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Stated preferences based estimation of power interruption costs in private households: An example from Germany

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ABSTRACT

Concerns regarding supply security are increasingly raised in reaction to the transition of the German energy system toward a renewable and nuclear-free system called "Energiewende". The goal of this work is to contribute to a measurability of supply security by quantifying the consequences of power interruptions monetarily. The focus lies within the investigation of power interruption costs in private households. An online survey with 859 participants in 2011 is used to gather the necessary data. Based on this data, a two-staged bottom-up regression model was estimated to describe interruption costs for durations of 15 min, 1 h, 4 h, 1 day and 4 days. Finally, micro-data from 55,000 households were used to perform Monte Carlo simulations to increase the representativeness of the estimations. The frequency distributions of the estimated interruption costs indicate potentials for load-shedding measures. Such measures could be an economically viable contribution to a successful integration of large shares of renewable fluctuating generation like wind or solar power.

1. Introduction

In his Review on the Economics of Climate Change, Stern [1] quantified the consequences of a climate change monetarily and created a measurability between the following two goals of energy policy: environmental sustainability and affordability. Stern's argument is that the consequences of non-action are more expensive than costs of action to protect the environment.

In reaction to this argument, the German electricity system is engaging in a very fundamental transition called "Energiewende" from fossil toward a renewable supply. The goals of the government are to increase the shares of renewables to 35 percent by 2020, to 50 percent by 2030, to 65 percent by 2040, and finally to 80 percent by 2050. In addition to these efforts to integrate renewables, as well as following the events of the nuclear catastrophe in the Japanese prefecture of Fukushima, the German government has decided to completely phase out nuclear energies by the year of 2022.

Facing the government's ambitious plans, more and more concerns regarding the security of supply are being expressed, see Ref. [2]. One of the greatest challenges of the German energy transition for the electricity supply lies in growing temporal discrepancies between electricity consumption and generation. Most of the renewable electricity is currently, and probably will be in the future, generated from fluctuating generators like wind or photovoltaic power plants. In 2013, 53.1 percent of the renewable electricity originated in these two types of power plants (a share of 12.4 percent of the total power generation in 2013), see Fig. 1 and Ref. [3]. The power generation is thus mostly independent from the actual demand and instead dependent on uncontrollable meteorological factors. In order to cover the demand even in times with low wind and sun, one of three options is to reduce demand by shedding load, aside from continuing to use conventional power plants and the operation of storage systems. The shedding of load seems to be an interesting possibility because of the following factors: conventional power plants are struggling more and more with decreasing full load hours and shrinking contribution margins, making it more difficult to cover fixed costs; and storage systems are still very expensive and dependent on arbitrage possibilities. However, in order to estimate these economic potentials, fundamental knowledge of supply security and interruption costs is necessary, see also Refs. [4,5].

The goal of this study is to contribute to a measurability of supply security by quantifying the consequences of power interruptions monetarily. In this work, we focus on interruption costs in private households. In contrast to companies, private households do not use electricity with the intention to generate monetary profit. Rather, private household use electricity to facilitate everyday tasks, to gain additional comfort or to pursue leisure activities, see Ref. [6]. For further references on interruption costs in companies, see Ref. [7].

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Nomenclature

Δt	Duration of a power interruption
$y_{\Delta t}$	Power interruption costs of a household for a duration of Δt in Euro
$p^y_{\Delta t}$	Probability that a household has costs for a power interruption with a duration of Δt
n_{hh}	Size of the household
w_{hh}	Monthly household income in Euro per month
bt_{dummy}	Dummy variable whether or not a household is living in a freestanding or duplex family house
$u_{\Delta t}$	Regression residual for a duration of Δt
$VOLL_{\Delta t}$	Value of lost load for an interruption duration of Δt
I	Surveyed individual
c_i	Share of area of inconvenience i for Individual I

To enable a better understanding of this topic, this work starts in Section 2 by giving a short overview of the assumptions and theoretical fundamentals. I present data that was used as input parameters for the models to estimate interruption costs in Section 3. These models are presented in Section 4. The results of the estimations are shown in Section 5. I interpret and discuss the results' implications in Section 6 and conclude this work in Section 7.

2. Theoretical background on the estimation of interruption costs

This section gives a brief overview over the assumptions and theoretical fundamentals regarding the willingness to pay (WTP) and the willingness to accept (WTA), log–log regression models, as well as binary discrete choice decision models. In order to improve the understanding of the conducted steps, the theoretical framework and the used assumptions shall be presented below.

2.1. Willingness to pay and willingness to accept

If a consumer's supply with a certain good is being interrupted, the quantity of this good's consumption decreases. This is also the case for electrical power interruptions. According to Ref. [8] the utility of goods is equal to its ability to satisfy needs of an economic decision maker. If the consumer is forced to reduce the consumption of a demanded good, its utility decreases. In order to monetarily quantify the utility loss caused by the forced reduction of consumed quantity, there are three different available empirical practices based on stated preferences: direct surveys and surveys on willingness to pay and willingness to accept. For reasons described by Sullivan and Keane [9], the two last approaches are particularly suitable for obtaining costs figures for reductions in private households. These shall be explained in the following. The first approach is the analysis of the maximum amount of money an individual would be willing to pay (WTP) to avoid the reductions. The second one is to figure out the minimum amount of money an individual would be willing to accept (WTA) as a compensation for the unavailability of the good.

