

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

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## Abstract

Energy system optimization models (ESOM) are widely used to inform about energy transition strategies. The heterogeneity of consumers, especially in the heat sector, is rarely considered in these model types. Integrating consumer heterogeneity and behavioral factors into ESOMs may generate new insights for energy policy. In this study a literature review was conducted, identifying empirical data on consumer behavior for adopting residential heating systems. This data was integrated into an ESOM for the German heat sector, combining established methods for integrating consumer heterogeneity and a novel approach for calculating indirect costs, representing behavioral factors. The incorporation of consumer choice leads to a higher diversity in technology market shares in a business as usual and an ambitious measures scenario. Especially, 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. Still, these findings need to be handled with care, since the empirical data basis and the methodological basis is limited.

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

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## 1. Introduction

Germany has set the target to reduce GHG emissions by 80–95% until 2050 compared to 1990, including emissions from the heat sector, responsible for 53.5% of the German energy demand [10]. The heat sector is not only from a technical view characterized by its heterogeneity. Beside varying heat demand profiles, applications and infrastructures, various stakeholders with different interests and consumer behavior are in place. For instance, millions of homeowners in the private household sector, consuming 43% of the German heat demand [10], make their own heating system investment decision. Hence, future market development is not only influenced by pure economically rational behavior. It is well known that private investment and consumption decisions can be influenced by many factors that deviate from the assumption of economic rationality [18, 27]. Energy system optimization models (ESOM) are widely used to inform about energy transition strategies. Investment behavior beyond economic rationality may influence future, projected market developments and raises a methodological challenge for ESOMs, which rely on the assumption of cost minimization.

In the heat sector, 14.5% of the heat demand was supplied by renewable energy sources in 2019 [54]. From over

32 Mio heating systems installed [1], ~ 12 Mio are bioenergy heating systems [1, 48], supplying the major share of renewable heating. Today, as well as in the future, a variety of bioenergy concepts are expected to provide renewable heating [25], also in a flexible way [33]. Bioenergy users are further influenced by e.g. the local availability of wood, for instance through forest ownership. Consequently, projections from ESOM's are limited and might be too optimistic or misleading for relying on cost minimization alone. Purely cost-based analyses need to be complemented with methods including consumer heterogeneity and behavioral factors influencing investment decisions beyond cost minimization, in order to inform policy.

There is a need to combine insights from energy transition disciplines investigating e.g. economic development, policy change or consumer behavior [12]. However, in ESOMs, consumer choice is often poorly represented, using e.g. hurdle rates, market share constraints or technology growth rates to smooth out projections [14]. Instead, modeling methods are required, based on strong theoretical support and conclusive empirical observations.

Methodological progress was made in recent years especially for ESOM projections in the transport sector. The most common approach, identified in reviews by DeCarolis et al. [14] and Venturini et al. [55], is to create different consumer segments to represent the heterogeneity in consumer choice [9, 11, 13, 34, 35, 37, 46, 53]. A bottom-up model structure with a high level of detail is identified to be

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most promising for this purpose [55]. Different approaches exist to incorporate more realistic consumer choice within the consumer segments. Some optimization models are linked with a nested nominal logit model (MNL)<sup>1</sup> [24]. Another approach is to introduce indirect costs such as disutility costs, the willingness to pay or the quantification of modal preferences via monetization of intangible costs [53] for the different technology concepts. McCollum et al. [36] first introduced disutility costs, allowing the consideration of (non-monetary) discomfort costs. This approach was carried on more extensively and applied in different model frameworks [9, 37, 46].

For the heat sector, only little progress in implementing consumer choice into ESOMs has been made so far, despite the heterogeneity of consumers. Cayla and Maïzi [11] conducted a survey and identified three key parameters influencing consumer choice in the French heat sector. Based on these three parameters, a segmentation in the TIMES model was conducted. Li et al. [35] also applies consumer segmentation for the heat sector in the UK TIMES model to represent technology investment behavior. The actual technology adoption behavior is then purely based on survey results, excluding economic factors. Influential factors on the investment decision are found to vary considerably among countries [35], and an application to the German case is therefore not applicable. To the authors' knowledge, investment behavior in relation to heating technologies in Germany has not yet been assessed in ESOM's.

For this study, a literature review was conducted, identifying behavioral factors influencing consumer heating system investment decisions beyond cost minimization. Subsequently, the identified empirical data 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 the actual heating behavior after the installation of the system, are not considered in this study.

The optimization model was developed and used in former studies to determine the optimal use of bioenergy in the German heat sector in different scenarios and under future uncertainties [19, 25, 26]. In this study, the model is extended, considering households' investment behavior for different heating technologies to produce more credible projections or policy insights and to assess the following research question:

- Which model projections develop in the German heat sector under consideration of consumer choice in different scenarios?

<sup>1</sup>The basic idea of multinomial logistic regression is the calculation of the probability that a certain event occurs by fitting data to a logistic curve [4].

## 2. Materials and methods

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

For the identification of empirical data on consumer behavior, which can be implemented into an ESOM, we proceeded in three steps: first, we conducted a literature review to identify behavioral factors influencing consumer investment decisions on 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 ESOM model.

