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

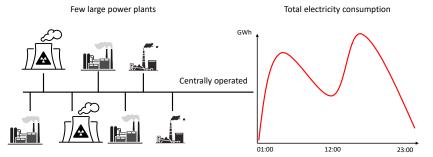
## Elise VIADERE

ULB

## September 28, 2023



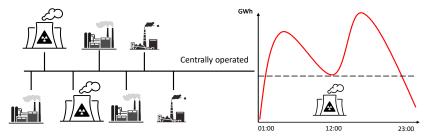
#### European Electricity Market in the 1990's



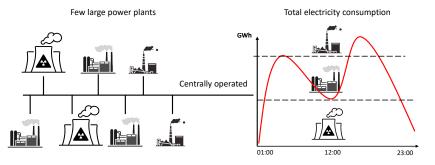
#### European Electricity Market in the 1990's

Few large power plants

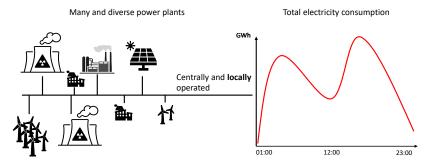
Total electricity consumption



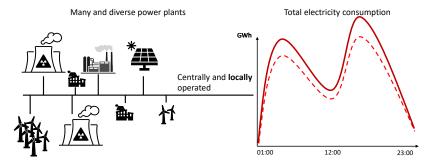
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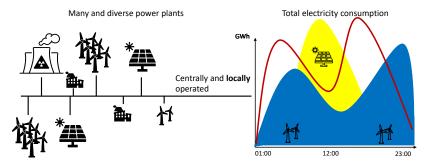
#### European Electricity Market today



#### **European Electricity Market today**

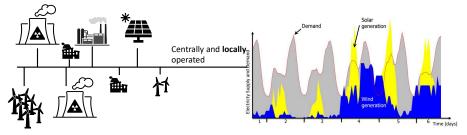


#### European Electricity Market in the future



#### European Electricity Market in the future

Many and diverse power plants

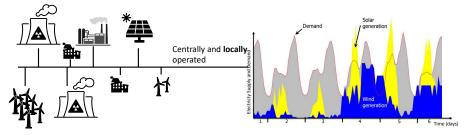


To integrate renewable sources and manage the grid scarcity

- Storage
- Increase grid capacity
- Demand-response

#### European Electricity Market in the future

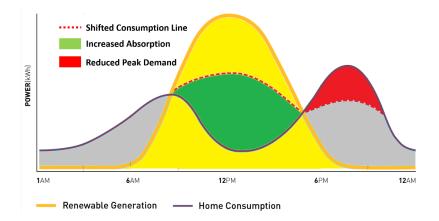
Many and diverse power plants



To integrate renewable sources and manage the grid scarcity

- Storage
- Increase grid capacity
- Demand-response

## Demand response: definition

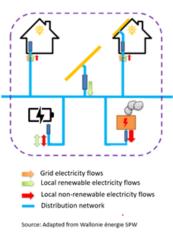


### **Electricity consumers**

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

Energy communities are often considered as challengers to this low-elasticity paradigm (Koirala et al. (2016), Rossetto (2023))

# Energy communities: exposing consumers to time-variable electricity prices



Graphical example

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- 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

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- 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
- 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 Graphical example

- 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
- Hospital
- · Nursing home
- · Psychiatric centre
- Offices
- Offices

#### Phase 2

- Nursing home
- · Psychiatric center
- · Small company
- · Small industrial company

1.	/11/2020 1/11 Phase 1	/2021 Phase 2 28/02	2/2023 J
Allocation key	Static distribution key by time range (day, night, week-end)	Dynamic proportional distribution key	
Network tariff adjustment	<ul> <li>Reduced proportional tariff for self- consumption</li> <li>Specific public service and non- periodic tariff</li> </ul>	- Specific public service and non-periodic tariff	

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
- Stimation 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