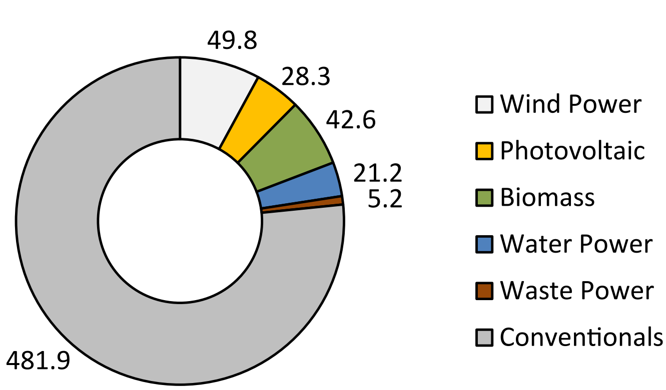

Fig. 1. Estimated power generation in 2013 in TWh.

Early studies in the field of economics suggested that WTA and WTP should be identical in theory, see Ref. [10,11]. However, empirical studies often reveal large disparities between WTA and WTP with WTA being higher than WTP. This means that interviewed individuals often mentioned a very high amount, which they would require as compensation payment, while at the same time the amount they would pay for avoidance, is significantly lower.

Hanemann [12] derives a theory from the Slutsky equation, which originates in the field of microeconomics, to explain these differences in WTA and WTP. The Slutsky equation describes demand changes due to price changes by means of an income effect and a substitution effect. It is suggested that the disparities in WTA and WTP can also be explained by means of an income effect, but more importantly with the help of a substitution effect, see Hanemann [12]. In the following, the consequences of income and substitution effects on the disparities between WTA and WTP will be shortly explained.

- Income effect

  The pure income effect reflects the impact of a change in the purchasing power (due to changes in income or prices) on consumers' behavior. The income elasticity provides a relative quantification of this effect. According to Hanemann [12], the disparity between WTA and WTP increases with an increase in income elasticity.

- Substitution effect

  The substitution effect describes the effect that relative price changes between several goods have on the demand of these goods. This effect is described by the elasticity of substitution (also called Allen–Uzawa elasticity). A low elasticity of substitution means that the product under investigation is difficult to substitute by other goods. The lower the (Allen–Uzawa) elasticity of substitution is, the greater is the disparity between the WTA and WTP.

  According to Hanemann [12], the substitution effect has a far greater influence on disparities between WTA and WTP than the income effect. He concludes that this disparity indicates that all other available goods are rather imperfect substitutes for the considered good. For further details on microeconomic theory and the Slutsky equation see Varian [13].

Assumption

> The greater the difference is between willingness to accept (WTA) andwillingness to pay (WTP) regarding the scarcity of a good, the more difficult it isfor affected consumers to substitute the scarce good with other goods.

2.2. Log–log regressions

In this section, log–log regressions are shortly discussed to facilitate later interpretations of results.

A logarithmic transformation of regressors (independent variables) and regressand (dependent variable) may be appropriate if non-linear, multiplicative relations between regressors and regressand exist, like in the case of the Cobb–Douglas production function for example. Thanks to the mathematical characteristics of the logarithm, multiplicative relationships are transformed into additive relationships. With that, regression coefficients can be estimated using linear regression methods again.

Log–Log regression coefficients β can be interpreted in that way, that a one percent change in the respective regressor leads to a change of the regressand in the magnitude of β percent, see Ref. [14] for example.

2.3. Binary discrete choice models

Models like the binary Probit or binary Logit model are non-linear regression models where the dependent variable can only have two values. These types of models belong to the discrete choice models. To estimate such models, it is necessary to use a linear link function as an auxiliary for the discrete regressand. The codomains of the auxiliary regressands are divided into two sub-domains which represent the two possible values in the case of a binary choice.

Residuals of the linear link function from the Probit models should be distributed standard normally whereas residuals of the linear link function from Logit models should be distributed logistically. If a binary discrete decision model is applicable, then probabilities of occurrences for each choice can be derived.

For a further reading on discrete choice models, see Train [15].

3. Data collection

After having shortly described the theoretical foundations, the data required for the modeling and simulation are presented below. On the one hand, the data consist of results from a proprietary survey. In addition, results from the income and expenditure survey of DESTATIS (the German Federal Statistical Office) were used.

3.1. Collecting data with an online survey

The design of the online survey, which was applied for the determination of interruption costs according to the stated preference method, will be explained below.

In order to collect the necessary data to estimate interruption costs, hypothetical power interruption scenarios were employed with different interruption durations of 15 minutes, 1 hour, 4 hours, 1 day and 4 days.

With these scenarios, the surveyed individuals were asked to estimate both, their willingness to pay (WTP) and their willingness to accept (WTA). In order to grasp these figures, two questions were used with the phrasing described in the following.

- Estimation of the WTP to avoid power interruptions with the specified durations ex-ante (e.g. with a backup generator),
- Estimation of monetary ex-post compensations considered fair (WTA) for power interruptions with the specified durations (e.g. from their electricity provider).

Furthermore, households are asked to evaluate any inconvenience caused by the power interruption on a scale of 0 (no inconvenience at all) to 10 (highly disturbing). The following categories of inconvenience are applied.

- Food spoilage,
- Restriction of activities at home during a power interruption,
- Data loss and reconfiguration of electrical equipment,
- Interruption of heating and hot water supply,
- Other unspecified areas of inconvenience.

Households are also asked to provide the following additional personal information.