The literature review was conducted in two phases. First, two publications that were randomly selected from the relevant literature [38, 50] 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. [28], a search strategy, inclusion and exclusion criteria were specified. The Google Scholar and Web of Science databases were searched using a combination of the identified keywords, as shown in Fig. 1. Thereby, all terms under A) were combined with B) and all terms of C); similarly, all keywords in boxes D) and E) were combined with each other. The search was conducted both in English and German language. 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 refurbishment, with hypothetical selection options, or a sole focus on heating behavior were excluded. This resulted in 16 publications relevant to assess the influences on consumers heating system choices in Germany.

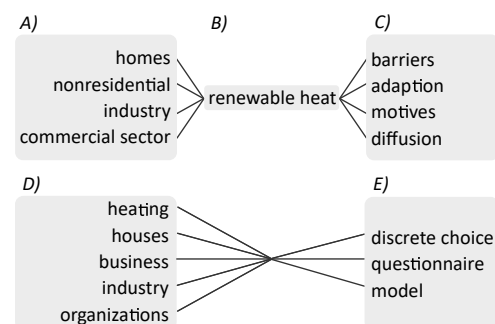


Figure 1: Keywords used in literature search. Keywords under A) were combined with B) and C); all keywords of D) and E) were combined with each other.

One finding of this literature review is that empirical data on heating system consumer choice is only available for single and two family houses. For multifamily houses, the trade and commerce sector as well as the industry no

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 [39], 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
	<i>Influence on value of the house</i>	Renewable heating	3
	Risk aversion/preference for certainty		2
	Preference for short amortization period	Gas/ Oil	2
	<i>Aversion against debt/ taking credit</i>		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
	<i>Concern for quality (e.g. fear of construction damage)</i>		2
	Attitudes regarding / evaluation of fuel type		1
heuristic/imperfect information processing	Incomplete / imperfect knowledge via different channels		6
	<i>Laziness, indifference (avoiding a complicated process)</i>	Gas/ Oil	3
	Imitation ( e.g. neighbors)		3

empirical data on consumer heating system choice could be found.

The 16 identified studies analyzing consumer choice in one or two family houses were reviewed in more detail and the identified factors influencing the consumer heating system choice were analyzed qualitatively and grouped into three categories, see Table 1. Beside financial motives, which were found to be influential in all studies, non-financial motives such as the comfort in operating and preferences on eco-friendliness of the heating system were most often found to be influential on the 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, which can be incorporated into an optimization model for the German heat sector, also representing the picture found in the literature review. For the optimization model, only data on the heating system choice is relevant, as the refurbishment of the building stock is an external input and not determined within the model. Additionally, data on fossil, bioenergy and alternative renewable technologies are sought for the modeling. Consequently, studies related exclusively to solar photovoltaics [29, 31], focusing only on one type of heating technology [7, 45, 57] or review studies [20], were excluded. As a result, three survey-based empirical data sets were found to be potentially suitable to be incorporated into the optimization model. These are described here in more detail.

Stieß et al. [52] surveyed 1009 homeowners in 2008 on the factors influencing their refurbishment decision and further analyzed the data [51, 58]. In this survey, the

choice of the 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. [16] surveyed 775 homeowners in 2007 on the motives of adopting a residential heating system. On the acquired data, a factor analysis and a cluster analysis was performed using a multinomial logistic regression model (MNL) [15–17]. One of the main findings is that mostly the membership to different ecological clusters influences the choice of a certain heating system. An ecological cluster is defined by the general attitude of a consumer towards environmental conservation. However, compared to other studies dealing with the purchase of a certain heating system, the response rate of the survey was at the lower end [15].

The empirical basis for the investigations of Michelsen and Madlener [38, 39, 40, 41] is a questionnaire survey (N=2440) conducted in 2010 among homeowners who had recently installed a residential heating system. A MNL model was applied on the data by Michelsen and Madlener [39]. As a result, motivational factors influencing the homeowners' decision on adopting residential heating systems (RHS) were identified. Additionally, by using a principal component analysis, a characterization of the motivational factors was conducted and the participants of the survey were grouped in 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 influential factors, which were grouped around six components by

Michelsen and Madlener [39]. The probability of belonging to one of the three clusters was predicted by means of a MNL model [39], considering the interaction of all 25 influential factors influencing the heating technology consumer choice, see also Tab. 2. The identified factors represent all of the factors identified in literature except for four, summarized in Tab. 1.

The empirical data of Michelsen and Madlener [39] are thoroughly analyzed, are one of the the latest with a high number of participants and the findings are mostly in line with the general findings of the literature review and the findings of Decker and Menrad [15]. Consequently, the results of Michelsen and Madlener [39] were selected in this study to be incorporated into the optimization model in order to represent consumer choice in the model.

Table 2: Identified clusters by Michelsen and Madlener [39]: The convenience-oriented (C1) RHS adopter is mainly motivated by comfort considerations and the general attitude towards the RHS. 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.) [39].

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

## 2.2. The optimization model

The optimization model was used in former research to determine the future, cost optimal use of biomass in the German heat sector under different long term climate mitigation scenarios [19, 25, 26]. In this study, the model structure and data is extended to represent the consumer investment behavior, see section 2.3. Apart from this extension and not setting a upper limit for greenhouse gas emissions, the same model formulations are applied as in Jordan et al. [25]. In this study, the model is used to project the future market development under the assumption of economically rational behavior of all actors, except for the behavioral aspects integrated into the model. This includes that all actors have perfect foresight, and future price and demand developments are known by the consumers.