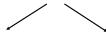
= 14400 MWh





Electricity self-consummed with energy sharing

= 5076 MWh



Energy component

Network component



Residual electricity provided by supplier

= 14400 MWh

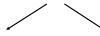


Network component



Electricity self-consummed with energy sharing





Energy component

Network component

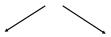
Fixed allocation key

= 52.3€/MWh on average



Residual electricity provided by supplier

= 14400 MWh



Network component





Electricity self-consummed with energy sharing





Energy component Fixed allocation key

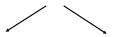
= 52.3€/MWh on average



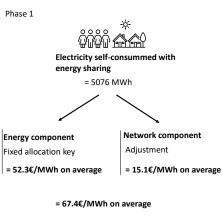


Residual electricity provided by supplier

= 14400 MWh



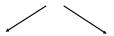
Network component





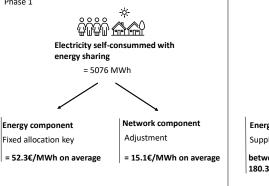
Residual electricity provided by supplier

= 14400 MWh



Network component



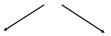


= 67.4€/MWh on average

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Residual electricity provided by supplier

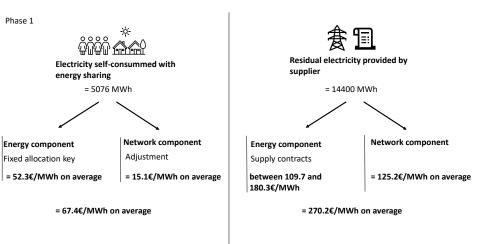
= 14400 MWh

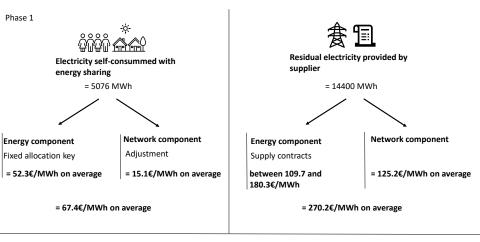


Energy component Supply contracts

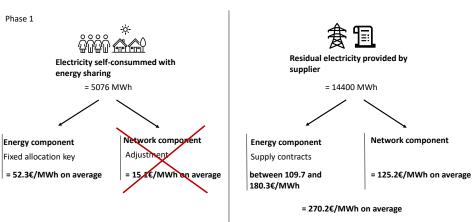
between 109.7 and 180.3€/MWh

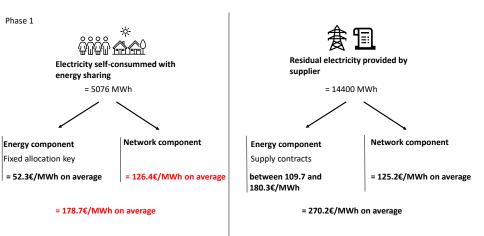
Network component

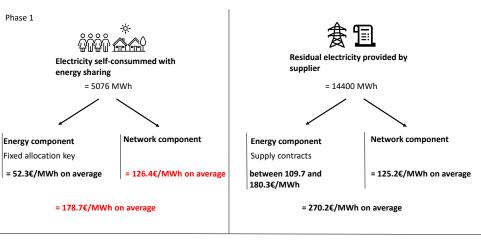




Savings on the energy bills from 21% to 31%

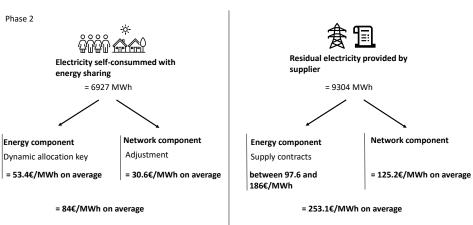


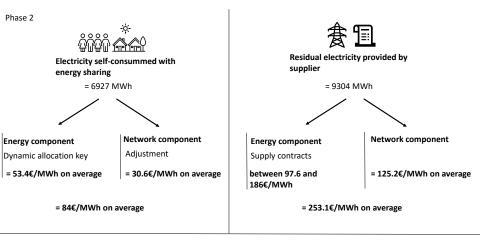




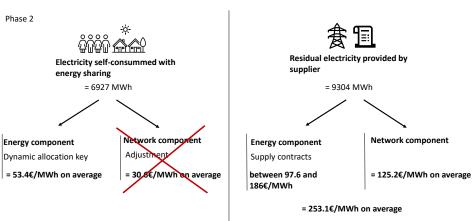
Savings on the energy bills from 8% to 12%

