Promoting Energy-sharing Communities: why and how?
Lessons from a Belgian Pilot Project

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Promoting energy-sharing communities: why and how? Lessons from a Belgian pilot project[1]

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Abstract

This paper explores why energy-sharing communities need policy support via network tariff adjustments and how to optimally design that support. Findings from a case study indicate that, even with high self-consumption, the energy-sharing model may not ensure participants reach break-even. Counterfactual analyses, using machine-learning techniques, indicate that capacity-term adjustments alone had minimal impact on peak consumption. Policy recommendations suggest limiting capacity-term adjustments to communities capable of actively managing peak loads through real-time data and flexible assets.

1. Introduction

Energy-sharing communities have gained political traction as a mean to engage citizens in the energy transition. These communities support local energy generation and self-consumption, potentially helping reduce reliance on the traditional grid. As these initiatives expand, it becomes important to evaluate the impact of support policies, like network tariff adjustments, on their economic model and grid impact. This paper addresses two questions through a case study. First, why should energy-sharing communities receive support? Second, how can policymakers provide support that aligns with grid costs? This trade-off highlights the need for policies that provide support while ensuring energy-sharing communities contribute to the overall energy transition.

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In 2019, the European Union's (EU) Clean Energy Package defined the broader term of *energy communities* as not-for-profit entities governed by their members, aiming to deliver environmental, social, and economic benefits (European Commission (2019a)). Across the EU, energy communities are still emerging, engaging in activities such as electricity generation, energy-sharing, storage, and awareness campaigns.[2] As of January 2024, 69% of these initiatives focus on energy-sharing, emphasizing the use of locally generated renewable electricity.[3] This paper focuses on energy communities that implement energy-sharing, hereafter referred to as energy-sharing communities.

More specifically, energy-sharing sets up a system where locally generated electricity is attributed and billed among participants. This allows them to pay a reduced price for the electricity they consume locally, rather than the standard retail price. This incentivizes self-consumption and encourages the integration of local renewable generation units.[4] Through this structure, energy-sharing communities have the potential to facilitate grid management. By responding to local production and price signals, participants can engage in demand-response behaviors, such as peak shedding (reducing maximum level of consumption) and peak shifting (moving peak consumption to off-peak times), which can ease grid pressure during peak times.

To support energy-sharing communities, several EU member states have introduced favorable network tariff adjustments that reduce charges for community members.[5] These adjustments aim to provide financial support and incentivize grid-beneficial demand-response. However, the effectiveness of these incentives and their cost-reflectivity, meaning whether they accurately align with the actual grid costs imposed by community participants, remains largely untested. If not cost-reflective, these adjustments could create advantages for community members while placing a disproportionate burden on other network users. This issue becomes more pressing as rising electricity demand, increased peak loads, and declining network load factors put additional strain on system operators, requiring significant investments in grid infrastructure.[6] Network tariffs are specifically regulated to ensure fairness, transparency, and non-discrimination, aiming to reflect the true costs of grid use (European Commission (2019b), ACER (2021)). However, it remains unclear if these adjustments

[2]The European Commission Energy Communities Repository maps 108 initiatives as of January 2024.

[3]European Commission Energy Communities Repository database, accessed in January 2024. Details are presented in Appendix A.

[4]The self-consumption ratio represents the proportion of locally produced electricity used directly by participants. The specific method of calculating this ratio depends on the setup of each energy-sharing system.

[5]National Regulation Agencies in nine member states (Austria, Belgium (Brussels region), Denmark, Finland, France, Greece, Italy, Portugal, and Spain) have implemented such adjustments.

[6]EU electricity demand is projected to rise by 60% by 2030, necessitating €584 billion in grid upgrades (European Commission (2023)).

for energy-sharing communities fully meet the goals of fairness and cost-reflectivity, leading to questions about whether the benefits align with the communities' actual grid impact.

The first part of this case study examines whether network tariff adjustments are necessary for the energy-sharing community to *break even*, meaning its revenues cover its operating costs for each member. Findings indicate that, with high self-consumption rates and relatively low retail prices, these adjustments were needed to reach break-even. During high retail price periods, like the energy crisis, the community could break even without network tariff support. Given the political will to engage citizens in the energy transition with energy-sharing communities, this suggests that policy support may be essential: under typical market conditions, the energy-sharing model alone may not allow communities to cover their costs entirely.

The second part of the case study evaluates whether the network tariff adjustments and energy-sharing had any impact on peak consumption patterns. The results indicate only weak reductions in both individual and aggregate peak consumption, alongside minor shifts in peak timing. These modest effects confirm the lack of cost-reflectivity of the capacity-term adjustment, as they suggest the adjustments did not effectively incentivize participants to alter their consumption patterns in a way that would reduce grid strain during peak periods.

The results indicate that network tariff adjustments can be essential for energy-sharing communities to break even. However, a trade-off exists between supporting these communities and maintaining cost-reflective, fair policies for all grid users, including system operators. Specifically, capacity-term adjustments should be reserved for situations where participants have the means to effectively manage their peak consumption, such as through real-time pricing and shiftable loads. In cases where these conditions are not met, alternative support measures could better sustain the community's viability while ensuring fair cost allocation across the grid.

2. Literature review

This paper builds on existing literature regarding energy-sharing communities and their impact on energy systems. These communities enable participants to move from passive consumption to active prosumption, engaging in both local energy management. They are often seen as potential enablers for renewable integration, flexibility, and optimized grid management. Specifically, Koirala et al. (2016) provide an overview of different energy community structures and highlights their role in local renewable integration, decentralized management, and grid services. Rossetto (2023) examines how these communities can optimize grid operations and boost flexibility across the EU: by bringing together individual prosumers, energy communities can amplify their benefits through scale, aiding overall grid efficiency. Building on these perspectives, this paper's case study investigates how community consumption patterns, self-consumption rates, and local energy generation affect peak behaviors and grid dependency.

This paper also contributes to the literature on electricity network tariff design. The impact of network tariffs on electricity consumers' behavior is a critical aspect of the energy transition. For instance, properly structured tariffs can incentivize prosumers to self-consume their generated energy or invest in energy storage systems (Gautier et al. (2018)). Network tariffs design need to align with broader policy objectives to ensure the efficient functioning of the energy system. As Schittekatte et al. (2018) explain, adapting network tariffs to account for increasing distributed generation is essential to using grid infrastructure efficiently. Similarly, De Villena et al. (2019) emphasize that cost-reflective tariffs, which ensure consumers pay according to their network usage, promote fairness among grid users. Striking a balance between promoting decentralised energy management and ensuring the financial stability of system operators through cost-reflectivity of tariff is a complex challenge (Eid et al. (2014)). However, there is a consensus that flexibility sources such a consumers' demand-response can delay network expansion (Poudineh & Jamasb (2014), Neetzow et al. (2019), Nouicer et al. (2023)). This paper builds on these findings by examining the pilot project's network tariff adjustments and their role in encouraging behaviors like peak shedding and shifting, assessing their impact on the grid.

This paper adds to the broader discussion on optimal network tariff adjustments to enhance cost-reflectivity and fairness, particularly within energy-sharing communities. As summarized by Passey et al. (2017), cost-reflective tariffs offer advantages like improved price alignment, smarter energy usage, better utility cost recovery, and reduced cross-subsidies. As noted in a theoretical model of a non-cooperative game by Abada et al. (2020), poorly designed network tariffs can lead to an over-adoption of energy community structures, potentially placing excess strain on the grid during peak times. Furthermore, Johannsen et al. (2023) highlight that without cost-reflective network tariffs, energy-sharing communities could increase grid pressure during low-production periods. This paper provides empirical evidence supporting both these concerns, as it examines whether the pilot project's network tariff adjustments might disproportionately benefit community members, potentially complicating grid management.

By constructing counterfactual electricity consumption profiles with machine-learning forecasting methods, following the approach of Fabra et al. (2022), the study contributes to the growing literature that applies machine learning for energy analysis. Similar methodologies have been applied to estimate counterfactual consumption and analyze individual patterns in electricity use (Gonzalez-Briones et al. (2019), Burlig et al. (2020), Valentini et al. (2022)). This study builds on that work, advancing the application of machine learning specifically to the context of an energy-sharing community.

3. Characteristics of the pilot project

3.1. HospiGREEN: energy-sharing community in Belgium

The HospiGREEN pilot project was implemented in Tournai (Belgium) from November 2020 to March 2023, involved ten participants, mostly healthcare facilities like hospitals and retirement homes. This Renewable Energy Community (REC), the first of its kind in Wallonia following the EU directive (European Commission (2019b)), aimed to promote local renewable energy generation, demand-response, and decentralized energy management (CWaPE (2020)). Table 1 outlines the details of Phases 1 and 2, which ran from November 2020 to October 2021 and November 2021 to February 2023, respectively.

The project did not implement real-time feedback information about local production and shiftable assets.[7] For production units, Luminus, a project partner but not a direct participant, contributed a wind turbine, motivated by the incentive of stable monthly rent and the ability to avoid imbalance costs from surplus production. Smaller photovoltaic prosumers participated to maximize self-consumption, aligning with the project's goal of increasing local renewable energy usage.

The project implemented two different allocation keys to operate the energy-sharing: static in Phase 1, dynamic in Phase 2. In energy-sharing communities, allocation keys are used to economically distribute the local electricity production among the participants based on their overall electricity consumption. In Phase 1, energy-sharing was operated with a fixed allocation key that assigns a pre-set share of local renewable electricity supply to each participant for each quarter-hour intervals.[8]

At each quarter-hour, if a participant's consumption matched their allocated share of the production, they were billed at the shared energy tariff.[9] Consumption beyond the allocation was billed at the standard retail price, while any under-consumption (less than the allocation) was valued for the community at the imbalance price. This structure incentivizes participants to consume their allocated share to maximize the benefits of the shared energy electricity price.[10]

[7] Shiftable assets include batteries, heat-pumps or large shiftable load can be actively managed or controlled to regulate the electricity demand.

[8] Additional details about the fixed allocation key implemented in the pilot project are available in Appendix B.

[9] While the energy component of self-consumed electricity is free, the average price per MWh reflects the community's operating costs. These costs are distributed among participants in proportion to their consumption, as the energy community operates on a not-for-profit basis. See Section 3.3 for additional details.

[10] A specific feature of HospiGREEN pilot project is that the community takes responsibility for the imbalance by selling its surplus electricity to Luminus at the imbalance market price. Addtional details in Section 3.3.

In Phase 2, energy-sharing was operated with a dynamic proportional key. With this allocation rule, for each quarter hour t, in the community of P participants, for the participant i the allocation share of the local energy supply was defined as c_{it}:

$$c_{it} = \frac{\text{Conso}_{it}}{\sum_{j=1}^{P} \text{Conso}_{jt}} \tag{1}$$

This mechanism distributed local energy production based on each participant's share of the total community consumption at every quarter hour. The dynamic allocation was introduced in Phase 2 to evaluate its effect on demand-response, as it was expected to increase individual incentives for self-consumption compared to the fixed allocation key used in Phase 1.

