Incorporating consumer choice into an optimization model for the German heat sector: Effects on projected bioenergy use

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Abstract

The energy transition requires policy makers to adopt a holistic view that also considers non-economic factors when developing cleaner technology deployment schemes. In particular, a broad knowledge base is required to ensure an efficient energetic use of the limited biomass potential. Energy system optimization models are widely used to inform decision makers about energy transition strategies. The heterogeneity of consumers, especially in the heat sector, is rarely considered in these models and therefore these models lack of completion to contribute to this holistic approach. In this study, a literature review was conducted to find empirical data on consumer behavior regarding the adoption of residential heating systems. This data was integrated into an optimization model for the German heat sector, combining established methods for integrating consumer heterogeneity with a novel approach for calculating indirect costs representing behavioral factors. The incorporation of consumer choice leads to a broader distribution of market shares of different technologies in both a "business-as-usual" scenario and an "ambitious measures" scenario. In particular, the future role of log wood technologies in the private household sector may have been underestimated in previous studies and should be discussed, when designing policies. With this study, the knowledge base for decision makers was extended to discuss the future efficient use of biomass within the German heat sector.

Keywords: heat sector, bioenergy, optimization, consumer choice, investment behavior

1. Introduction

Germany has set itself the target of reducing GHG emissions by 80–95% by 2050 compared to 1990, including emissions from the heat sector, which are responsible for 53.5% of German energy demand [10]. The heat sector is characterized by its heterogeneity – not only from a technical point of view. In addition to varying heat demand profiles, applications and infrastructures, the sector has a wide variety of stakeholders with different interests and consumer behaviors. For instance, millions of homeowners in the private household sector, which account for 43% of German heat demand [10], choose a heating system based on their own investment decisions. Thus, future market development is not influenced by economically rational behavior alone: as is well known, private investment and consumption decisions can be influenced by many factors that deviate from the assumption of economic rationality [19, 28]. Energy system optimization models (ESOMs) are widely used to inform about energy transition strategies. Investment behavior that does not conform to standard economic rationality may influence projected market developments in the future and poses a methodological challenge to ESOMs, which rely on the assumption of cost minimization.

In the German heat sector in 2019, 14.5% of heat demand was supplied by renewable energy sources [58]. Of more than 32 million heating systems installed [1], $\sim$ 12 million are bioenergy heating systems

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[1, 51], constituting the major share of renewable heat. Today as well as in the future a variety of bioenergy strategies are expected to provide renewable heat [26] also in a flexible way [36]. Bioenergy users are influenced, among other things, by the local availability of log wood, for instance through forest ownership. Consequently, projections produced by ESOMs are limited and might be too optimistic or misleading when relying on cost minimization alone. In order to inform policy in a more robust way, purely cost-based analyses need to be complemented by methods that include consumer heterogeneity and the behavioral factors other than cost minimization that influence investment decisions.

There is a need to combine insights from different energy transition disciplines, such as those concerned with economic development, policy change and consumer behavior [13]. However, consumer choice is often poorly represented in such models, with hurdle rates, market share constraints or technology growth rates, among other factors, being used to smooth out projections [15]. Instead, modeling methods are required that are based on robust theoretical underpinnings and conclusive empirical observations.

Methodological progress has been made in recent years, especially for ESOM projections in the transport sector. The most common approach, identified in reviews by DeCarolis et al. [15] and Venturini et al. [60], is to create different consumer segments to represent the heterogeneity in consumer choice [9, 11, 14, 37, 38, 40, 49, 57]. A bottom-up model structure with a high level of detail has been found to be most promising for this purpose [60]. Different approaches exist to incorporate more realistic consumer choice within the consumer segments. Some optimization models are linked with a nested nomial logit model (MNL) [25]. The basic aim of multinomial logistic regression is to calculate the probability of a certain event occurring by matching data to a logistic curve [4]. Another approach is to introduce indirect costs such as disutility costs, willingness to pay, or the quantification of modal preferences via the monetization of intangible costs [57] for the different technology concepts. McCollum et al. [39] first introduced disutility costs, which make it possible to consider (non-monetary) discomfort costs. This approach has been applied fairly extensively in different model frameworks [9, 40, 49].

For the heat sector, little progress has been made so far in incorporating consumer choice into ESOMs, despite the heterogeneity of consumers. Cayla and Maïzi [11], Cayla and Osso [12] conducted a survey and identified three key parameters influencing consumer choice in the French heat sector. Based on these parameters, a segmentation in the TIMES model was conducted. Li et al. [38] also applies consumer segmentation for the heat sector in the UK TIMES model to represent technology investment behavior. Actual technology adoption behavior is then based purely on survey results, excluding economic factors. In literature, the relevance of behavioral factors that influence investment decisions is found to vary considerably between countries [38]. Depending on the country on which the study is performed, the methodological approaches for calculating indirect costs vary depending on the country specific influencing factors. A simple transfer of the methods from e.g. the French region to the German case is therefore not applicable.

In the literature, an understanding exists that economic and non-economic determinants need to be considered whenever technology deployment schemes are developed [13, 29, 30]. Policy makers need to adopt a holistic view in order to understand how to encourage heat consumers to adopt cleaner heating systems [56, 59]. In the case of Germany, there is a lack of research addressing this issue. Empirical data on consumer behavior related to heating systems is available [42], but its influence on heat transition scenarios has not yet been assessed in ESOMs. The goal of the present study is to provide a broader basis for designing a cleaner system of heat production in housing and industry applications.

For this purpose, a literature review was conducted to identify the behavioral factors, other than cost minimization, that influence investment decisions in relation to consumer heating systems. The empirical data gathered from this review was integrated into an optimization model for the German heat sector using methods derived from recent studies. The concept of consumer segmentation, in which different indirect costs are introduced, is applied. Factors influencing actual heating behavior after the installation of the system are not considered in this study.

The optimization model used in this study was developed to determine the optimal use of bioenergy in the German heat sector in different scenarios and given future uncertainties [20, 26, 27]. In this study, the model is extended to include consideration of households' investment behavior in relation to different heating technologies, the aim being to produce more credible projections or policy insights and to address the following research question: Which model projections arise in the German heat sector under consideration of consumer choice in different scenarios?

2. Materials and methods

2.1. Behavioral factors influencing the adoption of residential heating systems: A literature review

In order to find empirical data on consumer behavior that can be incorporated into an ESOM, we proceeded in three steps: first, we conducted a literature review to identify behavioral factors that influence consumer investment decisions around heating systems in Germany. Second, we searched the literature for empirical data to understand the relevance and strength of influence of the different factors. Third, we selected data and a typology of consumer segments that was compatible with the requirements of the model.

The literature review was conducted in two phases. First, two publications that were randomly selected from the relevant literature [41, 52] and the literature cited within them (n=75) were analyzed to extract relevant keywords. Second, following the recommendations for literature reviews by Khan et al. [31], a search strategy was specified that contained inclusion and exclusion criteria. The Google Scholar and Web of Science databases were searched using a combination of the keywords thus identified, as shown in Fig. 1. All the terms under A) were combined with B) and all terms of C); similarly, all keywords in boxes D) and E) were combined with one another. The search was conducted in both English and German. Relevant literature was identified by title and abstract, resulting in 135 publications of interest. Articles were included in the review and analyzed in more detail if they contained surveys (both quantitative and qualitative), causal analysis, discrete choice models, cluster analysis or literature reviews based on data collected in Germany. Studies based on social demography, surveys related exclusively to system refurbishment, with hypothetical selection options, or a sole focus on heating behavior were excluded. This resulted in 16 publications that were relevant for assessing influences on consumers' heating system choices in Germany.

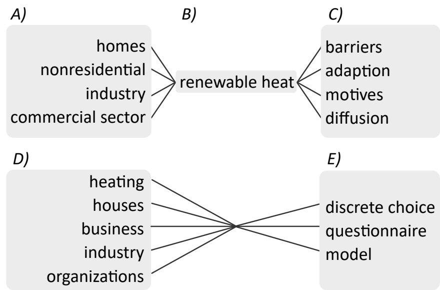

Figure 1: Keywords used in literature search. Keywords under A) were combined with B) and C); all keywords of D) and E) were combined with each other.

One finding of this literature review is that empirical data on consumer choice regarding heating systems is available only for single- and two-family houses. No empirical data on consumer heating system choice could be found for multi-family houses, the trade and commerce sector or industrial facilities.

The 16 studies thus identified were reviewed in more detail and the factors influencing consumer choice in relation to heating systems were analyzed qualitatively and grouped into three categories, see Tab. 1. Alongside financial motives, which all the studies found to be influential, non-financial motives such as the comfort in operating and preferences on eco-friendliness of the heating system were most often found to influence consumer choice. Factors related to heuristic/imperfect information processing, were also found in various studies.