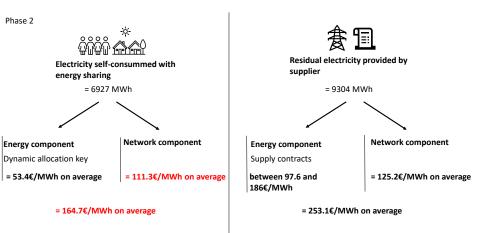
Phase 2

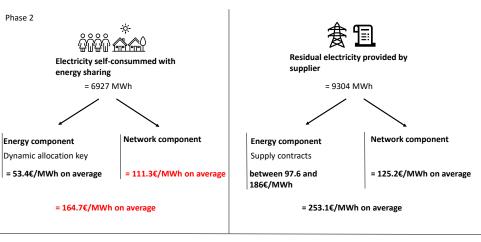




Savings on the energy bills from 19% to 22%







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

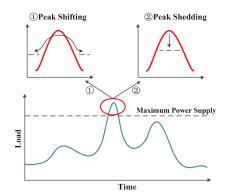
= 270.2€/MWh on average

= 253.1€/MWh on average

# 2 - Estimation

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

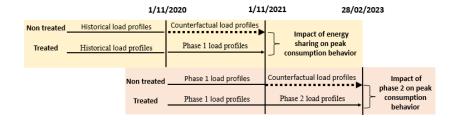
- Peak shifting
- Peak shedding



Source: Xu et al. (2017)

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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)):
  - 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.

 $Y_{it} = \alpha_{it} + \beta_1 (\text{Treatment}_i * \text{Postevent}_t) + \\ \beta_2 \text{Treatment}_i + \beta_3 \text{Postevent}_t + \text{Controls}_{it} + \epsilon_{it}$ 

- Control variables: time-related factors, weather data (-----, 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

+

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

	Dependent variable:	Dependent variable:	Dependent variable:
	Individual daily peak (KNN)	Individual daily peak (RF)	Individual daily peak (XG)
Interaction term	0.098***	0.109***	0.093***
	(0.007)	(0.007)	(0.007)
Treatment	-0.081***	-0.087***	-0.073***
	(0.007)	(0.007)	(0.007)
Postevent	-0.0002***	-0.0002***	-0.0002***
	(0.00004)	(0.00004)	(0.00004)
Observations	8,760	8,760	8,760
R <sup>2</sup>	0.088	0.095	0.089
Adjusted R <sup>2</sup>	0.084	0.091	0.085
F Statistic	30.131*** (df = 28; 8720)	32.580*** (df = 28; 8720)	30.270*** (df = 28; 8720)

*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.

	Dependent variable:	Dependent variable:	Dependent variable:
	Individual daily peak (KNN)	Individual daily peak (RF)	Individual daily peak (XG)
Interaction term	0.333***	0.354***	0.347***
	(0.006)	(0.006)	(0.006)
Postevent	-0.331***	-0.353***	-0.345***
	(0.005)	(0.005)	(0.005)
Treatment	-0.0001***	-0.0001***	-0.0001***
	(0.00002)	(0.00002)	(0.00002)
Observations	14,580	14,580	14,580
R <sup>2</sup>	0.311	0.342	0.329
Adjusted R <sup>2</sup>	0.309	0.340	0.327
F Statistic	234.398*** (df = 28; 14540)	269.569*** (df = 28; 14540)	$254.116^{***}$ (df = 28; 14540

*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.

