Analysis of Ontario's Full Scale Roll-out of TOU Rates

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ABSTRACT

Besides the nation of Italy, the Canadian province of Ontario is the only region in the world to have rolled out smart meters to all its residential customers and to deploy Time-of-Use (TOU) rates for generation charges to all customers who stay with the regulated supply option. TOU rates were deployed as a load shifting measure in Ontario, to persuade customers to curtail electricity usage during the on-peak period and/or to shift that usage to less expensive mid-peak and off-peak periods, and possibly to reduce overall electricity usage. Residential customers show relatively consistent patterns of load shifting behavior across study years, but little evidence of conservation. For the province as a whole, TOU reduced usage during the summer on-peak by 2.96 percent in the pre-2012 period, 2.18 percent in 2012 and 2.29 percent in 2013, relative to what usage would have been in the absence of TOU. These results are consistent with those seen in other jurisdictions. General Service class customers show mixed evidence of load shifting behaviors and are less responsive to the TOU prices than residential customers. However, general service class customers show more conservation than the residential customers.

Introduction

Besides the nation of Italy, the Canadian province of Ontario is the only region in the world to have rolled out smart meters to all its residential customers and to deploy Time-of-Use (TOU) rates for generation charges to all customers who stay with the regulated supply option. TOU rates were deployed as a load shifting measure in Ontario, to persuade customers to curtail electricity usage during the on-peak period and/or to shift that usage to less expensive mid-peak and off-peak periods, and possibly to reduce overall electricity usage.

This impact evaluation of Ontarioœs full-scale roll-out of TOU rates is a three-year project with the following objectives: (i) Quantify the change in energy usage by pricing period for the residential and general service customers (defined below) using a few select local distribution companies (LDCs); (ii) Estimate the elasticity of substitution between the pricing periods and the overall price elasticity of demand.

This report presents the findings from the second year of the study, examining impacts from TOU rates from their inception through to the end of 2013.[1]

The LDCs analyzed in the second year study constitute more than 50% of the Ontario population. LDCs were recruited for the study in waves, with 5 LDCs recruited in the first year and a further 3 in the second.[2] The original LDCs in the first year study were chosen based on their previous experience with TOU pilots, general size and geographic location. The LDCs added in the second year of the study were chosen

[1] While all LDCs in the study were offering TOU rates by 2012, they started offering these rates at different points in time from 2009 onwards.
[2] Due to data issues, only 4 LDCs participated in the first year evaluation and 7 in the second.

based on geographic and demographic factors. In order to be eligible for the study, LDCs had to have a sufficiently long pre-TOU data record. In order to implement TOU rates, LDCs had to first install smart meters that recorded electricity usage at different times of the day (interval data). Once they had smart meters installed, they could roll-out the TOU rate to their customers. Each LDC in Ontario managed its TOU rate deployment independently. Both smart meters and the TOU rate were rolled out at different dates and over different time scales across the LDCs. Participant LDCs were included because they had sufficiently long pre-TOU periods, where customers had interval data but were not yet on the TOU rate. The deployment of TOU rates in Ontario was not part of an experiment and this posed an analytical challenge for constructing a control group for the impact evaluation purposes. However, heterogeneous timing of the TOU deployment worked in our favor as we were able to include customers who were at the tail end of the deployment as a proxy control group in our study (at least through the end of 2012).[3] However, because we have included pre-TOU implementation data for the entire sample, there is a second set of control data across time. Finally, retail customers who are not on TOU rates act as a third set of controls.

TOU impacts are estimated at the regional level for four regions within Ontario, each consisting of multiple LDCs. Each region has a distinctive climate and census-profile.[3] Impacts within a region are allowed to vary by socio-demographic factors corresponding to census districts. These heterogeneous impacts are then reweighted to obtain representative regional impacts that correspond to the regional populations. Representative provincial impacts are then calculated by weighting each region by its customer count shares and aggregating. Impacts are calculated by calendar year.

For each region, we examined two customer classes: residential and general service. Single family homes and individually metered apartment buildings constitute the residential class and general service customers are non-residential with demands less than 50 kW. Only customers with a sufficient history of hourly data in the pre-TOU period were able to be included in the study. The final second year study sample included 112,642 residential customers and 35,991 general service customers, out of a total customer population of 2,162,063 residential customers and 147,450 general service customers for the participating LDCs. Due to insufficient pre-TOU data we were unable to include general service customers for Toronto Hydro and Newmarket-Tay Power.[4]

TOU in Ontario

Pursuant to the *Electricity Restructuring Act, 2004*, the Ontario Energy Board (ñOEBò) is mandated to develop a regulated price plan (the ñRPPò), which includes a Time-of-Use (TOU) pricing structure whose purpose is to provide stable and predictable electricity pricing for consumers that more accurately reflects the actual costs of generation. TOU prices are set by the OEB and reviewed bi-annually in May and November.[5] The OEB price review is based on an analysis of electricity supply cost forecasts for the year ahead and a true-up between the price paid by consumers and the actual cost of generation in the previous billing period. Consumers may be exempted from TOU pricing by executing a fixed-price contract with an electricity retailer for a term generally between three to five years. The rationale for TOU pricing is clear. Electricity cannot be stored economically in large quantities and the demand for electricity varies throughout the day. On

[3] The regions were selected to be consistent with the way in which Hydro One divides its service territory. Hydro One was rebranded from Ontario Hydro Services Company soon after the restructuring of Ontarioôs electricity market and is divided into 4 different regions based on a geographic grouping of operating centers.

