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ORIGINAL ARTICLE

Response of industrial customers to hourly pricing in Ontario's deregulated electricity market

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Abstract This paper uses hourly data from Ontario (Canada) between 2005 and 2008 to estimate the effects of real time wholesale electricity prices on demand by industrial customers. Nonlinear SUR estimates from Generalized Leontief (GL) specifications reveal elasticities of substitution from 0.02 to 0.07, confirming that industrial customers (connected to the transmission grid) shift consumption across peak and off-peak periods in order to reap benefits of lower prices. Estimates from FGLS and IV models suggest that this reduction in demand by industrial customers results in lower wholesale prices, which benefits all consumers. The policy lesson is that market based schemes that encourage Real Time Pricing (RTP) pricing should result in positive spillovers to all consumers.

Keywords Deregulation · Elasticities of substitution · Industrial customers · Wholesale electricity prices · Demand response

JEL Classification Q41 · Q48

1 Introduction

How do industrial customers moderate their electricity consumption in response to wholesale prices? And does their behavior impact system wide electricity prices? The answers to these questions have considerable policy implications, as they reveal the

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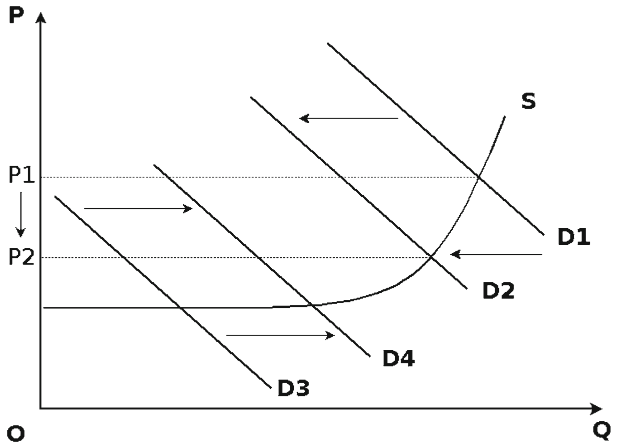

Fig. 1 The Effects of Shifting Demand from Peak to Off-Peak Hours

efficacy of demand response (DR) programs focused on industrial customers.[1] The past decade has witnessed the implementation of Real Time Pricing (RTP) schemes through the introduction of competitive wholesale markets in North America. The benefit of such pricing is that consumers are directly exposed to prices that change on an hourly basis and can adjust their consumption accordingly. Large industrial customers that are directly connected to the transmission grid may be able to reap considerable benefits by responding dynamically and in real time to changes in wholesale electricity prices, such as in peak hours. Further, as noted by Borenstein et al. (2002), RTP participants have the option of choosing hedge options in order to reduce price volatility.

However, load shifting by industrial customers—the biggest consumers of electricity in Ontario—from peak to off-peak hours could theoretically benefit all consumers through a reduction in wholesale electricity prices. A significant amount of research suggests that the supply curve for electricity in Ontario and for many other jurisdictions to be J-shaped. In other words, the supply curve is relatively elastic, with curvature determined by the marginal cost of supply generation. Incremental changes to prices from higher demand will not be large until capacity constraints are approached and the supply curve becomes roughly vertical (Fig. 1). Therefore, a reduction in system demand from D_1 to D_2—generated by demand response by industrial customers—may result in a considerable reduction in wholesale electricity prices and hence lower costs to *all* consumers.

The key consideration is whether the benefits of such a reduction will be offset by the corresponding increase in demand by industrial customers at some point in time. If the increase occurs during off-peak hours, or the elastic portion of the supply curve (D_3 to D_4 in Fig. 1), then the resulting increase in price will be marginal. Consequently,

[1] As noted in FERC (2011), Demand Response, or DR, "….refers to any scheme designed to encourage peak load reduction or load shifting away from peak demand periods—whether achieved through direct load controls (DLCs) such as air conditioner cycling programs, though interruptible tariffs, which allow a utility to cut off service during peak periods based on prior agreements, or through more sophisticated pricing schemes that offer financial incentives to consumers to reduce discretionary usage during critical hours."

the spillover benefits from lower demand or load reduction during peak hours will not be offset by equivalent increases in demand and higher prices in off-peak hours. If there is a strong offsetting effect, then society may be no better off than with Time of Use (TOU) or even flat rates.

This paper attempts to contribute to the literature by offering empirical magnitudes on the above relationships. First, we estimate elasticities of substitution between peak and off-peak hours with respect to electricity consumption by industrial customers; the value added from this exercise is that we use data based on all industrial customers in the province of Ontario that are directly connected to the transmission grid and are consequently exposed to Real Time Pricing. These elasticities are of policy importance, given the relatively thin empirical literature on the effects of RTP on electricity consumption by industrial customers; moreover, most studies are based on subsets of firms, rather than the universe of industrial customers enrolled in such programs. Our research is based on publicly available data (2005–2008), and some that were obtained on special request from the Independent Electricity Supply Operator (IESO) of Ontario. These data contain aggregate demand, wholesale prices (the Hourly Ontario Electricity Price, or HOEP), and specific hourly demand by six industrial sectors (2005–2007).

The use of Ontario data should be of interest to U.S. policy-makers, given similarities in the design of wholesale electricity markets in Canada and the United States as well as in the concentration of peak demand in the top 1% of hours.[2,3] Second, to the best of our knowledge this paper is the first study to use an econometric model to evaluate the effects of shifts in demand by industrial customers on system-wide electricity prices in order to assess (1) benefits from potential demand response programs; and (2) whether such benefits might be attenuated as industrial customers shift their load away from peak hours. In contrast, most publicly available demand response studies rely on simulation methods.

Our estimates of elasticities of substitution from Generalized Leontief (GL) specifications suggest that, on aggregate, industrial customers shift demand between peak and off-peak periods. Specifically, a 10% increase in peak hour prices is, on average, significantly correlated with a 0.2–0.7% increase in electricity consumption by industrial customers during off-peak hours. Further, the marginal effect of electricity load on the HOEP during peak hours for summer months exceeds the impacts of corresponding effects of demand during off-peak summer hours.

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[2] Competitive retail and wholesale electricity markets opened in May 2002 in Ontario. This changed on 9 December 2002 with the passage of the *Electricity Pricing, Conservation and Supply Act*, which capped the retail price of electricity for low-volume consumers. The amendment was in response to the significant spike in electricity prices and costs to consumers during the summer of 2002. The wholesale electricity market in Ontario remained competitive, with consumers such as industrial customers and local distribution companies (LDCs) submitting demand requirements and suppliers offering electricity generated by different types of fuel—including nuclear, coal, natural gas, and hydro. Bids are submitted to a clearing system managed by the province's Independent Electricity Supply Operator (IESO). However, final consumers pay prices that include other charges determined by the Ontario Energy Board (OEB). See Trebilcock and Hrab (2005) and Melino and Peerbocus (2008) for further institutional details.