-	Dependent variable:	Dependent variable:	
	Daily peak in peak hours (KNN)	Daily peak in peak hours (RF)	Daily peak in peak hours (XG)
Interaction term	0.160***	0.058***	0.070***
	(0.017)	(0.017)	(0.017)
Treament	-0.103***	-0.001	-0.005
	(0.017)	(0.017)	(0.017)
Postevent	-0.0002**	-0.0001	-0.00001
	(0.0001)	(0.0001)	(0.0001)
Observations	8,760	8,760	8,760
R <sup>2</sup>	0.223	0.251	0.248
Adjusted R <sup>2</sup>	0.219	0.247	0.245
F Statistic	89.339*** (df = 28; 8720)	104.139*** (df = 28; 8720)	102.883*** (df = 28; 8720)

*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.

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

	Dependent variable:	Dependent variable:	
	Daily peak in peak hours (KNN)	Daily peak in peak hours (RF)	Daily peak in peak hours (XG)
Interaction term	0.130***	0.125***	0.105***
	(0.016)	(0.016)	(0.016)
Treatment	-0.00004	-0.0002***	-0.0001
	(0.0001)	(0.0001)	(0.0001)
Postevent	-0.038***	-0.015	-0.008
	(0.014)	(0.014)	(0.014)
Observations	14,580	14,580	14,580
R <sup>2</sup>	0.031	0.027	0.027
Adjusted R <sup>2</sup>	0.028	0.024	0.024
F Statistic	16.389*** (df = 28; 14540)	14.280*** (df = 28; 14540)	14.390*** (df = 28; 14540)

*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.

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- 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

Name (Region)	Legal status	Applicable EU regulation	Households	Other participants	Production units' ownership	Production technology	Installed power	Energy sharing	Network tariff adjustmen/
Allons en Vent (W)	Cooperative	n/a	950	None	All initiative's members	Wind	800kW	No	No
AltERcoop (W)	Cooperative	n/a	430	SMEs	All initiative's members	СНР	1350kWe	No	No
BocagEn (W)	Cooperative	REC	450	Local authorities, SMEs	All initiative's members	Solar PV, Hydro power	300kWc, 240kW	No	No
Brupower (BC)	Cooperative	CEC	10	Local authorities, SMEs	All initiative's members	Solar PV	0 (obj. 1,5MWc in 2024)	No	No
Courant Alternatif (BC)	Nonprofit	LEC	15	Local authorities, SMEs	Third-party investor	Solar PV	100kWc	Yes	Yes
Coléco (W)	Cooperative	REC	150	Local authorities, School, SMEs	Prosumers	Solar PV	450kWc	Yes	No
Enduro Assenede (F)	Nonprofit	REC	20	Local authorities	Third-party investor	Solar PV	18kWc	Yes	Yes
Energ'Ittre (W)	Cooperative	REC	12	None	Third-party investor	Solar PV	18kWc	Yes	No
Greenbizz (BC)	Public company	n/a	0	SMEs	Prosumers	Solar PV	240kWc	Yes	Yes
HospiGREEN (W)	Nonprofit	REC	0	Local authorities, SMEs	Third-party investor	Solar PV, Wind	200kWc, 2.2MW	Yes	Yes
Illuminous notre quartier (BC)	Non profit	LEC	3	None	Prosumers	Solar PV	4	4	1
Marius Renard (BC)	Nonprofit	n/a	150	Local authorities	Third-party investor for cogen	Cogen, Wind	72kW {expected}	Yes (copen only)	Yes
Noordlitch (F)	Cooperative	REC	350	None	All initiative's members	Solar PV, Hydro power	230kWc	Yes	No
Nos Bambins (BC)	Nonprofit	LEC	10	Local authorities, School, SMEs	Third party investor and prosumers	Solar PV	44kWc	Yes	Yes
Strommvloed (F)	Cooperative	REC	530	Local authorities	All initiative's members	Wind	NA	Yes	No
Sunsud (BC)	Nonprofit	n/a	35	Local authorities, SISP	All initiative's members	Solar PV	35kWc	Yes	Yes
ZuidtrAnt (F)	Cooperative	REC	750	Local authorities, School, SMEs	All initiative's members	Solar PV, Storage	1MWc	Yes	Yes