The principal goal of this literature review was to find empirical data on consumer choice capable of being incorporated into an optimization model for the German heat sector and simultaneously reflecting the picture found in the literature review. As the refurbishment of building stock is an external input and not determined within the model, only data on the choice of heating system is relevant for the optimization model. Additionally, the model deals solely with data on fossil fuel, bioenergy and alternative renewable technologies so that studies related exclusively to solar photovoltaics [32, 34], studies focusing on only one

Table 1: Influential factors on the heating technology consumer choice identified in literature. The number of studies indicates in how many studies a statistical significant influence was identified. Factors marked in italic are not represented in the chosen data set from Michelsen and Madlener [42], which is used in this study.

Category	Motivational factors	Influence in the direction of ...	Study numbers
financial motives	Costs (investment/ annual costs/ maintenance/ fuel)		16
	Technological efficiency		1
	Financial support	Renewable heating	5
	Influence on value of the house	Renewable heating	3
	Risk aversion/preference for certainty		2
	Preference for short amortization period	Gas/ Oil	2
	Aversion against debt/ taking credit		1
non-financial motives	Comfort in operating/ "climate" of living	Gas/ Heat pump	9
	Preference for eco-friendliness (energy saving)	Renewable heating	8
	Preference for modern/ progressive technology	Renewable heating	4
	Preference for independence from fossil fuels/ autarky	Renewable heating	3
	aesthetics (appearance of the house)		3
	Prestige/ social status	Renewable heating	3
	Concern for quality (e.g. fear of construction damage)		2
	Attitudes regarding / evaluation of fuel type		1
heuristic/imperfect information processing	Incomplete / imperfect knowledge via different channels		6
	Laziness, indifference (avoiding a complicated process)	Gas/ Oil	3
	Imitation (e.g. neighbors)		3

type of heating technology [7, 48, 62] and review studies [21] were excluded. As a result, three survey-based empirical data sets were found to be potentially suitable for incorporation into the optimization model. These are described here in more detail.

Stieß et al. [55] surveyed 1009 homeowners in 2008 on the factors influencing their heating refurbishment decision and analyzed the data generated [54, 63]. In this survey, the choice of heating system is included in the refurbishment decision. Additionally, not all required heating systems are differentiated within this study. Consequently, this data set was not considered to be incorporated into the optimization model.

Decker et al. [17] surveyed 775 homeowners in 2007 regarding their motivation for adopting a residential heating system. A factor analysis and cluster analysis were performed on the data collected using a multinomial logistic regression model (MNL) [16–18]. One of the main findings is that membership in different "ecological clusters" is the main influencing factor on the choice of a certain heating system. An ecological cluster is defined as the general attitude of a consumer towards environmental conservation. However, compared to other studies dealing with the purchase of a certain heating system, the survey response rate was fairly low [16].

The empirical basis for the studies conducted by Michelsen and Madlener [41, 42, 43, 44] is a questionnaire survey (N=2440) conducted in 2010 among homeowners who had recently installed a residential heating system. An MNL model was applied to the data by Michelsen and Madlener [42]. This made it possible to identify the motivational factors influencing homeowners' decisions about adopting a residential heating system (RHS). Additionally, a characterization of the motivational factors was conducted using a principal component analysis, the participants of the survey being grouped into three clusters using a cluster analysis: the convenience-oriented (C1), the consequences-aware (C2), and the multilaterally-motivated (C3) RHS adopter, see Tab. 2. The clusters cover 25 influencing factors, which were grouped around six components by Michelsen and Madlener [42]. The probability of belonging to one of the three clusters was predicted by means of a MNL model [42] that considers the interaction between all 25 influencing factors affecting the consumers' choice of heating technology, see also Tab. 2. The factors identified reflect all those identified in the literature except four, as summarized in Tab. 1.

The empirical data presented by Michelsen and Madlener [42] are analyzed by them in detail, their study is one of the most recent ones available with a high number of participants, and their findings are largely in line with the general findings of the literature review and the findings of Decker and Menrad [16]. Consequently, the results of Michelsen and Madlener [42] were selected in this study for incorporation into the optimization model to represent consumer choice.

2.2. The optimization model

The optimization model has been used in previous research to determine the future cost optimal use of biomass in the German heat sector in different long term climate mitigation scenarios [20, 26, 27]. In the

Table 2: Identified clusters by Michelsen and Madlener [42]: The convenience-oriented (C1) RHS adopter is mainly motivated by comfort considerations and the general attitude towards the RHS. The heating system should fit well into his daily routines. The consequences-aware (C2) RHS adopter considers financial benefits, rising energy prices, supply security (e.g. independence of fossil fuels) and environmental reasons. The multilaterally-motivated (C3) RHS adopters strongly engage in the decision, based on a variety of aspects (in particular cost aspects, grants, comfort considerations and influence of peers). In addition, the MNL analysis results for predicting the probability of belonging to one of the three clusters (cluster membership) are presented as average marginal effect (M.E.) [42].

	C1	**C2**	**C3**
Consumer share	54.4 %	32.2 %	13.4 %
Gas + solar termal	0.064	-0.096	0.033
Heat pump	-0.132	0.026	0.105
Wood pellet	-0.398	0.330	0.068

present study, the structure of the model and the data have been extended to depict consumer investment behavior, see section 2.3. Apart from this extension and not setting an upper limit for greenhouse gas emissions, the same model formulations are applied as in Jordan et al. [26]. In this study, the model is used to project future market development assuming that all the actors behave in an economically rational way, except for the behavioral aspects that are integrated into the model. This includes that all actors have perfect foresight and consumers are aware of future price and demand developments.

The approach of the model follows the BENOPT (BioENergyOPTimisation) model developed for biofuels assessment in the transport sector [45–47]. The model is structured as follows: the three main sectors of the German heat sector – private household, industry and trade/commerce – are further divided into several sub-sectors, each with different properties in terms of demand profiles and infrastructures. In total, 19 sub-sectors are defined and described: five sub-sectors for single-family houses (SFH), four for multi-family houses , five for the trade and commerce sector and five for industry and district heating. The future development of heat demand in buildings is based on the results of the building stock model 'B-STar' [33], which models the future refurbishment of German building stock at a yearly resolution using an agent based approach . As a result, consumers' decisions regarding refurbishment cannot be represented in this model. Within the optimization model, representative bioenergy, fossil and other renewable (hybrid) heat technology concepts are described for each sub-sector [35], including, e.g. gas boilers, heat pumps, direct electric heating, solar thermal, log wood, wood pellet and wood chip technologies. In total, 23 biomass products (including wood based residues, log wood, straw, manure, two perennial crops and seven types of energy crops) and three fossil feedstocks are possible inputs [35]. For the single technology components, infrastructure emissions as well as the feedstock specific emissions are considered within the model.

The various components of the power price (e.g. taxes and levies) are treated separately in the model and their future development is set according to projected trends [2, 22, 23]. This leads to different power prices in the heat sub-sectors (private households, trade/commerce and industry), despite applying the same projection for the stock market power price. A detailed description of the method and the time series applied are attached in the supplementary material.

Choice of technology is optimized between 2015 - 2050 at a yearly resolution. The objective function minimizes the total system costs across all technologies, sub-sectors and the full time span, using the Cplex solver for the linear optimization problem. The spatial boundary is Germany as a whole and the sectoral coverage exclusively encompasses the heating sector. For a detailed description of the model formulations, the linkage to the power sector, the definition of the sub-sectors and technology concepts, as well as the possible feedstock and technology pathways, the reader is referred to Jordan et al. [26]. Detailed economic and technical data for the technology concepts can be found in a data publication [35].

2.3. Integrating consumer behavior into the optimization model

The integration of consumer choice into the model depicting the adoption of residential heating systems is based on the studies conducted by Michelsen and Madlener [41, 42, 43, 44]. Specifically, the results from the cluster analysis and from the analysis predicting cluster membership are used in this study [42], see

Tab. 2. The cluster segmentation is the basis for splitting the relevant heating sub-sectors into consumer segments, the same approach as in Li et al. [38]. In this case, the heat demand of all five single-family sub-sectors, responsible for $\sim 23\%$ of German heat demand, were further segmented into three consumer segments (C1..C3) each, representing the clusters identified from Michelsen and Madlener [42]. A schematic representation of how the consumer segmentation and the application of indirect costs is realized in the model is shown in Fig. 2.

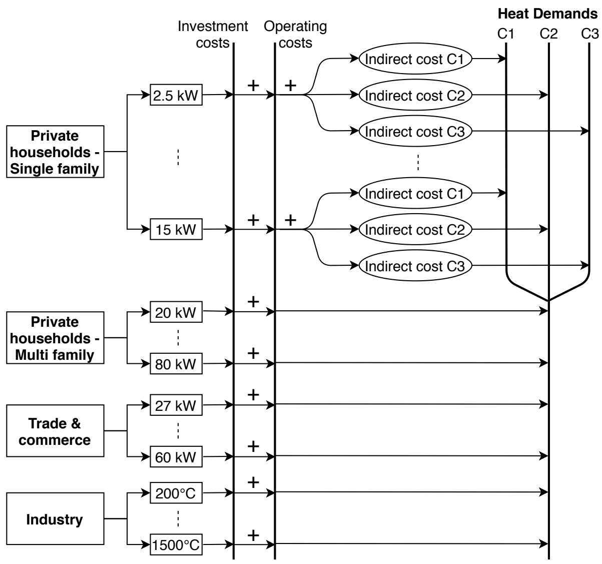

Figure 2: Schematic of applying indirect costs in the different consumer segments C1..C3 within the optimization model. The sub-sectors are defined by the size of the heating system, e.g. 2.5 kW.

