but reducing the amount purchased by using their PV [Photovoltaic System] to supply a portion of their own electricity needs (and potentially get remunerated for any surplus generation that they may inject into the grid)”, and (c) self-providers (or off-grid prosumers) that “supply 100% of their own electricity needs with PV, storage, and other technologies”.

We use this broader definition of prosumers due to limitations of the data set. While there are no comprehensive statistics publicly available on residential prosumer households’ electricity supply and self-consumption for the case of Germany (cf. Flaute et al. 2017; Bardt et al. 2014), it is reasonable to assume that the group of commercially selling prosumers is predominant on account of the privileged feed-in in accordance with the Renewable Energy Sources Act (EEG). The second group of primarily self-consuming producers is assumed to be relatively small, but has been gaining relevance since 2012, due to decreasing guaranteed rates in the feed-in scheme. Before 2012, self-consumption was economically unattractive, since the feed-in tariffs for renewable energy were higher than a household’s electricity prices. These changes make it financially beneficial for households to self-consume instead of feeding power into the grid (Flaute et al., 2017; Oberst and Madlener, 2014 (revised September 2015)). The last group of self-providers can be assumed to be negligibly small for main residences in Germany.² The economic feasibility of the installation of battery storage units, a key technology to increase self-consumption, remains questionable in 2018.

Prosumer households can play a crucial part in a socio-ecological transformation of the energy system towards a more decentralized energy system based predominantly on renewable energies. How the general prosumer potential is used depends on a number of factors, including market conditions, regulation, and preferences. Prosumer households have the potential to disrupt energy markets in a variety of ways (Gähns et al., 2016). Firstly, prosumer households can change the load curve by using micro-generation and storage technologies, particularly by shaving and reducing peak loads, which might reduce the need for (transport) grid expansion (Bost et al., 2016). In the future, prosumer households might even (cooperatively) provide flexibility to the grid, e.g. via supply network and system services with interconnected smart controllable demand response as well as distributed energy storage and generation. Whether prosuming contributes to grid stability or causes additional expenses due to increasing volatility and complexity in local grids depends on the type of prosuming patterns and local technology concentration, which in turn depend heavily on the legal framework and market conditions. Secondly, prosumer households have the potential to exert competitive pressure on traditional energy providers, to diversify the technology mix, and to promote the democratization of the energy sector due to the increase in distributed energy generation and ownership. Other possible benefits include the advancement of sector coupling, e.g. the interconnection with the heat sector via power-to-heat applications, or with the transport sector and the possible mutually beneficial co-evolution of prosuming and electric vehicles. A potential drawback of prosuming is the potential loss of system-wide efficiency (Schill et al., 2017). Further, there is a risk of technological path dependency in the case of a strong governmental promotion prior to technological maturity. The social

¹ Slightly adapted from the case of PV, as reported in IEA (2014) to the more general case of MGT.

² In 2014, 81.3% of electricity generated by microgeneration solar technology was EEG-feed-in, 16.1% was direct marketing, and 2.6% was remunerated self-consumed electricity (BDEW, 2016). However, the remuneration for self-consumption can only be claimed for solar photovoltaic systems that were brought into service between January 1, 2009 and December 31, 2012 or which requested a network connection before February 24, 2012. Therefore, self-consumption of newer or older systems is not reported in BDEW data (or any other publicly available data to our knowledge) and limits the informative value of these statistics.

objective associated with energy prosuming is an efficient development of renewable energies that decarbonizes, decentralizes, and diversifies the technology mix in the energy system. In particular, for a decentralized energy system, prosumer households have to be taken into account and their potential and their behavior must be investigated. Possible positive or negative market externalities are decisive for an economic policy evaluation.

The direct effects of the diffusion of prosumer households that change the process of energy production and consumption arise from the technical aspects related to the emergence of MGT. Focusing purely on these technical aspects neglects the possibility of any behavioral changes resulting from prosuming. Technical innovations often trigger unanticipated behavioral responses of adopters regarding the consumption of goods and services related to that innovation. For example, energy rebound effects reduce the effectiveness of efficiency-increasing measures, because consumer demand for an energy service that has become more efficient, and therefore cheaper to use, will typically increase (see, e.g., Sorrell and Dimitropoulos 2008).

Recent research has explored the role of behavioral mechanisms in energy decision making, such as exogenous and endogenous inattention or biased beliefs (see, e.g., Allcott 2016). This could also be the case when private households become prosumers by adopting MGTs. Through prosuming, households might develop changing attitudes that would result in increasing energy consumption. Households could consider prosuming to be a sufficient contribution to sustainability and therefore allow themselves to use more energy - a phenomenon that is known as ‘moral licensing’ (see, e.g., Brown et al. 2011). While this has been examined in the field of energy use (see, e.g., Tiefenbeck et al. 2013), no clear evidence exists yet specific to energy prosumers.

There might be a rebound-like behavior occurring with prosumers. Traditionally, rebound is defined as the phenomenon where an increase in efficiency leads to behavioral changes that increase demand for energy services. While still reducing overall consumption (unless the size of rebound is above 100%), the actual savings are lower than theoretically possible. Similarly, households might also increase demand in response to becoming a prosumer. For example, prosumer households might consider their self-produced energy to be “free”, thus neglecting the opportunity costs of selling it to the grid. The lower costs of self-produced electricity could therefore lead to a rebound effect caused by prosuming (Schill et al., 2017). In this case, it is not an efficiency improvement that causes rebound behavior, but the actual switch itself from consuming to prosuming. However, prosuming might also induce households to become more aware of their energy usage, which could result in lower energy consumption. If there is evidence that prosumer households change their consumption behavior so that they use less energy compared to comparable non-prosuming households, this would indicate social benefits that go beyond the mere substitution of nonrenewable energy for (decentralized) renewable energy produced by prosumers. So far, there is little empirical evidence on the existence and magnitude of prosumer rebound effects (Schill et al., 2017). More generally, Luthander et al. (2015) review the literature on behavioral changes following the installation of a PV system. As the authors point out, “From these previous studies, it is not possible to draw any general conclusions on the responses to PV installations. Many results have been based on self-reported data through questionnaires and interviews.” (Luthander et al., 2015). In contrast to this primarily qualitative approach, we apply a quantitative framework.

In this paper, we focus on providing evidence for an overall (positive or negative) effect of prosuming on households’ energy consumption and on providing insights on the role of behavioral aspects. Specifically, the objective of this paper is to quantify differences in energy usage between prosumers

and comparable consumer households. Therefore, our contribution to the existing literature is at least twofold: Firstly, we empirically investigate the overall effect of prosuming on energy consumption behavior. Secondly, we aim to lay the groundwork for further research and, more specifically, to derive implications for designing experimental settings in the field. Our findings have implications for energy policy: given the increasing presence of prosumer households in Germany, an effect of prosuming on individual energy use would have to be taken into account when projecting future aggregate energy demand and supply. Furthermore, a prosumer rebound effect would shift the optimal scheme of subsidization (or taxation) of micro-generation technologies in relation to alternative generation technologies of renewables. *Ceteris paribus*, a substantial rebound effect resulting from prosuming would make the subsidization of prosuming less attractive. In the case of a negative rebound effect of prosuming, the opposite would be the case, justifying additional support measures. In this way, a behavioral prosuming effect should change how governments support prosuming and the market diffusion of prosuming technologies. This is similar to other areas of energy use: for example, rebound effects for a particular energy service reduce the usefulness of energy efficiency standards for achieving the policy goal of reducing energy consumption. When assessing the effectiveness of a policy measure, it is therefore important that behavioral effects be taken into account adequately.

In our study, we employ data from an online survey among homeowners in Germany conducted by Oberst and Madlener (2014 (revised September 2015)). The sample consists of homeowners living in detached and semi-detached owner-occupied residences. The case of Germany is particularly interesting, because the diffusion process of electricity generation based on renewable energy sources has long been encouraged by a range of political measures and subsidies. In particular, these incentives encompass a relatively stable support system with guaranteed feed-in tariffs, preferential dispatch, and grid connection requirements. In addition, the country is pursuing a nuclear phase-out in combination with ambitious goals to reduce GHG emissions by 2050 (Brunekreeft et al., 2016), which increases the importance of the energy transition process. We use self-reported revealed preference data on energy consumption as well as building and household characteristics. We define our treatment group (prosumers) based on the ownership of an MGT for producing electricity. We apply propensity score matching (PSM) in order to ensure a quasi-randomized comparison. This ensures comparability between the treatment and control groups with regard to socio-economic and housing characteristics, given that we cannot assume random selection into the treatment group of being a prosumer. Since many respondents are unaware of their electricity consumption in Kilowatthours (kWh), we use monetary values in the form of energy expenditures instead. Following on from this, we focus on heating expenditures as the dependent variable instead of electricity expenditures in order to avoid endogeneity problems, and we statistically control for heating generation technology and other relevant aspects.

The remainder of this paper has the following structure. Section 3.2 describes the data set. Section 3.3 discusses the methods employed for the matching procedure and presents the results from the matching. In Section 3.4, we then investigate the relationship between energy consumption, being a prosumer, and further explanatory variables (socio-demographics, energy, home and preference characteristics) with a comprehensive estimation approach. We compare estimation results for the full data set and two matching data sets and subsequently discuss our results. Section 3.5 concludes.

3.2 Data and Descriptive Statistics

For our analysis, we use data from a demographically stratified internet-based survey among German homeowners, carried out in November 2014 via 1030 interviews.³ The data provide cross-sectional information on a variety of variables that reflect socio-demographic and technical characteristics of the participating households, including data on the specific technology used for heating and hot water. Prosuming is mainly relevant for households that (a) live in 1- and 2-family houses, as opposed to apartments, and (b) own their homes (Oberst and Madlener, 2014 (revised September 2015)). Therefore, the dataset only consists of respondents who live in owner-occupied houses. We eliminate incomplete observations and extreme outliers, which reduces our sample to 849 observations.⁴ For information on the geographical location of the homeowners, the dataset is conjoined with spatial information obtained from BBSR (2016) via zip and district codes.⁵

As the dependent variable in our analysis, we use households' yearly heating expenditures, which serve as a proxy variable for household energy consumption. Note that using electricity expenditures would not be feasible, since self-consumption by prosumers is not reported in our data, and any technological control variable would be endogenous. This means that if prosumers were to spend less on electricity, we would be unable to distinguish how much of this is due to electricity-saving behavior from how much is due to self-consumption. When controlling for differences in technology, being an (electricity) prosumer should not influence heating expenditures beyond the effect that we can control for by heating technology (most notably heat pumps). Therefore, if we do find differences between the two groups, this will yield evidence of a behavioral effect, provided that the two groups are similar in all other covariates besides ownership of a micro-generation system. In line with related research on heating demand (e.g. Rehdanz 2007; Schmitz and Madlener 2019) we consider heating expenditures in Euros per square meter of living space. Figure 3.1 shows the distribution of heating costs across the two groups, with prosumers in dark gray and consumers in light gray. The figure shows that the density is skewed slightly to the left for prosumers, indicating lower heating expenditures. The less peaked distribution of prosumers indicates a more heterogeneous group.

Table 3.1 shows descriptive statistics for selected variables, both for the full sample and divided by treatment group. The observational unit in our analysis is the household, and only the variables 'Age' and 'Gender' refer specifically to the individual who is answering the survey.

The binary treatment variable of being a prosumer is negatively correlated with heating expenditures, suggesting a possible negative prosumer rebound effect. A means comparison of yearly heating costs between prosumers and consumers reveals a difference of 120.75 Euros; however, a t-test rejects that this difference is statistically significant. The proportion of prosumers who have an eco-friendly ("green") electricity tariff is 46% compared to 27% of consumers. Prosumers commonly live in newer buildings and it is more common for prosumers to own a solar thermal system, heat pump, combined heat and power (micro-CHP) plant, or an electric heating system. Prosumers are associated with higher incomes and household members are more likely to be in full-time employment, while those variables are in turn correlated with lower heating expenditures in Euros per m². Households in rural areas are more likely to be prosumers.

³ Stratification variables are 'Age' and 'Gender'. More information on the survey can be found in Oberst and Madlener (2014 (revised September 2015)).

⁴ Specifically, we remove observations where the heating expenditures were not reported (173 observations) and those where heating expenditures deviate from the mean by more than five standard deviations (8 observations).

⁵ BBSR stands for 'Federal Institute for Research on Building, Urban Affairs and Spatial Development' (in German: 'Bundesinstitut für Bau-, Stadt- und Raumforschung').

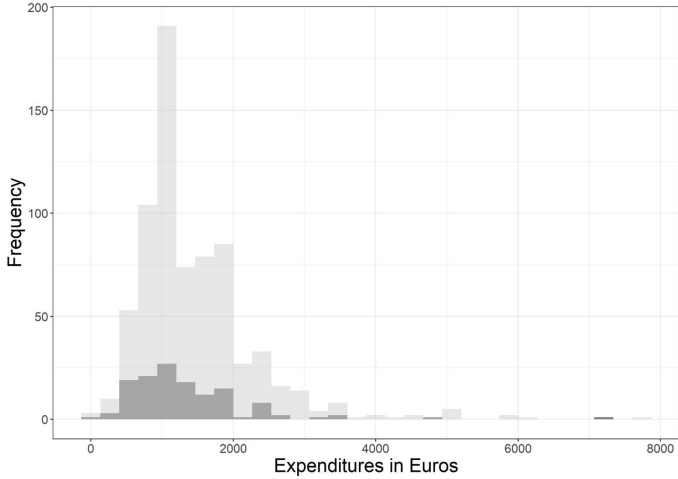


Figure 3.1: Distribution of heating costs

Notes: Prosumers are depicted in dark gray, consumers in light gray.

Table 3.1: Descriptive statistics of selected variables

	Full sample		Prosumers		Consumers		Difference in means
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	
Heating costs in Euros	1,459.18	859.72	1,357.21	891.64	1,477.95	853.03	-120.75
Heating costs in Euros/m ²	10.79	9.32	9.52	6.67	11.03	9.71	-1.51
E-Tariff: eco-friendly ("green")	0.30	0.46	0.46	0.50	0.27	0.45	0.18
E-Tariff: standard	0.57	0.50	0.46	0.50	0.59	0.49	-0.14
E-Tariff: unknown	0.13	0.34	0.09	0.29	0.14	0.34	-0.04
Household income	3.65	1.61	3.79	1.49	3.63	1.63	0.16
Employment status ^a	0.57	0.50	0.67	0.47	0.55	0.50	0.13
Partner employment status ^a	0.45	0.50	0.52	0.50	0.44	0.50	0.08
Age in years ^a	50.82	11.20	47.17	11.23	51.50	11.07	-4.32
Household size in no. of people	2.80	1.16	2.86	1.16	2.79	1.16	0.08
Living space in m ²	146.32	62.13	160.74	100.93	143.67	51.61	17.07
Gender: male ^a	0.58	0.49	0.64	0.48	0.57	0.50	0.07
Gender: female ^a	0.42	0.49	0.36	0.48	0.43	0.50	-0.07
Building age: <1949	0.21	0.41	0.11	0.32	0.23	0.42	-0.12
Building age: 1949-1978	0.26	0.44	0.19	0.39	0.27	0.45	-0.08
Building age: 1979-1986	0.10	0.30	0.11	0.31	0.10	0.29	0.01
Building age: 1987-1990	0.06	0.24	0.06	0.24	0.06	0.24	0.00
Building age: 1991-2000	0.18	0.38	0.20	0.40	0.17	0.38	0.02
Building age: 2001-2009	0.14	0.35	0.24	0.43	0.12	0.33	0.12
Building age: >2009	0.06	0.23	0.09	0.29	0.05	0.22	0.04
Building type: (semi-)detached	0.67	0.47	0.78	0.42	0.64	0.48	0.14
Building type: row house	0.30	0.46	0.18	0.39	0.32	0.47	-0.14
Building type: other	0.04	0.19	0.04	0.19	0.04	0.19	0.00
Heating: electric	0.07	0.25	0.13	0.34	0.06	0.23	0.07
Heating: solar thermal	0.10	0.30	0.33	0.47	0.06	0.24	0.27
Heating: CHP	0.01	0.10	0.04	0.19	0.01	0.08	0.03
Heating: heat pump	0.08	0.27	0.17	0.37	0.06	0.24	0.11
Heating: single stove	0.34	0.48	0.35	0.48	0.34	0.48	0.00
Region type: urban	0.43	0.50	0.44	0.50	0.42	0.49	0.02
Region type: mixed	0.33	0.47	0.24	0.43	0.34	0.48	-0.10
Region type: rural	0.25	0.43	0.32	0.47	0.23	0.42	0.08
No. of observations	849		132		717		

Notes: Unitless variables are binary (taking values of 0 or 1). Variables marked with ^a refer to the individual respondent.

