Working Paper Sustainability and Innovation
No. S 20/2018

Mark Olsthoorn
Joachim Schleich
Katharina Wohlfarth
Marian Klobasa

How much load flexibility can a euro buy?

Findings from a choice experiment with companies in the German commerce and services sector

Fraunhofer
ISI

Abstract

Demand-side load management is considered a cost-efficient solution for accommodating growing shares of intermittent renewable electricity production. Here, we use double-bounded dichotomous choice (DBDC) contingent valuation (CV) to estimate the effectiveness of a subsidy for companies to make available their HVAC and cooling systems for automated load management. Our sample includes 1131 companies in the German commerce and services sector with ≥10 employees of which we elicit the willingness to accept (WTA) automated load management in exchange for an annual subsidy payment. To our knowledge, our study is the first CV study on load management among companies.

Key words: load management, demand response, subsidies, contingent valuation

Acknowledgement: This work has been financially supported by the German Federal Ministry for Economic Affairs and Energy in the context of the project "EnSYS-FlexA – Flexible demand as an important contribution to the energy transition and a building block in the energy system analysis" as a part of the 6th Energy Research Program of the Federal Government.

Table of Contents

Page

1 Introduction

Demand-side load management is considered a key and cost-efficient strategy to help integrate fluctuating renewable energy sources into the electricity system and thus to meet climate and energy security targets in many countries (e.g. Barton et al. 2013; Siano 2014). For example, the energy “Winter Package” proposed by the European Commission in 2016 also highlights the importance of load management while generally foreseeing a more active role for consumers to play in the future electricity market (EC COM(2016) 864 final 2). The value of load management will be particularly high at times when the feed-in from renewables is low while electricity demand is high, and when the feed-in from renewables is high but electricity demand is low. Load flexibility potentials may be offered at the spot or the balancing markets. Special importance is also given to the building sector, where users should be encouraged to use ICT and smart technologies to ensure an efficient operation of the building (EC COM(2016) 765 final).

Supply of such flexible loads may be incentivized via time-of-use (TOU) pricing, i.e. dynamic pricing, real time pricing or critical peak pricing (CPP). With CPP, customers receive prior notice when they will face particularly high prices during certain times of some days. Thus, CPP provides particular incentives to shift loads. TOU pricing involves voluntary demand responses and has mostly been studied for the residential sector[1]. In contrast, with controllable demand response such as direct load control and interruptible load programs, customers allow their system operator to automatically curtail their electricity demand under certain, pre-specified conditions. For example, to support the German energy transition (*Energiewende*), which foresees an 80% share of renewable energy sources in the power mix by 2050, the recent Ordinance on Agreements on Sheddable Loads (Sheddable Loads Act, AbLaV 2016) incentivizes electricity consumers to offer their flexible loads.[2] To qualify, providers of flexible loads have to comply with certain requirements such as a prequalification of the flexible appliances and minimum bids. Thus, only large companies are currently

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1 For an overview see Faruqui and Sergici (2010). The empirical studies analyzing the response of industrial and small commercial electricity usages to TOU pricing include Hirshberg and Aigner (1983), Jessoe and Rapson (2014), Faruqui et al. (2015), and Qiu et al. (2018).

2 Accordingly, industrial electricity consumers may receive €500 per MW per day and €400 per MWh offered.

offering loads under this ordinance. While TOU pricing primarily affects the wholesale spot market, load management primarily affects the balancing market.

Several engineering-economic studies have assessed the technical potential for load shift in Germany, thereby typically focusing on electricity-intensive production processes in large manufacturing (e.g. Dena 2010; Apel 2012; Klobasa et al., 2013a; Ausfelder et al. 2018). The findings suggest that these companies may provide flexible loads of up to ca 5 GW, corresponding to ca. 2.5 percent of total installed electricity generation capacity in Germany. Few studies have explored the technical flexibility potential in the commerce and services sector, which contributes to 29% to the electricity consumption in Germany (AGEB, 2015)[3]. While production processes determine the flexibility potential in the industrial sector, cross-sectional technologies define the load flexibility potential in commerce and services sector. Ventilation, air-conditioning and cooling/freezing services appear to offer the largest potentials for load management (Klobasa 2007; Apel 2012; Gils 2014). So far though, only a small fraction of these technical potentials is realized. Barriers to realization include inadequate regulation (e.g. Rüster et al., 2014), and, especially for the manufacturing sector, the perceived risk of disruption of production operations, negative impacts on product quality, investment costs, and uncertainty about cost savings (Olsthoorn et al. 2015).

For load flexibility from cross-cutting ancillary technologies or for cooling/freezing services, little is known about the potential, its responsiveness to financial incentives, or to particular design features of controllable demand response contracts. Also, no study has yet explored the factors explaining heterogeneity in company response to incentive payments. Aiming to fill this gap, this paper explores the required financial incentives to promote flexibility measures, and how these incentives relate to duration and to the frequency of the measure, whether it can be activated any time or only during agreed-upon times, and how the required incentives vary with company characteristics such as experience with load shift. The flexibility measures considered provide ventilation, air-conditioning, cooling and freezing services in the commerce and services sector.

3 The German energy balances partitions final energy consumption into four end-use sectors: industry, private households, transportation, and the combined commerce and services sector.

Methodologically, our empirical analysis relies on contingent valuation choice experiments carried out in a survey of nearly 1600 companies in Germany in 2017. With the large and fast-growing share of renewable electricity resulting from its *Energiewende*, realizing cost-efficient load flexibility potentials is particularly relevant in Germany (Müller and Möst, 2018). Respondents' choices are used to estimate (for each technology) the probability that companies participate in the proposed load shift measure as a function of the subsidy offered, and to construct curves for the specific subsidy costs – i.e. the costs of load shift (in €/MWh). Further simulations explore the potential of these load shift measures for Germany. Our estimates for the subsidies required to offer demand flexibility are also compared to the prices at the balancing markets, and to the costs of other flexibility options such as battery systems. Thus, our findings are expected to provide tentative guidance for designing efficient controllable demand response programs and to contribute to an overall cost-efficient supply of flexibility options.

The remainder of the paper is organized as follows. Section 2 presents the methodology, describing an analytical model to evaluate the effectiveness of a subsidy policy, the company survey, and the choice experiment. Section 3 presents the results, showing findings for subsidy levels across technologies and for the determinants of the subsidy level. Section 3 also includes simulation analyses on the efficiency of subsidies across technologies and compares findings with prices on the markets for flexibility. Finally, section 4 summarizes and discusses our main findings and identifies policy implications.

2 Methodology

In this section, we first present a simple analytical model for evaluating the effectiveness of a subsidy payment for load shift/curtailment in firms. Then, we describe our survey, the choice experiment, and the econometric model that we employed to estimate the subsidy level and to conduct simulations. Finally, we present the data by including the descriptive statistics of the choice experiment and the firm characteristics used as covariates in our econometric model.

2.1 Analytical model of subsidy effectiveness

The model presented in this section will be parameterized with econometric estimates based on a contingent valuation survey and from information on participants' load flexibility measures elicited from the survey and the literature. Specific cost curves will then be constructed as a function of the subsidy level, which allows simulating the effects of a subsidy/controllable demand response program for various load shift measures (here: ventilation, air conditioning, cooling and freezing).