The approach of the model follows BENOPT (BioENERgyOPTimisation model), which was developed for biofuels assessments in the transport sector [42–44]. The model structure is as follows: the three main sectors of the German heat sector, private household, industry and trade/commerce are further divided into several sub-sectors, with

different properties in terms of demand profiles and infrastructures. In total, 19 sub-sectors were 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 the industry and district heating. The future development of the heat demand in buildings is based on the external results of the building stock model 'B-STAR' [30], which models the future refurbishment of the German building stock in a yearly resolution using an agent based approach. Consequently, consumer choice on refurbishment decisions can not be represented in this model. Within the optimization model, for each sub-sector, representative bioenergy-, fossil- and other renewable (hybrid-) heat technology concepts are described [32], incl. e.g. gas boiler, heat pumps, direct electric heating, solar thermal, log wood, wood pellet and wood chip technologies. In total 23 biomass products (incl. wood based residues, log wood, straw, manure, two perennial crops and seven types of energy crops) and 3 fossil feedstocks are possible inputs [32]. For the single technology components, infrastructure emissions as well as the feedstock specific emissions are considered within the model.

The several 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, 21, 22]. This leads to different power prices in the heat sub-sectors (private household, trade/ commerce and the industry), despite applying the same projection for the stock market power price. A detailed description of the method and the applied time series are attached in the supplementary material.

The technological choice is optimized between 2015 -

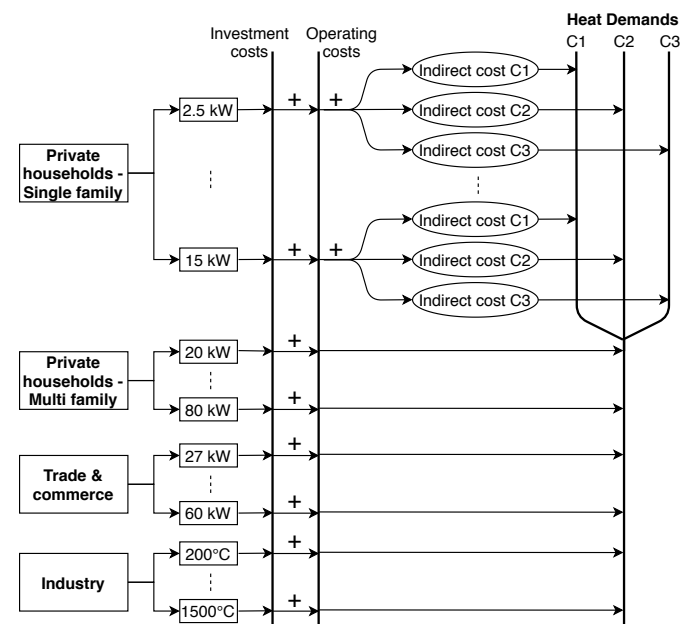


Figure 2: Schematic of applying indirect costs in the different consumer segments C1..C3 within the optimization model. The sub-sectors are defined by the size of the heating system, e.g. 2.5 kW.



2050 in a yearly resolution. The objective function is minimizing the total system costs over all technologies, sub-sectors and the complete time span, using the Cplex solver for the linear optimization problem. The spatial boundary is Germany as a whole and the sectoral coverage exclusively includes 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. [25]. Detailed economic and technical data of the technology concepts can be found in a data publication [32].

### 2.3. Integrating consumer behavior into the optimization model

The integration of consumer choice for adopting residential heating systems is based on the investigations of Michelsen and Madlener [38, 39, 40, 41]. Specifically, the results from the cluster analysis and from the analysis predicting cluster membership are used in this study [39], see Tab. 2. The cluster segmentation is the basis for splitting the relevant heat sub-sectors into consumer segments, the same approach as in Li et al. [35]. In this case, the heat demand of all five single-family sub-sectors, responsible for  $\sim 23\%$  of the German heat demand, were further segmented into three consumer segments (C1..C3) each, representing the identified clusters from Michelsen and Madlener [39]. A schematic of how the consumer segmentation and the application of indirect costs is realized in the model is shown in Fig. 2.

As shown in section 2.1 the adoption of a heating system is mostly driven by financial motives, but also by non-financial motives (mainly comfort and environmental reasons, see Tab. 1). The financial aspects are comprehensively represented 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 literature [9, 36, 37, 46, 53]. In this case, the indirect costs are derived from the membership prediction of different heating systems to 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  $c_1/c_2$  [59], with the parameter  $g$  indicating the extent to which cost differentials between competing technologies affect their market shares.

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

As a conclusion derived from this causality, an increased probability of technology market shares (probability of cluster membership, see Michelsen and Madlener [39]) is

Table 3: Indirect cost factor (icf) derived from the M.E., see Table 2 for the different consumer segments (C1..C3). As there is no differentiation for 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 average of the applicable M.E..

	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

translated into a decrease in costs and vice-versa. Since market shares in the optimization model are purely based on costs, represented in the objective function, we here 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 implemented into the objective function by adding the inverted indirect technology costs proportional to the investment and variable costs of each technology, see equation (2). With this method, also negative indirect costs can apply, representing a willingness to pay.

