



# Modelling weather effects for impact analysis of residential time-of-use electricity pricing



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## ABSTRACT

Analyzing the impact of pricing policies such as time-of-use (TOU) is challenging in the presence of confounding factors such as weather. Motivated by a lack of consensus and model selection details in prior work, we present a methodology for modelling the effect of weather on residential electricity demand. The best model is selected according to explanatory power, out-of-sample prediction accuracy, goodness of fit and interpretability. We then evaluate the effect of mandatory TOU pricing in a local distribution company in southwestern Ontario, Canada. We use a smart meter dataset of over 20,000 households which is particularly suited to our analysis: it contains data from the summer before and after the implementation of TOU pricing in November 2011, and all customers transitioned from tiered rates to TOU rates at the same time. We find that during the summer rate season, TOU pricing results in electricity conservation across all price periods. The average demand change during on-peak and mid-peak periods is  $-2.6\%$  and  $-2.4\%$  respectively. Changes during off-peak periods are not statistically significant. These TOU pricing effects are less pronounced compared to previous studies, underscoring the need for clear, reproducible impact analyses which include full details about the model selection process.

## 1. Introduction

Pricing schemes intended to reduce peak electricity consumption such as time-of-use (TOU) are becoming tractable as advanced metering proliferates. The Ontario Energy Board established a three-tier TOU pricing scheme with three objectives: (i) to more accurately reflect the wholesale market cost of electricity in the price consumers pay; (ii) to encourage electricity conservation across all hours of the day; and (iii) to shift electricity use from high-demand periods to lower-demand periods (Ontario Energy Board, 2004). Properly evaluating the impact of such policies is critical for policy makers trying to reduce demand, reduce emissions and defer new generating capacity. However, isolating the moderate effects of TOU pricing is challenging in the presence of substantial confounding factors. For example, a mild or extreme summer may skew the estimated impact of TOU pricing if the effects of weather are not adequately modelled.

We observe that there is no consensus in prior work for modelling weather effects and discussion of variable selection criteria is limited. To ensure reliable results, policy makers should insist on clear, reproducible impact analyses which include details of the explanatory variable selection process and justification for any variable transformation used. To help produce such analyses, this paper presents a

methodology for modelling the effects of weather on residential demand in the context of pricing policies.

The crux of our methodology is to compare a number of aggregate electricity demand models which have each modelled the effects of weather differently. We use statistical measures of their explanatory power, out-of-sample prediction accuracy, and goodness of fit to select a model that is both well-performing and readily interpretable. After careful analysis, we have chosen a multiple regression modelling structure for its interpretability, tractability, and modularity. To enumerate the possible models, we define three independent components: coincident weather (e.g., incorporating humidity and windchill in addition to temperature), delay or build-up of temperature that household thermal controls react to (e.g., moving average of temperature or cooling/heating degree-hours) and the non-linear relationship of temperature with demand (e.g., piecewise linear and natural spline transformations). We hypothesize that the effect of temperature on aggregate residential electricity demand is non-linear. Furthermore, we hypothesize that past temperature observations and coincident weather observations each provide additional explanatory value.

The second contribution of this paper is an application of the proposed methodology to evaluate the effects of Ontario's mandatory TOU implementation according to two of its stated objectives: energy

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conservation and shifting consumption out of peak demand periods. We use a smart meter dataset of over 20,000 households in south-western Ontario, Canada that is particularly suited to our analysis. It has an adequate numbers of observations before and after the implementation of TOU pricing. Furthermore, the local distribution company transitioned all customers from tiered rates to TOU rates at a single point in time, meaning that there is no uncertainty introduced by a staggered TOU billing roll-out. Though the sample size and rate transition are positive assets of the dataset, the sample time period does not include adequate pre-TOU observations during the winter rate season to assess its effectiveness. Given this limitation, we present results only for the summer TOU rate season and make conclusions in that context.

## 2. Prior work

A literature review performed by Newsham and Bowker (2010) discusses the impacts of three types of dynamic pricing pilots: critical peak pricing, time-of-use, and peak time rebates. Their review includes 13 TOU pilot studies conducted after 1997. They conclude that basic TOU pricing programs like Ontario's can expect to see residential on-peak demand change by -5%. An earlier TOU literature review by Faruqui and Sergici (2010) covering 12 TOU pilot studies concluded that TOU pricing induces a -3% to -6% change in residential on-peak demand. From 2010 onwards, there have been several impact studies of mandatory TOU pricing. We summarize these recent studies as well as several of the older ones in Table 1.