[4] For each LDC and customer class we required at least 6 months of pre-TOU incremental data. Incremental data were obtained from the installation of smart meters. If the window between smart meter installations and TOU rates was too short, then adequate pre-TOU data did not exist. This was the case for general service customers for both Toronto Hydro and Newmarket-Tay Power.

[5] www.ontarioenergyboard.ca/OEB/Consumers/Electricity/Smart+Meters/FAQ+-+Time+of+Use+Prices

weekdays, demand starts to rise in the morning as people get up and continues to its peak in the late afternoon or evening as people come home. On weekends and holidays, demand is lower overall

Weather exercises a very important influence on how much and when Ontarians consume electricity. Over the last few decades, peak demands have become much more pronounced over the summer months as more people install air conditioning in homes and businesses. Peaks in the summer usually take place in the mid- to late-afternoon. The amount of daylight also affects peak. In the winter, increases in usage typically occur in the morning, when people wake-up in darkness to begin their day and peaks in the afternoon when the sun sets relatively early. TOU rates were deployed as a load shifting measure in Ontario, to incentivize customers to curtail electricity usage during the on-peak period and/or to shift that usage to less expensive mid-peak and off-peak periods, and possibly to reduce overall electricity usage.

Ontarioôs TOU consists of three pricing periods. Only the commodity (generation) prices are time varying. These are determined by the OEB and are seasonal and may be adjusted every six months to reflect changes in system conditions and market prices. An illustration of the relevant TOU periods and commodity prices (effective November 2013) is shown in Figure 1.[6] It should be noted that these TOU prices account for roughly only half of the average customerôs bill; other charges that the customers face are not time-varying. Differentials between the on-peak and off-peak prices have remained relatively stable since 2010. As of November 2013, the on-peak to off-peak price ratio is 1.8 for the generation component only. When other non-volumetric bill components are included (excluding customer charges) to result in an ñall-inò rate, the on-peak to off-peak price ratio is roughly 1.5.

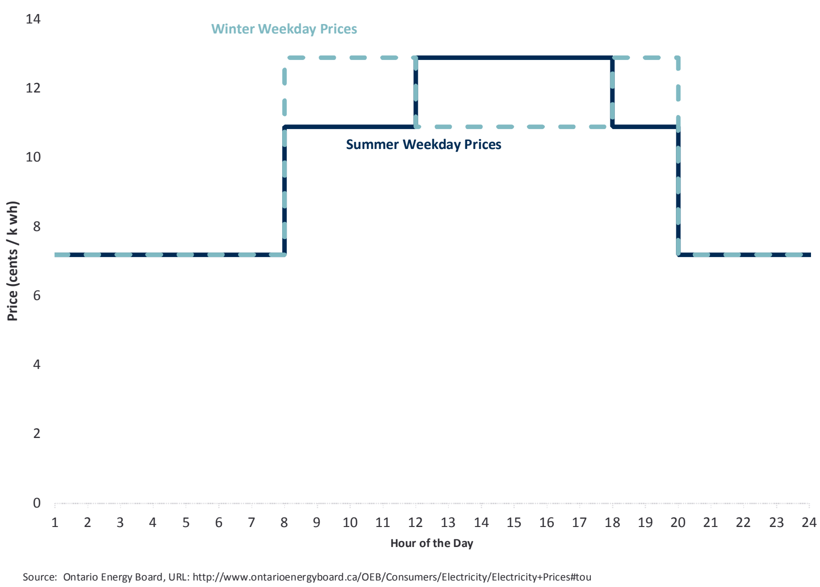

Figure 1: Electricity Prices across a day (in effect as of November 2013)

[6] Source: Ontario Energy Board website. http://www.ontarioenergyboard.ca/OEB/Consumers/Electricity/Electricity+Prices

Methodology

We employ a two-pronged approach to achieve the objectives of the TOU study: (i) estimation of an advanced model of consumer behavior called the ñAddilog Demand Systemò to discern load shifting effects that are caused by the TOU rates and to estimate inter-period elasticities of substitution; (ii) estimation of a simple monthly consumption model to understand the overall conservation behavior of the customers and estimate an overall price elasticity of demand. By using the parameter estimates from these two models and solving them together, we calculate the impact that TOU rates have had on energy consumption by period and for the month as a whole.