As shown in section 2.1 while the adoption of a heating system is driven largely by financial motives, non-financial ones are also relevant (mainly in terms of comfort and environmental concerns, see Tab. 1). The financial aspects are represented comprehensively in the optimization model (investment, fixed and variable costs). The non-financial motives are represented via indirect technology costs. In each consumer segment, different indirect costs are applied, following established approaches in the literature [9, 39, 40, 49, 57]. In this case, the indirect costs are derived from predicting which heating systems belong to which one of the three clusters, see Tab. 2, presented as average marginal effect (M.E.). This marginal effect is translated into indirect costs derived from an economic textbook approach: according to economic theory, market shares of two technologies sh_1 and sh_2 should be inversely related to their relative cost c_1/c_2 [64], with the parameter g indicating the extent to which cost differentials between competing technologies affect their market shares.

$$\frac{sh_1}{sh_2} = \left(\frac{c_2}{c_1}\right)^g \quad with \; g > 0 \tag{1}$$

As a conclusion derived from this causality, an increased probability of technology market shares (probability of cluster membership, see Michelsen and Madlener [42]) is translated into a decrease in costs and vice-versa. Since market shares in the optimization model are based on costs alone, represented by the objective function, here we translate the probability of cluster membership directly into an indirect cost factor icf for each applicable technology system within the consumer segments, see Table 3. In an ideal case, the indirect costs factor would be calibrated with the parameter g, which was not possible in this study. The indirect cost factor is incorporated into the objective function by adding the inverted indirect technology costs proportional to the investment costs ic and variable costs mc of each technology i, see equation (2). With this method, negative indirect costs can also apply, representing a willingness to pay. The investment

Table 3: Indirect cost factor (icf) derived from the M.E., see Table 2 for the relevant technology concepts in the different consumer segments (C1..C3). As there is no differentiation between adopting a wood pellet or log wood technology, the M.E. for log wood technologies is set equal to the one of wood pellets. For hybrid systems the indirect cost factor is calculated from an equal average of the applicable M.E. PV systems are not explicitly considered.

	C1	**C2**	**C3**
Heat demand share	54.4 %	32.2 %	13.4 %
Gas cond. boiler	0.064	-0.096	0.033
Gas boiler+Log wood stove+ST	-0.167	0.117	0.0505
Gas cond. boiler + ST	0.064	-0.096	0.033
Gas fuel cell+ST	0.064	-0.096	0.033
Heat pump+PV	-0.132	0.026	0.105
Heat pump+PV+ST	-0.132	0.026	0.105
Heat pump+PV+ Log wood stove	-0.265	0.178	0.0865
Pellet boiler	-0.398	0.33	0.068
Buffer integrated pellet burner+ST	-0.398	0.33	0.068
Log wood gasif. boiler+ST	-0.398	0.33	0.068
Log wood stove+ST	-0.398	0.33	0.068
Torrefied wood pellet gasifier CHP	-0.398	0.33	0.068
Tor. wood pellet gasif. CHP+HP+PV	-0.265	0.178	0.0865

costs are discounted using the annuity method (discount rate q, lifetime $\hat{t}$). Finally, the objective function minimizes the total system costs over all technology modules j, all sub-sectors s, feedstock products b and the complete timespan $t = 2015...2050$.

Objective function

$$\begin{aligned} min \sum_{t,i,s,b} mc_{t,i,s,b} \cdot \pi_{t,i,s,b} \\ + \sum_{t,i,j,s} ic_{t,i,j,s} \cdot n^{cap}_{t,i,j,s} \cdot \frac{q(1+q)^{\hat{t}_j}}{(1+q)^{\hat{t}_j}-1} \\ + \sum_{t,i,s,c} -icf_{i,c} \cdot mc_{t,i,s} \cdot \pi_{t,i,s,c} \\ + \sum_{t,i,j,s,c} -icf_{i,c} \cdot ic_{t,i,s} \cdot n^{cap}_{t,i,j,s,c} \cdot \frac{q(1+q)^{\hat{t}_j}}{(1+q)^{\hat{t}_j}-1} \end{aligned} \tag{2}$$

subject to

$$\delta_{t,s,c} = \sum_i \pi_{t,i,s,c}, \forall (t, i, s = 1..5, c) \in (T, I, S, C) \tag{3}$$

$$\sum_c \pi_{t,i,s,c} = \pi_{t,i,s}, \forall (t, i, s = 1..5, c) \in (T, I, S, C) \tag{4}$$

$$n^{cap}_{t,i,s,c} \cdot \kappa_{t,s} = \pi_{t,i,s,c}, \forall (t, i, s = 1..5, c) \in (T, I, S, C) \tag{5}$$

$$\sum_c n^{cap}_{t,i,s,c} = n^{cap}_{t,i,s}, \forall (t, i, s = 1..5, c) \in (T, I, S, C) \tag{6}$$

In order to incorporate consumer choice, four additional restrictions were added to the original model formulation, which is described in Jordan et al. [26]. The heat demand δ in each cluster c of the five sub-sectors s needs to be met by the sum of the heat produced π of all technologies i within one cluster (3). The sum of heat produced over all clusters needs to equal the heat production within its sub-sector (4). The sum of heating systems installed n^{cap} multiplied by their individual capacity κ equals the yearly heat production of each technology within its cluster (5). Equation (6) is equivalent to equation (4) in relation to n^{cap}. In each sub-sector, premature decommissioning of heating systems is only allowed for fossil fuel technologies and limited to 1%/a. This restriction is not set within the clusters, i.e. consumers/heating systems can switch clusters over time within one sub-sector.

2.4. Scenarios and sensitivity analysis

In this study, a business as usual (BAU) and an ambitious measures scenario (AMS) are analyzed, both calculated with and without consumer choice. In the BAU scenario energy prices are kept at a constant level and no CO_2 pricing is in place. Additionally, current investment incentives for heating technologies are considered (except for biogas feed-in compensation) and a moderate refurbishment rate is assumed.

In the AMS scenario, energy only prices increase moderately and an ambitious pricing of CO_2 is set, increasing constantly up to 200 €/tCO_2eq in 2050. The CO_2 price increase is derived from current scenario analyses that project prices in that range to reach a 95% reduction target [50]. Furthermore, all planned future incentives in the heat sector as well as an ambitious refurbishment rate are set in the AMS scenario. The main scenario parameter settings are shown in Tab. 4.

Table 4: Setting of the main scenario parameters.

	Business as usual (BAU)	**Ambitious measures scenario (AMS)**
Stock market power price	32 €/MWh	32 €/MWh
Gas price (energy only)	19.8 €/MWh	19.8 → 26,6 €/MWh
Biomass price increase	0%/a	1%/a
CO_2 price	not in place	act. status → 200 €/tCO_2eq.
Refurbishment	1-2%/a	2-3%/a
Incentives	Investment subsidies valid until 2019	Investment subsidies valid from 2020
Consumer choice	yes /no	yes /no

A few parameters are set equally in all four scenarios: in the power sector GHG emissions are assumed to decrease linearly up until 2050 (17 gCO_2eq./kWh in 2050). Further, the national potential for biomass residues is derived from the upper and lower range of current energetic use and the exploitable potential described in Brosowski et al. [8], [3], see Fig. 3. The potential of available land for energy crops is set to decrease linearly to 0 ha in 2050. From the overall available biomass potential (residues and energy crops), a share of $\sim$ 70% is pre-allocated to the heat sector (incl. CHP applications) within the model, according to the method described in Jordan et al. [26].

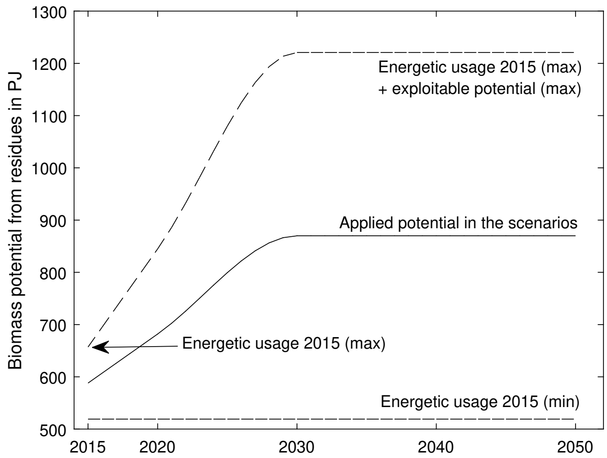

Figure 3: Applied biomass potential from residues derived from national monitoring of residues [3, 8]. The range between the upper and lower curve is investigated in the sensitivity analysis.

