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Revisiting Heat Energy Consumption Modeling: Household Production Theory Applied to Field Experimental Data

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Authors' addresses:

Florian Heesen
RWTH Aachen University
Templergraben 55
52056 Aachen, Germany
E-Mail: florian.heesen@rwth-aachen.de

Reinhard Madlener
Institute for Future Energy Consumer Needs and Behavior (FCN)
School of Business and Economics / E.ON Energy Research Center
RWTH Aachen University
Mathieustrasse 10
52074 Aachen, Germany
E-Mail: RMadlener@eonerc.rwth-aachen.de

Publisher: Prof. Dr. Reinhard Madlener
Chair of Energy Economics and Management
Director, Institute for Future Energy Consumer Needs and Behavior (FCN)
E.ON Energy Research Center (E.ON ERC)
RWTH Aachen University
Mathieustrasse 10, 52074 Aachen, Germany
Phone: +49 (0) 241-80 49820
Fax: +49 (0) 241-80 49829
Web: www.fcn.eonerc.rwth-aachen.de
E-mail: post_fcn@eonerc.rwth-aachen.de

Revisiting Heat Energy Consumption Modeling: Household Production Theory Applied to Field Experimental Data

Florian Heesen and Reinhard Madlener*

Institute for Future Energy Consumer Needs and Behavior (FCN), School of Business and Economics / E.ON Energy Research Center, RWTH Aachen University, Mathieustraße 10, 52074 Aachen, Germany

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Abstract

This paper offers new insights on utility-driven heat energy consumption. The research question addressed is whether economic aspects affect short-term, less conscious behavior in the same way as long-term, more conscious behavior. The model proposed is based on Becker's household production theory and integrates economic, engineering and behavioral elements. Comparative statics enables an interdisciplinary integration of price- and income functions to cover economic influences, the production function to cover technical influences, and the utility-based choice architecture. Based on a functional representation of the theories, a panel data model of heat energy consumption is estimated. The empirical analysis is based on data from 60 adjacent apartments in South-West Germany. We find empirical evidence that the price elasticity of demand is only statistically significant when using yearly aggregated data. This result provides evidence that occupants apparently do not act upon energy price signals when following their daily home heating routine. In less frequent considerations, as e.g. according to their yearly billing cycles, occupants adjust their heat energy consumption with respect to the fuel price influence. Furthermore, in relation to the other influences on heat energy consumption, we find that the price impact is less pronounced than the impact of comfort conditions.

Keywords: Heat energy consumption, household production theory, price elasticity of demand

* Corresponding author. Tel. +49 241 80 49 820, RMadlener@eonerc.rwth-aachen.de

1. Introduction

Private households do not consume heat energy as an end in itself; rather, they pursue the maximization of wellbeing (or in microeconomics jargon: the maximization of utility). Human wellbeing is determined by multiple influences. The resulting complexity derives from the fact that almost every part of one's life influences wellbeing. Furthermore, individuals have different needs and preferences concerning wellbeing, i.e. there is heterogeneity.

Our approach assesses utility using the household production theory (Becker 1965). Most important from a conservationist's perspective is the dependency of utility on energy consumption. The reduction in energy consumption can be part of utility maximization, but is only one of several other objectives. A reduction in energy consumption reduces the costs of energy, as the supply of energy commodities is commonly paid per unit consumed. This relation embedded in the utility function is explicitly (e.g. as the price elasticity of demand) as well as implicitly (e.g. as an energy efficiency elasticity) theorized and tested in the energy economics literature on heat energy consumption (HEC) (Borenstein 2015; Chan & Gillingham 2015). The use of the household production approach enables to integrate further influences on HEC, e.g., from the engineering sciences, into the theoretical HEC model. A holistic approach is necessary because the deviation of HEC from prior calculated energy performance ratings reported in the literature for most energy efficiency measures (Heesen & Madlener 2016) is problematic from an energy, environmental and economic perspective and thus calls for policy action. For instance, for households it might be important economically to know the true cost-saving potentials of energy efficiency measures. In contrast, policy-makers need to know the cause-effect relationships, for example when implementing incentives to raise energy efficiency. Society as a whole suffers from the adverse ecological consequences of global warming driven by excess fossil energy consumption, with HEC in private households contributing a major share of greenhouse gas emissions also in Germany.

In the energy economics literature, the deviations from *ex ante* anticipated energy savings potentials to *ex post* realized energy consumptions, are analyzed according to the price elasticity of demand, which adopts an increased demand for energy services because of a lower price per unit of service (Berkhout et al. 2000). This paper shows theoretically as well as empirically that the price elasticity of demand relationship to energy consumption does hold true, but in order to assess its full predictive power the price elasticity of demand needs to be incorporated into an

interdisciplinary framework. As the theoretical HEC model follows an interdisciplinary approach, it interprets the price elasticity of energy demand as one influence among competing others and thus prevents possible biases caused by the omission of utility-relevant components. The theoretical HEC model proposed explains interdependencies that result in HEC that are explained based on economic, engineering as well as psychological principles and reasoning. This is necessary because e.g. the physiological influences from comfort taking may overshadow the economic price influence. Based on panel estimation of monitoring data from a field experiment in South-West Germany the price elasticity of demand is shown to have no significant influence on the daily to monthly HEC and thus the habits or routines of the occupants. Yet the estimation shows a significant influence of the price elasticity of demand on a yearly (and thus likely more considered) economic decision-making process concerning HEC. Furthermore, we find that thermal comfort conditions influence HEC up to 500% more than the price elasticity of demand. Through the interdisciplinary integration the results gained are more meaningful and robust than otherwise. A further benefit of the proposed theoretical HEC model is that the field experiment becomes comparable to others. This is because the model provides a full range of possible economic, efficiency as well as psychological responses to the change of one of the variables. Based on the theoretical model as well as empirical evidence, future research can identify similarities as well as differences. In particular, different empirical research can be compared based on the theoretical underpinning of this paper. Thus, the theoretical HEC model proposed enables future meta-analysis on the benchmarking of different empirical HEC studies. This in turn enables a more holistic assessment of future energy saving potentials from HEC reductions in residential buildings.

This paper proceeds as follows. In section 2, a literature review identifies the developments to date of the academic discussion on the economics of HEC. In section 3, the theoretical HEC model incorporating the interdisciplinary rationale is introduced. Section 4 transforms the theoretical HEC model from section 3 to a mathematical derivation of a utility-maximizing household using household-produced commodities. Section 5 describes the field experiment data. The results of an empirical panel regression analysis of the price elasticity of HEC are presented in section 6. Section 7 discusses, compares, and contrasts the results obtained from the theoretical and empirical parts of our study. Section 8 concludes.