Our first observation is that results from opt-in experiments and pilot studies such as Hydro One (2008); Lifson and Miedema (1981); Ontario Energy Board et al. (2007) and Train and Mehrez (1994) are often more pronounced than mandatory studies such as Faruqui et al. (2013b); Navigant Research and Newmarket-Tay Power Distribution (2010) and Navigant Research and Ontario Energy Board (2013). Our second observation is that most studies in our review either have a pronounced demand shift from on-peak to off-peak hours or conservation across all hours. Only two subsets of one study by Jessoe et al. (2013) showed the opposite effect. Finally, we observe that the tiered roll-out of TOU to high-use customers first, analyzed by Jessoe et al.

**Table 1**  
Results from prior TOU electricity pricing studies.

Study	Pilot	Mand.	Season	Total Change (%)	On-Peak (%)	Mid-Peak (%)	Off-Peak (%)	Weekend
Hydro One (2008)	Yes	No	summer	-3.30	-3.70	NR	NR	NR
Lifson and Miedema (1981)	Yes	No	summer	-3.17	-8.84	-3.95	+2.86	NA
Ontario Energy Board et al. (2007)	Yes	No	summer	-6.00	-2.40 (NS)	NR	NR	NR
Train and Mehrez (1994)	Yes	No	full year	NR	-9.02	NA	+6.51	NA
Jessoe et al. (2013)	No	Yes	Summer	-3.14 <sup>a</sup>	-6.09 <sup>a</sup>	NA	-2.00 <sup>a</sup>	NA
			Summer	+0.39 <sup>b</sup>	+1.16 <sup>b</sup>	NA	+0.06 <sup>b</sup>	NA
			summer	+2.64 <sup>c</sup>	+3.11 <sup>c</sup>	NA	+2.4 <sup>c</sup>	NA
Faruqui et al. (2013b)	No	Yes	Summer	0 to -0.45 <sup>d</sup>	-2.60 to -5.70	Decrease	Increase	NR
			Winter	0 to -0.45 <sup>d</sup>	-1.60 to -3.20	Decrease	Increase	
Navigant Research and Newmarket-Tay Power Distribution (2010)	No	Yes	Full year	-0.66 (NS)	-2.80	-1.39	+0.16 (NS)	+2.21
Navigant Research and Ontario Energy Board (2013)	No	Yes	Summer	0 to -0.10	-3.30	-2.20	+1.20	+1.90
			Summer shoulder	NR	-2.20	-1.50	+1.50	+1.40
			Winter	NR	-3.40	-3.90	-2.50	-1.20
			Winter shoulder	NR	-2.10	-2.30	-1.10	+0.50 (NS)
Maggiore et al. (2013)	No	Yes	Jan–Jun	NR	-0.83	NA	NR	NA
Mei and Qiulan (2011)	No	Yes	Feb–Dec	increase	increase	NA	increase	NA

NR – not reported, NA – not applicable, NS – not statistically significant.

<sup>a</sup> High-use customers only.

<sup>b</sup> Medium-use customers only.

<sup>c</sup> Low-use customers only.

<sup>d</sup> Annual.

**Table 2**

Categories of temperature transformations found in prior work, used when modelling residential electricity demand.

Coincident weather transformations	
Humidity	Mountain and Lawsom (1992)
Humidex	Faruqui et al. (2013b)
Temperature	Faruqui et al. (2013a); Navigant Research and Ontario Energy Board (2013)
Humidity Index	Energy Board (2013)
Wind Speed	Friedrich et al. (2014); Mountain and Lawsom (1992)
Temporal transformations	
Lagged Observations	Harvey and Koopman (1993)
Heating and Cooling Degree-Days	Pardo et al. (2002); Cancelo et al. (2008)
Heating and Cooling Degree-Hours	Navigant Research and Newmarket-Tay Power Distribution (2010)
Moving Average	Mountain and Lawsom (1992)
Weighted Moving Average	Friedrich et al. (2014); Bruhns et al. (2005)
Non-linear transformations	
Switching Regression	Moral-Carcedo and Vicéns-Otero (2005); Faruqui et al. (2013b); Navigant Research and Newmarket-Tay Power Distribution (2010); Navigant Research and Ontario Energy Board (2013); Lifson and Miedema (1981); Train and Mehrez (1994)
Linear Regions with Smoothed Transitions	Bruhns et al. (2005); Friedrich et al. (2014); Moral-Carcedo and Vicéns-Otero (2005)
Regression Splines	Engle et al. (1986); Harvey and Koopman (1993)

(2013), showed substantial flexibility to shift demand.

Across these TOU studies, we observed many different techniques being used to model weather. When deciding on which modelling techniques to consider in our methodology, we broadened our literature review to residential electricity demand analysis in general. Table 2 summarizes this broadened literature review, grouping prior work by the technique used to transform temperature observations. An explanatory variable transformation is a mathematical process that creates derived values from observed values. For example, a series of dry-bulb temperature observations may be transformed using humidity and wind chill to become a series of perceived temperatures. The derived variable would be used as input to the modelling procedure in place of the observed variable.

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