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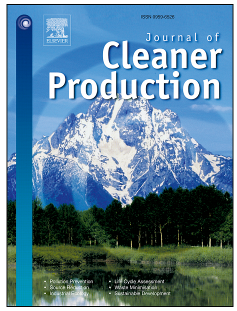

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Analyzing the energy system impacts of price-induced demand-side-flexibility with empirical data

Russell McKenna[a,b], Diana Abad Hernando[a], Till ben Brahim[a], Simon Bolwig[a], Jed J. Cohen[c], Johannes Reichl[c]

[a]*DTU Management, Technical University of Denmark, Kongens Lyngby, Denmark*
[b]*School of Engineering, University of Aberdeen, Aberdeen, UK*
[c]*Energy Institute at Johannes Kepler University, Linz, Austria*

Abstract

This paper assesses the potential effects on the energy system from a full roll out of a smart phone app designed to connect household electricity consumers with their consumption and price data. The effects of the app in allowing greater demand-side flexibility from household consumers is estimated based on data from an 18-month field trial involving 1,557 Austrian households. These estimates are given as hourly price elasticities of electricity demand and hourly energy efficiency treatment effects from consumer engagement with the app. In a novel methodological coupling, the econometric estimates are input into the Balmorel energy system model, which is used to analyze future scenarios of full renewable energy deployment in the Austrian energy system. The results demonstrate that the impact of the flexible residential demand for electricity is small but significant to future system costs. The total discounted system cost increases by 20-24% in the renewable energy scenarios, compared to a business as usual scenario, due to heavy investments in renewable generation. However, system cost is reduced by 4-7% in renewable energy scenarios where the observed demand-side flexibilities are considered. The results are subject to several methodological caveats, but they give a clear signal that ICT-enabled demand side flexibility can be an important cost-saving element that should be integrated into the future energy system and considered in system-level models.

Keywords: Flexible demand, Smart meters, Balmorel, Energy system analysis, Energy efficiency

Sets		$\boldsymbol{\lambda}_t$	Temporal fixed effect
I	Set of all households	μ_i	Fixed heterogeneity effect
R	Set of all renewable scenarios	$\epsilon_{i,t}$	Error term
S	Set of all scenarios w/o elasticity	ι_r	Intensity of treatment effect
T	Set of all time steps	$D_{i,t}$	Elec. demand
		$D_{t,r}$	Elec. demand
Parameters			
$\boldsymbol{\beta}_0$	Treatment effect coefficients	**Variables**	
$\boldsymbol{\beta}_1$	Price elasticities of electricity demand coefficients	$\pi^{el}_{t,s}$	Elec. price w/ large peaks
$\pi_{i,t}$	Elec. price	$\pi^{el'}_{t,s}$	Elec. price w/o large peaks
$user_{i,t}$	User indicator	$\pi^{el''}_{t,s}$	Elec. price w/ large peaks
$season_t$	Season indicator	δ^{π}_t	Elec. price difference
$hour_t$	Hour indicator	$J_{i,t}$	Control variable for app messages
$group_i$	Group indicator		

Nomenclature for Equations (1) to (3).

1. Introduction

In the context of rapid developments in renewable energy generation, the energy system requires increasing amounts of flexibility. One promising area lies in exploiting the flexibility on the demand side of the energy system with demand-side management (DSM) or demand-side flexibility (DSF). This idea has existed for several decades, but recently more attention has been paid to exploiting this approach in the residential sector (Bastida et al., 2019). Residential consumers are typically not exposed to short-term price differentials. Instead, the majority pay a constant price per unit of electricity consumed (Azarova et al., 2018). In order to exploit the potential for DSF in the residential sector, consumers need to be experience temporal fluctuations in electricity prices as seen on wholesale markets.

In our case study region of the Austrian federal state of Upper Austria, consumers have the option to sign up for time of use electricity tariffs through the major utility company in the state. These consumers are then exposed to market-based fluctuations in electricity prices. To connect consumers with easy-to-understand information about these fluctuating prices a smart phone app was developed[1]. The app forwards users' information about their electricity prices, expenditures, and consumption based on their 15-min smart meter data. Thus, the app gives users the ability to change

[1]For details of the PEAKapp smart phone application please visit PEAKapp.eu.

their behaviour in response to dynamic electricity prices and increased information about their own usage. The realisable potential of households to shift loads from the peak times, which correspond to higher price periods, to times with lower grid-wide consumption can have effects on the market price and distribution costs for electricity, and stands to make renewable electricity more competitive.

1.1. Objectives and scope

In this paper we seek to assess the potential effects that a comprehensive information and communication technology (ICT) to human ecosystem, the developed smart phone app, can have at the system level. Such ICT tools have been shown in previous work to have the potential to influence household behavioural savings in energy of up to 5%, and can cause loadshifting to off peak times of up to 17% of household electricity loads (Bastida et al., 2019). To understand the system-wide effects of the developed app, we first estimate the price responsiveness of residential electricity demand, and the effects of app-supplied information on household energy efficiency. Both of these quantities are estimated econometrically, using data from an Austrian field trial of the developed smart phone app.

In the second step, the empirical estimates of price responsiveness and energy efficiency are used as inputs for the Balmorel energy system model of Austria to calculate the potential system effects from a large-scale rollout of the app, or similar ICT tools. In the context of a scenario analysis, elastic demands are derived from the field trials and employed in the model to assess the system-level cost savings that might be expected from such a rollout. An overview of the employed method is given in Figure 1.

Price elasticities are employed within this paper in order to analyze the responsiveness of households to changes in electricity prices under different framework conditions. Thus, a first objective of this paper is to estimate the short-term price elasticities of electricity demand for the Austrian households participating in the field test. We estimate these elasticities for two groups of participants that we term the active (A) group, those with access to the app, and the control (C) group, those households without access to the app. We posit that the increased access to electricity price information available to those in the A group will lead to increased responsiveness to price, i.e. greater magnitude price elasticities.

In addition to price responsiveness, we are also interested in the potential for information provided in the ICT tool to influence behavioral changes in household energy efficiency. A survey of 156 previous studies shows a potential for information effects to decrease overall energy consumption by

7.4%, on average (Delmas et al., 2013). We investigate the energy efficiency effects within the A group over the field trial and also analyze a subset of the A group that we term heavy users, those who interact with the app at least on a monthly basis over the duration of the field trial. Thus, the second objective of the paper is to estimate the energy efficiency impacts of the ICT to human ecosystem on household energy efficiency in the medium term.

With the econometric estimates of price responsiveness and energy efficiency in hand we turn to the second stage of the analysis, namely to evaluate the potential system-level impacts of our ICT tool. To this end we employ an energy system model (Balmorel) that allows for a comparative static analysis of the electricity market equilibrium, assuming different aggregated consumption profiles under alternative pricing regimes. The overall objective is to analyse the economic benefits to the whole Austrian energy system of exploiting residential demand side flexibility and improved household energy efficiency at the national scale. More specifically, the objective of this stage is to analyze the impact on economic, technical and environmental indicators of a widespread exploitation of DSF via the developed app.

1.2. Overview

This paper is structured as follows. Section 2 contains a literature review, which puts this work into context and demonstrates the innovative aspects. Section 3 then presents the dataset and econometric methodology to derive the price elasticities and shows the intermediate results. Section 4 then focuses on the Balmorel model, the model's extension to Austria, and the scenario framework. Section 5 presents the main Balmorel results while section 6 discusses the implications of the results on various technical, economic and environmental criteria. Section 7 closes the paper with a summary and conclusions.

2. Literature review

A literature review was carried out to identify research gaps and to place this paper in a wider scientific context. Seventeen articles were reviewed that analyse system-wide aspects of flexibility options involving energy system modelling with a geographical extent from the municipal to supra-national scale. All studies include analyses of DSF and several articles consider both DSF and other forms of flexibility, notably distribution and/or transmission networks, storage, power-to-heat, power-to-gas, and supply-side measures.

Features of the articles that are of relevance to this paper are the main focus of this section.

2.1. Previous studies of demand-side flexibility

The detailed analyses of DSF are of particular interest in the present context (Mishra et al., 2016; Andersen et al., 2006; Matar, 2017; Ali et al., 2015; Li and Pye, 2018; Grohnheit and Klavs, 2000; Tveten et al., 2016; Katz et al., 2016; Marañón-Ledesma and Tomasgard, 2019). They consider load shifting (reducing demand at a given price level) or peak clipping (reducing peak demand where the demand appears later on), or both, for either the electricity sector alone, or for both the electricity and heating sectors. Five such studies (Katz et al., 2016; Mishra et al., 2016; Matar, 2017; Gils, 2016; Li and Pye, 2018) focus on household appliances as a DSF, including automatic control of appliances (Mishra et al., 2016; Li and Pye, 2018). Especially relevant here is the study by Katz et al. (2016) that compares intra-hour and intra-day demand-side flexibility, corresponding to consumer participation in, respectively, hourly spot (balancing) and reserve markets. It concludes that consumers can gain the most by participating in reserve markets where price differences are large. Several studies assess the flexibility of electric vehicle charging (G2V) or de-charging (V2G) (Panos et al., 2019; Child et al., 2017; Pilpola et al., 2019; Sijm et al., 2019; Li and Pye, 2018) as potentially important DSF measures.

2.2. System-level effects of flexibility

Most studies identify significant system-level benefits from flexibility, including lower overall system costs, less need for energy storage, higher shares of renewable energy, and lower carbon emissions. In the UK, for example, the use of smart appliances and passenger EVs as DSF providers leads to overall cost savings of 4.6 billion GBP per year (1.03%) in 2050, due to a higher penetration of (less expensive) wind power (Li and Pye, 2018). The authors also identify large reductions in the marginal cost of electricity during the winter (5.3%) and summer (56%) peak periods (Li and Pye, 2018). The economic benefits of flexibility options in low-carbon energy scenarios are often greater for the producers than for the consumers of electricity, especially variable renewable energy producers (Tveten et al., 2016; Lund et al., 2019). This suggests that there are important distributional issues associated with increasing the flexibility of energy systems (Lund et al., 2019) and that households may have weak incentives to adopt flexible consumption behaviours and technologies (Tveten et al., 2016).

2.3. Data sources

Only two studies (Mishra et al., 2016; Li and Pye, 2018) use experimental data on energy consumption from smart meters recording consumption at hourly or sub-hourly intervals as inputs to system-level modelling. All other studies rely on secondary data. In this context, our paper is unique in applying experimental data on household demand response in an energy-system modelling framework.

2.4. Time resolution and time scale

Several studies, e.g. Katz et al. (2016), Mishra et al. (2016) and Anjo et al. (2018), concern short-term (intra-day) flexibility options, typically 1-6 hours and up to 24 hours, such as household appliances, V2G, G2V, and processes in industry and services (see Anjo et al. (2018) for an overview). These analyses of DSF are based on load profiles with hourly or sub-hourly resolution and covering a period from one week (Jensen et al., 2006) up to one year (e.g. Gils (2016); Katz et al. (2016)). Katz et al. (2016) focus on the time of day with the greatest load shift potential for household appliances, the evening. Other studies, such as Panos et al. (2019), consider both short- and long-term flexibility options, including batteries (daily), pumped storage (weekly), power-to-gas, and seasonal power-to-heat (seasonal). Our present study adds to the understanding of short-term flexibility by assessing the systemic effects of ICT-enabled intra-day load shifting over a period of 18 months.

