Do energy communities foster demand-side flexibility? Evidence from a Belgian pilot project

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September 28, 2023

European Electricity Market in the 1990's

European Electricity Market in the 1990's

Few large power plants

Total electricity consumption

European Electricity Market in the 1990's

European Electricity Market today

European Electricity Market today

European Electricity Market in the future

European Electricity Market in the future

Many and diverse power plants

To **integrate renewable sources** and **manage the grid scarcity**

- Storage
- Increase grid capacity
- Demand-response

European Electricity Market in the future

Many and diverse power plants

To **integrate renewable sources** and **manage the grid scarcity**

- Storage
- Increase grid capacity
- **Demand-response**

Demand response: definition

Electricity consumers

- Are almost always not exposed to time-variable electricity prices
- When they are, they are *inelastic* [\(Ito \(2014\)](#page-84-1), [Fabra et al. \(2021\)](#page-84-2), [Fowlie et al. \(2021\)](#page-84-3))
- But why ?
	- Electricity is a low interest product [\(Fischer \(2008\)](#page-84-4))
	- Its costs is relatively complex to understand and usually does not make up for an important share of a household's budget [\(Borenstein](#page-84-5) [\(2009\)](#page-84-5))

Energy communities are often considered as challengers to this low-elasticity paradigm [\(Koirala et al. \(2016\)](#page-84-6), [Rossetto \(2023\)](#page-84-7))

Energy communities: exposing consumers to time-variable electricity prices

Source: Adapted from Wallonie énergie SPW

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- Energy communities with energy sharing can challenger this low-elasticity paradigm
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- To spread these incentives, energy communities often benefit from network tariffs adjustments or exemption. [Examples](#page-55-0)
- Demand-response is needed in the electricity system to integrate renewable sources and manage the grid scarcity.
- Energy communities with energy sharing can challenger this low-elasticity paradigm
- To spread these incentives, energy communities often benefit from network tariffs adjustments or exemption. [Examples](#page-55-0)
- However, the impact of energy sharing incentives on driving desired demand-response outcomes remains uncertain.
- Demand-response is needed in the electricity system to integrate renewable sources and manage the grid scarcity.
- Energy communities with energy sharing can challenger this low-elasticity paradigm
- To spread these incentives, energy communities often benefit from network tariffs adjustments or exemption. [Examples](#page-55-0)
- However, the impact of energy sharing incentives on driving desired demand-response outcomes remains uncertain.
- In my case study analysis I find no proof of grid beneficial outcomes after energy sharing incentives' implementation.

List of variable per quarter hour from 1/10/2020 to 28/02/2021 for each participant of the pilot project [Summary tables](#page-56-0) [Graphical example](#page-60-0)

- Consumption (kWh)
- Self-consumption (kWh)
- Residual consumption (kWh)
- Coefficient (distribution key)
- Production (kWh)
- Allocated production (kWh)
- Non-allocated production (kWh)
- Surplus injected to the grid (kWh)

Case study : REC pilot project in Wallonia

Phase 1

- Hospital \bullet
- Hospital
- Nursing home
- Psychiatric centre \bullet
- Offices \bullet
- Offices

Phase 2

- Nursing home \bullet
- \bullet Psychiatric center
- Small company \bullet
- Small industrial company ٠

The empirical analysis involves a two-fold approach.

- **•** Characterization of incentives from energy sharing, including energy and network tariff components throughout project phases, computation of the energy bills saving
- ² Estimation of the impact of the implementation of energy sharing incentives

1 - Characterising the incentives

Electricity self-consummed with energy sharing

Electricity self-consummed with energy sharing

= 5076 MWh

Electricity self-consummed with energy sharing

= 5076 MWh

Residual electricity provided by supplier

Electricity self-consummed with energy sharing

= 5076 MWh

Residual electricity provided by supplier

 $= 14400$ MWh

Electricity self-consummed with energy sharing

= 5076 MWh

Energy component

Residual electricity provided by supplier

 $= 14400$ MWh

Energy component

Energy component

Residual electricity provided by supplier

 $= 14400$ MWh

Network component Energy component Network component

Electricity self-consummed with energy sharing

Energy component

Fixed allocation key

= 52.3€/MWh on average

Residual electricity provided by supplier

 $= 14400$ MWh

Network Energy component component Network component

Residual electricity provided by supplier

Savings on the energy bills from 21% to 31%

= 270.2€/MWh on average

Savings on the energy bills from 8% to 12%

Phase 2

Savings on the energy bills from 19% to 22%

= 253.1€/MWh on average

Savings on the energy bills from 7% to 11%

Electricity self-consummed with energy sharing

Phase 1

= 67.4€/MWh on average

= 178.7€/MWh on average

Phase 2

= 84€/MWh on average

= 164.7€/MWh on average

Residual electricity provided by supplier

= 270.2€/MWh on average

= 253.1€/MWh on average

2 - Estimation

We want to measure the existence of grid beneficial outcomes to analyze the energy sharing incentives design.