2. Literature Review

The study presented in this paper builds on the household production theory (Becker, 1965; Lancaster, 1966; Muth, 1966). The household production model emphasizes that market goods and services are not themselves carrying utility, but are inputs to a process that yields household-produced commodities, which, in turn, yield utility. The household production theory stresses that certain goods do not affect a household's utility directly, but rather through intermediate goods which are produced by the household using market-based goods and services and time as inputs. In his theoretical discourse, Muth (1966) points out that energy is one input for providing different household services, an observation which is reflected in the HEC demand function presented in section 3.

The demand for energy is dependent on the amount of energy services a household wants to consume in the form of heating, hot water, lighting etc. The energy services, resulting from a conversion process of energy to e.g. a comfortable room temperature, yield the corresponding utility. According to Madlener (1996), Archibald and Gillingham (1980) were the first to apply household production theory in energy economics research, investigating household gasoline consumption. Focusing on energy consumption with respect to personal automotive transport, they estimate rather large price elasticities of demand (43 %) for gasoline consumption. Willett and Nagshahpour (1987) (theoretical paper) also refer to the theory of the household production when modelling the optimal time path for energy purchases and investments. They show that the marginal rate of substitution of two utility-yielding goods (one consuming energy and the other one not) serves as an explanation of the level of consumption. The impact of the marginal rate of substitution of energy-consuming and non-energy-consuming goods is further discussed in the theoretical HEC model presented in section 3. Flaig (1990) applies the household production theory in the context of a residential electricity partial least squares path-modeling estimation for Germany. He finds low price elasticities of demand in the short- (-0.15) as well as in the long-run (-0.25). Interestingly, the substitute for electricity considered, fuel oil, is estimated to have a lower impact on the demand for energy (-0.07 to -0.11). In contrast, Filippini (1995) estimates large short-run price elasticities of electricity demand (-0.60 to -0.79) and even larger long-run effects (-0.71 to -1.92) in reaction to time-of-use tariffs in Switzerland also based on household production theory. The study suggests that peak- and off-peak electricity are substitutes, justifying the applicability of time-of-use pricing schemes.

With their application of a dynamic household production function to analyze the flexibility of electricity demand, Halvorsen and Larsen (2001) show that the long-run elasticities do not differ significantly from those for the short run. They credit this observation to energy as a good, which in their case does not show to have high substitutability. Their empirical estimate of the price elasticity is 44 %. Filippini and Pachauri (2004) estimate similar price elasticities of demand for electricity in India. From the literature review it becomes apparent that HEC was not in the direct focus of these earlier studies. Sardianou (2007) is an exemption to this, estimating space-heating determinants in relation to energy conservation patterns of Greek households. Sardianou estimates energy conservation based on building and socio-demographic variables applying household production theory. To our knowledge, the above-mentioned publications are all relevant applying household production theory in an energy economic framework, on which the theoretical model presented in section 3 builds upon. We identified a research gap on utility-driven HEC, as previous authors tend to either rely on simplified proxies (such as e.g. room temperature only, as used by Schwarz & Taylor 1995, amongst others) or perceived and thus subjective data (Galassi & Madlener 2017) to overcome the burden of the cumbersome measurement of indoor comfort influences on utility.

The lack of HEC research in relation to household production theory does not mean that there is little research available on HEC, quite the contrary is true. Summarizing all existing work on residential HEC is beyond the scope of this paper; the short review that follows is restricted to studies with comparable data sources and methodologies only. The closest study to ours is Haas and Biermayer (2000). Their insights on HEC regarding different energy efficiency levels derived from an Austrian panel data set are derived from a comparable research setup. The change in the energy efficiency elasticity, resulting from an energy efficiency upgrade which indirectly leads to a price effect, has been investigated further since. This strand of literature partly substitutes the more common price elasticity of demand discussion in this research field. Noteworthy, Maxwell et al. (2011) give a useful overview of the relevant empirical literature. They report a direct efficiency elasticity for HEC of -0.01 to -0.60, with a direct efficiency elasticity only measuring the effect of a lowered price per unit of one good on the good itself. Our empirical analysis is restricted to direct energy efficiency elasticities, for which Borenstein (2015) and Chan and Gillingham (2015) recently offered theoretical advancements in the context of energy rebound. Parsing the demand

response in the microeconomic framework of income and substitution effects enables us to compare some of the empirical research results obtained in the literature with ours.

Noteworthy, there are several publications on the energy efficiency elasticity in relation to HEC for German private households. Rehdanz (2007), Madlener and Hauertmann (2011) and Schmitz and Madlener (2015, 2017) on determinants of residential space heating expenditures deliver useful starting points, with rebound estimates ranging from -0.12 to -0.49 for Germany. They show significant differences in effects for different owner structures of homes. Schmitz and Madlener (2015) provide a basis for our analysis of HEC in the German private household sector, as their analysis draws on a representative data set for Germany, the Socio-Economic Panel (SOEP) provided by DIW Berlin. Analyzing Germany's heterogeneity in HEC, the authors deliver valuable insights on the cause-effect relationships and determinants underlying the HEC of a representative sample of German households. Especially the building age, and thus individual buildings' energy efficiency levels, seems to be a strong determinant of HEC. This in turn fuels the discussion on whether consumers are effectively demanding the observed utility levels, or whether the buildings provide some sort of technological constraint that a household cannot overcome. Galvin (2015) methodologically takes a glimpse into the future, predicting an energy efficiency elasticity of HEC of 0.28 to 0.39 for the German residential building stock as a whole, in the context of the governmental goal of an 80 % reduction in HEC.

In the field of HEC, research has also been done in the engineering sciences (Calì et al. 2016) as well as in psychology (Abrahamse & Steg 2009). Focusing on research in energy economics, our paper is one of the first applying household production theory to HEC and the underlying behavioral and utility-generating influences. Furthermore, the literature shows that energy services are of special interest in behavioral HEC research. We expand this research in our empirical analysis by not just analyzing proxies for energy services, but estimating jointly their direct effect as well as the price elasticity and the HEC based on monitoring data.

3. Theoretical Rationale

Building on Scott (1980), we develop a new theoretical HEC model that allows to evaluate household energy consumption behavior based on utility maximization. Due to the reduced functional form, comparative statics yields all changes resulting from a change in one parameter.

The model explains consumption behavior as a matter of economic and technical influences and behavioral choice. The focus lies on the separation of the production from the consumption process, which becomes visible in the quasi-Cartesian coordinate system, with different quadrants for the price, production and utility function (Figure 1).