- Size of household (number of adults and children),
- Power consumption and billing period,
- Individual and total household net-income,
- Weekly working hours of respondent,
- Subjective assessment of personal dependence on electricity during leisure time,
- Type of building, which is inhabited by the household.

The survey was designed and programmed using HTML Internet pages with CGI scripts written in the programming language Perl. SQL databases were used to store the participants' entries. Multiple data entries from one individual were avoided.

The survey was conducted in 2011 for a total duration of six months from January till June. A total of 859 individuals participated in the survey. The survey was advertised through a variety of platforms including e-mails, online forums and social media but also via handouts and press advertisements. For reasons of data protection, results were recorded anonymously.

Statistical outliers should be excluded from further investigations in order to avoid unnecessary distortions (bias), see Blatna [16]. In this work the method of Walsh is used for the identification of statistical outliers, see Walsh [17]. The test is performed as a one-sided test for the largest values of WTA and WTP-based cost per power interruption. The Walsh test is a non-parametric test, as it compares jumps from one data point to the next in an ordered sample. The advantage of the Walsh test lies in the fact that a frequency distribution of the observed sample is not required. A significance level of 5% is chosen in a sufficiently large sample size. According to Lohninger [18], such a significance level can be selected when the sample size is greater than 220, which is the case here due to the existing sample size of 859. In total, statistical outliers were identified for the returned data of 18 households. The exclusion of these data results in a final data set with a sample size of 841, which is available for further analysis.

3.2. Economic survey of private households (EVS)

The Economic Surveys of Private Households (*EVS* in German) are official statics of the German Federal Statistical Office DESTATIS regarding the living conditions in Germany. Most of the information presented in this section is from the quality report of the EVS 2008 from DESTATIS [19].

The EVS is a census that is repeated every five years and was lastly carried out in 2008. The data from the 2008 EVS were published in late 2010. The goal of the EVS is to give an overview of socio-demographic and socio-economic characteristics, incomes, expenditures, assets and liabilities, possession of commodities and housing situations of the German population. The surveyed entities are households with a permanent address in Germany and a monthly net-income of below 18,000 Euro.

The goal is to select 0.2% of the population's households proportional to each of the 16 Federal States in Germany, which results in a total of 77,648 selected households in 2008. Furthermore a

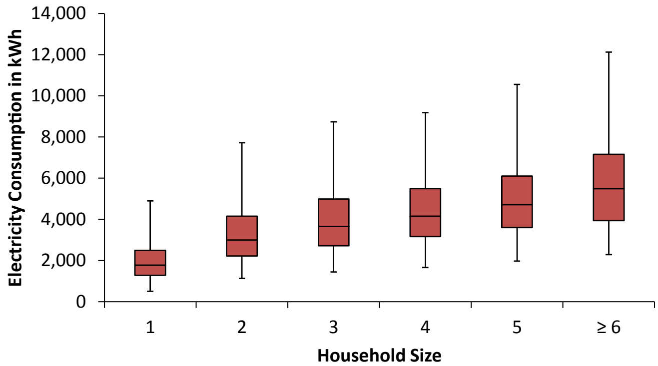

Fig. 2. Annual electricity consumption and household size.

quota system is used for the attributes household type (single, family, etc.), social situation of the principal income earner (employee, self-employed person, etc.), and monthly household net-income. Participation in the EVS is voluntary and households that decide to participate in the written survey are offered financial compensations. Nevertheless, not all households finish the survey. In the 2008 EVS a total number of 55,100 households finished the survey.

The census claims very high representativeness and data quality. Many important political decisions are based on these statistics such as the standard rates for unemployment payments.

To give an example of the data, the number of people living in the household is asked as well as the expenditures for electricity. Together with the average household price for electricity in 2008 from BDEW [20], the electricity consumption in dependence of the household size can be estimated as illustrated in Fig. 2.

4. Modeling and simulation

This section first describes the model estimation and the simulation process to quantify interruption costs in private households. Following this, the approaches to derive the value of lost load and cost shares for inconveniences during a power interruption are presented.

In the process of building the following models, we tested all available parameters in the survey to identify possible significant variables for each desired model. The significant variables were then used for the models presented below.

4.1. Interruption costs

Following four steps were used to estimate the costs of power interruptions in this work.

4.1.1. Binary model part

In several cases, interviewed households stated that they had no WTA-based interruption costs $y_{\Delta t,\mathrm{WTA}}$, and/or WTP interruption costs $y_{\Delta t,\mathrm{WTP}}$. In a first step, the probabilities that households have interruption costs needed to be estimated. To do so, it was tried to use binary Probit and Logit regression models. If a household has interruption costs, the result of the binary regression would be one ($X = 1$). For the case where a household has no interruption costs the result of the binary regression would be zero ($X = 0$), see Ref. [21].

$$y_{\Delta t} = X \cdot y^*_{\Delta t} \text{ and } \begin{cases} X = 0 & \text{with } p\left(X = 0\right) = 1 - p^y_{\Delta t} \\ X = 1 & \text{with } p(X = 1) = p^y_{\Delta t} \end{cases}$$

4.1.2. Ordinary least square modeling

In the next step, WTA and WTP-based interruption costs were estimated for the cases, where a household has costs greater zero.[1] For that, Log–Log regression models were used.