For a particular measure, the specific payment *c* are the subsidy level *S* per average load shift Δl (curtailment) per adopted measure

(1) $$c = \frac{S}{\Delta l}$$

The total expenditure for payments C is then

(2) $$C = N_{adopt} \times S$$

where N_{adopt} is the total number of firms adopting a particular load management measure if S > 0. N_{adopt} = 0 if *S* = 0, i.e. we assume that firms would not implement those measures if there was no subsidy payment. This also means that there is no free riding.

We denote the number of adopters as:

(3) $$N_{adopt}(S) = N_{pop} \times b(S), \text{ for } S > 0$$

Where N_{pop} stands for the population of firms, and $b(S)$ is the probability of adoption, i.e. Pr(adoption | S); $b(S)$ is a function of the subsidy *S* with $b'(S) > 0$ (for $S > 0$).

Total program costs are then:

(4) $$C = N_{pop} \times b(S) \times S$$

The load shift potential by all adopters ΔL can be written as:

(5) $$\Delta L = b(S) \times N_{pop} \times \Delta l$$

Note that dividing total costs C, i.e. equation (4), by the total load shifted via the subsidy program ΔL, i.e. equation (5) yields specific subsidy costs *c*, i.e. equation (1).

As further detailed in section 2.4., we employ a double-bounded willingness-to-accept choice experiment and interval data model estimation to predict the probability of adoption and to estimate $b(S)$.

2.2 Survey

A standardized quantitative survey on companies of the German commerce and service sector was conducted between May and July 2017, with the help of a market research institute (Gesellschaft für Konsumforschung, GfK). Our focus was on companies from the subsectors displayed in Table 1. These account for more than 50% of electricity consumption of the commerce and services sector (Schlomann et al, 2015). In addition, these subsectors avail of large shares of flexible cross-sectional appliances. A total of 1587 companies completed the survey. We made sure to achieve at least 100 responses in each of the subsectors office-type firms, retail/wholesale, and hospitality. Sampling prioritized medium-size and large companies because we expect larger firms to possess most load management potential.

The interviews took about 30 minutes and were conducted with the person in charge of energy issues at each company by trained interviewers via computer assisted telephone interviews (CATI). The items of the survey covered, among others, companies' characteristics, experiences with load management, perception and readiness towards load management, technical information on availability of flexibility options and a hypothetical choice experiment to elicit participants' willingness to participate in a controllable load management program for varying subsidy payments. Before leading the participants to the choice experiment, more general questions about electricity consumption and appliances were asked.

The survey also included a question to rate participating companies' willingness to implement automated load management. Only participants who expressed some willingness to implement (a rating between "maybe" and "definitely yes") were asked to participate in the choice experiment. This left us with 342 companies considered to be "in the market" for automated load management and to respond, with increased probability, from an informed position.

Table 1 shows the structure of our subsample of interested companies compared to the total of Germany. The numbers show that companies from the sectors trade with food and companies including restaurants are overrepresented in our subsample compared to the distribution of companies in Germany.

Table 1: Structure of the subsample in comparison the total in Germany

Sector	Number of employees	Compa-nies in subsample	Share within Subsectors	Compa-nies in Germany (2015)	Share within Subsector	Share in subsample	Share in Germany
Office-type	1 - 9	16	13.6%	1,061,984	93.5%	34.5%	60.3%
	10 - 49	42	35.6%	54,678	4.8%		
	≥ 50	60	50.8%	19,024	1.7%		
Retail food	1 - 9	3	7.9%	60,190	89.7%	11.1%	3.6%
	10 - 49	22	57.9%	5,844	8.7%		
	≥ 50	13	34.2%	1,074	1.6%		
Retail Non-Food	1 - 9	11	36.7%	298,214	92.3%	8.8%	17.2%
	10 - 49	11	36.7%	21,623	6.7%		
	≥ 50	8	26.7%	3,375	1.0%		
Wholesale Food	1 - 9	2	13.3%	17,296	81.7%	4.4%	1.1%
	10 - 49	6	40.0%	3,053	14.4%		
	≥ 50	7	46.7%	831	3.9%		
Wholesale Non-Food	1 - 9	4	14.3%	72,190	79.5%	8.2%	4.8%
	10 - 49	8	28.6%	14,334	15.8%		
	≥ 50	16	57.1%	4,306	4.7%		
Hotel with restaurant	1 - 9	10	20.8%	26,986	86.2%	14.0%	1.7%
	10 - 49	28	58.3%	3,520	11.2%		
	≥ 50	10	20.8%	805	2.6%		
Hotel without restaurant	1 - 9	2	28.6%	16,002	88.1%	2.0%	1.0%
	10 - 49	5	71.4%	2,060	11.3%		
	≥ 50	0	0.0%	103	0.6%		
Restau-rants	1 - 9	19	32.8%	185,215	95.1%	17.0%	10.3%
	10 - 49	27	46.6%	8,508	4.4%		
	≥ 50	12	20.7%	1,018	0.5%		
Total		342		1,882,233			

We excluded the smallest category of companies (1-9 employees) from our analyses, because they are considered to have relatively low potential. This improves representation but reduces the subsample to 275 companies.

2.3 Choice experiment

With the subsample of 275 firms, we conducted a choice experiment on automated load management. Each company was asked to answer choice questions regarding two randomly selected technologies from a set of six with potential flexibility: ventilation, air conditioning, refrigeration, freezing, heat pump, cogeneration. If a company did not avail of a selected technology, the observation was recorded as missing.

Table 2 shows how many of the eligible companies responded by technology. Of the 275 eligible companies, 34 did not have any of the two randomly selected technologies and 112 availed of only one of the two. Very few companies appeared to have a heat pump or a cogeneration installation. The small number prohibits application of econometric analysis to those two technologies, which is why they are excluded from our analyses. That leaves us with 237 companies that participated in the choice experiment for at least one of four technologies: ventilation, air conditioning, cooling, and freezing.

Table 2: Distribution of eligible, responding companies across combinations of technologies.

	2nd technology						
1st technology	Air conditioning	Refrigeration	Freezing	Heat pump	Cogeneration	None	Total
Ventilation	46	32	11	1	5	18	113
Air conditioning	0	15	6	2	5	50	78
Refrigeration	0	0	34	0	5	6	45
Freezing	0	0	0	0	1	0	1
Heat pumps	0	0	0	0	0	1	1
Cogeneration	0	0	0	0	0	3	3
None	0	0	0	0	0	34	34
Total	46	47	51	3	16	112	275

For each type of measure the structure of our choice experiment questions is outlined in Figure 2. The choice experiment design is similar to Alberini and Bigano (2015) and Olsthoorn et al. (2017) to analyze rebates and free riding, respectively, in the context of heating system replacement by private households.

The experiment part of the survey first described a hypothetical load curtailment measure. Respondents were asked to imagine that one of the six energy-using technologies, say the ventilation system, was switched off regularly for a certain period of time. In return the respondents would receive a yearly compensation payment from their electricity provider. To this end, the ventilation system would be equipped with control technology enabling external controlling of the ventilation system. The participating firms were informed that they would not have to bear any of the costs for these control technologies. They were further told that all air quality standards (or equivalent for other applications) would be met, but that tolerance levels would be exploited more flexibly. The firms were assured that, in case of need, they would be able to take back control over their systems at any time. In this case, compensation payment would be adjusted downward pro rata. The subsidy is therefore assumed to reflect respondents' perceived net costs of shifting these loads.