Regarding the time scale of the scenarios, ten studies cover longer periods, i.e. up to 2030 (e.g. Tveten et al. (2016); Child et al. (2017)), 2035 (e.g. Katz et al. (2016)), and 2050 (e.g. Li and Pye (2018); Pilpola et al. (2019); Lund et al. (2019)), while 'proof-of-concept' studies (Alhamwi et al., 2017; Bolwig et al., 2018) do not specify a time period. The studies performing in-depth analyses of household demand response mechanisms (Mishra et al., 2016; Jensen et al., 2006; Matar, 2017; Ali et al., 2015) typically do not include long-term scenarios. The exception here is Li and Pye (2018), which covers the period 2010-2050, as well as the present study, which analyses scenarios up to 2030.

2.5. Geographical scale and scope

The geographical scale of energy system models ranges from the supra-national (e.g. Balmorel (Wiese et al., 2018), COMPETES (Sijm et al., 2017)) to the national (e.g. Balmorel (Wiese et al., 2018), TIMES (Loulou and Labriet, 2008), KAPSARC (King Abdullah Petroleum Studies and Research Center ("KAPSARC"), 2020), REMix-OptiMo (Scholz et al., 2017), OseMOSYS (Howells et al., 2011)) and sub-national (e.g. EnergyPLAN (Department of Development and Planning, Aalborg University, 2020), FlexiGIS (Alhamwi et al., 2018)), with a clear dominance of national-scale analyses. Thirteen studies concern Northern Europe and the Baltics, while two studies are from central (Switzerland) and southern Europe (Portugal) respectively, and one from outside Europe (Saudi Arabia). Hence, while this article like many others also addresses the national scale, it contributes to a better geographical distribution of modelling flexibility across Europe.

2.6. Claims of novelty and synthesis

The novelty in the studies reviewed above centre on the ability to reliably assess the system-wide effects of flexibility options over longer periods, typically up to 2030-2050, regarding especially overall system costs, consumer and producer benefits, greenhouse gas emissions, and the integration of variable renewable energy technologies - especially wind, solar and hydro. Often the improved analysis of flexibility involves adding modules to existing energy models, soft-linking different models, or in a few cases building new models. Adding new data on flexibility technologies to the models are always prominent features of the studies. As in this article, about half of the studies concern only DSF, often with a focus on residential DSF (appliances and electric vehicles), while few address DSF in industry and services. Only two such studies use experimental data but rely on estimates of potentials from secondary sources. While two studies of DSF include automated controls of appliances, none of the articles analyse the system-wide effects of ICT-enabled DSF technologies. In summary, the central novelties in the present paper are the use of primary data from a field trial, to analyze system-wide flexibility potentials with a transferable methodology.

3. Econometric estimations and input data

The Austrian field study of the ICT tool involved 1,557 households as participants[2]. Smart meter electricity consumption and price data were collected for these households in 15-min time slices from May 2017 until October 2018. Of the 1,557 households that were recruited into the field test, 1,042 were given access to the app by November 2017 and fall into the A group, while 515 were not given access to the app and are denoted

[2]For a full explanation of the experimental design, sample composition and recruitment procedure please see Reichl et al. (2019).

as the C group. All participants in the A group were given access to the app, but may or may not have downloaded it, or interacted with it during the study period. As such, we use Google Analytics data from app usage to denote a third group of participants as 'heavy users', who used the app at least once a month over the duration of the field test (Nov. 2017 - Oct. 2018). Participants in the heavy users group were exposed to the information contained in the ICT tool on a regular basis over a prolonged period. Amongst our sample households in the A group, 17% of them are heavy users of the app based on the above definition.

The data were cleaned to remove readings that were obviously faulty, such as meters that never registered a positive consumption value, or readings that were unrealistically high. After the data cleaning step, the full dataset contains 65,092,913 observations from May 2017 - October 2018. Households in the study have various electricity tariffs (pricing plans), some of which are based on a price schedule and thus can vary throughout the day, while other tariffs will only adjust the price per kWh annually or semi-annually. From our sample of over 65 million observations, 31.4% of them are subject to time-of-use pricing. Consumption readings only from primary meters are included in observed consumption values, so that secondary meters, mostly those that govern automated systems, such as heat pumps or pool cleaners, are not included here. Households are generally unable to interact with the devices linked to secondary meters, and thus cannot change the consumption on these meters in response to prices or information.

3.1. Price elasticity estimation

Own price elasticities are a measure of the responsiveness of demand to price changes, and are expressed as the percent change in demand for a good given a 1% change in the price of that good. Many past studies have estimated price elasticities of demand for residential electricity consumption, usually using aggregated demand data (country level, regional, etc). A recent synopsis and meta-analysis of these studies finds that amongst the 175 estimations of short-term residential price elasticities in peer-reviewed literature, the mean value is -0.228, with a minimum value of -0.948 and a maximum value of 0.610 (Zhu et al., 2018). The substantial majority of these estimates are less than zero, indicating that higher prices lead to a decrease in quantity consumed, as would be expected by economic theory if electricity is a normal good. Also notice, that the entire range of estimated elasticities is less than 1 in absolute value, indicating that short term residential electricity demand is relatively inelastic. Thus, we expect to find elasticities in Austria that are between 0 and -1.

The general econometric strategy employed here is panel data estimation, and follows prominent papers estimating price elasticities and treatment effects on residential electricity consumption (Jessoe and Rapson, 2014; Martin and Rivers, 2018; Gilbert and Zivin, 2014). Specifically, we estimate the models in eq. (1), where the dependent variable $log(D_{i,t})$ is the natural logarithm of the total household electricity demand for each household i in a unique 15-minute interval t.

$$\begin{aligned}
&\text{Average Specification:}\\
&log(D_{i,t}) = \boldsymbol{\beta}_1\big[log(\pi_{i,t}) * \boldsymbol{group_i}\big] + \beta_2 * J_{i,t} + \boldsymbol{\lambda}_t + \mu_i + \epsilon_{i,t}\\
&\text{Hourly Specification:}\\
&log(D_{i,t}) = \boldsymbol{\beta}_1\big[log(\pi_{i,t}) * \boldsymbol{group_i} * \boldsymbol{hour}_t\big] + \beta_2 * J_{i,t} + \boldsymbol{\lambda}_t + \mu_i + \epsilon_{i,t}
\end{aligned} \tag{1}$$

The construct of interest from eq. (1) is the vector of coefficient estimates $\boldsymbol{\beta}_1$, which contains the price elasticities of demand for electricity. The Euro price per kWh of electricity is given in log form as the variable $log(\pi_{i,t})$. Critical to our purpose is the matrix $\boldsymbol{group_i}$, which contains a set of two indicator variables denoting the experimental group to which household i belongs, either A or C. Thus, we estimate a separate price elasticity for those that have access to the app (A) and those that do not (C), simultaneously. The model in eq. (1) is specified in log-log form, for two reasons. Firstly, this ensures that both the dependent variable $log(D_{i,t})$ approximates the normal distribution, and secondly to allow for $\boldsymbol{\beta}_1$, the price coefficients, to be easily interpreted as elasticities.

The μ_i terms are fixed effects at the household level, absorbing general heterogeneity in average electricity consumption between households. These terms will account for factors such as household temperature preferences, appliance ownership, home size, and the number of people in the home, which are all relevant for overall electricity consumption (McKenna et al., 2016). The $\boldsymbol{\lambda}_t$ construct is a vector of temporal fixed effects that includes a fixed effect for each day of the sample period, and hourly fixed effects (i.e. the time resolution of Balmorel) for each day of the week. Thus, in each model we have $24 * 7$ hourly fixed effect terms that control for the average household load profile throughout each day. These are allowed to vary between days of the week since load profiles are often different between days, most notably between weekends and weekdays. The day fixed effects control for daily heterogeneity in household electricity use across the sample. Sources of daily heterogeneity can include holidays, special events, and weather conditions. Since our sample is geographically contained within the state of Upper Austria, sample households will be subject to generally the same weather conditions on each day, allowing the $\boldsymbol{\lambda}_t$ day fixed effect terms to control for this important driver of electricity use. The variable $J_{i,t}$ accounts for messages that were sent out to some users of the app during points in the field test. These messages tested other potential features of the app that would allow the utility company to connect directly to their customer base. These treatments are not of primary interest here, so we simply control for their presence in the model with the $J_{i,t}$ dummy variable, which takes a value of one if a treatment message was sent out for time t to household i. The error term $\epsilon_{i,t}$ is clustered at the household level and is assumed to have a within-cluster mean of zero and normal distribution.

The only difference between the "Average Specification" model and the "Hourly Specification" model in eq. (1) is the interaction of a suite of indicators for hour of the day ($\boldsymbol{hour}_t$) with the price in the Hourly Specification. This addition allows the model to estimate a separate price elasticity of demand for each hour of the day for each group (A or C). In the Hourly Specification models this results in a vector of 24 slope coefficients per group in $\boldsymbol{\beta}_1$, which relate electricity price to consumption.

In order to allow for sufficient variation in $\pi_{i,t}$ within panel and fixed-effect groupings, we employ fixed effects at a broader temporal scale than those used in Martin and Rivers (2018) and Jessoe and Rapson (2014), and similar to the strategy taken in Gilbert and Zivin (2014). The problem encountered while using more flexible fixed-effect specifications that allow $\boldsymbol{\lambda}_t$ to also vary across households, is that within a given household, price rarely changes across days for a specific hour of the day, and price changes within days follow a schedule that does not vary strongly from day to day. Thus to identify an elasticity for each hour of the day in a given month, as is our goal, broader fixed effects terms are needed that still control for the critical factors causing household electricity consumption to vary across time, which we believe is accomplished with the specification described above.

The models in eq. (1) are estimated using the field test data described above. For the elasticity estimations, the dataset is limited to observations after November 21, 2017, the date when all participants in the A group had been given the link to access the app. This constrains the estimation sample to almost exactly one calendar year (Nov. 2017 - Oct. 2018) and ensures a 1:1 overlap between the observations from the A and C groups in terms of the time periods observed. In total we estimate each specification of the model in eq. (1) 13 times, using a different set of data for each estimation. The first estimation uses data from the entire year, and thus results in sample average elasticity estimates across the entire time period of the sample.

The other 12 estimations use only data from a specific month, resulting in month-specific elasticity estimations. The estimated elasticities are shown in table C.2. From these elasticities the monthly estimates are those included in Balmorel, while the average (full year) effects are presented in case of reader interest.

The elasticity estimates, given in table C.2, show that the average elasticity across the full year is -0.12 for the C group and -0.184 for the A group. While the group with the app has a greater magnitude elasticity, suggesting a higher degree of responsiveness to price, the elasticities are not statistically different between the A and C groups on average over the full year of data. The interpretation of the A elasticity, for example, is that a 10% increase in short-term price leads to a 1.84% decrease in household electricity consumption. This falls within the expected range found in the synthesis of elasticity estimations (Zhu et al., 2018), and also agrees with past findings that the short-term electricity demand is price-inelastic.

Furthermore, the estimated elasticities show that the demand elasticity is essentially zero during the typical sleeping hours (11pm - 7am). The elasticity then increases in magnitude, peaking between 9 - 10am, and again between 12 - 1pm, and remains large until around 4pm and then gradually falling back towards zero. We note that elasticities have very low magnitudes when consumption is also low. This makes sense as most consumers are sleeping at these times and unable to turn on/off household devices. Comparing elasticities to average prices during a day, we note a strong negative correlation where times with higher prices also have greater magnitude elasticities, suggesting a scale effect.