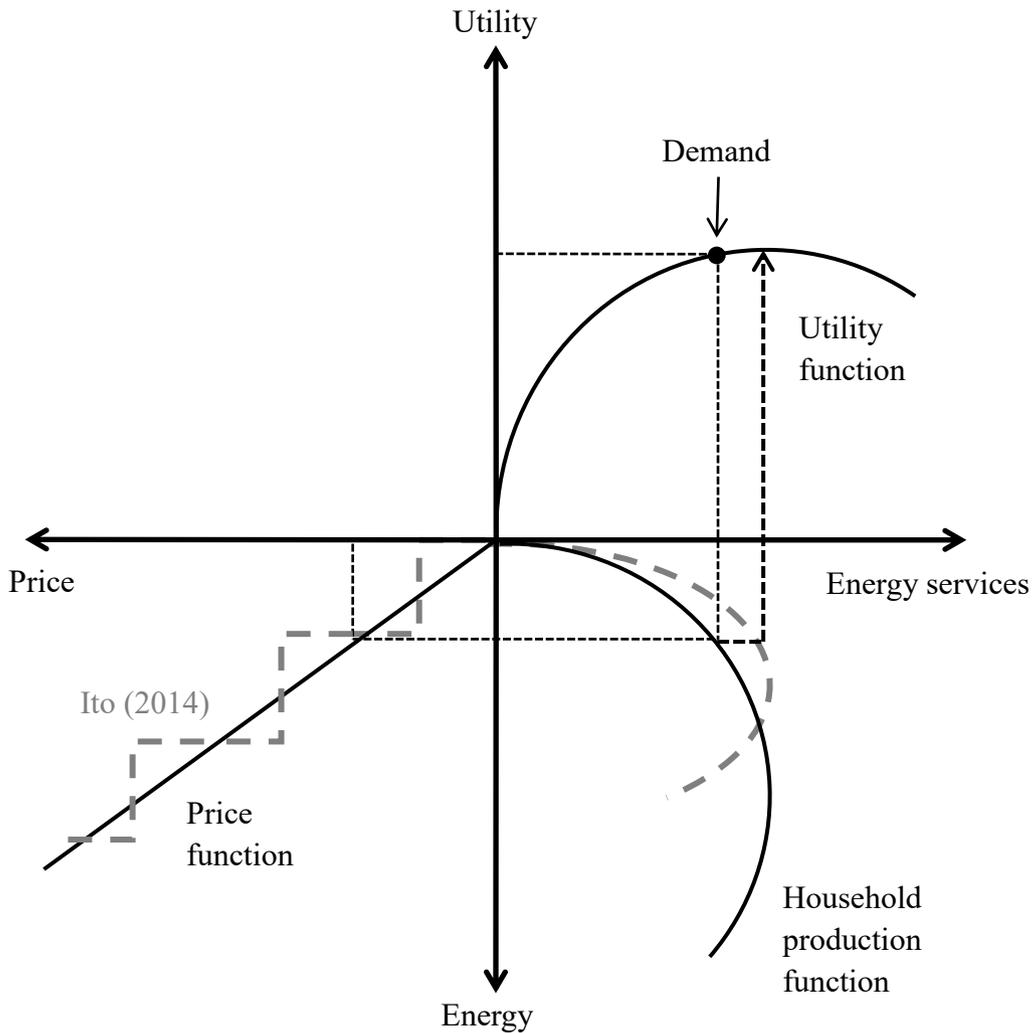


Figure 1: The theoretical HEC model.

More specifically, Figure 1 presents a functional system of the relationships given by the price function of energy (bottom left corner), the production function of energy services (bottom right corner), and the occupant's comfort choices represented through the utility function (top right corner). The novelty of the theoretical HEC model presented is the utility function used and its derivation. Deriving utility from energy services contributing to human wellbeing indoors addresses a critical element of human behavior research. There still exists a research gap as to what

the determinants of utility are in the context of human wellbeing indoors at home. This paper aims at closing part of this research gap, both theoretically and empirically. The theoretical HEC model incorporates the latest findings in microeconomics regarding the perception of energy prices: The stepwise price function, indicated by the suspended grey line, follows Ito (2014) by crediting the observation that consumer demand for energy reacts to average rather than marginal energy prices. This limits marginal price effects' predictive relevance on energy consumption.

The production function describes the energy service level attainable due to energy as an input and the system's (technical) conversion characteristics. The function captures all physical influences on the process of turning energy from a commodity into energy services consumed within a household. Sorrell (2007) provides some valuable further insights on this rather technical process, visualized schematically in Figure 1 of that publication. The production function in the theoretical HEC model enables us to incorporate different restrictions and system configuration details, e.g. the system's efficiency as a result of a retrofit measure. An increase in the system's efficiency, e.g., leads to a shift in the production function, as indicated by the grey dashed line in the lower right quadrant of Figure 1. The new production function will use less energy input to generate the same (or a higher) utility level as the old one.

According to the utility function a theoretical anticipation of potential behavioral reactions becomes possible. Considering an increase in the energy efficiency of the energy conversion stock through any energy efficiency measure, the consumer's adaptation to this change of the indoor living environment mainly depends on the level of utility attained *a priori*. If the choice prior to the increase is way off from the maximum utility attainable, the change will likely be translated into an increase of the utility demanded, because a small change in the amount of energy used results in a proportionally large increase in utility.

On the contrary, when the user is already close to the maximum utility level attainable, an efficiency increase does not necessarily lead to further increases in the utility gained by the same energy services. This is because realized income effects do not only allow to increase the same good's consumption but potentially also the consumption of any other good. The model thus explains which behavioral reactions concerning energy services are to be assumed, following changes in the economic as well as technical circumstances. The model explains cause and effect relationships based on economic and technical influences, as they would be found for economically rational decisions of an idealized household. This implies that the model relies on neoclassical

microeconomics assumptions and thus is bound to the known assumptions as well as shortcomings. Nevertheless, most engineering calculations do not even account for such simplistic behavioral relations.¹

The theoretical HEC model can further be expanded to account for a difference in the household's disposable income. The relevant function relates the total amount of the household's income spent on either energy services or all other goods. For our empirical analysis, the income function is of a lesser interest, as the research population is from the same income class.² Nevertheless, income is an important influence on HEC, cf. Cayla et al. (2011) and Schmitz and Madlener (2017), among others. Hastings and Shapiro (2010) show that the marginal allocation of income is not the best empirical predictor of how households allocate their resources. They show that users tend to bundle expenditures, like e.g. heat energy costs, which are bundled with the