The Addilog System, first formulated by Houthakker 1960 and more recently extended by Conniffe (2006) and Jensen et al. (2011), is a well-behaved demand system, which is capable of estimating small elasticities of substitution.[7] Unlike more flexible demand systems, the Addilog System, like the Constant Elasticity of Substitution (ñCESò) demand system, is known to satisfy regularity conditions (e.g., concavity) globally. As noted in Mountain and Hsiao (1989), even though the intent of flexible functional forms is to permit testing of hypotheses about elasticities of substitution over a wide range of possible data points, the available Monte Carlo studies (e.g., Gallant 1981) and Guilkey, Lovell & Sickles (1983) and the results of Caves & Christensen (1980) suggest that the available flexible functional forms cannot totally serve the purposes for which they were originally produced. Consequently, the CES was also used in earlier work by Caves & Christensen (1980) who analyzed data from the Wisconsin TOU experiment and later in a meta-analysis of data from five TOU experiments (Caves, Christensen, & Herriges, 1984). Moreover, as a reflection of the advantages of these more parsimonious demand systems for estimating the impact of dynamic pricing, many recently published papers in applied energy journals has used the CES demand system. For example, see the published papers of Faruqui & Sergici (2011), Faruqui & George (2005), Faruqui, Sergici & Akaba (2014) and Faruqui, Sergici & Akaba (2013), in their analyses of the pricing experiments in Baltimore, California, Connecticut, and Michigan, respectively.

We estimated the Addilog system separately for summer and winter seasons over six pricing periods.

Period	Hours	Summer TOU Window (May - October)	Winter TOU Window (January - April, November & December)
1	-	Weekends & Holidays	Weekends & Holidays
2	9 pm - 7 am	Off-peak	Off-peak
3	7 am - 11 am	Mid-peak	Peak
4	11 am - 5 pm	Peak	Mid-peak
5	5 pm - 7 pm	Mid-peak	Peak
6 (*)	7 pm - 9 pm	Off-peak	Off-peak

(*) Before May 2011, period 6 was a summer mid-peak and winter peak period.

Figure 2. TOU Study Time Periods

[7] Unlike more flexible functional forms, which can violate the second-order conditions for utility maximization, the Addilog Demand System is globally concave and always satisfies those conditions. This property is not only valuable for estimating theoretically consistent elasticities but also essential for estimating out-of-sample province-wide impacts. (This is a reason Addilog Sytems are often used in Computable General Equilibrium models for long-term simulations.)

Following is a generalized Addilog System for the six TOU periods, with period 1 acting as base:

$$\ln\left(\frac{q_{2ht}}{q_{1ht}}\right)-\ln\left(\frac{q_{2ht-12}}{q_{1ht-12}}\right)=\beta_2\left(\ln\left(\frac{P_{2ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{2ht-12}}{Y_{ht-12}}\right)\right)-\beta_1\left(\ln\left(\frac{P_{1ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{1ht-12}}{Y_{ht-12}}\right)\right)+\sum_{k=1}^{K}\gamma_{k2}\left(X_{k2ht}-X_{k2ht-12}\right)+\nu_{2ht}$$

$$\ln\left(\frac{q_{3ht}}{q_{1ht}}\right)-\ln\left(\frac{q_{3ht-12}}{q_{1ht-12}}\right)=\beta_3\left(\ln\left(\frac{P_{3ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{3ht-12}}{Y_{ht-12}}\right)\right)-\beta_1\left(\ln\left(\frac{P_{1ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{1ht-12}}{Y_{ht-12}}\right)\right)+\sum_{k=1}^{K}\gamma_{k3}\left(X_{k3ht}-X_{k3ht-12}\right)+\nu_{3ht}$$

$$\ln\left(\frac{q_{4ht}}{q_{1ht}}\right)-\ln\left(\frac{q_{4ht-12}}{q_{1ht-12}}\right)=\beta_4\left(\ln\left(\frac{P_{4ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{4ht-12}}{Y_{ht-12}}\right)\right)-\beta_1\left(\ln\left(\frac{P_{1ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{1ht-12}}{Y_{ht-12}}\right)\right)+\sum_{k=1}^{K}\gamma_{k4}\left(X_{k4ht}-X_{k4ht-12}\right)+\nu_{4ht}$$

$$\ln\left(\frac{q_{5ht}}{q_{1ht}}\right)-\ln\left(\frac{q_{5ht-12}}{q_{1ht-12}}\right)=\beta_5\left(\ln\left(\frac{P_{5ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{5ht-12}}{Y_{ht-12}}\right)\right)-\beta_1\left(\ln\left(\frac{P_{1ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{1ht-12}}{Y_{ht-12}}\right)\right)+\sum_{k=1}^{K}\gamma_{k5}\left(X_{k5ht}-X_{k5ht-12}\right)+\nu_{5ht}$$

$$\ln\left(\frac{q_{6ht}}{q_{1ht}}\right)-\ln\left(\frac{q_{6ht-12}}{q_{1ht-12}}\right)=\beta_6\left(\ln\left(\frac{P_{6ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{6ht-12}}{Y_{ht-12}}\right)\right)-\beta_1\left(\ln\left(\frac{P_{1ht}}{Y_{ht}}\right)-\ln\left(\frac{P_{1ht-12}}{Y_{ht-12}}\right)\right)+\sum_{k=1}^{K}\gamma_{k6}\left(X_{k6ht}-X_{k6ht-12}\right)+\nu_{6ht}$$

Where X refers to non-TOU variables such as weather characteristics; h refers to customer; t refers to month; q and P refer to the consumption and prices in the specific time period, respectively; Y refers to overall electricity expenditure, and ν is a random disturbance. The price and weather terms are implemented as vectors of parameters that allow us to obtain:

1) Separate impacts estimates for pre-2012, 2012 and 2013 periods
2) Heterogeneous responses to prices and weather based on postal code level demographics.