As summarised in Table 1, during Phase 1, participants benefited from network tariff adjustment. These adjustments were exclusively applied to distribution network and not to the transmission network charges. Therefore, participants were invoiced on their residual peak consumption, which is the peak of their electricity consumption after subtracting self-consumed electricity, on average 6.2% lower than their overall peak consumption level.[11] Additionally, participants located under the same Medium Voltage (MV) cabin as the production units are partially exempted of the proportional-term of their network tariff.

3.2. Data: electricity load profiles

The HospiGREEN dataset consists of quarter-hourly electricity consumption data, both from before the energy community's launch in 2019 and from post-establishment periods, including self-consumption and local production allocations on a quarter-hour basis. These load profiles were confidentially provided by IDETA.[12]

For the estimation process, I augmented this dataset with additional variables, specifically weather conditions, regional COVID-19 trends, and Belgian day-ahead electricity prices, covering the period from January 1, 2019, to December 31, 2019, and November 1, 2020, to February 28, 2023. A detailed description of each data source and corresponding descriptive statistics is provided below.[13]

The main dataset includes quarter-hourly electricity load profiles for participants and production units during the project period (01/11/2020 to 28/02/2023). For each

[11] See Table C.10 in Appendix C

[12] To maintain confidentiality, results are presented in an anonymized or aggregated form.

[13] The 2019 data serves as the baseline for participants' electricity usage before the energy community was established.

Table 1: Distinctive characteristics of the HospiGREEN pilot project phases

	Phase 1	**Phase 2**
Period	1/11/2020 - 31/10/2021	1/11/2021 - 28/02/2023
Production capacity	Wind power (2.2 MW) Solar power (120 kWp)	Wind power (2.2 MW) Solar power (160 kWp)
Number of participants	6	10
Energy-sharing allocation key	Static distribution key by time range (day, night, week-end)	Dynamic proportional distribution key (see equation (1))
Distribution network tariff adjustments	**Capacity-term (euros/kW/month)** applied on residual consumption (total consumption minus self-consumption) **Proportional-term reduction (euros/kWh)** for participants under the same MV cabin as local production units: 30% reduction for MV network participants, 85% reduction for LV network participants	**None**

Source: Author's compilation of the final report of the HospiGREEN pilot project and the CWAPE decision in terms of network tariff adjustment. Note: This table shows the differences in network tariffs for community members compared to the original tariff applied to other regional users. It was created by comparing the initial network tariff table to the adjusted table from the energy regulator (CWAPE)'s decision in terms of network tariff adjustment. For solar power, production capacity is measured in kilowatt peak (kWp) for the standardised peak output. The capacity-term in the network tariff charges is based on the highest consumption peak, while the proportional-term charges based on overall consumption volumes.

participant, data includes consumption (kWh), allocation share (%), production allocated (kWh), self-consumption (kWh), and residual consumption (kWh). For each production unit, it records production (kWh) and surplus (kWh). Figure 1 outlines the monthly production, self-consumption rate (share of local production consumed by participants), and coverage rate (proportion of consumption met by local production).[14] Self-consumption rates remained stable above 80%, and the coverage rate varied between 30% and 43% during the pilot, with consistent distribution among participants despite varying residual consumption.

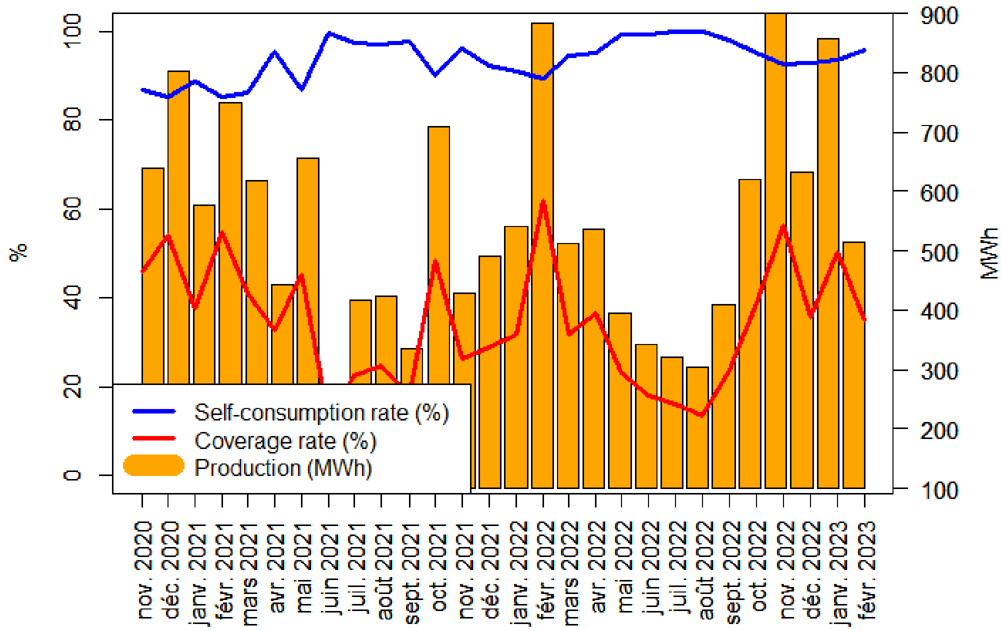


Figure 1: Dynamics of local production, self-consumption rate, and coverage rate in the Hospi-GREEN project

The detailed electricity load profiles allow for an analysis of levels and timing of peak consumption. Table 2 how significant variability in daily peak consumption across participants during 2019, Phase 1, and Phase 2. Daily peaks consumption generally occur between 7 am and 12 pm, while the aggregate peak for the community typically falls between 7 and 8 am. These timings largely overlap with system peak hours (8-10 am and 6-9 pm on weekdays), suggesting that participants' peaks often coincide with broader grid demand.

[14] More details about consumption and allocation variables by participants for Phase 1 and 2 can be found in Appendix D, in tables D.11 and D.12.

Table 2: Daily peak consumption (kWh) per participant per time period

Participants	Period	Mean	Median	Min	Max	Sd	Most freq (24h)
Participant 1	2019	55	54	40	82	7	10
	Phase 1	53	52	41	71	6	9
	Phase 2	53	52	38	74	7	9
Participant 2	2019	436	439	283	573	60	8
	Phase 1	456	457	176	605	77	7
	Phase 2	439	440	298	576	62	7
Participant 3	2019	461	458	169	702	117	8
	Phase 1	432	398	200	711	130	8
	Phase 2	475	477	203	738	130	9
Participant 4	2019	1159	1176	847	1760	156	11
	Phase 1	1178	1158	793	1816	198	12
	Phase 2	1144	1153	822	1715	167	8
Participant 5	2019	31	30	15	49	8	9
	Phase 1	37	36	15	68	11	8
	Phase 2	32	32	11	64	13	8
Participant 6	2019	40	37	3	84	17	9
	Phase 1	51	50	18	95	15	7
	Phase 2	51	50	20	98	17	8
Energy community	2019	2100	2154	1452	2843	280	8
	Phase 1	2114	2149	1449	2998	297	7
	Phase 2	2401	2481	1618	3104	345	8

Source: HospiGREEN quarter-hourly load profiles. Note: The Phase 1 of the project takes place between the 1/11/2020 and the 31/10/2020. The Phase 2 of the project takes place between the 1/11/2021 and the 28/02/2023. Note: The variable Most freq (24h) denotes the most frequent hour of the daily peak consumption occurrence in a 24 hour format.

Additional datasets, described in Appendix E, Appendix F, and Appendix G, are used to train machine learning models for predicting counterfactual consumption profiles. These include weather data, regional COVID-19 statistics, and Belgian day-ahead electricity prices.

Overall, the energy community maintained high levels of self-consumption and coverage throughout both phases, despite variability in individual consumption and peak characteristics. The following section explores the revenue sources of the energy community: self-consumption, surplus sales, and peak adjustments. It analyzes whether these can generate enough revenues for participants to break even.

3.3. Revenues by activity

To assess whether participants reach break-even, I analyze revenues from three sources: self-consumption, surplus selling, and peak adjustments. The revenue equations essentially measure the savings achieved by comparing traditional procurement costs with those under the energy-sharing community model. This analysis clarifies the need for policy support by focusing on two key aspects: first, whether network tariff adjustments provided substantial revenue, and second, whether these adjustments were necessary for the community to break even at observed consumption levels.

Network tariff adjustments were applied only in the first project phase, while the allocation key varied across phases (See Table 1). This distinction is crucial for isolating the specific impact of network tariff adjustments from other factors.

Electricity billing consists of three components: energy, network, and taxes. Taxes are disregarded in this analysis as they remained unchanged throughout the implementation of the energy community. Therefore, community revenues arise from differences in both energy and network billing. Total revenues with ($\tilde{\Pi}$) and without (Π) network tariff adjustments are defined as the sum of individual participant revenues:

$$\tilde{\Pi} = \sum_i \tilde{\pi}_i \quad \text{and} \quad \Pi = \sum_i \pi_i \tag{2}$$

Participant i individual revenues ($\tilde{\pi}_i$ and π_i) are defined as the sum of revenues from self-consumption ($\tilde{\pi}_i^{SC}$ and π_i^{SC}), surplus selling (π_i^X) and peak management ($\tilde{\pi}_i^P$ and π_i^P) both with and without network tariff adjustments.

$$\tilde{\pi}_i = \tilde{\pi}_i^{SC} + \pi_i^X + \tilde{\pi}_i^P \quad \text{and} \quad \pi_i = \pi_i^{SC} + \pi_i^X + \pi_i^P \tag{3}$$

Equation (3) can be written as the sum of revenues from self-consumption, surplus selling, and peak management for the relevant sub-periods of computation: quarter-hour t and month m. Self-consumption and surplus selling are calculated for each quarter-hour, whereas the peak is billed only on a monthly basis.

$$\tilde{\pi}_i = \sum_t \left[\tilde{\pi}_{it}^{SC} +_i \pi_t^X\right] + \sum_m \tilde{\pi}_{im}^P \quad \text{and} \quad \pi_i = \sum_t \left[\pi_{it}^{SC} + c_i \pi_t^X\right] + \sum_m \pi_{im}^P \tag{4}$$

Self-consumption revenues. For each quarter hour t, participant i individual revenues from self-consumption, with ($\tilde{\pi}_{it}^{SC}$) and without (π_{it}^{SC}) network tariff adjustments, are:

$$\tilde{\pi}_{it}^{SC} = s_{it} c_i Power_t \left[(e_i - \bar{e}) + (n_t - \tilde{n}_{it})\right] \tag{5}$$
$$\pi_{it}^{SC} = s_{it} c_i Power_t \left[(e_i - \bar{e})\right] \tag{6}$$

Where s_{it} is the self-consumption rate of participant i for the quarter-hour t, expressed as a percentage of the allocated production ($c_i Power_t$). The allocated production (kWh) is decomposed by c_i and $Power_t$, where c_i denotes the allocation coefficient for participant i from the allocation key, and $Power_t$ represents the total power production within the community at quarter-hour t.[15]

The self-consumed electricity includes both an energy and a network component. In the energy-sharing community, the energy component of the self-consumed energy is free, with $\bar{e}$ distributing the community's operating costs across each MWh self-consumed, as the energy community operates on a not-for-profit basis [16]:

$$\bar{e} = \frac{TotalCosts}{\sum_t s_t Power_t} \quad \text{where} \quad s_t = \sum_i s_{it} \tag{7}$$

In Phase 1 and Phase 2, the average energy-sharing prices were $\bar{e}^{P1} = \frac{259{,}550}{5{,}075} = 51.11$ euros/MWh and $\bar{e}^{P2} = \frac{361{,}937}{6{,}927} = 52.25$ euros/MWh.