Finally, the variance-based sensitivity analysis of Sobol' was applied to the model to systematically assess which uncertain input parameters affect the model output. A particular focus is placed on the effect of applying consumer choice within the model and on viewing it in interaction with the other uncertain input parameters. The uncertainty range in which 45 input parameters were varied is documented in the supplementary material. A detailed description of how the Sobol' method is applied to the optimization model can be found in Jordan et al. [27].

3. Results and discussion

The results show that future market shares for log wood, wood pellet and also heat pump technology are less represented in the BAU scenario without consumer choice being applied, see Fig. 4. A typical picture emerges from the optimization results: only a few technologies gain major market shares compared to the broader "portfolio" of the start year, 2015. When heterogeneous consumer choice is incorporated into the BAU scenario, the market shares of the start year portfolio remain more or less constant, especially for the private household sector. In this case, the optimization model delivers more diverse projections.

A more detailed depiction of market shares for bioenergy shows the effect on competitiveness of the individual bioenergy technology concepts in the private household sector, see Fig. 5. Without applying consumer choice in the model, none of the recent bioenergy technology concepts remains competitive and all of the available solid biomass is distributed in high temperature industry applications, see Fig. 4. This is in line with findings from previous studies, where this technology option was found to be a robust result [27]. In contrast, when applying consumer choice, log wood and wood pellet technologies in the private household sector maintain a constant market share or increase their market share slightly. Here, the type of technology remains the same but a switch in the technology deployment concept occurs: the use of log wood switches from gas boilers combined with a log wood stove and solar thermal system to being used in log wood gasification boilers combined with solar thermal. The use of pellets switches from pellet boilers in the private household and trade/ commerce sector to use in pellet burners with an integrated buffer combined with solar thermal.

A similar picture emerges for the ambitious measures scenario. Without applying consumer choice, biomass is shown to be used almost entirely by industry while the use of biomass in the private household sector phases out almost completely, see Fig. 4 and 5. If consumer choice is applied, the general trend remains that most of the biomass is used competitively in high temperature industry applications. Furthermore, bioenergy is used in the private household sector, especially in the form of log wood. In this case, wood pellet technologies do not remain competitive.

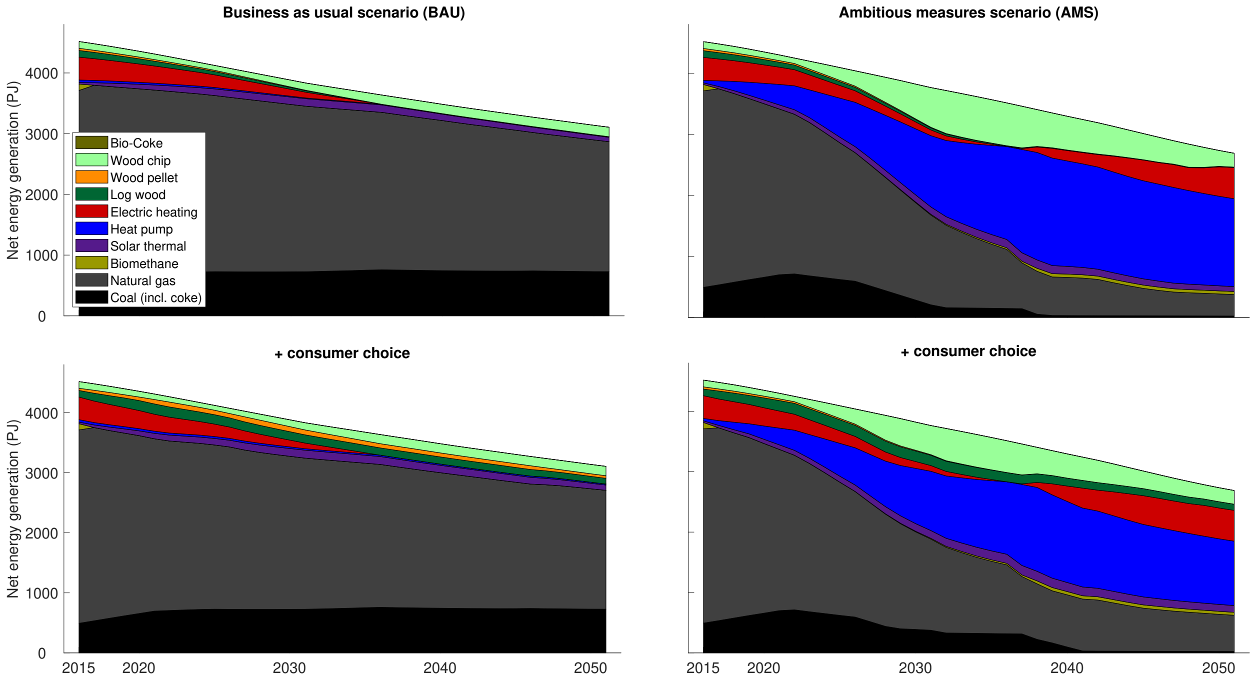

Figure 4: Model resulting development of the technology market shares for the complete heat sector for the different scenarios in a yearly resolution.

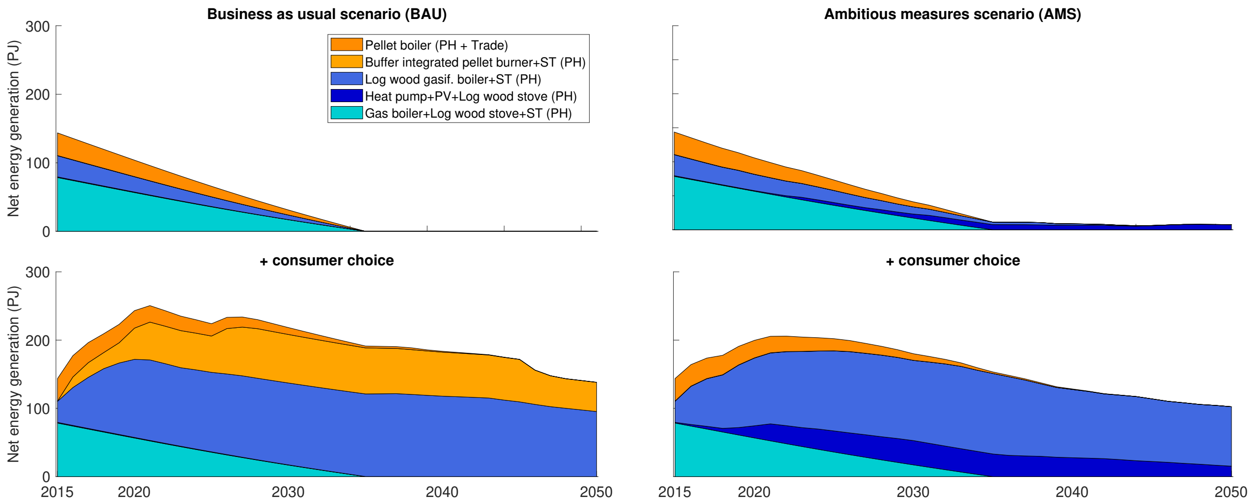

Figure 5: Net energy market shares of the relevant bioenergy technologies in the private household sector. Within the figure only the relevant bioenergy technology concepts are shown, leaving out fossil references, alternative renewable technologies and unrelevant bioenergy concepts. For hybrid systems, only the biomass net energy shares of the concepts are displayed in order to have a depiction of the biomass utilization. Ind = Industry; DH = District Heating; PH = Private Households; CHP = Combined Heat and Power; HP = Heat Pump; PV = Photovoltaic; ST = Solar Thermal.

A detailed depiction of the market shares within the consumer segments of the five single-family housing sub-sectors shows that the method of implementing consumer choice leads to the expected results, see Fig. 6 and 7. In three out of five sub-sectors, the technology types with the largest market shares are those which, according to the findings of Michelsen and Madlener [42], are preferred by the consumers of the different segments C1..C3. Exceptions are the sub-sectors with a system size of 2.5 and 5 kW. This finding, contrary to what would be expected, can be explained on the basis that these sub-sectors represent a high insulation standard: in this case the price advantage of heat pumps or gas technologies overrule the non-economic factors. In addition, the survey on which the identified consumer choices are based was conducted in 2010. At that time, houses with such high insulation standards were underrepresented and therefore did not fall within the scope of the survey.