Note that since 2009, owners of newly constructed buildings are obliged by the Renewable Energies Heat Act (EEWärmeG) to use a certain percentage of renewable energy for their heating purposes (water and space heating).⁶ However, various alternative measures are permitted, and compliance is questionable at best. In our sample, we find 37 consumer households living in buildings built after 2009 (compared to 12 prosumer households). Further, Table 3.1 shows that buildings built between 1949 and 1978 represent a high share of the building stock (26% of respondents) and that these are characterized by higher heating expenditures. The situation highlights this type of buildings as a primary target group for policies aiming to increase energy efficiency. It raises the question of whether there are long-term differences in the response by consumption behavior to voluntary adoption of modern energy technology compared to obligatory adoption induced by regulation. While this question is generally beyond the scope of our paper, we perform a robustness check for prosumers living in buildings from different time periods and thereby control for the impact by different institutional frameworks.

The comparison of means and correlations supports the hypothesis that prosumer households are systematically different from consumer households. However, in order to ensure an unbiased comparison of energy consumption between consumers and prosumers, we apply a matching analysis.

3.3 Matching Analysis

3.3.1 Methodology

The starting point of the matching analysis is that random selection of a household into the treatment group “prosumer” cannot be assumed, since a household’s decision in favor of prosuming is likely to be correlated with the dependent variable of energy expenditures, and therefore affecting comparability between prosumer and consumer households. Given the amount of monetary and cognitive effort associated with installing and operating prosuming technologies, a random assignment by researchers as part of a field experiment is extremely difficult to implement due to high costs. Propensity score matching (PSM) enables a quasi-randomized comparison. The concept of PSM for causal effects was originally introduced by Rosenbaum and Rubin (1983) and has seen many adjustments since, spawning numerous empirical applications in a variety of fields, including political science and economics.

In matching, an observation in the treatment group is paired with one or more observations from the control group, with the goal of creating two groups that are as similar as possible in the distribution of their covariates. The fundamental idea of matching is that by doing so, the mean difference in the outcome variable between treatment and control group can be attributed solely to the treatment. This simplicity of the matching approach is one of its advantages, since assessing treatment effects can be as simple as the comparison of two means. The straightforward nature of analyzing matched data makes it a suitable option for mimicking an experimental setting when experimental data are not available. As in our case, running a randomized controlled trial is not always possible due to monetary, technical, legal, or ethical concerns. For further discussions on matching methods, see, e.g., Dehejia and Wahba (2002); Heckman et al. (1997); Imbens (2004). Imbens and Wooldridge (2009) present an overview of the last three decades of research in this area. For a set of guidelines on the practical implementation of PSM, see Caliendo and Kopeinig (2008).

⁶ We are thankful to an anonymous referee for pointing out this fact.

3.3.2 Estimation of the Propensity Score

The observations are matched based on so-called (single) balancing scores, which is a function of the vector of covariates. A variety of methods exist to obtain this score; we use the propensity score, originally introduced by Rosenbaum and Rubin (1983), which is defined as the probability of receiving treatment, given the covariates. As we consider a binary treatment, we use a standard logit model to estimate the propensity score. Generally, all variables that simultaneously affect both treatment and outcome should be included in the estimation. The main goal of estimating the propensity score is not to predict the treatment as accurately as possible, but to create a balance in the covariates between the treatment and control groups. However, the variables for which the two groups differ significantly are also the ones that are good predictors for the treatment status. Therefore, a model that proves to be unable to predict the treatment is likely to be misspecified. Table 3.2 shows the estimation results of the propensity scores of being a prosumer.

Table 3.2: Propensity score estimation results

	Prosumer
E-Tariff: standard	−0.751*** (0.214)
E-Tariff: unknown	−0.742** (0.354)
Respondents' age	−0.030*** (0.010)
Household size	−0.061 (0.090)
Living space	0.003** (0.001)
Gender: female	−0.195 (0.210)
Building age: <1949	(base)
Building age: 1949–1979	0.363 (0.362)
Building age: 1979–1986	0.975** (0.420)
Building age: 1987–1990	0.840* (0.501)
Building age: 1991–2000	0.686* (0.367)
Building age: 2001–2009	1.215*** (0.366)
Building age: >2009	0.772* (0.465)
Building type: (semi-)detached	(base)
Building type: row house	−0.698*** (0.257)
Building type: other	0.075 (0.551)
Region type: urban	(base)
Region type: mixed	−0.389 (0.249)
Region type: rural	0.231 (0.244)
Constant	−0.200 (0.752)
No. of observations	849
Log likelihood	−331.508
Akaike inf. crit.	697.017
McFadden's R ²	0.096
Correctly classified	0.850
Area under ROC curve	0.714

Notes:***,**, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

The results of the propensity score estimation reported in Table 3.2 show that the type of electricity tariff (E-Tariff), respondents' age, building age, living space, and building type are good predictors for being a prosumer, while household size, respondents' gender, and region type are not. Specifically, households that have an eco-friendly (“green”) electricity tariff or live in newer and larger homes are more likely to be prosumers, while households living in a row house and those who do not know their type of electricity tariff are less likely to be prosumers. The negative influence of row houses is likely

due to technical reasons, since detached homes are generally better suited for the installation of PV systems, which account for a large share of microgeneration systems used by private households.⁷ Adding to the previous discussion on the impact of the Renewable Energies Heat Act of 2009 on households' energy technology choice, and thereby the likelihood of being a prosumer, we observe that respondents living in buildings newer than 2009 are less likely to be prosumers than those in buildings built between 2001 and 2009.

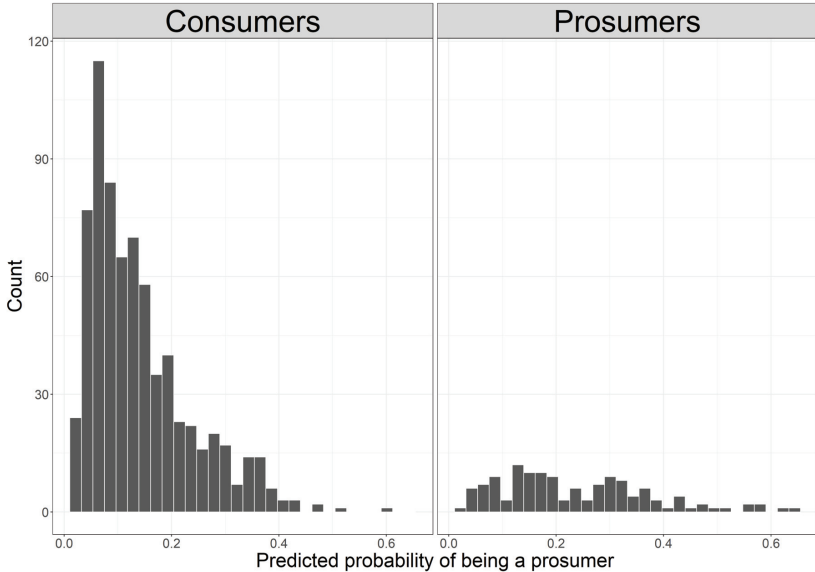


Figure 3.2: Common support and the probability distribution of being a prosumer household.

An important condition when using PSM is that of common support. This means that in order to avoid biased estimations, there has to be at least some overlap in the density distribution of the estimated propensity scores between the treatment and control groups. Otherwise, e.g. if the model is able to perfectly predict treatment, the two groups are not comparable anymore (Heckman et al., 1998). Figure 3.2 shows this distribution of the predicted probability of being a prosumer for our matching analysis with the control group (0) on the left and the treatment group (1) on the right. The x-axes show the estimated propensity scores from the logit estimation. As Figure 3.2 shows, the common support condition is fulfilled. For the control group, the range of the propensity score is given by $[0.02, 0.60]$, whereas for the treated households, the range is $[0.03, 0.64]$. The overlap between the two groups is evidence that they are indeed comparable for further analysis.

3.3.3 Matching Results

A variety of algorithms exist for conducting matching, each with its different strengths and limitations. In many cases, the choice between different options constitutes a tradeoff between creating better, i.e.

⁷ Note that we do not report heteroscedasticity-robust standard errors. This is due to the many practical issues surrounding robust standard errors in logit models (Williams, 2009)

more accurate, matches and lowering the variance of the estimator (Caliendo and Kopeinig, 2008). We use the nearest neighbor matching algorithm, which, for every observation in the treatment group, assigns the control observation that has the lowest difference in propensity score to that of the treatment observation. At first, we match without replacement, meaning that every control observation is matched once, even in the case where it is the nearest neighbor for two (or more) treatment households. Allowing replacement potentially increases the matching quality, but at the cost of increased variance (Smith and Todd, 2005). In an alternative specification, we also allow replacement. For an extensive discussion of other matching algorithms, see Caliendo and Kopeinig (2008).

Table 3.3: Mean values of relevant variables before and after matching

	Prosumers	Consumers before matching	Consumers, matching with replacement	Consumers, matching without replacement
Heating costs in Euros	1,357.21	1,477.95	1,390.99	1,378.60
Heating costs in Euros/m ²	9.52	11.03	9.56	9.39
E-Tariff: ecofriendly ("green")	0.45	0.27	0.48	0.45
E-Tariff: standard	0.45	0.59	0.43	0.43
E-Tariff: unknown	0.09	0.14	0.09	0.12
Respondents age in years	51.50	47.17	48.70	47.94
Household size in no. of persons	2.86	2.79	2.80	2.92
Living space in m ²	160.74	143.67	155.67	156.95
Respondents gender (M=1, F=2)	1.36	1.43	1.30	1.30
Building age: <1949	0.11	0.23	0.11	0.11
Building age: 1949–1978	0.19	0.27	0.20	0.21
Building age: 1979–1986	0.11	0.09	0.08	0.08
Building age: 1987–1990	0.06	0.06	0.07	0.06
Building age: 1991–2000	0.20	0.17	0.23	0.23
Building age: 2001–2009	0.24	0.12	0.26	0.23
Building age: >2009	0.09	0.05	0.07	0.09
Building type: (semi-)detached	0.78	0.64	0.79	0.80
Building type: row house	0.18	0.32	0.18	0.17
Building type: other	0.04	0.04	0.03	0.03
Region type: urban	0.44	0.42	0.41	0.44
Region type: mixed	0.24	0.23	0.20	0.23
Region type: rural	0.32	0.34	0.39	0.34
No. of observations	132	717	108	132

Notes: Unitless variables are binary (taking values of 0 or 1).

Table 3.3 depicts the results of the matching by comparing the mean values of relevant variables for the different observation groups, i.e. the treatment group (prosumers), the unmatched control group (all nonprosumers), and the two matched control groups (comparable consumers) for matching with and without replacement. The comparison in Table 3.3 illustrates that the imbalance between the treatment and control groups is significantly mitigated by matching. The most obvious differences between the treatment and matched control groups compared to the unmatched control group are shown for the variables ‘Eco E-Tariff’ and ‘Building age’. This implies that prosumers and comparable consumers are significantly more likely to have a green electricity tariff and more often live in newly constructed buildings. As Table 3.3 shows, the balance also improves for the other variables. Furthermore, the results between matching with and without replacement are nearly identical.⁸

Apart from comparing the means of the different covariates between the groups, there are other ways to evaluate the quality of the matching. One of them is to estimate the propensity scores again

⁸ Note that when matching with replacement, the control group is smaller, because the same control observations can be used multiple times if they are closest to more than one treatment observation. Here, 90 observations were matched once, 16 were matched twice, one was matched four times, and one was matched six times, for a total of 108 observations.

on the matched data, using the same logit specification as before, and comparing the predictive power of the new model with the original model used for the unmatched data in Section 3.3.

If the matching works as intended, we can expect the model to be unable to explain treatment given the covariates, because the distribution of covariates should be fairly similar between both groups (Sianesi, 2004). In our case, estimating on the matched data results in a McFadden- R^2 of about 0.02 to 0.03 for matching with replacement and without replacement, compared to 0.10 for the initial estimation (in Table 3.2). Furthermore, a likelihood ratio test on joint significance is rejected for the matched data with and without replacement, respectively, whereas it cannot be rejected in the initial propensity score estimation. We take these results as an indication that the matching is working as intended.

3.4 Empirical Analysis of Energy Consumption

Generally, the matched data can be examined in different ways. For the assessment of a prosumer treatment effect, we use a comparison of means, correlation, and estimation analysis. Ideally, after performing the matching analysis, the difference in means of the variable in question, which in our case is household heating expenditures, provides an unbiased estimate of the treatment effect. Compared with comparable consumer households in our sample, the average prosumer’s heating expenditures are between 21 and 34 Euros lower. Before the matching, compared to the unmatched control group of all consumers, the difference between prosumer and consumer heating expenditures would be greatly overestimated at about 120 Euros (see Table 3.3). Results of a correlation analysis are in line with the means comparison presented above. In the following, we focus on logarithmic values of heating expenditures in Euros per m^2 of living space and year, $\log(\text{HeatCosts}/\text{LivingSpace})$, as our dependent variable, which is in line with related research. Furthermore, Figure 3.1 shows a fat tail for the distribution of heating costs, which means that taking the logarithm makes the distribution more normal.

In a more systematic approach, we investigate the relationship between energy consumption and being a prosumer household further with a regression analysis, where we control for the type of electricity tariff as well as building, technical, household socio-demographic characteristics, and stated preferences by the respondent. For the estimation, we use standard ordinary least squares (OLS) regression, and use heteroscedasticity-consistent covariance matrix estimation in order to obtain robust standard errors.⁹ We develop four models with increasing complexity, each of which is estimated with the full sample (without matching) and with both matching samples (with and without replacement) for comparison purposes. The number of attribute levels is reduced for some variables in the regression analysis due to the smaller number of observations in the matching sample. The total number of observations in the full sample is 849, whereas in the estimation with matching samples it is 260 and 261, respectively.¹⁰

We build our models from specifications M1 to M4 with increasing complexity, starting with the most parsimonious model in order to isolate the effects of the variables that appear most relevant to our research questions. In our first model specification (M1), we only consider the key variables of this analysis: prosumer and type of electricity tariff (being a consumer household and having a standard electricity tariff are the respective baselines). In the second model specification (M2),

⁹ See Zeileis (2006) for implementation details.

¹⁰Note that three and four observations, respectively, were removed from the original sample due to missing values.