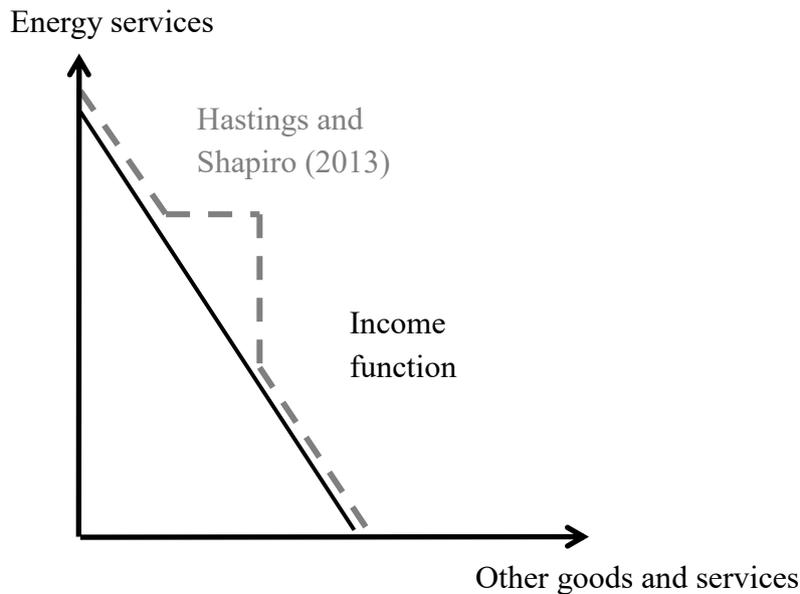


Figure 2: Income function, applicable to the theoretical HEC model.

housing as ancillary costs of housing, as demonstrated by the grey dashed line in Figure 2.

The discrete price and income mechanisms described are valuable to keep in mind when drawing conclusions on the empirical results presented, especially as it is not always possible, or

¹ For example, energy performance calculations of buildings do not incorporate a price reaction (Galvin & Sunnikka Blank 2012).

² The population of the field experiment needs to provide income statements, certifying that they do not exceed a certain income, in order to be eligible to rent one of the apartments.

rational, to build subgroups or income clusters. In the following section, the theoretical rationale developed is applied to the field experiment in order to judge its empirical explanatory power of predicting HEC.

4. Utility from Heating Services

Following Davis (2008), we consider a utility-maximizing household in order to estimate the HEC. Each household maximizes the utility u gained from the consumption of all goods x_j to x_M over all time periods t , i.e.:

$$\max_x \sum_{j=1}^M \sum_{t=1}^T u(x_{j,t}). \quad (4.1)$$

Treating the household rather than the occupant as the consumer is a necessary simplification. This is so because we can observe indoor parameters on a household level only. Disaggregating all x_j and maximizing utility u over the variables influencing indoor thermal comfort (room temperature (RT) and room humidity (RH)) and air quality (volatile organic compounds (VOC) and carbon dioxide (CO_2)), results in eq. (4.2).

$$\max \sum_{t=1}^T (u_{i,t}) = \max(RT_{i,t}, RH_{i,t}, VOC_{i,t}, CO_{2,i,t}) - (P_{e,t} \cdot e_t) \quad (4.2)$$

While focusing on indoor thermal comfort and air quality, those energy services e_t come at a certain price per unit of energy service consumed ($P_{e,t} \cdot e_t$), which must be subtracted from the total utility. The price of the energy service is defined by the relation of the per-unit price of the energy source used as input and the energy-efficiency of the conversion process, turning the energy source into the final product e.g. the energy service. The costs of an energy service decrease the total utility that can be achieved.³ Thus, in order to reach the maximum utility, the costs paid for the energy services are reduced. The reduction of the costs paid for energy services is bound by two factors. First, an investment decision in the energy conversion stock influences the efficiency at which

³ We do not find evidence for any energy services being Giffen goods, i.e. we assume energy services to be normal goods with a standard price mechanism (negatively sloped demand curve).

energy services can be produced. Notice that this aspect is not in the focus of our paper, as in the empirical part we do not evaluate different investment decisions (for a useful paper on that issue see Kumbaroğlu and Madlener, 2012). The reason for this is that the observed households are tenants who are, by assumption, not in a position to take any major investment decision (Davis 2011). Second, once the energy conversion stock and thus the system's efficiency is fixed, the reduction in energy costs is bound to the energy services demanded. Cost minimization is thus a tradeoff between energy services demanded and the price paid for those services. In eq. (4.2), the maximum utility is not measurable directly, because the comfort parameters are not directly comparable to the monetary variable. Therefore, we rearrange eq. (4.2) such that the total cost for energy paid is conditional on the requested maximized thermal comfort and air quality by household i at time t , which yields

$$(P_{e,t} \cdot e_t) = \max(RT_{i,t}, RH_{i,t}, VOC_{i,t}, CO2_{i,t}). \quad (4.3)$$

Higher income households can afford to utilize more energy-intensive goods and thus may incur higher energy costs. It could also be that higher income households incur lower energy costs as they have a more energy-efficient capital stock. As the total income in our field experiment is homogenous, and since we can empirically assume that the share of income devoted to the purchase of energy is consistent over the sample population investigated, we can neglect this constraint. Depending on the population and research question, this constraint may or may not have to be included.

The next step provides insights on the maximized parameters according to their specific energy expenditures. There are multiple optima for thermal comfort and air quality parameter combinations, yet the energy consumed delivers a distinct optimum against which these two parameters can be measured. Furthermore, this rearrangement assures the possibility of estimating the impact of the maximized parameters on energy consumption. A further simplification in terms of the empirical estimation is possible, since by assumption all households pay the same price per unit of energy at time t , which is why $P_{e,t}$ can be eliminated. The final problem for energy service i in time t is expressed as follows:

$$e_{it} = \max(RT_{i,t}, RH_{i,t}, VOC_{i,t}, CO2_{i,t}). \quad (4.4)$$

$$\text{s.t. } RT_{i,t} = (RT_{i,t} - OT_t) + e \cdot \varepsilon_{RT} \text{ and}$$

$$VOC_{i,t}, CO2_{i,t} = \varepsilon_{Build} + WO.$$

Outdoor conditions are supposed to influence energy consumption, mediated by the efficiency of the building's insulation that is displayed in the first constraint, with OT being the outside temperature. Air quality conditions are mediated through outside conditions with respect to the building's efficiency as well as the ventilation/window opening behavior (WO) of the occupant/s, as stated in the second constraint. Equation (4.4) presents the production function referring to the theoretical HEC model. Before transferring the rationale behind eq. (4.4) to an empirical estimation, the data handling and the descriptive statistics deliver first insights into the influences of the mentioned variables on the HEC.