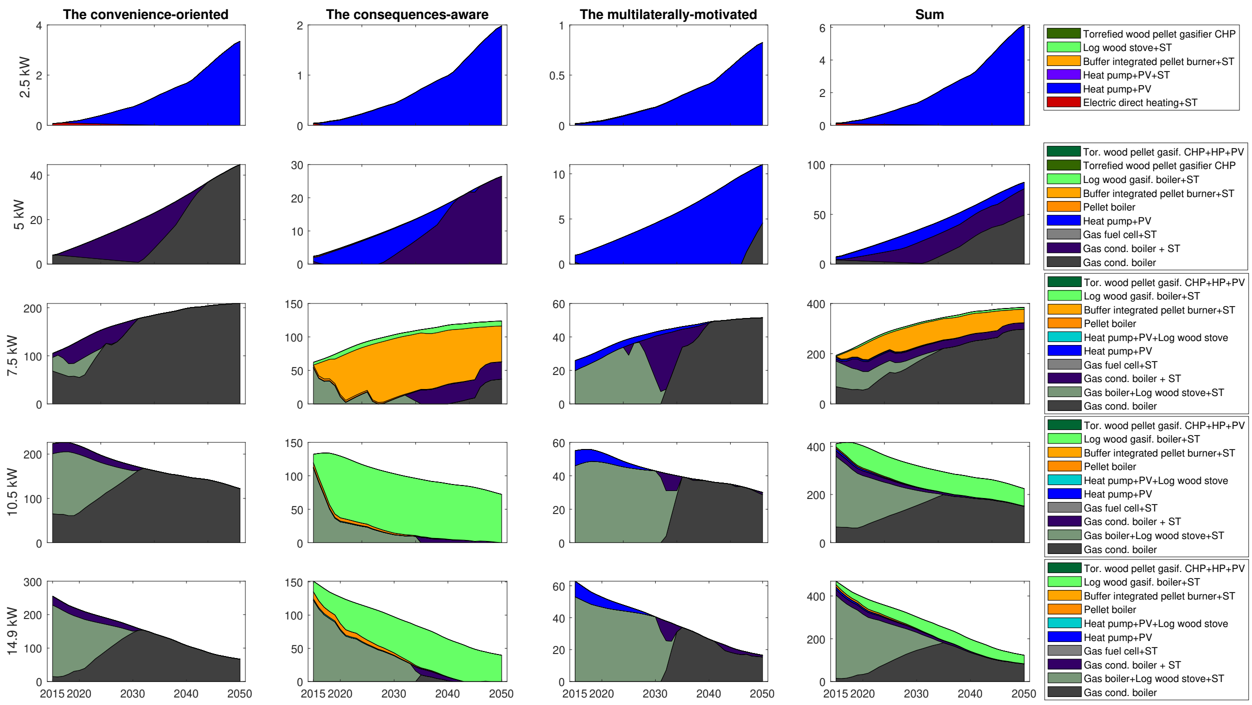

Figure 6: Net energy technology market shares in the consumer segments of the five single-family sub-sectors in the BAU scenario considering consumer choice (in PJ). CHP = Combined Heat and Power; HP = Heat Pump; PV = Photovoltaic; ST = Solar Thermal.

In general, we can see that implementing consumer choice leads to a broader diversity in technology market shares while the market penetration of heating technologies shows a gradual and smooth development. The model outcome shows a more plausible development than in the model runs without consumer choice applied. However, this conclusion has not been subjected to validation and would require historical data and a calibration of the model.

Based on this study's findings, one could conclude that log wood market shares have been underrepresented in previous studies. Jordan et al. [26] concluded that log wood technologies are the least cost-competitive wood-based bioenergy technology, as their market share decreases rapidly in the model with decreasing biomass potential in the scenarios investigated. In addition, a sensitivity analysis found that the use of biomass in large amounts of log wood is not a robust result, as indicated by the low market penetration of high log wood shares over a broad range of outcomes [27]. In this study, we show that the inclusion of consumer choice has an impact on market shares for log wood in both the scenarios investigated and the sensitivity analysis, see Fig. 8. The integration of consumer choice is found to influence market shares for log wood significantly, represented by a high Sobol' index.

It should be noted that investment considerations with regard to log wood technologies were not differ-

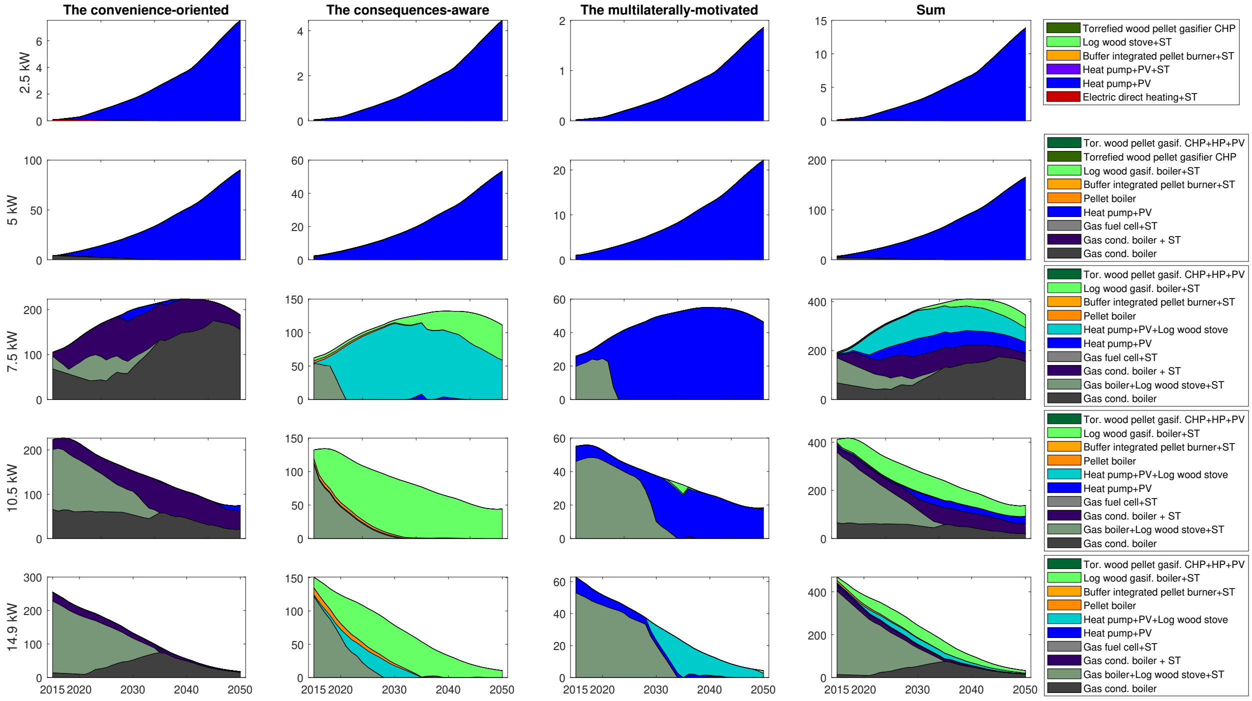

Figure 7: Net energy technology market shares in the consumer segments of the five single-family sub-sectors in the ambitious measures scenario considering consumer choice (in PJ). CHP = Combined Heat and Power; HP = Heat Pump; PV = Photovoltaic; ST = Solar Thermal.

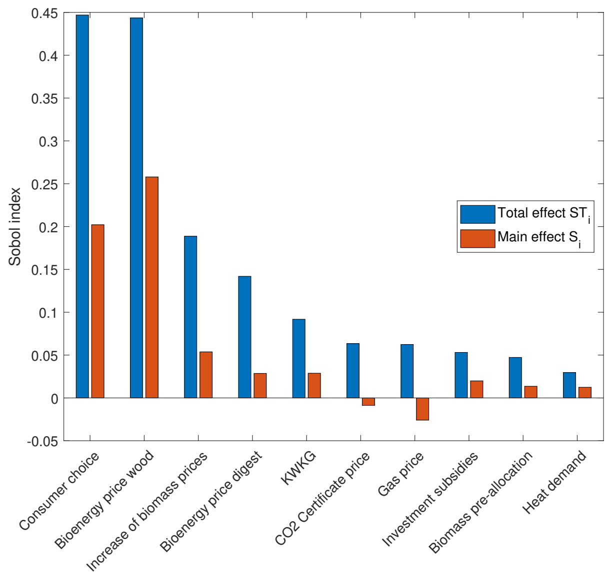

Figure 8: Sobol' indices on log wood market shares from 2030-2050 for the most influential input parameters. Both Sobol' indices range from 0 to 1. $S_{Ti} \geq S_i \geq 0$. If $S_{Ti} = S_i = 0$ the parameter is non-influential. If $S_{Ti} = S_i$ there is no interaction of the i^{th} parameter with other parameters. In this case S_i can become negative, as some of the varied input factors are correlated. For a detailed description of this phenomenon see [61].

entiated from those for wood pellet technologies in the survey conducted by Michelsen and Madlener [41]. Consequently, the indirect cost factor in the model was equalized for both the wood pellet and log wood options, which is a debatable move. Consumer choice is driven by economic and ecological factors as well as by comfort and individual factors, among others. Pellet and log wood technologies, for example, have different perceived comfort characteristics. While a pellet burner runs automatically, a log wood stove has to be piled up at least once a day. On the other hand, log wood might be readily available to forest owners (or those with authorized forest access), leading to the installation of a log wood heating system. This should be kept in mind when interpreting the results from this study. For future studies it would be helpful to conduct a more detailed survey on homeowners' investment decisions in relation to more differentiated heating technologies.