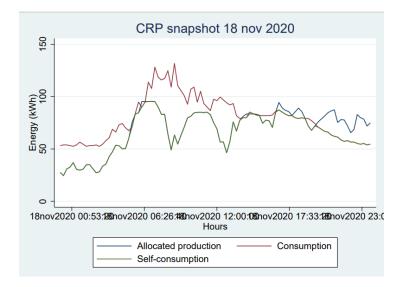
Notes: Authors' compilation from online interviews and projects' authorisation information from Brussels-Capital

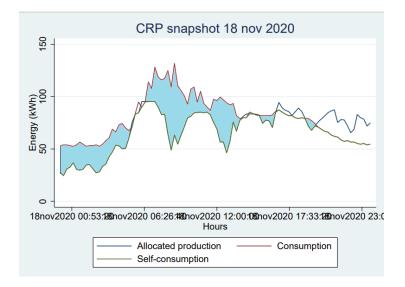
	CRP GP	ChWapi ND	ChWapi Union	IDETA CITé	CPAS MàC	Négundo	Total REC
Total yearly consumption (kWh)	462 981	288 443	1 358 301	41 515	56 990	52 277	2 260 506
Allocated production (kWh)	231 244	223 724	804 982	18 709	35 103	21 437	1 335 198
Self-consumption (kWh)	212 295	164 266	703 310	17 558	30 200	19 493	1 147 123
Self-consumption rate	92%	73%	87%	94%	86%	91%	86%
Self-production rate	50%	78%	59%	45%	62%	41%	59%
Distribution coefficient	17,4%	16,8%	60,1%	1,4%	2,6%	1,7%	100%

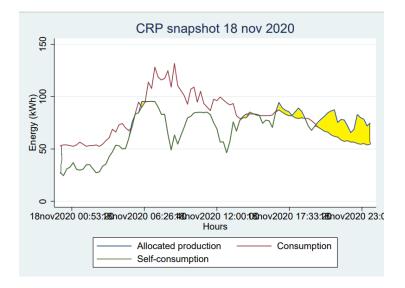
	CRP GP	ChWapi ND	ChWapi Union	IDETA CITé	CPAS MàC	Négundo	Vitrerie Landrieux	Global Net	CPAS HG	CRP KF	Total REC
Total yearly consumption (kWh)	2 460 135	2 442 507	8 682 293	208 164	310 198	302 766	3 867	45 579	190 <mark>6</mark> 10	72 787	14 718 906
Allocated production (kWh)	884 421	817 602	3 041 644	72 038	132 720	89 050	878	12 308	53 424	21 880	5 125 964
Self-consumption (kWh)	820 540	708 012	2 790 707	<mark>65 808</mark>	116 674	81 745	846	11 871	50 567	20 522	4 667 291
Self-consumption rate	93%	87%	92%	91%	88%	92%	96%	96%	95%	94%	92%
Self-production rate	36%	33%	35%	35%	43%	29%	23%	27%	28%	30%	32%
Average distribution coefficient	17,2%	15,8%	59,2%	1,4%	2,6%	1,7%	0,1%	1,6%	7,3%	2,9%	