5. The Field Experiment Data

The monitoring data used to assess the price elasticity of HEC stems from a monitoring campaign as part of a field experiment conducted in South-West Germany. In total, all rooms of 60 apartments in two adjacent multi-family homes were monitored individually, collecting information on *inter alia* energy flows, air quality, and thermal comfort conditions. The apartments all share the same floor plan and thus the same size. Individual energy performance ratings are calculated for every apartment.⁴ The data was gathered at fifteen-second to one-minute intervals, thus offering a high time resolution. Additionally, a weather station collected outside conditions at the same resolution.⁵ All data was recorded from September 1, 2010 to December 31, 2014. The monitored parameters of interest for our analysis are room temperature, room humidity, carbon dioxide, volatile organic compounds, HEC, window opening, and outside air temperature. Due to the structure of the data, statistical analysis of panel data is preferable to standard least squares regression, because panel

⁴ Our partner Institute for Energy Efficient Buildings and Indoor Climate (EBC) at the E.ON Energy Research Center, RWTH Aachen University, generously provided the individual ratings. Although every apartment has the same size, different floors in the building and different heating systems have considerable impacts on the energy performance rating (see also Heesen and Madlener, 2018).

⁵ The monitoring concept and execution was handled by Prof. Wolfrum, University of Applied Sciences Karlsruhe, Germany; further data processing and maintenance was arranged by EBC.

data usually contain more degrees of freedom and more sample variability than cross-sectional data (Hsiao 2007).

The first step in generating a balanced, ready-to-estimate data set is to identify missing or invalid data points and interpolate or exclude them. As the research focuses on HEC the months October to March are selected. This is because the heating system is supposed to be off during summer and thus the monitoring data would only create further noise in an HEC estimation. In a first step, the remaining data is aggregated to hourly means. This serves two purposes; first, the minute resolution matrix exceeds computational limitations; second, hourly means can be interpreted more easily, while still offering a high resolution to observe individual (behavioral as well as technical) influences.

HEC and window opening as explanatory variables need further explanation. Whereas all other variables are measured by sensors and presented as reported, HEC is monitored in adding up all kilowatt-hours (kWh) consumed continuously, only when there is an actual energy flow. The energy flow in kWh is calculated using hot water in the heating system, as the relation of two parameters – volume flow and temperature difference entering and exiting the apartment. In order to calculate the hourly HEC, the differences in kWh from $t + 1$ minus t represent the hourly HEC of each household. In contrast, window opening is a binary measure (closed, open) of the state of the window. Each apartment is fitted with two sensors, enabling a possible maximum of 200 % as for when all windows are opened during the time under observation.

Table 1: Descriptive statistics of the monitored variables in the field experiment. All variables are hourly averages and run from October to March in the years 2011-2014.

	Outside air temp. [in °C]	Global irradiation [in W/m²]	Window opening [in %]	Room temp. [in °C]	Carbon dioxide [in ppm]	Room humidity [in %]	Volatile organic compounds [in ppb]	Heat energy consumption [in kWh]
Mean	5.81	57.79	46	24.45	906.52	38.91	1164.42	0.28
Median	5.40	3.61	40	24.52	779.03	38.84	977.79	0
Standard deviation	5.68	115.29	41	1.72	467.70	8.78	674.78	0.46
Maximum	25.72	725.95	200	31.40	6288.74	68.48	14512.55	7.30

Minimum	-15.05	0.00	0.00	14.42	207.68	9.92	341.62	0
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Notes: ppm = parts per million, ppb = parts per billion

Table 1 reports the descriptive statistics of the time-varying variables influencing the HEC. The mean outside air temperature and global solar irradiation are slightly above the German average as given by the reference climate.⁶ Mean window opening reports that 46 % of the time the windows were open. At an assumed airflow of 100 m³ per hour the 46 % opening of an hour result in a 30 % deviation of the anticipated ventilation rate from the norm.⁷ The German norm DIN V 4108-6 is the basis for the annual HEC and thus energy performance rating calculation. In the norm, certain energy service demands are anticipated, like e.g. the room temperature of 19 °C. The mean indoor room temperature in our dataset deviates clearly from the 19 °C anticipated in DIN V 4108-6. Due to non-ideal placing of temperature sensors, the reported mean of 24.45 °C needs to be corrected downwards by about 2.5 K, but this would still be 15 % above the energy service level defined in the norm.⁸ On the contrary, carbon dioxide, room humidity and volatile organic compounds do not show any major abnormalities. The HEC, as reported, is somewhat cryptic and hard to grasp. This is because the reported values are hourly mean HEC in the apartments. The mean of 0.28 kWh/h translates to ~ 16 kWh/m²a, which is a more common unit used to describe HEC. A value of 16 kWh/m²a is quite low, compared to the apartments' theoretical mean rating of 18.8 kWh/m²a, but this is partly due to the data cleanup. Furthermore, the HEC declined steadily over the investigated period. Further evaluations on this aspect can be found in Heesen & Madlener (2018).

⁶ The reference climate is defined in DIN V 18599-10.

⁷ The 30 % deviation is a rather unsophisticated calculation, based on the norm DIN V 4108-6 and a 20 m² room. It is meant for illustration purposes only. Furthermore, the deviations in the field experiment are somewhat biased towards higher relative ventilation rates and thus a higher deviation from the norm, as the rooms tend to be smaller than the anticipated 20 m² and the 100 m³ are approximated for a tilted window.

⁸ The correction of about 2.5 K is necessary because the sensors are placed on the top of the wall (the temperature the occupant senses thus is about 2.5 K lower on average).

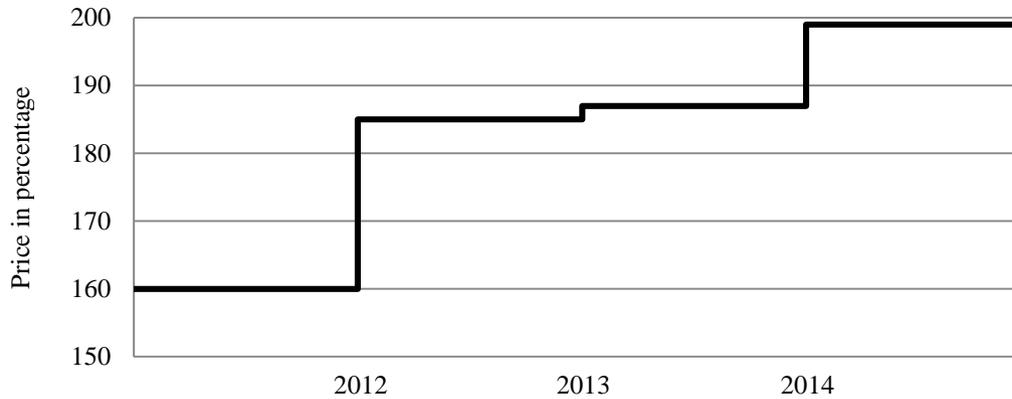


Figure 3: Development of the price for district heating, January 2011 – January 2015.