Limitations: Although we have been able to show that the integration of consumer choice leads to a broader diversity in market shares for different heating technologies and the model delivers more plausible results, the data available for doing so are subject to uncertainty and the methodological options are limited. In this study, the survey-based empirical data are limited to the consumer behavior of homeowners in single-family houses. Data on consumer behavior for multi-family houses or the heat consuming industry are not available on a national scale. It might be assumed that in these sectors investment decisions are driven purely by economical motivations. A review of company guidelines, ISO standardizations, annual and sustainability reports of the major heat consuming companies in the German industry sector did not lead to any conclusive findings that factors other than economic ones influence decisions on heating technology investment.

In addition, the data available for single-family houses are from 2010. Behavior change over the course of time, see e.g. Borgstedt et al. [6]. This factor can have a decisive impact, especially when modeling a time frame up to 2050. However, a projection of future consumer behavior in relation to investment decisions regarding heating system is not currently available. The identification of factors that drive such change could help to improve such projections. For future research, it would be helpful to have empirical data on the consumer behavior of multi-family house owners and stakeholders in the heat consuming industry in order to improve the representation of consumer choice for the heat sector as a whole.

The method used to integrate consumer choice into the optimization model is in some ways a novel approach. The concept of creating different consumer segments to represent the heterogeneity in consumer choice, however, is an established method [9, 11, 14, 37, 38, 40, 49, 57]. Applying indirect or intangible or disutility costs in these segments is also a common approach. It was not possible, however, to identify a standard methodological approach for calculating the indirect costs, representing consumer investment decisions. In all reviewed papers, indirect costs were calculated in a unique way for each case driven by the country specific influencing factors. A simple transfer of the method for calculating indirect costs to the German case is therefore not applicable. In this study, an increase in the probability of a higher market share is translated into indirect costs. This method is derived from the economic theory which states that the market shares of two technologies should be inversely related to their relative cost [64]. This methodological step can be discussed and, as stated in Section 2.3, a calibration of the factor g with historical data would be desirable. However, methodological alternatives are rare. Hedenus et al. [24] describe the use of distribution functions to make the model's results more diverse and to restrict the diffusion of single technologies. However, a method showing how to combine distribution functions with empirical data on consumer choice is, to the authors' knowledge, not available.

The tenant-landlord dilemma, describes the circumstance in rented houses/flats that investments in renewable energy are not made because the landlord cannot achieve a return on his investment in the long term, while the tenant would benefit. This dilemma could not be represented in this study and should be in the scope of future studies. However, this problem occurs mostly in multi-family houses, for which empirical data on consumer behavior was not available for Germany.

Some scholars have wondered whether some of the techniques introduced have in fact changed the modeling paradigm by introducing consumer choice into a pure cost minimization model [15]. They conclude that the theoretical basis needs to be better understood and that more empirical data and case studies are required to improve the integration of consumer choice in ESOMs. Agent-based models are suited to process probability data as marginal effects, for example, see Steinbach and Staniaszek [53]. With agent-based models, microeconomic behavior can be modeled in a way that reveals macroeconomic effects. However, optimal economic transition pathways cannot be determined using this model type, and if the quality of the solution is important, traditional approaches such as optimization tend to outperform agent-based approaches [5].

4. Conclusions

In this study, consumer behavior was integrated for the first time into an ESOM for the German heat sector. The model enabled consumer heterogeneity and behavioral factors influencing investment decisions other than cost minimization to be represented. The results show that the integration of consumer choice produces a broader range of technologies with market shares and thus more plausible results. Established methods representing consumer heterogeneity and a novel approach for calculating indirect costs were combined in the model to represent consumer investment decisions.

We were able to show in the case of Germany and in comparison to previous studies that solid biomass is not only optimally distributed in (high temperature) industry applications. The results indicate that, in the private household sector, a demand for bioenergy may persist in future energy scenarios: this therefore needs to be addressed. In particular, the future role of log wood and pellet technologies may have been underestimated in previous studies and should be discussed when designing policies. Still, these findings need to be handled with care, since the empirical data basis and the methodological basis is limited.

Another finding leads to the conclusion that in houses with high insulation standards, economic factors are predominant and exceed the willingness to pay for other, preferred technologies. In the future, the economic advantages of heat pumps in well-insulated houses overrule non-economic preferences and lead to exclusive market shares of heat pumps in these sub-sectors.

The results obtained from the study offer a broader basis for the design of a cleaner heat sector. The literature discusses how consumers can be encouraged to adopt cleaner heating systems. For this purpose, policy makers need to adopt a holistic view that includes non-economic factors and captures the heterogeneity of actors and their preferences. The results of this study provide a broader knowledge base that can help policy makers decide on deployment schemes for cleaner heat production. In particular, the conditions for future use of biomass in the German heat sector could be improved. In previous studies using pure cost optimized scenario projections for the future use of biomass, high temperature industry applications were identified as the cost optimal option for biomass. Our study shows that when non-economic behavior factors affecting consumer choice are considered, private households may demand an additional $\sim 100 - 200$ PJ/a of log wood. This projection of future demand should be discussed when designing technical schemes and policies for implementation. For the heat consuming industry we conclude that in a future heat sector based on renewable energy supplies, a competitive demand might persist for the limited biomass available in Germany. At the same time, according to the results of this study, there will continue to be demand for small-scale bioenergy combustion plants in the future.

In addition, the study contributes to the development of methods in terms of improving the integration of behavioral factors of consumer choice into ESOMs. In literature, a demand for further case studies is described [15], to which this conducted study contributes.

For future studies, the extended model provides an opportunity to describe the effect of different funding instruments given the factor of consumer choice. For this purpose, more recent and detailed empirical data on homeowners' investment decisions around a broader range of heating technologies would be helpful. It would also be helpful to advance the methodology further, e.g. with regard to calibration, in order to provide policy insights with a high level of confidence.

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Kathleen Cross helped improve the language.

6. Appendix A. Supplementary data

Supplementary data related to this article is attached.

References

[1] Surveys of the chimney sweep trade (Erhebungen des Schornsteinfegerhandwerks).

[2] Evaluation of reference studies and scenario analyses on the future development of grid charges for electricity (BMWi-Vorhaben Netzentgelte: Auswertung von Referenzstudien und Szenarioanalysen zur zukünftigen Entwicklung der Netzentgelte für Elektrizität). URL `https://www.agora-energiewende.de/fileadmin2/Projekte/2015/EEG-Kosten-bis-2035/Agora_EEG_Kosten_2035_web_05052015.pdf`.

[3] DBFZ - Data repository: Ressource database (Ressourcendatenbank), 2019. URL `http://webapp.dbfz.de/resources`.

[4] Klaus Backhaus, Bernd Erichson, Wulff Plinke, and Rolf Weiber. *Multivariate analysis methods (Multivariate Analysemethoden)*. Springer Berlin Heidelberg, Berlin, Heidelberg, 2016. ISBN 978-3-662-46075-7. doi: 10.1007/978-3-662-46076-4.

[5] M. Barbati, G. Bruno, and A. Genovese. Applications of agent-based models for optimization problems: A literature review. *Expert Systems with Applications*, 39(5):6020–6028, 2012. ISSN 09574174. doi: 10.1016/j.eswa.2011.12.015.

[6] Silke Borgstedt, Tamina Christ, and Fritz Reusswig. Environmental awareness in germany 2010 (Umweltbewusstsein in Deutschland 2010): Results of a representative population survey (Ergebnisse einer repräsentativen Bevölkerungsumfrage). URL `https://www.umweltbundesamt.de/sites/default/files/medien/publikation/long/4045.pdf`.

[7] Frauke G. Braun. Determinants of households' space heating type: A discrete choice analysis for German households. *Energy Policy*, 38(10):5493–5503, 2010. ISSN 03014215. doi: 10.1016/j.enpol.2010.04.002.

[8] André Brosowski, Tim Krause, Udo Mantau, Bernd Mahro, Anja Noke, Felix Richter, Thomas Raussen, Roland Bischof, Thomas Hering, Christian Blanke, Paul Müller, and Daniela Thrän. How to measure the impact of biogenic residues, wastes and by-products: Development of a national resource monitoring based on the example of Germany. *Biomass and Bioenergy*, 127:105275, 2019. ISSN 09619534. doi: 10.1016/j.biombioe.2019.105275.

[9] David Bunch, Kalai Ramea, Sonia Yeh, and Christopher Yang. Incorporating Behavioral Effects from Vehicle Choice Models into Bottom-Up Energy Sector Models.

[10] Bundesministerium für Wirtschaft und Energie. Energy data (Energiedaten): Complete edistion (Gesamtausgabe). URL `https://www.bmwi.de/Redaktion/DE/Downloads/Energiedaten/energiedaten-gesamt-pdf-grafiken.pdf?__blob=publicationFile&v=40`.