[3] Faruqui et al. (2007) note that the top 80–100 h account for roughly 11 and 16% of total demand in California and the PJM system. In Ontario, the top 32 h account for 2,000 MW of demand out of a peak demand of 27,000 MW.

The above results offer evidence that while more electricity demand by industrial customers during off-peak hours is significantly correlated with higher wholesale prices, the magnitude of this effect is smaller relative to the corresponding impact of electricity consumption (of industrial customers) during peak hours. The important policy lesson is that changes in demand by industrial customers directly connected to the transmission grid have a stronger impact on the HOEP relative to demand by other consumers and can result in system-wide effects. This finding should be of interest given the 2007 *Energy Independence and Security Act* that directed the Federal Energy Regulatory Commission (FERC) to conduct a national assessment of demand response (DR) potential and to report to Congress.[4] In tandem, the above results confirm that RTP schemes give industrial customers an incentive to shift demand from peak to off-peak periods and therefore result in considerable benefits to all consumers.

The remainder of our discussion is structured as follows. The next section offers a brief literature review. Section 3 discusses the data. Section 4 details our econometric methodology and models. Our key findings are discussed in Sect. 5. Section 6 concludes with a summary of our key findings.

2 Literature review

Table 1 summarizes key papers that have estimated elasticities of substitution with respect to RTP programs and intra-day load shifting.[5] Our research differs from these papers for the following reasons. First, we are only aware of two papers (Boisvert et al. 2004, 2007) that have specifically estimated elasticities of substitution between peak and off-peak hours. Second, it is fair to say that most of the econometric literature on the effects of RTP schemes with respect to industrial customers has been restricted to select groups of firms that obviously choose to participate in such programs. The potential of self-selection bias has been noted in the literature (Herriges et al. 1993). Most studies have been unable to condition their estimates to such bias due to data unavailability of firms that do not enroll in RTP programs. Further, a majority of these papers are only able to employ data on a subsample of firms, rather than for all firms participating in RTP schemes.

We share a similar shortcoming with previous studies in that we do not have data on firms that are not directly connected to the transmission grid, which would enable us to pool information across firms and thus contrast differences in electricity consumption between participating and non-participating firms or industries. On the other hand,

4 The Federal Energy Regulatory Commission was tasked to: (1) provide an estimate of the national DR potential in 5–10 years; (2) estimate how much of the potential could be achieved; (3) identify barriers to their achievement; and (4) provide recommendations to overcome the barriers. See FERC (2009) for further details.

5 Our review focuses on econometric based papers. Borenstein (2005), Borenstein and Holland (2005), and Holland and Mansur (2006) rely on simulations to estimate the gains to RTP schemes. There is, of course, literature on the effects of Time of Use (TOU) schemes on industrial customers and corresponding peak and off-peak elasticities. Schwarz et al. (2002) and Taylor et al. (2005) offer comprehensive overviews. We also acknowledge studies that estimate residential, commercial, and industrial demand elasticities with data from Ontario during the 1980s and 1990s. These include Yatchew (2000), Mountain (1993), Mountain and Lawson (1992, 1995), and Ham et al. (1997). However, these papers focus on the effects of TOU schemes.

Table 1 Literature review

	Data	Main results
Herriges et al. (1993)	Investigate the efficacy of an RTP program (with respect to 46 customers) introduced by the Niagara Mohawk Corporation in New York State	Using CES model they obtain elasticities of substitution from (roughly) 0.08 to 0.13
Patrick and Wolak (2001)	Estimate the real time price effects on demand for electricity from the England and Wales (E&W) electricity market based on customer level data from large and medium-sized industrial and commercial customers (1991–1995)	Results from Generalized McFadden (GM) cost functions suggest significant within-day inter-temporal cross price elasticities with considerable industry heterogeneity
Schwarz et al. (2002)	Estimate demand elasticities employing (June–September from 1994 to 1999) data from 110 large customers of the Duke Power Corporation	CES models yield obtain intra-day elasticities in the range of 0.11
Boisvert et al. (2004)	Data from 43 industrial and commercial customers that volunteered to participate in Central and Southwest Service's RTP programs between 1998 and 2001 in Oklahama	Employing Generalized Leontief (GL) models, they find elasticities of substitution from 0.10 to 0.18
Taylor et al. (2005)	Use hourly customer data (from 1994 to 2001) based on the Duke Hourly Energy Program during the summer months of June, July, August, and September	Focusing on intra-day hourly data, their results (from a GM specification) suggest electricity consumption to be complementary during adjacent hours but substitutable between hours that are further apart. However, they do not calculate elasticities between peak and off-peak hours
Boisvert et al. (2007)	Evaluate the effects of a RTP type scheme to consumers through hourly pricing and load data from 119 large customers of Niagara Mohawk from 2000 to 2004	Results from a Generalized Leontief (GL) model suggest that RTP pricing results in load shifting by large consumers as estimates reveal an elasticity of substitution of 0.11

we do possess industry level electricity consumption data of *all* firms that are directly connected to the transmission grid. We think that there is also something to learn from using industry level data (across sectors), as it reveals (on average) behavior, which impacts the entire system. In this respect, we emphasize that the use of these data is the key feature that allows us to evaluate the impacts of dynamic pricing.

Finally, to our knowledge, no study has used econometric models to evaluate the effects of load shifting by industrial customers on system wide wholesale electricity prices.[6] We did locate a relatively recent study conducted by The Brattle Group (2007)

[6] In terms of institutional details, Cappers et al. (2010) offer a comprehensive and contemporary overview of various DR programs across states.

that was commissioned by PJM Interconnection LLC and the Mid Atlantic Distributed Resources Initiative (MADRI).[7] The study is based on simulation methods and finds that a 3% reduction in each selected zone's super-peak load reduces PJM's peak load by a little less than 1% and yields an energy market price reduction of $8–$25 per megawatt-hour. However, the authors of the study note that they do not consider several secondary effects that could offset the benefits to demand reduction. Specifically, they do not estimate the increase in prices that could occur if consumers shift load to other hours. Given the relative lack of studies, we think that an econometric-based approach to estimating the effects of demand by industrial customers on wholesale electricity prices should be of interest to policy-makers.

