Residential electricity consumption patterns in northwestern Switzerland

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Motivation

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  - Energy supply security
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  - Residential sector is a major player
- Better knowledge of household consumption patterns is key:
  - for governments to implement demand-side management measures.
  - for electricity providers to design dynamic tariffs or tailored products.
- Field experiment to investigate the impact of the combination of monetary and non-monetary incentives on residential electricity consumption.
  - This analysis is used to detect anomalies in the data.
  - For example, several hundred smart meters have been excluded because they do not reveal plausible residential consumption data.

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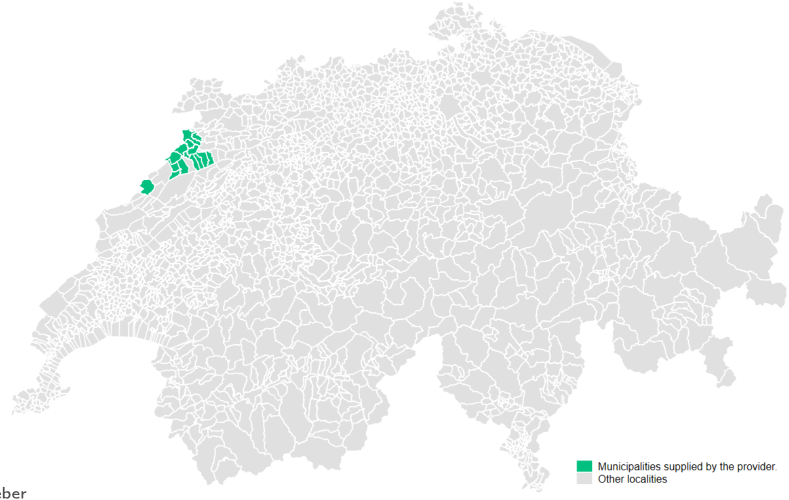
- Some technical characteristics (heating system, type of tariff, etc.).

Data II

Figure: Swiss municipalities supplied in electricity by the provider



Method

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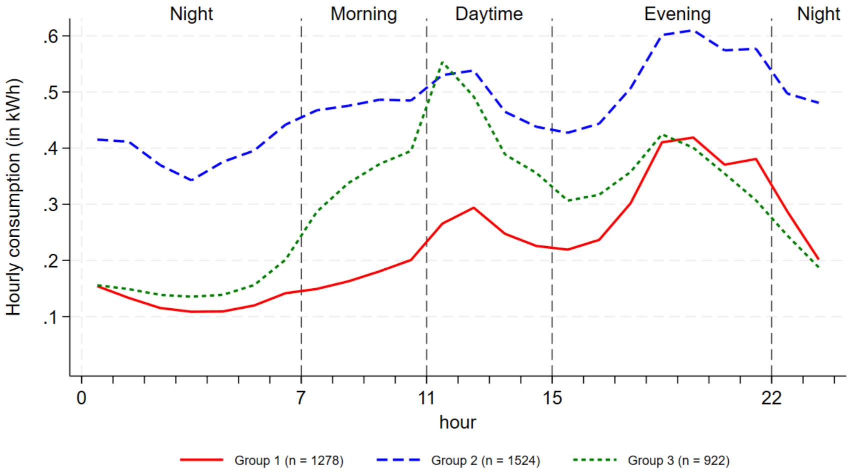
- Clustering is one of the most popular (e.g. McLoughlin et al., 2015; Viegas et al., 2016; Yilmaz et al., 2019b).
- Main idea: group households that exhibit similar load curves (clusters).

Method II

- Use K-means clustering and Calinski-Harabasz index as evaluating metric.
- Selection of 6 features to avoid “curse of dimensionality” (Räsänen and Kolehmainen, 2009; Yilmaz et al., 2019a).
  - 1 measure of **consumption level** (average daily consumption).
  - 4 measures of **consumption shape** (mean normalised consumption of the four periods of the day: night time, morning, daytime, and evening).
  - 1 measure of **consumption disparity** (standard deviation over the mean normalised consumption of the four periods).

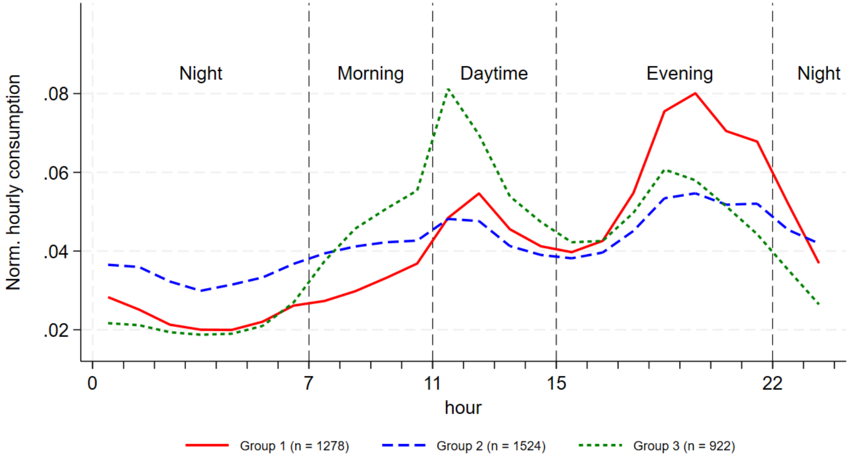
Results I: Load curves of the three clusters (in kWh)