Table 3.4: Regression results, M1 and M2

	M1 full sample	M1 matching with replacement	M1 matching without replacement	M2 full sample	M2 matching with replacement	M2 matching without replacement
Prosumer	-0.170***	-0.042	0.015	-0.045	-0.026	0.039
Eco E-Tariff	-0.091**	-0.075	-0.109	-0.053	0.013	-0.002
E-Tariff unknown	0.142**	0.175**	0.215**	0.104*	0.100	0.147*
Intercept	2.353***	2.212***	2.213***	5.351***	4.505***	4.030***
Home characteristics	No	No	No	Yes	Yes	Yes
Socio-demographics	No	No	No	Yes	Yes	Yes
Regional dummies	No	No	No	Yes	Yes	Yes
Observations	849	261	260	849	261	260
R ²	0.031	0.026	0.043	0.262	0.275	0.250
Adjusted R ²	0.027	0.014	0.031	0.229	0.155	0.125
logLik	-700.8	-179.2	-175.2	-589.3	-140.7	-143.4
AIC	1,413.5	368.4	360.3	1,256.6	359.4	364.8
BIC	1,442.0	366.2	378.1	1,441.6	498.4	503.6
Residual Std. Error	0.557	0.485	0.478	0.496	0.449	0.455
	(df = 845)	(df = 257)	(df = 256)	(df = 811)	(df = 223)	(df = 222)
F Statistic	8.955***	2.274*	3.807**	7.792***	2.285***	2.004***
	(df = 3; 845)	(df = 3; 257)	(df = 3; 256)	(df = 37; 811)	(df = 37; 223)	(df = 37; 222)
Max. variance Inflation factor	1.1	1.1	1.1	2.2	2.5	2.4

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 3.5: Regression results, M3 and M4

	M3 full sample	M3 matching with replacement	M3 matching without replacement	M4 full sample	M4 matching with replacement	M4 matching without replacement
Prosumer	-0.031	-0.043	0.045	-0.041	0.010	0.068
Eco E-Tariff	-0.055	0.003	-0.001	-0.056	-0.010	-0.032
E-Tariff unknown	0.107*	0.150*	0.167*	0.112*	0.141*	0.160*
Intercept	5.329***	4.508***	3.944***	5.418***	4.770***	4.228***
Home characteristics	Yes	Yes	Yes	Selected	Selected	Selected
Socio-demographics	Yes	Yes	Yes	Selected	Selected	Selected
Regional dummies	Yes	Yes	Yes	Selected	Selected	Selected
Stated preferences	Yes	Yes	Yes	Selected	Selected	Selected
Observations	849	261	260	849	261	260
R ²	0.270	0.337	0.301	0.260	0.290	0.257
Adjusted R ²	0.227	0.186	0.142	0.233	0.200	0.164
logLik	-584.6	-129.1	-124.3	-590.8	-138.0	-142.1
AIC	1,269.1	358.2	368.7	1,243.5	338.0	346.3
BIC	1,506.3	536.4	546.7	1,390.6	448.5	456.7
Residual Std. Error	0.496	0.440	0.450	0.494	0.436	0.444
	(df = 800)	(df = 212)	(df = 211)	(df = 810)	(df = 231)	(df = 230)
F Statistic	6.178***	2.240***	1.891***	9.906***	3.246***	2.750***
	(df = 48; 800)	(df = 48; 212)	(df = 48; 211)	(df = 29; 810)	(df = 29; 231)	(df = 29; 230)
Max. variance Inflation factor	3.0	3.4	3.2	2.5	2.1	2.0

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

we additionally include control variables for the home characteristics, socio-demographics of the household, and regional aspects. In the third model specification (M3), we further add variables on stated preferences regarding prosuming, as well as the usefulness of participating in the energy transition and expectations on the price development. In the fourth model specification (M4), we include all variables from M3 but exclude those that appear insignificant from a statistical point of view. Given that a large number of variables in model specifications M2 and M3 are shown to be not significant, the motivation of M4 is to check whether these models may lose efficiency due to multicollinearity caused by the larger number of included variables, which in turn may wrongly indicate the statistical insignificance of a coefficient. Tables 3.4 and 3.5 report the estimation results for the main variables of interest (prosumer and type of E-Tariff) for each model specification for three different samples (unmatched full sample, N=849, and both matching samples, with and without replacement, with N=260 and 261, respectively). A complete overview of estimation results for all control variables is given in the appendix. Being a prosumer is significantly associated with lower heating expenditures only in M1, which is the parsimonious model without control variables and estimated on the unmatched data. Here, being a prosumer relates to 17% lower heating costs.

In all other estimations, being a prosumer is shown to be an insignificant factor for households' heating expenditures. This indicates a spurious relationship between being a prosumer and lower heating expenditures, which can be identified by either including the relevant control variables or through matching analysis. We find a similar pattern for the effect of having an eco-friendly electricity

tariff on energy expenditures. Only for specification M1 and using the unmatched sample do we find a statistically significant effect, where an ecofriendly tariff relates to 9% lower heating costs on average. No statistically significant effect is shown for eco-friendly tariffs when employing a matching analysis or using control variables for building and household characteristics.

The results for E-Tariff unknown generally show that it is associated with significantly higher heating expenditures (between 10% and 17%, for specification M1 between 14% and 22%). Factors that are uniquely shown in our results to be associated with lower heating expenditures per m² are living space, a newer building (1990 and newer compared to the base group of 1979 to 1989), and a lower age of the respondent (under 50 years compared to the base group of 50 to 65 years). The negative estimation coefficient for the logarithm of 'LivingSpace' indicates economies of scale. Similarly, lower income and a higher level of education are associated with higher heating expenditures per m². The results are broadly in line with current literature (see e.g. Meier and Rehdanz 2010; Longhi 2015; Schmitz and Madlener 2019).

Resuming the discussion on the role of the Renewable Energies Heat Act of 2009 and the Thermal Insulation Ordinance of 1977, as a robustness check we re-estimate specifications M1, M3, and M4 for the matching set with replacement. This time, we include interaction terms between prosuming and building age for time periods that are largely in line with the periods of the respective regulation. We label these models M1r, M3r, and M4r. Table 3.6 reports the estimation results for this robustness check. Results of the robustness check are similar to previous results. Interaction effects of being a prosumer and building age are only statistically significant for the parsimonious model without control variables and estimated on the unmatched data. However, two exceptions indicate the necessity of both using comprehensive models to explain residential energy use (including technological and social characteristics) and matching analysis to ensure comparability. One exception is the estimation result of M3r on the full sample, where a significant negative relation between being a prosumer living in a building built between 1991 and 2009 and heating expenditures is shown. This finding is not confirmed by the estimates based on the matching samples. Our interpretation is that the linear regression analysis can fail to identify this potentially spurious relationship. One reason why matching might be more reliable in this case, compared to linear regression analysis, is that the effect could be caused by a nonlinear and unknown functional form. However, the second exception is the estimation result of M1r on the matching sample, where a significant negative relation between being a prosumer living in a building built after 2009 and heating expenditures is shown. Here, our interpretation is that matching analysis is no protection against incomplete models. However, the small size of this sub-sample (12 respondents, see Table 3.1) limits the interpretation of this effect. Moreover, the results indicate the limitations for model extensions. Finally, the variance inflation factor indicates some multi-collinearity problems for specifications M3r and M4r estimated with the matching sample.

Table 3.6: Regression results including interaction terms

	Mix full sample	M1: matching with replacement	M2: full sample	M2: matching with replacement	M3: full sample	M3: matching with replacement	M4: full sample	M4: matching with replacement
Prosumer * Building <1978	0.084	0.118	0.120	-0.010	0.113	0.063		
Prosumer * Building 1979-90	-0.066	0.044	-0.035	-0.043	-0.017	0.078		
Prosumer * Building 1991-2009	-0.340**	-0.150	-0.194	-0.046	-0.208	0.041		
Prosumer * Building 2001-09	-0.260***	-0.145	-0.091	-0.095	-0.115	-0.122		
Prosumer * Building >2009	-0.624***	-0.302*	-0.130	-0.012	-0.133	-0.100		
Eco E-Thrift	-0.078*	-0.061	-0.054	0.005	-0.053	0.004		
Log(Living Space)	0.130**	0.142*	0.065***	-0.441***	-0.608***	-0.465***		
Log(Living Space) ²			-0.005***	-0.046	-0.105***	-0.083		
Building Type: Row House			0.105	-0.112	0.103	-0.114		
Building Type: Other			0.002	-0.022	0.002	-0.021		
Building Age <1949			0.037	0.018	0.044	0.027		
Building Age 1949-1978			-0.145**	-0.223**	-0.151**	-0.243**		
Building Age 1991-2000			-0.066***	-0.066***	-0.066***	-0.066***		
Building Age >2009			-0.265***	-0.276**	-0.235**	-0.178		
Heating Single Stove			-0.138***	-0.124**	-0.128***	-0.131**		
Heating Heatpump			-0.271***	-0.192	-0.261***	-0.234*		
Solar Thermal			-0.007	0.014	-0.064	0.012		
Heat CHP			-0.098	-0.201				
Heat Central			-0.083	-0.078				
Heat Electric			-0.078*	-0.071				
Heatwater Gas			-0.031	0.016				
Intercept	2.251***	2.213***	5.361***	4.531***	5.445***	4.805***		
Controls	No	No	No	Yes	Yes	Yes		
Observations	849	261	849	261	849	261		
R ²	0.054	0.041	0.276	0.337	0.266	0.293		
Adjusted R ²	0.046	0.015	0.229	0.171	0.236	0.190		
logLik	-694.9	-177.1	-581.1	-129.0	-587.3	-137.4		
AIC	1,407.7	372.3	1,270.2	366.0	1,244.6	344.7		
BIC	1,408.4	372.3	1,270.2	366.0	1,244.6	344.7		
Residual Std. Error	(df = 841)	(df = 253)	0.484	0.444	0.439	0.439		
F Statistic	6.846***	1.552	5.845***	2.033***	8.936***	2.852***		
Max. variance inflation factor	(df = 7; 841)	(df = 7; 253)	(df = 52; 796)	(df = 52; 208)	(df = 33; 815)	(df = 33; 227)		
	1.1	1.2	4.0	18.4	3.4	8.4		

Notes: ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

3.5 Conclusions and Outlook

In this paper, we discuss whether being an energy prosumer affects energy-using behavior in ways that are unrelated to technical differences between prosumers and non-prosumers. To ensure an appropriate quasi-randomized comparison, we create a quasi-experimental setting by using propensity score matching. While we find that prosumer households differ significantly in their socio-economic, building and other household characteristics, and as a group are notably more heterogeneous in their energy consumption, we find no evidence of different energy consumption behavior. Our results show no clear evidence of either negative or positive aggregated effects of prosuming on residential energy consumption, and therefore no evidence of an overall prosumer rebound effect. With the specific view to energy consumption behavior, the result indicates no need for shifting the taxation and subsidy scheme of micro-generation technologies in a way that they specifically target behavioral changes due to prosuming. With the given information we cannot verify whether different rebound-like and efficiency-enhancing behaviors might cancel each other out.

Considering the policy relevance and the vested interests of different groups aiming to influence the political debate, it is important to show that overly simplistic statistical comparisons regarding energy behavior may lead to premature or even wrong conclusions. We conclude that neither additional energy savings nor additional consumption are induced by the adoption of prosuming technologies due to behavioral changes. With this interpretation, we have to stress the higher heterogeneity of the prosumer group in the sample, so it is conceivable that both consumer behaviors exist, but that they cancel each other out on average. However, frequently stated learning effects and a more conscious use of energy in the home due to the ownership of prosuming technologies should not be overrated, but neither should the effect of moral licensing within the considered sphere of energy consumption at home.

Even in the absence of behavioral changes due to prosuming, private households in general and prosumer households specifically can play a crucial part in the socio-ecological transformation of the energy system. Results and the preliminary theoretical discussion can rather be interpreted in favor of a policy framework that is characterized by an openness for different technological solutions and stakeholder groups. In this sense, possible subsidies should preferably be based on realized savings rather than technology options. Policy measures addressing specifically prosumer households might be appropriate for other reasons, for example to address possible externalities on energy grids. However, other focus groups, e.g. buildings built between 1949 and 1978 that represent a high share of the building stock (26% of respondents) and are characterized by higher heating expenditures, are likely to be more effective target groups for increasing energy efficiency and reducing carbon emissions of the building sector. However, neither other prosumer externalities nor other focus groups were part of our investigation.

Furthermore, the results show that residential energy use cannot easily be explained by a small number of factors. Instead, both technological and social characteristics of households matter, and they often involve complex processes and interactions that researchers do not yet fully understand. In future research, the increasingly important group of prosumer households, the different types of which were discussed at the beginning of the article, should be studied in more detail and with a larger sample, taking preferences and social groups into account. From a behavioral point of view, it seems interesting to investigate differences in behavioral changes caused by voluntary, as opposed to obligatory, (regulation) adoption.

A limitation of the present study is the relatively small sample size of the data set. An opportunity for future research is therefore to repeat the analysis with other data sets including larger sample sizes and longitudinal data. Ideally, the behavior of prosumers would be examined in a number of carefully designed, large-scale, controlled randomized trials. In such analyses, the dependent variable should be the households' energy consumption level, rather than energy expenditures. This would allow researchers to distinguish clearly between price and consumption effects. However, for this approach to be feasible, researchers would first have to overcome a number of technical, political, and legal barriers.

The main contribution of this study is twofold. Firstly, the illustrated methodological framework and research questions pave the way for future studies on this topic. Secondly, our empirical results may serve to alleviate the high expectations that some stakeholders have regarding the future role of prosumer households as part of the energy transition in Germany. Still, as the role of prosumers and distributed generation in energy markets increases, we consider more research on prosumers, across disciplines and methods, to be both worthwhile and necessary.

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Chapter 4

Direct and Indirect Rebound Effects in German Households: A Linearized Almost Ideal Demand System Approach

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4.1 Introduction

Improvements in energy efficiency are often considered to be effective and cost-efficient for mitigating both energy consumption and greenhouse gas (GHG) emissions. However, these advances are prone to triggering rebound effects – behavioral changes that stem from the decreased price of an energy service due to the increased efficiency, leading to an increased demand for that specific service. *Direct rebound effects* are a standard reaction to a price decrease and are easily explained by basic microeconomics. They consist of an income effect and a substitution effect. Additionally, *indirect rebound effects* exist. These occur when an efficiency increase related to one good or service increases the demand for other goods and services. For example, buying a more fuel-efficient car can cause a number of different reactions: driving more frequently and longer distances in the new car is a direct energy rebound effect, whereas using some or all of the monetary savings to undertake more trips by airplane would be an indirect effect.

The magnitude of rebound effects has implications for energy policy: namely, the higher a rebound effect is, the less effective efficiency improvements are in achieving environmental goals, because more of the potential savings remain unrealized due to higher consumption. Since these improvements are sometimes induced by government activity, for example in the form of mandatory efficiency standards or research funding for efficiency technologies, rebound effects should be taken into account when evaluating these policy measures *ex ante* and *ex post*. Conversely, due to the close relationship

between price elasticities and rebound, high rebound effects suggest that households are highly price-sensitive with regard to the demand for energy. High price sensitivity increases the effectiveness of price-based measures, such as taxes on energy consumption.

Ultimately, one of the main goals of energy and environmental policy is not only to reduce energy consumption but also to decrease GHG emissions. Most goods and services have some amount of embodied emissions that are released during the production process, even though the exact relationship between consumption and energy use is highly heterogeneous across goods. For some goods, this emission might be largely invisible to the consumer, such as sleeping in a hotel or going to the movies. Other goods, such as furniture or books, typically require no energy while in use, but still need energy along their production chains. In order to measure the real overall effects of an efficiency improvement, we need to include its impact on the demand for all goods and services of an economy, not just energy goods and services.

Numerous studies have estimated rebound effects across different goods and services and for different countries.¹ Many of those exploit the close relationship between price elasticities of energy demand and rebound effects. However, this identity relies on strong assumptions. Namely, energy prices need to be exogenous, energy efficiency needs to be constant, and energy service demand needs to be dependent on energy service prices only (Sorrell and Dimitropoulos, 2008; Chan and Gillingham, 2015). Since these assumptions are unlikely to hold in practice, Hunt and Ryan (2014) suggest explicitly incorporating energy efficiency in the estimations so that price elasticities can serve as unbiased estimates of a rebound effect. However, most studies so far have not addressed this issue. Furthermore, most empirical estimations of direct and indirect rebound effects only take into account immediate energy use, omitting the embodied energy that is used in the production and shipping of all goods, including food or clothing (Chitnis and Sorrell, 2015). In view of this gap in the current literature, our research question is the following: what is the magnitude of direct and indirect rebound effects for energy carriers used by German households? To the best of our knowledge, our study is the first to include the embodied energy and CO₂ intensity of all goods and services consumed by households, while explicitly accounting for energy efficiency in the estimations. The analysis is undertaken for the case of Germany.

Several studies have estimated direct and indirect energy rebound effects for different countries and time periods by using a systems approach and by incorporating both income and substitution effects. Brännlund et al. (2007) investigate monthly household data for Sweden for 1980-1997. Employing a three-stage budgeting model that separates spending into durable and non-durable goods before using four groups in the second stage, and 13 goods and services in the third stage, the authors estimate own- and cross-price elasticities in a Linearized Almost Ideal Demand System (LAIDS) framework. They find excessively large total rebound effects, ranging from 121% to 175% across categories.²

Mizobuchi (2008) examines monthly Japanese expenditure data ranging from 1990 to 1998. Unlike Brännlund et al. (2007), who simulate a costless efficiency improvement, Mizobuchi (2008) explicitly takes capital costs into account. To this end, the author considers actual efficiency and price data for different energy-consuming appliances such as TV sets and water heaters. His paper finds a combined

¹ For an extensive review of direct rebound estimates, see e.g. Sorrell et al. (2009); Azevedo (2014).

² Note that the authors report their results differently. In the transport sector, for example, CO₂ emissions would decrease by 6.2% without rebound, but in reality increase by 1.3% due to rebound. The authors denote this as a rebound effect of $6.2\% + 1.3\% = 7.5\%$. As Chitnis and Sorrell (2015) point out, standard convention would report the rebound estimate as $7.5\% / 6.2\% = 121\%$.

rebound effect of 27% when including capital costs and 115% when excluding them, the latter result being similar to the lower end of the values found by Brännlund et al. (2007).