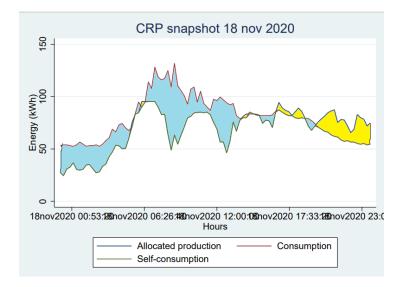
	CRP GP	ChWapi ND	ChWapi Union	IDETA CITé	CPAS MàC	Négundo	Vitrerie Landrieux	Global Net
Total yearly consumption (kWh)	2 363 876	2 922 534	8 440 317	159 370	296 368	269 540	29 532	229 852
Allocated production (kWh)	811 442	931 400	2 857 594	51 259	101 946	92 482	<b>9 9</b> 57	67 566
Self-consumption (kWh)	764 422	885 029	2 682 019	48 483	95 962	87 598	9 457	65 559
Self-consumption rate	94%	95%	94%	95%	94%	95%	95%	97%
Self-production rate	34%	32%	34%	32%	34%	34%	34%	29%
Average distribution coefficient	14,61%	17,43%	53,12%	0,98%	1,84%	1,66%	0,18%	1,28%

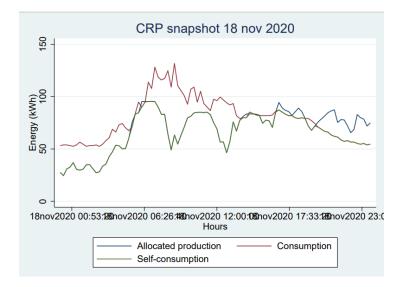
	CRP GP	ChWapi ND	ChWapi Union	IDETA CITé	CPAS MàC	Négund o	Vitrerie Landrie ux	Global Net	CPAS HG	CRP KF	Total REC
Total yearly consumption (kWh)	417 307	541 816	1 288 054	23 797	49 372	41 922	8 002	35 372	165 899	70 309	2 641 850
Allocated production (kWh)	186 789	257 540	604 101	10 281	22 450	17 173	3 246	13 340	73 198	32 552	1 220 669
Self-consumption (kWh)	176 886	242 608	567 112	9 754	21 236	16 418	3 104	12 979	69 536	30 683	1 150 316
Self-consumption rate	95%	94%	94%	95%	95%	96%	96%	97%	95%	94%	95%
Self-production rate	45%	48%	47%	43%	45%	41%	41%	38%	44%	46%	44%
Average distribution coefficient	15,6%	20,1%	49,8%	0,9%	1,9%	1,5%	0,3%	1,2%	6,1%	2,7%	