- For WTA interruption costs, $y^*_{\Delta t,\mathrm{WTA}}$, the regressors are household size n_{hh} [persons], monthly household net-income w_{hh} in [Euro per month], and the building type as a dummy variable bt_{dummy} [−] (freestanding/duplex family house yes [1] or no [2]).

$$y^*_{\Delta t,\mathrm{WTA}} = \mathrm{const} \cdot n^{\alpha}_{\mathrm{hh}} \cdot w^{\beta}_{\mathrm{hh}} \cdot e^{\gamma \cdot bt_{\mathrm{dummy}}}$$

$$\ln\left(y^*_{\Delta t,\mathrm{WTA}}\right) = \ln(\mathrm{const}) + \alpha \cdot \ln(n_{\mathrm{hh}}) + \beta \cdot \ln(w_{\mathrm{hh}}) + \gamma \cdot bt_{\mathrm{dummy}}$$

- For WTP interruption costs, $y^*_{\Delta t,WTP}$, the regressors are WTA interruption costs, $y^*_{\Delta t,\mathrm{WTA}}$. Therefore both types of costs have indirectly the same regressors.

$$y^*_{\Delta t,\mathrm{WTP}} = \mathrm{const} \cdot {y^*_{\Delta t,\mathrm{WTA}}}^{\alpha}$$

$$\ln\left(y^*_{\Delta t,\mathrm{WTP}}\right) = \ln(\mathrm{const}) + \alpha \cdot \ln\left(y^*_{\Delta t,\mathrm{WTA}}\right)$$

4.1.3. Parameter estimation

Following the previous steps, the model parameters were estimated and the variables tested for significance. Furthermore, the distributions of the resulting residuals, $u_{\Delta t}$, are analyzed. For that, I use the Kolmogorov–Smirnov test, see Ref. [22].

4.1.4. Simulation

A simulation is applied out of concern that the limited sample might not fully represent the distribution of the population in order to increase representativeness. To do so, the regression models estimated on the basis of the survey are applied on the 52,254 data entries from the EVS statistics. A Monte Carlo simulation with 1000 runs for each EVS data entry is then being implemented in order to take uncertainties associated with the model estimations into account. With that, a total of 52,254,000 interruption costs are being simulated.

$$y^*_{\Delta t,\mathrm{WTA}} = \mathrm{const} \cdot n^{\alpha}_{\mathrm{hh}} \cdot w^{\beta}_{\mathrm{hh}} \cdot e^{\gamma \cdot bt_{\mathrm{dummy}}} \cdot e^{\hat{u}_{\Delta t,\mathrm{WTA}}}$$

$$y^*_{\Delta t,\mathrm{WTA}} = \mathrm{const} \cdot {y^*_{\Delta t,\mathrm{WTA}}}^{\alpha} \cdot e^{\hat{u}_{\Delta t,\mathrm{WTP}}}$$

4.2. Values of lost load

After having estimated WTA and WTP interruption costs, Values of Lost Load needed to be derived. In order to do so, the simulated interruption costs, $y_{\Delta t}$, are divided with the average electricity consumptions, EC, of the analyzed interruption durations, Δt.

[1] This two-staged approach has been used rather than a Tobit model because the data have not been censored (there were no negative values for willingness to pay or willingness to accept). Sigelmann and Zeng [18] argue that, even though the Tobit model is often used in such cases, the results from a Tobit regression creates a bias and is therefore inappropriate if the underlying data has not been censored. Literally, they argue that “the standard Tobit model is applicable only if the underlying dependent variable contains negative values that have been censored to zero in the empirical realization of the variable” and “if no censoring has occurred or if censoring has occurred but not at zero, then the standard Tobit specification is inappropriate”.

$$\mathrm{VOLL}_{\Delta t} = \frac{y_{\Delta t}}{\frac{\mathrm{EC}\cdot\Delta t}{8.760}}$$

4.3. Cost shares for areas of inconveniences

Furthermore, the shares of the inconveniences of the costs, c_i, was estimated for each of the four surveyed areas of inconveniences spoilage of food, limitation of household activities, data losses and comfort issues.

The subjective assessments from the surveyed individuals I_i were used to derive these shares for the different interruption durations.

$$c_i = \frac{I_i}{\sum_{i=0}^{i=4} I_i}$$

5. Results of the modeling and simulation

5.1. Interruption costs

5.1.1. Binary model part

For the model's binary discrete choice part, all available variables of the survey were used to identify significant Probit or Logit models. However, with these variables, no significant model could be identified. The McFadden coefficient of determination was always below a level of one percent. Eventually, the distributions obtained in the survey were used to describe the probabilities of a household having WTA and WTP interruption costs greater than zero, see Fig. 3.

5.1.2. Ordinary least square part

In contrast to the binary model part, a significant OLS model could be identified with the collected data. The estimated coefficients WTA and WTP-based interruption costs are shown in Table 1.

Interestingly, the dummy variable bt_{dummy} was only significant for interruption durations of 4 hours, 1 day and 4 days. For that reason, the coefficient for the dummy variable bt_{dummy} in the case of interruption durations below 4 hours (15 minutes and 1 hour) was set to $\gamma = 0$.