To this end we have

$$\beta_i = \beta_{i\,pre-2012} + \beta_{i\,2012} * I(2012) + \beta_{i\,2013} * I(2013) + \beta_{ic1}PCX1 + \beta_{ic2}PCX2$$

And

$$\gamma_{ki} = \gamma_{ki0} + \gamma_{kic1}PCZ1 + \gamma_{kic2}PCZ2$$

Where:

- I(2012) is an indicator if the calendar year is greater than or equal to 2012
- I(2013) is an indicator if the calendar year is greater than or equal to 2013
- PCX1 and PCX2 are the first two principal components of census variables that would influence price responsiveness
- PCZ1 and PCZ2 are the first two principal components of census variables that would influence weather responsiveness

The above system of equations was estimated using the ñSeemingly Unrelated Regression (SUR)ò estimation routine. Even though the set of equations seem unrelated to each other, they are actually related through the correlation in their error. This routine also allows us to enforce cross-equation restrictions, i.e., the coefficient of the period 1 price will take the same coefficient in all five equations, etc. SUR employs random effects estimator in the context of unbalanced panels (time-invariant fixed effects are accounted for using first differences). This systems estimation is consistent with the procedure used by Ham, Mountain, & Chan 1997, where household specific effects (for which we have very little information) are differenced out avoiding possible selection biases regarding those who opted for not choosing a retail rate. Separate systems were estimated for the summer and winter. It is important to note that the demand systems approach is needed not only to predict the impact of the TOU rates that have actually been deployed but also to predict the impact of alternative TOU rates in the future.

The Addilog system and the load shifting behavior is only one piece of the puzzle. The other piece is the monthly conservation model. We estimate a monthly conservation model to estimate the overall price elasticity of demand and the conservation impact. Our model takes the following generalized form:

$$\ln Q_{ht} - \ln Q_{ht-12} = \theta\left(\ln\left(\frac{PE_{ht}}{CPI_t}\right) - \ln\left(\frac{PE_{ht-12}}{CPI_{t-12}}\right)\right) + \sum_{k=1}^{K} \tau_k \left(X_{hkt} - X_{hkt-12}\right) + e_{ht}$$

Where X refers to non-TOU variables such as weather; h refers to customer; t refers to month; *PE* is the overall monthly price of electricity; CPI is the consumer price index; *Q* is the monthly consumption of electricity; and *e* is a random disturbance. As with the Addilog model we allow for heterogeneous reactions to price and weather. Price terms are interacted with pricing Principal Components

$$\theta = \theta_1 + \theta_{2c1} PCX1 + \theta_{2c2} PCX2$$

Weather terms are interacted with weather Principal Components and vary by season

$$\tau_k = \begin{array}{l} \tau_{k1S} I(summer) + \tau_{k1c1S} I(summer) PCZ1 + \tau_{k1c2S} I(summer) PCZ2 \\ + \tau_{k1W} I(winter) + \tau_{k1c1W} I(winter) PCZ1 + \tau_{k1c2W} I(winter) PCZ2 \end{array}$$

As before, PCX1 and PCX2 are the first two principal components of census variables that would influence price responsiveness and PCZ1 and PCZ2 are the first two principal components of census variables that would influence weather responsiveness. We estimate the monthly conservation model using fixed effects estimation corrected for the 1st order autocorrelation. Parameter estimates from this equation yield the overall price elasticity of demand.

After estimating the Addilog system and monthly consumption models for summer and winter seasons by class, we then solve these equations together and calculate the impacts by period.

Results

The analysis is conducted at the regional level and aggregated to the provincial level. Load shifting impacts are split into three separate periods: pre-2012, 2012 and 2013. The pre-2012 period reflects all of the years that LDCs within a region were on TOU rates prior to 2012. Some LDCs started TOU as early as 2009, while others only began in 2012, resulting in compositional changes potentially affecting the comparison between pre-2012 and later years. By 2012, all LDCs in the study were on TOU rates. The key findings are summarized below:

- Residential customers show relatively consistent patterns of load shifting behavior across regions and study years, but little evidence of conservation.
- General Service class customers show mixed evidence of load shifting behaviors and are less responsive to the TOU prices than residential customers. However, general service class customers show more conservation than the residential customers.
- The load shifting model parameters are generally well-behaved and have magnitudes that have been observed in other pilots.

- There are some unexpected positive elasticities in the conservation models, likely due to little price variation during the study period. None of these elasticities are statistically significant.