To contain a potential hypothetical bias, we used a cheap talk design. Prior to making their choices, respondents were told that people in general respond differently when asked to make hypothetical choices. They were asked to put themselves into the situation of their firm when answering to the subsequent questions.

The choice experiment proposed a load curtailment measure which was characterized by a given *frequency* and a given *duration* in addition to a given annual *payment*. *Frequency* referred to the number of times (per day or week) the measure would be implemented. *Duration* referred to the length (in minutes) the measure would be effective if implemented. In addition, any load curtailment was either restricted to agreed time slots only or could be activated any time.[4] Table 3 shows the levels of the attribute for each application.

Table 3: Attribute levels by application

Attribute	Ventilation	Air conditioning	Refrigeration	Freezing
Payment (Euros)	250/500/1000/1500/ 2500	250/500/1000/1500/ 2500	500/1000/2000/ 4000/8000	500/1000/2000/ 4000/8000
Frequency	2 times daily / daily / weekly			
Duration (minutes)	30 / 60 / 90			
Time constraint	Can be activated any time / at agreed time slots only			

4 These attributes were identified in the literature as being relevant features of load management options (e.g. Klobasa et al. 2013b).

Since data on the costs of providing flexibility is not available for these measures, they had to be estimated. Regarding the payments, we based our assumption on the findings of a study on load management in the German industry (Klobasa et al., 2013b). Accordingly, to participate in load management measures, companies expect incentive payments corresponding to about 15% of their annual electricity costs. To transfer these findings to our case, we estimated the share of electricity costs of each appliance using the data available on energy consumption of the tertiary sector (Schlomann et al., 2015). For the technologies considered in our study, this resulted in incentive payments ranging between 5% and 25% of the annual electricity costs for the companies considered.

Besides the subsidy, the duration and the frequency of the load curtailment were chosen as additional attributes of the proposition. We expected both attributes to have an influence on the willingness to accept. the required payment to use the specific appliance for load management. Both attributes influence the degree to which the load management affects the regular operation of the appliance as well as the value of the appliance for load management measures in general, being a proxy for the share of shiftable electricity. The fourth attribute concerned the absence or presence of a constraint on the times load management actions would be allowed. This attribute varies the potential surprise factor and thus the risk on the part of the company. These attribute levels result in 18 different load management propositions (treatments).

Each respondent was shown, at random, a first proposition S1 and could either accept or reject it. In a follow up question, respondents who rejected the initial proposition were offered a second proposition S2, where the initial subsidy payment was doubled. Similarly, respondents who accepted the initial proposal were offered a second proposition, where the initial subsidy payment was halved. The levels for *duration* and *frequency* and the *time constraint* were the same in both propositions. Since the values for the levels of the subsidy, frequency, duration, and the time constraint were all randomly assigned to respondents, our design mimics a randomized controlled experiment.

The choice options yielded four types of respondents:

Type 1: Respondents who accepted both the initial and the second proposition. For this type of respondent, the latent reservation incentive is between $-\infty$ and S2 (= ½ S1).

Type 2: Respondents who accepted the initial proposition but rejected when the subsidy was halved. For this type of respondent, the latent reservation incentive is between S1 and S2 (= ½ S1).

Type 3: Respondents who rejected the initial proposition but accepted when the subsidy was doubled. For this type of respondent, the latent reservation incentive is between S1 and S2 (= 2 S1).

Type 4: Respondents who rejected both the initial and the second proposition. For this type of respondent, the latent reservation incentive is between S2 (= 2 S1) and ∞.

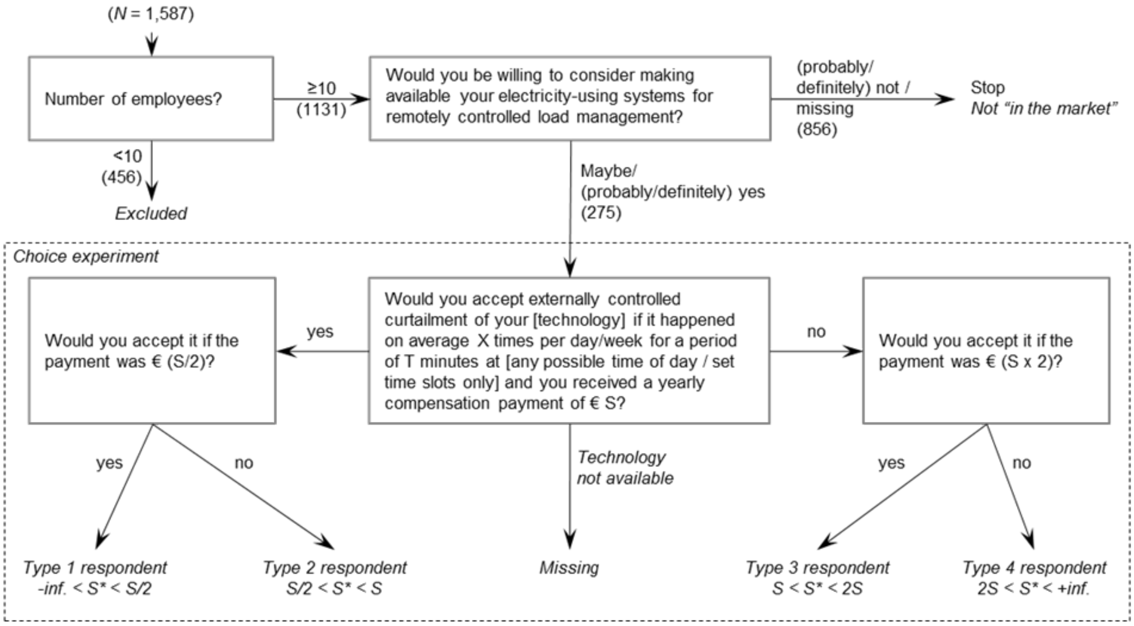

Figure 1: Structure of the choice experiment questions.

2.4 Econometric model

We use an adapted double-bounded willingness-to-pay approach (Cameron and James 1986; Hanemann et al. 1991) to estimate the probability of adopting a load management measure as a function of the subsidy offered. Similar to Alberini and Bigano (2015) and Olsthoorn et al. (2017), the adaptation reflects a focus on willingness-to-accept a subsidy rather than on willingness-to-pay and a follow-up subsidy question with a halved or doubled subsidy, depending on whether the first subsidy was accepted or rejected, respectively (e.g. Cameron and Quiggin 1994).