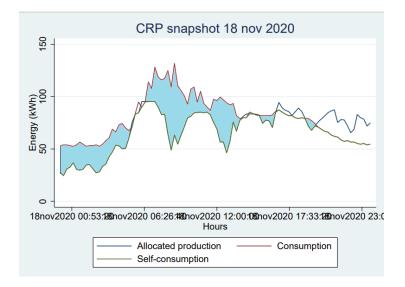


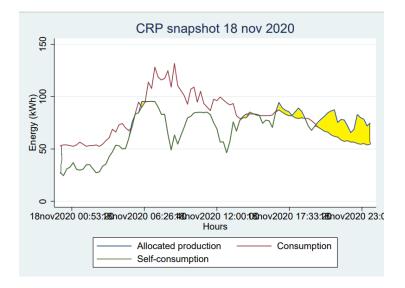


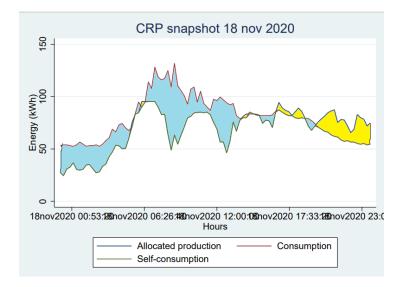












## Weather data

#### Hourly data

Direction du vent moyen 10 mn	Précipitations dans les 6 dernières heures
Vitesse du vent moyen 10 mn	Précipitations dans les 12 dernières heures
Température	Précipitations dans les 24 dernières heures
Point de rosée	Nébulosité couche nuageuse 1
Humidité	Type nuage 1
Visibilité horizontale	Hauteur de base 1
Temps passé 2	Nébulosité couche nuageuse 2
Nebulosité totale	Type nuage 2
Nébulosité des nuages de l'étage inférieur	Hauteur de base 2
Hauteur de la base des nuages de l'étage inférieur	Nébulosité couche nuageuse 3
Type des nuages de l'étage inférieur	Type nuage 3
Type des nuages de l'étage moyen	Hauteur de base 3
Type des nuages de l'étage supérieur	Nébulosité couche nuageuse 4
Variation de pression en 24 heures	Type nuage 4
Rafale sur les 10 dernières minutes	Hauteur de base 4
Rafales sur une période	Température (°C)
Periode de mesure de la rafale	Température minimale sur 12 heures (°C)
Précipitations dans la dernière heure	Température minimale sur 24 heures (°C)
Précipitations dans les 3 dernières heures	Température maximale sur 12 heures (°C)
Précipitations dans les 6 dernières heures	Température maximale sur 24 heures (°C)

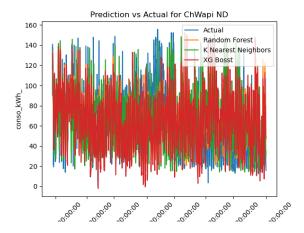
Incentive feature		Phase 1		Phase 2	
Self-consumption tariffication	Energy tariff	Fixed allocation key Net cost of purchasing self-consumed commodity + Monthly rent for local production units - Collective surplus selling revenues - Green certificates selling revenues + Management costs = 52.3€/MWh of self-consumed local energy on average	Energy tariff	Dynamic proportional allocation key Net cost of purchasing self-consumed commodity + Monthly rent for local production units - Collective surplus selling revenues - Green certificates selling revenues + Management costs = 53.4E/MWh of self-consumed local energy on average	
	Network tariff	Proportional term adjustement Capacity tariff adjustment = 15.1 €/MWh for self-consumed local energy on average	Network tariff	No more proportional term adjustement No more capacity tariff adjustment = 30.6 €/MWh for self-consumed local energy on average	
	Total	= 67.4 €/MWh for self-consumed local energy on average	Total	= 84 €/MWh for self-consumed local energy on average	
Residual consumption	Energy tariff	Traditional supply contracts Between <b>109.7€/MWh</b> and <b>180.3€/MWh</b> depending on the category of the consumer based on prices in January 2020	Energy tariff	Traditional supply contracts Between 97.6€/MWh and 186€/MWh depending on the category of the consumer based on prices in January 2021	
tariffication	Network tariff	No adjustment <b>125.2€/MWh</b> for residual electricity consumption	Network tariff	No adjustment <b>111.3€/MWh</b> for residual electricity consumption	
	Total	= 270.2 €/MWh for residual energy on average	Total	= 253.1€/MWh for residual energy on average	

Incentive feature without network tariff adjustment		Phase 1	Phase 2		
	Energy tariff	= 52.3€/MWh of self-consumed local energy on average	Energy tariff	= 53.4€/MWh o energy on avera	
Self-consumption tariffication	Network tariff	= 126.4 €/MWh for self-consumed local energy on average	Network tariff	= 111.3 €/MWh energy on avera	
	Total	= 178.7 €/MWh for self-consumed local energy on average	Total	= 164.7 €/MWh energy on avera	
Residual	Energy tariff	Traditional supply contracts Between <b>109.7€/MWh</b> and <b>180.3€/MWh</b> depending on the category of the consumer based on prices in January 2020	Energy tariff	Traditional suppl Between <b>97.6€/I</b> depending on the consumer based	
consumption tariffication	Network tariff	Network tariff No adjustment 125.2€/MWh for residual electricity consumption		No adjustment <b>1</b> electricity consur	
	Total	= 270.2 €/MWh for residual energy on average	Total	= 253.1€/MWh average	

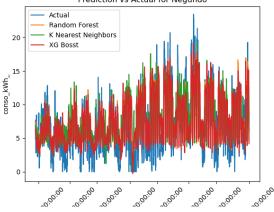
#### Based on historical data only

	Avg R2 score from cross-validation		
	Random Forest	KNN	XG Boost
Consumer 1	87%	76%	88%
Consumer 2	90%	77%	90%
Consumer 3	76%	71%	78%
Consumer 4	91%	84%	91%
Consumer 5	58%	49%	52%
Consumer 6	79%	<mark>68</mark> %	76%