WTA interruption costs

$$y^*_{\Delta t,\mathrm{WTA}} = \mathrm{const}\cdot n_{\mathrm{hh}}^{\alpha}\cdot w_{\mathrm{hh}}^{\beta}\cdot e^{\gamma\cdot bt_{\mathrm{dummy}}}$$

$$\ln\left(y^*_{\Delta t,\mathrm{WTA}}\right) = \ln(\mathrm{const}) + \alpha\cdot\ln(n_{\mathrm{hh}}) + \beta\cdot\ln(w_{\mathrm{hh}}) + \gamma\cdot bt_{\mathrm{dummy}}$$

WTP interruption costs

$$y^*_{\Delta t,\mathrm{WTP}} = \mathrm{const}\cdot y^*_{\Delta t,\mathrm{WTA}}{}^{\alpha}$$

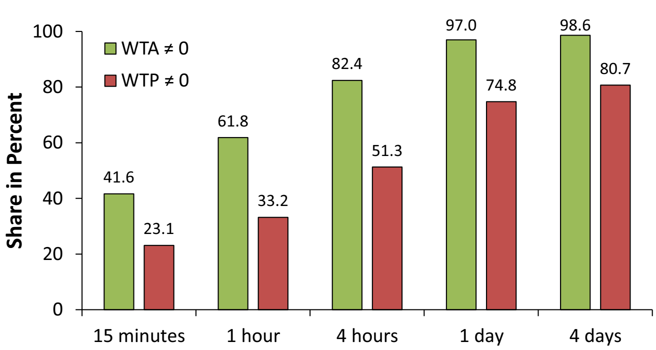

Fig. 3. Shares of WTA and WTP interruption costs greater than zero in percent.

$$\ln\left(y^*_{\Delta t,\mathrm{WTP}}\right) = \ln(\mathrm{const}) + \alpha\cdot\ln\left(y^*_{\Delta t,\mathrm{WTA}}\right)$$

where $y^*_{\Delta t,\mathrm{WTA}}$, WTA interruption costs in [Euro]; $y^*_{\Delta t,\mathrm{WTP}}$, WTP interruption costs in [Euro]; n_{hh}, household size [persons]; w_{hh}, monthly household net-income in [Euro per month]; bt_{dummy}, dummy building type [−] (freestanding/duplex house).

5.1.3. Simulation

The 1000 runs of the Monte Carlo simulation resulted in 52,254,000 simulation entries for WTA and WTP interruption costs for each of the analyzed durations.

The simulations' results are shown as boxplots in Fig. 4 in dependence of the interruption duration. For the boxplots, we chose 5% and 95% percentiles as whisker boundaries.

The simulated WTA and WTP costs increase with the duration of the power interruption. However, the frequency distribution shows that interruption costs are strongly right-skewed as a comparison between mean average and median shows.

Furthermore, the ratios between the mean average WTA and WTP cost figures are shown in Table 2. The figures show that WTA costs are generally a lot higher than WTP costs.

5.2. Value of lost load

As already previously described, the value of lost load is derived from the simulated interruption costs. The value of lost load represents the average interruption costs per unit of unconsumed electrical energy.

Fig. 5 shows the distribution of the calculated Values of Lost Load again as boxplots in dependence of the interruption's duration.

The simulated WTA and WTP-based VOLL decrease with ongoing duration of the power interruptions. The frequency distribution of the VOLL is also strongly right-skewed. Furthermore, the WTA VOLL figures are generally higher than the WTP VOLL figures.

5.3. Cost shares for areas of inconveniences

Using the available regressors to estimate the shares in the different areas of interruption costs with OLS, it was regrettably not possible to identify significant models for the cost shares. The coefficients of determination were all below a level of two percent, so that eventually distributions obtained in the survey were used instead. By doing so, we obtained the distribution of the shares in dependence of the interruption duration shown in the boxplots of Fig. 6.

6. Discussion of the results

For power interruptions of durations of 4 or more hours, the results of the OLS part of the model for households' interruption costs reveal a significant correlation between the level of costs and the attributes *household size*, *monthly net-income* and *type of building*. For shorter interruptions of 15 minutes and 1 hour, another model (without dummy-variable type of building) was applied. Therefore, the influence of the variables on these models will be discussed separately in the following. As previously explained, the coefficients of the log–log regression can be interpreted in such a way that a change of one percent of a respective regressor leads to a change of the regressand at the amount of the coefficients (in percent).

The household size is almost linearly proportional to the amount of interruption costs. For all five examined interruption

Table 1
Parameter estimations for the OLS part.