- **1** Peak shifting
- **2** Peak shedding

Source: [Xu et al. \(2017\)](#page-84-0)

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- Counterfactual electricity consumption time series for each individual have been computed using three different machine learning techniques [\(Gonzalez-Briones et al. \(2019\)](#page-84-1)):
	- K Nearest Neighbors (KNN) identifies future patterns by averaging the outcomes of 'k' nearest historical neighbors.
	- Random Forest (RF) uses an ensemble of decision trees, trained on subsets of data, and averages their predictions.
	- Gradient Boosting iteratively improves model accuracy by correcting errors, aggregating multiple models' predictions for final outcomes.
- Each of these algorithms have been trained on historical data to predict for each individual the counterfactual based on calendar and weather data. $+$

 $Y_{it} = \alpha_{it} + \beta_1$ (Treatment_i * Postevent_t)+ β_2 Treatment: + β_3 Postevent_t + Controls_{it} + ϵ_{it}

- Control variables: time-related factors, weather data \Box , and COVID-19 cases.
- **Outcome variables**
	- Daily peak consumption to measure whether participants reduced their peak electricity usage after joining the energy community
	- Binary variable indicates whether individuals shifted their daily peak consumption away from system-wide peak hours

The implementation of the energy sharing incentives led to

- A small increase in the daily peak consumption by participants
- An ncrease in the probability that the peak consumption occurs in traditional system-wide peak hours

Results: peak shedding phase 1

Table: Regression Results: Phase 1 impact on individual daily peak.

Note: The dependent variable is the individual daily peak, and the mentions KNN, RF, and XG refer to the synthetic counterfactual prediction machine learning methods associated with the estimation. The displayed results in the tables correspond to the coefficients of interest in the estimation. Weather data and calendar data were included as control variables in the analysis but are not shown here. Standard errors are reported in parentheses. Significance levels are denoted as *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.
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Table: Regression Results: Phase 2 impact on individual daily peak.

Note: The dependent variable is the individual daily peak, and the mentions KNN, RF, and XG refer to the synthetic counterfactual prediction machine learning methods associated with the estimation. The displayed results in the tables correspond to the coefficients of interest in the estimation. Weather data and calendar data were included as control variables in the analysis but are not shown here. Standard errors are reported in parenthe-

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Table: Regression Results: Phase 1 impact on daily peak in system-wide peak hours.

Note: The dependent variable is the daily peak in peak hours, and the mentions KNN, and RF refer to the synthetic counterfactual prediction machine learning methods associated with the estimation. System-wide peak hours are defined from 7 to 9 am and from 5 to 8 pm. The displayed results in the tables correspond to the coefficients of interest in the estimation. Weather data and calendar data were included as control variables in the analysis but are not shown here. Standard errors are reported in parentheses. Significance levels are denoted as *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

Table: Regression Results: Phase 2 impact on daily peak in system-wide peak hours.

Note: The dependent variable is the daily peak in peak hours, and the mentions KNN, and RF refer to the synthetic counterfactual prediction machine learning methods associated with the estimation. System-wide peak hours are defined from 7 to 9 am and from 5 to 8 pm. The displayed results in the tables correspond to the coefficients of interest in the estimation. Weather data and calendar data were included as control variables in the analysis but are not shown here. Standard errors are reported in parentheses. Significance levels are denoted as *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

- The study analyzed energy sharing incentives' impact on demand-response outcomes, focusing on peak shedding and shifting within a renewable energy community.
- Findings indicate that despite substantial incentives, there is no evidence of grid-beneficial outcomes, potentially even worsening peak consumption behaviors.
- These results align with existing literature showing that electricity end-consumers often do not significantly respond to price incentives.
- Public policy expectations of energy communities as drivers of retail demand-response may need adjustment, particularly regarding network tariff adjustments and exemptions.

Network tariff adjustments

Table 2 : Main characteristics of interviewed energy communities

Notes: Authors' compilation from online interviews and projects' authorisation information from Brussels-Capital

[-](#page-13-0)

Weather data

Hourly data

Based on historical data only

RF feature importance

RF feature importance

RF feature importance

Event study results

PHASE 1

Event study results

PHASE 2

[-](#page-49-0)

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