We assume that a firm (represented by the survey participant) ***i*** has a reservation subsidy level S_i^*. A subsidy $S_i \geq S_i^*$ would lead a firm to adopt the proposed load management measure; a subsidy $S_i < S_i^*$ would lead to rejection. S_i^* is a function of both the load management package and characteristics of the firm. It can be written as:

$$(9) \quad S_i^* = \alpha + \boldsymbol{x}_i\boldsymbol{\beta} + \boldsymbol{z}_i\boldsymbol{\delta} + \varepsilon_i$$

where $\boldsymbol{x}_i$ defines the load management package consisting of the frequency f_i, the duration of the measure t_i, and whether or not load can only be curtailed on agreed-upon time slots; $\boldsymbol{z}_i$ is a set of control variables defining a firm's characteristics; and ε_i is the normally distributed error term with standard deviation σ and an expected value of $E(\varepsilon) = 0$. This means that the model implicitly assumes that respondents know their opportunity costs of the load management measure and that their choices do not suffer from a starting-point (anchoring) bias, i.e. the possibility that respondents adjust their WTA between choices, anchoring it to the first subsidy level (Herriges and Shogren, 1996)[5]. The firm characteristics comprise a firm's stated intention to accept and experience with load management, its size and sector, and, for cooling, specific attributes of the cooling installations. Firm characteristics are described in section 2.5 and Table 5.

S_i^* cannot be observed, but it can be estimated in a double-bounded contingent valuation model. The probability that S_i^* lies between the lower (S_i^L) and upper bound (S_i^U) obtained from the respondent's answers in the choice experiment is written as the following interval data model:

$$(10) \quad Pr\left(S_i^L < S_i^* \leq S_i^U\right) = Pr\left(S_i^L < \alpha + \boldsymbol{x}_i\boldsymbol{\beta} + \boldsymbol{z}_i\boldsymbol{\delta} + \varepsilon_i \leq S_i^U\right) =$$

$$Pr\left(\frac{\left(S_i^L - (\alpha + \boldsymbol{x}_i\beta + \boldsymbol{z}_i\delta)\right)}{\sigma} < \varepsilon_i/\sigma \leq \frac{\left(S_i^U - (\alpha + \boldsymbol{x}_i\beta + \boldsymbol{z}_i\delta)\right)}{\sigma}\right) =$$

$$\Phi\left(\frac{\left(S_i^U - E(S_i^*)\right)}{\sigma}\right) - \Phi\left(\frac{\left(S_i^L - E(S_i^*)\right)}{\sigma}\right) = \Phi^U - \Phi^L$$

5 Hanemann et al. (1991) illustrate the efficiency gains obtainable by moving from a single bounded dichotomous choice, thus substantially tightening the confidence interval around the parameter estimates. Efficiency gains of higher order bounded dichotomous choice approaches appear to diminish quickly (Cooper and Hanemann 1995; Scarpa and Bateman, 2000) Prasenjit (2009) shows that for a systematic choice of bid vectors efficiency gains from using a DBDC may outweigh the biases.

where Φ denotes the standard normal cumulative density function, and $E(S_i^*)$ is the expected value of the reservation subsidy level.

For the four types of respondents (Figure 2), Φ^U and Φ^L are as follows:

For type 1 respondents, $\Phi^U = \Phi\left(\frac{½\, S1_i\ - E(S_i^*)}{\sigma}\right)$ and $\Phi^L = \Phi(-\infty) = 0$.

For type 2 respondents, $\Phi^U = \Phi\left(\frac{S1_i - E(S_i^*)}{\sigma}\right)$ and $\Phi^L = \Phi\left(\frac{½\, S1_i\ - E(S_i^*)}{\sigma}\right)$

For type 3 respondents, $\Phi^U = \Phi\left(\frac{2S1_i - E(S_i^*)}{\sigma}\right)$ and $\Phi^L = \Phi\left(\frac{S1_i - E(S_i^*)}{\sigma}\right)$.

For type 4 respondents, $\Phi^U = \Phi(\infty) = 1$ and $\Phi^L = \Phi\left(\frac{2S1_i - E(S_i^*)}{\sigma}\right)$.

We estimate the coefficients α, $\boldsymbol{\beta}$, and δ via a maximum likelihood procedure. With these coefficients, we can predict the probability of adoption for the sample.

2.5 Data

In this section, we present the descriptive results of the choice experiment (Table 4, Figure 4) and the firm characteristics used in our econometric model (Table 5).

2.5.1 Choices

Table 4 shows that, unlike expected, the likelihood of agreeing to the hypothetical load management proposition does not clearly increase with the level of the subsidy, except for freezing.

Table 4: Proportion of “yes” responses by subsidy offered and by load management measure.

Subsidy (€)	Ventilation	Air conditioning	Subsidy (€)	Refrigeration	Freezing
250	64.0	53.6	500	59.1	20.0
500	66.7	46.2	1000	62.5	45.5
1000	45.5	58.3	2000	84.2	50.0
1500	54.6	34.8	4000	79.0	68.8
2500	60.0	47.8	8000	56.3	75.0
Total	58.0	48.4	Total	68.5	57.7
N	112	124	N	92	52

Figures 2 and 3 show the distribution of response types. In Figure 2, the share of respondents per response type is shown per technology and for all technologies combined when they are stacked. Figure 3 shows the distribution of the response types for the 1st technology and for the 2nd technology for those respondents who took the choice experiment for two technologies. The double-bounded approach reveals that those who accepted the first subsidy very likely also accepted the halved subsidy, and, even more so, those who rejected the first subsidy also very likely rejected the doubled subsidy. Similarly, when responding for a 2nd technology, type1 and type 4 respondents tended to repeat the choices they had made for the first technology.