To compute the revenues from self-consumption, I collect the average medium-voltage retail price for each participant from the Walloon energy regulator (CWAPE), categorized based on their total yearly electricity consumption[17]: $e_i^{P1} \in [51, 57.33]$ euros/MWh and $e_i^{P2} \in [88.35, 85.5]$ euros/MWh. Therefore, the energy-sharing scheme incentivizes to maximize self-consumption because each MWh consumed under the energy-sharing price is cheaper than retail prices.

[15] The formalization is presented with a fixed allocation key. For Phase 2 revenue characterization, the allocation coefficient associated with participant i would vary by quarter-hour, as the allocation key becomes dynamic, denoted as c_{it} instead of c_i as depicted in equation (1).

[16] Management and operating cost figures are sourced from the '*Report on Phase 1 Implementation of the HospiGREEN Pilot Project: November 2020 to October 2021*'. Phase 2 costs were estimated from Phase 1 data, adjusted for the two-month longer duration.

[17] For additional information on CWAPE medium voltage average electricity prices data, refer to Appendix H.

For the network component, revenues from self-consumption arise due to network tariff adjustments on the proportional-term for the self-consumed volumes. This is defined as the difference between the *initial-optimal* proportional network tariff n_t and the *adjusted* tariff $\tilde{n}_{it}$ for each quarter t. The adjusted $\tilde{n}_{it}$ depends on participant i.[18] As shown in Table 1, in Phase 1, only participants under the same MV cabin as the local production unit benefit from the network tariff adjustment on the proportional-term. This further incentivizes to maximize self-consumption since the proportional tariff on each self-consumed kWh is free.

Surplus selling revenues. When the community's power production, $Power_t$, is not entirely consumed by participants at quarter-hour t, the surplus is sold at the *imbalance price*. This price reflects the system's marginal cost of balancing in real-time and can vary depending on current grid conditions. The community bears any positive or negative financial impact of this surplus at the imbalance price, directly linking their costs to the broader grid's balancing needs. In the pilot project, participants contracted with Luminus for the purchase of surplus, at a price linked to the Belgian Transmission System Operator (TSO) Elia's imbalance prices I_t. The revenues affiliated with surplus selling are not linked to network tariff adjustments. For each quarter hour t, the community's revenues from surplus are:

$$\pi_t^X = (1 - s_t) Power_t I_t \tag{8}$$

Peak adjustment revenues. The capacity-term adjustment encourages participants to lower their residual peak by shifting consumption to periods when self-consumption is possible, thereby maximizing financial benefits. Consuming more during self-production hours reduces their residual peak, leading to lower capacity charges. As shown in Table 1, during Phase 1, the capacity-related network tariff was applied to the residual peak, rather than the total load peak. Typically, electricity consumers are billed based on their peak monthly network usage, which reflects the maximum consumption within a month. Therefore, for each month m, participant i's individual revenue from peak adjustments is calculated as:

$$\tilde{\pi}_{im}^P = \left[\max_{t \in m}(Conso_{it}) - \max_{t \in m}(Residual_{it})\right] \hat{n}_{im} \tag{9}$$

Where the residual consumption $Residual_{it} = Conso_{it} - s_{it} c_i Power_t$.

$$\pi_{im}^P = \max_{t \in m}(Conso_{it}) \hat{n}_{im} \tag{10}$$

[18] Without the detailed information needed for a full cost-reflectivity analysis, the initial network tariffs before the energy community are assumed to be optimally cost-reflective. Since the production units existed before the community, any tariff deviations should be justified by a reduced grid impact from altered consumption patterns.

Revenue analysis. The revenue results across each phase are summarized in Tables 3, 4, and 5. In Phase 1 (Table 3), positive self-consumption revenues $\tilde{\pi}_i^{SC}$ were clearly reliant on network tariff adjustments. Without these adjustments (Table 4), revenues would have been negative or close to zero due to the narrow price difference between the retail price (51 to 57.33 euros/MWh) and the fixed energy-sharing price (51.14 euros/MWh). Additionally, surplus energy revenues $c_i\pi^X$ remained consistently negative, showing that surplus energy was not beneficial for system balancing in Phase 1.[19]

To assess the impact of the allocation key on the community's economic viability, Phase 1 revenues were estimated using a counterfactual dynamic allocation key. Under this scenario, the community still required network tariff adjustments to break even due to persistent losses from surplus sales.[20] This key finding emphasizes that network tariff adjustments were necessary for sustaining the community in Phase 1, regardless of allocation strategy.

Table 3: Phase 1 - Participants' revenues by activity with network tariff adjustments

Participants	$\tilde{\pi}_i^{SC}$			$c_i\pi^X$	$\tilde{\pi}_i^P$	$\tilde{\pi}_i$
	Energy	Network	Total			
Participant 1	70	9 596	9 666	-180	180	9 666
Participant 2	-127	36 438	36 311	-1 150	285	35 446
Participant 3	-111	653	542	-1 170	48	-580
Participant 4	-431	31 058	30 627	-3 790	220	27 057
Participant 5	40	492	532	-94	24	462
Participant 6	46	950	996	-117	40	919
Energy community	-513	79 187	78 674	-6 501	797	72 970

Source: Author's computations based on HospiGREEN electricity consumption profile of Phase 1 (1/11/2020 - 31/10/2021), Transmission System Operator (TSO) Elia's imbalance prices, average energy-sharing price ($\bar{e}^{P1}$ = 51.14 euros/MWh), average price of energy per MWh of electricity by consumption class (€/MWh excluding VAT) for December 2020 (varied between 51 and 57.33 euros/MWh), fixed allocation key described in Appendix B, and network tariff provided by the CWAPE decision relative to ORES network tariff suggestion for HospiGREEN of 13/10/2020. Note: The values presented in the table are initially calculated for each sub-period (quarter-hour or month) for each participant. Subsequently, they are aggregated over the entire duration of Phase 1 to provide the summarized computation.

In Table 5, unlike the revenues of Phase 1, the revenues of Phase 2 were positive without the implementation of network tariff adjustments. Revenues from surplus

[19]Notably, Luminus benefited by avoiding the imbalance costs associated with surplus energy, as these were borne by the energy community.

[20]Refer to Appendix I for detailed revenues calculations with the counterfactual dynamic allocation key in Phase 1.

Table 4: Phase 1 - Participants' revenues by activity **without** network tariff adjustments

Participants	π_i^{SC}			$c_i\pi^X$	π_i^P	π_i
	Energy	Network	Total			
Participant 1	70		70	-180		-110
Participant 2	-127		-127	-1 150		-1 277
Participant 3	-111		-111	-1 170		-1 281
Participant 4	-431		-431	-3 790		-4 221
Participant 5	40		40	-94		-54
Participant 6	46		46	-117		-71
Energy community	-513		-513	-6 501		- 7 014

Source: Author's computation based on the HospiGREEN electricity consumption profile of Phase 1 (1/11/2020 - 31/10/2021), the Transmission System Operator (TSO) Elia's imbalance prices, average energy-sharing price ($\bar{e}^{P1} = 51.14$ euros/MWh), the average price of energy per MWh of electricity by consumption class (€/MWh excluding VAT) for December 2020 and the fixed allocation key described in Appendix B. Note: The values presented in the table are initially calculated for each sub-period (quarter-hour or month) for each participant. Subsequently, they are aggregated over the entire duration of Phase 1 to provide the summarized computation.

Table 5: Phase 2 - Participants' revenues by activity

Participants	π_i^{SC}			$c_i\pi^X$	π_i^P	π_i
	Energy	Network	Total			
Participant 1	5 518		5 518	-210		5 308
Participant 2	37 737		37 737	-1 670		36 067
Participant 3	43 004		43 004	-1 887		41 117
Participant 4	129 772		129 772	-5 903		123 869
Participant 5	2 790		2 790	-111		2 679
Participant 6	4 930		4 930	-189		4 741
Participant 7	16 365		16 365	-733		15 632
Participant 8	7 401		7 401	-275		7 126
Participant 9	3 767		3 767	-146		3621
Participant 10	317		317	-21		296
Energy community	251 605		251 605	-11 145		240 460

Source: Author's computation based on the HospiGREEN electricity consumption profile of Phase 2 (1/11/2021 - 28/02/2023), the Transmission System Operator (TSO) Elia's imbalance prices Imbalance prices, average energy-sharing price ($\bar{e}^{P2} = 52.25$ euros/MWh), the average price of energy per MWh of electricity by consumption class (€/MWh excluding VAT) for December 2021 (varied between 88,35 and 85.5 euros/MWh) and the dynamic proportional allocation key described in Appendix H. Note: The values presented in the table are initially calculated for each sub-period (quarter-hour or month) for each participant. Subsequently, they are aggregated over the entire duration of Phase 1 to provide the summarized computation.

energy sales ($c_i\pi^X$) remained negative, but revenues from self-consumption (π_i^{SC}) were positive for all participants. In fact, in Phase 2, retail prices were higher, ranging between 85.5 and 88.35 euros/MWh, which increased the difference between the energy-sharing price and the retail price, resulting in higher self-consumption revenues. This difference grew during Phase 2 (from 01/11/2021 to 28/02/2023) due to the energy crisis triggered by the end of the COVID-19 crisis and the Russian invasion of Ukraine, lasting until early 2023. During this crisis, wholesale electricity prices soared, reaching a maximum day-ahead price of 871 euros/MWh.[21] To reflect the impact of the energy crisis on retail prices, I used the average medium-voltage retail prices from CWaPE for the years 2020, 2021, and 2022 as proxies. However, since I lacked access to participants' actual retail contracts, I assumed their contracts changed every year.

These results indicate that policy support, such as network tariff adjustments, can be essential for energy-sharing communities. In typical market conditions, these communities may not achieve break-even on energy-sharing revenues alone to cover their operational costs. This suggests that the economic model of energy-sharing communities may often require policy support to remain viable. Network tariff adjustments, implemented here as both proportional and capacity-related adjustments, represent one way to provide that support. However, this support exists within a larger trade-off where policies must be carefully designed to avoid placing undue burdens on other users or compromising grid efficiency for system operators. The next section further analyses the cost-reflectivity of the capacity-based network tariff adjustments and the incentives of the pilot project.