	Willingness to accept				Willingness to pay			
			Coeff.	*p*-value			Coeff.	*p*-value
15 min	$p(\text{WTA} > 0) = 0.42\%$	ln const.	−0.029	0.97	$p(\text{WTP} > 0) = 0.23\%$	ln const.	0.819	0.00
		$\alpha\ [n_{HH}]$	0.861	0.00		$\alpha\ [y^*_{WTA}]$	0.659	0.00
		$\beta\ [w_{HH}]$	0.260	0.01				
		$e^{\gamma}\ [bt_{dummy}]$	1.00*	–				
		p-Value	0.00			*p*-Value	0.00	
		Adj. R^2	0.17			Adj. R^2	0.41	
1 h	$p(\text{WTA} > 0) = 0.62\%$	ln const.	0.955	0.07	$p(\text{WTP} > 0) = 0.33\%$	ln const.	0.736	0.00
		$\alpha\ [n_{HH}]$	0.982	0.00		$\alpha\ [y^*_{WTA}]$	0.673	0.00
		$\beta\ [w_{HH}]$	0.182	0.01				
		$e^{\gamma}\ [bt_{dummy}]$	1.00*	–				
		p-Value	0.00			*p*-Value	0.00	
		Adj. R^2	0.18			Adj. R^2	0.44	
4 h	$p(\text{WTA} > 0) = 0.82\%$	ln const.	1.667	0.00	$p(\text{WTP}>0) = 0.51\%$	ln const.	0.909	0.00
		$\alpha\ [n_{HH}]$	0.937	0.00		$\alpha\ [y^*_{WTA}]$	0.612	0.00
		$\beta\ [w_{HH}]$	0.169	0.00				
		$e^{\gamma}\ [bt_{dummy}]$	1.418	0.01				
		p-Value	0.00			*p*-Value	0.00	
		Adj. R^2	0.23			Adj. R^2	0.42	
1 day	$p(\text{WTA} > 0) = 0.97\%$	ln const.	1.050	0.04	$p(\text{WTP}>0) = 0.75\%$	ln const.	0.819	0.00
		$\alpha\ [n_{HH}]$	1.089	0.00		$\alpha\ [y^*_{WTA}]$	0.634	0.00
		$\beta\ [w_{HH}]$	0.326	0.00				
		$e^{\gamma}\ [bt_{dummy}]$	1.494	0.00				
		p-Value	0.00			*p*-Value	0.00	
		Adj. R^2	0.26			Adj. R^2	0.45	
4 days	$p(\text{WTA} > 0) = 0.99\%$	ln const.	1.962	0.00	$p(\text{WTP}>0) = 0.81\%$	ln const.	0.939	0.00
		$\alpha\ [n_{HH}]$	1.061	0.00		$\alpha\ [y^*_{WTA}]$	0.608	0.00
		$\beta\ [w_{HH}]$	0.362	0.00				
		$e^{\gamma}\ [bt_{dummy}]$	1.463	0.00				
		p-Value	0.00			*p*-Value	0.00	
		Adj. R^2	0.26			Adj. R^2	0.44	

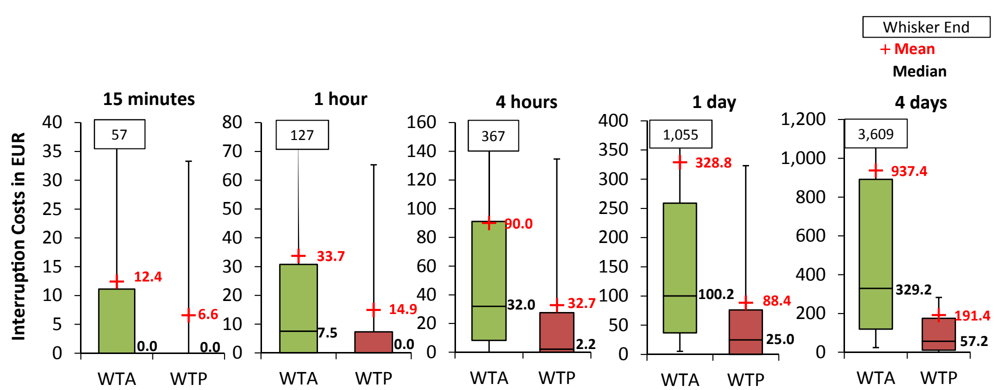

Fig. 4. Distribution of the simulated interruption costs in EUR.

durations, coefficients vary between 86 and 110 percent. The household size has a smaller influence on the cost of the 15-minute breaks (86 percent) compared with the 1-hour interruptions (98 percent). A possible explanation could be that the larger the household, the more likely there are multiple people who share the same electrical equipment. Therefore, necessary reconfiguration of certain electronic devices, such as telecommunications systems, will occur to the same extent in small as well as large households. Data losses tend to account for the majority of costs of the short supply interruptions. A more detailed interpretation on this effect will follow in the course of this discussion.

Regarding the monthly net household income, the impact on interruption costs is higher for 15-minute power interruptions (26 percent) compared to those of a 1-hour duration (18 percent). Presumably there is a relationship between the available income and the equipment of households with electrical devices, which involve interruptions of electricity supply with data loss. In the particularly short interruptions data losses are the predominant cost driver. In the case of the longer-term interruptions, the income's impact on the costs increases from 17 percent (4-h interruption) to 33 percent (1-day interruption) and to 36 percent (4-

Table 2
Ratios of mean averages for WTA to WTP interruption durations.

	15 min	1 h	4 h	1 day	4 days
Ratio WTA/WTP	2.1	2.7	3.1	3.5	5.2

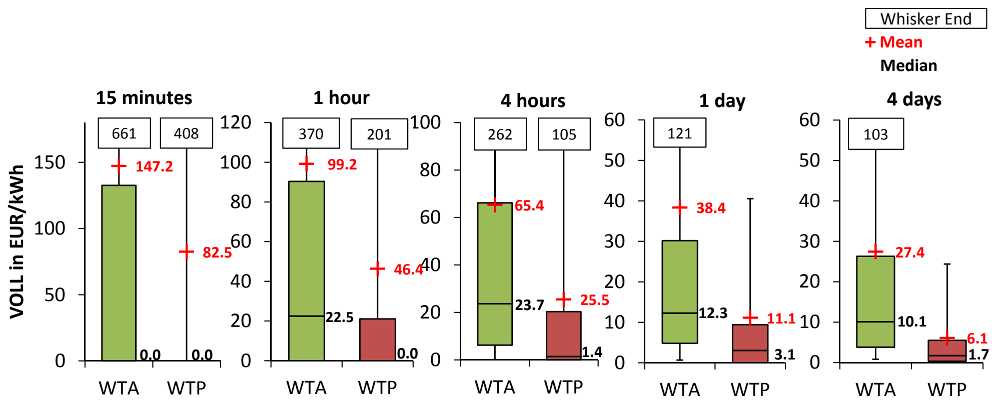

Fig. 5. Distribution of WTA and WTP-based VOLL in EUR/kWh.