Residential Class:

Figure 3 shows the impacts during the summer on-peak period across the regions and province as a whole for residential customers. The impacts are the percentage change in electricity usage during this period relative to what would have been consumed in the absence of TOU. A negative impact represents curtailment of energy usage during the summer on-peak period. For the province as a whole, TOU reduced usage during the summer on-peak by 2.96 percent in the pre-2012 period, 2.18 percent in 2012 and 2.29 percent in 2013, relative to what usage would have been in the absence of TOU. The confidence intervals on these impacts are narrow relative to the magnitude of the impacts and lie far away from zero, leading us to be highly confident that we can reject the null hypothesis of zero load-shifting in all years and regions. For the provincial impact measures we can see that summer on-peak period impacts were slightly larger in the pre-2012 period, but very similar in 2012 and 2013.

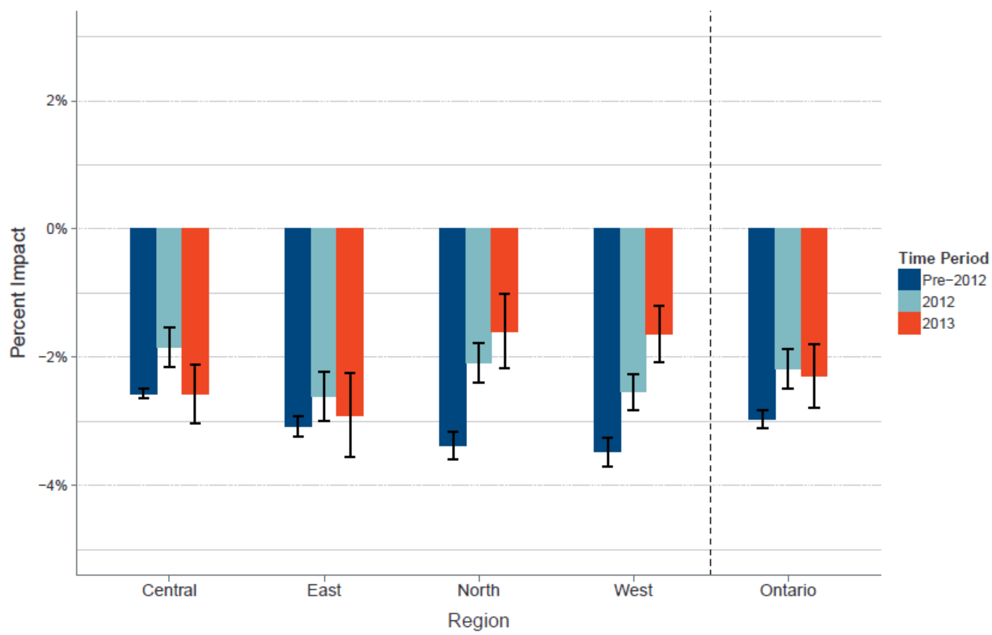

Figure 3. Residential Load Shifting Results (Summer On-Peak Period)

Figure 4 and Figure 5compare the Ontario residential summer TOU on-peak period results to results collected from 77 pilots around the world using The Brattle Groupǿs Arcturus database. The OPA impacts are the only impacts reported in both figures obtained from a full scale roll-out rather than a pilot. On the y-axis is the percentage peak reduction, while the x-axis shows the peak to off-peak price ratio. The blue curve is Brattleǿs Arc of Price Responsiveness, which is an econometric estimation of the curve that best fits the data. The Arc can be used to make predictions of peak reductions for various peak to-off peak price ratios. In Ontario the peak-to-off peak price ratio for all of the LDCs was approximately 1.5. A peak to off-peak price ratio of such a magnitude would correspond to a 3 percent reduction in peak usage in the Brattle Arc of Price Responsivess, which is slightly higher than the impacts estimated in each region in 2012 and 2013. The lower bound of the 95 percent confidence bound on the impacts for these years were 2.49 and 2.78 percent respectively.