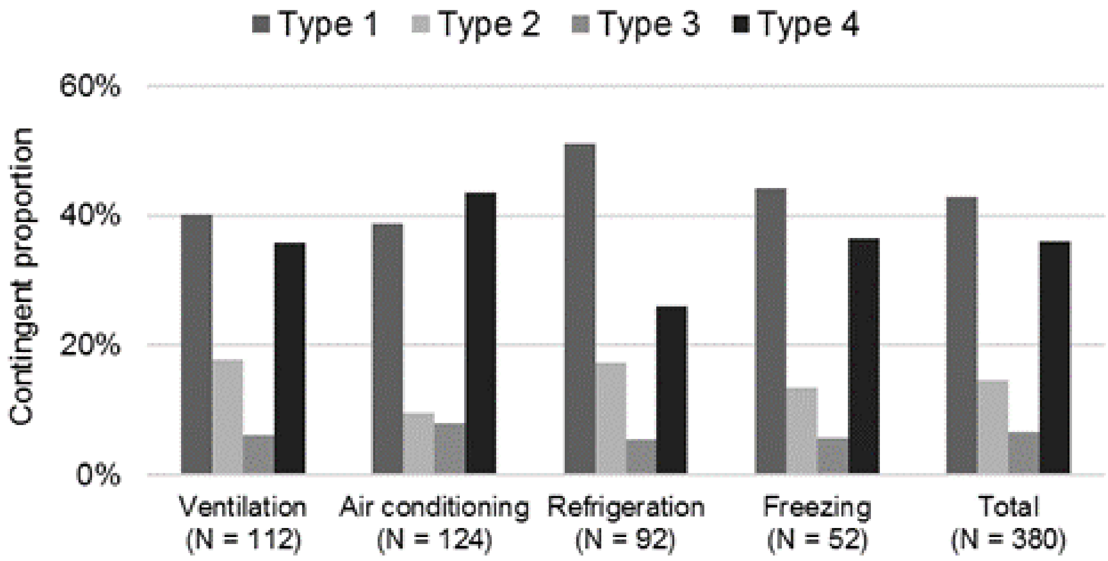

Figure 2: Distribution of respondent types by technology

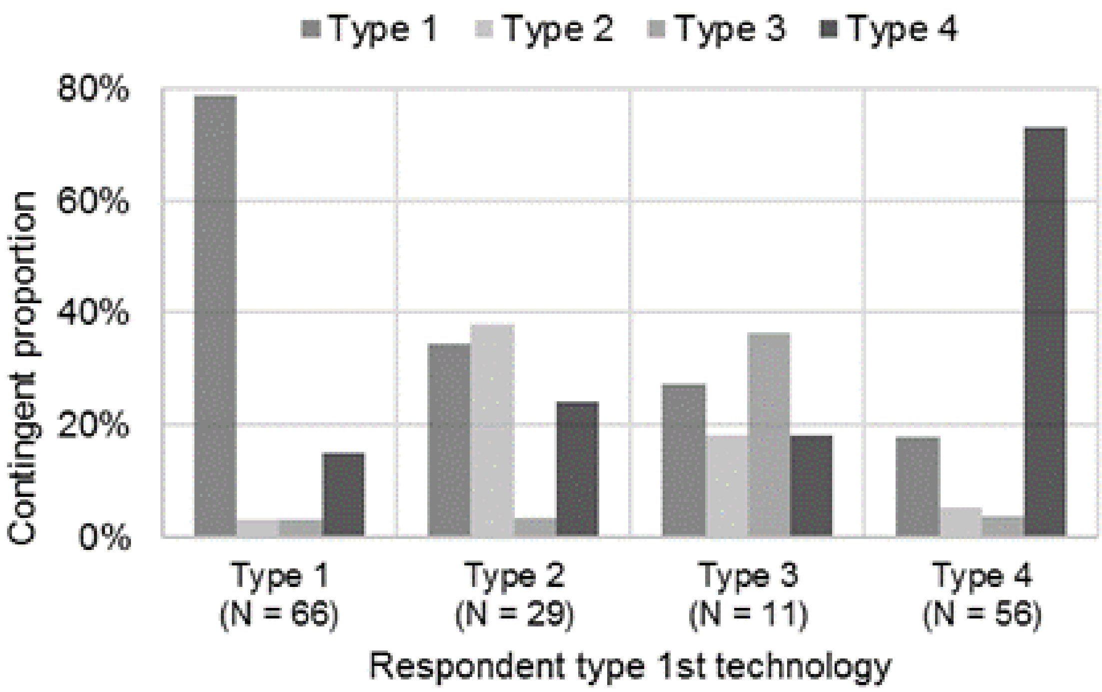

Figure 3: Respondents' response type for 2nd technology by response type for 1st technology. Includes only companies who responded to two technologies (N = 162)

2.5.2 Covariates

We test how companies' reservation subsidies depend on the attributes of the load management proposition and on attributes of the companies. Company attributes that we include as covariates are the prior intention to accept and experience with load management, company size and sector, and, for Cooling, specific attributes of the cooling installations.

Stated intention to accept load management. Descriptive results showed a polarized sample whose responses show no clear relation to the subsidy levels. This raises the suspicion that prior beliefs regarding load management may contribute to explaining respondents' WTA. Therefore, we test the role of a firm's intention to accept as stated prior to the experiment, using the same variable based on which we selected the companies that were "in the market." Three levels remain in the variable that reflects observed answers to the question whether the company would consider automated load management: maybe, probably yes, and definitely yes.

Load management used. To control for experience while testing for the effect of stated intention, we include a dummy variable that takes the value of 1 if the company currently uses load management and 0 otherwise.

Company size. Despite our framing explicitly stating that the company would incur no capital costs, load management involves transaction costs, which in large companies with larger volumes of shiftable consumption may be relatively less important. On the other hand, larger companies have larger systems and thus more potential to offer for which they may incur higher opportunity costs and thus require larger subsidies. We expect that the size effect outweighs the lower transaction costs and, thus, that larger companies have higher reservation subsidies. We control for size by means of the log of the number of the company's employees.

Sector. The importance of the services that the technologies included in this study deliver may vary by sector. For example, client comfort may be essential in the hospitality sector and offices, but maybe less so in trade, which may influence the willingness to accept flexibilization of HVAC systems. We include three sector dummies, for office-type firms, trade (wholesale/retail), and hospitality.

Attributes of cooling appliances. The willingness to make cooling installations available for load management may depend on the attributes of the cooling systems in use. If the number of cooling installations is large, chances are that there is one or more that are less crucial and allow for flexibility. Also, the temperature may matter. On the one hand, temperatures below freezing may offer more bandwidth to exploit (freezing is freezing?). On the other hand, flexibility may be lower because freezing requires more energy and incites to freeze no more than necessary; besides, deeper freezing means steeper temperature gradients when load is reduced. Therefore, for cooling (i.e., refrigeration and freezing), we include three attributes of the cooling systems. We control for the number of cooling appliances, the average temperature (°C) in the cooling appliances (fridges and freezers), and the average temperature (°C) in cold storage installations.

In Table 5, we list the descriptive statistics of all covariates used, using the subsample of 275 firms that qualified for the choice experiment.

Table 5: Covariates: descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Stated intention					
Maybe	275	0.498	0.501	0	1
Probably yes	275	0.313	0.464	0	1
Definitely yes	275	0.189	0.392	0	1
Load management used	206	0.252	0.435	0	1
Employees	264	336	1444	10	20000
Ln(Employees)	264	4.075	1.520	2.303	9.903
Sector					
Office-type	275	0.371	0.484	0	1
Wholesale/retail	275	0.331	0.471	0	1
Hospitality	275	0.298	0.458	0	1
Number of cooling appliances	81	10.83	17.83	0	150
Average T(deg. C) in cooling appliances	79	4.620	6.300	-20	23
Average T(deg. C) in cold stores	103	3.184	6.709	-22	20

3 Results

We first present our econometric findings on expected mean and median subsidy levels per technology. To increase the degrees of freedom, we then aggregate the results for similar technologies and identical attribute levels. Ventilation and air conditioning are combined and labeled *HVAC*. We also aggregate refrigeration and freezing and label it *Cooling*. For these two amalgamated technology classes, we present results of constant-only models alongside estimations for models including the attributes of the load management measure and company characteristics.

3.1 Econometric results for reservation subsidy levels

Table 6 shows the estimated mean and median reservation subsidy level for the four technologies ventilation, air conditioning, refrigeration, and freezing. The constants represent the expected mean and median reservation subsidies, and the sigma represents the standard deviations of the reservation subsidies, assuming they follow a normal distribution.

Table 6: Results of the maximum likelihood estimations of the constant-only model for four technologies.

	Ventilation	Air conditioning	Refrigeration	Freezing
Constant	1186***	1668***	244	2971**
	(0.002)	(0.001)	(0.853)	(0.036)
Sigma	3465***	4581***	9969***	8574***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	112	124	92	52
Log-likelihood	-157.25	-151.17	-130.40	-57.09

p-values in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

For ventilation, we find that for a subsidy of €1186, 50% of the companies represented by the sample would agree to a load management measure. However, the spread is considerable as per the standard deviation of €3465. For air conditioning the estimated mean subsidy is €1668 with a standard deviation of €4581. For refrigeration we find the lowest expected mean subsidy at €244, but with a large standard deviation of almost €10,000. For freezing the expected mean subsidy is highest at close to €3000 and the spread is large with sigma estimated at €8574. The large spreads result from the polarized positions in the sample as shown in Figure 4. In addition, the larger spread for refrigeration and freezing may result from the larger range of subsidy levels proposed in the choice experiment.