Chitnis and Sorrell (2015) estimate direct and indirect rebound effects for a wide variety of goods and services consumed by private households in the UK, encompassing both durables and non-durables. By mapping GHG emissions to the different categories, the authors manage to evaluate the full impact of rebound effects for households in the UK. Their paper finds a combined rebound effect for gas, electricity, and vehicle fuels of 55%, with most of this effect stemming from substitution rather than from income effects. Direct effects are significantly larger than indirect ones. The authors find that the direct rebound is mostly driven by substitution effects, while indirect rebound is caused by income effects. Due to the limitations of their approach, the authors suspect that their results overestimate the magnitude of the combined rebound effect. The present paper conducts a similar analysis to that of Chitnis and Sorrell (2015) but using a German dataset. It also extends the analysis by representing energy efficiency improvements through the incorporation of time trends, price growth rates, and price asymmetries across various model specifications, respectively.

None of these three studies incorporate efficiency explicitly in their estimations, as proposed by Hunt and Ryan (2014). So far, the only contribution that does so is that of Peters and McWhinnie (2015). Here, the authors use micro-level data from a repeated cross-sectional household survey for Australia. The rich demographic nature of the dataset allows them to estimate a variety of models that find robust direct rebound effects. These effects range from 103% to 120% for electricity and from 138% to 284% for natural gas. However, the authors' analysis is limited to finding direct rebound effects, and it disregards any kind of indirect rebound stemming from either other energy sources or other goods that contain embodied energy. There are several other studies that estimate direct and indirect rebound without taking substitution effects into account, focusing only on income effects instead (e.g. Druckman et al. 2011; Thomas and Azevedo 2013). If substantial substitution effects exist, focusing only on income effects would significantly bias rebound estimates. For a recent overview of these studies, we refer to Chitnis and Sorrell (2015).

As Hunt and Ryan (2014) show, estimating rebound effects by using price elasticities can lead to biased estimates when energy efficiency is not explicitly accounted for in the estimations. Given that the exact energy efficiency for most energy services is usually unobserved, it remains an open question how to implement efficiency in the empirical estimations (Hunt and Ryan, 2014). A straightforward option is to implement a linear or non-linear time trend. However, this assumes that all efficiency increases are exogenous. Since increasing efficiency might also be induced by rising prices, another way is to include past prices for different energy sources, for example by using price growth rates or relative prices. In the model specifications used, we implement (a) a linear and quadratic time trend, (b) time trends and lagged price growth rates, (c) time trends and lagged cumulated price increases and decreases reflecting asymmetric price responses, in order to overcome the shortcomings of previous research.

The remainder of this paper has the following structure. In Section 4.2, we describe our methodological approach and the data used. Section 4.3 presents and discusses the results of our econometric estimations. Section 4.4 presents a conclusion and suggests avenues for future research.

4.2 Methodology and Data

4.2.1 Methodology

We derive direct and indirect rebound effects for all goods and services consumed by private households in the German economy by using a LAIDS approach. The original AIDS was first proposed by Deaton and Muellbauer (1980) and possesses a number of desirable characteristics that contribute to its long-lasting popularity and widespread use in analyzing consumer demand. Specifically, the AIDS allows perfect aggregation across consumers and can serve as a first-order approximation for any demand system (Holt and Goodwin, 2009).

The original AIDS model is defined by Deaton and Muellbauer (1980) as

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln(p_j) + \beta_i \ln\left(\frac{x}{P}\right) + \epsilon_i \quad (4.1)$$

where $i, j \in \{1, \dots, n\}$ indicate the commodity, w_i is the budget share for good i , p_j is the price of good j , x are expenditures, and α , β , and γ are coefficients to be estimated. This means that we estimate one α and one β respectively for each good, in addition to one γ for each pair of goods. The total number of coefficients is therefore $n + n + n^2$. Furthermore, ϵ is the error term, and P is a price index. In the original AIDS framework, the non-linear nature of this index makes its estimation computationally challenging. However, when prices are highly collinear, P can be approximated linearly, for example by using Stone's price index (Deaton and Muellbauer, 1980). While many empirical applications use this price index proposed by Stone (1954), it suffers from simultaneity bias since the expenditure shares appear on both sides of the equation to be estimated (Eales and Unnevehr, 1988). To avoid this issue, we use a simplified Laspeyres index as proposed by Moschini (1995), which is defined as

$$\ln(P_t) = \sum_k w_{k0} \ln(p_{kt}). \quad (4.2)$$

As (4.2) shows, the simplified Laspeyres index weights the prices of the different goods and services p_k by their respective initial budget shares w_{k0} . As is common in the literature for estimating consumer demand, we impose a number of restrictions on the parameters. Firstly, the sum of expenditures on each good has to sum up to total expenditures (the *adding-up* restriction).³ Formally, this means that

$$\sum_{i=1}^n \alpha_i = 1, \sum_{i=1}^n \gamma_{ij} = 0, \sum_{i=1}^n \beta_i = 0. \quad (4.3)$$

Secondly, the demand system has to be homogeneous of degree zero, meaning that the quantity demanded remains constant when prices and total expenditures change by an equal proportion (the *homogeneity* restriction, which implies the absence of the so-called ‘money illusion’). This implies that

³ Note that this implies that the budget shares w_i have to sum up to unity.

$$\sum_j \gamma_{ij} = 0. \quad (4.4)$$

Thirdly, the Slutsky matrix has to be symmetric (the *symmetry* condition), which means that

$$\gamma_{ij} = \gamma_{ji}. \quad (4.5)$$

In addition to ensuring consistency with consumer demand theory, these restrictions reduce the number of parameters that need to be estimated in the demand system.

Consistent with similar studies (Mizobuchi, 2008; Chitnis and Sorrell, 2015), we use multi-stage budgeting as proposed by Edgerton (1997). With this approach, goods are first split into broad categories which are then further divided into subcategories. This allows the estimation of each category separately, which increases the total number of (sub-)categories that can be used. When using this approach, we need to assume weakly separable preferences. This implies that the distribution of spending within a category is not influenced by the total spending in other categories.

Table 4.1 shows our chosen classification of goods and services, along with their respective expenditure shares in 2017, based on data from the German Federal Statistical Office (2018). The second column shows the respective codes following the Classification of Individual Consumption According to Purpose (COICOP, see United Nations Statistics Division 2000). There are several factors to consider when choosing the breakdown of goods into (sub-)categories. On the one hand, the number of groups has to be limited, as otherwise the number of coefficients that need to be estimated would be too large. On the other hand, the number of (sub-)groups must not be too small either, because otherwise the assumption of weak separability cannot be reasonably maintained. As our focus is on energy, creating a separate category for different energy carriers appears sensible. Finally, the number and division of categories is also restricted by the aggregation level of the available data.⁴

For each of these commodity groups, we simultaneously estimate the corresponding equation system using Iterated Seemingly Unrelated Regression (ISUR). ISUR is used for equation systems in which the error terms are correlated, but the regressors themselves are not (Zellner, 1962). ISUR is usually estimated using Feasible Generalized Least Squares (FGLS).

The parameter estimates are not intuitively easy to interpret. However, Edgerton (1997) shows how short-run elasticities for both expenditures and prices can be obtained from the coefficients in a two-stage LAIDS framework. Specifically, the expenditure elasticity is defined as

$$\eta_{q_i, x} = \eta_{q_r, x} \eta_{q_i, x_r}^r. \quad (4.6)$$

This elasticity describes the change in the quantity demanded for good i when total expenditures x change, and is defined as the product of the within-group elasticity and the between-group elasticity. The expression $\eta_{q_r, x}$ denotes the between-group elasticity for group r , which describes the change in the quantity demanded for commodity group r when total expenditures x change. The within-group expenditure elasticity, which is the change in quantity demanded for good $i \in r$ following a change

⁴ As numerous studies have pointed out, formally testing the separability assumptions is computationally demanding due to the large number of restrictions that have to be tested. In our case, we would need to conduct 89 separate tests. Furthermore, restriction tests in large demand systems are prone to over-rejection (Laitinen, 1978). For these reasons, we abstain from formally testing the separability assumptions.

Table 4.1: Classification of goods and services

Category	COICOP category	Expenditure share in 2017 (in %)
1 Food & beverages	01+02	13.92
11 Food & non-alcoholic beverages	01	10.73
12 Alcoholic beverages & tobacco	02	3.20
2 Transportation	07	14.08
21 Vehicle fuels & lubricants	0722	3.10
22 Other transport	Rest of 07	10.98
3 Energy	045	4.16
31 Electricity	0451	2.21
32 Gas	0452	1.13
33 Liquid fuels	0453	0.43
34 Other fuels ^a	Rest of 045	0.39
4 Housing		29.32
41 Rent	Rest of 04	19.57
42 Furniture	05	6.88
43 Communication	08	2.87
5 Other goods		38.52
51 Recreation, culture & education	09+10	10.15
52 Restaurants & hotels	11	5.56
53 Clothing	03	4.82
54 Health goods and services	06	5.23
55 Other	12	12.76

^a In this context, ‘Other fuels’ mainly consists of coal, coke, and biomass.

in expenditure for group r , is defined as η_{q_i, x_r}^r . The total expenditure elasticity shown in (4.6) is the product of the two.

The total uncompensated price elasticity for goods i, j can be expressed as

$$\eta_{q_i, p_j} = \delta_{rs} \eta_{q_i, p_j}^r + \eta_{q_i, x_r}^r (\delta_{rs} + \eta_{q_r, p_s}) w_j^s, \quad (4.7)$$

where η_{q_i, p_j}^r is the within-group price elasticity for goods $i, j \in r$, η_{q_i, x_r}^r is the within-group expenditure elasticity as defined in (4.6), η_{q_r, p_s} is the between-group price elasticity, and δ_{rs} is the Kronecker delta, which takes the value of 1 for $r = s$, i.e. when goods i and j are part of the same group, and 0 otherwise.

The total compensated price elasticity is defined analogously as

$$\tilde{\eta}_{q_i, p_j} = \delta_{rs} \tilde{\eta}_{q_i, p_j}^r + \eta_{q_i, x_r}^r \tilde{\eta}_{q_r, p_s} w_j^s, \quad (4.8)$$

which consists of the between-group elasticity $\tilde{\eta}_{q_r, p_s}$, the within-group elasticity $\tilde{\eta}_{q_i, p_j}^r$, the within-group expenditure elasticity η_{q_i, x_r}^r , and the Kronecker delta δ_{rs} . In the first stage, the model that we develop for the analysis has the following structure:

$$w_t^r = \alpha^r + \sum_s \gamma^{rs} \ln(p_t^s) + \beta^r \ln\left(\frac{x_t}{P_t}\right) + \sum_s \lambda^{rs} w_{t-1}^s + c_t + \epsilon_t^r. \quad (4.9)$$

At this stage, the total expenditures are distributed among the five commodity groups depicted in Table 4.1. We include one-period lagged shares to avoid potential serial correlation (Edgerton, 1997; Chitnis and Sorrell, 2015). This adds λ^{rs} as additional coefficients to be estimated. We estimate four out of the five equations in the first stage, omitting the ‘Other goods’ category from the system in order to reduce the number of coefficients that need to be estimated. The parameter values for ‘Other goods’ are then obtained via the adding-up restriction from (4.3).

The obtained price and expenditure elasticities can be used to derive direct and indirect rebound effects for the corresponding goods and services. Both direct and indirect rebound effects are each composed of income and substitution effects, meaning that there are four specific effects that add up to the total rebound effect, viz.: (i) direct substitution, (ii) direct income, (iii) indirect substitution, and (iv) indirect income effects. Specifically, the income component of the direct rebound effect for good j can be expressed as (Chitnis and Sorrell, 2015):

$$\hat{R}_D = w_j \eta_{q_j, x}, \quad (4.10)$$

whereas the substitution component is defined as

$$\tilde{R}_D = -\tilde{\eta}_{q_j, p_j}. \quad (4.11)$$

The indirect income rebound effect of good j on commodity i can be expressed as

$$\hat{R}_{I_i} = \psi_i w_j \eta_{q_i, x}, \quad (4.12)$$

where ψ_i is the relative emission intensity u and expenditure share w of the two commodities

$$\psi_i = \frac{u_i^x w_i}{u_j^x w_j}. \quad (4.13)$$

Finally, the indirect substitution rebound effect is defined as

$$\tilde{R}_{Fi} = -\psi_i \tilde{\eta}_{q_i, p_j}. \quad (4.14)$$

Unless the good in question is inferior, we can expect the direct income effect to be larger than zero. However, this is not necessarily the case for substitution effects: since all goods and services in our demand system have a non-zero amount of emissions that are associated with them, any substitution of expenditures away from good j to good i will increase the total emissions caused by good i , but lower those from j . Depending on the relative emission intensities of the goods in question, substitution effects can therefore also be negative. If these outweigh the income effect, total rebound may subsequently be negative as well (cf. Borenstein, 2015).

4.2.2 Data

For our estimations, we utilize data from different sources. Price data for the different commodity groups and the number of households for the years 1970–2017 are taken from the respective statistical yearbooks of the German Federal Statistical Office. Prices are indexed using the base year 2010. Aggregate expenditure data per spending category are taken from Federal Statistical Office (2018) and divided by the number of households to obtain the mean expenditures per household.⁵ To account for climatic variation between years, we include the sum of heating degree days (HDD) per year in Germany, taken from Eurostat (2018). HDD are calculated as:

$$HDD = \begin{cases} 18^\circ C - T & T \leq 15^\circ C \\ 0 & T > 15^\circ C \end{cases} \quad (4.15)$$

with T as the mean air temperature on a given day. All data are for West Germany for 1970–1990 and for reunified Germany for 1991–2017. Table 4.2 shows descriptive statistics for per capita expenditures, prices, and additional variables used in our estimations. All expenditures in this table are in 2010 prices.

We assess rebound not in terms of energy consumption, but with regard to CO₂ emissions. This is especially relevant when discussing indirect effects: the money saved due to an efficiency gain is likely to be spent elsewhere. However, additional spending on goods such as clothing or furniture also causes emissions caused by production and shipping processes. Therefore, we assign CO₂ emission intensities to all spending categories in our demand system, derived from own calculations based on data from Federal Statistical Office (2011).⁶ Emission intensity data is only available for the year 2007. Table 4.3 shows the emission intensity per (sub-)category in kgCO₂/Euro and the respective

⁵ The number of households was unavailable for 1983 and 1984 and was estimated by using linear regression.

⁶ In Federal Statistical Office (2011), emission levels in tons per capita are given for the year 2007 for 31 different categories of goods and services, while our system uses 16 categories in total. We calculate the emission intensity in kgCO₂ per Euro by: (i) aggregating the original 31 categories in the data to fit into our category scheme; (ii) multiplying the per capita emissions by the population in Germany in 2007 to obtain total emission levels; (iii) dividing those total emissions by total spending levels in 2007 for each category. Due to a lack of data for emission levels in other years, we assume constant emission intensities over time.

Table 4.2: Descriptive statistics

Variable	Mean	St. Dev.	Min	Max
Consumption expenditures, per capita in Euros				
Food & Beverages	5,641.32	709.84	4,610.61	6,665.67
Transportation	4,363.04	679.75	2,895.95	5,225.19
Energy	1,441.74	234.51	957.04	1,928.00
Housing	9,208.40	1,237.30	6,495.47	10,642.82
Other goods	12,336.63	1,107.80	9,610.00	13,923.30
Total	32,991.13	2,438.06	26,680.65	36,135.31
Price indices, 2010 = 100				
Food & Beverages	77.24	20.44	39.55	117.07
Transportation	67.39	26.26	24.00	107.70
Energy	63.23	29.03	18.20	120.60
Housing	80.04	19.09	40.67	106.96
Other goods	72.30	24.88	28.00	112.37
Total	74.81	22.61	32.60	109.30
Other variables				
Heating Degree Days ^a , in $^{\circ}\text{C} \times \text{d}$	3,223.14	267.77	2,660.86	3,815.5
Median age of population, in years	39.61	3.63	34.63	46.42

^a Values for 1970-1973 were estimated through linear regression due to a lack of data.

expenditure and emission shares in 2007. The table shows that some goods, such as energy, are emission-intensive, while representing only a small share of total expenditures. Consumption from the ‘Energy’ category accounts for only 4% of expenditures but for 34% of CO₂ emissions. For other categories, such as ‘Rent’ or ‘Recreation, Culture & Education’, this relationship is reversed. In our framework, the indirect rebound effects associated with a good depend on the respective cross-price elasticities, the relative expenditure shares of the goods in question, and the emission intensity, while the direct rebound effect only depends on the own-price elasticity of demand for that good (cf. Chitnis and Sorrell 2015).