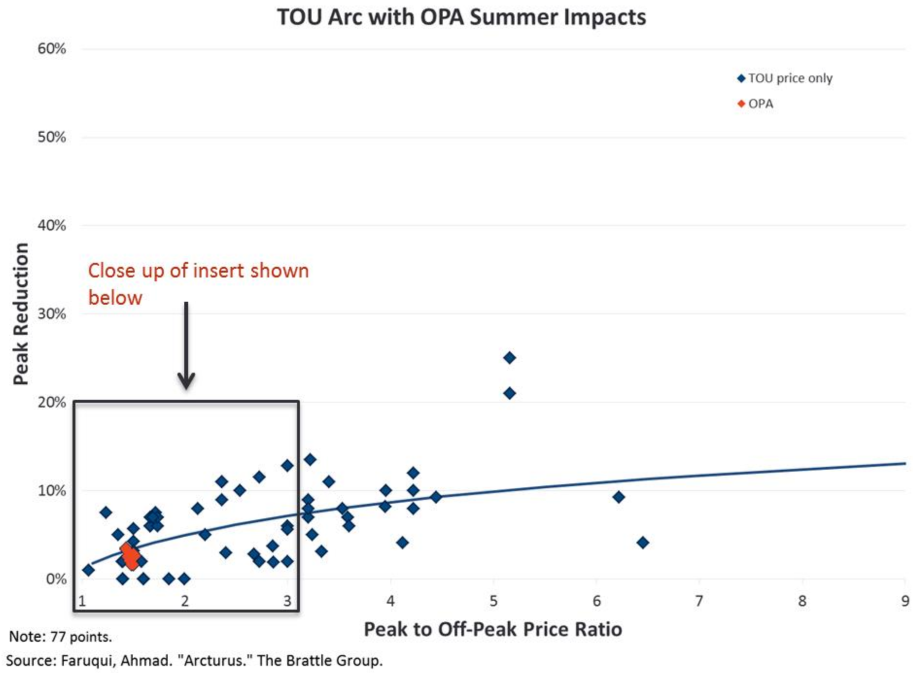

Figure 4. Ontario Residential TOU Impacts Compared to TOU Pilots from around the World

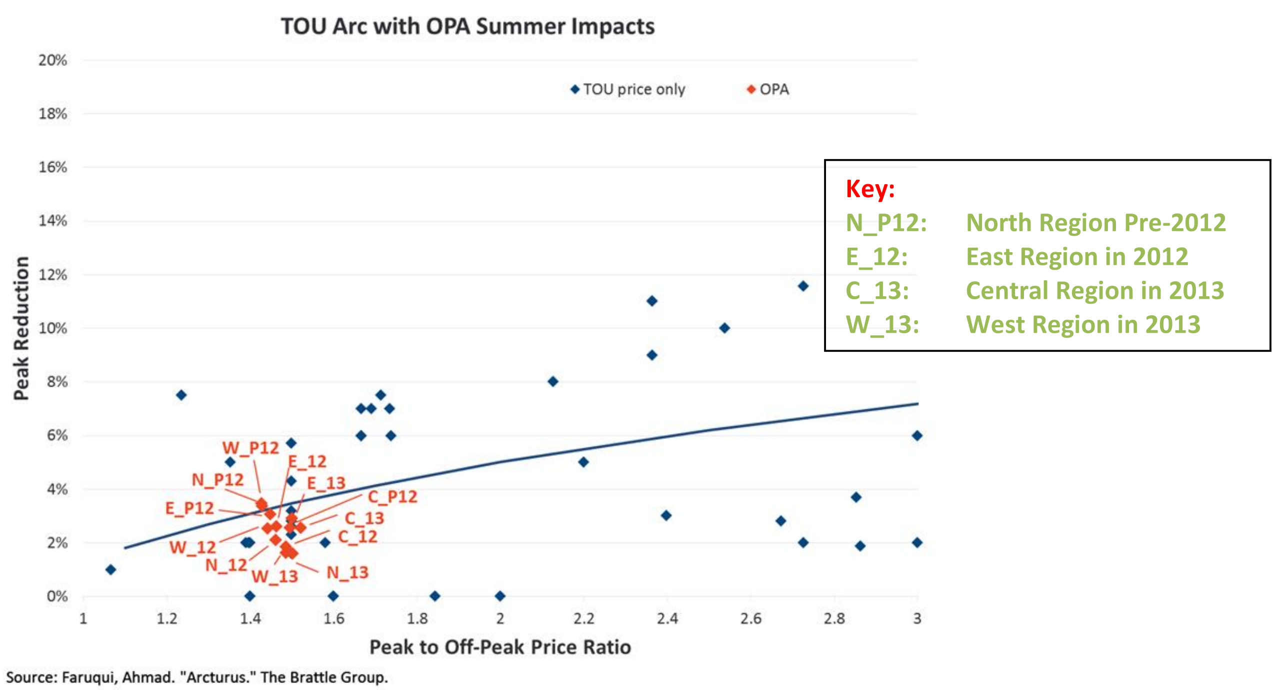

Figure 5. Close up of Ontario Residential TOU Impacts Compared to TOU Pilots from around the World with Peak to Off-Peak Price Ratios

Figure 6 shows substitution elasticities from several other studies alongside the provincial residential summer on-peak elasticities. The provincial elasticities, which lie between -0.1 and -0.15, are shown on the right. Altogether, they are very similar in magnitude to elasticities observed in other studies.