### Objective function

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

subject to

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

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

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

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

For the incorporation of consumer choice, four additional restrictions were added to the original model formulation, which is described in Jordan et al. [25]. The heat demand  $\delta$  in each cluster  $c$  of the five sub-sectors  $s$  needs to be fulfilled by the sum of the produced heat  $\pi$  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 with their individual capacity  $\kappa$  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 technologies and limited to 1%/a. This restriction is not set within the clusters, i.e. consumers/heating systems can switch the 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 the implementation of consumer choice. In the BAU scenario energy prices are kept at a constant level and no CO<sub>2</sub> pricing is in place. Additionally, current investment incentives for heat technologies are considered (except for biogas feed-in compensation) and a moderate refurbishment rate is assumed.

In the AMS scenario, energy only prices are increasing moderately and an ambitious CO<sub>2</sub> pricing, constantly increasing up to 200 €/tCO<sub>2</sub>eq in 2050 is set. The CO<sub>2</sub> price increase is derived from current scenario analysis projecting prices in that range to reach a 95% reduction target

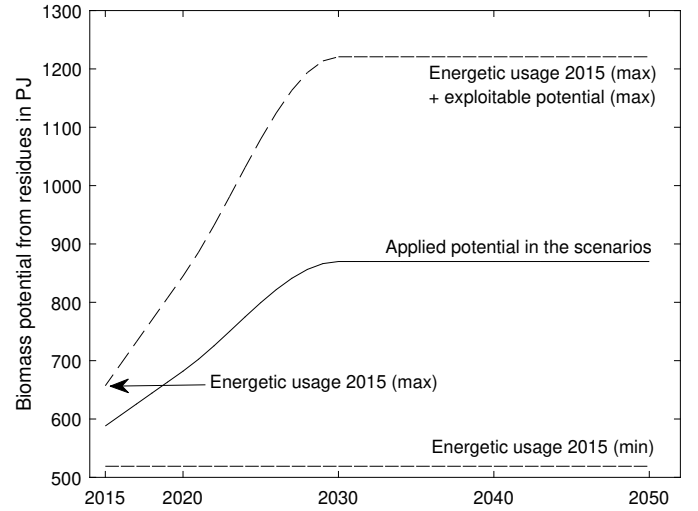


Figure 3: Applied biomass potential from residues derived from national monitoring of residues [3, 8]. The range between the upper and lower curve is investigated in the sensitivity analysis.

[47]. 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.

A few parameters are set equally in all four scenarios: in the power sector GHG emissions are assumed to decrease linearly until 2050 (17 gCO<sub>2</sub>eq./kWh in 2050). Further, the national potential for biomass residues is derived from the upper and lower range of the 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 ~70% is pre-allocated to the heat sector (incl. CHP applications) within the model, according to the method described in Jordan et al. [25].

Finally, the variance-based sensitivity analysis of Sobol' was applied on the model to systematically assess which uncertain input parameters affect the model output. A special focus is laid on the effect of applying consumer choice within the model, also 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

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 <sub>2</sub> price	not in place	act. status → 200 €/tCO <sub>2</sub> eq.
Refurbishment	1-2%/a	2-3%/a
Incentives	Investment subsidies valid until 2019	Investment subsidies valid from 2020
Consumer choice	yes /no	yes /no

the Sobol' method is applied to the optimization model can be found in Jordan et al. [26].

### 3. Results and discussion

The results show that future log wood, wood pellet and also heat pump technology market shares are less represented in the BAU scenario without consumer choice being applied, see Fig. 4. A typical picture for optimization results develops: only a few technologies gain the major market shares compared to the wider portfolio of the starting year. When heterogeneous consumer choice is implemented in the BAU scenario, the market shares of the starting 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 the bioenergy market shares shows the effect on the 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 former studies, where this technology option was found to be a robust result [26]. In contrast, when applying consumer choice, log wood and wood pellet technologies in the private household sector keep constant market shares or increase their market shares slightly. Nevertheless, the

technology type remains, but a switch in the technology concept occurs: the use of log wood switches from gas boilers combined with a log wood stove and a solar thermal system to the use 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 the use in buffer integrated pellet burners combined with solar thermal.

For the ambitious measures scenario a similar picture develops. Without applying consumer choice, biomass is distributed to the industry and the use of biomass in the private household sector nearly completely phases out, see Fig. 4 and 5. If consumer choice is applied, the general trend that most of the biomass is competitively used in high temperature industry applications remains. 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.

