Exploring the direct rebound effects for residential electricity demand in urban environments: evidence from Nice

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Marco Baudino

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Introduction

This paper investigates the direct rebound effect in residential electricity consumption using district-level data for the French city of Nice for the year 2016.

- **Rebound effects in energy usage**
    - Rebound effects in domestic energy consumption occur when increased housing energy efficiency translating into a decrease in the energy price does not lead to a decrease in residential demand for energy usage.
    - Generally speaking, the literature distinguishes between indirect and direct rebound effects. The latter are considered in this study.
    - Direct rebound effects are usually driven by the basic principles of microeconomic theory; namely, income and substitution effects.

Classical framework

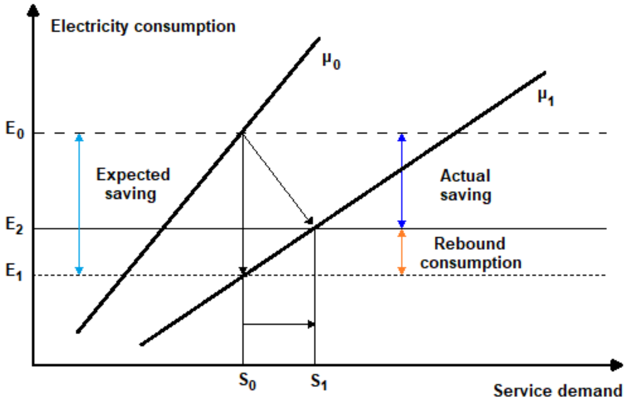

Figure: Direct rebound effect in residential electricity consumption.

Subsequent developments

A more refined approach to compute the direct rebound effect takes into account energy efficiency measures; defining the economic definition for energy efficiency (Wirl, 1997):

$$\epsilon \equiv S/E \tag{1}$$

where E is energy demand and S is an indicator for the efficiency of energy services, the direct rebound effect writes as:

$$\text{RE} = \eta_\epsilon(E) = \eta_\epsilon(S) - 1 \tag{2}$$

So that:

- $\eta_\epsilon(E) = -1$ $(\eta_\epsilon(S) = 0) \rightarrow$ no rebound effect.
- $-1 < \eta_\epsilon(E) < 0$ $(\eta_\epsilon(S) > 0) \rightarrow$ partial rebound effect.
- $\eta_\epsilon(S) = 1 \rightarrow$ full rebound effect.
- $\eta_\epsilon(S) > 1 \rightarrow$ backfire effect.

Issue

The derivation of ϵ is usually a cumbersome task due to data availability (theoretically, one would need information on all the energy factors impacting on household residential facilities, such as indoor-outdoor air exchange, heating fluid distribution system, ...).

To overcome this problem, a large number of studies have simply utilized the price elasticity ($\eta_{P_E}(E)$) to derive an estimate for the direct rebound effect:

$$\eta_\epsilon(E) = -\eta_{P_E}(E) - 1 \tag{3}$$

Nevertheless, energy prices must not depend on energy efficiency; also, potential overestimation effects might arise (Sorrell et al., 2009).

Recent contribution have proxied energy efficiency as the inverse of energy intensity (D):

$$\epsilon = 1/D \tag{4}$$

where D measures the average energy quantity of kWh consumed per square meter of residential living surface (see Belaid et al., 2020).

Rebound effects at the macro-level

Although a microeconomic phenomenon, an expanding strand of the literature has been focused on more aggregated data at the macro-level (regional, national and urban level (Balezentis, 2020; Shao et al. (2019); Zhang and Peng, 2017; Orea et al., 2015)).

Relevance of employing urban-level data:

- Environment-specific factors such as population density, congestion, etc., which are generally more pronounced in cities than in rural areas, have been proven to influence households' energy consumption behavior (Shao et al., 2019; Orea et al., 2015).
- Within urban environments, differences in terms of energetic performance of districts and household consumption behavior often arise (Tian et al., 2016, Tian et al., 2014).
- Using urban/district level data allows to evaluate the effectiveness of urban energy amelioration programs (Balezentis, 2020; Zhang and Peng, 2017).

Data, Context and Research questions

Data

For this analysis we exploited two original data sources (from INSEE and ENEDIS) by which we constructed a cross-sectional dataset of 146 observations.