3.2. Energy efficiency effect estimation

Alongside the short-term access to price information, households with access to the app also had the possibility to view detailed graphics about their electricity consumption and electricity price schedules. Recent studies have tested the effects of such general price and consumption information on household consumption behavior. However, the reduction in energy consumption that can be expected from additional information varies strongly between studies (Buchanan et al., 2015). An empirical review of these results was completed in 2013, and found that the average estimated reduction in household energy use from the provision of energy consumption feedback was 7.4% across the 156 studies surveyed (Delmas et al., 2013). However, of these 156 studies only 22 were robust to respondent socio-demographic, geographic, and climate differences. The 22 robust studies showed an average energy reduction of 2% due to the increased information. A separate review of past literature has the less optimistic finding that there may be no medium to long-term reductions in energy use from ICT-based information provision (Buchanan et al., 2015).

Furthermore, the type of feedback and information provided strongly influences the level of energy-use-reduction achieved (Buchanan et al., 2015). In a large-scale field test in the city of Ontario, Canada, in-home displays of electricity consumption and current prices were installed by households. Households with the display decreased electricity consumption by 3.1% on average (Martin and Rivers, 2018). In a similar, yet smaller scale study in Austria it was found that providing informational feedback via ICT reduces electricity consumption by 4.5% on average amongst households (Schleich et al., 2013). Years after this Austrian field test a follow-up study was completed that found this decrease in electricity consumption was persistent amongst households with consumption feedback (Schleich et al., 2017). Thus, the literature in this vein suggests that finding a 0-7.4% decrease in overall electricity consumption from information effects would be reasonable.

To estimate the medium-term treatment effect of app usage on household electricity consumption we use a similar econometric strategy as for the elasticity estimation, with slight changes to account for the time-scale and the effect of interest.

$$\begin{aligned}
&\text{Average Specification:}\\
&log(D_{i,t}) = \boldsymbol{\beta}_0\big[user_{i,t} * \boldsymbol{season_t}\big] + \beta_2 * J_{i,t} + \boldsymbol{\lambda}_t + \mu_i + \epsilon_{i,t}\\
\\
&\text{Hourly Specification:}\\
&log(D_{i,t}) = \boldsymbol{\beta}_0\big[user_{i,t} * \boldsymbol{season_t} * \boldsymbol{hour}_t\big] + \beta_1 * log(\pi_{i,t}) + \beta_2 * J_{i,t}\\
&\qquad\qquad + \boldsymbol{\lambda}_t + \mu_i + \epsilon_{i,t}
\end{aligned} \tag{2}$$

The econometric model in eq. (2) has the same elements as that in eq. (1), explained in section 3.1, with the following differences. First and foremost, the construct of interest is now $\boldsymbol{\beta}_0$, which gives the average effect of app usership on consumption. This effect is broken down into seasonal energy efficiency effects through the inclusion of three season indicators in the $\boldsymbol{season_t}$ matrix that denote winter (Dec., Jan., and Feb.), summer (June - Aug.) and transition times (March - May, Sept. - Nov.). Thus, in the Average Specification in eq. (2) we estimate three energy efficiency effects, one per season, and in the Hourly Specification we estimate $24 * 3$ energy efficiency effects. The $user_{i,t}$ variable is an indicator, which takes a value of one if household i is a 'heavy user' of the app during time t. Recall that a heavy user is defined as a household that used the app at least once during every month that they had access to it. Also recall, that our data series begins in May 2017, but that the last households to gain access to the app did so in November 2017. Thus, for many heavy users we observe their behavior both before and after they gained access to the app; once they gained access to the app the $user_{i,t}$ variable switches to one for the remainder of the sample period if the household qualifies as a heavy user. In this way, the $\boldsymbol{\beta}_0$ coefficients can be thought of as 'differences in differences' treatment effect estimates.

It should be noted that we also tested a definition of the $user_{i,t}$ variable that indicated all users in the A group once they gained access to the app. However, we detect no statistically significant average energy efficiency effect on this broader group of users, likely because many of them did not use the app frequently (or at all) during the field test. As such, we narrow the definition of the $user_{i,t}$ variable to relate to the 17% of A households who were heavy users of the app. In this way we can explore the energy efficiency effects on this group who have shown an interest in energy topics and in using an ICT to human ecosystem.

A second change from the specification in eq. (1) to that in eq. (2) is that the $\boldsymbol{\lambda}_t$ construct is expanded to include *season-specific* hourly fixed effects unique to each day of the week, along with the fixed effects for each day of the sample period. Thus, in each model we have $24*7*3$ hourly fixed effect terms that control for the average household load profile throughout each day of the week for each season. This accounts for seasonal changes in electricity consumption patterns that may be present due to changing weather and hours of daylight. In the case of the elasticity estimations described in section 3.1, accounting for season-specific patterns is not critical, because the econometric inputs for Balmorel come from monthly models, which then, by default, account for seasonal effects at the finer, monthly scale within $\boldsymbol{\lambda}_t$.

The model in eq. (2) is estimated once for the Average and once for the Hourly Specification. As noted above, these estimations use the full sample time period (May 2017 - Oct. 2018) and the full sample of available 15-min consumption observations. The results are shown in table C.1.

The estimated 'treatment effects' shown in table C.1 give the average percentage change in electricity consumption from becoming a heavy user of the app ICT tool, defined as users who engage with the app at least once per month. For example, heavy app users were able to decrease electricity consumption by 6-7% in the summer and transition months, on average. While in the winter months we do not find an energy efficiency effect from heavy usership of the app, on average. This could be due to the generally much higher electricity consumption in the winter cancelling out small behavioral improvements in energy efficiency (e.g. turning off the lights/appliances, fewer cycles of washing machines, purchases of more efficient appliances, etc.) that are identifiable under the statistical power of the study during the lower consumption times of summer, autumn and spring. The hourly energy efficiency effects show a similar pattern to the hourly price elasticities: the strongest effects are present during the day when electricity consumption is generally high. No statistically significant energy efficiency effects are observed from 8pm - 6am, when the majority of consumers are sleeping and not performing active electricity consuming activities.

4. Balmorel model of the Austrian energy system

4.1. Introduction to Balmorel

Balmorel (BALtic Model Of Regional Electricity Liberalized) is an open-source, bottom-up, partial equilibrium energy system capacity development and dispatch model that employs linear programming, originally developed by Ravn (2001) and subsequently extended and employed in many national and international applications (e.g. Wiese et al. (2018)). Balmorel minimizes total system costs for a combined electricity and district heating system in an international context in the long term, but on an hourly basis, including investment in new generation plants, operational costs and in some cases additional transmission line capacities.

In the Balmorel model, as for many similar energy system models (Ringkjøb et al., 2018; Keles et al., 2017; DeCarolis et al., 2017), the starting point is the exogenously-defined regional demands for electricity and heat, which are provided as inputs alongside macroeconomic developments in energy and carbon prices. The model meets these predefined demands by employing existing generation technologies, as long as technically and/or economically feasible, as well as new generation plants.

Geographically, the model is divided into three categories: countries, regions and areas. Each country is divided into a number of regions and the regions are divided into areas. The model allows for electric power transmission between regions via inter-connectors. Within areas, the heat demand is balanced by district heating. The version of Balmorel employed in this research includes the Nordics and neighbouring countries, and is extended to include Austria.

4.2. Scenario framework and implementation of the price elasticities in Balmorel

In order to estimate the impact of a potential roll-out of the smart phone app to the whole of Austria, we utilize the energy modelling framework Balmorel. The underlying hypothesis is that an energy system with high shares of variable renewable energy sources and therefore potentially more fluctuating electricity price profiles could benefit economically from an increase in demand side flexibility. To test this hypothesis, the following five scenarios are defined and analysed:

- Business As Usual (BAU), reflecting an expected development of the energy system with current policies
- Renewable Energy System (REN), reflecting a rapid shift to a 100% renewable energy system
- Renewable Energy System with Elastic demand (REN-E), as REN but with an elastic demand captured by the estimated price elasticities (Section 3.1)
- Renewable Energy System with Elastic demand and 17% treatment effect (REN-E-17), as REN-E but with 17% of households subject to the energy efficiency treatment effect by being heavy users of the app (Section 3.2)
- Renewable Energy System with Elastic demand and 100% treatment effect (REN-E-100), as REN-E but with 100% of households subject to the energy efficiency treatment effect by being heavy users of the app

The BAU scenario represents a truly descriptive approach. It takes the mainstream assumptions for e.g. fuel costs or technology characteristics into account and describes where this could lead to in the future, if nothing changes, e.g. by policy decisions. In contrast, the four renewable scenarios can be seen as artificial normative scenarios. They comply with the Austrian policy decision to de-carbonise the power system by 2030, without having introduced an additional constraint in the model. Instead, to ensure carbon-neutrality by 2030 in the model, the fossil fuel prices have been increased accordingly. Hence, the REN scenarios use an exploratory methodology. Figure 1 illustrates the employed methodology, including the five scenarios and the use of price elasticities to determine new electricity demands.

In the REN-E scenarios, elastic electricity demand is introduced through the price elasticities of demand estimated from the field trail, as described in Section 3. There is no balancing constraint imposed such that increases or decreases in the hourly amount of consumed electricity is compensated for in the later course of the year (i.e. no load shift). Therefore, applying the elasticities likely leads to an overall change in annual household electricity consumption.

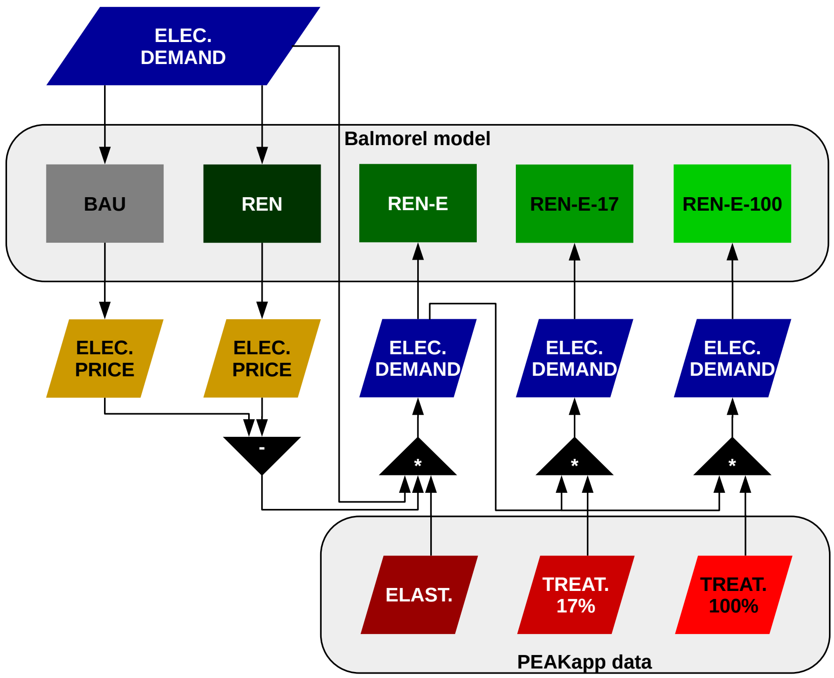

Figure 1: Conceptual illustration of the scenario setup for elasticity implementation using Balmorel (for details of the scenario framework, see text

The econometric analysis of the field trial data provided hourly point estimates for price elasticity of demand as described in section 3 and shown in table C.2. Elasticities were estimated for two groups: those with and without the ICT application, called active (A) and passive (i.e. control, C) groups, respectively. The elasticities are an estimation of the household's willingness to vary electricity consumption in response to changes in price within a given hour of the day.