A detailed depiction of the market shares within the introduced consumer segments of the five single family sub-sectors shows that the method of implementing consumer choice leads to the expected results, see Fig. 7 and 8. 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 [39], 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 repre-

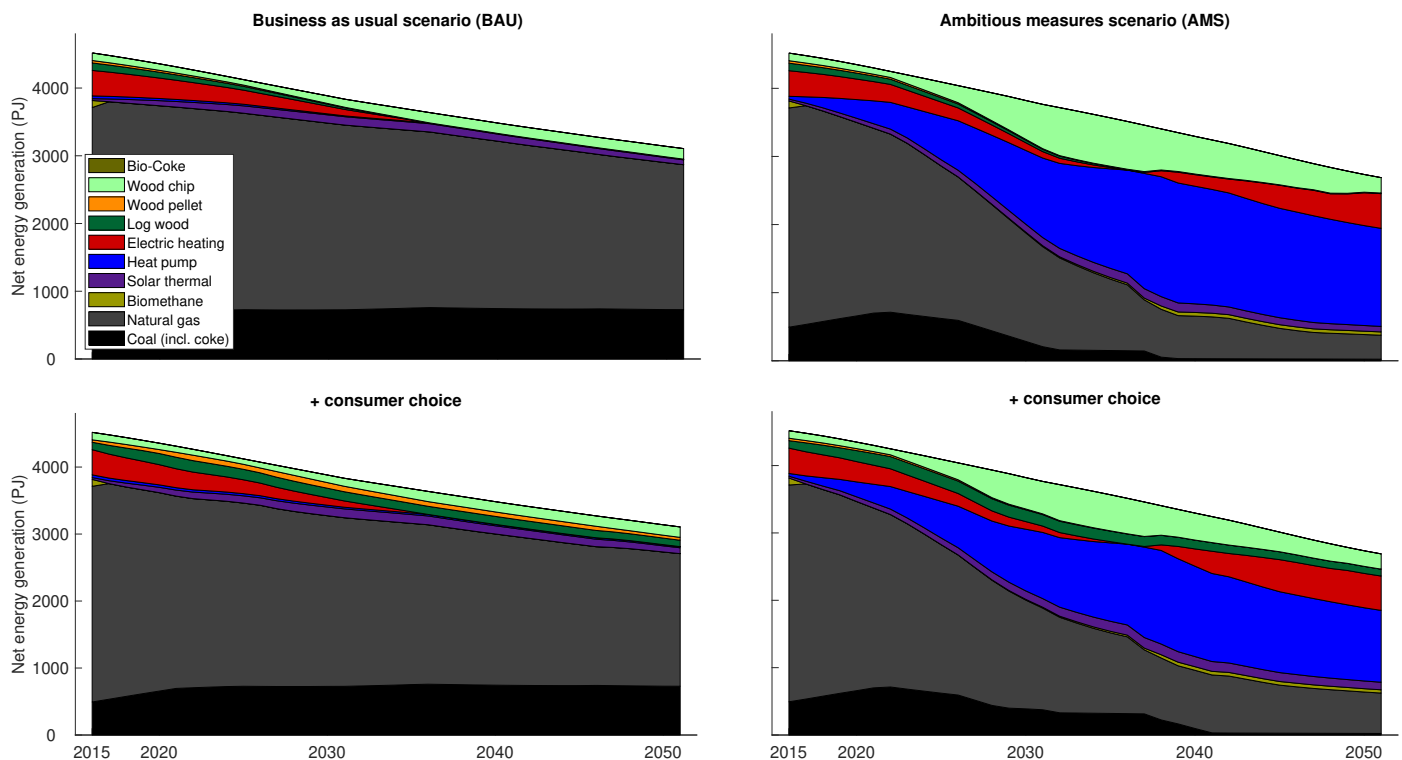


Figure 4: Model resulting development of the technology market shares for the complete heat sector for the different scenarios in a yearly resolution.

sent a high insulation standard and in this case the price advantage of heat pumps or gas technologies rule out the non-economic factors. In addition, the survey on which the identified consumer choices are based on, was conducted in 2010. At this time, houses with such high insulation standards were underrepresented and therefore not in the scope of the survey.

In general, we can see that implementing consumer choice leads to a higher diversity in technology market shares and the 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, a validation of that conclusion was not done and would require historical data and a calibration of the model.

Based on the findings in this study, one could conclude that log wood market shares were underrepresented in former studies. Jordan et al. [25] 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 under investigated scenarios. In addition, a sensitivity analysis identified that the use of biomass in great amounts of log wood is not a robust result, indicated by a low penetration of high log wood shares over a wide range of outcomes [26]. In this study we show, that the consideration of consumer choice has an impact on log wood market shares in the investigated scenarios and also in the sensitivity analysis, see Fig. 6. The integration of consumer choice is identified to be significantly influential on log wood market shares, represented by a high Sobol' index.

However, investment motives in regard to log wood tech-

nologies were not differentiated from wood pellet technologies in the survey conducted by Michelsen and Madlener [38]. Consequently, the indirect cost factor in the model was set equal for both, wood pellet and log wood options, which can be discussed. Consumer choice is driven by economic, ecological, comfort and individual factors, among others. Pellet and log wood technologies have e.g. different comfort properties. While a pellet burner runs automatic, a log wood stove has to be piled up at least once a day. On the other hand, log wood might be easily available for forest owners, leading to the installation of a log wood heating system. This has to be kept in mind, when interpreting the results from this study. For future investigations, a more detailed survey on homeowners' investment decisions in regard to further differentiated heating technologies would be desirable.