Context

Nice is a medium-size city characterized by substantial variation in socio-economic conditions of dwellers. Additionally, city authorities have financed the development of a zero-energy district characterized by a high degree of energy efficiency; contrariwise, other parts of the city lagged behind.

Research questions

$\Rightarrow$ Do districts characterized by higher levels of energy efficiency denote lower rebound effects in household electricity consumption?

$\Rightarrow$ Do districts characterized by higher levels of income denote higher rebound effects in household electricity consumption?

Descriptive statistics

Table: Descriptive statistics.

Variable	Description	Mean/Frequency	St. dev.	Min.	Max.
Residential electricity demand (MWh)		3.475	1.305	2.105	10.023
Electricity price (€/MWh)		165.420	6.514	149.532	180.396
Building efficiency (1/energy intensity)		0.0068	0.0031	0.0021	0.0151
Gas price (€/MWh)		77.908	9.597	59.526	109.410
Household net personal income (€)		22946.250	8865.847	7240.292	51238.060
Residential density (residents/m2)		0.0091	0.0069	0.0001	0.0306
Average house surface (m2)		62.061	7.739	11.357	82.775
Heating system	Individual	71.97			
	Shared	28.03			
Housing unit	Apartment	90.74			
	House	9.26			

Descriptive statistics

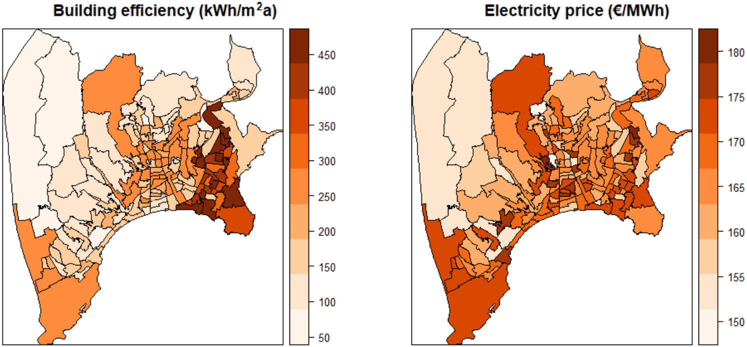

Figure: Building efficiency and electricity price distribution maps.

Empirical strategy

Model specification:

$$ln(E_i) = \beta_0 + \beta_1 ln(P_{Ei}) + \beta_2 ln(\epsilon_i) + \boldsymbol{\chi_i}\gamma + u_i \tag{5}$$

Methodology:

- OLS
- SAR (spatial autoregressive model)
- GWR-SAR (geographically weighted-regression with spatial autoregressive coefficient)

Recent contributions on individual energy behavior have demonstrated how in urban environments domestic electricity demand is likely to display both *spatial autocorrelation* (Tian et al., 2016; Tian et al., 2014) and *spatial nonstationarity* (Mashhoodi and van Timmeren, 2018; Akarsu, 2017).

Empirical strategy (follows)

Spatial autocorrelation

Spatial dependence in household energy behavior can arise for different reasons; e.g., due to socio-economic linkages characterizing proximate areas. Indeed, similar life-styles and household characteristics, as well as continuous movements of people within a city that contribute to convey information, are likely to generate and foster spatial correlation among electricity demand levels (Gomez et al., 2013). Spatial dependence in domestic electricity demand has been detected in different cities such as London, Shanghai and Beijing (see Tian et al., 2014).

Spatial nonstationarity

Within urban areas, different districts are characterized by heterogeneous socio-economic conditions, and this reflects into heterogeneous responses in variations to the electricity price, whose impact on residential electricity demand can hence vary geographically (Mashhoodi and van Timmeren, 2018; Akarsu, 2017).