3.2 Econometric results for determinants of the reservation subsidy

3.2.1 HVAC

Table 7 reports the results of the maximum likelihood estimates of companies' WTA for HVAC systems, using various model specifications. The first panel contains the results for a constant-only model, where the constant is the expected mean and median reservation subsidy. As expected, at €1407 this is in between the separate estimates for ventilation and air conditioning reported in section 3.1, Table 6. The standard deviation is nearly €4000, estimating a substantial share of companies with negative reservation subsidies. The second model controls for technology and shows that for air conditioning the median subsidy is estimated almost €500 higher than for ventilation, which is consistent with the difference in Table 6, but the difference is not statistically significant.

The third panel reports the relationships between the reservation and the attributes of the load management measure. We see no statistically significant effect of the frequency or duration of load curtailment. The time constraint treatment, however, appears to affect the WTA, where a limitation of the time of day that curtailment is allowed carries an estimated worth of €1737.

The fourth panel adds stated intention and experience. It shows how, controlling for current use, WTA strongly relates to a company's stated intention to accept load management. Stronger intentions to accept are associated with considerably lower reservation subsidies. At the same time, it cannot be said that experience leads to acceptance, as companies who currently use load management tend to require higher subsidies for acceptance. Here, a caveat is that we do not know which systems are currently subject to load management and whether HVAC systems are concerned.

Finally, in the fifth panel, we include company size and sector and do not find that either is significantly related to WTA.

Table 7: Results of the maximum likelihood estimations for ventilation and air conditioning services

	HVAC					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Technology						
Ventilation		(base)				
Air conditioning		477.8				
		(0.429)				
Attributes						
Frequency (#/week)			19.32	42.00	31.22	31.53
			(0.727)	(0.466)	(0.573)	(0.571)
Duration (min)			-3.799	-6.296	-4.978	-5.198
			(0.751)	(0.622)	(0.676)	(0.665)
Only on predefined time slots			-1737***	-1359**	-1854***	-1859***
			(0.004)	(0.031)	(0.002)	(0.002)
Stated intention						
Maybe				(base)		
Probably yes				-1677**		

	HVAC					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
				(0.029)		
Definitely yes				-2756***		
				(0.002)		
Load management used				1535**		
				(0.044)		
Ln(Employees)					-65.39	-64.61
					(0.736)	(0.748)
Sector						
Office-type						(base)
Wholesale/retail						101.6
						(0.881)
Hospitality						53.44
						(0.945)
Constant	1407***	1159***	2353**	2572**	2573**	2535*
	(0.000)	(0.008)	(0.014)	(0.014)	(0.040)	(0.056)
Sigma	3981***	3976***	3841***	3502***	3760***	3761***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	236	236	236	183	227	227
Log-likelihood	-309.4	-309.1	-304.9	-231.8	-294.9	-294.9
Chi^2		0.624	8.498**	16.06**	10.05**	10.07
Prob > Chi^2		0.429	0.037	0.013	0.040	0.122
p-values in parentheses						
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$						

3.2.2 Cooling

Table 8 reports the results of the maximum likelihood estimates of companies' WTA for cooling systems and its relation to select covariates. Again, the first panel contains the results for a constant-only model and shows that the expected mean and median reservation subsidy is €1250, with the standard deviation approaching €10,000. This result is in between the separate and disparate estimates for refrigeration and freezing reported in section 3.1, Table 6. Controlling for technology in panel 2, we find that for freezing the median subsidy is estimated €2500 higher than for refrigeration, which is approximately equal to the difference in Table 6, but the difference is not statistically significant. In panel 3, we add the attributes of the load management measure, for none of which we find a statistically significant association with the reservation subsidy. Other than for HVAC functions, for cooling, the time of day at which load is curtailed does not appear to be of any concern. An explanation may be that cooling is a largely continuous function and much less likely to be subject to a daily cycle such as HVAC. HVAC systems directly affect the comfort of a company's workers and clients and companies are thus likely to have much less tolerance for variation during operating hours.

The fourth panel adds stated intention and experience. As we found for HVAC, for cooling, too, WTA strongly relates to a company's stated intention to accept load management. Favorable intentions are associated with much lower reservation subsidies than a more neutral or reserved position. Again, as for HVAC, here, too, participating companies who currently use load management (on any system) tend to require higher subsidies for acceptance, but the evidence is not statistically significant.

Panel 5 shows that larger companies require higher subsidies; a 1% increase in company size is expected to increase the reservation subsidy by €13. This result supports our expectation that larger companies weigh the subsidy against larger loads and opportunity costs than smaller firms and that this size effect outweighs any transaction cost advantage larger firms may enjoy. Still, specific subsidy costs (per MWh) are expected to be lower for larger firms, due to economies of scale in transaction costs.

In panel 6 sector dummies are added, none of which exhibit a statistically significant effect. The signs, however, are plausible. Cooling is probably closer to the core business in the trade and hospitality sectors, therefore suggesting higher business risk associated with flexibility.

In the last panel, we see that the attributes of the cooling systems do not relate to WTA in a statistically significant way. The lack of statistical significance of the coefficients for the number of cooling appliances and the temperature of cold storage could be partly attributable to a lack of degrees of freedom. Their signs seem consistent with expectations, though: a larger number of appliances would associate with lower subsidies, and colder cold storage would decrease WTA. The latter is consistent with the idea that deeper freezing is associated with less tolerance and/or more sensitivity to load reduction.

Table 8: Results of the maximum likelihood estimation for refrigeration and freezing services.

	Cooling						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Technology							
Refrigeration		(base)					
Freezing		2524					
		(0.200)					
Attributes							
Frequency (#/week)			-19.90	185.8	88.81	104.0	-40.24
			(0.918)	(0.362)	(0.620)	(0.563)	(0.857)
Duration (min)			11.72	-0.29	-7.76	-8.23	15.35
			(0.769)	(0.995)	(0.832)	(0.822)	(0.725)
Only on predefined time slots			1536	350.6	269.1	211.0	1882
			(0.421)	(0.862)	(0.878)	(0.904)	(0.396)
Stated intention							
Maybe				(base)			
Probably yes				-7177***			
				(0.004)			
Definitely yes				-5183**			
				(0.047)			
Load management used				2665			
				(0.205)			
Ln(Employees)					1267**	1344**	
					(0.046)	(0.049)	
Sector							
Office-type						(base)	
Wholesale/retail						3365	
						(0.413)	
Hospitality						2899	
						(0.481)	
Number of cooling appliances							-60.56

	Cooling						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
							(0.393)
Average T(deg. C) in cooling appliances							-4.809
							(0.979)
Average T(deg. C) in cold stores							-250.1
							(0.183)
Constant	1250	367.5	-165.4	2606	-4382	-7644	1093
	(0.205)	(0.765)	(0.957)	(0.423)	(0.238)	(0.192)	(0.753)
Sigma	9618***	9531***	9578***	8422***	8501***	8476***	8254***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	144	144	144	113	137	137	83
Log-likelihood	-188.4	-187.6	-188.1	-139.9	-173.6	-173.2	-111.7
Chi^2		1.646	0.714	10.47	4.267	4.863	2.979
Prob > Chi^2		0.200	0.870	0.106	0.371	0.561	0.811
p-values in parentheses							
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$							

3.3 Subsidy effectiveness simulations

Based on our estimate of the subsidy required to have companies realize the flexibility measures, we calculate the annual flexible volume as a function of the subsidy per technology, using the analytical model described in 2.1. We restrict the simulations to ventilation and air conditioning for which we hold our estimates to be most robust.