4. Empirical strategy

I examine the impact of joining the energy community across both phases on peak consumption. As shown in Table 1, Phase 1 combined network tariff adjustments with static allocation energy-sharing, while Phase 2 involved only energy-sharing with a dynamic allocation key and no network tariff adjustments. The simultaneity of mechanisms in Phase 1 prevents isolating the separate effects of each incentive. Therefore, I treat each phase as a distinct incentive change compared to the pre-community period. In Phase 1, participants received significant capacity-term and proportional-term tariff reductions alongside a static allocation key. In Phase 2, participant shared electricity with a dynamic allocation key and did not obtain any network tariff adjustments. The effects of the features of each phase are assessed ex post on peak electricity consumption, as peak values are the primary drivers of network infrastructure investments and operational costs.

[21] Additional details about the Belgian electricity day-ahead price are available in Appendix G.

To assess the impact, I first construct counterfactual electricity consumption profiles using a method similar to Fabra et al. (2022) and using machine-learning forecasting algorithms based on pre-community consumption data. Using prediction errors across the entire period, I estimate the effects of the features of each phase on peak consumption compared to the pre-community period. The analysis reveals a slight increase in peaks and a minor shift in peak timing, raising doubts about cost reflectivity of the capacity-term adjustment implemented in Phase 1. Since the production units were already operational before the community was established, any justified deviation from the initial network tariff would need to be based on clear, observable changes in peak consumption patterns. The initial tariff is considered optimal within the pilot project, meaning it reflects current system costs and usage. Defining a more precise optimal tariff would require additional, complex data outside the project's scope. Without significant shifts in peak behavior, deviations from this standard tariff would not be justified.

4.1. Counterfactual electricity consumption profiles

I first construct counterfactual profiles in the absence of the energy-sharing community. I do so because of the limited number of participant load profiles available in the HospiGREEN dataset and the unavailability of non-member profiles in Belgium. Consequently, constructing a synthetic control group is not feasible. Additionally, the participants are predominantly small industrial and healthcare centers, exhibiting distinct load profiles from typical residential electricity consumption patterns. Therefore, I predict the counterfactual profile for each of the first six participants for each phase of the project.[22]

Similarly to Fabra et al. (2022), let $Y_t(p)$ represent individual electricity consumption in (kWh) at time t and under potential state p. Where, $p = 1$ indicates outcomes influenced by the energy community establishment, while $p = 0$ signifies outcomes unaffected by the community establishment. Additionally, I assume the existence of a covariate vector $\mathbf{X}_t(p)$, the realization of which do not dependent on p in this analysis. Time periods preceding the energy community are denoted by $t = pre$, while those during the energy community are represented as $t = post$. The counterfactual potential outcome I seek to identify is $Y_{post}(0)$, unobservable by definition.

I use pre-energy-community data to forecast $Y_{post}(0)$ based on the covariate vector $\mathbf{X}_t(p)$. The first necessary assumption is that the electricity consumption behaviour did not change in anticipation of the establishment of the energy community. Hence, the outcomes observed during periods before the energy community (Y_{pre}) are assumed to align with potential outcomes had the energy-community never occurred. This can be formally expressed as follows:

[22]The analysis is limited to the first six participants and excludes the four additional participants who joined in Phase 2 due to data availability constraints.

Assumption 1. *(No Anticipatory Effects).*

$$Y_{pre} = Y_{pre}(0) \tag{Asm.1}$$

Another assumption is that the covariates $\mathbf{X}_t(p)$ are independent of the energy community establishment itself:

Assumption 2. *(Covariates are Independent of Treatment (Energy Community Participation)).*

$$\boldsymbol{X}_t(0) = \boldsymbol{X}_t(1) = \boldsymbol{X}_t \tag{Asm.2}$$

Assumption 2 holds here as the covariates used are only exogenous: weather and date/time fixed effects. I define the relationship between covariates and participant electricity consumption in the absence of the energy community as follows:

$$\begin{aligned} &Y_{pre}(0) = g(\mathbf{X}_{pre}(0)) + \varepsilon_{pre} \\ &\text{such that} \quad \mathbb{E}[Y_{pre}(0)|\mathbf{X}_{pre}(0)] = g(\mathbf{X}_{pre}(0)) \end{aligned} \tag{11}$$

Under Assumption 1 and Assumption 2, equation (11) can be rewritten as equation (12).

I also assume that the impact of covariates variables on consumption are constant over time. This assumption is key to identify the effect of the energy-community establishment. Then, equation (12) can be formalised for post-energy-community time periods:

$$\begin{aligned} &Y_{pre} = g(\mathbf{X}_{pre}) + \varepsilon_{pre} \\ &\text{such that} \quad \mathbb{E}[Y_{pre}|\mathbf{X}_{pre}] = g(\mathbf{X}_{pre}) \end{aligned} \tag{12}$$

Assumption 3. *(Stability of the Counterfactual Function).*

$$\begin{aligned} &Y_{post}(0) = g(\boldsymbol{X}_{post}(0)) + \varepsilon_{post} \\ &\textit{such that} \quad \mathbb{E}[Y_{post}(0)|\boldsymbol{X}_{post}(0)] = g(\boldsymbol{X}_{post}(0)) \end{aligned} \tag{Asm.3}$$

Assumption 3 indicates that the function $g(.)$ derived from the pre-energy-community period can be also used to predict the counterfactual electricity consumption in the post-energy-community period. Building on Assumptions 1 and 2, Assumption 3 implies that $\mathbb{E}[Y_{post}(0)|\mathbf{X}_{post}] = g(\mathbf{X}_{post})$, enabling me to identify the counterfactual outcome.

As $g(.)$ is unknown in practice, I estimate it. For the outcome variable (Y_t), I consider the historical electricity consumption load profiles of the first six participants to the HospiGREEN project from January 1, 2019, to December 31, 2019, in kWh with hourly step.[23] To stay consistent with Assumption 2, I collect exogenous covariate data $\mathbf{X}_t$, including weather variables, date/time dummy variables. For the weather data, I gather hourly weather data from Lille-Lesquin Airport, located 25 kilometres away from the community. The weather data includes temperature, humidity, cloud cover and height, precipitation, wind speed, direction and gust. Lagged variables are incorporated for temperature and precipitation, representing the same variables from 3, 6, 12, and 24 hours ago, as past weather conditions can also influence electricity consumption.[24] Date/time fixed effects include month, day of the month, week number, day of the week, week-end day, public and school holidays in the Hainaut region of Belgium and hour of the day. Including these covariates, I accounted for a total of 25 variables. With these data, I detail below the estimation approach.

- Step 1. Estimate: $Y_{pre} = g(\mathbf{X}_{pre}) + \varepsilon_{pre}$, such that $\hat{Y}_{pre} = \hat{g}(\mathbf{X}_{pre})$, where *pre* denotes the year 2019.
- Step 2. Predict: $\hat{Y}_{post} = \hat{g}(\mathbf{X}_{post})$, where *post* starts from the 1st of November 2020.

I use the data from the year 2019 to build participants' electricity consumption hourly profiles over the entire period of the energy community. By using only pre-energy-community data, I argue that Assumption 1 stands for two reasons. First, the pre-energy-community data cover the year 2019, and the energy community was established starting from 1st of November 2020. Therefore, it seems very unlikely that any anticipatory effects influenced the electricity consumption pattern observed in 2019. Second, considering that participants knew about upcoming energy community establishment as early as 2019, they were lacking financial incentives to change their electricity consumption habits yet (Section 3.3).

Several models are applicable for the predictive task. In a similar fashion to Fabra et al. (2022), I employ a machine learning algorithm, for which I demonstrate its high predictive accuracy. Recent studies have indicated that machine learning techniques enhance predictive precision for energy consumption forecasts by effectively capturing nonlinearities and complex interactions in the relationships between demand and available covariates (Gonzalez-Briones et al. (2019), Schneider et al. (2019)). Machine learning is increasingly used in causal frameworks within energy economics (Burlig et al. (2020); Fabra et al. (2022)), likely because the field typically fulfills the required assumptions for these estimations, like Assumption 3. Previous

[23] Using hourly data instead of quarter-hour data, significantly enhances data manipulation efficiency and reduces computation time. To transition from quarter-hourly to hourly data, the kWh variable for each participant was summed for each hour.

[24] For additional details about weather data included in the construction of the counterfactual, see Appendix Appendix E.

research has demonstrated the ability to accurately forecast energy demand using solely exogenous covariates, such as weather data (Kim & Kim (2021), Lee & Cho (2022)). Moreover, concerns regarding indirect effects through prices can be alleviated, as electricity consumption is largely found to be inelastic (Ito (2014); Fabra et al. (2021)). In this analysis, electricity prices and network tariffs may indeed affect participants' electricity consumption behavior, all else being equal. The identification is specifically designed to quantify this impact of changes in price schedules (both energy and network components) on electricity consumption. Nonetheless, I argue that Assumption 3 remains valid, even if it is essentially untestable, as any potential effect of price is the only variable that could result in a prediction error, thus measuring the effect of the establishment of the energy community.

4.2. Counterfactual results

To estimate counterfactual electricity consumption, I use the algorithm eXtreme Gradient Boosting (XGBoost). XGBoost is a machine learning algorithm based on boosted decision trees. In this approach, multiple trees are trained sequentially, with each tree aiming to correct the errors made by the previous one. Research sources such as the original XGBoost paper by Chen & Guestrin (2016) provide details about the algorithm's design principles and performance evaluation. I train the XGBoost algorithm on 2019 data of participants' consumption profiles, including exogenous covariates as predictors: weather variables, date/time dummy variables.

To benchmark the performance of XGBoost algorithm, I conduct a regression analysis using the same predictors as the XGBoost model, including multiple time fixed effects and weather variables. The linear regression benchmark is specified as follows:

$$Y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j T_{jt} + \sum_{k=1}^{K} \gamma_k W_{kt} + \epsilon_{it} \tag{13}$$

Where Y_{it} is the electricity consumption of participant i at hour t. T_{jt} is the jth time fixed effect at time t, where $j = 1, 2, \ldots, J$. Time fixed effects include, year, month, week, week days, week end, holidays, and hour of the day. The relevant coefficients are denoted β_j, where $j = 1, 2, \ldots, J$. W_{kt} denote the kth weather variable at time t, where $k = 1, 2, \ldots, K$. The relevant coefficients are denoted γ_k. Finally, ϵ_{it} is the error term. This specification is regressed on 2019 data and used to predict the hourly electricity consumption profiles over the energy community period from November 2020 to February 2023.

The XGBoost algorithm is the most efficient for each participant. The hyperparameters by participant are presented in Appendix J Table J.19. This model, when trained and optimised on 2019 data for prediction over the energy community period, on achieved a Mean Average Error (MAE) out-of-sample error of 33.49 kWh and a Root Mean Square Error (RMSE) 32.01 kWh across the six participants. In contrast, the regression specification yielded an average error of 58.77 kWh, 1.7 times the average error from the XGBoost machine learning approach. The RMSE from the fixed effects approach is also substantially higher, at 71.90 kWh. For consistency, two other machine learning prediction algorithms are trained, fine tuned and tested out-of-sample similarly to compare the predictive accuracy with XGBoost: Random Forest (RF) and K-Nearest Neighbors (KNN).[25] Appendix J Tables J.19 present the MAE and RMSE from all models considered.