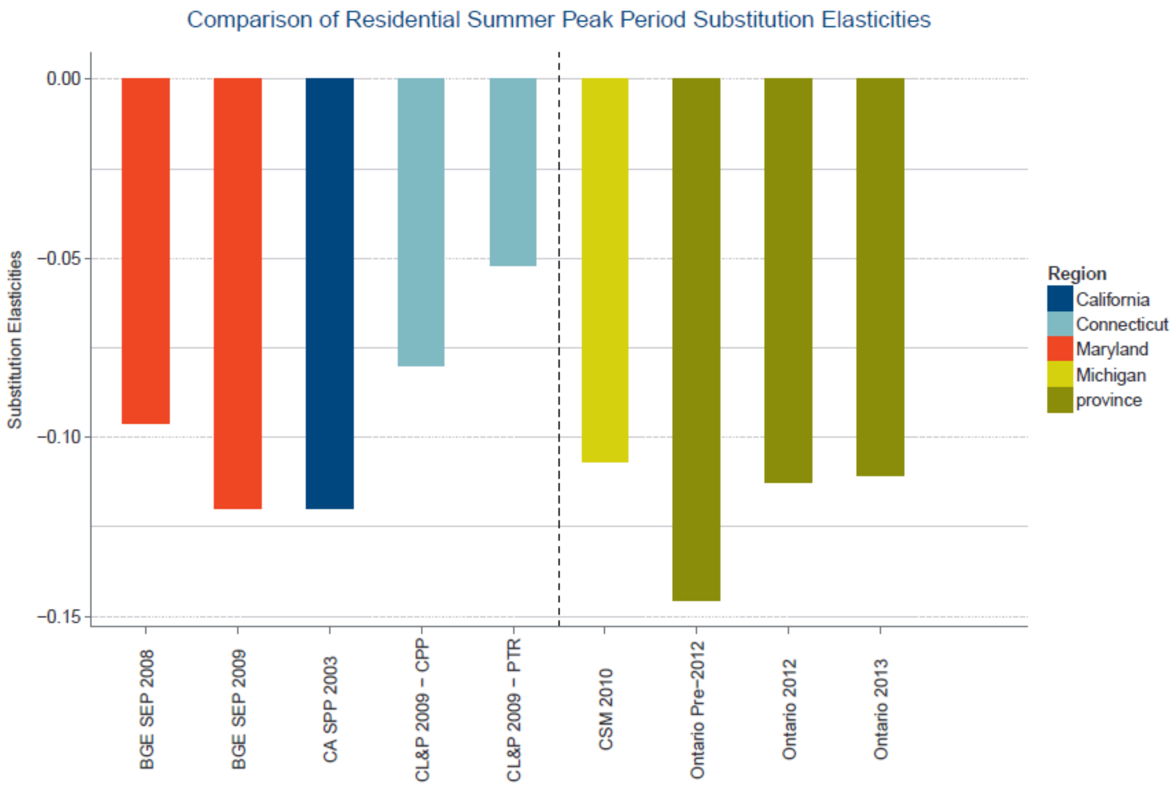

Figure 6. Residential Substitution Elasticities compared to Other Pilots (summer peak period)[8]

While we chose to focus on summer results, we also estimate load shifting impacts for the winter. These are smaller than in the summer rate period in the earlier years, but are more or less equal by 2013. Lastly, there is no evidence of energy conservation.

General Service Class:

In terms of the *general service class* results, we find that there is some evidence of load shifting across all regions, with reductions in usage in the on-peak and mid-peak periods and small increases in the

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[8] Data drawn from several studies, see respectively:

1) Faruqui, A., and S. Sergici. 2011. ñDynamic pricing of electricity in the mid-Atlantic region: econometric results from the Baltimore gas and electric company experiment.ò *Journal of Regulatory Economics* 40 (1): 82-109.

2) Faruqui, A., and S. George. 2005. ñQuantifying Customer Response to Dynamic Pricing.ò *The Electricity Journal* 18 (4): 53ï 63.

3) Faruqui, A., S. Sergici, and L. Akaba. 2014. ñThe Impact of Dynamic Pricing on Residential and Small Commercial and Industrial Usage: New Experimental Evidence from Connecticut.ò *The Energy Journal* 35 (1): 137-161.

4) Faruqui, A., S. Sergici, and L. Akaba. 2013. ñDynamic pricing of electricity for residential customers: the evidence from Michigan.ò *Energy Efficiency* 6 (3): 571-584.

off-peak periods. Impacts are far smaller than those estimated for the residential customer class, the results are not as unambiguous, and there are some odd substitution patterns. Further, impacts are largely not statistically significant. This is most likely an artifact of the heterogeneity in the general service class data.

During the summer on-peak period, TOU reduced usage by 0.78 percent in the pre-2012 period, 0.21 percent in 2012 and 1.28 percent in 2013, relative to what usage would have been in the absence of TOU. Both the pre-2012 and 2013 impacts were statistically significant and distinguishable from a zero impact, while the 2012 impact was not. Evidence on energy conservation was limited, with all estimates showing very small (smaller than 0.5%) conservation impacts. Figure 7 shows General Service impacts during the summer on-peak period across all regions and years. Confidence bands are wide relative to the magnitude of the impacts and we cannot confidently reject the null hypothesis of no load shifting in most of the regions and years.