To do so, we first determine the number of companies within the target sectors (see Table 1) which the choice experiment's subsample can be assumed to represent (N_{pop}). In Table 9, we combine the sample selections from Figure 1 with the population numbers from Table 1 and estimate that the 275 companies in our subsample of firms with 10 or more employees that are "in the market" scale to 35,051 German companies in total.

Table 9: Extrapolation factor for the simulations

Quantity	Symbol	Number
Number of firms in included sectors in Germany	N_{all}	1,882,233
…with 10 or more employees	$N_{all,\geq 10}$	144,156
Number of firms in sample with 10 or more employees	$N_{obs,\geq 10}$	1,131
Number of firms qualifying for choice experiment	N_{exp}	275
Represented population: potentially adopting firms in target sectors with ≥10 employees	$N_{pop} = \frac{N_{exp}}{N_{obs,\geq 10}} \times N_{all,\geq 10}$	35,051

Next, we estimate Δl, the companies' average load flexibility potential per technology based on participants' responses in the survey. We used the answers given in our survey regarding the availability of technologies to calculate the average of energy consumption caused by each flexible technology used in our choice-experiment (ventilation, air conditioning, cooling and freezing). Using the ratio of flexible energy on the electricity demand for each technology presented in Klobasa (2007), we derived the shares of flexible consumption of each technology to calculate the average of flexible electricity demand for each technology per company of our subsample. Hence, for Δl for technology *j* we have

(11) $\Delta l_j = \frac{1}{N} \sum_{i=1}^{N} E_{ij} \times \varphi_j,$

where E_{ij} is the energy consumption of technology *j* in company *i*, and φ_j is the share of flexible energy consumption of technology *j* from Klobasa (2007). Table 10 shows the average potentials for the medium category of attributes presented in the choice experiment (i.e. use of flexible load for 60 minutes per day). We assumed that air conditioning is used during six months of the year only.

Table 10: Average load flexibility potential per technology and company

Technology	Share of flexible energy of technology consumption φ_j	Flexible potential in GWh of our subsample	Average flexible potential per company in MWh (Δl)
Ventilation	4.1%	0.326	1.92
Air conditioning	10.7%	0.866	5.25

To then estimate the flexible annual volume and the subsidy cost per unit of volume as a function of the subsidy level, we use the probability distributions estimated for the individual technologies in Table 6. We assume that all companies in the choice experiment subsample use these technologies so that the companies who were asked about them can be taken to be representative of all companies in the subsample. Results are shown in Figure 4 and Figure 5.

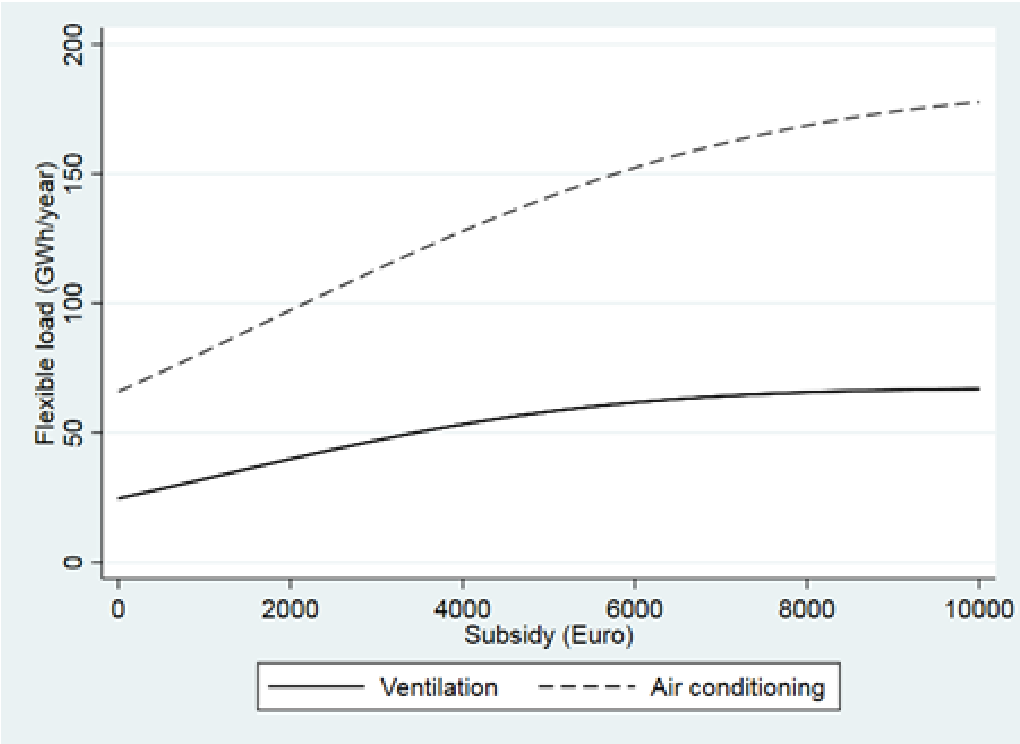

Figure 4: Estimated flexible volume as a function of the subsidy (in €)

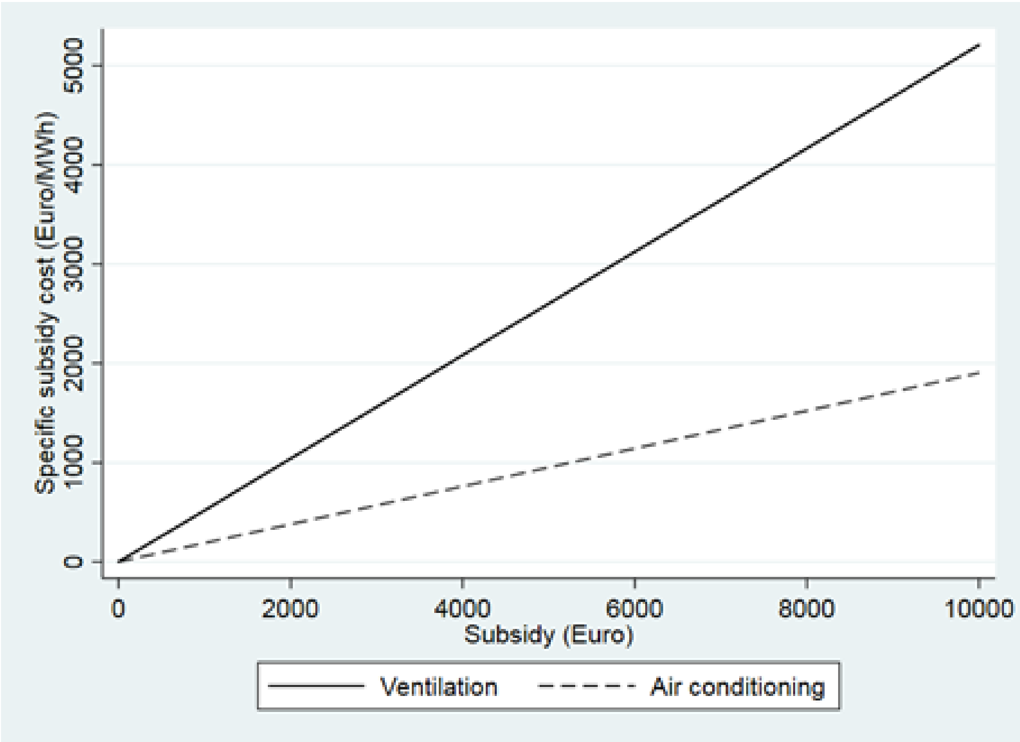

Figure 5: Estimated specific subsidy cost as a function of the subsidy (in €).