Figure 2 compares realized (in black) and predicted (in blue) average daily total electricity consumption in 2019 and during the pilot project. A smoothed hourly series (for real electricity demand) is presented, based on 30-day moving averages. All predictions are based on the best-performing XGBoost described above. The comparison of predicted and realized curves in 2019 serves as an additional check that the model performs well. While predictions for any given day must be interpreted with caution, real and predicted seasonality patterns are closely matched.

4.3. Estimation specification: prediction errors

To evaluate the impact of the energy community on participants' electricity peak consumption behavior, I follow a two-step methodology. First, I generate counterfactual as outlined in the above section. I construct participant-specific electricity consumption denoted $\hat{Y}_{it}$ for each hour t during each relevant phase of the energy community. Second, I estimate the effect of each phase of the energy community on participants' electricity peak consumption behavior by comparing the predicted counterfactual consumption with the actual electricity usage during the energy community project.

Identification strategy. The identification strategy assumes that the only change introduced is the energy community phases, while predictions are based on participants' pre-community electricity consumption profiles. Each phase's incentives, as outlined in Table 1, are assessed by comparing overall electricity consumption, without distinguishing between self-consumed and residual consumption.This method is used for several reasons. First, self-consumption cannot be estimated prior to the community's formation, as it was not an option for participants. Second, the renewable units already existed before the community, meaning that any relevant grid impact would depend on changed consumption patterns.

The combined implementation of static energy-sharing and network tariff adjustments in Phase 1 makes it impossible to isolate their individual effects, a limitation

[25] Random Forest builds many decision trees in parallel and averages their predictions. K-Nearest Neighbors predicts by averaging the values of the closest data points (neighbors) to each observation.

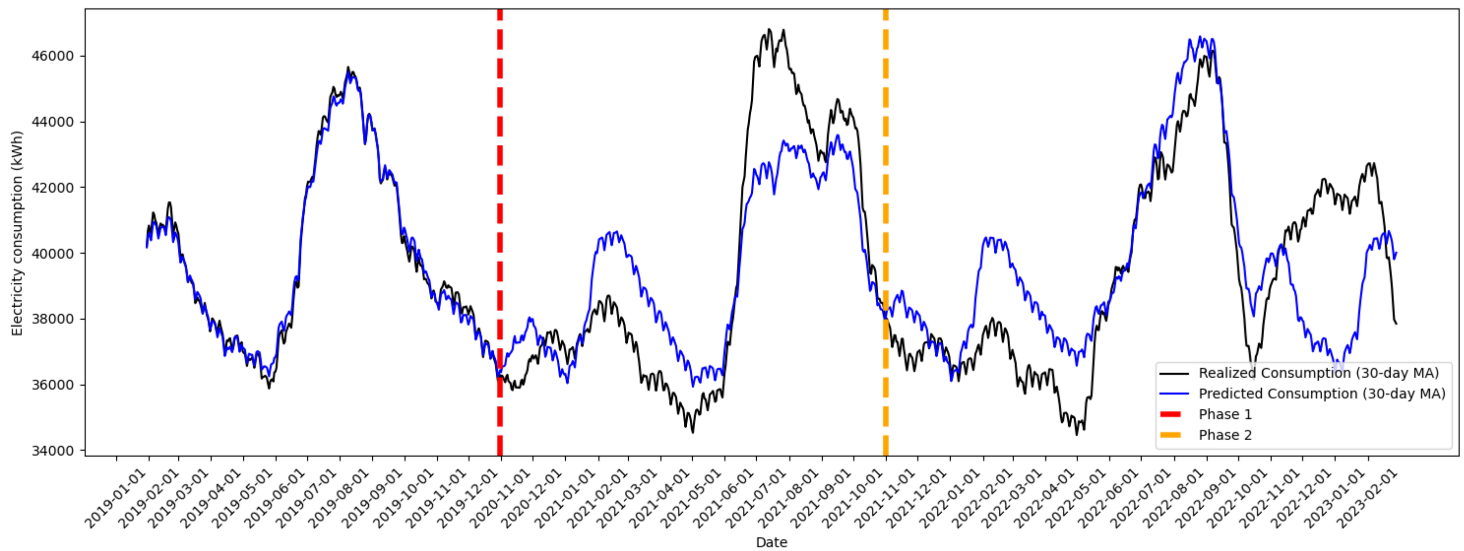


Figure 2: Realized and counterfactual electricity consumption (kWh) in the energy community project

Note: This figure illustrates the average daily electricity consumption in the HospiGREEN energy community, both the realized consumption (in black) and predicted consumption (in blue). The predictions are generated using XGBoost, as detailed in Section 4.1. To mitigate intra-day and intra-month variations, the presented series are smoothed using 30-day moving averages. The vertical red line signifies the end of 2019 and the establishment of the energy community, the vertical orange line signifies the establishment of Phase 2 of the pilot project. Notably, the absence of data between 01/10/2020 and 31/10/2020 is omitted, visually hidden at the level of the red line. Participant-specific graphs are displayed in Appendix J in Figure J.4.

rooted in the pilot project's design. However, analyzing Phase 2, without network tariff adjustments, provides valuable insights into the impact of dynamic energy-sharing on peak consumption.

Estimation. In a similar fashion to Burlig et al. (2020), the prediction error serves as the dependent variable. The objective is to compare machine learning predictions of electricity consumption with actual electricity use. Controlling for confounding factors that occurred during the pilot project but were not present in the 2019 data used for prediction, such as COVID-19 and the energy crisis, I compare the predicted counterfactual energy consumption with the actual electricity usage. The difference reflects the causal impact of establishing the energy community, as formalized in equation (14):

$$Y_{it} - \hat{Y}_{it} = \alpha_{it} + \beta_1 \text{Phase1}_t + \beta_2 \text{Phase2}_t + \gamma \mathbf{X}_t + \varepsilon_{it} \tag{14}$$

Where Y_{it} is the prediction error of the relevant outcome variable participant i at date t. The phase implementation indicators, Phase1_t and Phase2_t, are dummy variables that signal whether the energy community Phase 1 or 2 was initiated by date t. Once Phase 2 is implemented, the Phase 1 dummy returns to zero. The coefficients of interest, β_1 and β_2, capture the average change of the outcome variable with the establishment of relevant phase. Participant and time fixed effects, denoted by α_{it}, are incorporated to control for observable and unobservable characteristics that vary across participants and time periods. $\mathbf{X}_t$ represents the set of control variables included in the various estimations, encompassing factors such as COVID-19 cases, periods of lockdown, and Belgian day-ahead electricity market prices. These controls are added because their variations have been exceptionally pronounced after 2019. Therefore, they are included to capture the effect of the COVID-19 and the energy crisis.[26] Lastly, ε_{it} represents the error term, clustered at the participant level to allow for within-participant correlations.

Outcome variables. The analysis focuses one two key outcome variables: daily peak consumption level and hour of occurrence of that peak. Although the capacity-term adjustment is applied to the residual peak (see Table 1), only peak consumption is analyzed to assess consumption adjustment.

- **Peak shedding**. The first outcome variable is the prediction error for daily peak electricity consumption (kWh), split into participant-level and aggregate errors. This separation captures the effects of both individual and collective

[26]The first lockdown in Belgium occurred from March 18, 2020, to June 2, 2020, while the second lockdown was implemented from November 2, 2020, to December 13, 2020. Data is missing between December 31, 2019, and November 1, 2020. Consequently, the lockdown control variable used in the estimation primarily reflects the effects of the second lockdown.

peak adjustments. Therefore, from equation (14), Y_{it} s the actual daily peak electricity consumption of participant i on date t, and $\hat{Y}_{it}$ is the estimated daily peak electricity consumption from the prediction method presented in Section 4.1. This variable shows whether participants reduced their individual and aggregate peak consumption after each phase, considering the energy-sharing scheme and capacity tariff adjustments.

- **Peak shifting**. The second outcome variable is the prediction error in the hour when actual (Y_{it}) and estimated ($\hat{Y}_{it}$) daily peak consumption occurs (0-23) to identify peak shifting. This variable is split into participant-level and aggregate peak-hour errors.

Controls. Control variables include the number of COVID-19 hospitalizations and ICU cases in Hainaut province, where the energy community is based. With four of the six Phase 1 participants being healthcare centers, responsible for 97% of the community's electricity use, the pandemic's impact on their activity is significant. By controlling for COVID-19 cases, the analysis adjusts for the unusual activity levels caused by the pandemic. Since the prediction models are based on 2019 data, which predates the pandemic, these controls help isolate the effect of the energy community's establishment during Phase 1 from COVID-related shocks. An additional control variable is the daily maximum Belgian day-ahead electricity price, accounting for the energy crisis between the end of COVID-19 and early 2023. This period saw significant disruptions, including rising gas prices, the Russian invasion of Ukraine, and low nuclear output in France, which affected energy supply. Though retail electricity prices were pre-agreed and not directly impacted, this variable captures the the peak of the energy crisis.

5. Results

The results of the estimation are presented in Tables 6 and 7 which present the impact of each project phase on peak shedding and peak shifting, respectively. Appendix K presents an event study performed as a robustness check of the main results presented in this section.

Peak shedding effects. Table 6 shows the estimated peak shedding effects, with columns (1) to (3) indicating that Phase 1 led to a 13.69 kWh average increase in participants' daily peak consumption, even after controlling for COVID-19 and lockdowns. Columns (4) to (6) reveal a 65.39 kWh increase in the community's aggregate peak after Phase 1. However, the impact of Phase 2 on peak loses significance when controlling for day-ahead electricity prices, implying a potential link to the energy crisis. Despite these increases, the effects on peak consumption are not only not significantly different with (i.e., Phase 1) and without network tariff adjustments (i.e., Phase 2), but also small in relative value. As shown in table 2, the average peak consumption for the six participants in 2019 was 2100 kWh. This suggests no significant rebound effect.