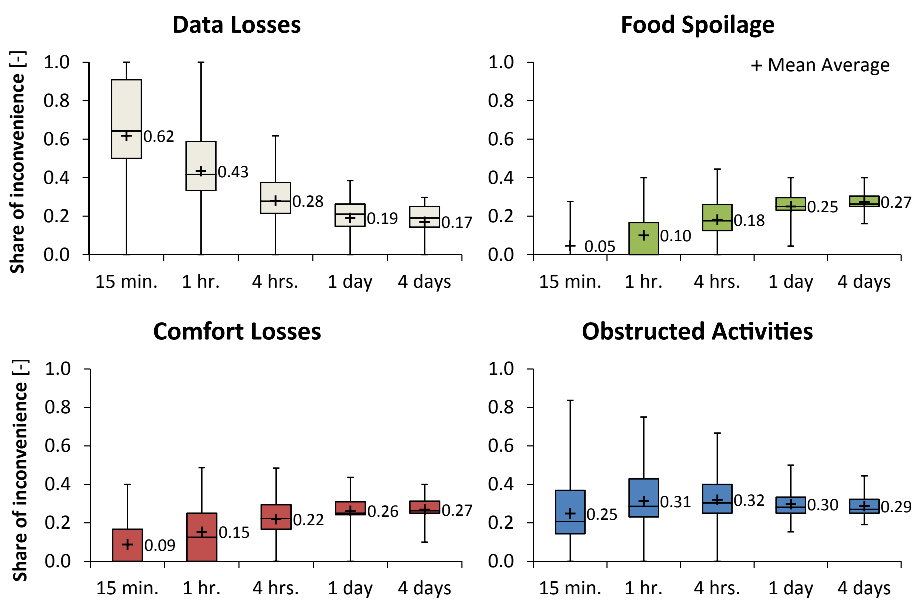

Fig. 6. Distribution of the shares of the four areas of inconveniences on interruption costs.

day break). Possibly, the influence of income on the interruption costs further increases with the duration of the interruption, because households with higher income are probably more likely willing to pay a higher amount to avoid loss of comfort or they demand higher compensation payments in order to relinquish on comfort. In addition, households with high incomes tend to store more expensive foods. The cost fraction of the attributes loss of comfort and food spoilage increases with the duration of power interruptions. Detail will be examined in the further course of this discussion.

For power interruptions of longer durations (4 h, 1 day and 4 days), the interruption costs of households that inhabit one- or two-family houses are on an average 42 and 49 percent higher than those of other households. With the shorter interruption durations (15 min and 1 h), no significant correlation between building type and the level of interruption costs can be determined. This observation is presumably based on the fact that living space in one- or two-family houses is generally larger than in apartment buildings. Restrictions of everyday life that becomes apparent only with longer interruption durations, probably go along with higher opportunity costs associated with unused living space. In this context, I propose the following new hypothesis.

> It is irrelevant for relatively short power interruptions up to an hour in what type of building the household is living. However, for relatively long power interruptions with at least 4 hours, the households have significantly greater costs if they are living in one- or two-family houses compared to households living in apartment buildings.

Assuming that the cumulative leisure time of all household members depends on the total number of household members, these results reaffirm the assumption which was formulated in a previous work (Ref. [23]) that the interruption costs are dependent on available leisure time and available income.

Interruption costs identified here are distributed in a strongly right-skewed manner. This indicates that the majority of the population has very low interruption costs, while a small minority of the population has very high interruption costs.

The ratios of average WTA to WTP failure costs indicate that WTA-based failure costs are generally much higher than WTP-based failure costs. Depending on the duration of interruption this discrepancy continues to rise. In a 15-min break, the ratio of

WTA to WTP is around 2 whereas this ratio increases to 5 for a 4 day interruption period. For the following conclusions the previously stated theory regarding WTA and WTP (Ref. [12]) is adopted. The high disparity between WTA and WTP suggests that it is difficult for households to substitute the good electricity. Furthermore, the fact that the relative distance between WTA and WTP increases with longer interruptions suggests that the possibility to find substitutes for electricity decreases with the duration of the interruption. Here, I also propose the following new hypothesis.

> The electricity supply is a good that is hardly substitutable with other goods for private households. With ongoing interruption duration, the substitutability of the electricity supply with other goods decreases even further.

In case households should participate in measures of switch off in the future, two configurations are conceivable. On the one hand, households may participate in shutdown actions on a voluntary basis and get paid for compensation. For this purpose, the determined higher WTA costs would be relevant. On the other hand, households may be obliged to take part in shutdown actions for system stability reasons. Households that require a higher degree of supply security would have to pay it, accordingly. In this case, the determined, lower WTP costs would be relevant.

Although interruption costs increase with the duration of supply interruption this is not observable for WTA and WTP-based VOLLs. The results show that the derived VOLL decreases instead of increasing with the duration of interruption. The VOLL represents a kind of average cost. With increasing interruption duration the total costs increase and the average costs decrease. This suggests that also the marginal costs tend to decrease with increasing interruption duration.