**Limitations:** Even though we could show that the integration of consumer choice leads to a higher diversity in technology market shares and the model delivers more plausible results, the data basis for implementing consumer choice into the model is attached with uncertainty and the methodological possibilities are limited. In this study, the survey-based empirical data is limited to consumer behavior of homeowners in single family houses. Data on consumer behavior for multi-family houses or the heat consuming industry is not available on a national scale. One could assume, that in these sectors investment decisions are purely driven by economical motives. A review of company guidelines, ISO standardizations, annual and sustainability reports of the major heat consuming companies in the German industry did not lead to any conclusive findings that factors other than economic mo-

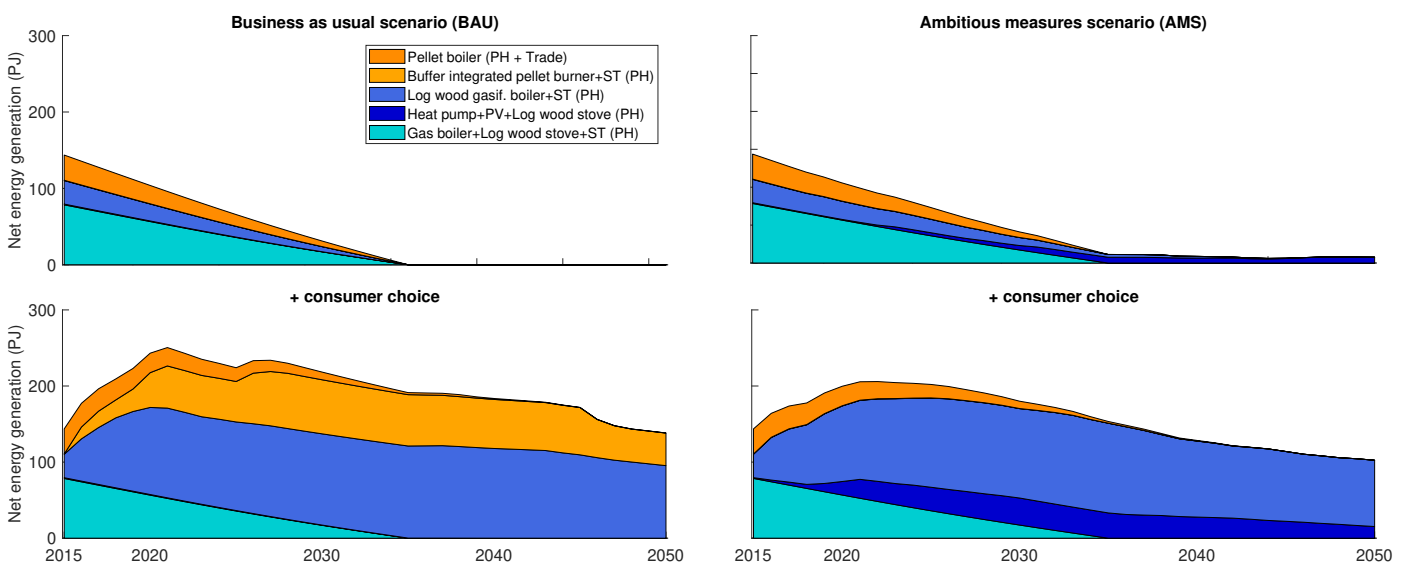


Figure 5: Net energy market shares of the relevant bioenergy technologies in the private household sector. Within the figure only the relevant bioenergy technology concepts are shown, leaving out fossil references, alternative renewable technologies and irrelevant bioenergy concepts. For hybrid systems, 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.



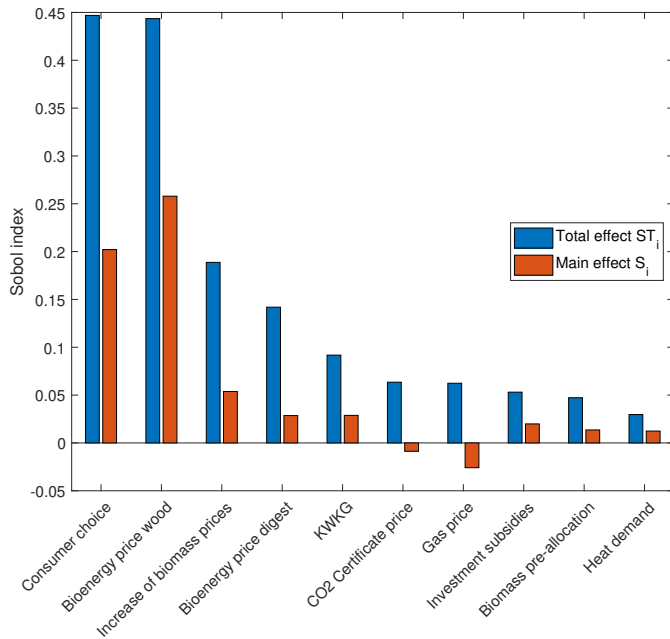


Figure 6: Sobol' indices on log wood market shares from 2030-2050 for the most influential input parameters. Both Sobol' indices range from 0 to 1.  $ST_i \geq S_i \geq 0$ . If  $ST_i = S_i = 0$  the parameter is non-influential. If  $ST_i = S_i$  there is no interaction of the  $i^{th}$  parameter with 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 [56].

tives, influence heating technology investment decisions.