Empirical results

Table: Results from global models.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
electricity price	**-0.513****	**-0.522****	**-0.491****	**-0.490****	**-0.517****	**-0.521****	**-0.501*****
	(0.2894)	(0.2953)	(0.2942)	(0.3113)	(0.2776)	(0.2773)	(0.2730)
building efficiency	**-0.667*****	**-0.626*****	**-0.643*****	**-0.605****	**-0.632*****	**-0.642*****	**-0.661****
	(0.2115)	(0.2152)	(0.2148)	(0.2238)	(0.2029)	(0.2031)	(0.1998)
residential density	0.046***	0.047***	0.051***	0.064***	0.044***	0.044***	0.044***
	(0.0126)	(0.0128)	(0.0124)	(0.0127)	(0.0120)	(0.0121)	(0.0119)
gas price	0.224***				0.248***	0.253***	0.275***
	(0.0867)				(0.0838)	(0.0848)	(0.0838)
household income	0.054*	0.030			0.053**	0.056*	0.058*
	(0.0286)	(0.0276)			(0.0273)	(0.0273)	(0.0269)
house surface	0.219***	0.261***	0.262***		0.027***	0.216***	0.217***
	(0.0629)	(0.0620)	(0.0620)		(0.0603)	(0.0602)	(0.0593)
shared heating	0.072***	0.081***	0.086***	0.078***	0.072***	0.072***	0.072***
	(0.0112)	(0.0107)	(0.0098)	(0.0102)	(0.0106)	(0.010)	(0.0105)
apartment	-0.580***	-0.600***	-0.602***	-0.627***	-0.577***	-0.575***	-0.552***
	(0.0504)	(0.0508)	(0.0508)	(0.0534)	(0.0482)	(0.0483)	(0.0485)
ρ					0.189**	0.184**	0.195***
					(0.0996)	(0.0779)	(0.1069)
$\boldsymbol{W}$					Inv. dist.	Queen	kNN-5
Adjusted R2	0.8503	0.8442	0.8439	0.8251	0.8529	0.8533	0.8507
Residual sum of squares	1.6332	1.7130	1.728382	1.9505			
Log Likelihood					122.6039	122.3054	121.0849
AIC	-221.65	-216.69	-216.3874	-201.7302	-223.2079	-222.6108	-220.1698

Note: all variables are expressed in natural logarithms. Levels of significance: *$p<0.10$, **$p<0.05$, and ***$p<0.01$. Standard errors in parenthesis. Constant coefficient estimates omitted.

Results from the GWR-SAR local model

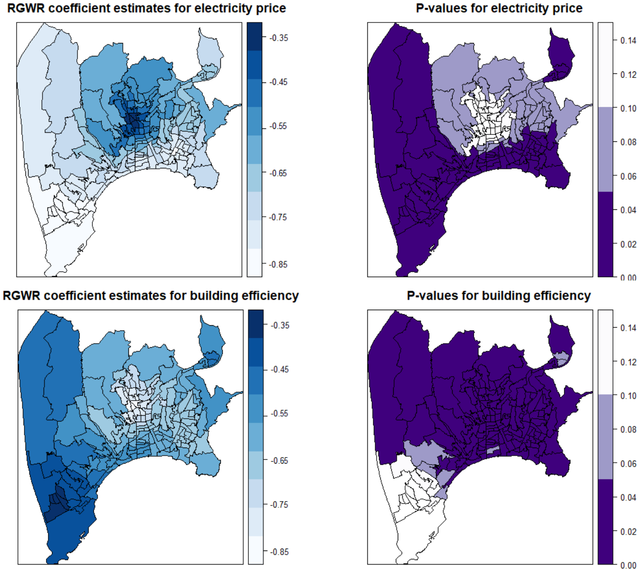

Figure: Local estimates for Building efficiency and Electricity price.

Summary of results

From the empirical results of our analysis:

- We detect the emergence of heterogeneous partial direct rebound effects, ranging from 39% to 80% for the electricity price, and from 20% to 60% for energy efficiency measures.
- Lower-income districts do not always denote lower magnitudes for the rebound effect compared to higher-income districts.
- Higher-energy efficiency districts register on average higher magnitudes for the rebound effects compared to lower-energy efficiency districts.
- The highest significant rebound effects for energy efficiency are detected in the districts of the Nice eco-valley, whose residential facilities are endowed with the most efficient energy-saving technologies in the city of Nice. Specifically, for these districts, we detect that only the 45% of energy saving potential has been achieved from energy technological improvements.

Conclusion and Policy recommendations

In the light of our findings, we provide a series of recommendations:

- A policy shift from purely technically oriented efficiency programs towards a mix of technological and behavioral change campaigns could represent a valuable effective strategy.
- This calls for the need of a better investigation for the exact reasons behind rebounds in domestic electricity usage (energy invisibility issue, habitual practices, individual carelessness for energy-saving technologies (Hargreaves et al., 2010; Burges and Nye, 2018, Dorner, 2019)).
- Energy optimization policies shall be designed by city authorities without jeopardizing citizens' welfare, notably in those districts characterized by lower levels of income.

Thank you

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