[11] Jean-Michel Cayla and Nadia Maïzi. Integrating household behavior and heterogeneity into the TIMES-Households model. *Applied Energy*, 139:56–67, 2015. doi: 10.1016/j.apenergy.2014.11.015.

[12] Jean-Michel Cayla and Dominique Osso. Does energy efficiency reduce inequalities? Impact of policies in residential sector on household budget. URL `https://www.eceee.org/library/conference_proceedings/eceee_Summer_Studies/2013/5a-cutting-the-energy-use-of-buildings-projects-and-technologies/does-energy-efficiency-reduce-inequalities-impact-of-policies-in-residential-sector-on-household-budget/`.

[13] Aleh Cherp, Vadim Vinichenko, Jessica Jewell, Elina Brutschin, and Benjamin Sovacool. Integrating techno-economic, socio-technical and political perspectives on national energy transitions: A meta-theoretical framework. *Energy Research & Social Science*, 37:175–190, 2018. ISSN 22146296. doi: 10.1016/j.erss.2017.09.015. URL `https://www.umweltbundesamt.de/sites/default/files/medien/publikation/long/4045.pdf`.

[14] Hannah E. Daly, Kalai Ramea, Alessandro Chiodi, Sonia Yeh, Maurizio Gargiulo, and Brian Ó. Gallachóir. Incorporating travel behaviour and travel time into TIMES energy system models. *Applied Energy*, 135:429–439, 2014. doi: 10.1016/j.apenergy.2014.08.051.

[15] Joseph DeCarolis, Hannah Daly, Paul Dodds, Ilkka Keppo, Francis Li, Will McDowall, Steve Pye, Neil Strachan, Evelina Trutnevyte, Will Usher, Matthew Winning, Sonia Yeh, and Marianne Zeyringer. Formalizing best practice for energy system optimization modelling. *Applied Energy*, 194:184–198, 2017. doi: 10.1016/j.apenergy.2017.03.001.

[16] Thomas Decker and Klaus Menrad. House owners' perceptions and factors influencing their choice of specific heating systems in Germany. *Energy Policy*, 85:150–161, 2015. ISSN 03014215. doi: 10.1016/j.enpol.2015.06.004.

[17] Thomas Decker, Marina Zapilko, and Klaus Menrad. PURCHASE BEHAVIOUR RELATED TO HEATING SYSTEMS IN GERMANY WITH SPECIAL CONSIDERATION OF CONSUMERS' ECOLOGICAL ATTITUDES. 2009.

[18] Thomas Anton Decker. *Consumer behavior when buying a private consumer good using heating as an example (Verbraucherverhalten beim Kauf eines privaten Gebrauchsguts am Beispiel Heizung)*, volume 3 of *Nachwachsende Rohstoffe in Forschung und Praxis*. Attenkofer, Straubing, 2010. ISBN 393651187X.

[19] Diane F. DiClemente and Donald A. Hantula. Applied behavioral economics and consumer choice. *Journal of Economic Psychology*, 24(5):589–602, 2003. ISSN 01674870. doi: 10.1016/S0167-4870(03)00003-5.

[20] ETA-Florence Renewable Energies, editor. *Competitive Biomass Key Applications to Fulfill Climate Targets in the German Heat Sector: Findings from Optimization Modelling*, 2019. ETA-Florence Renewable Energies. doi: 10.5071/27thEUBCE2019-5BV.3.10. URL `http://www.etaflorence.it/proceedings/?detail=16385`.

[21] Maike Gossen and Carolin Nischan. Regional differences in the perception of energetic refurbishment (Regionale Differenzen in der Wahrnehmung energetischer Sanierung): Results of a qualitative survey of building owners on energetic refurbishment in two different regions. (Ergebnisse einer qualitativen Befragung von GebäudeeigentümerInnen zu energetischer Sanierung in zwei unterschiedlichen Regionen). URL `https://www.gebaeude-energiewende.de/data/gebEner/user_upload/Dateien/GEW_AP1_Ergebnisbericht_Interviews_final_141126.pdf`.

[22] Philipp Götz, Johannes Henkel, and Thorsten Lenck. Relationship between power exchange prices and end customer prices (Zusammenhang von Strombörsenpreisen und Endkundenpreisen): Study commissioned by Agora Energiewende (Studie im Auftrag der Agora Energiewende). URL `https://www.bmwi.de/Redaktion/DE/Publikationen/Studien/netzentgelte-auswertung-von-referenzstudien.pdf?__blob=publicationFile&v=6`.

[23] Markus Haller, Mara Marthe Kleiner, and Verena Graichen. The development of renewable act costs until 2035 (Die Entwicklung der EEG-Kosten bis 2035): How the expansion of renewables works along the long-term goals of the energy transition (Wie der Erneuerbaren-Ausbau entlang der langfristigen Ziele der Energiewende wirkt). URL `https://www.agora-energiewende.de/fileadmin2/Projekte/2015/EEG-Kosten-bis-2035/Agora_EEG_Kosten_2035_web_05052015.pdf`.

[24] Fredrik Hedenus, Daniel Johansson, and Kristian Lindgren. A Critical Assessment of Energy-economy-climate Models for Policy Analysis. *Journal of Applied Economics and Business Research*, (3 (2)):118–132, 2013. URL `http://www.aebrjournal.org/uploads/6/6/2/2/6622240/joaebrjune2013_118_132.pdf`.

[25] Matt Horne, Mark Jaccard, and Ken Tiedemann. Improving behavioral realism in hybrid energy-economy models using discrete choice studies of personal transportation decisions. *Energy Economics*, 27(1):59–77, 2005. ISSN 01409883. doi: 10.1016/j.eneco.2004.11.003.

[26] Matthias Jordan, Volker Lenz, Markus Millinger, Katja Oehmichen, and Daniela Thrän. Future competitive bioenergy technologies in the German heat sector: Findings from an economic optimization approach. *Energy*, 189:116194, 2019. ISSN 03605442. doi: 10.1016/j.energy.2019.116194.

[27] Matthias Jordan, Markus Millinger, and Daniela Thrän. Robust bioenergy technologies for the German heat transition: A novel approach combining optimization modeling with Sobol' sensitivity analysis. *Applied Energy*, 262:114534, 2020. doi: 10.1016/j.apenergy.2020.114534.

[28] Daniel Kahneman and Amos Tversky. Choices, values, and frames. *American Psychologist*, 39(4):341–350, 1984. ISSN 0003-066X. doi: 10.1037/0003-066X.39.4.341.

[29] Matthew Kennedy and Biswajit Basu. A study on the implementation of renewable heating technologies in the domestic sector in Ireland with implications on consumers' decision-making. *Journal of Cleaner Production*, 44:133–142, 2013. ISSN 09596526. doi: 10.1016/j.jclepro.2013.01.018.

[30] Matthew Kennedy, Van-Nguyen Dinh, and Biswajit Basu. Analysis of consumer choice for low-carbon technologies by using neural networks. *Journal of Cleaner Production*, 112:3402–3412, 2016. ISSN 09596526. doi: 10.1016/j.jclepro.2015.10.035.

[31] Khalid S. Khan, Regina Kunz, Jos Kleijnen, and Gerd Antes. Five Steps to Conducting a Systematic Review. *Journal of the royal society of medicine*, (96), 2003.

[32] Martin Klein and Marc Deissenroth. When do households invest in solar photovoltaics? An application of prospect theory. *Energy Policy*, 109:270–278, 2017. ISSN 03014215. doi: 10.1016/j.enpol.2017.06.067.

[33] Matthias Koch, Klaus Hennenberg, Katja Hünecke, Markus Haller, and Tilman Hesse. Role of bioenergy in the electricity and heating market until 2050, taking into account the future building stock (Rolle der Bioenergie im Strom- und Wärmemarkt bis 2050 unter Einbeziehung des zukünftigen Gebäudebestandes). URL `https://www.energetische-biomassenutzung.de/fileadmin/Steckbriefe/dokumente/03KB114_Bericht_Bio-Strom-W%C3%A4rme.pdf`.

[34] Liridon Korcaj, Ulf J.J. Hahnel, and Hans Spada. Intentions to adopt photovoltaic systems depend on homeowners' expected personal gains and behavior of peers. *Renewable Energy*, 75:407–415, 2015. ISSN 09601481. doi: 10.1016/j.renene.2014.10.007.

[35] Volker Lenz and Matthias Jordan. Technical and economic data of renewable heat supply systems for different heat sub-sectors., 2019. URL `http://dx.doi.org/10.17632/v2c93n28rj.2`.

[36] Volker Lenz and Daniela Thrän. Flexible heat provision from biomass. In Daniela Thrän, editor, *Smart Bioenergy*, pages 83–105. Springer International Publishing, Cham, 2015. ISBN 978-3-319-16192-1.

[37] Francis G.N. Li and Neil Strachan. Take me to your leader: Using socio-technical energy transitions (STET) modelling to explore the role of actors in decarbonisation pathways. *Energy Research & Social Science*, 51:67–81, 2019. ISSN 22146296. doi: 10.1016/j.erss.2018.12.010.