In addition, the available data for single family houses represent the status quo of the year 2010. Behavior changes over the course of time, see e.g. Borgstedt et al. [6]. This factor can have a decisive impact, especially when modeling a long time frame until 2050. However, a projection of future consumer behavior in relation to heating system investment decisions is not available today. The identification of factors that drive such a change could help to improve such projections. For future research, empirical data on consumer behavior of especially multi family house owners and stakeholders in the heat consuming industry would be desirable to improve the representation of consumer choice for the complete heat sector.

The method of how to integrate consumer choice into the optimization model is partly a novel approach. The concept of creating different consumer segments to represent the heterogeneity in consumer choice is an established method [9, 11, 13, 34, 35, 37, 46, 53]. Applying indirect or intangible or disutility costs in these segments is also a common approach. For the actual procedure of how to calculate the indirect costs, representing the consumer investment decisions, no standard methodological approach could be identified. In all reviewed papers, indirect costs were calculated in a unique way for each case. In this study, an increase in technology market share probability is translated into indirect costs. This method is derived from economic theory, stating that market shares of

two technologies should be inversely related to their relative cost [59]. 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. On the contrary, methodological alternatives are rare. Hedenus et al. [23] describe the use of distribution functions to make model results more diverse and constrain 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. Agent based models are suitable to process probability data as e.g. marginal effects, see Steinbach [49]. With agent based models, micro economic behavior can be modeled resulting in macro economic effects. However, optimal economic transition pathways can not be determined with this model type and if the quality of the solution is important, traditional approaches as optimization tend to outperform agent-based approaches [5].

#### 4. Conclusions

For the first time, consumer behavior was integrated into an ESOM for the German heat sector. In the model, consumer heterogeneity and behavioral factors influencing investment decisions beyond cost minimization could be represented. The results show, that the integration of consumer choice leads to a higher diversity in technology market shares and therefore more plausible results develop. Established methods representing consumer heterogeneity and a novel approach for calculating indirect costs were combined to represent consumer investment decisions in the model. The performed method can serve as a case study or inspiration for other researchers and helps to inform policy about energy transition strategies, also considering consumer heterogeneity and behavioral factors influencing investment decisions beyond cost minimization.

In the case of Germany, we were able to show 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, which needs to be addressed. In particular, the future role of log wood and pellet technologies may have been underestimated in former 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 preferred technologies. In the future, the economic advantages of heat pumps in high insulated houses rule out non-economic preferences and lead to exclusive sub-sector market shares of these technologies.

For future investigations, the extended model offers the possibility to describe the effect of different funding instruments, under consideration of consumer choice. For