The simulation results suggest that for both technologies higher subsidies can give access to more potential but at decreasing marginal rates and thus increasing specific cost. Air conditioning appears to offer more volume at lower cost than ventilation. We consider our estimates most reliable for subsidies values nearer to the center of the probability distributions estimated in Table 6. At a subsidy of €1500 per company per year, a volume of 36.1 GWh can be mobilized in ventilation for €28.2 million total subsidy expenditure and €781 per MWh specific cost. In air conditioning, the same subsidy is expected to unlock a potential volume of 89.3 GWh for €25.5 million total and €286 per MWh specific cost.

The specific costs at this level of subsidy can be compared to alternative options for delivering balancing services. At the German balancing market, payments amount to €644 per MWh activated. For batteries, Newbery (2018) reports estimates for levelized costs between GB£76 per MWh (Tesla in 2020) and GB£586 per MWh (lead-acid). For pumped storage, Newberry (*ibid.*) estimates levelized costs between GB£43 and GB£91 per MWh for six existing plants in the UK. Hence, our estimates suggest that load management in the commerce and services sector could potentially be valorized on the balancing market and offer a competitive alternative to storage technologies.

4 Discussion and conclusions

In this contingent valuation study, we estimated companies' willingness to accept (WTA) automated, externally controlled load management on their electricity using systems in exchange for an annual subsidy payment. We applied a double-bounded dichotomous choice (DBDC) experimental design to a sample of 1587 companies from the German commerce and services sector. We used a standard interval data model to find respondents' mean and median threshold subsidy level for each of four systems (ventilation, air conditioning, refrigeration, and freezing) and to test how the threshold subsidy relates to attributes of the load management measure and characteristics of the firm.

4.1 Findings

We find that mean and median subsidy levels vary by technology.[6] For ventilation and air conditioning we find expected mean reservations subsidies of approximately €1200 and €1700, respectively. The respective standard deviations of ~€3500 and ~€4500 may seem large but are not uncommon for DBDC contingent valuation studies (e.g., Cameron and Quiggin 1994; Alberini and Bigano 2015; Olsthoorn et al. 2017). For refrigeration and freezing, we find expected mean subsidies of ~€250 and ~€3000, respectively. The respective standard deviations of ~€10,000 and ~€8500 are even larger, which may be due to the bar-bell shaped response pattern in combination with the wider range of bids and lower degrees of freedom.

We find that companies' WTA increases if load can be curtailed at agreed time slots only, but only for HVAC systems. For cooling systems, we find no evidence that such a restriction is valued. This may be due to cooling being a continuous function, whereas demand on HVAC system services varies according to occupancy and the quality of service may be more sensitive to load variations. For neither HVAC nor cooling systems we find evidence that companies value the frequency and duration of the load curtailments under the load management scheme. We find no evidence that experience with load management (on unspecified systems) increases WTA.Our results seem to suggest a negative effect when HVAC is concerned, which may be because the low-cost potential is already used and unavailable.

Using estimated distributions of the reservation subsidy for ventilation and air conditioning, we estimated that air conditioning promises more and more cost-effective potential. Subsidy levels in the center of the distribution yield specific subsidy costs per available MWh that suggest that load management in the commerce and services sector may become a competitive option on the balancing market.

6 Please, note that mean and median refer to the mean and median of the companies that took the choice experiment, i.e. companies that were identified as potential adopters based on their stated willingness to consider implementation of automated load management and had 10 or more employees.

4.2 Limitations

Our study is not without limitations. The following needs to be considered when taking in the findings. Our approach assumes that our respondents participate on behalf of their companies as economic agents with well-developed preferences that respond to incentives. However, for three of the four flexibility technologies considered we did not find that acceptance rates were higher for higher subsidy levels. Furthermore, the response pattern appeared rather polarized, with many yes-yes and no-no responses and few in between (yes-no and no-yes). With such a pattern, the double bounded dichotomous choice experiment may not have contributed to lowering the standard errors compared to a single bounded dichotomous choice experiment (Cameron and Quiggin 1994). Moreover, automated load management may be a new phenomenon to many companies in the commerce and services sector, most of which are SMEs, even in general. They probably lack “market experience” with load management and do not have well-developed preferences, which are two conditions for robust findings using a standard interval model that assumes constant preferences (Carson and Hanemann, 2005, p. 875-6). We are less concerned with hypothetical bias, because this has been shown to be generally minor compared to other biases such as strategic bias. When observing the commissioner of the survey and the resources allocated to it, a respondent is unlikely to believe that the outcome is inconsequential and may thus respond strategically in the interest of his/her firm (regardless whether questions are framed as hypothetical) (Carson and Hanemann, 2005, p.877). Strategic behavior may have contributed to the high shares of yes-yes and, especially, no-no answers for all technologies.

4.3 Implications

We have shown that a subsidy may incite a significant share of companies in the commerce and services sector to accept automated load management. At the same time, the large shares of yes-yes and no-no responses for all technologies, the large spreads of estimated reservation subsidies, and the discussed limitations, raises the question: can the cost-effectiveness of a subsidy scheme be improved and its uncertainty reduced, if it is preceded or accompanied by policy instruments (e.g. informational, experimental) that help companies form their preferences? We encourage further research that can contribute to the efficient unlocking and use of load management in companies.

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Authors' affiliations

Mark Olsthoorn

Grenoble Ecole de Management, Univ Grenoble Alpes comUE, Grenoble, France

Joachim Schleich

Fraunhofer Institute for Systems and Innovation Research (Fraunhofer ISI), Competence Center Energy Policy and Energy Markets, Karlsruhe, Germany

Grenoble Ecole de Management Univ. Grenoble Alpes ComUE, Department of Management & Technology, Grenoble, France

Katharina Wohlfarth

Fraunhofer Institute for Systems and Innovation Research (Fraunhofer ISI), Competence Center Energy Policy and Energy Markets, Karlsruhe, Germany

Marian Klobasa

Fraunhofer Institute for Systems and Innovation Research (Fraunhofer ISI), Competence Center Energy Technology and Energy Systems, Karlsruhe, Germany

Contact: Joachim Schleich

Fraunhofer Institute for Systems
and Innovation Research (Fraunhofer ISI)
Breslauer Strasse 48
76139 Karlsruhe
Germany
Phone: +49 721 6809-203
E-Mail: joachim.schleich@isi.fraunhofer.de
www.isi.fraunhofer.de

Karlsruhe 2019