Since there is a linear dependency between price and electricity consumption change, their temporal resolution consists of two data points (i.e. A and C) for each hour of the day and each month of the year - in total 576 data points. To derive a chronological elasticity profile for the entire year, copies of those days are concatenated to represent the full month. Afterwards, the resulting monthly profiles, which consist entirely of copies of the one day, are again concatenated to make up a full year. This enables us to multiply the electricity price differences in each hour of the year between two scenarios with the elasticity estimate for these hours. This results in an annual electricity demand change profile eq. (3). The latter can then be used to manipulate the electricity demand profiles in the successive scenario runs.

Equation (3) defines the mathematical implementation of the estimated elasticities ($\boldsymbol{\beta}_1$ in eq. (1)) and energy efficiency treatment effects ($\boldsymbol{\beta}_0$ in eq. (2)) in the different scenarios REN-E, REN-E-17, and REN-E-100.

$$\begin{aligned}
&\text{Hourly electricity demand } D \text{ by } R \text{ and } T\text{:}\\
&D_{t,r} = D_{t,BAU} \cdot \delta_t^{\pi} \cdot \boldsymbol{\beta}_1 \left(1 + \boldsymbol{\beta}_0 \cdot \iota_r\right), \forall r \in R, \forall t \in T\\
&\\
&\text{s.t.}\\
&\text{Hourly electricity price difference by } T\text{:}\\
&\delta_t^{\pi} = \frac{\pi_{t,REN}^{el} - \pi_{t,BAU}^{el}}{\pi_{t,BAU}^{el}}, \forall t \in T\\
&\text{Intensity of treatment effect } (\boldsymbol{\beta}_0) \text{ by } R\text{:}\\
&\iota_{REN-E} = 0\\
&\iota_{REN-E-17} = 0.17\\
&\iota_{REN-E-100} = 1\\
&\text{Set of all time steps:}\\
&T := \{1, 2, 3, ..., 8760\}\\
&\text{Set of all renewable scenarios w/ elasticities:}\\
&R := \{\text{REN-E, REN-E-17, REN-E-100}\}
\end{aligned} \tag{3}$$

4.3. Harmonizing price profiles

Balmorel calculates different electricity price profiles consisting of marginal or wholesale prices for each model time step. Among a number of different factors that can influence these price profiles, the setting, whether endogenous investments are allowed or not, and the different fuel prices in the BAU and REN scenarios showed the biggest impacts. When running the model with endogenous investments, which is the case for BAU and REN, very high price spikes are observed. These spikes correspond to the marginal electricity prices and are thus related to the investment decisions in particular time steps. In contrast to the empirical elasticities employed in this research, price spikes are not currently encountered for this reason (but for others) in reality, thus these two time-series need to be harmonized by removing these outliers. Equation (4) defines the mathematical approach to the harmonization adopted for this analysis.

$$
\begin{aligned}
&\text{Eliminating large peaks:}\\
&\pi^{el'}_{t,s} = \begin{cases} \overline{\pi}^{el}_{T,s} & \pi^{el}_{t,s} > \sigma(\pi^{el}_{T,s}) \\ \pi^{el}_{t,s} & \pi^{el}_{t,s} \leq \sigma(\pi^{el}_{T,s}) \end{cases} \forall t \in T, \forall s \in S\\
&\text{Re-scaling } \pi^{el'}_{t,REN}\text{:}\\
&\pi^{el''}_{t,REN} = \frac{\pi^{el'}_{t,REN} \cdot \overline{\pi}^{el}_{T,REN}}{\overline{\pi}^{el}_{T,BAU}}\\
&\text{s.t.}\\
&\text{Electricity price profiles:}\\
&\pi^{el}_{t,s}\text{ : original electricity prices w/ large peaks by } T \text{ and } S\\
&\pi^{el'}_{t,s}\text{ : electricity prices w/o large peaks by } T \text{ and } S\\
&\pi^{el''}_{t,REN}\text{: re-scaled electricity prices in REN w/o large peaks by } T\\
&\text{Set of all time steps:}\\
&T := \{1, 2, 3, ..., 8760\}\\
&\text{Set of all scenarios w/o elasticities:}\\
&S := \{\text{BAU,REN}\}
\end{aligned}
\tag{4}
$$

The outcome of the peak scaling procedure is shown in Figure 2. All prices greater than the standard deviation of the respective annual price profile are replaced by the annual mean prices. The new average prices are much lower than the previous spikes. This effect is resolved by re-scaling the new price profile where the peaks were eliminated, i.e. *REN w/o peaks* (see Figure 2). The re-scaling is done by taking the annual average electricity price ratio of *BAU original* (83 €/MWh) and *REN original* (102 €/MWh) of 0.8137 and multiplying the profile by it. This results in the *REN w/o peaks re-scaled* profile and ensures the same average annual electricity price as in *REN w/o peaks*. The former is used for the subsequent steps.

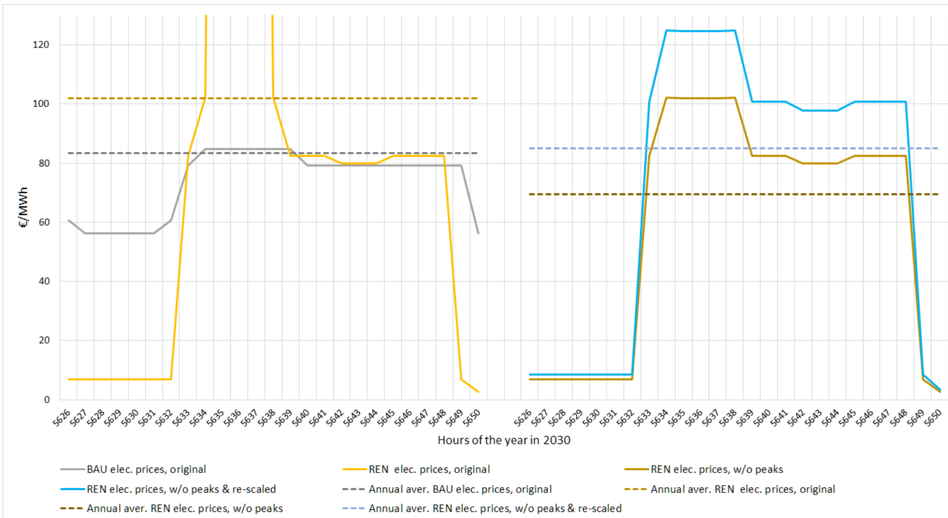

Figure 2: Example of electricity price profiles adjustments in 2030, based on eq. (4) and scenarios BAU and REN

5. Results of system-level analysis

5.1. Model validation

During the model development, attempts were made to ensure a close agreement with real-world data for 2016 in terms of electricity generation, international exchanges and electricity prices. For brevity, we focus here on the electricity generation in the context of an Austrian energy system with exogenously-fixed interconnector capacities and flows.

The validation, shown in Figure 3, focuses on a comparison of two cases, the real world based on empirical data from E-Control (2019) called "Historical data" and the model of the Austrian system in isolation (with interconnector capacities and transfers exogenously fixed) called "Balmorel results".

In the base year, the existing power plant capacity is fixed. Due to this, the focus is on the amount of electricity by fuel and technology in this base year. Figure 3 shows the generation by fuel type and generally illustrates a close agreement between both cases, especially for coal, hydro-power, solar energy and wind. There is substantially more deviation between these two cases for the generation from wood-chips, due to uncertainties in the assumed fuel price - this is at least partly compensated by higher coal generation in the Balmorel results.

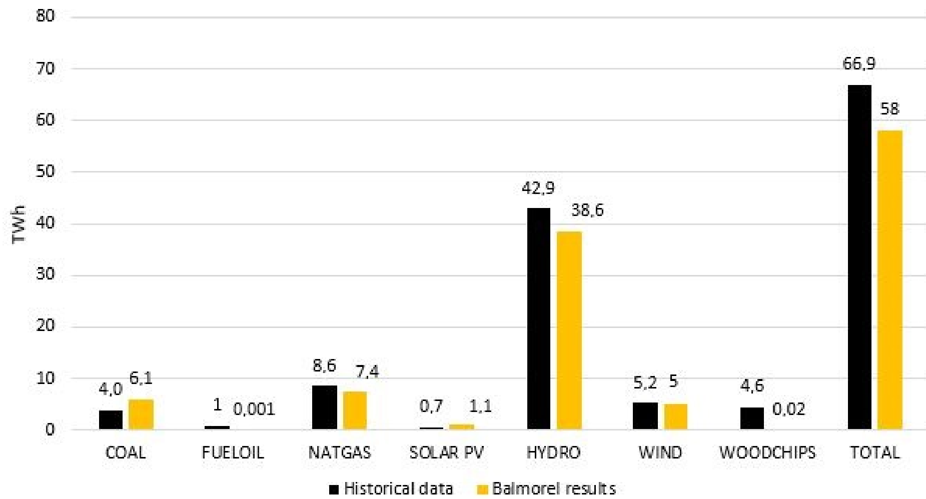

Figure 3: Comparison of electricity generation by fuel from Balmorel in 2016 with historical data based on E-Control (2019).

Overall, then, we encountered results in terms of generation that are broadly aligned with those seen in reality. The RMSE of the Balmorel results compared to the historical data across all fuel types is 11 TWh, which is a reasonable precision for a model of this type.

5.2. Capacity

Figure 4 shows the endogenous and exogenous generation capacities in 2030 for the five analyzed scenarios. The BAU scenario has substantial investments in solar PV (14.5 GW) and onshore wind (2.7 GW), and the lowest investments in electric battery storage (4 GW), which is incentivized by very high fossil fuel prices. This scenario is also the only one with additional gas-fired combined heat and power (CHP-extraction) capacity investments (1 GW), since the fossil fuel prices are kept almost constant in this scenario as shown in Appendix A. In contrast to the BAU, the REN scenario represents a completely renewable energy system, with substantially more solar PV (16.4 GW), wind (5.5 GW) and electrical storage (11.4 GW) than in the BAU scenario, but equal amounts of hydropower, due to the fact that this capacity is exogenously fixed.

The first scenario with the price elasticities but no energy efficiency treatment effect (REN-E, Figure 4) has even more installed capacity, which is due to increased solar PV (16.9 GW), wind (5.9 GW) and battery storage (12.2 GW) technologies. The treatment effect involving 17% heavy users encountered in the context of the field trials leads to a very slight capacity reduction compared to scenario REN-E, again mainly relating to onshore wind and PV, with a small increase in storage capacity. Finally, in the scenario assuming 100% heavy users in the Austrian population who are subject to the estimated energy efficiency treatment effects, a more substantial reduction in capacity is encountered compared to the REN-E scenario, especially in solar PV (15.9 GW), wind (5.7 GW) and storage (12.0 GW) technologies.