▸ More results



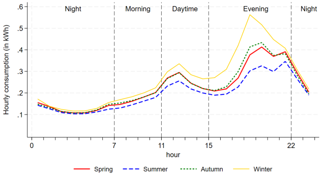
Results II: Load curves of the three clusters (normalised consumption)

▸ More results

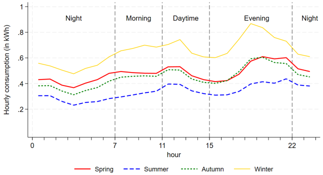


Results III: Load curves by season (in kWh)

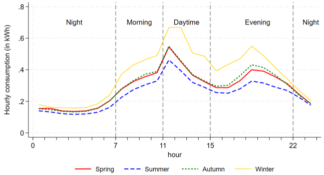
Cluster 1



Cluster 2



Cluster 3



Cluster 1	Difference max. (in %)
night	13.441
morning	20.499
daytime	23.431
evening	35.743
Mean	23.279

Cluster 2	Difference max. (in %)
night	46.546
morning	53.058
daytime	46.007
evening	49.588
Mean	48.800

Cluster 3	Difference max. (in %)
night	22.912
morning	35.480
daytime	37.136
evening	35.652
Mean	32.795

Next steps

- Characterize the structure of the clusters by linking them to relevant characteristics (heating system, household composition, etc.).

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- Preliminary results, using a multinomial logit model and the technical characteristics:
  - Housing types and heating systems seem to explain households' cluster affiliation, whereas tariff types do not.

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- Characterize the structure of the clusters by linking them to relevant characteristics (heating system, household composition, etc.).
- Preliminary results, using a multinomial logit model and the technical characteristics:
    - Housing types and heating systems seem to explain households' cluster affiliation, whereas tariff types do not.
- Other characteristics (particularly socio-demographic) will be collected as part of a survey in July 2024.

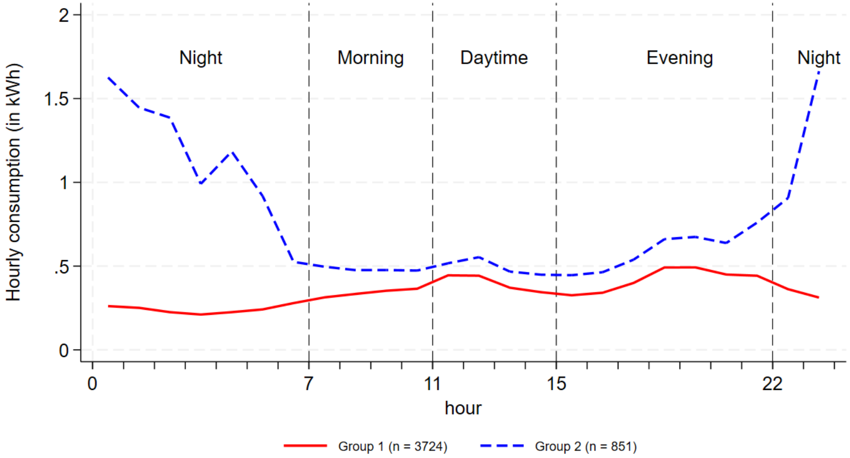
Conclusion

- 3 distinct consumption patterns in terms of shape and level.
- Differences between seasons and days of the week.
- Need to consider **consumption heterogeneity** and **equity** when implementing demand-side measures.

Thank you for your attention

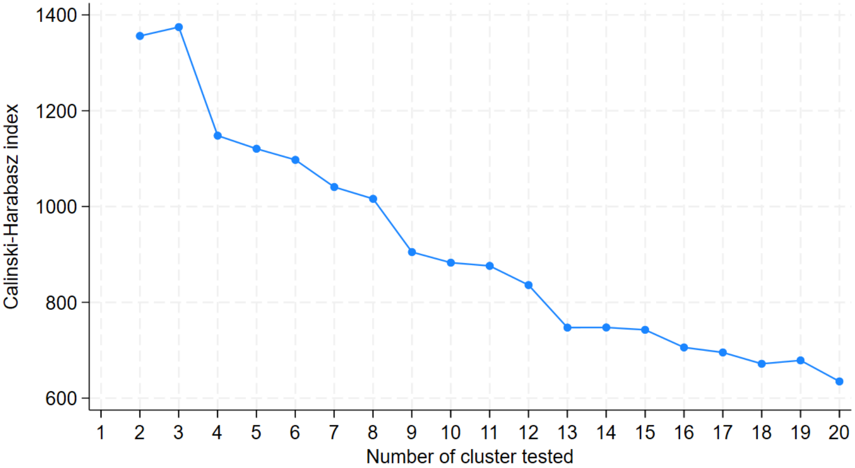
Additional results: Load curves of the two clusters (in kWh) before cleaning