In economic theory, diminishing marginal costs indicate positive economies of scale, see Ref. [13]. For the investigation of interruption costs of private households this is an indication that each additional time unit of a power interruption causes a lower increase in interruption costs on average.

An explanation for this might be the fact that a household's blackout costs can be divided into a fixed and a variable component. With a change of the interruption duration Δt, the variable costs C_{var} change while the fixed costs C_{fix} remain constant.

$$C_{\mathrm{total}}(\Delta t) = C_{\mathrm{fix}} + C_{\mathrm{var}}(\Delta t)$$

$$\text{with } \frac{\mathrm{d}C_{\mathrm{fix}}}{\mathrm{d}\Delta t} = 0 \text{ and } \frac{\mathrm{d}C_{\mathrm{var}}(\Delta t)}{\mathrm{d}\Delta t} > 0$$

The results of studies on the proportions of the four pre-defined inconvenience classes also indicate the presence of fixed costs. Out of the four studied areas in the context of private households, the sudden loss of data can best be regarded as mainly independent of the duration of the power cut. Thus, the relative proportion of the component *data loss* in total costs is the highest within short interruption durations and decreases with increasing interruption durations. In the case of a 15-minute break, the share of this component in the total cost is on average 62 percent and decreases in the case of 4-day break back to 17 percent.

As described in the previous section, no significant correlation is observed between the proportions of inconveniences and the level of interruption costs. For this reason, it can be concluded that in the case of 15-minute breaks the costs for data losses amount to an arithmetic WTA-based mean of 7.67 EUR and WTP-based mean of 4.07 EUR.[2] The median of these costs amounts to 0 EUR. This cost component will probably amount to this level, regardless of the interruption duration. Moreover, this cost component is likely to be reduced when households are alerted in advance of a supply disruption. Assuming that the proportion of households with computers continues to increase, it is expected that the importance and magnitude of these costs in the context of unplanned interruptions will increase.

> A power interruption leads to fixed costs that are independent of the interruption's duration. A main reason for such costs is the area of data losses. Very short power interruptions lead to average costs of 4.10 EUR (WTP) and 7.70 EUR (WTA) per household.

The VOLL as an average magnitude of interruption costs will approach infinity if the time intervals of interruption duration (and thus also the actually intended power consumption) approach zero. Consequently, the VOLL is rather unsuitable as an indicator for very brief interruptions of electric power supply in the presence of fixed costs.

> The value of lost load is a rather unsuitable indicator for very short power interruptions if these estimations include fixed costs.

The average proportions of the areas of *food spoilage* and *loss of comfort*, however, increase with the duration of interruption. During a 15-minute interruption the area of *food spoilage* accounts for about 5 percent of the total cost. This proportion rises to 27 percent for interruption durations of 4 days. The area *loss of comfort* accounts for 9 percent of total costs during 15 minute interruptions and increases to around 27 percent for interruptions of 4 days.

Limitations of activities due to power interruptions have a more or less constant proportion of the total interruption costs for the investigated interruption durations. Thus, the share of this area increases from around 25 percent for a 15-minute interruption to only 32 percent for a 4-hour interruption and decreases again to a share of around 29 percent for a 4-day power interruption. With increasing numbers of electrical appliances in households, comparable to increasing equipment with computers it is assumed that the costs in this area are expected to increase in the future.

According to the approach of stated preferences, the cost of a 1-hour supply interruption ranges from 14.88 EUR (WTP) to 33.68 EUR (WTA). Limitations of recreational activities represent about 31 percent of these costs on an average. Consequently, the average costs for the restriction of activities per household are between 4.65 EUR (WTP) and 10.53 EUR (WTA).[3]

[2] These cost figures may be hard to measure or to justify even though they have been stated. However, there are several scientific methods that could be applied to measure these costs in detail. In the example of costs from data losses, the value of the time required to create the data that has been lost could be estimated. Another option used in a recent legal case in Germany is to identify the costs to recover the data. A construction company has been sued over 16,500 Euro for damaging a power cable which resulted in power outages and data losses. The costs of the data recovery had this magnitude, see OLG Oldenburg, 24.11.2011, 2 U 98/11.

[3] The compensation of costs resulting from power interruptions however is different from legal system to legal system. In many systems, the power consumers will probably need to cover their own costs whereas power suppliers or system operators could be the ones being charged by these costs. The impact on the whole economy has been estimated in Ref. [3].

7. Conclusion

The German energy transition toward a carbon and nuclear-free electricity generation poses high challenges for the supply security. The transition will make it more and more difficult (and with that more costly) to maintain the currently very high level of supply security. If the costs to maintain and increase supply security remain constant, this means that the optimal level of supply security in Germany is going to decrease. The present work seeks to make a scientific contribution to the question of what the worth of electrical supply security is by quantifying the consequences of power interruptions monetarily.

The results indicate that failing supply security in form of power interruptions is in average relatively expensive for residential consumers. This means that the utility for a reliable electricity supply is generally very high. Furthermore, the duration of a power interruption has a significant impact on the magnitude of the interruption costs as well as on the value of lost load.

However, the frequency distribution of these interruption costs is very right-skewed indicating interesting potentials of demand reduction measures. Selective interruptions of costumers with the lowest costs (if technically feasible) may, under certain circumstances (e.g. smart grids), be more cost-efficient than the construction of storage or generation capacities in a system with high shares of installed intermittent generation capacities. In the future, further scientific efforts regarding load reduction measures and optimal generation capacities should be carried out as contributions for the energy transition.

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