3 Data

The Ontario wholesale electricity market shares some features with deregulated electricity markets in New York and Pennsylvania-New Jersey-Maryland (PJM). The wholesale electricity market in Ontario is competitive, with consumers such as industrial customers and local distribution companies (LDCs) submitting demand requirements and suppliers offering electricity generated by different types of fuel, including nuclear, coal, natural gas, and hydro. Bids are submitted to a clearing system managed by the province's Independent Electricity Supply Operator (IESO). However, a key difference between the Ontario and U.S. markets is the existence of different prices across zones in the New York and PJM markets, which reflect local market clearing. On the other hand, the HOEP, the system wide wholesale electricity price in Ontario, is the result of market equilibrium of all bids and offers in the province.[8]

Data on the HOEP and corresponding market demand, hourly exports, and hourly imports of electricity are all publicly available data, which can be downloaded from the IESO website.[9] Hourly demand by industry sector—total industry demand; iron and steel mills and ferro-alloy manufacturing; metal ore mining; motor vehicle manufacturing; petroleum and coal products manufacturing; pulp, paper and paperboard mills; electric power generation, and transmission and distribution (excluding local distribution companies, or LDCs)—were obtained on special request from the IESO. [10] These data consist of electricity consumption of industrial customers that are directly connected to the transmission grid and can thus react directly to the HOEP and benefit from dynamic pricing. The IESO also provided us with data on hourly supply by each

[7] We are grateful to an anonymous referee for pointing us to this study.

[8] Retail prices paid by final consumers include wholesale prices and other charges determined by the Ontario Energy Board (OEB). Retail electricity rates are also regulated in many states in the U.S.

[9] As noted on its website (http://www.ieso.ca/imoweb/siteShared/whoweare.asp), the Independent Electricity Supply Operator (IESO) is a not-for-profit organization established in 1998 by the Electricity Act of Ontario. The IESO is basically responsible for monitoring and ensuring the efficient working of the Ontario electricity market. It connects all participants—generators, transmitters, retailers, industries and businesses that purchase electricity directly from the system, and local distribution companies (LDCs). All market participants must meet the standards enacted and enforced by the IESO.

[10] Some may find it surprising that we also analyze electricity consumption by electric utilities. However, as detailed in Table 1, their consumption is a non-trivial portion of demand by industrial customers connected to the transmission grid.

Table 2 Electricity demand (in MW) by industry

	Summer of 2005	Summer of 2006	Summer of 2007	Summer of 2008
A. Total industrial	6,385,711	6,152,129	5,593,258	5,822,908
As % of A				
B. Iron and steel mills and ferro-alloy manufacturing	17.24%	19.03%	18.27%	20.18%
C. Metal ore mining	17.69%	17.57%	20.13%	19.90%
D. Motor vehicle manufacturing	6.18%	6.50%	5.88%	4.73%
E. Petroleum and coal products manufacturing	7.01%	7.65%	8.55%	8.82%
F. Pulp, paper, and paperboard mills	23.70%	21.56%	17.72%	19.07%
G. Electric power generation, transmission, and distribution	8.91%	8.95%	10.26%	9.06%
Ontario demand	41,626,431	39,702,447	38,988,305	37,891,802
Industrial demand as % of Ontario demand	15.34%	15.50%	14.35%	15.37%

Source Data obtained on special request from the website of the Independent Electricity Supply Operator (IESO)

generator in the province. These data contain not only details on firm affiliation but on the type of power, allowing us to capture the effects of market power among suppliers as well as control for the effects of different sources of electricity generation on an hourly basis.

Table 2 contains some descriptive statistics for electricity consumption by industrial customers during summer months (June, July, and August) from 2005 to 2008. Consumption by industrial customers that are directly connected to the transmission grid constitutes roughly 15–16% of total Ontario demand, a statistic that is consistent over time. Iron and steel mills, metal ore mining, and pulp and paper are the largest consumers, accounting for roughly 17% to just over 20% of total demand of industrial customers (connected to the grid).

Figure 2 offers some further insight into the relationship between wholesale prices (HOEP) and total demand by industrial customers. All the data are averaged across summer months for 2008.[11] The trends conform to intuition as industrial customers consume a significant amount of electricity during off-peak hours when prices are low, and reduce demand during high price period peak hours.

4 Econometric models

We use the well-established model of industrial electricity response developed by Caves and Christensen (1984) and Schwarz et al. (2002). The firm has to decide on

[11] This is a representative year. Data from other years are similar.

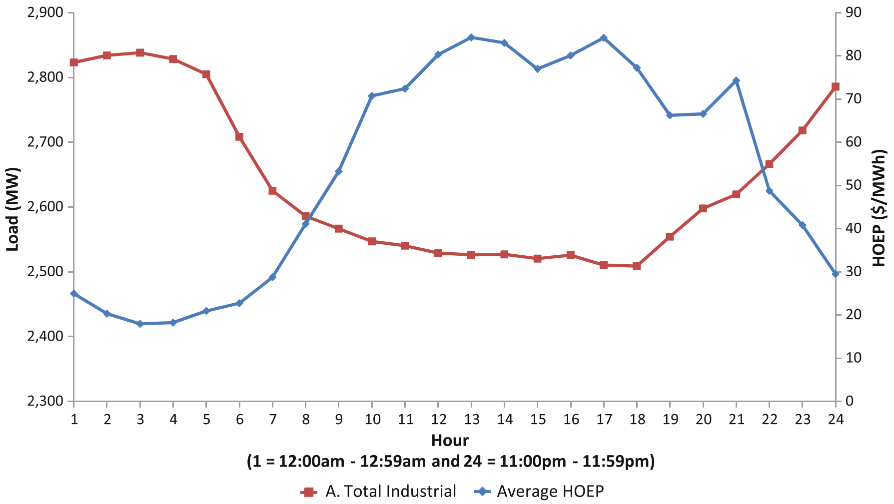

Fig. 2 Average hourly demand-total industrial (Summer 2008). *Source* Electricity price data (in Canadian dollars) obtained from the website of the Independent Electricity Supply Operator (IESO) (http://www.ieso.ca/imoweb/siteShared/whoweare.asp). Industrial load data obtained on special request from the IESO

the optimal allocation of electricity during peak (high price) and off-peak (low price) hours of the day. As noted by Boisvert et al. (2007), this approach is consistent with other studies that find that business customers bifurcate the day between peak and off-peak hours (Neenan et al. 2002a,b) and accordingly choose business activity across different hours of the day.[12] Following previous studies we use a Generalized Leontief (GL) cost function to model aggregate industry costs (C) relating to electricity consumption[13,14];

$$C = E(d_{pp} P_p^{1/2} P_p^{1/2} + d_{po} P_p^{1/2} P_o^{1/2} + d_{op} P_o^{1/2} P_p^{1/2} + d_{oo} P_o^{1/2} P_o^{1/2}) \quad (1)$$

[12] The discussion in this section is largely based on Boisvert et al. (2007) and Braithwait (2000).