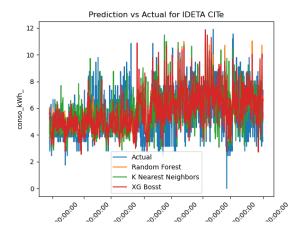
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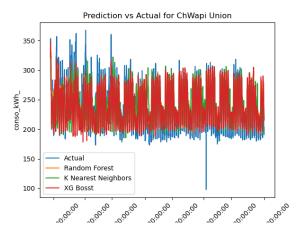


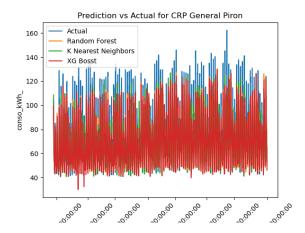
#### Based on historical data only

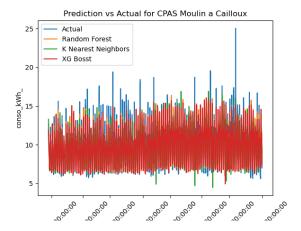


Prediction vs Actual for Négundo

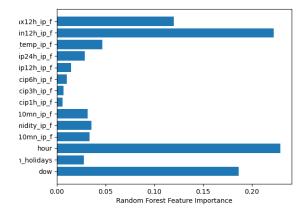


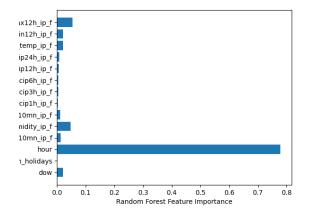




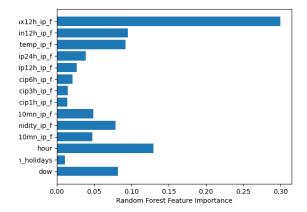


### RF feature importance

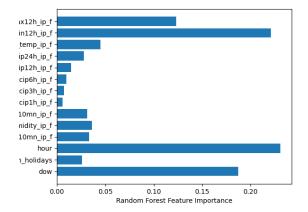




### RF feature importance



### RF feature importance



## Event study results

### PHASE 1

Variable	Estimate	Std. Error	Significance	
(Intercept)	7174.69	(434.03)	***	
$event_indicator$	-53.48	(62.30)		
dm_holidays	106.58	(67.12)		
dow	237.04	(23.13)	***	
dm_wk	-1290.24	(102.40)	***	
average_w_wdspeed_10mn_ip_f	34.17	(150.66)		
average_w_humidity_ip_f	18.34	(3.93)	**	
average_w_gust10mn_ip_f	-67.33	(99.31)		
average_w_precip1h_ip_f	11.49	(274.50)		
average_w_precip3h_ip_f	-427.49	(540.61)		
		0.36		
Adj. R <sup>2</sup>		0.35		
Num. obs.		1214		

## Event study results

### PHASE 2

Variable	Estimate	Std. Error	t-value	p-valu
(Intercept)	7654.31	(509.41)	***	< 0.00
event_indicator	-6.01	(70.14)		
dm_holidays	54.67	(81.04)		
dow	240.47	(28.34)	***	< 0.00
dm₋wk	-1312.85	(125.23)	***	< 0.00
average_w_wdspeed_10mn_ip_f	-27.05	(184.23)		
average_w_humidity_ip_f	14.25	(4.59)	**	0.01
average_w_gust10mn_ip_f	-34.81	(120.90)		
average_w_precip1h_ip_f	49.76	(311.83)		
average_w_precip3h_ip_f	-512.04	(610.95)		
R <sup>2</sup>		0.37		
Adj. R <sup>2</sup>		0.35		
Num. obs.		849		

Elise VIADERE

Do energy communities foster demand-side fle

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