Table 4.3: Emission intensities and expenditure shares

Category	Emission intensity in 2007 (in kgCO ₂ /Euro)	Expenditure share in 2007 (in %)	Emission share in 2007 (in %)
1 Food & beverages		14.05	7.21
11 Food & non-alcoholic beverages	0.272	10.68	5.80
12 Alcoholic beverages & tobacco	0.210	3.37	1.41
2 Transportation		14.41	24.66
21 Vehicle fuels & lubricants	2.042	3.64	14.84
22 Other transport	0.457	10.77	9.82
3 Energy		4.25	34.22
31 Electricity	3.830	2.03	15.54
32 Gas	3.003	1.33	7.95
33 Liquid fuels	4.328	0.54	4.69
34 Other fuels	8.750	0.35	6.04
4 Housing		29.42	3.95
41 Rent ^a	0.026	19.93	1.02
42 Furniture	0.090	6.67	1.20
43 Communication ^a	0.308	2.82	1.73
5 Other goods		37.79	29.96
51 Recreation, culture & education	0.096	10.31	1.97
52 Restaurants & hotels	0.269	4.97	2.66
53 Clothing	0.158	5.24	1.66
54 Health goods and services	0.489	4.36	4.24
55 Other	0.751	12.98	19.43

^a The intensities for these two categories were calculated based on Federal Statistical Office (2010) due to a lack of data in the original source.

Figure 4.1 shows the development of the expenditure shares for the different categories and subcategories over time. Among the first-stage categories, the expenditure share of ‘Food’ has been steadily declining, whereas the share spent on ‘Transport’ is increasing. Within the ‘Energy’ category, we observe significant fluctuations in expenditure shares between goods. In the ‘Other goods’ category, we find an increasing expenditure share for ‘Health’ since 1990, while the share for ‘Clothing’ is steadily decreasing.

Figure 4.2 presents the inflation-adjusted per capita expenditures for all (sub-)categories over time. The figures show that real consumption for almost all categories has been steadily increasing over the last 48 years. The only exceptions are ‘Liquid fuels’, for which expenditures fluctuate significantly over time with a peak in 1979, ‘Food’, and ‘Clothing’. Overall, per capita consumption expenditures in 2010 terms increased from 26,680.65 Euros in 1970 to 35,983.66 Euros in 2017, reflecting economic growth and an increase in the standard of living during this period.

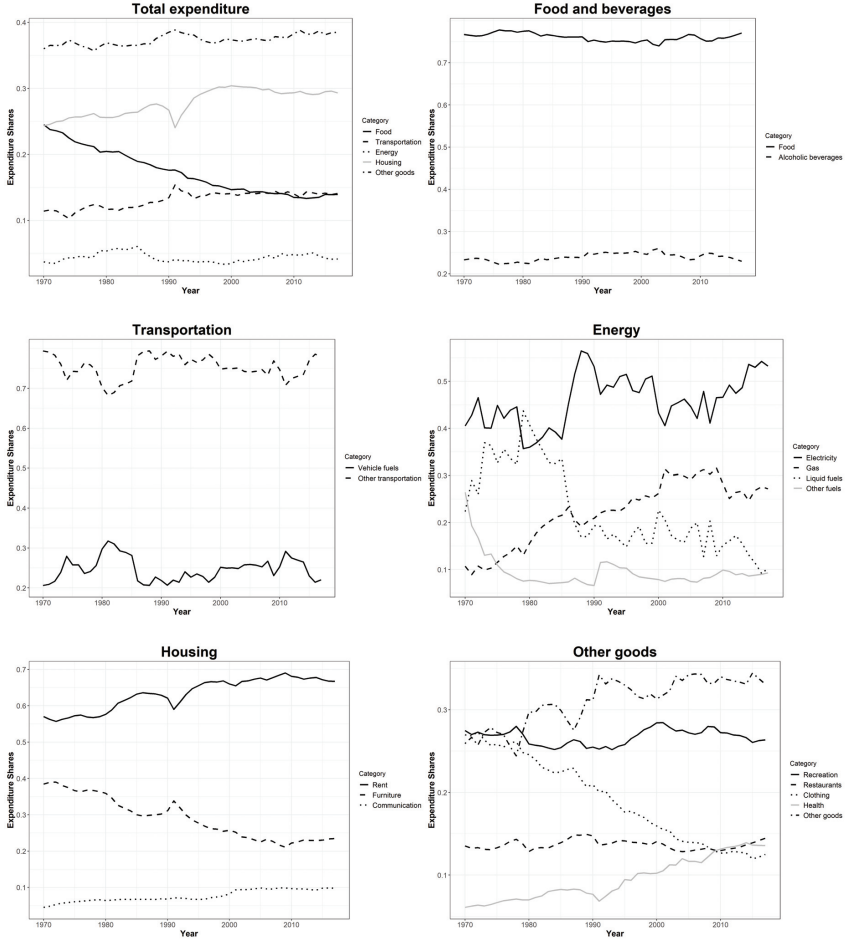


Figure 4.1: Expenditure shares, 1970-2017

4.3 Results

4.3.1 Model Specification

Using the methodology laid out in the previous section, we estimate a total of six demand systems; one at the first stage and five for the respective commodity groups at the second stage. In order to be able to use the Linearized AIDS model as an appropriate approximation of the original AIDS model, prices need to be highly collinear so that the price index P^* is proportional to the original index P . To test this condition, we check for the correlation between the different prices in each system as

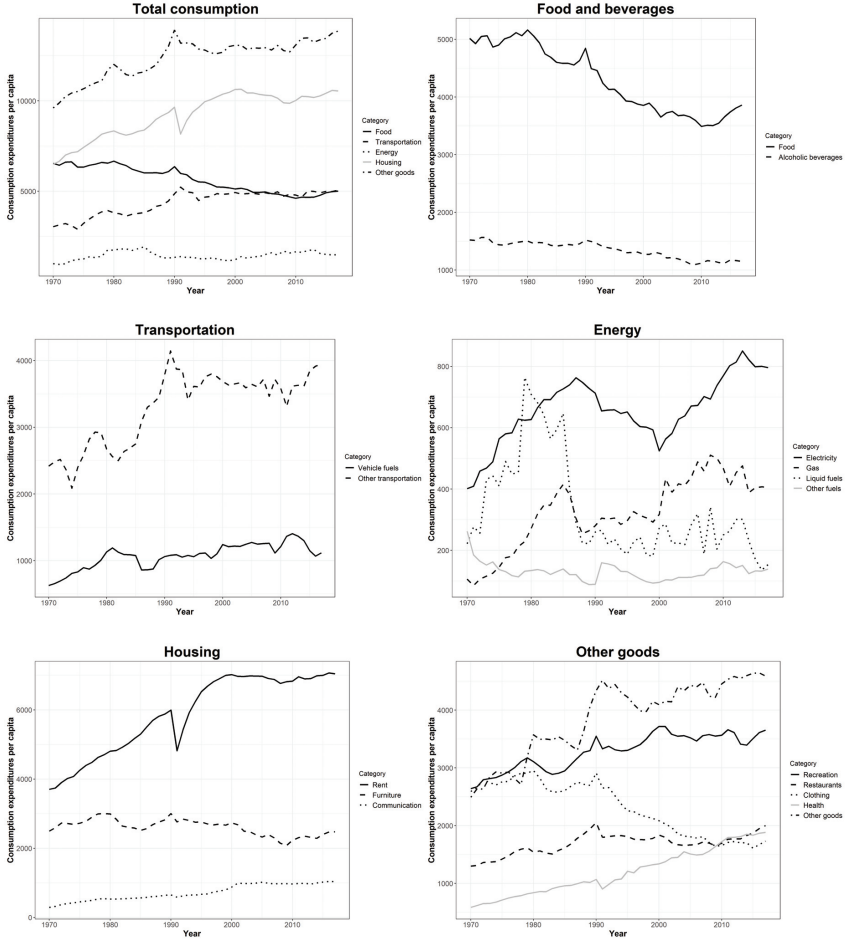


Figure 4.2: Consumption expenditures per capita in Euros (2010 prices), 1970-2017

well as estimating separate Ordinary Least Squares (OLS) regressions for each price, which explain that price by all the other prices in the respective category of goods. If the R^2 values are close to unity, we can conclude that prices are highly collinear, which allows us to use the simplified Laspeyres price index as an approximation of the original index P (Nygård, 2013). With the exception of the Communication category, which shows a very unusual price development, all adjusted R^2 values are higher than 0.87, with the majority being in the range of 0.983 to 0.996.⁷ These results show that prices are indeed highly collinear within systems, which allows us to use P^* in the estimations.

⁷ For all R^2 values, see Table A.1 in the appendix.

Based on the methodology laid out in Section 4.2.1, we estimate the demand systems for the different commodity groups using an ISUR approach and derive expenditure, own-, and cross-price elasticities as well as direct and indirect rebound effects for the different goods and commodities. As discussed in Section 4.2.1, our base model (Model 1) has the specification

$$w_t^r = \alpha^r + \sum_{s=1}^4 \gamma^{rs} \ln(p_t^s) + \beta^r \ln\left(\frac{x_t}{P_t}\right) + \sum_{s=1}^3 \lambda^{rs} w_{t-1}^s + \epsilon_t^r \quad (4.16)$$

in the first stage, including one-period lagged expenditure shares.⁸ In the first stage, total expenditure x_t is distributed between the groups. In the second stage, group expenditures x_t^r are distributed analogously between the different commodities within that group. Following Chitnis and Sorrell (2015), we denote the expenditure on good i in group r in period t as x_{it}^r , and w_{it}^r as the expenditure share of i within group r :

$$w_{it}^r = \frac{x_{it}^r}{x_t^r} \quad (4.17)$$

In the second stage, our base model has the following specification:

$$w_{it}^r = \alpha_i^r + \sum_j \gamma_{ij}^r \ln(p_{ij}^r) + \beta_i^r \ln\left(\frac{x_t^r}{P_t^r}\right) + \sum_j \lambda_{ij}^r w_{jt-1}^r + \epsilon_{it}^r \quad (4.18)$$

For the ‘Energy’ subgroup, we additionally include c_t as the HDD in Germany of year t to account for temperature differences between years, which is of particular importance when modeling energy demand. Furthermore, we use three additional model specifications in order to incorporate efficiency explicitly in our estimations. Note that we include the following three models only for the ‘Transportation’ and ‘Energy’ subgroups. For the other categories, we utilize the specification outlined in (4.16) for the first stage and (4.18) for the second stage, respectively. Hunt and Ryan (2014) suggest several ways to include efficiency in order to obtain unbiased rebound estimates. In this paper, we include a simple and quadratic time trend (t, t^2) in Model 2, for a specification of

$$w_t^r = \alpha_i^r + \sum_j \gamma_{ij}^r \ln(p_{ij}^r) + \beta_i^r \ln\left(\frac{x_t^r}{P_t^r}\right) + \sum_j \lambda_{ij}^r w_{jt-1}^r + c_t + \epsilon_{it}^r + b_{r,t}t + b_{r,tt}t^2. \quad (4.19)$$

A time trend is a straightforward way to model efficiency improvements as a result of technological progress. However, this assumes that all progress is exogenous. In addition to these time trends, Model 3 also includes once-lagged three- and five-year growth rates for the prices in the respective demand systems, which results in the following specification:

$$w_t^r = \alpha_i^r + \sum_j \gamma_{ij}^r \ln(p_{ij}^r) + \beta_i^r \ln\left(\frac{x_t^r}{P_t^r}\right) + \sum_j \lambda_{ij}^r w_{jt-1}^r + c_t + \epsilon_{it}^r + b_{r,t}t + b_{r,tt}t^2 + \sum_j \theta_{i,j} g3_{j,t-1} + \sum_j \phi_{i,j} g5_{j,t-1}. \quad (4.20)$$

This reflects the possibility that efficiency gains can also be induced by periods of large price in-

⁸ To avoid multicollinearity, we only include three lagged shares in each equation (Chitnis and Sorrell, 2015).

creases, as households are more likely to demand high efficiency appliances when prices are increasing (Hunt and Ryan, 2014). As several studies point out, price reactions in energy demand might be asymmetric (see e.g. Gately and Huntington 2002; Frondel and Vance 2013). When facing price increases, households are assumed to make efficiency investments that are not reversed when prices decrease again. In this case, the effect of a price increase would be stronger in magnitude compared to that of a price decrease. Furthermore, periods of sustained price increases would generally reduce the responsiveness to price changes (Hunt and Ryan, 2014). In Model 4, we use a variation of the method suggested by Gately and Huntington (2002) by including the once-lagged cumulated price increases and decreases, separately for all goods in the particular system. For instance, this adds eight variables in the ‘Energy’ category, since it comprises four goods. Model 4 has the following specification:

$$w_t^r = \alpha_i^r + \sum_j \gamma_{ij}^r \ln(p_{ij}^r) + \beta_i^r \ln\left(\frac{x_t^r}{P_t^r}\right) + \sum_j \lambda_{ij}^r w_{j,t-1}^r + c_t + \epsilon_{it}^r + b_{r,t}t + b_{r,tt}t^2 + \sum_j \theta_{i,j} PINC_{j,t-1} + \sum_j \phi_{i,j} PCUT_{j,t-1}, \quad (4.21)$$

where $PINC_{j,t-1}$ and $PCUT_{j,t-1}$ are the cumulated price increases and decreases of good j , respectively.

The reunification of Germany in 1990 might have caused structural change in consumption. We therefore conduct Chow tests separately for each equation in our demand system. The Chow tests reveal that for some of the equations, the null hypothesis of the existence of a structural break in 1991 cannot be rejected. Therefore, we include $\alpha_i^d D$ in these equations, where D is a dummy variable that takes the value of zero for the years 1970-1990 and unity for the years 1991-2017.⁹

Table 4.4 gives an overview of the four different model specifications used.

Table 4.4: Model overview

Model	Lagged expenditure shares	Time trend	Price growth	Price increases & decreases
1	X			
2	X	X		
3	X	X	X	
4	X	X		X

For all categories except ‘Transportation’ and ‘Energy’, we use Model 1 across specifications. In the ‘Transportation’ and ‘Energy’ categories, we additionally use Models 2-4 to incorporate efficiency. The ‘Energy’ category also includes HDD as an explanatory variable in all four models.

⁹ We thank an anonymous referee for this suggestion. The exact results of the Chow tests can be found in the appendix.

4.3.2 Estimation Results

4.3.2.1 Elasticities

Table 4.5 shows the total expenditure elasticities across model specifications and categories, derived from the ISUR estimations and calculated with the expenditure shares from 2017. Based on these elasticities, we can classify ‘Vehicle fuels’ and ‘Other fuels’ as necessities (expenditure elasticity < 1), whereas ‘Liquid fuels’ and ‘Gas’ are luxury goods (expenditure elasticity > 1). For ‘Electricity’, the evidence is inconclusive across specifications. ‘Liquid fuels’ in particular show exceptionally high expenditure elasticities, ranging from 5.4 to 7.1. These unusually high values may be a result of the energy price shocks of the 1970s, which seem to have affected ‘Liquid fuels’ in particular. As Figures 4.1 and 4.2 show, both expenditure share and per capita consumption expenditure for ‘Liquid fuels’ increased significantly between 1970 and 1979, in a period of rising prices for ‘Liquid fuels’. The values for ‘Electricity’ and ‘Gas’ are significantly higher than those reported by Chitnis and Sorrell (2015), who find values of 0.07 and 0.09, respectively. For ‘Vehicle fuels’, in contrast, they find an expenditure elasticity of 0.87, which is similar to our findings.

Table 4.5: Total expenditure elasticities

Category	Model 1	Model 2	Model 3	Model 4
1 Food & beverages				
11 Food & non-alcoholic beverages	1.058	—	—	—
12 Alcoholic beverages & tobacco	1.156	—	—	—
2 Transportation				
21 Vehicle fuels & lubricants	0.659	0.832	0.868	0.525
22 Other transport	1.259	1.211	1.200	1.297
3 Energy				
31 Electricity	1.101	0.736	1.042	0.844
32 Gas	1.425	1.530	1.041	1.328
33 Liquid fuels	5.368	7.105	6.044	6.134
34 Other fuels	0.569	0.433	1.284	1.479
4 Housing				
41 Rent	0.823	—	—	—
42 Furniture	0.593	—	—	—
43 Communication	0.915	—	—	—
5 Other goods				
51 Recreation, culture & education	0.749	—	—	—
52 Restaurants & hotels	0.712	—	—	—
53 Clothing	0.920	—	—	—
54 Health goods and services	0.829	—	—	—
55 Other	1.518	—	—	—

The derived expenditure elasticities are dependent on the expenditure shares at both the first and second stage. Since expenditure shares fluctuate over time, the resulting elasticities vary as well. Figure 4.3 shows the variation of the elasticity derived from Model 1 based on the expenditure shares used. ‘Liquid fuels’ have the highest variation, with values ranging from 2.3 to 5.8. Tables 4.6 and 4.7 show the uncompensated and compensated price elasticities, respectively, across the four model specifications for the energy-related goods in our demand system.