To identify the price elasticity of the households’ energy demand we use the real price development for district heating during the years 2011 to 2015. The price time series is based on information from the municipal utility, handling the heat energy delivery and billing of the apartments of the field experiment. The district heating price deviates from the fuel price as it subsumes three different price components.⁹ The reference year (with a 100 % price) for the price time series investigated is the year 1996. As indicated in section 3, households might already perceive the price of energy in combination with other costs for housing, which is why this bundled price movement can be justified. Figure 3 depicts the district heating price development during the investigation period. It becomes obvious that the price increased during the whole period, especially from 2011 to 2012, and from 2013 to 2014 increases were particularly significant. As the price time series does not vary for different households, we weigh the price by the individual households’ energy performance rating. Through this, we ensure that the effective price elasticity estimated is related to the technological need for heat energy. Furthermore, this enables us to identify a time- and household-/panel-specific estimate of the price elasticity of demand.

As Brounen et al. (2012) show, socio-demographic variables can have significant impacts on the HEC. In our analysis, these parameters are derived from a questionnaire survey conducted in 2013.¹⁰ As not all households of the field experiment participated in the questionnaire the number of panels shrinks to $N = 30$. The socio-demographic variables do not vary over time. In the

⁹ District heating prices are made of a yearly fixture, a maximum load-dependent charge and the price per consumed kWh stipulated in the respective contract type.

¹⁰ From the questionnaire, we know that the occupants moved in prior to the investigation period, and due to the lack of information we must assume that they did inhabit the same apartment until the end of our investigation period.

estimation, we include the household size and the age and gender of the head of the household. Due to the statistical properties of a panel estimation, time-invariant variables are grouped as fixed effects for each panel. The final data set enables an analysis of latent behaviors in contrast to technically resulting HEC.

6. The HEC Panel Data Estimation

Equation (5.1) presents the HEC panel data model to be estimated, with the log naturalis of q_{it} as the dependent variable.

$$\ln(q_{it}) = \alpha_i + \beta_{p_e} \ln(p_{e,t} \cdot \varepsilon_i) + \beta_x \ln(X_{it}) + e_{it} \quad i = 1, \dots, n, t = 1, \dots, T \quad (5.1)$$

The explanatory variables are the price p_{it} plus all dynamic (i.e. time-dependent) variables X_{it} , as introduced in Table 1. We choose a log-log configuration of the HEC, the energy price*efficiency rating, and the dynamic energy services variables in order to straightforwardly be able to investigate the pairwise elasticities. The constant term α_i incorporates all time-constant effects of each household, thus incorporating the time-constant socio-demographics. The error term e_{it} models the remaining variance in the data set.

Note that we do not just estimate one model specification, but in total five of them. The models vary neither in the estimates nor in the method. The only difference between them is the time aggregation of the data. This not only addresses time fixed effects in the time-varying data, but is conducive for the interpretation of the price elasticity of demand. We formulate the hypothesis that people do not perceive the price elasticity of demand as constant over the different time aggregation levels. Intuitively, this is because of the annual billing of the energy consumption. This leads to the conclusion that the yearly price elasticity of demand should show a statistically significant effect on the HEC in contrast to, for example, the daily one.

The HEC panel data model is estimated using R, an open-source programming environment. R offers the plm-package devoted to panel data manipulation and estimation.¹¹ Prior to a final estimation, the data needs to be specified in order to select the right model type and check for possible barriers and inadequacies. At first, we specify the models to be estimated, therefore an F-

¹¹ <http://www.r-project.org/>, plm package (Croissant & Milo 2008).

test proves whether an ordinary least squares (OLS) regression is more efficient for estimating the models than panel estimation. Table 2 shows that the F-test rejects all null hypotheses, providing evidence for individual effects; hence panel estimations are indeed more efficient. A Hausman test specifies whether the data incorporates significant fixed effects. In general, the random effects panel model is more efficient. If the Hausman test rejects the null hypothesis, the random effects model is biased and a fixed effects model should be chosen. Table 2 summarizes all Hausman tests and reports that the χ^2 tests reject all null hypotheses that the preferred model is random effects; hence, fixed effects models will be estimated.

Table 2: F-test for individual effects and Hausman test on random effects panel model.

F-test for individual effects					
Model	Yearly	Monthly	Weekly	Daily	Hourly
<i>F</i>	7.3325	20.221	64.488	300.34	3473.4
p-value	1.021e-12	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16
Hausman test					
χ^2	21.5	40.716	13.971	15.5	52.18
p-value	0.0006516	1.071e-07	0.0158	0.008428	4.955e-10

After clarifying the estimation model, the data to be estimated needs to be checked for further inadequacies that might bias the estimation results. In order to deduce properties of an underlying distribution by analysis of data, the data should be stationary. If unit roots are present, the estimation will need to be differenced once or multiple times (depending on the degree of integratedness) to become stationary. Table 3 reports the results of the Dickey-Fuller test used to check for stochastic trends. The null hypotheses are that the series have unit roots (i. e. are non-stationary), which can be rejected based on the p-values.

Table 3: Augmented Dickey-Fuller test for stationarity (Lag order = 2).

Model	Yearly	Monthly	Weekly	Daily	Hourly
Augmented					
Dickey-Fuller	-6.035	-7.933	-12.196	-28.779	-147.01

p-value < 0.01 < 0.01 < 0.01 < 0.01 < 0.01

Cross-section dependency, as the correlation between panels (in our case households), is tested via the Breusch-Pagan LM test. The null hypothesis tests whether the residuals between the panels are correlated. In our data, cross-section dependency can be anticipated. This is because the households are all in close proximity to each other, having the same outdoor condition, floor plans etc. Additionally, some of the apartments share internal walls and thus e.g. enable heat transmission from one apartment to the other. Engineering evidence for that argument is offered by Osterhage et al. (2016) based on the same field experiment. Furthermore, households' daily life schedules might be similar, which may be a reason for similar data patterns. In the end, it does not come as a surprise that contemporaneous correlation is found in the data, based on the rejection of the null hypothesis of the χ^2 test. Serial correlation is checked via a Breusch-Godfrey/Wooldridge test for serial correlation in panel models. If present, serial correlation can cause the standard errors of the estimation, and the results, to be less significant due to the serial correlation in the idiosyncratic errors (Drukker 2003). The estimated standard errors are smaller than the true standard errors, thus the estimates seem to be more precise than they actually are. The null hypotheses of the χ^2 tests are rejected, indicating positive serial correlation in the panel. Again, this result does not come as a surprise since the time series of the monitored variables are correlated in the short run. For instance, the room temperature from the last hour is a very good predictor of the current room temperature. The existence of heteroscedasticity is a concern, as it can invalidate statistical tests of significance that assume that the modeling errors are uncorrelated and uniform. In Table 4 it becomes apparent that all five models estimated do feature some problems of heteroscedasticity (the Breusch-Pagan tests rejects the null hypotheses of homoscedasticity).