[13] As noted by Boisvert et al. (2007), there are other flexible second-order functional forms that have been used in the literature. The Translog (TL) specification is one such common form, which has the advantage of being linear in parameters and not requiring information on aggregate electricity consumption as it relies on electricity cost shares. However, as pointed out by Caves and Christensen (1980a,b) this model does not perform well when substitution elasticities are likely to be small, or with small shares or large differences among shares. In a seminal study, Patrick and Wolak (2001) find the TL model to perform poorly with respect to predicting residential customer demand response to real time pricing; they recommend the GL model, as an alternative. This is because the fixed coefficient Leontief technology can capture modest substitution possibilities. They use a Generalized McFadden (GM) model in their analysis, as their objective is to capture changes in consumption between hours within the same day, which allows them to acknowledge the possibility of positive as well as negative elasticities of substitutions. However, as noted by Boisvert et al. (2007), the assumption of two demand periods within the same day—as we do in our study by dividing the day into peak and off-peak periods - necessitates the assumption of a positive elasticity of substitution, which ensures global concavity (footnote 9, p. 61). Therefore, like them, we rely on a GL rather than a GM specification.

[14] We could have also employed a simpler Constant Elasticity of Substitution (CES) specification as we divide the day into two time periods. However, for almost all years, Akaike-Schwartz and Bayesian Information Criterion values are much higher for GL models.

E is effective electricity, P_p is peak price, P_o is off-peak price, and $d_{pp}, d_{po},, d_{op},$ and d_{pp} are parameters to be estimated. Specifically, $d_{pp}(d_{oo})$ is the marginal effect of a change in peak (off-peak) price on peak (off-peak) demand, while $d_{po}(d_{op})$ is the marginal effect of a change in peak (off-peak) price on off-peak (peak) demand. This function is linear homogenous in all prices, which is a requirement for a well-behaved indirect cost function. That is, if all prices are changed in the same proportion, then C changes in the same proportion as well. Following Shepard (1970), optimal (constant output) demand for peak and off-peak electricity can be obtained by differentiating (1) with respect to each price;

$$\partial C/\partial P_p = k_p = E\left|d_{pp} + d_{po}(P_p/P_{o)}^{1/2}\right| \tag{2}$$

$$\partial C/\partial P_o = k_o = E\left|d_{oo} + d_{op}(P_o/P_{p)}^{1/2}\right| \tag{3}$$

Berndt (1991) derives the Allen partial elasticities of substitution of the GL model as

$$\sigma_{op} = \left|Cd_{op}(P_p P_{o)}^{1/2}\right| / 2\left|Ea_p a_o\right| \tag{4}$$

where $a_o = k_o/E$ and $a_p = k_p/E$

Equation 4 is the elasticity of substitution which measures the change in the ratio of daily peak to off-peak usage in response to changes in the off-peak to peak price. Assuming an additive error structure for the input cost equations a_o and a_p, it is possible to estimate the parameters of the GL model. However, E is an unspecified aggregate of peak and off-peak electricity use, and cannot be observed from the data. Following previous studies, and assuming separable within day electricity consumption, we use the ratio of the natural logarithm of a_p and a_o;

$$\ln\ \left|a_p/a_o\right| = \ln\ \left|k_p/k_o\right| = \ln\ \left\{\left|d_{pp} + d_{po}(P_p/P_{o)}^{1/2}\right| / \left|d_{oo} + d_{op}(P_o/P_{p)}^{1/2}\right|\right\} \tag{5}$$

Denoting the estimated parameters of (5) as d^* and employing sample means of P_o and P_p, it is possible to obtain approximations of (C/E). Along with (5) and the estimated parameters d^*, the Allen partial elasticities of substitution can be derived as

$$\sigma_{op} = \left|(C/E)d^*_{po}(P_p P_{o)}^{1/2}\right| / 2a_p a_o \tag{6}$$

Further simplification of (5) yields an estimable non-linear specification

$$\ln\ \left|k_{p,it}/k_{o,it}\right| = \beta_0 + \ \ln\ \left\{\left|d_{pp} + d_{po}(P_{p,it}/P_{o,it)}^{1/2}\right| / |d_{oo} + d_{op}(P_{o,it}/P_{p,it)}^{1/2}|\right\} \tag{7}$$

This is further modified as

$$\ln\ \left|k_{p,it}/k_{o,it}\right| = \beta_0 + \beta_1 \ln\ \left\{\left|d_{pp} + d_{po}(P_{p,it}/P_{o,it)}^{1/2}\right| / |d_{oo} + d_{op}(P_{o,it}/P_{p,it)}^{1/2}|\right\}$$
$$+ \beta_2 Temp_{it} + \Sigma Day_{\mathrm{i}} + \Sigma Month_t + \varepsilon_{it} \tag{8}$$

where i refers to the specific day in month t and ε_{it} is the error term, which is assumed to be independently and identically distributed. Consistent with the trends observed from Fig. 2, $k_{p,it}$ and $k_{o,it}$ are average hourly consumption in MWh during peak (7 a.m. to 6:59 p.m.) and off-peak (7 p.m. to 6:59 a.m. the next day) hours, respectively. Similarly, $P_{p,it}$ and $P_{o,it}$ are average daily prices in \$/MWh during peak (7 a.m. to 6:59 p.m.) and off-peak (7 p.m. to 6:59 a.m. the next day) hours.[15] We estimate (8) for aggregate electricity consumption by all industrial customers as well as for the six sectors for which data are available for June, July, and August of each year from 2005 to 2008.

We also employ other controls. $Temp_{it}$ is the average daily temperature. Dummy variables for each day (ΣDay_i) are used to distinguish variation in electricity consumption across days during the week, which in turn reflects variation in industry output.[16] Dummy variables are used for July and August as well in order to account for unobserved month specific shocks. Table 3 contains summary statistics.

Given the obvious potential for correlation in electricity prices within the day, we ran a Gauss Newton Regression test for first-order autocorrelation generated by an AR(1) process.[17] The null hypothesis of no first order autocorrelation was rejected in all specifications. Therefore, consistent with previous studies (Herriges et al. 1993; Schwarz et al. 2002), we assume a first-order autocorrelation in the error term. Further, given the likelihood that the error term is correlated across industries, we use the non-linear Seemingly Unrelated Regressions (NLSUR) methodology proposed by Gallant (1975). Specifically, we jointly estimate seven equations (total industrial demand and the six subsectors). Finally, following Braithwait (2000) and Boisvert et al. (2004, 2007), we impose the symmetry condition $d_{\mathrm{op}} = d_{\mathrm{po}}$ and the adding up constraint $d_{\mathrm{oo}} + d_{\mathrm{po}} + d_{\mathrm{oo}} + d_{\mathrm{op}} = 1$.[18]

Estimating the effects of hourly load on the HOEP

The above discussion outlines our approach to estimating industry specific elasticities. The other contribution of this research is through our analysis of the effects of province specific demand on the Hourly Ontario Electricity Price (HOEP). The empirical specification that we employ is a standard reduced form expression:

[15] There are studies (e.g., Taylor et al. 2005) that exploit variation across all hours, treating each hour as a separate electricity commodity, as opposed to aggregating hours according to peak and off-peak. However, as noted by Boisvert et al. (2004), there is evidence that some U.S.firms implicitly characterize the day as being comprised of a peak and off-peak period (Neenan et al. 2002b; Goldman et al. 2004). This is certainly our understanding, based on conversations with industrial customers in Canada.