◂ Main results



Additional results: Calinski-Harabasz index after cleaning

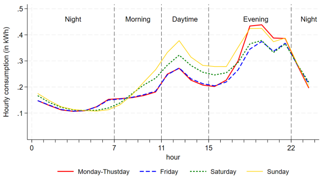
Main results



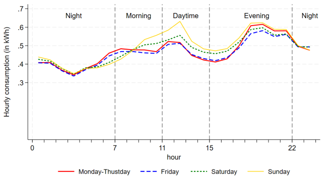
Additional results: Load curves by day of the week (in kWh)

◂ Main results

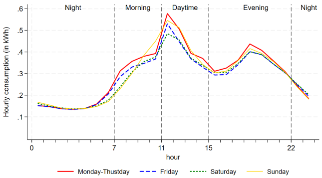
Cluster 1



Cluster 2



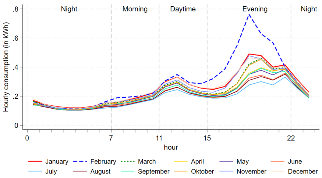
Cluster 3



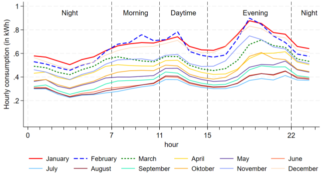
Additional results: Load curves by month (in kWh)

◂ Main results

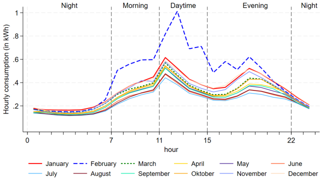
Cluster 1



Cluster 2



Cluster 3



Additional results: Mlogit model and averaged marginal effect

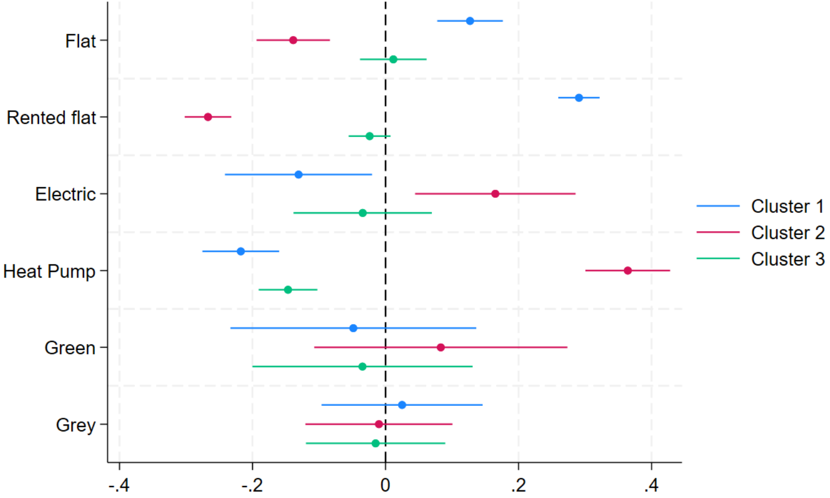
Main results

	(1) Multinomial logit model		(2) Av. marginal effect Cluster 1	(3) Av. marginal effect Cluster 2	(4) Av. marginal effect Cluster 3
	2	3	_	_	_
House	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Flat	-0.864***	-0.519**	0.128***	-0.144***	0.0153
	(-5.91)	(-3.23)	(5.06)	(-4.92)	(0.59)
Rented flat	-1.689***	-1.101***	0.296***	-0.278***	-0.0181
	(-17.24)	(-10.27)	(18.55)	(-15.43)	(-1.12)
Other	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Electric	0.897*	0.365	-0.138*	0.177**	-0.0387
	(2.52)	(0.90)	(-2.46)	(2.73)	(-0.71)
Heat Pump	1.756***	0.210	-0.224***	0.383***	-0.159***
	(7.03)	(0.68)	(-8.22)	(12.12)	(-6.98)
Blue	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Green	0.395	0.0256	-0.0550	0.0949	-0.0399
	(0.74)	(0.04)	(-0.56)	(0.87)	(-0.45)
Grey	-0.110	-0.139	0.0269	-0.0118	-0.0151
	(-0.34)	(-0.39)	(0.40)	(-0.18)	(-0.27)
Constant	1.100***	0.433***			
	(13.27)	(4.67)			
Observations	3716		3716	3716	3716

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Additional results: Explaining cluster affiliation: averaged marginal effect

◂ Main results



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