Table 4.6: Total uncompensated price elasticities

Category	Electricity	Gas	Liquid fuels	Other fuels	Vehicle fuels
Model 1: base case					
Electricity	-0.069	0.054	-0.086	0.081	-0.105
Gas	0.103	-0.103	-0.075	0.050	-0.136
Liquid fuels	-0.485	-0.219	0.552	0.054	-0.514
Other fuels	0.467	0.151	0.069	-0.697	-0.054
Vehicle fuels	-0.060	-0.030	-0.012	-0.010	-0.778
Model 2: time trend					
Electricity	-0.015	-0.005	-0.079	0.085	-0.070
Gas	-0.017	-0.087	-0.089	0.165	-0.146
Liquid fuels	-0.468	-0.262	0.617	-0.016	-0.680
Other fuels	0.488	0.490	-0.005	-0.981	-0.041
Vehicle fuels	-0.075	-0.038	-0.015	-0.013	0.023
Model 3: time trend and lagged price growth					
Electricity	-0.076	0.044	-0.067	0.080	-0.100
Gas	0.085	-0.118	-0.118	0.131	-0.100
Liquid fuels	-0.393	-0.335	0.547	0.071	-0.578
Other fuels	0.459	0.383	0.088	-0.954	-0.123
Vehicle fuels	-0.079	-0.040	-0.015	-0.014	0.010
Model 4: time trend and cumulated price changes					
Electricity	0.070	0.026	-0.083	-0.028	-0.081
Gas	0.047	-0.075	-0.090	0.094	-0.127
Liquid fuels	-0.480	-0.261	0.628	0.003	-0.587
Other fuels	-0.168	0.275	0.012	-0.145	-0.142
Vehicle fuels	-0.048	-0.024	-0.009	-0.008	0.026

Table 4.7: Total compensated price elasticities

Category	Electricity	Gas	Liquid fuels	Other fuels	Vehicle fuels
Model 1: base case					
Electricity	-0.045	0.067	-0.081	0.085	-0.074
Gas	0.134	-0.087	-0.069	0.056	-0.096
Liquid fuels	-0.366	-0.158	0.575	0.075	-0.363
Other fuels	0.480	0.157	0.071	-0.695	-0.038
Vehicle fuels	-0.757	-0.023	-0.009	-0.008	-0.628
Model 2: time trend					
Electricity	0.002	0.004	-0.075	0.087	-0.050
Gas	0.017	-0.070	-0.082	0.171	-0.103
Liquid fuels	-0.311	-0.182	0.648	0.012	-0.480
Other fuels	0.498	0.495	-0.003	-0.979	-0.029
Vehicle fuels	-0.056	-0.029	-0.011	-0.010	0.049
Model 3: time trend and lagged price growth					
Electricity	-0.053	0.055	-0.062	0.084	-0.070
Gas	0.108	-0.106	-0.113	0.135	-0.070
Liquid fuels	-0.259	-0.267	0.573	0.094	-0.409
Other fuels	0.488	0.398	0.093	-0.949	-0.087
Vehicle fuels	-0.059	-0.030	-0.011	-0.010	0.037
Model 4: time trend and cumulated price changes					
Electricity	0.088	0.036	-0.079	-0.025	-0.057
Gas	0.076	-0.060	-0.084	0.099	-0.090
Liquid fuels	-0.345	-0.192	0.654	0.026	-0.415
Other fuels	-0.136	0.292	0.018	-0.140	-0.100
Vehicle fuels	-0.035	-0.018	-0.007	-0.006	0.042

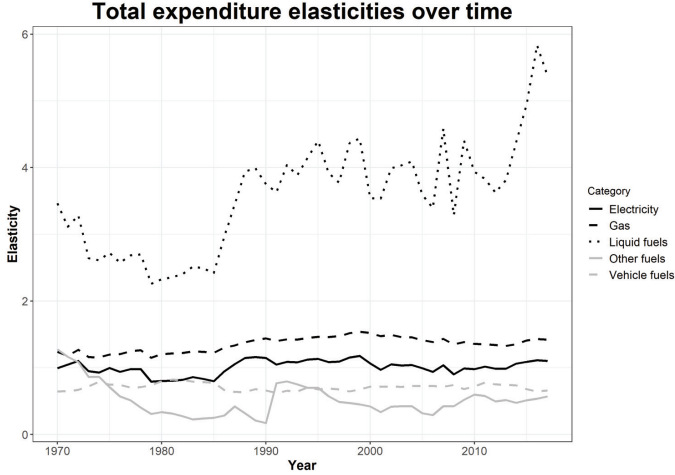


Figure 4.3: Expenditure elasticities over time, Model 1

Most of the total uncompensated own-price elasticities are consistent in sign and magnitude across specifications, with some exceptions. For example, the uncompensated own-price elasticity for ‘Electricity’ is positive in Model 4, but negative in the other models. For ‘Vehicle fuels’, the elasticity is strongly negative (-0.778) in Model 1, but slightly positive (between 0.010 and 0.026) in Models 2 to 4. These elasticities are sensitive to the expenditure shares used. Depending on the expenditure shares, the elasticity values range from -0.24 to 0.09 across Models 2 to 4. ‘Liquid fuels’ have high positive own-price elasticities across specifications, ranging from 0.573 to 0.654. As with the expenditure elasticities, these results appear to be driven by the unusual development of expenditures and prices for liquid fuels in the 1980s. Between 1970 and 1979, per capita expenditures in real terms increased by 245%. Afterwards, the trend reversed, and expenditures dropped sharply until they returned to the 1970 level in 1989 (see Figure 4.2). In a recent meta-study, Labandeira et al. (2017) find short-term own-price elasticities of -0.126 for electricity, -0.180 for natural gas, -0.017 for heating oil, -0.293 for gasoline, and -0.153 for diesel. Considering total cross-price elasticities, we find that ‘Electricity’ is a substitute for ‘Gas’ and ‘Other fuels’ and a complement to ‘Liquid fuels’ and ‘Vehicle fuels’. ‘Other fuels’ are a complement to all other energy carriers except ‘Vehicle fuels’, while ‘Vehicle fuels’ are a substitute for all other energy goods.

4.3.2.2 Rebound Effects

Based on expenditure and price elasticities, we derive rebound effects for the goods in the Energy group and for vehicle fuels following the expressions previously described, which are summarized in Table 4.8.

Table 4.8 shows that the direct rebound effect for a good depends on the expenditure share of that commodity, its expenditure elasticity, and its own-price elasticity. The indirect rebound effect additionally depends on the relative emission intensity and the relative expenditure share between the two goods in question.

Table 4.8: Components of the rebound effect

	Direct rebound	Indirect rebound
Income effect	$w_i \eta_{q_i, x}$	$\psi_j w_i \eta_{q_j, x}$
Substitution effect	$-\tilde{\eta}_{q_i, p_i}$	$-\psi_j \tilde{\eta}_{q_j, p_i}$

Source: Chitnis and Sorrell (2015)

For the sake of clarity, we report the rebound estimates in two separate tables. We use the example of ‘Electricity’ to explain the presentation of our results. The indirect rebound effects for non-energy goods caused by ‘Electricity’ can be seen in the first two columns of Table 4.9. For example, a 1% efficiency increase in ‘Electricity’ causes emissions from ‘Food’ to increase by 0.8% due to income effects and by 0.5% due to substitution effects for a total indirect rebound effect of 1.3%. Since we only estimate Model 1 for the non-energy related categories, there is only one result to report for each energy good. We find the effects to be small in magnitude, with small positive income effects counterbalanced by small negative substitution effects. These small absolute values can be explained by the relatively low emission intensity of most of these goods, compared to ‘Electricity’, and by the cross-price elasticities between ‘Electricity’ and these non-energy related goods and services.

Table 4.10 shows our rebound estimates for the energy related goods. Here, we have four different sets of results based on the four model specifications used. For ‘Electricity’, the results across models range from 6.4% to 20.3%. Model 4 is the only specification where indirect and overall substitution effects are positive. Subsequently, total rebound is also larger in Model 4 compared to the other specifications. Income effects, both direct and indirect, show only minimal variation between models. The non-energy goods from Table 4.9 are also included as aggregated values. Note that these do not change between specifications since we only estimate Model 1 for these goods and services.

Table 4.9: Indirect rebound effect estimates for non-energy goods, in %

Category	Electricity		Gas		Liquid fuels		Other fuels		Vehicle fuels	
	Income	Substitution	Income	Substitution	Income	Substitution	Income	Substitution	Income	Substitution
Food	0.8	0.5	1.0	0.7	0.7	0.5	0.4	0.2	1.5	0.0
Alcohol	0.2	0.1	0.3	0.2	0.2	0.1	0.1	0.1	0.4	0.0
Rent	0.1	-0.1	0.1	-0.1	0.1	-0.1	0.0	0.0	0.2	-0.4
Furniture	0.1	-0.1	0.1	-0.1	0.1	0.0	0.0	0.0	0.2	-0.3
Communication	0.2	-0.1	0.3	-0.1	0.2	-0.1	0.1	0.0	0.4	-0.8
Recreation	0.2	-0.2	0.2	-0.3	0.2	-0.2	0.1	-0.1	0.4	-0.3
Restaurants	0.3	-0.3	0.4	-0.4	0.2	-0.3	0.1	-0.1	0.5	-0.4
Clothing	0.2	-0.2	0.2	-0.3	0.2	-0.2	0.1	-0.1	0.3	-0.3
Health	0.6	-0.6	0.7	-0.8	0.5	-0.5	0.2	-0.003	1.0	-0.9
Other	3.8	-4.1	4.8	-5.2	3.4	-3.6	1.7	-1.8	7.1	-5.9
Sum	6.4	-4.9	8.2	-6.3	5.7	-4.3	2.8	-2.2	12.0	-9.3

Similarly to ‘Electricity’, the second part of Table 4.10 shows the rebound estimates for ‘Gas’. Across specifications, total rebound ranges from -7.3% to 9.8%. We find relatively large negative substitution effects for ‘Electricity’ and ‘Other fuels’, with small to moderate positive income effects. Moving on to ‘Liquid fuels’, we find a similar pattern to the two previous goods regarding indirect effects on non-energy goods, i.e. small positive income effects that are partially counterbalanced by small negative substitution effects. Total rebound effects range from -6.6% to 3.4% across models. Specifically, we find large negative direct substitution effects between -57.3% and -65.4% and large positive indirect substitution effects for ‘Electricity’, ranging from 28.5% to 37.1%. For ‘Other fuels’, we find substantial positive direct substitution effects that range from 14.0% to 97.9%. Overall effects range from 47.0% to 64.1%. One reason for the large direct substitution effect could be the

Table 4.10: Rebound effect estimates, energy goods, in %

Category	Model 1		Model 2		Model 3		Model 4		
	Income	Substitution	Income	Substitution	Income	Substitution	Income	Substitution	
Electricity	Direct Effects								
	Energy: Electricity	2.4	4.5	1.6	-0.2	2.3	5.3	1.9	-8.8
	Indirect Effects								
	Transportation: Vehicle fuels	1.1	3.3	1.4	4.2	1.4	4.4	0.9	2.7
	Transportation: Other transport	1.7	5.0	1.6	4.8	1.6	4.8	1.7	5.2
	Energy: Gas	1.3	-5.4	1.4	-0.7	0.9	-4.3	1.2	-3.0
	Energy: Liquid fuels	2.6	8.0	3.4	6.8	2.9	5.7	3.0	7.5
	Energy: Other fuels	0.5	-19.1	0.4	-19.8	1.1	-19.4	1.3	5.4
	Sum of Non-energy goods (from Table 4.9)	6.4	-4.9	6.4	-4.9	6.4	-4.9	6.4	-4.9
	Sum of Indirect Effects	13.5	-13.0	14.6	-9.6	14.4	-13.8	14.4	12.8
Sum of Direct + Indirect Effects	16.0	-8.6	16.2	-9.7	16.7	-8.5	16.3	4.0	
Gas	Direct Effects								
	Energy: Gas	1.6	8.7	1.7	7.0	1.2	10.6	1.5	6.0
	Indirect Effects								
	Transportation: Vehicle fuels	1.1	4.2	1.8	5.4	1.8	5.6	1.1	3.4
	Transportation: Other transport	2.1	6.4	2.0	6.2	2.0	6.1	2.2	6.6
	Energy: Electricity	3.1	-16.6	2.1	-0.9	2.9	-13.8	2.4	-8.9
	Energy: Liquid fuels	3.3	8.6	4.4	9.9	3.7	14.6	3.8	10.5
	Energy: Other fuels	0.6	-15.6	0.5	-49.2	1.4	-39.6	1.7	-29.0
	Sum of Non-energy goods (from Table 4.9)	8.2	-6.3	8.2	-6.3	8.2	-6.3	8.2	-6.3
	Sum of Indirect Effects	18.7	-19.2	18.9	-34.9	20.1	-33.4	19.3	-23.8
Sum of Direct + Indirect Effects	20.3	-10.5	20.6	-27.9	21.3	-22.8	20.8	-17.8	
Liquid fuels	Direct Effects								
	Energy: Liquid fuels	2.3	-57.5	3.0	-64.8	2.6	-57.3	2.6	-65.4
	Indirect Effects								
	Transportation: Vehicle fuels	1.0	2.9	1.2	3.7	1.3	3.9	0.8	2.3
	Transportation: Other transport	1.5	4.5	1.4	4.3	1.4	4.2	1.5	4.6
	Energy: Electricity	2.2	37.1	1.4	34.5	2.0	28.5	1.7	36.3
	Energy: Gas	1.1	12.7	1.2	15.1	0.8	20.7	1.0	15.4
	Energy: Other fuels	0.4	-13.0	0.3	0.6	1.0	-17.0	1.2	-3.3
	Sum of Non-energy goods (from Table 4.9)	5.7	-4.3	5.7	-4.3	5.7	-4.3	5.7	-4.3
	Sum of Indirect Effects	11.8	39.9	11.3	53.9	12.2	36.0	11.8	51.1
Sum of Direct + Indirect Effects	14.1	-17.6	14.3	-10.9	14.8	-21.4	14.4	-14.3	
Other fuels	Direct Effects								
	Energy: Other fuels	0.2	69.5	0.2	97.9	0.5	94.9	0.6	14.0
	Indirect Effects								
	Transportation: Vehicle fuels	0.5	1.5	0.6	1.8	0.6	1.9	0.4	1.2
	Transportation: Other transport	0.7	2.2	0.7	2.1	0.7	2.1	0.7	2.3
	Energy: Electricity	1.1	-21.3	0.7	-22.0	1.0	-21.2	0.8	6.3
	Energy: Gas	0.6	-5.6	0.6	-17.2	0.4	-13.6	0.5	-10.0
	Energy: Liquid fuels	1.1	-4.1	1.5	-0.6	1.3	-5.2	1.3	-1.4
	Sum of Non-energy goods (from Table 4.9)	2.8	-2.2	2.8	-2.2	2.8	-2.2	2.8	-2.2
	Sum of Indirect Effects	6.8	-29.5	6.9	-38.0	6.8	-38.1	6.6	-3.9
Sum of Direct + Indirect Effects	7.0	40.1	7.1	59.9	7.3	56.7	7.1	10.1	
Vehicle fuels	Direct Effects								
	Transportation: Vehicle fuels	2.0	75.7	2.6	-4.9	2.7	-3.7	1.6	-4.2
	Indirect Effects								
	Transportation: Other transport	3.1	-2.9	3.0	15.2	3.0	14.9	3.2	15.0
	Energy: Electricity	4.6	10.0	3.1	6.7	4.3	9.4	3.5	7.6
	Energy: Gas	2.4	5.2	2.5	5.5	1.7	3.8	2.2	4.8
	Energy: Liquid fuels	4.9	10.6	6.4	14.0	5.5	11.9	5.6	12.1
	Energy: Other fuels	0.9	2.0	0.7	1.6	2.1	4.6	2.4	5.3
	Sum of Non-energy goods (from Table 4.9)	12.0	-9.3	12.0	-9.3	12.0	-9.3	12.0	-9.3
	Sum of Indirect Effects	27.9	15.5	27.8	33.6	28.6	35.3	28.9	35.5
Sum of Direct + Indirect Effects	29.9	91.2	30.3	28.7	31.3	31.6	30.6	31.3	

Notes: The exact breakdown of the indirect effects for non-energy goods is depicted in Table 4.9.

high emission intensity of the ‘Other fuels’ category. Since the emission intensity of ‘Other fuels’ is significantly higher than for all other categories, any substitution away from the other goods to ‘Other fuels’ leads to higher emissions. Finally, we consider ‘Vehicle fuels’. Here, we find large direct substitution effects in Model 1 and small negative effects in Models 2-4. Overall rebound estimates are larger than for the other energy goods, ranging from 59.0% to 121.1%. These high estimates are mainly driven by indirect effects. In Models 2-4, income and substitution effects are similar in magnitude. Note that in our estimations, rebound is defined at the CO₂ level. This means that the spending effects in monetary terms are translated into CO₂ emissions in order to calculate rebound effects.¹⁰

By definition, the estimated rebound effects depend on the expenditure shares used, which vary over time. Until now, we used the expenditure shares of the most recent year of our sample (2017). To evaluate the robustness of our results, we also estimate rebound effects separately with the expenditure shares of every year in the sample. Figure 4.4 shows the estimated rebound effects derived from Model 4 depending on the expenditure shares used. The graphs show that rebound estimates are highly sensitive to the expenditure shares assumed. We find that direct and indirect effects partially offset. For ‘Liquid fuels’, for example, direct effects are negative whenever indirect effects are positive and vice versa. As Chan and Gillingham (2015) have shown theoretically, direct and indirect rebound effects are not necessarily countervailing when several energy services and non-energy services are involved.