Table 4: Tests for cross-sectional dependence, serial correlation and heteroscedasticity.

Breusch-Pagan LM test for cross-sectional dependence in panels					
Model	Yearly	Monthly	Weekly	Daily	Hourly
χ^2	758	1092.1	3312.9	10031	97659
p-value	< 2.2e-16				
Breusch-Godfrey/Wooldridge test for serial correlation in panel models					

χ^2	36.151	233.53	1497.3	10048	97552
p-value	2.694e-07	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16
Breusch-Pagan test on heteroscedasticity					
BP	29.37	211.55	916.22	5788.5	89433
p-value	0.000273	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

Cross-sectional dependence, serial correlation, and heteroscedasticity are of concern for our estimation. Therefore, we use a consistent covariance matrix estimator following Driscoll and Kraay in order to obtain robust standard errors (Hoechle 2007). This extension of common nonparametric covariance matrix estimation techniques yields standard error estimates that are robust to very general forms of cross-sectional and temporal dependence and heteroscedasticity. The use of this robust estimator becomes necessary, as our time dimension in the data is quite large, except for the yearly model. The estimation results presented in Table 6 are estimated based on the prior described method. Furthermore, the distributions of the residuals deliver a good evidence for univariate outliers. In Table 5, it becomes obvious that the chosen model specification describes a good part of the dependent variable, HEC. Furthermore, one can observe that the distribution of the residuals is homogenous around the mean value of zero, indicating a normal distribution.

Table 5: Distributions of the residuals of the five models estimated.

Model	Min.	1st Quantile	Median	3rd Quantile	Max.
Yearly	-0.229	-0.0403	0.0109	0.0361	0.309
Monthly	-0.42	-0.0617	0.000994	0.0651	0.478
Weekly	-0.536	-0.0758	0.00131	0.076	0.641
Daily	-0.858	-0.0999	-0.0999	0.0875	1.12
Hourly	-1.240	-0.145	-0.043	0.096	2.080

Table 6 summarizes the estimation results. Except for the price elasticity of demand, all variables are significant at least at the 1 % level (except $\log(\text{WO} + 1)$). Moreover, the variables

room temperature, window opening, and outside temperature are all significant at the 1 % level. The efficiency-weighted price elasticity of demand is significant at the 1 % level in the yearly estimation only. The F-statistics show that the estimations deliver valid descriptions of the models. The Adjusted R² shows that the hourly estimation model captures a minimum of 17 % of the variance of the HEC, reaching a maximum of 43 % for the Adjusted R² of the monthly estimation model.

Table 6: Panel regression estimation results (dependent variable: $\log(\text{HEC})$).

Model	Yearly	Monthly	Weekly	Daily	Hourly
$\log(\text{AT} + 16)$	-0.5953*** (0.0447)	-0.5643*** (0.0816)	-0.3921*** (0.0848)	-0.3304*** (0.0441)	-0.2291*** (0.0140)
$\log(\text{WO} + 1)$	0.4284*** (0.0734)	0.2528*** (0.0658)	0.0903* (0.0484)	0.0687*** (0.0255)	0.0434*** (0.0067)
$\log(\text{RH} + 1)$	-0.2401*** (0.0132)	-0.1546*** (0.0426)	-0.2183*** (0.0547)	-0.2383*** (0.0314)	-0.2918*** (0.0110)
$\log(\text{RT})$	0.9502*** (0.1710)	1.0929*** (0.1233)	0.9487*** (0.1276)	0.9749*** (0.0822)	1.0522*** (0.0329)
$\log(\text{R.P})$	-0.2287*** (0.0134)	-0.0819 (0.1077)	-0.0614 (0.0946)	-0.0481 (0.0593)	-0.0318 (0.0237)
No. of obs.	120	609	2.726	18.531	444.744
R ²	0.3424	0.4639	0.4305	0.3280	0.1749
Adjusted R ²	0.2397	0.4372	0.4250	0.3273	0.1749
F-Statistic	7.2883*** (df = 6; 84)	82.7806*** (df = 6; 574)	339.0506*** (df = 6; 2691)	1.504.2940*** (df = 6; 18496)	15.708.6300*** (df = 6; 444709)

Note: * p<0.1; ** p<0.05; *** p<0.01; standard errors in brackets

7. Discussion of Results

Before interpreting the estimation results and, in addition to the statistical specification tests, it is recommendable to check the estimation results logically. Since the logic of the results between the models does not change, there is no need to go into the details of every model though. The most influential variables are room temperature and window opening or, depending on the estimation model, outside temperature. This does make sense, as the indoor temperature and air quality, according to the norms (DIN V 18599-10; DIN V 4108-6) as well as scientific literature (Heesen and Madlener 2018; Cali et al. 2016; Yu et al. 2011), are supposed to have great impact on the HEC. Additionally, the sign of the mentioned variables make sense. One can assume that an increase in the room temperature increases the HEC as well. The same holds true for window opening, i.e. an increase in the window opening is likely to raise the HEC. In contrast, the outside air temperature has a negative effect on the HEC since the only observed time of the year is winter. Usually, during winter time, outside conditions are typically colder than indoor temperatures. Hence an increase in the outside temperature reduces the heat load and thus the HEC. The influence of irradiation is almost negligible and that of room humidity is not as intuitively interpretable as the above-mentioned variables. Still, nothing abnormal can be detected from a plausibility check of these two variables. The price elasticity of demand, which is in the focus of this paper, does show a reasonable relation, in that a one percent price increase leads to a 0.22 percent HEC decrease in the yearly model.