[16] What would be desirable are measures of actual industry output in dollars. However, we were unable to obtain such data, and are not aware of any other study that has managed to control for industry output. Taylor et al. (2005) also use time dummy variables to control for variation in relative levels of output across these days.

[17] Please refer to Davidson and MacKinnon (2003), pp. 275–277, for further details on the test.

[18] Imposing the adding up constraint affects the estimates of d_{oo}, d_{po}, d_{oo}, d_{op} but does not affect the elasticities of substitution.

Table 3 Summary statistics of variables used in (A) industry demand regressions[a]. (B) price regressions[b]

		Obs	Mean	Std. Dev.	Min	Max
Years = 2005–2008						
(A) Industry demand regressions						
Demand variables						
Total industrial (MW/h)	P	368	2600.54	173.13	2161.17	3019.42
	O	368	2823.98	183.73	2356.75	3257.42
Iron and steel mills and ferro-alloy manufacturing (MW/h)	P	368	497.13	56.39	299.67	616.50
	O	368	514.79	55.35	381.50	647.50
Metal ore mining (MW/h)	P	368	499.43	55.43	276.08	588.17
	O	368	519.09	54.14	300.92	605.92
Motor vehicle manufacturing (MW/h)	P	368	162.46	56.84	59.83	252.25
	O	368	153.93	52.29	58.25	241.17
Petroleum and coal products manufacturing (MW/h)	P	368	215.92	35.84	133.75	259.17
	O	368	216.45	36.29	136.17	260.92
Pulp, paper and paperboard mills (MW/h)	P	368	511.78	105.97	301.83	801.08
	O	368	607.31	100.15	381.92	832.92
Electric power generation, transmission	P	368	203.72	29.38	155.92	293.17
and distribution (MW/h)	O	368	299.39	34.58	217.17	409.33
Other variables						
HOEP ($/MWh)	P	368	72.79	31.71	24.99	234.61
	O	367	41.06	16.75	4.84	123.95
Toronto temperature (°C)		368	21.6	3.46	9.35	31.10
Years = 2005–2007						
(B) Price regressions						
Variable						
Electricity price ($/MWh)		6624	58.01	38.46	2.41	533.17
HHI		6624	5389.05	302.36	4549	6294
Ontario demand (MW/h)		6624	18163.83	3114.61	11699	27005
Exports (MW/h)		6624	1277.51	613.61	0	3298
Imports (MW/h)		6624	940.93	583.86	0	4028
Coal (MW/h)		6624	3616.58	1132.34	292	5659
Gas (MW/h)		6624	1261.33	683.61	449	3542
Nuclear (MW/h)		6624	9646.35	683.31	5670	11180
Hydro (MW/h)		6624	3383.54	969.44	1369	5744
ON's monthly unemployment rate		6624	6.90	0.51	5.80	7.40
CAD-USD exchange rate		6624	1.13	0.07	1.04	1.26
Weekend dummy		6624	0.28	0.45	0	1
Holiday dummy		6624	0.02	0.15	0	1
Day		6624	15.84	8.85	1	31

[a] Summer Months, Daily Data, *P* Peak Hours, *O* Off Peak Hours
[b] Summer Months, Hourly Data

$$P_i = \beta_0 + \beta_1 InDem_i + \beta_2 ODem_i + \beta_3 EXP_i + \beta_4 IMP_i + \beta_5 HHI_i$$
$$+\beta_6 NUCPi + \beta_7 COAL_i + \beta_8 HYDRO_i + \beta_9 GAS_i + \beta_{10} EXCHR_i \quad (9)$$
$$+\beta_{11} UNEMP_i + \beta_{12} day_t \sum_i h + \sum_t m + \varepsilon_i$$

where i refers to the specific hour. The above model is a common methodology for evaluating the impacts of demand, costs, and market structure on observable energy prices in a given market.[19] P_i is the HOEP expressed in $/MWh and is a function of electricity demand and usage of industrial customers directly connected to the transmission grid ($InDem_i$), electricity demand and usage of industrial customers not directly connected to the transmission grid, residences, and commercial establishments ($ODem_i$), imports (IMP_i), exports (EXP_i) and the mix of power supply between coal ($COAL_i$), nuclear ($NUCP_i$), gas (GAS_i), and hydro ($HYDRO_i$) all in MWh—in each hour i. By employing constructs for the source of electricity supply (coal, nuclear, gas, or hydro generated), we are not only controlling for the impacts of supply but also conditioning empirical estimates of load demand to whether the source of supply has differential impacts on electricity prices.

We also construct a Herfindahl-Hirschman Index (HHI_i) which is a measure of market power within an industry. Specifically, it is the sum of the square of the percentage of total electric supply generated by each individual firm for each hour.[20] Finally, we employ the average daily U.S.-Canada Exchange Rate ($EXCHR_i$) and the average monthly Ontario Unemployment Rate ($UNEMP_i$) in order to capture the effects of macro-economic variables. Day_t is simply the day of the month and is intended at reflecting the effects of trends within the month. Dummy variables are constructed for each hour ($\sum_i h$) and month ($\sum_t m$) in order to control for the potentially confounding effects of other time specific unobserved determinants of wholesale electricity prices.

Equation 9 is estimated by Feasible Generalized Least Squares (FGLS) based on a Prais-Winsten correction for heteroskedasticity and AR(1) serial correlation. We use a levels specification, based on results from Likelihood Ratio tests (from Box-Cox regressions) that do not reject the use of a levels specification. We did not obtain any difference in our results by clustering the standard errors by hour or day, and these results are omitted for the sake of brevity. Summary statistics are in Table 3. Finally, we note that unlike the case with demand elasticities, our estimates of the effects of demand on price are derived from 2005, 2006, and 2007 (summer months) data, as this is the time span of generator specific supply that we obtained from the Independent Electricity Supply Operator (IESO).

[19] For example, with respect to gasoline prices, see Sen (2003) and Sen and Townley (2010).

[20] The Herfindahl-Hirschman Index (HHI) is the metric typically employed by antitrust agencies in different countries to measure industry-specific competitive effects or market structure and to identify and establish enforcement and investigative thresholds in the analysis of horizontal mergers. The HHI is quite easy to construct, being simply the sum of the squared market shares of firms, with market shares typically being constructed from firms' sales. Suppose that there are two firms supplying electricity, each of which supplies 50% of total market needs. The HHI in this case is $(50 \times 50) + (50 \times 50) = 5000$.