Table 6: Peak shedding estimation - Impact of Phase 1 and Phase 2 on daily peak electricity consumption

Dependent variable:	Participants daily peak consumption prediction error (kWh)			Energy community daily peak consumption prediction error (kWh)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Phase 1	6.69^{***}	16.49^{***}	13.69^{***}	24.32^{*}	80.69^{***}	65.39^{***}
	(1.55)	(2.01)	(2.09)	(9.61)	(12.09)	(12.51)
Phase 2	2.02	13.16^{***}	4.94	13.19	79.95^{***}	35.06^{*}
	(1.45)	(1.95)	(2.61)	(9.00)	(11.70)	(15.58)
Hosp. COVID-19		-0.05^{***}	-0.05^{***}		-0.33^{***}	-0.33^{***}
		(0.01)	(0.01)		(0.05)	(0.05)
Hosp. COVID-19 ICU		0.08	0.10^{*}		0.52^{*}	0.64^{**}
		(0.04)	(0.04)		(0.24)	(0.24)
Lockdown		20.03^{***}	19.14^{***}		121.46^{***}	116.62^{***}
		(4.74)	(4.74)		(28.49)	(28.31)
Daily Max DAP			0.03^{***}			0.16^{***}
			(0.01)			(0.04)
R^2	0.00	0.02	0.02	0.01	0.08	0.09
Adj. R^2	0.00	0.01	0.02	0.00	0.07	0.09
Num. obs.	7290	7290	7290	1215	1215	1215

Note: The participant daily peak Consumption prediction error represents the difference between each participant's actual daily peak electricity consumption observed and the corresponding predicted daily peak consumption for each participant. Similarly, the energy community daily peak consumption prediction error reflects the disparity between the actual synchronized daily peak electricity consumption and its predicted value. The regressors 'Phase 1' and 'Phase 2' are dummy variables that activates respectively starting from 01/11/2020 and 01/11/2021. The COVID-19 controls consist of the daily counts of COVID-19 cases hospitalized and in Intensive Care Units (ICU) within the Hainaut region, where the energy community HospiGREEN is situated. Additionally, the daily maximum of Belgium day-ahead prices (Daily Max DAP) is incorporated into the control variables to address the impact of the energy crisis. The prediction is based on 2019 electricity consumption profiles as described in Section 4.1 . Significance levels are indicated as $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Peak shifting effects. Table 7 shows the estimated peak shifting effects. Phase 1 resulted in an average peak time shift of 0.9 hours (54 minutes) earlier, while Phase 2 resulted in an average shift of 0.67 hours (40 minutes) relatively to pre-comunity level. These small shifts remained consistent after controlling for COVID-19, lockdowns, and the energy crisis. At the community level, similar shifts were observed with Phase 1 and Phase 2 showing earlier peaks by 0.97 hours (48 minutes) and 1.1 hours (66 minutes) respectively. However, the shifts are relatively minor and do not significantly alter participants' alignment with system peak hours (See Table 2), questioning whether the capacity-term adjustment is cost-reflective.

Table 7: Peak shifting estimation - Impact of Phase 1 and Phase 2 on daily peak electricity consumption timing

Dependent variable:	Participant Daily peak hour Prediction error (hours)			Energy Community Daily peak hour Prediction error (hours)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Phase 1	-1.07^{***}	-0.94^{***}	-0.90^{***}	-0.85^{***}	-0.90^{***}	-0.97^{***}
	(0.11)	(0.15)	(0.15)	(0.13)	(0.16)	(0.17)
Phase 2	-0.89^{***}	-0.79^{***}	-0.67^{***}	-0.99^{***}	-0.90^{***}	-1.10^{***}
	(0.11)	(0.14)	(0.19)	(0.12)	(0.16)	(0.21)
Hosp. COVID-19		-0.00	-0.00		-0.00	-0.00
		(0.00)	(0.00)		(0.00)	(0.00)
Hosp. COVID-19 ICU		-0.00	-0.00		0.00	0.00
		(0.00)	(0.00)		(0.00)	(0.00)
Lockdown		0.40	0.41		0.34	0.31
		(0.35)	(0.35)		(0.39)	(0.39)
Daily Max DAP			-0.00			0.00
			(0.00)			(0.00)
R^2	0.01	0.01	0.01	0.06	0.06	0.06
Adj. R^2	0.01	0.01	0.01	0.06	0.06	0.06
Num. obs.	7290	7290	7290	1215	1215	1215

Note: The participant daily peak hour prediction error represents the difference between each participant's actual daily peak hour and the corresponding predicted daily peak hour. Similarly, the energy community daily peak hour prediction error reflects the difference between the synchronized actual daily peak hour and the corresponding predicted daily peak hour. The regressors 'Phase 1' and 'Phase 2' are dummy variables that activates respectively starting from 01/11/2020 and 01/11/2021. The COVID-19 controls consist of the daily counts of COVID-19 cases hospitalized and in Intensive Care Units (ICU) within the Hainaut region, where the energy community HospiGREEN is situated. Additionally, the daily maximum of Belgium day-ahead prices (Daily Max DAP) is incorporated into the control variables to address the impact of the energy crisis. The prediction is based on 2019 electricity consumption profiles as described in Section 4.1. Significance levels are indicated as $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

The peak shedding and shifting analysis reveals only minor adjustments in participants' consumption behavior throughout both phases. In Phase 1, there was a slight increase in peak consumption, and while some peak shifting did occur, it was minimal and did not significantly change the alignment with system peak hours. Given that the production units were already in place before the community was established, a substantial shift in peak patterns would be needed to justify deviations from the initial network tariff.

These limited changes can be rationalised by two lacking features of the project: the pilot project did not implement real-time information feedback on local production and community consumption, which could help participants adjust their usage in response to local conditions; and it did not have identified shiftable loads to effectively achieve potential grid-beneficial adjustments. This context confirms the lack cost-reflectivity of the capacity-term adjustment in Phase 1, as participants lacked both the information and tools to modify their behavior in a way that would support grid management.

6. Conclusion and policy implications

The case study of this energy-sharing community addresses two main policy questions: the need for policy support, particularly through network tariff adjustments, and whether these adjustments accurately reflect the community's impact on the grid. The results show that policy support, in form of network tariff adjustments, was crucial for the energy-sharing communities to stay financially viable. In Phase 1 of the case study, even with high self-consumption rates (89% and 94%), energy-sharing and surplus selling alone could not generate enough revenues, regardless of the allocation key used. However, in Phase 2, with the spike in retail electricity prices during the crisis, participants managed to generate positive revenues solely through energy-sharing and surplus selling, without relying on network tariff adjustments. This shows that policy support may be essential for the viability of energy-sharing communities, as their economic model may not sustain positive revenues outside of extraordinary price hikes.

The findings apply to energy-sharing communities with similar features, such as pre-existing production units and limited access to information feedback or shiftable loads. However, the policy implications have broader relevance, showing that while support for energy-sharing communities is needed, policy makers must ensure that these communities do contribute to the wider energy transition.

There is a clear trade-off between promoting energy-sharing communities and ensuring network tariff adjustments remain cost-reflective and fair for other users. In this pilot, capacity-term adjustments, designed to reduce peak consumption, did not significantly alter participants' behavior. Peak consumption levels and timings largely remained aligned with system peaks, raising concerns about the justification of such adjustments when energy-sharing communities fail to deliver measurable grid benefits.

To ensure that network tariff adjustments for energy-sharing communities are both supporting energy-sharing initiatives and cost-reflective, policymakers should focus on two key aspects:

1. **Self-consumption rate:** energy-sharing communities with high self-consumption rates may qualify for proportional-term adjustments if they demonstrate reduced reliance on the grid. National regulatory agencies should assess eligibility

based on specific criteria such as self-consumption rates, coverage levels, and grid proximity to ensure the adjustments are justified.

2. **Information feedback and shiftable loads:** Capacity-term adjustments should be applied only to energy-sharing communities where participants can actively manage their peak consumption. This requires access to real-time feedback on local production and grid status, along with the use of shiftable assets like batteries or heat pumps. Without these tools, capacity-term adjustments fail to significantly impact peak behavior, rendering the network tariff adjustments misaligned with the grid's needs.

Given the political will to engage citizens in the energy transition through such initiatives, when this necessary conditions are not met, policymakers might consider alternative support mechanisms (European Commission (2019a)). In these cases, direct subsidies or targeted financial assistance might be more suitable for communities that lack the infrastructure or flexibility to effectively adjust their consumption patterns.

These policy recommendations emphasize the importance of aligning financial support with measurable grid benefits. By ensuring that network tariff adjustments are cost-reflective and applied only where they lead to actual improvements in grid management, policymakers can balance the need to support energy-sharing communities with the principles of fairness and cost-reflectivity. These findings contribute to the broader discussion on how best to integrate energy-sharing communities into the energy transition while maintaining the financial and operational integrity of the grid.

7. Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT 3.5 in order to improve readability and language. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Appendix A. Energy-sharing communities in European Union

The Energy Communities Repository, launched by the European Commission, aimed to assist local stakeholders like citizens, authorities, and businesses in developing clean energy projects in urban areas across Europe. As part of this effort, an interactive map was created to showcase the diversity of energy community initiatives, open for public access.

In January 2024, I used this map to gather information on all initiatives and their self-reported energy-related activities. I categorized initiatives as energy-sharing communities if they indicated involvement in both self-consumption and energy-sharing. Self-consumption was included in this characterization because it aligns with the incentives of energy-sharing: using electricity when it is plentiful locally. Table A.8 provides a summary of the reported energy-sharing communities by Member State.

Table A.8: Energy-sharing communities reported by member states: January 2024

Member state	Reported Energy-sharing Communities	Total Reported Communities	Share of total
Austria	2	2	100%
Belgium	7	13	54%
Bulgaria	1	1	100%
Croatia	1	1	100%
France	2	6	33%
Germany	1	1	100%
Greece	7	8	87%
Hungary	2	1	100%
Ireland	1	1	100%
Italy	5	7	71%
Lithuania	1	1	100%
Luxembourg	3	7	43%
Netherlands	1	10	10%
North Macedonia	2	2	100%
Poland	1	1	100%
Portugal	4	5	80%
Spain	31	35	89%
Total	72	105	69%

Source: Author's computations based on Energy Communities Repository map consulted in January 2024.

Appendix B. Fixed allocation key for energy-sharing

Table B.9: Fixed allocation key implemented in HospiGREEN pilot project for energy-sharing from 01/11/2020 to 01/11/2021

	Keys used by the DSO			
REC Participants	Day (Monday to Friday, 7 AM to 10 PM)	Night (Monday to Sunday, 10 PM to 7 AM)	Weekend (Saturday and Sunday, 7 AM to 10 PM)	Contractual Key
Participant 1	3%	2%	2%	2.7%
Participant 2	18.3%	16.3%	17.3%	17.6%
Participant 3	19.5%	12.9%	18.5%	18%
Participant 4	54.9%	66.5%	59.3%	58.3%
Participant 5	1.7%	1.2%	1.2%	1.44%
Participant 6	2.6%	0.9%	1%	1.8%

Source: CWaPE (2020). Note: REC stands for Renewable Energy Community.

Appendix C. Average monthly peak and residual peak phase 1

Table C.10: Summary of average monthly peak and residual peak phase 1

Participant	Average monthly peak (kW)	Average monthly residual peak (kW)	Difference
Participant 1	70.8	64.9	-8%
Participant 2	580.4	556.4	-4%
Participant 3	642.2	596.5	-7%
Participant 4	1488.1	1385.6	-7%
Participant 5	58.4	55.8	-5%
Participant 6	86.8	81.8	-6%

Source: HospiGREEN dataset quarter-hourly load profiles from the second phase of the project (1/11/2021 - 28/02/2023).