According to the research question, we investigate whether there is any difference in the price elasticity of demand depending on the investigated time aggregation level. In the literature, price elasticities of demand are analyzed according to the time resolution (usually, short- and long-term is differentiated) though normally not for heat energy but rather for electricity (Halvorsen & Larsen 2001; Filippini 1995) and gasoline (Brons et al. 2008; Dalhuisen et al. 2003). The results show that time resolution also has an influence on the level of the price elasticity with regard to HEC. The estimates based on the yearly aggregated data in our panel estimation are significant at the 1 % level. All other variables are not significant. Furthermore, the yearly model yields the largest price elasticity, with a 23 % influence of the weighted price elasticity of demand on the HEC. Based on these insights we conclude that habits, regarding the daily operation of the heating system, do not

seem to be based on economic decisions. In a more conscious (but less frequent) consideration of the HEC status (e.g. reflecting on the energy efficiency of the heating system), economic influences affect HEC in the magnitude identified by the estimation results. Yearly billing cycles logically enhance this argument. Households are typically made aware of their heating costs only once a year through the annual billing. As the estimation results mimic billing cycles, the observation can be compared to the results from Allcott and Rogers (2014), where significant effects based on behavioral interventions are found. In the end, our results indicate that during the daily operation, price signals do not influence HEC behavior.

This last finding is corroborated when putting the weighted price elasticity of demand in perspective with the influences of the other variables. Room temperature has the largest influence on HEC. Unsurprisingly, an elasticity of around 100 % is found between these two variables. This means that each extra degree Celsius of indoor room temperature demanded will translate into a corresponding increase in HEC. The second-most influential variable is outside temperature, the elasticity ranging between a -0.60 and -0.22, depending on the aggregation level. Since all estimated models cover winter month data in the northern hemisphere only, a negative relation between outside temperature and HEC can be anticipated. Noteworthy, the window opening influences HEC with an elasticity in the range of a 0.42 to 0.04, depending on the model specification. Room humidity is as influential on the HEC as the yearly price elasticity of demand. These four variables are significant and considerably more influential to HEC than the price elasticity of demand. This shows that comfort considerations have a much greater impact than price signals in general. Especially in the short term, habitually driven behavior is not influenced by economic signals.

8. Conclusion

This paper investigates the influences of technical, psychological and economic aspects on heat energy consumption (HEC) in a set of 60 German tenant households. The empirical results support the hypothesis of a time-resolution-dependent price elasticity of demand. A separation between habitual everyday heating behaviors versus a yearly, most likely conscious decision regarding HEC costs becomes evident. This observation is an important contribution to the understanding of the economic HEC decision-making mechanisms. It suggests that the occupants

only seldomly consider economic factors when engaging with the heating system on a daily basis. This in turn reduces the effectiveness of economic incentives aimed at decreasing HEC. Our results find scope for measures based on economic incentives, but only within the limits of its effectiveness over time. For example, incentives based on price signals might only be effective during the yearly billing of the ancillary costs. The price elasticity of demand estimates are within a comparable range to the literature reviewed. However, the 23 % influence of the efficiency-weighted price elasticity of demand most likely is neither constant nor representative for the whole population of Germany, referring to the theoretical HEC model.

Considering the theoretical model developed in section 3, the research population empirically investigated in this paper needs to be classified, and only thereafter the magnitude of the weighted price elasticity of demand (-0.23) becomes comparable. The reason is that, due to deviations in the respective starting points on each function, differences in the magnitude of the price elasticity within different populations need to be anticipated. For example, wealthier households with the same technological conditions as the ones portrayed in this paper should reveal a lower price elasticity of demand. A better understanding of the theoretical rationale enables decision-makers to enhance their judgement the real options and potentials of their actions and measures. Furthermore, the underlying economic framework of household production suits the presented HEC research, as it adapts to the interdisciplinary research focus. Based on this theory, a separation between the consumption and the production process enables us to differentiate between technical and behavioral influences on the HEC. This paper shows that an integration of economic influences with engineering predictions enhances our understanding of how HEC is determined. Within the limitations of objective wellbeing, psychological cause-effect relationships further enhance the presented model. Future HEC predictions, based on the interdisciplinary rationale derived, help to yield more realistic scenario outcomes and thus provide a better guidance for decision-makers.

Especially because of the interdisciplinary approach adopted, we think that this paper delivers new and more encompassing insights to better understand HEC. The theoretical HEC model and the underlying household production theory are shown to be a versatile platform to develop and test further theoretical as well as empirical advancements. The data available enables us to demonstrate the usefulness of an econometric panel estimation not just for economic modeling, but also for engineering predictions. Our estimation delivers a broad overview on a detailed separation of influences constituting HEC. Further, we show that the household production theory does not

just integrate interdisciplinary research, but also combines different conceptual approaches. This is because HEC research also divides between habitual and rational decision-making. Although the theoretical background chosen in this paper resides on a rational actor, the estimation shows a potential link with approaches that are based on habits or practices, as they are reportedly influential to the HEC (Maréchal 2010; Gram-Hanssen 2011). Finally, yet importantly, we show that the price elasticity of demand of occupants' HEC behavior is time-sensitive with regard to the time resolution of the data. This aspect contributes to the general understanding of associated economic decision-making.

Some caveats and further research ought to be addressed as well. First, we report on influences on the data that could not be visualized. In the beginning, we did not estimate any influence of income, as our sample population is homogenous in that respect. Nevertheless, low-income households might *per se* have higher price elasticities of demand, as any consumption decision affects their total budget more strongly than those of wealthier households (Madlener & Hauertmann 2011). On the contrary, the households in the field experiment live in highly energy-efficient homes; thus, they are not as dependent on energy as an input in order to reach their desired energy service level in comparison to households living in low energy efficiency homes.

Apart from this, the small sample size of the field experiment might affect representativeness. Monitoring data of the quality investigated is hard to get, yet according to the research question asked a sufficient resolution of the data needs to be available. A tradeoff between sample size and resolution was often a matter of discussion during the design phase of the field experiment. The presented analysis benefitted from the data resolution available, not just in terms of the analysis done in this paper. The high-resolution monitoring data in connection with the occupants' insights enable a comparison of revealed behaviors versus perceptions. In the end, such a comparison enhances the robustness of the presented results, which, due to its focus, is not demonstrated in this paper.

Future research needs to investigate whether the time sensitivity of the price elasticity of demand is a general, commodity-independent trend, and whether this observation has further implications on the microeconomic theory used. Further research in this field might expand on the income dependency of the price elasticity of demand. Identifying income elasticity thresholds for energy services and their influence on HEC behavior could offer promising insights. Accordingly, price elasticities of demand thresholds can be analyzed with appropriate data. This would enable

insights with regard to the magnitude of the discrete price influence steps. Furthermore, the theoretical rationale could be used to integrate different results from the literature to harmonize and/or weigh them in a meta study. In general, the heterogeneity in HEC within one efficiency group has been analyzed rigorously in this article. However, there are still e.g. psychological factors affecting the utility function of households that need to be incorporated in the model, in order to ultimately gain a holistic view on HEC. A disaggregation of the household as an aggregate research unit into the individual occupants and their interconnections would also be promising in this respect.

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