5 Results

Demand elasticities by industry

Table 4 contains nonlinear SUR estimates of the key parameter d_{po} (from Eq. 8), which is the foundation for the partial Allen elasticity of substitution.[21] While we estimate Eq. 8 using demand data for all industrial customers and all the six sectors (iron and steel mills and ferro-alloy manufacturing; metal ore mining; motor vehicle manufacturing; petroleum and coal products manufacturing; pulp, paper and paperboard mills; electric power generation; transmission and distribution), we only report statistically significant estimates. Further, we conduct estimates for each year (2005 to 2008) in order to assess possible changes over time. As discussed above, econometric estimates are based on year-specific samples over summer months (June, July, and August) with hourly prices and demand averaged across peak (7 a.m.–6:59 p.m.) and off-peak (7 p.m.–6:59 a.m.) hours. Therefore, each day has a single observation. Finally, we report robust standard errors.

The first key finding is that, on average, estimates of d_{po} with respect to total demand by all industrial customers are statistically significant (at either the 10%, 5%, or 1% levels) across most columns. In contrast, there is considerable variation in estimates across specific industries and over time. Specifically, d_{po} is always statistically insignificant for most years for the metal, iron and steel, and motor vehicle industries.[22] However, estimates with respect to demand by petroleum and the pulp and paper industries are statistically significant for most years. Specifically, the estimate of d_{po} with respect to the petroleum industry ranges from 0.02 to 0.09 and is significant for 2006, 2007, and 2008. The corresponding estimates for the pulp and paper industry are from 0.02 to 0.06 and significant for all years except for 2005.[23] Finally, only the 2008 estimate for electricity power and generation is statistically significant.

Table 5 contains estimates of the elasticities of substitution that correspond to the above results (based on Eq. 8). Standard errors were estimated using the recursive-design wild bootstrap method developed by Goncalves and Kilian (2004), which also produces bias-corrected 95% confidence intervals. With respect to total consumption by all industrial customers, the results yield elasticities of substitution from 0.02 to 0.065. Elasticities of substitution for the petroleum and coal products industry range from 0.045 to 0.07. The highest elasticities are for the pulp and paper industry and are

[21] Consistent with the literature, we focus on the cross-price effect (d_{po}) between peak and off-peak consumption. Complete results are available on request.

[22] These estimates are available on request.

[23] These findings correspond to intuition offered to us by industry experts associated with the Association of Major Power Consumers of Ontario (AMPCO), an organization representing energy policy interests of major industrial customers in the province. The pulp and paper industry is supposed to be relatively flexible in terms of with- and across-day operations and has the capability to adjust operation hours in order to reap the benefits of lower prices during off-peak hours. On the other hand, the petroleum industry in Ontario is quite concentrated and dominated by a few firms. Apparently most of these firms possess internal generators that may be used if the HOEP becomes too expensive. So while they do have the ability to shift consumption during off-peak hours, our results probably also reflect the shift towards internal energy production and consumption during high price hours.

Table 4 Generalized Leontief (GL) estimates

	(1) 2005	(2) 2006	(3) 2007	(4) 2008
Total industrial customers				
d_{po}	0.011**	0.032*	0.026	0.017**
	(0.004)	(0.017)	(0.022)	(0.009)
Petroleum and coal products manufacturing				
d_{po}	0.0002	0.034**	0.036*	0.021**
	(0.005)	(0.017)	(0.019)	(0.007)
Pulp, paper, and paperboard mills				
d_{po}	0.0355**	0.046*	0.002	0.023*
	(0.013)	(0.025)	(0.03)	(0.012)
Electric power generation, transmission, and distribution				
d_{po}	0.0113	0.0004	0.048	0.043*
	(0.016)	(0.044)	(0.044)	(0.022)
N	92	92	92	90

The dependent variables are industry specific log (peak demand /off-peak demand). Robust standard errors in parentheses, where $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. An AR(1) correction was added to the models. For each year, the seven industries were estimated together using nonlinear seemingly unrelated regressions developed by Gallant (1975). Daily mean temperature and month dummies and day of week dummies were included in all regressions. Peak hours are from 7:00 a.m. to 6:59 p.m. of each day. The data are daily for June, July, and August. Two 2008 observations were dropped due to negative off-peak HOEP

between 0.05 and 0.10. In summary, our estimates of elasticities of substitution are slightly lower in magnitude than the 0.08–0.18 range suggested by previous studies.

Estimating the effect of load on the HOEP

The above results offer evidence that some industries do shift consumption over hours in order to reap the benefits of lower electricity prices. The next question is whether there are differences in the effects of overall demand on the hourly electricity price. A larger marginal effect during peak hours would suggest that the benefits of reduced consumption during peak periods will not be offset by a corresponding increase over off-peak hours. Further, differences in coefficient estimates of demand by consumers would reveal whether industrial customers directly connected to the transmission grid have an independent and direct effect on the HOEP. Tables 6 and 7 contain Feasible Generalized Least Squares (FGLS) and second stage Instrumental Variables (IV) estimates of Eq. 9 with respect to peak and off-peak hours, respectively.

The IV results allow us to evaluate the possibility of measurement error in single equation estimates of electricity demand by industrial customers, arising from simultaneity bias. This is important given our findings from GL models specifications. We employ two hour lagged demand by industrial customers and the average daily temperature in Toronto as instruments for electricity demand by industrial customers. The use of two hour lagged demand assumes the existence of a correlation in hourly

Table 5 Elasticities of Substitution between peak and off-peak hours

Industry	Estimate	Bootstrap_SE	95% CI_Lower	95% CI_Upper
Total industrial customers				
2005	0.0232*	0.0113	0.0027	0.0319
2006	0.0659*	0.0343	0.0166	0.0882
2007	0.0540*	0.0308	0.0123	0.0804
2008	0.0359*	0.0175	0.0127	0.0554
Petroleum and coal products manufacturing				
2005	0.0004	0.0137	0	0.0197
2006	0.0692*	0.0324	0.0056	0.1328
2007	0.0734*	0.0281	0.0103	0.1043
2008	0.0455*	0.0149	0.0180	0.0594
Pulp, paper, and paperboard mills				
2005	0.0731*	0.0276	0.0188	0.1273
2006	0.0966*	0.0494	0.0114	0.1712
2007	0	0.0472	0	0.1221
2008	0.0516	0.0305	0	0.1071
Electric power generation, transmission, and distribution				
2005	0.0231	0.0298	0	0.0736
2006	0	0.0771	0	0.0930
2007	0.1020	0.0747	0	0.2839
2008	0.0892*	0.0445	0	0.1683

* Significant at 5% level based on bias corrected confidence intervals. Standard errors were estimated using a recursive design wild bootstrap method developed by Goncalves and Kilian (2004). Peak hours are from 7:00 a.m. to 6:59 p.m. of each day. The data are daily for June, July, and August

demand within the same day and that lagged demand should not directly affect current price.[24] With respect to our second instrument, an increase in temperature should be associated with more electricity demand, all else being equal.