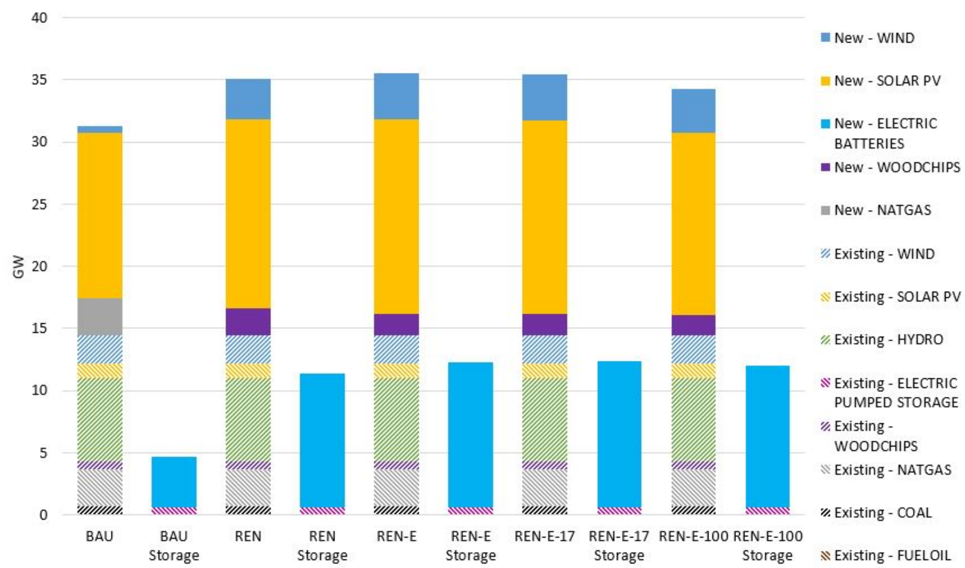

Figure 4: Endogenous (New) and exogenous (Existing) generation capacity in 2030 for the five analyzed scenarios.

5.3. Generation, fuel use and emissions

Figure 5 below shows the total electricity generation by fuels for the five analyzed scenarios. The total generation in BAU amounts to 67 TWh, which increases marginally in the REN scenario to 67.2 TWh, before reducing to 66.7, 66.5 and 65.4 TWh in the REN-E, REN-E-17 and REN-E-100 scenarios respectively. The main differences in generation source occur in moving between the BAU and REN scenarios, in which natural gas generation is mainly displaced by a combination of woodchips and other renewables (as also demonstrated for capacity in Figure 4). The main reason for slightly higher generation in the REN scenarios is the exploitation of storage technologies with a full-cycle efficiency of less than 100%.

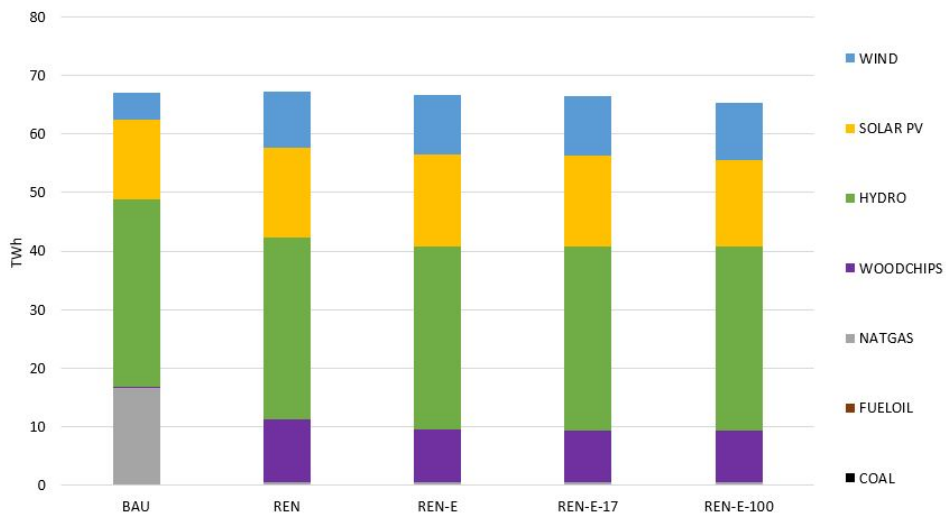

Figure 5: Electricity generation by fuel type in 2030 for the five analyzed scenarios.

The annual CO_2 emissions in the five analysed scenarios are shown in Table 1. According to these results, the annual CO_2 emissions amount to about 5.7 Mt CO_2 in the BAU, consisting mainly of emissions from natural gas and small amounts of coal and fuel oil. The emissions in all four of the other scenarios are substantially lower, in the range 0.15-0.16 Mt CO_2 (i.e. 3% of the BAU). Amongst the renewable scenarios, the REN scenario has the lowest emissions. Introducing the elasticities into the model results

Table 1: Annual CO_2 emissions in the five analyzed scenarios [Mt CO_2]

fuel type/scenario	BAU	REN	REN-E	REN-E-17	REN-E-100
Coal	86.3	1.1	3.2	2.9	2.2
Natural gas	5610.2	147.8	163.7	160.8	152.0
Fuel oil	0.04				
Total	5696.54	148.9	166.9	163.7	154.2

in the need for more flexible generation, and therefore increases the overall emissions in REN-E. The introduction of the treatment effects in the subsequent scenarios seems to have a linear effect on the reduction of the emissions – but even with a 100% treatment effect, the emissions do not reach the same level as in the REN scenario.

5.4. Objective function

Figure 6 below shows the difference in the objective function value (i.e. overall total discounted system costs) relative to the BAU scenario. As expected, the highly-renewable scenarios result in substantially higher system costs than the BAU scenario, by around 24% in the case of REN. The introduction of the elasticities in scenario REN-E and the subsequent heavy users (in REN-E-17 and REN-E-100) reduce the overall system costs, to a minimum of 20% higher than BAU in the case of the REN-E-100 scenario.

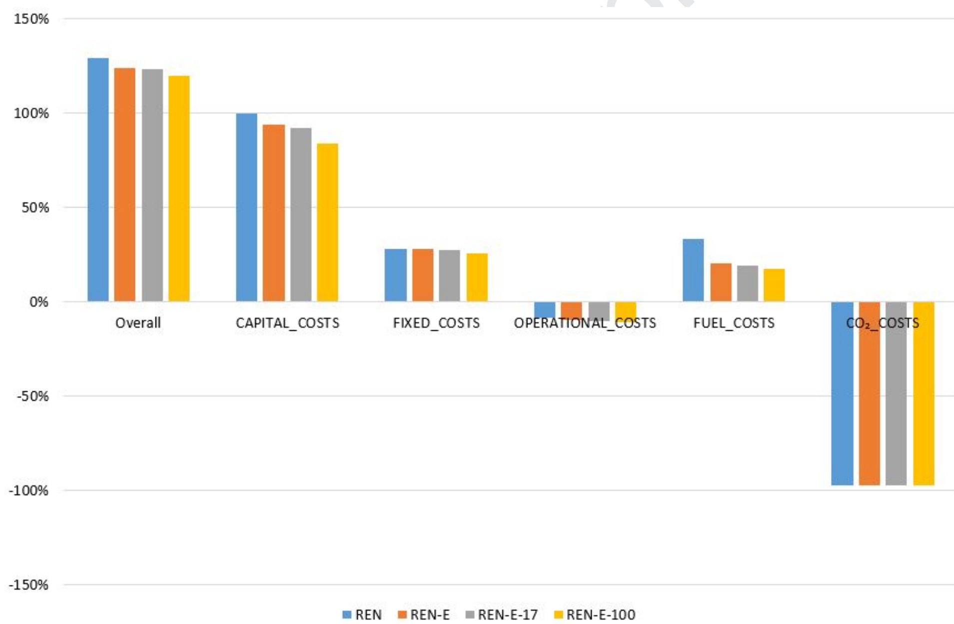

Figure 6: Objective function values for total system discounted costs in the four renewable scenarios relative to the BAU scenario

All of the renewable scenarios benefit from a reduction in CO_2 costs, reflecting the complete elimination of all non-renewable generation by 2030 due to prohibitively high fossil fuel prices. Additional costs are mainly concentrated in the capital cost fraction, due to the additional required investment in renewable generation plants, especially wind and PV.

5.5. Sensitivity analysis

In order to better understand the model's behaviour towards the introduction of elasticities, we investigate the following results with regard to their sensitivity to change: 1) objective values; 2) total investments in electricity generation capacity; 3) total annual electricity demand profiles. In the course of this analysis, the elasticity profiles are multiplied by factors from 0.5 (-50%) to 1.5 (+50%) in steps of 0.1. With the resulting elasticity profiles, new demand profiles are derived as input to the REN-E scenario.

As shown in Figure 7, the relation between elasticity and objective value change is linear and inversely proportional. However, the total impact seems rather small and there is no threshold identifiable. An increase in the short-term price elasticity of electricity demand therefore holds potential for positive socio-economic effects in terms of cost savings at the system level.

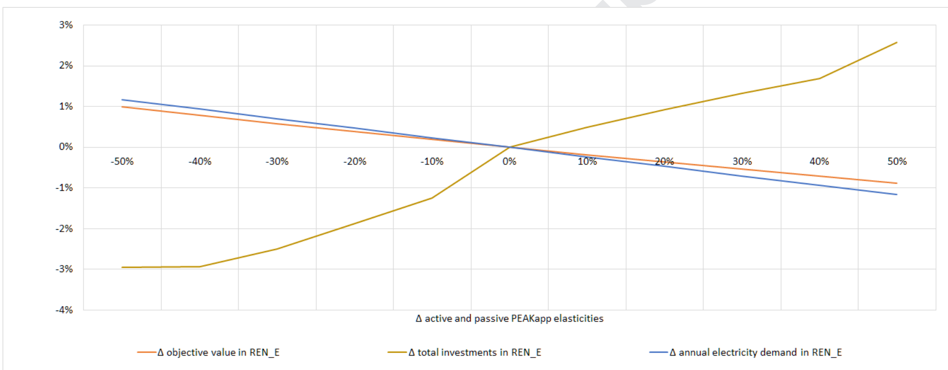

Figure 7: Sensitivity of the objective value, total capacity investment and electricity demand in the REN-E scenario compared to BAU in 2030.

An ascending, rather flat s-shape can be recognized for the total capacity investments. In our case, more elasticities entail lower total system costs by means of increasing investments into PV and battery capacity at relatively low costs. This can be explained by the demand peaks in hours where the prices as well as the demands are at high levels, which only occurs during daytime hours.

The relation between changing elasticities and total electricity demands follows a strong linear, inversely proportional trend. Again, the impact of the change stays relatively small and it does not show a threshold at any point. Overall, the results and trends of this analysis are as expected regarding the objective values and electricity demands, however with relatively small impacts.

6. Discussion

6.1. Discussion of results

The results show that increased DSF in the Austrian residential sector can provide the electricity system with benefits such as lower fuel use, lower overall and peak demands, a more efficient integration of renewable energies through lower total generation and storage capacities, and therefore lower total system costs. Overall, the trend towards an overall higher generation capacity in the REN scenario continues when flexible demand in the form of elasticities are introduced. The treatment/learning effect then reduces the required capacity as it tends to reduce also the peak demand and therefore the amount of secured capacity that is required to maintain security of supply. Two effects are observable in the results, namely the general flexibility through elastic demand and the energy efficiency effect encountered with heavy users of the app. Within the analytical framework employed here, the impact of both effects can be quantified and better understood in the broader context of the Austrian national energy system.