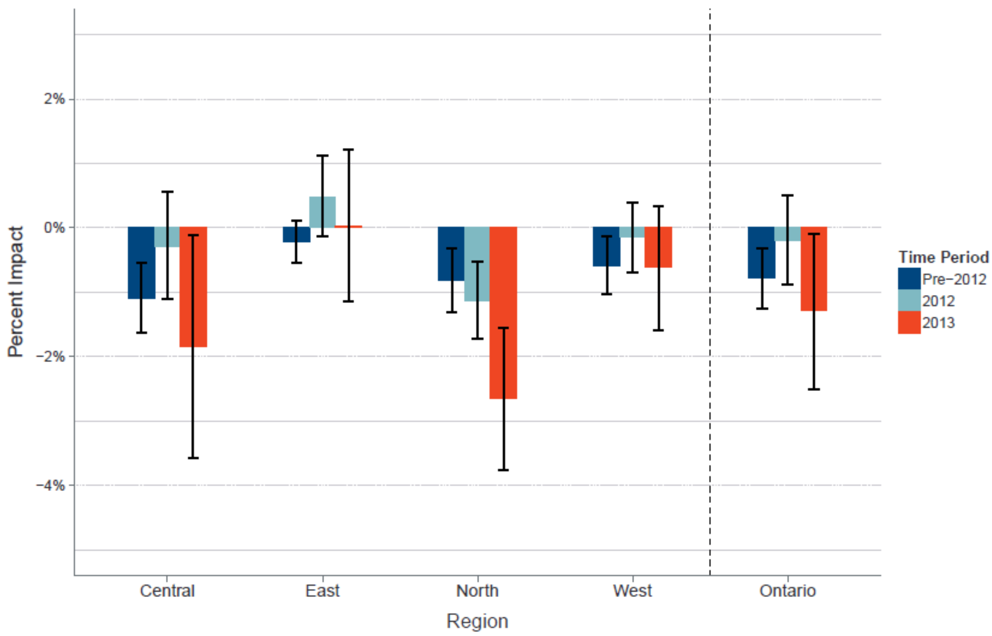

Figure 7. General Service Summer On-Peak Period Impacts (11am – 5pm)

Conclusions

The Second Year Study of Ontario’s Full-scale TOU Program revealed that the residential customers responded to the TOU rates by shifting their usage from peak to off-peak and mid-peak periods and have magnitudes that have been observed in pilots. The load shifting impacts for general service customers were far smaller than those estimated for the residential customer class and results are not as distinct, with some odd substitution patterns. This is most likely an artifact of large variability in customers that comprise the general service class. Evidence on energy conservation was non-existent for residential customers and negligible and generally insignificant for the general service class.

References

Caves, D.W., and L.R. Christensen. 1980. “Global Properties of Flexible Functional Forms.” *American Economic Review* 70 (3): 422-432.

Caves, D.W., and L.R. Christensen. 1980. ñResidential Substitution of Off-Peak for Peak Electricity Usage under Time-of-Use Pricing.ò *The Energy Journal* 1(2):85-142.

Caves, D.W., Christensen, L.R. and J.A. Herriges. 1984. ñConsistency of residential customer response in time-of-use electricity pricing experiments.ò *journal of Econometrics*, 26(1): 179-203

Conniffe, D. 2006. ñIndirect addilog translation of indirect utility functions.ò *Canadian Journal of Economics*, 39(4): 1388-1397

Faruqui, A., and S. George. 2005. ñQuantifying Customer Response to Dynamic Pricing,ò *The Electricity Journal*, 18(4): 53-63.

Faruqui, A., and S. Sergici. 2011. ñDynamic pricing of electricity in the mid-Atlantic region: econometric results from the Baltimore gas and electric company experiment.ò *Journal of Regulatory Economics* 40 (1): 82-109.

Faruqui, A., S. Sergici, and L. Akaba. 2013. ñDynamic pricing of electricity for residential customers: the evidence from Michigan.ò *Energy Efficiency* 6 (3): 571-584.

Faruqui, A., S. Sergici, and L. Akaba. 2014. ñThe Impact of Dynamic Pricing on Residential and Small Commercial and Industrial Usage: New Experimental Evidence from Connecticut.ò *The Energy Journal* 35 (1): 137-161.

Gallant, A.R. 1981. ñOn the Bias in Flexible Functional Forms and an Essentially Unbiased Form: The Fourier Flexible Form.ò *Journal of Econometrics* 15: 211-245.

Guilkey, D.K., C.A.K. Lovell, and R.C. Sickles. 1983. ñA Comparison of the Performance of Three Flexible Functional Forms.ò *International Economic Review* 24: 591-616.

Ham, J.C., D.C. Mountain, and M.W.L. Chan. 1997. ñTime-of-Use Prices and Electricity Demand: Allowing for selection bias in experimental data.ò *The RAND Journal of Economics* 28 (0): S113-S141.

Jensen, B.J., de Boer, P., van Daal, J., and P.S. Chan. 2011, ñGlobal restrictions on the parameters of the CDES indirect utility function.ò *Journal of Economics,* 102(3):217-235

Houthakker, H.S. 1960. ñAdditive Preferences.ò *Econometrica* 28: 244-257.

Mountain, D., and C. Hsiao. 1989. ñA Combined Structural and Flexible Functional Approach for Modeling Energy Substitution.ò *Journal of the American Statistical Association* 84 (405): 76-87.