In almost all specifications, both instruments are positive and statistically significant (at either the 1% or 5% levels), confirming that electricity demand by industrial customers increases with temperature and is also correlated with demand in earlier hours. For the sake of brevity, we only report the F statistics from joint tests of significance, which demonstrate that we can comfortably reject the null hypothesis that the coefficient estimates of the instruments are equal to zero. Detailed first stage estimates are available on request.

FGLS and IV estimates in Tables 6 and 7 are quite similar, suggesting the absence of significant simultaneity bias. Table 6 demonstrates that a 1000 MWh reduction in demand by industrial customers during peak hours is significantly associated (between 10% and 1% levels) with roughly a \$20–\$50 drop in the HOEP. On the other hand, a 1000 MWh reduction in demand by other consumers is correlated with a \$17–\$27 fall

[24] We also used five and six hour lagged demand as instruments in order to test the sensitivity of our results and obtained very similar estimates.

Table 6 Feasible Generalized Least Squares (FGLS) and Instrumental Variable (IV) Estimates with respect to Hourly Ontario Electricity Price (Dependent Variable) during Peak Hours

	2005		2006		2007	
	FGLS	IV	FGLS	IV	FGLS	IV
Ontario industrial demand	0.0260	0.0542***	0.0503***	0.0465***	0.0198	0.0319***
	(0.0224)	(0.0179)	(0.0086)	(0.0093)	(0.0135)	(0.0123)
Other industrial, commercial, & Residential demand	0.0196***	0.0195***	0.0271***	0.0278***	0.0146***	0.0170***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)
Exports	0.0162***	0.0177**	0.0264***	0.0260***	0.0145***	0.0148***
	(0.0061)	(0.0070)	(0.0037)	(0.0035)	(0.0032)	(0.0047)
Imports	−0.0076	−0.0012	−0.0206***	−0.0179***	−0.0132***	−0.0161***
	(0.0055)	(0.0061)	(0.0036)	(0.0036)	(0.0031)	(0.0051)
Coal	−0.0114**	−0.0134**	−0.0199***	−0.0224***	−0.0011	−0.0056
	(0.0057)	(0.0055)	(0.0037)	(0.0036)	(0.0034)	(0.0050)
Gas	0.0079	0.0075	−0.0060	−0.0060	0.0028	0.0002
	(0.0055)	(0.0056)	(0.0053)	(0.0045)	(0.0039)	(0.0051)
Nuclear	−0.0189***	−0.0183***	−0.0282***	−0.0294***	−0.0161***	−0.0174***
	(0.0073)	(0.0068)	(0.0043)	(0.0039)	(0.0037)	(0.0053)
Hydro	0.0144*	0.0096	−0.0105**	−0.0168***	0.0086**	0.0013
	(0.0083)	(0.0084)	(0.0042)	(0.0042)	(0.0041)	(0.0050)
Herfindahl Hirschman Index	−0.0267**	−0.0236**	−0.0069	−0.0003	−0.0476***	−0.0350***
	(0.0131)	(0.0115)	(0.0051)	(0.0039)	(0.0074)	(0.0052)
Exchange rate	451.576**	225.097	227.816*	194.478*	53.732	−19.786
	(219.669)	(188.492)	(116.637)	(99.892)	(127.844)	(96.358)
Weekend	37.453***	32.024***	22.944***	19.162***	34.522***	28.124***
	(6.752)	(6.043)	(3.895)	(3.007)	(4.297)	(3.106)
Holiday	15.925	14.948*	23.750***	23.216***	30.029***	24.394***
	(9.353)	(8.364)	(8.483)	(7.017)	(5.175)	(4.007)
Day	0.4080	0.2025	0.0439	−0.0915	0.0384	0.0051
	(0.3006)	(0.2638)	(0.1422)	(0.1154)	(0.0883)	(0.0777)
N	1104	1104	1104	1104	1104	1104
Adjusted R^2	0.2426	0.4736	0.4186	0.6757	0.3041	0.5223
Test of relevancy: H_0: Excluded instruments jointly zero						
F-statistic		639.142***		486.360***		277.408***

Peak hours are defined as 7 a.m. to 6:59 p.m. The data are hour specific. Feasible Generalized Least Square (FGLS) uses the Prais–Winsten method to correct for Heteroskedasticity and AR(1) Serial Correlation. IV estimation uses Lag 2 of Ontario Industrial Demand and Toronto's Temperature as Instruments for Ontario Industrial Demand and employs a Bartlett kernel with 1 lag when estimating standard errors to account for Heteroskedasticity and AR(1) Serial Correlation. Standard errors in *parentheses*. *, ** and ***Significant at 10, 5 and 1% level respectively. Month and hour dummies are included in this model but not reported

in the HOEP. In terms of other estimates, exports (imports) is positively (negatively) and significantly correlated (at the 1% level), with higher price. The one source of power generation that is significant (at the 1% level) across all columns is nuclear electricity, which possesses negative signs across all columns. Coefficient estimates of weekend and holiday dummy variables are positive and statistically significant

Table 7 Feasible generalized least squares (FGLS) and instrumental variable (IV) estimates with respect to hourly Ontario electricity price (dependent variable) during off peak hours