As seen in the previous section, the impacts of the elastic demand introduced in the REN-E scenario are small but significant. Compared to the renewable scenario with inelastic demand (REN), the system-wide flexibility introduced by connecting all residential consumers with their electricity price data through a smart phone app could reduce the overall system costs by 2.6%. Further reductions in system-level costs could be realized by achieving a high proportion of heavy users of the app who engage with their energy information at least monthly and improve their behavioral energy efficiency as a result. This is demonstrated at the system level in the REN-E-17 and REN-E-100 scenarios, where the impact of 17% and 100% of users qualifying as heavy app users is evaluated. In these two cases, additional cost savings compared to the REN-E scenario are 0.24% and 1.29%, respectively. This implies that a national roll out of an ICT to human ecosystem in electricity provision to all households in Austria could bring substantial costs savings in terms of avoided investments, fuel costs and more efficient integration of renewable energy, and that these savings are magnified as more households engage with the ICT system and critically evaluate their own electricity consumption behavior.

Although the economic benefits to the system increase with higher elasticities, this comes with a slightly negative impact on the environmental performance, due to different fuel utilization. This is in contrast to other studies, e.g. Li and Pye (2018). Another study employing the Balmorel model and an add-in to consider the techno-economic characteristics of load shifting potentials found similar results for the Nordic and Baltic region. Although they do not explicitly derive price elasticities, the authors identify a peak reduction of between 1% and 7% excluding and including electrical heating applications respectively (Kirkerud et al., 2019).

In the context of this analysis, these total discounted cost savings are of the order of €60 million annually, based on the above-mentioned differences between the REN and REN-E-100 scenarios, respectively. These figures should be put into context of the broader cost implications of this roll out. The smart phone app utilized in this research was developed by a specialized software company with the ambition to serve as an interface between an electricity supplier and its clients, potentially for millions of household customers. The development of the app built on an existing well-functioning app system for displaying smart metered electricity consumption, which at that time did not have the functionalities for handling dynamic electricity prices and informing households about their current consumption levels. The effort to develop and test these functionalities accumulated to about two person years of programming work. In addition to the development of the software, the provision of the app through an electricity supplier and the adaption of business processes to account for the new tariff structures requires the dedication of certain resources from the utility company. Among these efforts, changes to the existing IT infrastructure were among the more costly tasks. The execution of security tests and the training of the operating staff were also considerable efforts, and accounted for costs of about €100,000 for the electricity supplier.

Adding up the costs incurred by the utility company, a total effort equal to about €300,000 arose during this pilot project. While in this pilot only 1,000 households were served with the smart phone app, the provision of the system to all 4 million households in Austria would be much less than a linear increase in cost. Scale effects of the provision of software are substantial once a system has been carefully tested and the structures and processes for its operation have been set. Hence, we expect that the provision of an app like the one used for the presented field test to all Austrian households would cost in the range of €1 million annually. Nevertheless, changes in energy market regulation, smart metering technology, the threat landscape of cyber-security, the legislation for privacy and data protection, and other fields relevant for the provision of ICT tools to households, make this cost estimate subject to change. Even within the significant uncertainty associated with this cost approximation, there are clearly several orders of magnitude between the costs of supplying an ICT to human ecosystem and the expected benefits in terms of reduced energy system costs. This seems to imply the benefits greatly outweighing the costs, and emphasizes the need for further research and applications of ICT systems in energy.

6.2. Discussion of methodology

The model validation in section 5.1 as well as the sensitivity analysis in section 5.5 indicate that the developed Balmorel model is a reasonable representation of the Austrian power and district heating sectors. Whilst there were some relatively small deviations in the model outputs from expectations or historical data, these are considered to be minor in the context of this analysis. The focus in this work is on analyzing relative effects of assumption changes in a scenario framework, hence absolute results are secondary.

The econometric sample includes about 1,600 households in Upper Austria, mostly owner-occupiers with high levels of disposable income, as evidenced by the high ownership of saunas (20%). The implicit assumption in this work is that this sample is representative for the whole of the Austrian residential sector, which is likely not the case. The households in the sample have on average 24% more residents living in the home, 39% larger living areas, and 63% more often own their own properties (see Table B.1 for the detailed statistics). Hence the sample under-represents lower income groups, those living in rented accommodation and those with smaller dwellings and fewer appliances. The flexibility potential of the under-represented groups is constrained by their overall lower demand and smaller capital stock of appliances. The implication is therefore that the cost savings of DSF reported in this paper represent an upper limit.

In addition, there are caveats related to the elasticities. Elasticities are estimated using all of the participants in the field trial, some of whom had the time-variant electricity tariffs, and some of whom do not. One third of participants do not have the app (C group), so their knowledge of electricity prices may be low. Households with more electricity price information and feedback are expected to be more responsive to prices, which means the selection of households for this analysis is highly relevant. It is reasonable to expect that customers with time-variant tariffs have some knowledge of the pricing schedule, as they knowingly selected these tariffs. This presents a separate issue, which is self-selection of the choice of tariff; specifically, households who select a time-variant tariff may have different consumption patterns which make this tariff favorable to them. We argue that this is unlikely to be an issue for this estimation, since it is unclear how this would bias elasticity estimates within the context of the statistical models, and it is unlikely that households have enough knowledge to truly optimize tariff selection, as such optimization tools are not readily available to customers.

Furthermore, the modelling approach and scenario framework also has its weaknesses. Firstly, the focus in this work is on the flexibility of demand through active consumer participation, but there are strong synergies between these measures and others in the broader context of renewable energy integration. Examples include, but are not limited to, energy storage, supply-side flexibility, network expansion and densification, sector coupling, and flexibility in other demand sectors. By focusing on the residential sector we intentionally analyze the system-level impacts of DSF, but neglect potential flexibilities in other, large demand sectors, such as industry and services. Secondly, the employed approach adopts a central planner perspective assuming complete centralized decision-making and control over the energy system. In reality, of course, investment decisions for new power plants involve various stakeholders with different decision criteria. More importantly, the exploitation of widespread DSF, in this case throughout the Austrian residential sector, would require an equally widespread availability of technical infrastructure (e.g. smart meters, smart appliances) and market frameworks. Whilst the former is at an advanced stage in Austria, the latter does not yet enable real time/dynamic pricing to all customers. Thirdly, the employed approach does not take into account the strong current reductions in the costs of batteries and the associated trends in households to invest in stationary storage and/or electric vehicles. As these costs reduce further in the future, emerging niches, such as prosumers optimizing their own supply and consumption, and regional energy markets, could drastically impact the energy system and invalidate such a centralized perspective like the one taken in this work. Fourthly, this central planner perspective does not account for the so-called 'Lavine effect' that consumers could potentially have on prices when their behavior is non-marginal. The residential sector as analysed here represents 28% of the total electricity demand. The demand reduction for the residential sector in the REN-E-100 scenario of 8.5% represents just 2.4% of the total demand. So the practical impact of this assumption is likely to be small.

There are also some limitations relating to the general methodological framework employed and shown in fig. 1 above. Firstly, the employed elasticities represent point elasticities and are not necessarily valid for large price gaps. In other words, these point elasticities are assumed to be linear functions, which apply throughout the whole range of analysed price and demand. In reality, though, these elasticity functions would not necessarily be linear, especially at the extremes of demand where a marginal change is more significant than in mid-load regions. Secondly, these elasticities are short term, in the sense that they were derived from a field trial that measured the short term behaviour of households. But they are employed herein to represent how household load profiles could respond to short term price changes in the short and long term. In the longer term context of decades as analysed here, one would expect a larger adaptation of the demand side in response to longer term changes in price patterns - for example by households adapting their technology portfolios. This implies that our results are the lower bound of the actual behavioural change that would occur if people were made more aware of dynamic electricity prices over a long period of time.

Finally, we briefly discuss the application of the proposed method to other energy systems and extensions. The general method is transferable to other contexts, as long as several requirements are fulfilled. Firstly, fine-scale household consumption and price data from smart meters are required. Secondly, the market frameworks should allow consumers to respond to price signals by changing their demand profiles in the short term. Again, this requires a developed ICT infrastructure in order to provide consumers with real-time information, and the possibility for time-of-use tariffs. Thirdly, there should be sufficient renewable energy resources in the modelled country to make an analysis of highly-renewable future scenarios meaningful. Preferably the latter would be combined with social and political aspirations in the country to exploit some/more of these resources. If any of these requirements are not met, the method in its current form could not reliably be transferred and it would instead need to be adapted to reflect these differences. In terms of extensions, the coupling of energy system models with empirical estimates from field test data presented herein is a novel approach with plentiful opportunity for refinement and further work. For example, combining the broad behavioral literature on the adoption of energy technologies with scenario-based system-level models would allow for quantifying the effects of adoption subsidies on the cost of achieving energy transition pathways, providing policymakers with a direct cost-benefit analysis.

7. Summary and conclusions

This paper has assessed the effects of a hypothetical full roll out of an ICT to human ecosystem packaged as a smart phone app on the Austrian energy system. The paper uses 15-minute resolution electricity data from 1,557 households participants observed over a period of 18 months. In a randomized control trial framework, the participants were sorted into an active (A) group, who were given the app, and a control (C) group, who were not given the app. Based on this distinction, the consumption data are analyzed to derive short-term own price elasticities of electricity demand for both the A and C groups at the hour by month resolution (24×12 elasticity estimates per group). Households within the A group who engaged with the app at least once per month over the course of the field trial are labelled 'heavy users', and were shown to have improved their energy efficiency significantly. This effect is attributed to behavioral change brought about by the information provided on the app. This energy efficiency treatment effect of heavy app usership on electricity consumption is estimated for each hour of the day across three seasons of the year (winter, summer, and transition periods) using the field trial data.

The method extends the existing linear optimization energy system model Balmorel. The price elasticities mentioned above are employed as an exogenous input to derive changes in the exogenous electricity demand of the Austrian residential sector. The analysis is carried out for the time frame up to 2030 within a scenario framework of five scenarios. These include BAU (business as usual) and REN (full renewable deployment) scenarios, in both of which the demand is assumed to be inelastic. Three additional variants of the REN scenario consider the elasticities and varied levels of the energy efficiency effect, and therefore have flexible demands. By comparing these five scenarios in terms of diverse economic, technical and environmental criteria, we are able to explore the system level impact of an ICT roll out in Austria. The novelty of the method lies in the coupling of DSF estimates from a real-world field trial with a system model, as well as the application to the Austrian energy system.

The findings show that DSF can lower fuel consumption and electricity demands, promote investments in renewable technologies and lower total system costs in the context of building a carbon-neutral power system. Overall, the results demonstrate that the impact of residential DSF on the energy system is small but significant. In combination with other measures to integrate renewable energy technologies, this flexibility can play a crucial role. The total system cost increases by 24%, 23% and 20% in the REN-E, REN-E-17 and REN-E-100 scenarios, respectively, compared to the BAU scenario, due to heavy investments in renewable generation. However, the reduction in cost in the REN-E scenarios compared to the REN scenario is 4%, 5% and 7% respectively, which is due to DSF.

As detailed in section 6.2, the results are subject to several methodological caveats. The system-level impacts reported here should be interpreted as technical upper limits of the effects from short-term demand elasticity and energy efficiency improvements from an ICT system. Nevertheless, the results give a clear signal that ICT-enabled DSF can be an important cost-saving element that should be integrated into the future energy system and considered in system-level models.