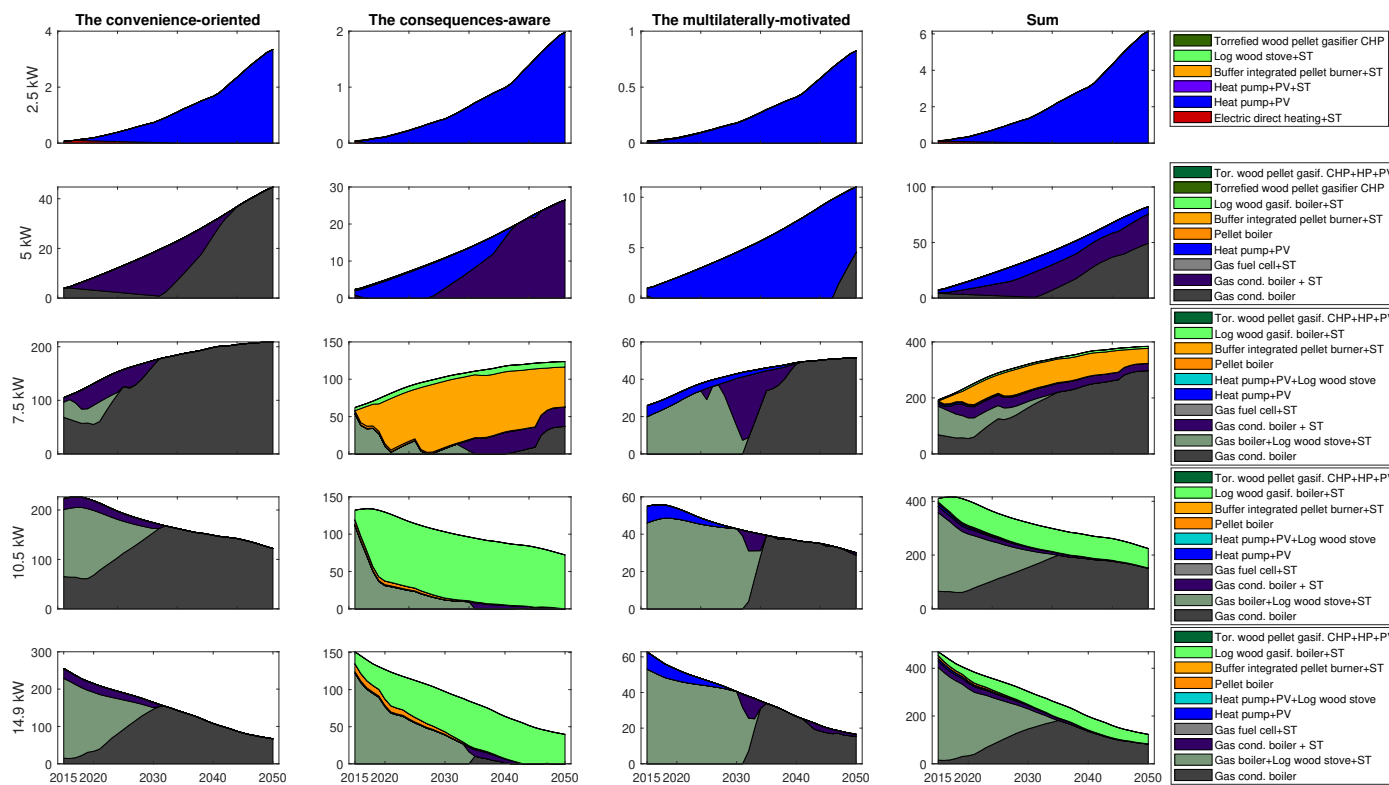


Figure 7: Net energy technology market shares in the consumer segments of the five single-family sub-sectors in the BAU scenario considering consumer choice (in PJ). CHP = Combined Heat and Power; HP = Heat Pump; PV = Photovoltaic; ST = Solar Thermal.

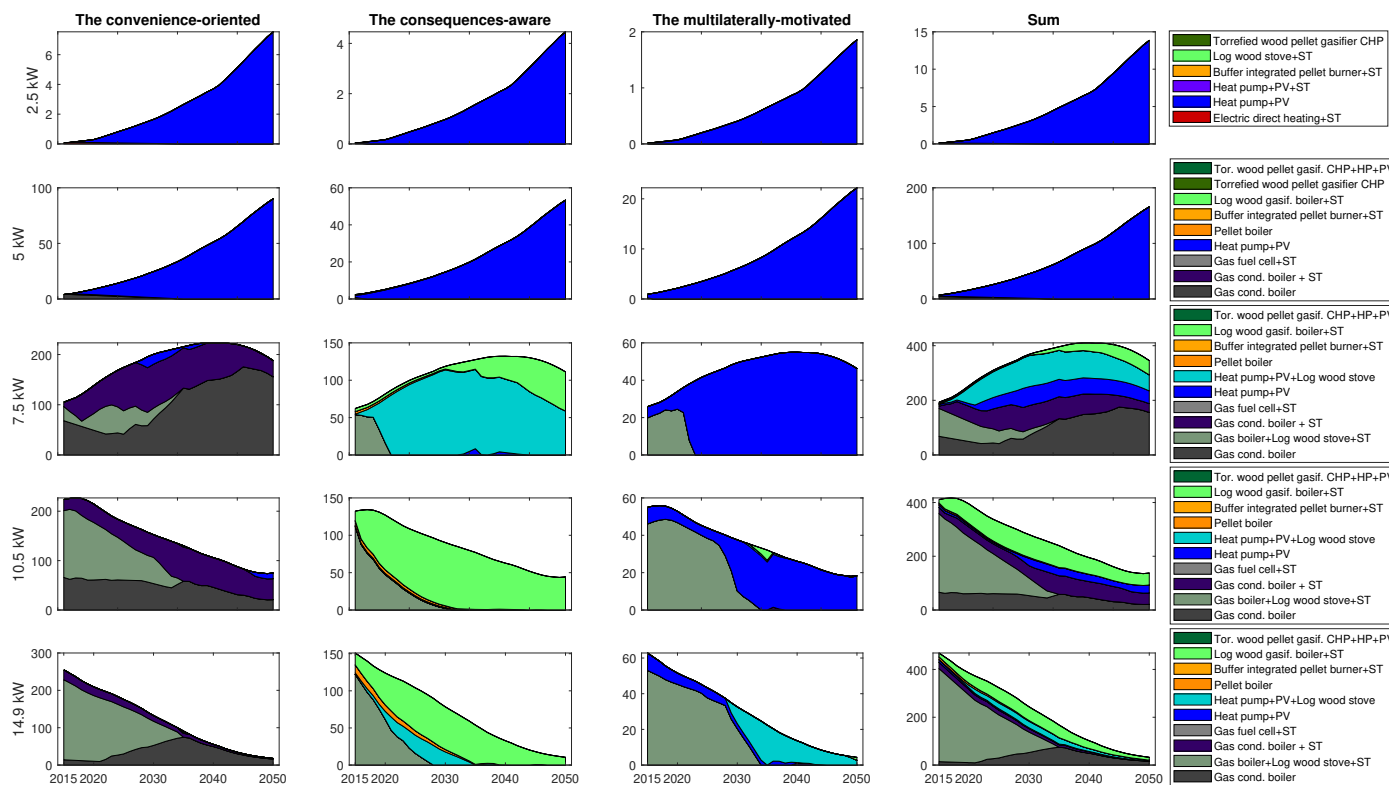


Figure 8: Net energy technology market shares in the consumer segments of the five single-family sub-sectors in the ambitious measures scenario considering consumer choice (in PJ). CHP = Combined Heat and Power; HP = Heat Pump; PV = Photovoltaic; ST = Solar Thermal.

this purpose, more recent and detailed empirical data on homeowners' investment decisions in regard to further differentiated heating technologies are desirable. In addition, further methodological progress, as e.g. a model calibration, should be strived for to provide policy insights with a high level of confidence.

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## 6. Appendix A. Supplementary data

Supplementary data related to this article can be found at ...

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