	2005		2006		2007	
	FGLS	IV	FGLS	IV	FGLS	IV
Ontario industrial demand	0.0024	0.0093	0.0255***	0.0276***	0.0079	0.0135*
	(0.0099)	(0.0117)	(0.0057)	(0.0070)	(0.0051)	(0.0071)
Other industrial, commercial, & Residential demand	0.0129***	0.0123***	0.0197***	0.0219***	0.0061**	0.0039
	(0.0027)	(0.0033)	(0.0031)	(0.0035)	(0.0024)	(0.0031)
Exports	0.0104***	0.0087**	0.0178***	0.0198***	0.0068**	0.0038
	(0.0032)	(0.0037)	(0.0034)	(0.0040)	(0.0028)	(0.0034)
Imports	−0.0106**	−0.0092*	−0.0142***	−0.0155***	−0.0018	0.0010
	(0.0047)	(0.0051)	(0.0034)	(0.0039)	(0.0029)	(0.0036)
Coal	−0.0080***	−0.0090***	−0.0140***	−0.0162***	−0.0008	0.0015
	(0.0029)	(0.0032)	(0.0033)	(0.0037)	(0.0030)	(0.0035)
Gas	0.0153***	0.0164***	0.0000	0.0013	0.0100***	0.0148***
	(0.0058)	(0.0057)	(0.0040)	(0.0047)	(0.0033)	(0.0042)
Nuclear	−0.0199***	−0.0196***	−0.0200***	−0.0207***	−0.0054*	−0.0028
	(0.0038)	(0.0039)	(0.0034)	(0.0037)	(0.0028)	(0.0033)
Hydro	−0.0068	−0.0069	−0.0160***	−0.0201***	−0.0018	0.0000
	(0.0044)	(0.0044)	(0.0034)	(0.0038)	(0.0032)	(0.0036)
Herfindahl Hirschman Index	0.0034	0.0078	0.0009	0.0046**	−0.0014	0.0007
	(0.0074)	(0.0064)	(0.0029)	(0.0023)	(0.0037)	(0.0027)
Exchange rate	301.504**	273.667**	176.653**	84.225	53.236	26.680
	(131.477)	(108.898)	(72.831)	(55.373)	(76.356)	(57.023)
Weekend	11.033***	11.065***	9.408***	11.224***	6.203***	8.398***
	(2.635)	(2.826)	(1.392)	(1.368)	(1.333)	(1.178)
Holiday	9.474	9.189	0.683	5.965***	6.593***	8.977***
	(7.331)	(5.947)	(3.730)	(2.185)	(1.961)	(1.304)
Day	0.4244**	0.3951**	−0.0614	−0.1482**	0.1985***	0.1728***
	(0.1791)	(0.1538)	(0.0749)	(0.0597)	(0.0564)	(0.0400)
N	1104	1104	1104	1104	1104	1104
Adjusted R^2	0.6255	0.6781	0.6972	0.7520	0.7102	0.7474
Test of relevancy: H_0: Excluded instruments jointly zero						
F-statistic		343.730***		230.297***		152.277***

Off peak hours are defined as 7 p.m. to 6:59 a.m. The data are hour specific. Feasible Generalized Least Square (FGLS) uses the Prais–Winsten Method to correct for Heteroskedasticity and AR(1) Serial Correlation. IV estimation uses Lag 2 of Ontario Industrial Demand and Toronto's Temperature as Instruments for Ontario Industrial Demand and employs a Bartlett kernel with 1 lag when estimating standard errors to account for Heteroskedasticity and AR(1) Serial Correlation. Standard errors in *parentheses*. *, ** and *** Significant at 10, 5 and 1% level respectively. Month and hour dummies are included in this model but not reported

(at the 10% or 1% levels) across all columns, possibly capturing the effects of increased load demand by residences.

Results contained in Table 7 offer some further evidence on the curvature of the elastic supply curve through empirical estimates of the effect of demand by industrial customers and other consumers on the HOEP during off-peak hours. The first observation is that coefficient estimates of industrial demand as well as demand by others are smaller in magnitude relative to estimates in Table 6. The estimates indicate that a 1000 MWh increase in demand by industrial customers during off-peak hours is significantly associated (between 10% and 1% levels) with an \$9–\$25 increase in the HOEP. In contrast, a 1000 MWh increase in demand by other consumers during off-peak hours is significantly correlated (between 10% and 1% levels), on average, with an \$6–\$20 increase in the HOEP. The estimates of other covariates are otherwise comparable to those in Table 6.

In summary, results contained in Tables 6 and 7 suggest that hourly demand by industrial customers have a stronger impact on the HOEP relative to other consumers. The estimates also reveal that hourly demand by industrial customers has a larger marginal effect on the HOEP during peak (relative to off-peak) hours.[25] Therefore, a price reduction from lower industrial demand during peak hours should not be offset by a corresponding increase in demand during off-peak hours.

6 Conclusion

The late 1990s and early 2000s witnessed considerable deregulation of electricity markets in North America. Sudden and sharp increases in retail prices accompanied by overall price volatility, as well as sudden blackouts, resulted in the imposition of price ceilings in California and Ontario still in effect today. Many states continue to regulate electricity prices. However, competitive wholesale markets exist alongside regulated retail sectors. The inability to allow retail prices to reflect changes in wholesale price shocks causes considerable market distortions and inefficiencies. As a result, focusing on the incentives to industrial customers and their impact on wholesale prices has assumed key policy importance.

This paper attempts to fill this gap by employing data for summer months from 2005 to 2008 for the province of Ontario. Using data over multiple years enables us to assess the sensitivity of our findings to year-specific shocks. Data obtained on special request from the IESO allows us to evaluate the effects of price on consumption across different industries. We obtain elasticities of substitution from 0.02 to 0.07, with considerable heterogeneity across industries. While these results are on the lower end of corresponding estimates from other papers, there are plausible explanations for our estimates. For example, as discussed earlier, most studies are based on sample of firms that voluntarily decide to enroll in RTP programs and are therefore more likely to engage in load-shifting than non-participating firms. They are unable to employ data on the universe of firms participating in such programs. In contrast, we use data on all firms that are connected to the transmission grid. Therefore, we interpret our estimates as modest evidence that industrial customers do shift consumption from peak to off-peak hours in order to exploit the benefits of lower prices during those times.

We also find that lower market demand by industrial customers during peak hours is significantly associated with a decline in the HOEP. On the other hand, the marginal impact of an increase in demand during off-peak hours is of a much smaller magnitude. Coefficient estimates of the effects of demand by industrial customers are larger in

[25] With respect to all the regressions in Tables 6 and 7, we used F tests to evaluate the null hypothesis that coefficient estimates of demand by industrial customers are larger in magnitude than coefficient estimates of demand by other consumers. In most cases, we could not reject the null hypothesis.

magnitude than corresponding estimates with respect to demand by other consumers. We think this to be an important finding, given the lack of econometric evidence and the inability of recent simulation based studies to account for such offsetting effects.

In tandem, these results offer support to the notion that policies that encourage efficient demand management by industrial customers will result in positive spillovers to all consumers. A good example would be the implementation of higher network transmission charges (for industrial customers) during peak hours. For example, Hydro One Networks Inc. (HONI), a corporation owned by the Government of Ontario, is responsible for the planning, construction, operation, and maintenance of most (97%) of the province's transmission and distribution network, which carries electricity from generating stations to local distribution companies and industrial customers. Currently, HONI bases network transmission charges for individual customers on their respective demand level, calculated each month as the higher of (1) the customer's demand at the time of the monthly coincident peak demand, or (2) 85% of the customer's maximum non-coincident demand between 7:00 a.m. and 7:00 p.m. on weekdays that are not holidays.

As evident, this system offers limited consumer benefits for moving consumption away from the month specific peak demand and provides little incentive for efficient demand management for shifting consumption from peak to off-peak hours. More response could potentially be achieved through higher network charges during peak hours. Some papers suggest that the potential for cost savings from even small reductions in peak demand might be significant.[26] Our study has gone further by demonstrating that a particular group of consumers—through incentives generated by Real Time Pricing—can impact system wide electricity prices and result in efficiencies from reduced peak hours consumption. The implication is that policies focused on industrial customers may benefit all consumers.

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