Acknowledgements

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Appendix A. Employed data and assumptions

In this paper, Austria was modelled alone as a country which contains one region and two areas (the one with District Heating called AT_DH and one without it called AT_A_NoDH). Interconnectors were added as net exchange capacities with neighbouring countries: Germany, Italy, Hungary, Switzerland, Czech Republic and Slovenia. The available time slices in Balmorel are years, seasons (as weeks) and terms (as hours). The set for weeks is from S01 to S52 weeks and for hours is from T1 to T168 hours. In order to obtain a high level of precision in the dispatch optimization, the hourly time resolution was adopted for the full year.

The input data consists among others of energy demand, wind and solar profiles, wind, solar PV and solar heating full load hours, existing and future transmission capacities and generation plants, technical restrictions, technology costs, technology efficiency's and their lifetime, fuel prices, CO_2 taxes.

The employed data is based on multiple sources at the national level: E-control, ENTSO-E, APG, AIT, NETP, Technology Roadmap (International Energy Agency, 2010) and Windatlas & Windpotentialstudie Österreich (Energiewerkstatt, RSA - Studio iSPACE, Meteotest, Wegener Center, 2014). Below, the main sources used for the most relevant data of the model are stated.

- CO_2 prices:
  The emission policy data used in the model was from E-Control (2019). In fig. A.1 the CO_2 price development throughout the modelled time horizon is illustrated.

- System capacity:
  The system capacity power data was taken from Austrian Power Grid AG (2020) i.e. Austrian Power Grid. The employed data assumed decommissioning of 100% of the technologies capacities when their economic lifetime comes to the end. Within the scenario framework defined below, endogenous and exogenous investments in new capacity are possible.

- Energy demand:
  The source used for the energy demand data was ENTSO-E (European

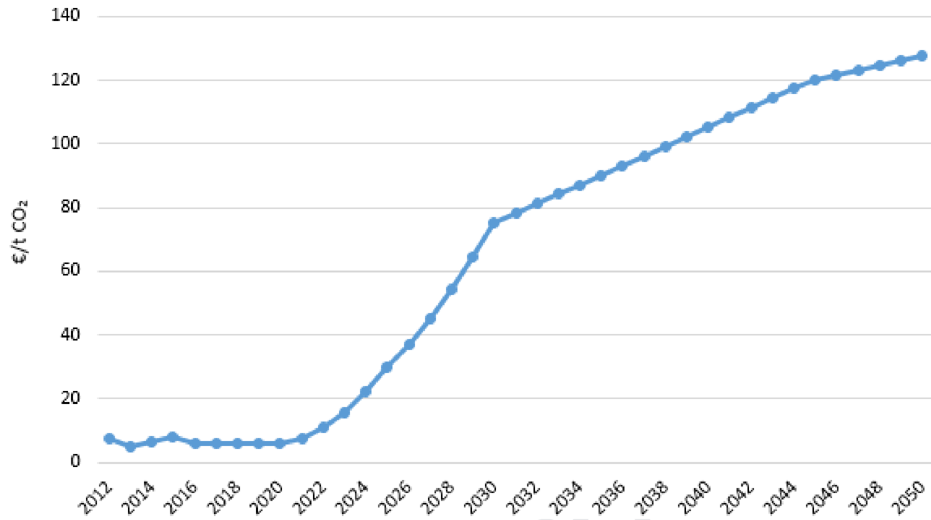

Figure A.1: Assumed CO_2 price development in all scenarios based on E-Control (2019)

Network of Transmission System Operators - Electricity) (2020), the European Network of Transmission System Operators for Electricity. Load profiles were taken from APCS Power Clearing and Settlement AG (2020).

- Fuel prices:
  Fuel prices were obtained from NETP 2016 (International Energy Agency, Nordic Energy Research, 2016), which was launched by the International Energy Agency and Nordic Energy Research. However, fuel data was collected from the European Environment Information and Observation Network (Eionet) (2020).

  Figure A.2 depicts the fuel fossil fuel price development for BAU (orange) and REN (blue). Obviously, the developments are very different from 2030 onwards. The fossil fuels in the Austrian energy system consist of coal (coal and lignite), oil (heavy fuel oil and fuel oil) and natural gas. In the BAU scenario fossil fuel prices stay at a relatively constant level. The prices in the REN scenario follow the same trend for the first 10 years (2020 to 2030) but then jump to an artificial price of 100€ per gigajoule and then all increase at the same annual rate of approximately 7%. The detailed prices and growth rates are presented in table A.1 for BAU and table A.2 for REN.

Table A.1: Fuel price development in BAU scenario based on International Energy Agency, Nordic Energy Research (2016)

	unit	natural gas	coal	lignite	fuel oil	heavy fuel oil	light oil
2020	€/GJ	5.64	2.31	0.75	5.43	12.60	9.93
aver. annual rate	%	5	2	3	9	0	6
2029	€/GJ	8.19	2.65	0.99	11.43	12.60	15.94
2030	€/GJ	8.32	2.67	1.01	12.10	12.60	16.61
aver. annual rate	%	1	0.2	0.1	0.1	0	0.1
2050	€/GJ	10.26	2.81	0.96	11.54	12.60	16.05

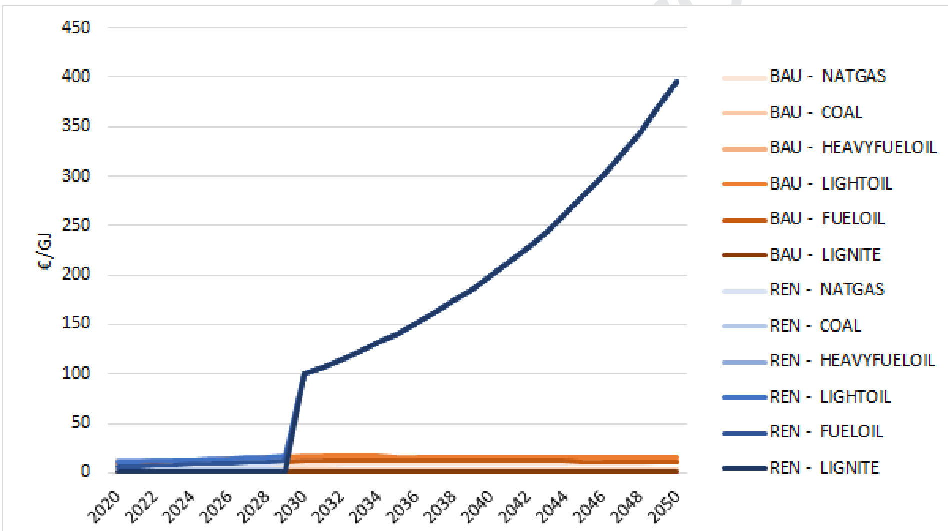

Figure A.2: Fuel price development in BAU and REN scenarios based on International Energy Agency, Nordic Energy Research (2016) & own assumptions for REN

Table A.2: Fuel price development in REN scenario based on International Energy Agency, Nordic Energy Research (2016) & own assumptions

	unit	natural gas	coal	lignite	fuel oil	heavy fuel oil	light oil
2020	€/GJ	5.92	2.43	0.79	5.70	13.23	10.43
aver. annual rate	%	5	2	3	9	0	6
2029	€/GJ	8.60	2.79	1.04	12.00	13.23	16.74
2030	€/GJ	100	100	100	100	100	100
aver. annual rate	%	7	7	7	7	7	7
2050	€/GJ	396.07	396.07	396.07	396.07	396.07	396.07

- Interconnectors:
  Austrian Power Grid AG (2020) and ENTSO-E (European Network of Transmission System Operators - Electricity) (2020) were the sources used for the interconnectors, representing the net transfer capacities between countries.

- Technology data:
  Suna and Aghaie (2019) from the Austrian Institute of Technology (AIT) provided technology data, which was collected in collaboration with the EEG group at the TU-Wien and from the Austrian private sector.

Appendix B. Statistical indicators

variable	units	AT_{all}*	PEAKapp sample	difference [%]
number of households (hhs)	[-]	3890000	1571	-99.96
number of residents	[mean/hh]	2.22	2.76	+24.32
area	[m^2/hh]	99.6	138.1	+38.66
home owned	[%/hh]	0.48	0.78	+63.18
dryer	[%/hh]	0.33	0.589	+78.48
swimming pool	[%/hh]	not specified	0.264	-
sauna	[%/hh]	not specified	0.205	-

Table B.1: Comparison of selected statistical indicators between the entire Austrian residential sector and the PEAKapp participants. *Based on: https://www.statistik.at/web_de/statistiken/menschen_und_gesellschaft/wohnen/index.html

Appendix C. Econometric estimations

Table C.1: Estimated energy efficiency effects of ‘heavy’ app usage by hour and season

	Transition times Spring and Fall effects		Summer time effects		Winter time effects	
	Treatment eff.	**Coeff. Est.**	**Treatment eff.**	**Coeff. Est.**	**Treatment eff.**	**Coeff. Est.**
Average	Specification:					
Avg. Effects	**-6.26%*****	-0.065	**-6.86%*****	-0.071	**-.68%**	-0.007
Hourly	Specification:					
Midnight - 1am	**-1.13%**	-0.011	**.39%**	0.004	**3.71%**	0.036
1 - 2am	**-1.12%**	0.011	**.15%**	-0.001	**4.04%**	-0.041
2 - 3am	**.65%**	-0.006	**.15%**	-0.001	**5.77%**	-0.059
3 - 4am	**1.75%**	-0.018	**1.08%**	-0.011	**6.22%**	-0.064
4 - 5am	**-.3%**	0.003	**-2.34%**	0.023	**5.38%**	-0.055
5 - 6am	**-1.%**	0.010	**-4.99%**	0.049	**5.11%**	-0.052
6 - 7am	**-3.58%**	0.035	**-11.32%*****	0.107	**2.22%**	-0.022
7 - 8am	**-11.5%*****	0.109	**-17.33%*****	0.160	**-2.27%**	0.022
8 - 9am	**-14.65%*****	0.137	**-12.69%*****	0.120	**-4.33%**	0.042
9 - 10am	**-13.64%*****	0.128	**-11.81%*****	0.112	**-6.75%**	0.065
10 - 11am	**-11.71%*****	0.111	**-10.56%****	0.100	**-5.79%**	0.056
11am - 12pm	**-10.96%*****	0.104	**-8.93%****	0.086	**-5.73%**	0.056
12 - 1pm	**-13.2%*****	0.124	**-10.85%*****	0.103	**-8.88%***	0.085
1 - 2pm	**-12.76%*****	0.120	**-11.38%*****	0.108	**-9.28%***	0.089
2 - 3pm	**-12.27%*****	0.116	**-10.87%****	0.103	**-6.7%**	0.065
3 - 4pm	**-12.75%*****	0.120	**-12.86%*****	0.121	**-5.2%**	0.051
4 - 5pm	**-13.3%*****	0.125	**-13.15%*****	0.124	**-3.82%**	0.037
5 - 6pm	**-12.86%*****	0.121	**-15.34%*****	0.143	**-2.04%**	0.020
6 - 7pm	**-9.37%*****	0.090	**-12.69%*****	0.119	**-2.47%**	0.024
7 - 8pm	**-5.25%***	0.051	**-9.55%****	0.091	**.08%**	-0.001
8 - 9pm	**-3.18%**	0.031	**-3.42%**	0.034	**.55%**	-0.006
9 -10pm	**-3.19%**	0.031	**-4.07%**	0.040	**3.26%**	-0.033
10 - 11pm	**-1.99%**	0.020	**-1.7%**	0.017	**2.8%**	-0.028
11pm - Midnight	**-2.15%**	0.021	**-2.62%**	0.026	**3.72%**	-0.038

The table gives β_0 estimates from regressions of models in eq. (2); $N = 65,092,913$ and adj. $R^2 = 0.45$ in both the Average and Hourly Specifications; * significant at $\alpha = 10\%$, ** significant at $\alpha = 5\%$, *** significant at $\alpha = 1\%$

Treatment effects are calculated from coefficient estimates following Halvorsen and Palmquist (1980), as we have a log dep. var. and dummy variable regressor.