Table 4.11 shows the corresponding descriptive statistics of the graphs depicted in Figure 4.4, disaggregated into the four components of the total rebound effect: i) direct income, ii) indirect income, iii) direct substitution, and iv) indirect substitution. As can be seen from the table, total rebound estimates vary substantially depending on the expenditure shares used for the calculations. We also find that most of this variation stems from substitution effects. For ‘Electricity’, indirect substitution effects are particularly volatile, while for the other fuel types both direct substitution and indirect substitution effects are the main drivers of volatility. In contrast, both direct income and indirect income effects show a significantly lower variation over time. Note that the calculation of direct effects is based on the expenditure shares of the good in question, whereas indirect effects are calculated from the expenditure shares of all goods, which is a possible explanation for the much larger variation in the indirect effects.

4.4 Conclusions and Outlook

In this paper, we derive emission rebound effects for different energy fuels used by German households, taking into account indirect effects stemming from embodied emissions from non-energy related goods. We also explicitly include energy efficiency in our estimations, which reduces bias in rebound estimates compared to the literature that uses only price elasticities as estimates for the rebound effect.

Depending on the model specification, we find a total rebound effect ranging from 6.4% to 20.3% for ‘Electricity’, -7.3% to 9.8% for ‘Gas’, -6.6% to 3.4% for ‘Liquid fuels’, 47.0% to 64.1% for ‘Other fuels’, and 59.0% to 121.1% for ‘Vehicle fuels’. Hunt and Ryan (2014) found that rebound estimates are biased upwards when efficiency is not explicitly taken into account. Overall, we do not find conclusive evidence for this assertion.

¹⁰For example, an efficiency change for one good might trigger large spending increases for other goods, which would imply large indirect income rebound effects. However, if these other goods have low emission intensities, the resulting rebound estimates would be quite low when measured in CO₂ terms.

Table 4.11: Disaggregated rebound estimates by base year, Model 4

Category	Rebound estimates			
	Mean	St. Dev.	Min	Max
Electricity	0.230	0.182	-0.175	0.569
<i>Direct income</i>	0.014	0.003	0.009	0.020
<i>Indirect income</i>	0.189	0.012	0.169	0.214
<i>Direct substitution</i>	-0.106	0.026	-0.150	-0.051
<i>Indirect substitution</i>	0.214	0.206	-0.244	0.626
Gas	0.118	0.210	-0.251	0.513
<i>Direct income</i>	0.012	0.005	0.003	0.019
<i>Indirect income</i>	0.195	0.011	0.176	0.218
<i>Direct substitution</i>	-0.139	0.316	-1.106	0.136
<i>Indirect substitution</i>	-0.003	0.319	-0.407	0.709
Liquid fuels	0.091	0.164	-0.269	0.406
<i>Direct income</i>	0.036	0.009	0.025	0.057
<i>Indirect income</i>	0.108	0.006	0.096	0.119
<i>Direct substitution</i>	-0.042	0.263	-0.829	0.357
<i>Indirect substitution</i>	-0.020	0.194	-0.410	0.572
Other fuels	0.153	0.076	-0.045	0.276
<i>Direct income</i>	0.006	0.002	0.004	0.016
<i>Indirect income</i>	0.065	0.004	0.056	0.073
<i>Direct substitution</i>	0.099	0.135	-0.146	0.429
<i>Indirect substitution</i>	-0.040	0.081	-0.241	0.099
Vehicle fuels	0.719	0.089	0.565	0.938
<i>Direct income</i>	0.019	0.004	0.012	0.027
<i>Indirect income</i>	0.285	0.014	0.261	0.315
<i>Direct substitution</i>	0.030	0.080	-0.100	0.189
<i>Indirect substitution</i>	0.367	0.061	0.290	0.559

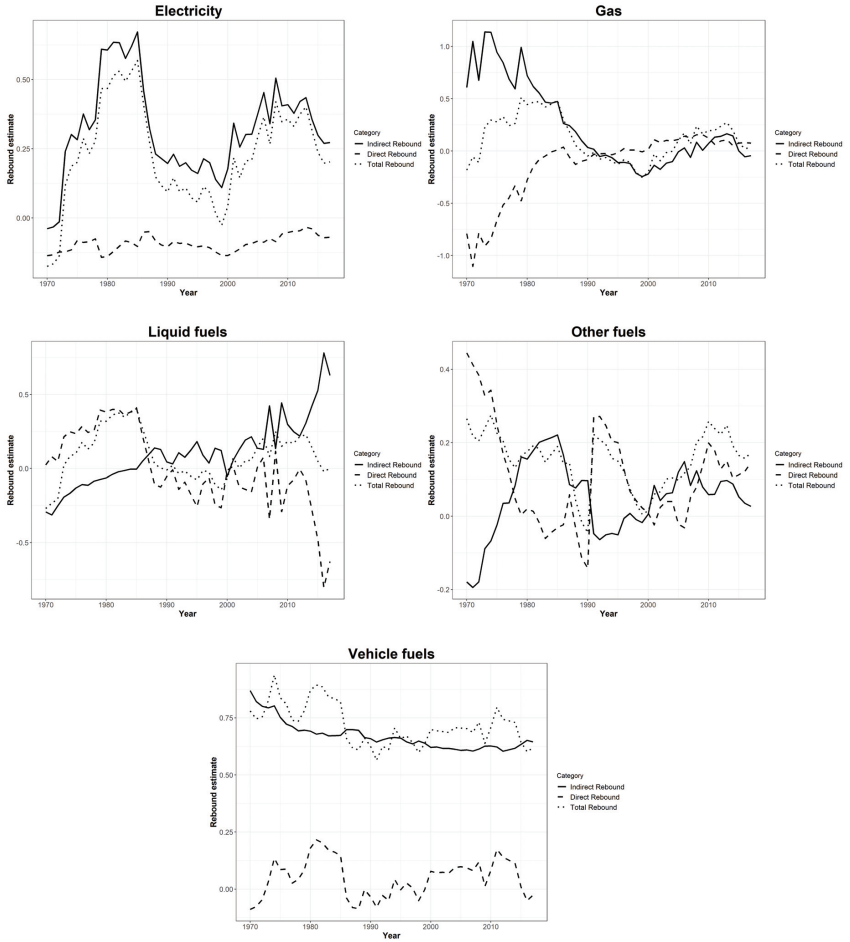


Figure 4.4: Rebound estimates by base year, Model 4

Substitution effects are mostly negative for ‘Electricity’, ‘Gas’, and ‘Liquid fuels’, whereas they are positive for ‘Other fuels’ and ‘Vehicle fuels’. This might be caused by the relative emission intensities of these goods. Compared to income effects, substitution effects are smaller in magnitude for ‘Electricity’, and roughly of the same size for ‘Gas’, ‘Liquid fuels’, and ‘Vehicle fuels’, but considerably larger for ‘Other fuels’. This shows that studies which only focus on income effects paint an incomplete picture and that they risk substantially misrepresenting the magnitude of total rebound effects.

Our results are sensitive to the exact model specification, the breakdown of commodity groups,¹¹ the emission intensities of the different goods and services, and especially to the base year for the expenditure shares. This shows that any credible attempt of estimating the magnitude of rebound effects needs to be precise on the exact methodology and data used in order to allow direct comparisons with other studies.

The relative emission intensities of the goods and services in our estimations can influence our indirect rebound estimates substantially. A 20% reduction of emission intensity for ‘Electricity’, for example, would increase our total rebound estimate for ‘Electricity’ (Model 4) from 20.3% to 27.1%, due to an increase in both indirect income and indirect substitution effects.¹² Furthermore, a reduction in emission intensity across multiple categories that leaves relative intensities unchanged would have no effect on rebound estimates. Still, this reduction would clearly be relevant from a CO₂ emissions perspective. Furthermore, emission intensity has no influence on direct rebound effects. This shows that high rebound effects are not automatically detrimental to the goal of emissions reduction, and low rebound effects are not a sufficient condition for low overall CO₂ emissions.

Our results open up several avenues for further research. One fruitful approach could be to directly model energy services rather than fuels. This might solve some of the issues related to the fact that certain energy carriers, especially electricity, provide different energy services, and that some energy services, e.g. space heating, can be provided by different fuels. Another possibility is to explore different ways to model efficiency, such as stochastic trends or an underlying energy demand trend (UEDT, see Hunt et al. 2003).

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¹¹In an alternative specification, we use only three groups in the ‘Energy’ category: ‘Electricity’, ‘Gas’, and ‘Other fuels’. The resulting rebound effects are slightly different for these three categories, but remain virtually unchanged for ‘Vehicle fuels’. Full results are available from the authors upon request.

¹²Note that indirect effects can increase or decrease in this case: if the majority of goods act as substitutes to the good in question, rebound increases, while rebound effects decrease if more goods are complements. Direct effects, in contrast, are not influenced by relative emission intensities.

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4.A Appendix

Table A.1: Collinearity of prices, adjusted R^2 values

Category	Dependent variable				
	p_1	p_2	p_3	p_4	p_5
Total	0.993	0.997	0.990	0.990	0.998
Food and Beverages	0.914	0.914	-	-	-
Transportation	0.889	0.889	-	-	-
Energy	0.885	0.984	0.905	0.987	-
Housing	0.973	0.966	0.699	-	-
Other goods	0.994	0.995	0.994	0.984	0.987

Table A.2: First stage estimates

	Category				
	Food	Transportation	Energy	Housing	Other
Intercept	0.113 (0.121)	0.123 (0.213)	-0.293 (0.101)***	0.176 (0.247)	0.881
$\log(p_1)$	0.045 (0.013)***	-0.019 (0.013)	-0.010 (0.006)	-0.041 (0.011)***	0.025
$\log(p_2)$	-0.019 (0.013)	0.033 (0.028)	-0.026 (0.011)**	0.020 (0.019)	-0.008
$\log(p_3)$	-0.010 (0.006)	-0.026 (0.011)**	0.041 (0.006)***	-0.007 (0.008)	0.002
$\log(p_4)$	-0.041 (0.011)***	0.020 (0.019)	-0.007 (0.008)	0.072 (0.024)***	-0.044
$\log(p_5)$	0.025	-0.008	0.002	-0.044	0.025
Price Index	0.011 (0.012)	0.018 (0.023)	0.024 (0.011)**	-0.065 (0.029)**	0.012
Lagged Shares 1	0.637 (0.144)***	-0.330 (0.263)	0.454 (0.121)***	0.164 (0.277)	-
Lagged Shares 2	-0.099 (0.111)	0.038 (0.217)	0.212 (0.101)**	0.361 (0.269)	-
Lagged Shares 3	0.153 (0.111)	0.037 (0.205)	0.521 (0.101)***	0.152 (0.244)	-
Lagged Shares 4	-0.018 (0.080)	-0.288 (0.147)*	0.282 (0.070)***	0.750 (0.179)***	-
Reunification	0.002 (0.003)	0.002 (0.005)	0.006 (0.002)***	-0.006 (0.006)	-
N	47	47	47	47	-
Adjusted R^2	0.995	0.858	0.909	0.916	-
Degrees of Freedom	36	36	36	36	-

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors in parentheses. Values for the *Other* category are calculated from the adding-up and homogeneity restrictions.

Table A.3: First stage parameters

Category	Parameter estimates						
	α	β	γ_{rs}				
			Food	Transportation	Energy	Housing	Other
Food	0.113	0.011	0.045	−0.019	−0.010	−0.041	0.025
Transportation	0.123	0.018	−0.019	0.033	−0.026	0.020	−0.008
Energy	−0.293	0.024	−0.010	−0.026	0.041	−0.007	0.002
Housing	0.176	−0.065	−0.041	0.020	−0.007	0.072	−0.044
Other	0.881	0.012	0.025	−0.008	0.002	−0.044	0.025

Table A.4: Second stage estimates, food category

	Category	
	Food	Alcohol
Intercept	0.196 (0.098)*	0.804
$\log(p_1)$	-0.005 (0.004)	0.005
$\log(p_2)$	0.005	-0.005
Price Index	-0.016 (0.011)	0.016
Lagged Shares 1	0.854 (0.085)***	—
N	47	—
Adjusted R^2	0.757	—
Degrees of Freedom	43	—

Notes:***,**, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors in parentheses. Values for the *Alcohol* category are calculated from the adding-up and homogeneity restrictions.

Table A.5: Second stage parameters, food category

Category	Parameter estimates			
	α	β	γ_{rs}	
			Food	Alcohol
Food	0.196	-0.016	-0.005	0.005
Alcohol	0.804	0.016	0.005	-0.005

Table A.6: Second stage estimates, transportation category

	Category							
	Vehicle fuels				Other transport			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Intercept	0.391 (0.138)***	-0.157 (0.109)	-0.175 (0.219)	0.065 (0.095)	0.609	-1.157	-1.175	0.935
$\log(p_1)$	0.023 (0.013)*	0.205 (0.015)***	0.203 (0.020)***	0.195 (0.012)***	-0.023	-0.205	-0.203	-0.195
$\log(p_2)$	-0.023	-0.205	-0.203	-0.195	0.023	0.205	0.203	0.195
Price Index	-0.091 (0.033)***	-0.058 (0.024)**	-0.051 (0.045)	-0.118 (0.021)***	0.091	0.058	0.051	0.118
Lagged Shares 1	0.854 (0.085)***	-0.111 (0.068)	-0.118 (0.113)	-0.073 (0.070)	-	-	-	-
Reunification	-0.011 (0.012)	-0.020 (0.005)***	-0.021 (0.012)	-0.014 (0.004)***	-	-	-	-
Time Trend	-	-0.006 (0.001)***	-0.007 (0.001)***	0.003 (0.002)	-	-	-	-
Squared Time Trend	-	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)***	-	-	-	-
3 Year Price Growth: Fuels	-	-	-0.015 (0.080)	-	-	-	-	-
3 Year Price Growth: Other	-	-	-0.041 (0.240)	-	-	-	-	-
5 Year Price Growth: Fuels	-	-	-0.039 (0.072)	-	-	-	-	-
5 Year Price Growth: Other	-	-	-0.140 (0.235)	-	-	-	-	-
Price Increases: Fuels	-	-	-	-0.001 (0.000)***	-	-	-	-
Price Decreases: Fuels	-	-	-	-0.004 (0.001)***	-	-	-	-
Price Increases: Other	-	-	-	-0.014 (0.004)***	-	-	-	-
N	47	47	47	47	-	-	-	-
Adjusted R^2	0.640	0.938	0.929	0.965	-	-	-	-
Degrees of Freedom	42	40	31	37	-	-	-	-

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors in parentheses. Values for the *Other Transport* category are calculated from the adding-up and homogeneity restrictions. Price Decreases: Other omitted because there were no price decreases over the observed time period, i.e. all values are zero.