[38] Pei-Hao Li, Ilkka Keppo, and Neil Strachan. Incorporating homeowners' preferences of heating technologies in the UK TIMES model. *Energy*, 148:716–727, 2018. ISSN 03605442. doi: 10.1016/j.energy.2018.01.150.

[39] David McCollum, Volker Krey, Peter Kolp, Yu Nagai, and Keywan Riahi. Transport electrification: A key element for

energy system transformation and climate stabilization. *Climatic Change*, 123(3-4):651–664, 2014. ISSN 0165-0009. doi: 10.1007/s10584-013-0969-z.

[40] David L. McCollum, Charlie Wilson, Hazel Pettifor, Kalai Ramea, Volker Krey, Keywan Riahi, Christoph Bertram, Zhenhong Lin, Oreane Y. Edelenbosch, and Sei Fujisawa. Improving the behavioral realism of global integrated assessment models: An application to consumers' vehicle choices. *Transportation Research Part D: Transport and Environment*, 55: 322–342, 2017. ISSN 13619209. doi: 10.1016/j.trd.2016.04.003.

[41] Carl Christian Michelsen and Reinhard Madlener. Homeowners' preferences for adopting innovative residential heating systems: A discrete choice analysis for Germany. *Energy Economics*, 34(5):1271–1283, 2012. ISSN 01409883. doi: 10.1016/j.eneco.2012.06.009.

[42] Carl Christian Michelsen and Reinhard Madlener. Motivational factors influencing the homeowners' decisions between residential heating systems: An empirical analysis for Germany. *Energy Policy*, 57:221–233, 2013. ISSN 03014215. doi: 10.1016/j.enpol.2013.01.045.

[43] Carl Christian Michelsen and Reinhard Madlener. Switching from fossil fuel to renewables in residential heating systems: An empirical study of homeowners' decisions in Germany. *Energy Policy*, 89:95–105, 2016. ISSN 03014215. doi: 10.1016/j.enpol.2015.11.018.

[44] Carl Christian Michelsen and Reinhard Madlener. Homeowner satisfaction with low-carbon heating technologies. *Journal of Cleaner Production*, 141:1286–1292, 2017. ISSN 09596526. doi: 10.1016/j.jclepro.2016.09.191.

[45] M. Millinger, K. Meisel, and D. Thrän. Greenhouse gas abatement optimal deployment of biofuels from crops in Germany. *Transportation Research Part D: Transport and Environment*, 69:265–275, 2019. ISSN 13619209. doi: 10.1016/j.trd.2019.02.005.

[46] Markus Millinger. BioENergyOPTimisation model, 2019.

[47] Markus Millinger, Kathleen Meisel, Maik Budzinski, and Daniela Thrän. Relative Greenhouse Gas Abatement Cost Competitiveness of Biofuels in Germany. *Energies*, 11(3):615, 2018. ISSN 1996-1073. doi: 10.3390/en11030615.

[48] Bradford F. Mills and Joachim Schleich. Profits or preferences? Assessing the adoption of residential solar thermal technologies. *Energy Policy*, 37(10):4145–4154, 2009. ISSN 03014215. doi: 10.1016/j.enpol.2009.05.014.

[49] Kalai Ramea, David S. Bunch, Christopher Yang, Sonia Yeh, and Joan M. Ogden. Integration of behavioral effects from vehicle choice models into long-term energy systems optimization models. *Energy Economics*, 74:663–676, 2018. ISSN 01409883. doi: 10.1016/j.eneco.2018.06.028.

[50] Julia Repenning, Lukas Emele, Ruth Blanck, Hannes Böttcher, Günter Dehoust, Hannah Förster, Benjamin Greiner, Ralph Harthan, Klaus Hennenberg, Hauke Hermann, Wolfram Jörß, Charlotte Loreck, Sylvia Ludig, Felix Matthes, Margarethe Scheffler, Katja Schumacher, Kirsten Wiegmann, Carina Zell-Ziegler, Sibylle Braungardt, Wolfgang Eichhammer, Rainer Elsland, Tobais Fleiter, Johannes Hartwig, Judit Kockat, Ben Pfluger, Wolfgang Schade, Barbara Schlomann, Frank Sensfuß, and Hans-Joachim Ziesing. Climate protection scenario 2050 (Klimaschutzszenario 2050): 2. Endbericht -Studie im Auftrag des Bundesministeriums für Umwelt, Naturschutz, Bau und Reaktorsicherheit. URL `https://www.oeko.de/oekodoc/2451/2015-608-de.pdf`.

[51] Cornelia Rönsch. Development of a method to use the data of the chimney sweep trade for the energy industry reporting (Entwicklung einer Methode zur Verwendung der Daten des Schornsteinfegerhandwerks für die energiewirtschaftliche Berichterstattung): PhD thesis (Dissertationsschrift).

[52] Jan Steinbach. *Model-based analysis of policy instruments to promote renewable energy and energy efficiency in the building sector (Modellbasierte Untersuchung von Politikinstrumenten zur Förderung erneuerbarer Energien und Energieeffizienz im Gebäudebereich)*. Dissertation, Fraunhofer-Institut für System- und Innovationsforschung and Fraunhofer IRB-Verlag, 2015.

[53] Jan Steinbach and Dan Staniaszek. Discount rates in energy system analysis: Discussion paper. 2015. URL `http://bpie.eu/uploads/lib/document/attachment/142/Discount_rates_in_energy_system-discussion_paper_2015_ISI_BPIE.pdf`.

[54] Immanuel Stieß and Elisa Dunkelberg. Objectives, barriers and occasions for energy efficient refurbishment by private homeowners. *Journal of Cleaner Production*, 48:250–259, 2013. ISSN 09596526. doi: 10.1016/j.jclepro.2012.09.041.

[55] Immanuel Stieß, Victoria van der Land, Barbara Birzle-Harder, and Jutta Deffner. Motives for action, obstacles and target groups for an energetic renovation of buildings (Handlungsmotive, -hemmnisse und Zielgruppen für eine energetische Gebäudesanierung).

[56] Dejin Su, Wenli Zhou, Yuandong Gu, and Bei Wu. Individual motivations underlying the adoption of cleaner residential heating technologies: Evidence from Nanjing, China. *Journal of Cleaner Production*, 224:142–150, 2019. ISSN 09596526. doi: 10.1016/j.jclepro.2019.03.113.

[57] Jacopo Tattini, Kalai Ramea, Maurizio Gargiulo, Christopher Yang, Eamonn Mulholland, Sonia Yeh, and Kenneth Karlsson. Improving the representation of modal choice into bottom-up optimization energy system models – The MoCho-TIMES model. *Applied Energy*, 212:265–282, 2018. doi: 10.1016/j.apenergy.2017.12.050.

[58] Umweltbundesamt. Renewable energies in germany (Erneuerbare Energien in Deutschland): Data on development in 2019 (Daten zur Entwicklung im Jahr 2019). URL `https://www.umweltbundesamt.de/sites/default/files/medien/1410/publikationen/2020-04-03_hgp-ee-in-zahlen_bf.pdf`.

[59] Annukka Vainio, Anna Pulkka, Riikka Paloniemi, Vilja Varho, and Petri Tapio. Citizens' sustainable, future-oriented energy behaviours in energy transition. *Journal of Cleaner Production*, 245:118801, 2020. ISSN 09596526. doi: 10.1016/j.jclepro.2019.118801.

[60] Giada Venturini, Jacopo Tattini, Eamonn Mulholland, and Brian Ó. Gallachóir. Improvements in the representation of behavior in integrated energy and transport models. *International Journal of Sustainable Transportation*, 13(4):294–313, 2018. ISSN 1556-8318. doi: 10.1080/15568318.2018.1466220.

[61] Pengfei Wei, Zhenzhou Lu, and Jingwen Song. Variable importance analysis: A comprehensive review. *Reliability Engi-*

neering & System Safety, 142:399–432, 2015. ISSN 09518320. doi: 10.1016/j.ress.2015.05.018.

[62] Julia Sophie Woersdorfer and Wolfhard Kaus. Will nonowners follow pioneer consumers in the adoption of solar thermal systems? Empirical evidence for northwestern Germany. *Ecological Economics*, 70(12):2282–2291, 2011. ISSN 09218009. doi: 10.1016/j.ecolecon.2011.04.005.

[63] Stefan Zundel and Immanuel Stieß. Beyond Profitability of Energy-Saving Measures—Attitudes Towards Energy Saving. *Journal of Consumer Policy*, 34(1):91–105, 2011. ISSN 0168-7034. doi: 10.1007/s10603-011-9156-7.

[64] Peter Zweifel, Aaron Praktiknjo, and Georg Erdmann. *Energy Economics*. Springer Berlin Heidelberg, Berlin, Heidelberg, 2017. ISBN 978-3-662-53020-7. doi: 10.1007/978-3-662-53022-1.