Appendix D. Summary tables HospiGREEN phases

Table D.11: HospiGREEN Phase 1 - Summary table

Participant	Consumption (MWh)	Self-consumption (MWh)	Production allocated (MWh)	Residual consumption (MWh)	Self-consumption (%)	Coverage (%)	Allocation key (%)
Participant 1	309	130	150	179	87	49	3
Participant 2	2483	910	985	1573	92	40	17
Participant 3	2435	792	956	1643	83	39	17
Participant 4	8637	3083	3406	5554	91	39	60
Participant 5	215	74	81	141	92	37	1
Participant 6	300	86	95	214	91	31	2
Energy community	14379	5075	5673	9304	89	39	

Source: HospiGREEN dataset quarter-hourly load profiles from the first phase of the project (1/11/2020 - 31/10/2021). Note: Consumption (MWh), Self-consumption (MWh), Production allocated (MWh) and Residual consumption (MWh) represent respectively the participant total volume of consumption, self-consumption, production allocation and residual consumption over Phase 1 in MWh. Self-consumption (%), Coverage (%) and Allocation key (%) represent respectively the average rate of self-consumption, coverage and allocation over Phase 1.

Table D.12: HospiGREEN Phase 2 - Summary table

Participant	Consumption (MWh)	Self-consumption (MWh)	Production allocated (MWh)	Residual consumption (MWh)	Self-consumption (%)	Coverage (%)	Allocation key (%)
Participant 1	402	132	140	274	94	35	2
Participant 2	3208	1053	1116	2155	94	35	15
Participant 3	3751	1200	1264	2552	95	34	17
Participant 4	11086	3620	3858	7466	94	35	53
Participant 5	216	67	71	150	95	33	1
Participant 6	365	118	125	247	95	34	2
Participant 7	41	13	14	29	95	34	0
Participant 8	1422	457	483	965	95	34	7
Participant 9	516	177	189	339	94	37	2
Participant 10	311	90	93	224	97	30	1
Energy community	21318	6927	7353	14401	94	34	

Source: HospiGREEN dataset quarter-hourly load profiles from the second phase of the project (1/11/2021 - 28/02/2023). Note: Consumption (MWh), Self-consumption (MWh), Production allocated (MWh) and Residual consumption (MWh) represent respectively the participant total volume of consumption, self-consumption, production allocation and residual consumption over Phase 2 in MWh. Self-consumption (%), Coverage (%) and Allocation key (%) represent respectively the average rate of self-consumption, coverage and allocation over Phase 2.

Appendix E. Weather data details

I collected weather data from the open-access repository at Lille-Lesquin Airport, covering hourly records from January 1, 2019, to February 28, 2023. For a detailed list of variables, please refer to Table E.13. I merge this dataset to the main data. The weather variables enable me to train machine learning algorithms for generating counterfactual electricity consumption profiles used in the empirical analysis.

Table E.13: Open access Lille-Lesquin Airport weather hourly data collected from 01/01/2019 to 28/02/2023

Parameter	**Unit**
Temperature	°C
Minimum temperature in the last 12 hours	°C
Minimum temperature in the last 24 hours	°C
Maximum temperature in the last 12 hours	°C
Maximum temperature in the last 24 hours	°C
Humidity	%
Total cloudiness	-
Height of the base of lower-level clouds	-
Precipitation in the last hour	-
Precipitation in the last 3 hours	-
Precipitation in the last 6 hours	-
Precipitation in the last 12 hours	-
Precipitation in the last 24 hours	-
Mean wind direction in the last 10 minutes	-
Mean wind speed in the last 10 minutes	-
Gusts	-

Appendix F. Regional COVID-19 statistics

Regional COVID-19 data is sourced from the open-access database of the Belgian Institute for Health. Given that the vast majority of participants in the HospiGREEN pilot project are healthcare facilities, including hospitals and retirement homes (representing 96% of the energy community consumption in both phases 1 and 2), and considering the project's duration coincided with the COVID-19 pandemic, I have integrated regional COVID-19 data related to hospitalized cases and ICU admissions from the Hainaut region in Belgium. This dataset is merged with the main data. The COVID-19 statistics variables are utilized as inputs for training machine learning algorithms to generate counterfactual electricity consumption profiles utilized in the empirical analysis. Descriptive statistics for each phase of the pilot project are presented in Table F.14.

Table F.14: Descriptive statistics of Covid cases hospitalised in the Hainaut region - Phases 1 and 2

	Phase 1		**Phase 2**	
	Total cases	Total cases in ICU	Total cases	Total cases in ICU
Min	46	11	72	1
1st Qu	85	21	133	8
Median	270	57	223	13
Mean	330	74	247	25
3rd Qu	433	112	311	32
Max	1387	262	627	101

Source: Sciensano - Belgian Institute for Health. Note: Phase 1 of the pilot project takes place from 1/11/2020 to 31/10/2021, while Phase 2 takes place from 1/11/2021 to 28/02/2023.

Appendix G. Day-ahead prices

Table G.15: Descriptive statistics of Belgian hourly day ahead prices (DAP) from 01/01/2019 00:00 to 28/02/2023 00:00

	Mean	Median	Min	Max	Sd
Belgian hourly DAP (EUR/MWh)	104	63	-500	871	106

Source: ENTSOE Transparency Platform, Belgium Day Ahead Prices from 01/01/2019 00:00 to 28/02/2023 00:00

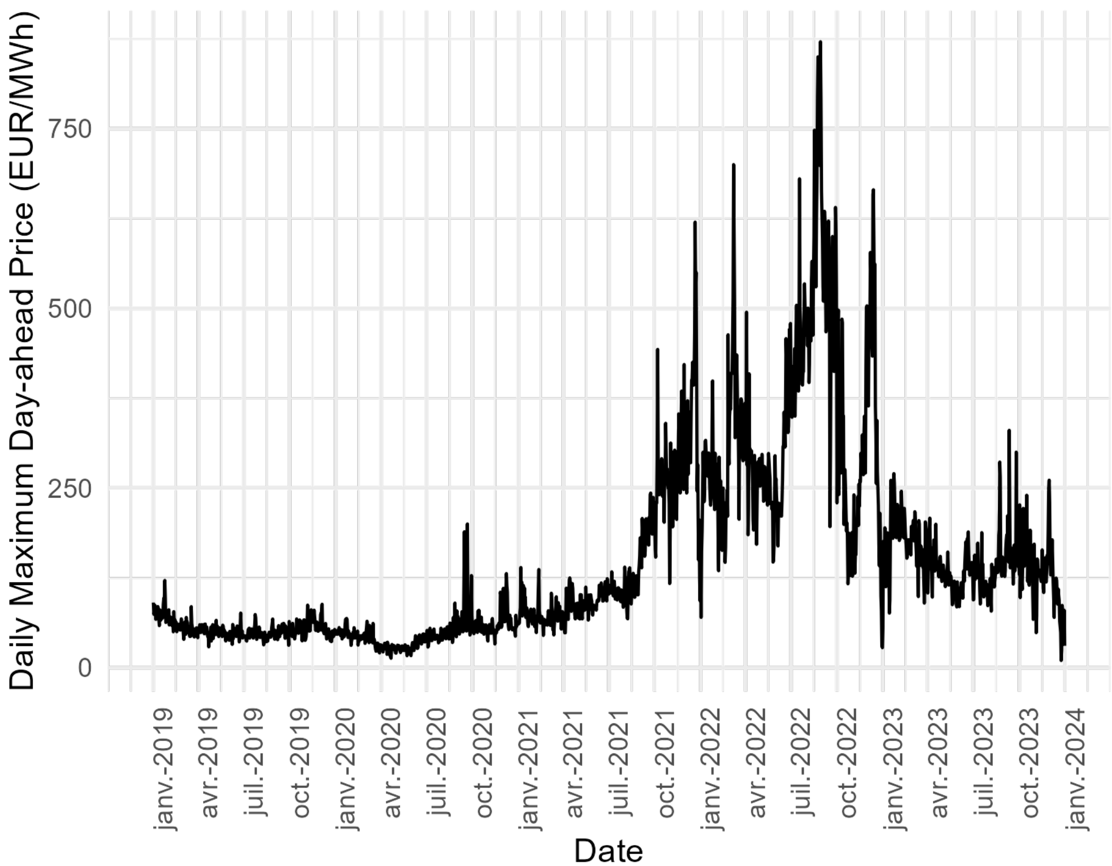


Figure G.3: Daily maximum day-ahead price (EUR/MWh) in Belgium from January 2019 to January 2024

Source: ENTSO-E Transparency Platform

Appendix H. Average CWAPE electricity prices across consumption categories

The following appendix provides a breakdown of average electricity prices as per consumption categories, sourced from CWAPE (Commission Wallonne pour l'Energie), offering insights into varying electricity prices based on usage patterns. Table H.16 displays the consumption categories based annual electricity consumption and Table H.17 displays the average price of energy per MWh of electricity by consumption class (€/MWh excluding VAT).

Table H.16: Electricity customer segmentation

Category	Annual electricity consumption
E1	< 40MWh
E2	40 à 100MWh
E3	100 à 700MWh
E4	700 à 1600MWh
E5	1600 à 6000MWh
E6	6 à 20GWh

Source: Analyse des prix de l'électricité et du gaz naturel en Wallonie (Clients professionels) sur le période de Janvier 2009 à Décembre 2021)-Table 1

Table H.17: Evolution of the average price of energy per MWh of electricity by consumption category (€/MWh excluding VAT)

€/MWh HTVA	E1: <40 MWh	E2: 40 - 100 MWh	E3: 100 - 700 MWh	E4: 700 - 1600 MWh	E5: 1.6 - 6 GWh	E6: 6 - 20 GWh
2009-01	91.35	92.51	83.61	79.64	73.82	72.61
2018-01	50.83	46.91	43.78	42.90	43.22	41.62
2019-01	58.32	52.69	51.82	53.81	54.85	51.19
2020-01	57.43	54.95	53.14	51.98	51.68	50.45
2020-12	57.33	55.32	53.00	51.98	51.68	51.00
2021-01	58.75	56.62	53.70	52.50	50.96	48.89
2021-12	85.50	88.72	76.16	84.06	94.24	88.35
2022-01	118.09	109.11	112.53	111.68	118.08	98.72
2022-12	199.05	171.32	176.40	140.05	150.44	140.64

Source: Analyse des prix de l'électricité et du gaz naturel en Wallonie (Clients professionels) sur le période de Janvier 2009 à Décembre 2022)-Table 7. Source link: https://www.cwape.be/publications/document/5535

Appendix I. Counterfactual dynamic allocation - Phase 1

This appendix outlines the revenues calculated using a counterfactual dynamic allocation key for Phase 1. This approach assesses whether changing the allocation mechanism could improve the energy-sharing community's financial viability. Unlike the fixed allocation key originally used, the dynamic key allocates local production based on individual consumption each quarter-hour.

With the dynamic key, self-consumption revenues increased due to a higher total of self-consumed energy—5,162 MWh compared to 5,075 MWh with the fixed key. However, this gain did not offset the ongoing losses from surplus energy sales, which remained negative.