Table C.2: Estimated own-price elasticities of electricity demand by hour and month

	Experimental Group	Full Year Elasticities	Jan. Elasticities	Feb. Elasticities	March Elasticities	April Elasticities	May Elasticities	June Elasticities	July Elasticities	Aug. Elasticities	Sept. Elasticities	Oct. Elasticities	Nov. Elasticities	Dec. Elasticities
Average	C	-0.115	-0.0110	-0.0250	-0.0712	-0.00795	-0.191	-0.227*	-0.194	-0.214*	-0.123	-0.136	-0.123	-0.0222
Specification	A	-0.184**	-0.183**	-0.220**	-0.168	-0.207**	-0.188**	-0.167*	-0.195**	-0.162*	-0.143	-0.172*	-0.279***	-0.154*
Hourly Specification:														
Midnight - 1am	C	-0.0425	-0.0190	-0.0379	-0.0807	-0.000313	-0.0468	-0.0835	-0.0196	-0.0646	0.00605	-0.110	-0.135	-0.0195
	A	-0.0919	-0.103	-0.131	-0.0796	-0.121	-0.0715	-0.0654	-0.0649	-0.0663	-0.0571	-0.110	-0.198*	-0.0942
1 - 2am	C	-0.0240	0.0193	-0.0612	-0.0661	0.0131	-0.0211	-0.0467	0.00588	-0.0601	0.00719	-0.0674	-0.0662	0.0112
	A	-0.0716	-0.0658	-0.153	-0.0597	-0.109	-0.0490	-0.0237	-0.0325	-0.0598	-0.0511	-0.0681	-0.127	-0.0630
2 - 3am	C	-0.0356	0.0165	-0.0587	-0.0755	0.0418	-0.0236	-0.0640	-0.0270	-0.112	-0.0165	-0.0976	-0.0962	-0.00162
	A	-0.0834	-0.0676	-0.155	-0.0739	-0.0831	-0.0441	-0.0357	-0.0626	-0.112	-0.0804	-0.0977	-0.161	-0.0763
3 - 4am	C	-0.0411	-0.0120	-0.0829	-0.0973	0.0349	-0.0497	-0.0382	-0.00475	-0.0821	0.00678	-0.0970	-0.152	-0.0164
	A	-0.0913	-0.103	-0.175	-0.0934	-0.0938	-0.0713	-0.0129	-0.0401	-0.0912	-0.0631	-0.0992	-0.217*	-0.0917
4 - 5am	C	-0.0137	-0.00591	-0.0483	-0.0975	0.0369	0.0491	0.00482	0.00106	-0.0221	0.0412	-0.0441	-0.121	-0.0225
	A	-0.0593	-0.0868	-0.137	-0.0912	-0.0841	0.0328	0.0384	-0.0387	-0.0314	-0.0280	-0.0442	-0.174	-0.0882
5 - 6am	C	0.0198	0.0746	0.00996	-0.0762	0.0783	0.0211	-0.0534	0.0261	-0.0334	0.102	0.0188	0.0524	0.0778
	A	-0.0317	-0.0131	-0.0844	-0.0725	-0.0487	-0.00408	-0.0240	-0.0187	-0.0546	0.0335	0.00692	-0.00581	0.00613
6 - 7am	C	-0.0577	0.0820	0.0473	-0.0191	-0.00267	-0.199	-0.189	-0.122	-0.129	-0.00641	-0.00541	-0.0482	0.0162
	A	-0.105	0.00497	-0.0433	-0.0183	-0.128	-0.211*	-0.157	-0.162	-0.150	-0.0756	-0.0164	-0.0944	-0.0491
7 - 8am	C	-0.143	0.00134	-0.0688	-0.171	-0.154	-0.250*	-0.213	-0.189	-0.166	-0.0929	-0.0765	-0.201	-0.0405
	A	-0.197**	-0.0846	-0.157	-0.168	-0.273**	-0.275***	-0.187*	-0.239**	-0.194*	-0.168	-0.108	-0.267**	-0.108
8 - 9am	C	-0.231*	-0.265*	-0.310*	-0.352**	-0.156	-0.291**	-0.231*	-0.233	-0.225	-0.159	-0.319*	-0.479***	-0.241*
	A	-0.271***	-0.348***	-0.391***	-0.338***	-0.268***	-0.300***	-0.189*	-0.260**	-0.238**	-0.219**	-0.331***	-0.525***	-0.301***
9 - 10am	C	-0.430***	-0.394***	-0.344**	-0.424***	-0.324**	-0.518***	-0.483***	-0.464***	-0.412**	-0.347**	-0.396**	-0.545***	-0.367***
	A	-0.466***	-0.469***	-0.409***	-0.403***	-0.430***	-0.531***	-0.443***	-0.487***	-0.419***	-0.407***	-0.396***	-0.578***	-0.423***
10 - 11am	C	-0.374***	-0.314**	-0.255	-0.297*	-0.229	-0.525***	-0.482***	-0.452***	-0.438**	-0.369**	-0.369**	-0.440***	-0.331**
	A	-0.419***	-0.385***	-0.332***	-0.280**	-0.346***	-0.552***	-0.452***	-0.491***	-0.451***	-0.446***	-0.374***	-0.481***	-0.392***
11am - 12pm	C	-0.397***	-0.321**	-0.315*	-0.320*	-0.270*	-0.527***	-0.464***	-0.515***	-0.445***	-0.423**	-0.428**	-0.487***	-0.330**
	A	-0.443***	-0.386***	-0.373***	-0.290*	-0.379***	-0.559***	-0.455***	-0.567***	-0.472***	-0.505***	-0.430***	-0.525***	-0.385***
12 - 1pm	C	-0.439***	-0.391**	-0.343**	-0.371**	-0.212	-0.560***	-0.563***	-0.567***	-0.552***	-0.443***	-0.421**	-0.521***	-0.381***
	A	-0.481***	-0.444***	-0.401***	-0.346**	-0.316**	-0.586***	-0.549***	-0.615***	-0.578***	-0.514***	-0.413***	-0.551***	-0.437***
1 - 2pm	C	-0.392***	-0.317**	-0.325*	-0.327**	-0.231	-0.481***	-0.525***	-0.508***	-0.504***	-0.359**	-0.446**	-0.487***	-0.294**
	A	-0.431***	-0.367***	-0.391***	-0.296**	-0.332***	-0.506***	-0.506***	-0.552***	-0.522***	-0.421***	-0.432***	-0.526***	-0.351***
2 - 3pm	C	-0.270**	-0.202	-0.220	-0.240	-0.185	-0.352**	-0.354**	-0.330**	-0.338**	-0.277*	-0.351*	-0.287*	-0.170
	A	-0.308***	-0.261**	-0.292**	-0.210	-0.278**	-0.360***	-0.318**	-0.372***	-0.351***	-0.348***	-0.354***	-0.328***	-0.229**
3 - 4pm	C	-0.253**	-0.235*	-0.234	-0.282*	-0.174	-0.327**	-0.380**	-0.284*	-0.275*	-0.174	-0.282	-0.300*	-0.144
	A	-0.296***	-0.300***	-0.308**	-0.255*	-0.276**	-0.348***	-0.348***	-0.329**	-0.293**	-0.249**	-0.284**	-0.348***	-0.206**
4 - 5pm	C	-0.315**	-0.179	-0.162	-0.312**	-0.234	-0.396**	-0.497***	-0.416***	-0.411**	-0.275*	-0.235	-0.277*	-0.122
	A	-0.362***	-0.252**	-0.243**	-0.292**	-0.338***	-0.429***	-0.472***	-0.468***	-0.433***	-0.345***	-0.238*	-0.329***	-0.188*
5 - 6pm	C	-0.268**	-0.136	-0.0408	-0.110	-0.211	-0.453***	-0.500***	-0.355**	-0.358**	-0.240	-0.199	-0.268*	-0.118
	A	-0.319***	-0.201*	-0.119	-0.0936	-0.323***	-0.492***	-0.493***	-0.415***	-0.386***	-0.323**	-0.202	-0.318**	-0.180*
6 - 7pm	C	-0.194	-0.0915	-0.0106	-0.0660	-0.208	-0.426***	-0.489***	-0.393**	-0.357**	-0.144	-0.174	-0.243	-0.0630
	A	-0.244**	-0.153	-0.0839	-0.0414	-0.317**	-0.468***	-0.485***	-0.453***	-0.395***	-0.226*	-0.180	-0.284**	-0.122
7 - 8pm	C	-0.149	-0.0548	-0.0484	-0.103	-0.0701	-0.267*	-0.280*	-0.219	-0.236	-0.0395	-0.209	-0.231	-0.0159
	A	-0.195**	-0.117	-0.116	-0.0811	-0.186	-0.296**	-0.267**	-0.274**	-0.268**	-0.121	-0.211*	-0.269**	-0.0698
8 - 9pm	C	-0.137	-0.0816	-0.118	-0.131	0.0140	-0.0729	-0.145	-0.195	-0.132	-0.0322	-0.155	-0.204	-0.0355
	A	-0.179**	-0.147	-0.196*	-0.119	-0.102	-0.0879	-0.112	-0.245**	-0.152	-0.0986	-0.145	-0.243**	-0.0935
9 -10pm	C	-0.100	-0.0840	-0.0986	-0.129	-0.0460	-0.0934	-0.175	-0.152	-0.0590	-0.0602	-0.150	-0.185	-0.0435
	A	-0.138	-0.148	-0.171*	-0.116	-0.153	-0.105	-0.141	-0.196*	-0.0686	-0.115	-0.126	-0.222**	-0.102
10 - 11pm	C	-0.0441	-0.0137	-0.0419	-0.0689	0.00491	-0.0840	-0.184	-0.124	-0.0755	-0.0663	-0.178	-0.195	-0.0239
	A	-0.0841	-0.0789	-0.117	-0.0556	-0.113	-0.102	-0.152	-0.171	-0.0819	-0.123	-0.157	-0.240**	-0.0853
11pm - Midnight	C	-0.0592	-0.0445	-0.0392	-0.0587	-0.00679	-0.0473	-0.115	-0.0607	-0.0958	-0.0516	-0.108	-0.137	-0.0222
	A	-0.110	-0.125	-0.130	-0.0565	-0.129	-0.0769	-0.0985	-0.109	-0.108	-0.117	-0.104	-0.204*	-0.0966
	N	42979662	4281113	3828788	4170381	3807952	4015978	3901014	3997958	3969912	3829244	1625110	1399704	4152508
	adj. R-sq	0.459	0.540	0.542	0.510	0.472	0.475	0.481	0.485	0.484	0.478	0.498	0.542	0.543

Table gives $\boldsymbol{\beta}_1$ estimates from eq. (1) regressions
* significant at $\alpha = 10\%$, ** significant at $\alpha = 5\%$, *** significant at $\alpha = 1\%$