Table A.7: Second stage parameters, transportation category

Category	Parameter estimates			
	α	β	γ_{rs}	
Model 1			Vehicle fuels	Other transport
Vehicle fuels	0.391	-0.091	0.023	-0.023
Other transport	0.609	0.091	-0.023	0.023
Model 2			Vehicle fuels	Other transport
Vehicle fuels	-0.157	-0.058	0.205	-0.205
Other transport	1.157	0.058	-0.205	0.205
Model 3			Vehicle fuels	Other transport
Vehicle fuels	-0.175	-0.051	0.203	-0.203
Other transport	1.175	0.051	-0.203	0.203
Model 4			Vehicle fuels	Other transport
Vehicle fuels	0.065	-0.118	0.195	-0.195
Other transport	0.935	0.118	-0.195	0.195

Table A.8: Second stage estimates, energy category, Model 1

	Category			
	Electricity	Gas	Liquid fuels	Other fuels
Intercept	0.529 (0.098)***	-0.383 (0.095)***	0.138 (0.128)	0.716
$\log(p_1)$	0.218 (0.098)***	-0.113 (0.018)***	-0.099 (0.012)***	-0.006
$\log(p_2)$	-0.113 (0.018)***	0.172 (0.029)***	-0.048 (0.010)***	-0.011
$\log(p_3)$	-0.099 (0.012)***	-0.048 (0.010)***	0.150 (0.017)***	-0.003
$\log(p_4)$	-0.006	-0.011	-0.003	-0.020
Price Index	-0.161 (0.042)***	-0.026 (0.036)	0.247 (0.056)***	-0.060
Lagged Shares 1	0.471 (0.130)***	0.559 (0.106)***	-0.558 (0.171)***	-
Lagged Shares 2	0.540 (0.117)***	1.047 (0.113)***	-1.065 (0.150)***	-
Lagged Shares 3	0.313 (0.131)**	0.429 (0.105)***	-0.278 (0.181)	-
Reunification	-0.024 (0.010)**	0.036 (0.008)***	-0.032 (0.014)**	-
Heating Degree Days	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-
N	47	47	47	-
Adjusted R ²	0.915	0.969	0.940	-
Degrees of Freedom	37	37	37	-

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors in parentheses. Values for the *Other Fuels* category are calculated from the adding-up and homogeneity restrictions.

Table A.9: Second stage estimates, energy category, Model 2

	Category			
	Electricity	Gas	Liquid fuels	Other fuels
Intercept	1.074 (0.138)***	−0.051 (0.088)	−0.623 (0.162)***	0.600
$\log(p_1)$	0.245 (0.021)***	−0.145 (0.017)***	−0.096 (0.009)***	−0.004
$\log(p_2)$	−0.145 (0.168)***	0.176 (0.020)***	−0.051 (0.006)***	0.020
$\log(p_3)$	−0.096 (0.009)***	−0.051 (0.006)***	0.157 (0.011)***	−0.010
$\log(p_4)$	−0.004	0.020	−0.010	−0.006
Price Index	−0.284 (0.063)***	−0.008 (0.036)	0.360 (0.076)***	−0.068
Lagged Shares 1	0.083 (0.140)	0.135 (0.080)*	0.166 (0.171)	—
Lagged Shares 2	−0.103 (0.191)	0.262 (0.113)**	−0.271 (0.226)	—
Lagged Shares 3	0.089 (0.123)	0.145 (0.071)**	0.201 (0.150)	—
Reunification	−0.043 (0.011)***	−0.001 (0.007)	0.014 (0.013)	—
Heating Degree Days	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)**	—
Time Trend	0.010 (0.002)***	0.011 (0.001)***	−0.019 (0.003)***	—
Squared Time Trend	−0.000 (0.000)***	−0.000 (0.000)***	0.000 (0.000)***	—
N	47	47	47	—
Adjusted R ²	0.951	0.989	0.974	—
Degrees of Freedom	35	35	35	—

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors in parentheses. Values for the *Other Fuels* category are calculated from the adding-up and homogeneity restrictions.

Table A.10: Second stage estimates, energy category, Model 3

	Category			
	Electricity	Gas	Liquid fuels	Other fuels
Intercept	0.694 (0.331)**	−0.140 (0.192)	−0.182 (0.399)	0.628
$\log(p_1)$	0.214 (0.024)***	−0.119 (0.019)***	−0.089 (0.011)***	−0.006
$\log(p_2)$	−0.119 (0.019)***	0.167 (0.022)***	−0.059 (0.007)***	0.011
$\log(p_3)$	−0.089 (0.011)***	−0.059 (0.007)***	0.150 (0.012)***	−0.002
$\log(p_4)$	−0.006	0.011	−0.002	−0.003
Price Index	−0.181 (0.083)**	−0.093 (0.048)*	0.291 (0.101)***	−0.017
Lagged Shares 1	0.171 (0.256)	0.459 (0.150)***	−0.027 (0.308)	—
Lagged Shares 2	0.657 (0.346)*	1.303 (0.214)	−0.323 (0.413)	—
Lagged Shares 3	0.334 (0.224)	0.407 (0.137)***	−0.080 (0.267)	—
Reunification	—	—	—	—
Heating Degree Days	−0.000 (0.000)	0.000 (0.000)***	−0.000 (0.000)	—
Time Trend	0.001 (0.003)	0.014 (0.002)***	−0.015 (0.004)***	—
Squared Time Trend	−0.000 (0.000)	−0.000 (0.000)***	0.000 (0.000)***	—
3 Year Price Growth: Electricity	0.024 (0.057)	−0.000 (0.033)	0.067 (0.069)	—
3 Year Price Growth: Gas	−0.073 (0.048)	0.033 (0.028)	0.021 (0.058)	—
3 Year Price Growth: Liquid	−0.028 (0.024)	0.009 (0.014)	0.033 (0.029)	—
3 Year Price Growth: Other	0.012 (0.034)	−0.022 (0.020)	0.011 (0.042)	—
5 Year Price Growth: Electricity	−0.020 (0.054)	−0.066 (0.031)**	0.013 (0.064)	—
5 Year Price Growth: Gas	−0.123 (0.058)*	0.034 (0.034)	0.085 (0.070)	—
5 Year Price Growth: Liquid	−0.032 (0.026)	−0.015 (0.015)	0.033 (0.031)	—
5 Year Price Growth: Other	−0.052 (0.032)	0.004 (0.018)	0.055 (0.038)	—
N	47	47	47	—
Adjusted R ²	0.961	0.985	0.978	—
Degrees of Freedom	23	23	23	—

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors in parentheses. Values for the *Other Transport* category are calculated from the adding-up and homogeneity restrictions. Reunification omitted on the basis of a Chow Test.

Table A.11: Second stage estimates, energy category, Model 4

	Category			
	Electricity	Gas	Liquid fuels	Other fuels
Intercept	0.900 (0.152)***	-0.135 (0.094)	-0.465 (0.169)***	0.700
$\log(p_1)$	0.290 (0.035)***	-0.129 (0.019)***	-0.098 (0.008)***	-0.063
$\log(p_2)$	-0.129 (0.019)***	0.179 (0.016)***	-0.052 (0.005)***	0.002
$\log(p_3)$	-0.098 (0.008)***	-0.052 (0.005)***	0.158 (0.009)***	-0.008
$\log(p_4)$	-0.063	0.002	-0.008	0.069
Price Index	-0.248 (0.054)***	-0.043 (0.034)	0.297 (0.064)***	-0.006
Lagged Shares 1	-0.130 (0.143)	0.301 (0.090)***	0.203 (0.172)	-
Lagged Shares 2	-0.245 (0.315)	0.387 (0.198)*	-0.053 (0.381)	-
Lagged Shares 3	0.075 (0.125)	0.209 (0.078)***	-0.060 (0.150)	-
Reunification	-0.031 (0.010)***	-0.011 (0.006)*	-0.003 (0.012)	-
Heating Degree Days	0.000 (0.000)	0.000 (0.000)***	-0.000 (0.000)	-
Time Trend	0.008 (0.003)**	0.009 (0.002)**	-015 (0.004)***	-
Squared Time Trend	-0.000 (0.000)*	-0.000 (0.000)***	-0.000 (0.000)**	-
Price Increases: Electricity	0.000 (0.001)	-0.001 (0.001)	0.001 (0.001)	-
Price Decreases: Electricity	0.002 (0.003)	0.000 (0.002)	-0.006 (0.004)	-
Price Increases: Gas	0.001 (0.001)	-0.000 (0.001)	-0.002 (0.001)*	-
Price Decreases: Gas	-0.003 (0.001)***	0.002 (0.001)***	0.002 (0.001)	-
Price Increases: Liquid	-0.001 (0.000)**	0.000 (0.000)*	0.000 (0.000)	-
Price Decreases: Liquid	-0.001 (0.000)	0.000 (0.000)	0.001 (0.001)*	-
Price Increases: Other	-0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	-
Price Decreases: Other	0.002 (0.001)*	-0.002 (0.001)***	-0.001 (0.001)	-
N	47	47	47	-
Adjusted R^2	0.974	0.993	0.987	-
Degrees of Freedom	27	27	27	-

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors in parentheses. Values for the *Other Transport* category are calculated from the adding-up and homogeneity restrictions.

Table A.12: Second stage parameters, energy category

Category	Parameter estimates					
	α	β	γ_{rs}			
Model 1			Electricity	Gas	Liquid	Other
Electricity	0.529	-0.161	0.218	-0.113	-0.099	-0.006
Gas	-0.383	-0.026	-0.113	0.172	-0.048	-0.011
Liquid	0.138	0.247	-0.099	-0.048	0.150	-0.003
Other	0.716	-0.060	-0.006	-0.011	-0.003	-0.020
Model 2			Electricity	Gas	Liquid	Other
Electricity	1.074	-0.284	0.245	-0.145	-0.096	-0.004
Gas	-0.051	-0.008	-0.145	0.176	-0.051	0.020
Liquid	-0.623	0.360	-0.096	-0.051	0.157	-0.003
Other	0.600	-0.068	-0.004	0.020	-0.010	-0.006
Model 3			Electricity	Gas	Liquid	Other
Electricity	0.694	-0.181	0.214	-0.119	-0.089	-0.006
Gas	-0.140	-0.093	-0.119	0.167	-0.059	-0.011
Liquid	-0.182	0.291	-0.089	-0.059	0.150	-0.002
Other	0.628	-0.060	-0.017	0.011	-0.002	-0.003
Model 4			Electricity	Gas	Liquid	Other
Electricity	0.900	-0.248	0.290	-0.129	-0.098	-0.063
Gas	-0.135	-0.043	-0.129	0.179	-0.052	0.002
Liquid	-0.465	0.297	-0.098	-0.052	0.158	-0.008
Other	0.700	-0.006	-0.063	0.002	-0.008	0.069

Table A.13: Second stage estimates, housing category

	Category		
	Rent	Furniture	Communication
Intercept	-0.029 (0.264)	0.145 (0.251)	0.884
$\log(p_1)$	-0.020 (0.028)	0.026 (0.024)	-0.006
$\log(p_2)$	0.026 (0.024)	-0.011 (0.023)	-0.015
$\log(p_3)$	-0.006	-0.015	0.021
Price Index	0.039 (0.026)	-0.056 (0.025)**	0.017
Lagged Shares 1	0.743 (0.218)***	0.100 (0.208)	—
Lagged Shares 2	-0.035 (0.215)	0.930 (0.204)***	—
Reunification	0.004 (0.005)	-0.008 (0.004)*	—
N	47	47	—
Adjusted R^2	0.961	0.980	—
Degrees of Freedom	40	40	—

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors in parentheses. Values for the *Communication* category are calculated from the adding-up and homogeneity restrictions.

Table A.14: Second stage parameters, housing category

Category	Parameter estimates				
	α	β	γ_{rs}		
			Rent	Furniture	Communication
Rent	-0.029	0.039	-0.020	0.026	-0.006
Furniture	0.145	-0.056	0.026	-0.011	-0.015
Communication	0.884	0.017	-0.006	-0.015	0.021

Table A.15: Second stage estimates, other category

	Category				
	Recreation	Restaurants	Clothing	Health	Other
Intercept	0.370 (0.109)***	0.208 (0.071)***	0.287 (0.110)***	0.159 (0.074)**	-0.024
$\log(p_1)$	0.004 (0.035)	0.013 (0.018)	-0.005 (0.029)	0.010 (0.011)	-0.022
$\log(p_2)$	0.013 (0.018)	-0.041 (0.020)**	-0.035 (0.019)*	0.002 (0.009)	0.061
$\log(p_3)$	-0.005 (0.029)	-0.035 (0.019)*	0.012 (0.030)	0.002 (0.010)	0.026
$\log(p_4)$	0.010 (0.011)	0.002 (0.009)	0.002 (0.010)	-0.002 (0.013)	-0.012
$\log(p_5)$	-0.022	0.061	0.026	-0.012	-0.053
Price Index	-0.072 (0.017)***	-0.045 (0.012)***	-0.013 (0.018)	-0.027 (0.013)**	0.157
Lagged Shares 1	0.760 (0.083)***	-0.198 (0.059)***	-0.213 (0.090)**	0.007 (0.067)	—
Lagged Shares 2	0.125 (0.133)	0.813 (0.096)***	0.089 (0.144)	-0.225 (0.111)**	—
Lagged Shares 3	-0.059 (0.104)	0.065 (0.075)	0.685 (0.114)***	-0.131 (0.086)	—
Lagged Shares 4	-0.250 (0.130)*	-0.095 (0.099)	-0.066 (0.138)	0.727 (0.101)***	—
Reunification	0.003 (0.004)	-0.004 (0.003)*	-0.005 (0.004)	0.002 (0.002)	—
N	47	47	47	47	—
Adjusted R^2	0.834	0.781	0.993	0.985	—
Degrees of Freedom	36	36	36	36	—

Notes:***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors in parentheses. Values for the *Other* category are calculated from the adding-up and homogeneity restrictions.

Table A.16: Second stage parameters, other category

Category	Parameter estimates						
	α	β	γ_{rs}				
			Recreation	Restaurants	Clothing	Health	Other
Recreation	0.370	−0.072	0.004	0.013	−0.005	0.010	−0.022
Restaurants	0.208	−0.045	0.013	−0.041	−0.035	0.002	0.061
Clothing	0.287	−0.013	−0.005	−0.035	0.012	0.002	0.026
Health	0.159	−0.027	0.010	0.002	0.002	−0.002	−0.012
Other	−0.024	0.157	−0.022	0.061	0.026	−0.012	−0.053

Table A.17: Chow test results, energy and vehicle fuels

Category	p-Value
Vehicle fuels, Model 1	0.003
Electricity, Model 1	0.001
Gas, Model 1	0.000
Liquid fuels, Model 1	0.008
Vehicle fuels, Model 2	0.007
Electricity, Model 2	0.102
Gas, Model 2	0.004
Liquid fuels, Model 2	0.126
Vehicle fuels, Model 3	0.077
Electricity, Model 3	0.730
Gas, Model 3	0.333
Liquid fuels, Model 3	0.750
Vehicle fuels, Model 4	0.043
Electricity, Model 4	0.259
Gas, Model 4	0.028
Liquid fuels, Model 4	0.077

Table A.18: Chow test results, other categories

Category	p-Value
Food	0.048
Transportation	0.001
Energy	0.159
Housing	0.000
Food and non-alcoholic beverages	0.182
Rent	0.000
Furniture	0.000
Recreation	0.048
Restaurants	0.119
Clothing	0.799
Health	0.034

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In order to reach the ambitious climate goals set out by the global community, a fundamental transition of the energy system is inevitable. To this end, a multitude of energy and climate policy measures and regulations aim at curbing energy consumption, promoting energy efficiency, and de-carbonizing the economy in numerous countries worldwide. Private households are at the core of many of these measures. Therefore, a better understanding of consumer energy demand is fundamental in assessing the effectiveness and economic efficiency of different policy measures that aim to influence this behavior. Virtually any human activity consumes energy, which makes analyzing energy consumption multifaceted and complex. This is further amplified by the fact that people usually do not consume energy directly, but rather use it as an input to provide an energy service, such as heating, cooling, transportation, or lighting. This dissertation uses a variety of econometric methods to derive insights into different aspects of household energy demand from consumer data. In particular, the three research articles in this thesis explore questions on heating demand in residential buildings, rebound effects for different goods and services, and the behavioral effects of energy prosuming.

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