While the dynamic allocation key raised self-consumption, it acts primarily as an accounting tool rather than a direct incentive. It altered the classification of self-consumed energy, affecting the necessary energy-sharing price to cover costs. This analysis shows that, although dynamic allocation boosts self-consumption revenues, it does not fully resolve the challenges posed by surplus losses.

Table I.18: Phase 1 - Participants' revenues by activity **without** network tariff adjustments and **counterfactual dynamic allocation key**

Participants	π_i^{SC}			$c_i\pi^X$	π_i^P	π_i
	Energy	Network	Total			
Participant 1	162		162	-147		15
Participant 2	681		681	-1186		-505
Participant 3	561		561	-1092		-531
Participant 4	2250		2250	-4153		-1903
Participant 5	114		114	-104		10
Participant 6	158		158	-147		11
Energy community	3926		3926	-6535		-2609

Source: Author's computation based on the HospiGREEN electricity consumption profile of Phase 1 (1/11/2020 - 31/10/2021), the Transmission System Operator (TSO) Elia's imbalance prices, average energy-sharing price ($\bar{e}^{P1_{dynamic}} = 50.28$ euros/MWh), the average price of energy per MWh of electricity by consumption class (€/MWh excluding VAT) for December 2020 and the counterfactual dynamic allocation key described in equation 1. Note: The values presented in the table are initially calculated for each sub-period (quarter-hour or month) for each participant. Subsequently, they are aggregated over the entire duration of Phase 1 to provide the summarized computation.

Appendix J. Counterfactual predictions additional details

Appendix J.1. Model selection and tuning

For the machine learning algorithm, I analyse 25 different setups for XGBoost (Chen & Guestrin (2016)) for each of the 6 participants. In term of hyper-parameters these configurations involve variations in the maximum depth of the trees (3, 5, or 7), the minimum number of observations per node (100, 200, or 300), and the learning rate options (0.01, 0.05, or 0.1).

In addition to the benchmark of Linear Regression, Random Forest (RF), and k-Nearest Neighbors (KNN), XGBoost is considered for counterfactual predictions. XGBoost has demonstrated superior performance in terms of out-of-sample error metrics (Root Mean Squared Error - RMSE, and Mean Absolute Error - MAE), as shown in Table J.19, consistently outperforming the other models for all participants.

In terms of model selection, I analyzed 25 different setups for XGBoost for each of the 6 participants. These configurations involved variations in key hyperparameters such as the maximum depth of the trees (3, 5, or 7), the minimum number of observations per node (100, 200, or 300), and the learning rate options (0.01, 0.05, or 0.1).

While Random Forest and KNN are considered as alternative machine learning models with optimized parameters, XGBoost demonstrated the best predictive performance across all participants, making it the most suitable model for this analysis. Random Forest with 100-200 trees and KNN with 9 neighbors are slower to run, especially when combined with cross-validation, and did not perform as well as XGBoost.

Based on these results, XGBoost is chosen as the final model for counterfactual electricity consumption predictions due to its higher predictive accuracy and computational efficiency in the context of the dataset and cross-validation framework used.

Appendix J.2. Prediction results details

Table J.19: Out-of-sample error metrics (RMSE and MAE) for Linear Regression, XGBoost, RF, and KNN

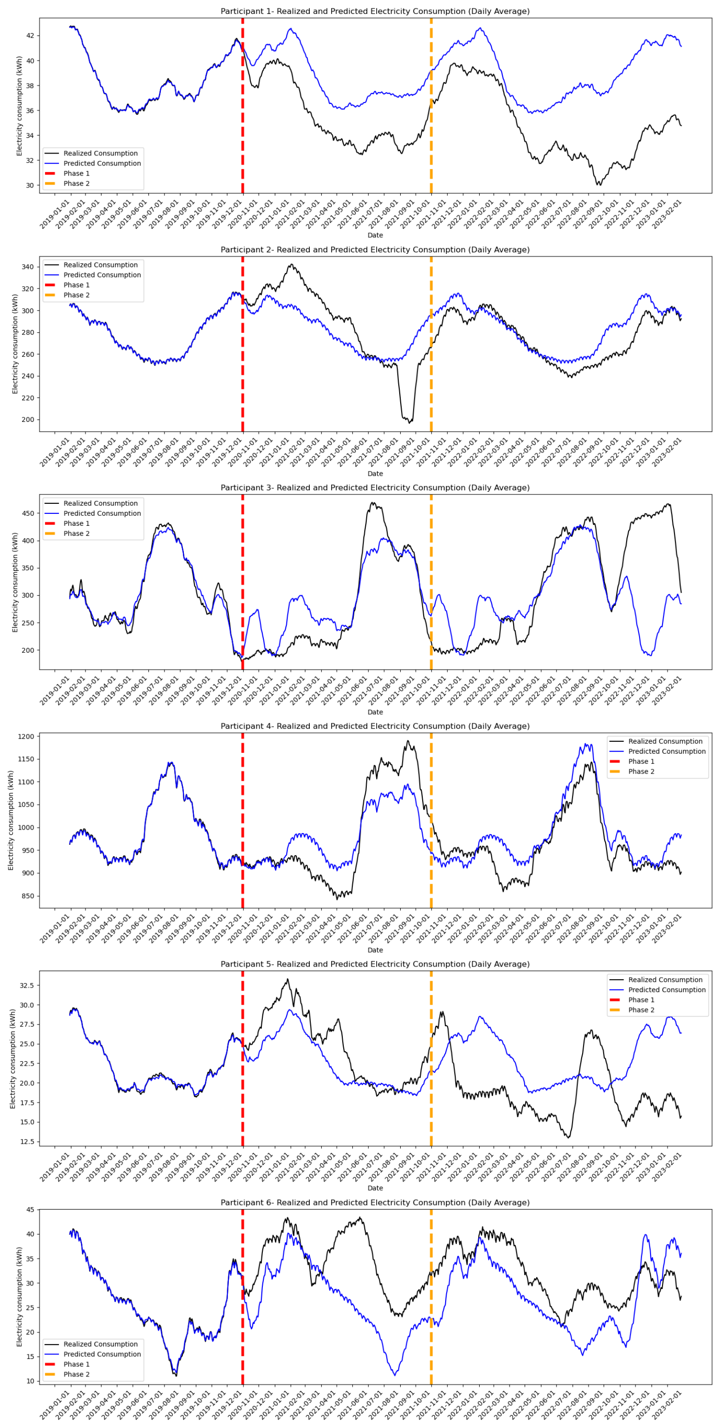
Participant	**Linear Regression**		**XGBoost (10-fold CV)**		**RF (3-fold CV)**		**KNN (5-fold CV)**	
	RMSE	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**
Participant 1	10.97	9.37	3.26	5.70	5.00	5.76	11.50	9.59
Participant 2	90.28	73.56	27.10	34.64	39.18	34.59	98.18	79.30
Participant 3	138.28	111.63	91.20	77.14	103.86	79.14	160.34	131.91
Participant 4	165.84	137.40	57.94	65.94	82.50	69.94	198.53	161.93
Participant 5	10.25	8.31	4.64	7.43	6.53	7.49	10.55	8.49
Participant 6	15.76	12.38	7.95	10.11	9.72	10.06	17.32	13.43
Average	71.90	58.77	32.01	33.49	41.13	34.83	82.73	67.29

Note: The table compares out-of-sample error metrics (RMSE and MAE) for Linear Regression, XGBoost (optimized with 10-fold cross-validation), Random Forest (optimized with 3-fold cross-validation), and KNN (optimized with 5-fold cross-validation). RMSE (Root Mean Square Error) measures the square root of the average squared differences between predicted and actual values, which gives more weight to larger errors. MAE (Mean Absolute Error) calculates the average of absolute differences between predicted and actual values, providing a linear measure of prediction accuracy.

XGBoost uses a learning rate of 0.05-0.10, 100-200 trees, and max depth of 3-7. It is efficient in terms of running time, allowing larger cross-validation folds (10-fold in this case), while still optimizing performance. On the other hand, Random Forest with 100-200 trees and a max depth of 10 is significantly slower to run, especially when combined with cross-validation. KNN uses 9 neighbors with uniform weighting.

This table shows model performance across multiple participants predicting counterfactual electricity consumption between 1/11/2020 - 28/02/2023.

Figure J.4: Realized and Counterfactual Electricity Consumption by Participant



Note: This figure illustrates the average daily electricity consumption in the HospiGREEN energy community, both the realized consumption (in black) and predicted consumption (in blue). The predictions are generated using Gradient Boosted Trees, as detailed in Section 4.1 To mitigate intra-day and intra-month variations, the presented series are smoothed using 30-day moving averages. The vertical red line signifies the end of 2019 and the establishment of the energy community, the vertical orange line signifies the establishment of the Phase 2 of the pilot project. Notably, the absence of data between 01/10/2020 and 31/10/2020 is omitted, visually hiden at the level of the red line.

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Appendix K. Event study robustness check

In this appendix, I include a robustness check using an event study analysis. This check validates the main findings by looking directly at the energy community's actual consumption profile. It examines how consumption patterns change when each phase of the energy community starts. This helps confirm the stability and consistency of the main results from Tables 6 and 7.

Table K.20: Regression results event study

Dependent variable:	Daily peak (kWh)	Daily peak hour (h)
Model:	(1)	(2)
Intercept	1545.62***	10.18***
	(53.83)	(0.61)
Phase 1	192.62***	−0.71
	(35.02)	(0.40)
Phase 2	1.89	−0.99***
	(25.05)	(0.28)
Daily Av. Wind Speed	−5.13*	−0.11***
	(2.43)	(0.03)
Daily Av. Humidity	1.97***	−0.02**
	(0.54)	(0.01)
Daily Av. Precipitation	43.31	−0.27
	(22.81)	(0.26)
Daily Av. Temperature	16.63***	0.13***
	(1.45)	(0.02)
Daily Max DAP	0.37***	−0.00
	(0.06)	(0.00)
Hops. COVID-19	−0.06	0.00*
	(0.07)	(0.00)
Hops. COVID-19 ICU	−0.01	−0.01**
	(0.35)	(0.00)
Year FE	Yes	Yes
Month-of-year FE	Yes	Yes
Day-of-week FE	Yes	Yes
Holidays control	Yes	Yes
R^2	0.76	0.37
Adj. R^2	0.76	0.35
Num. obs.	1215	1215

Note: The outcome variables of this table are computed on the actual aggregated electricity consumption profiles of the energy community. The regressors 'Phase 1' and 'Phase 2' are dummy variables that activates respectively starting from 01/11/2020 and 01/11/2021. The COVID-19 controls consist of the daily counts of COVID-19 cases hospitalized and in Intensive Care Units (ICU) within the Hainaut region, where the energy community HospiGREEN is situated. Additionally, the daily maximum of Belgium day-ahead prices (Daily Max DAP) is incorporated into the control variables to address the impact of the energy crisis. Significance levels are indicated as $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

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