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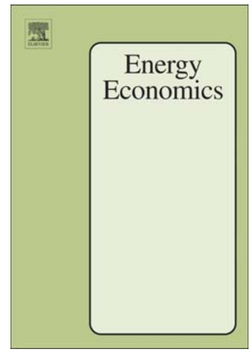

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Abstract: We investigate wholesale demand response to hourly price movements in the Ontario wholesale electricity market using detailed generator and market level data. We calculate hourly market power measures such as the Lerner Index and the Residual Supplier Index, which are utilized in a Cournot competition model to structurally estimate price elasticity of demand during peak hours of days, seasons and years. We find that price elasticities are small and statistically significant, and they exhibit large variations over the times of days/seasons and show differences over the years. For instance, while the elasticity estimates fall into the range [-0.021, -0.133] in 2007, they are in the interval of [-0.013, -0.053] in 2008. We also extend the study period to include 2006 (during which extreme weather conditions occurred) and 2009 (when the economic crisis hit and natural gas prices plummeted) to measure the demand responses to irregular price movements and find that price elasticities during the economic crisis were higher than a year earlier. Comparing high demand winter hours to high demand summer hours indicates that consumers' price responsiveness is lower in summer than in winter during 2006-2009. Moreover, we employ these indices along with the estimated price elasticities to project the likely impact of interconnection capacity expansions on market prices. Our calibrations show that even a small amount of transmission investment (and hence trade activity) can result in substantial market price reductions. In addition, we discuss how our approach could be used to estimate price elasticities for other goods such as crude oil and gasoline.

Keywords: Price elasticity of demand; wholesale electricity market; Cournot competition; GMM estimation.

JEL Codes: D22; D24; L13; L94; Q41

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1. Introduction

Electricity is an essential commodity and an input for production. While the process of reforming electricity markets continues, demand for electricity is growing at a fast pace and electricity prices are increasing at both wholesale and retail levels throughout the world. Electricity price affects the prices of many final goods, and the electricity industry is the largest single source of greenhouse gas emissions (EPA, 2014). It is associated with global warming and hence viewed as a negative externality in many jurisdictions.[1] To mitigate its side effects many Renewable Energy Laws in the world have been implemented by regulators and/or governments to encourage balanced electricity production portfolios and foster the share of green production technologies such as wind and solar. In addition, transmission investment and electricity market integration have gained momentum to overcome efficiency, security, reliability and sustainability issues, and reduce emissions. Given that electricity prices are increasing both at retail and wholesale levels, the recent demand management programs have targeted end-users to be part of the restructuring process and to respond to prices by reducing demand, purchasing efficient electrical equipment, and changing consumption habits. The success of these demand response programs depends on the pricing policies that customers are subjected to.

The analyses of demand response to new pricing policies have gained considerable attention in the recent literature. It is imperative for market designers, system operators, power producers, regulators, and policy makers to predict how wholesale and retail customers would respond to market-based rates (e.g., wholesale market clearing prices) or regulated rates (e.g., time-of-use prices). For example, in the case of low price responsiveness or near zero price elasticity of demand market price can theoretically increase up to the price cap and cause market failures. This has been observed in several wholesale power markets in the world.[2] On the other hand, a high price responsiveness may render welfare improving market outcomes (such as low prices, saving energy resources and reducing costly power generations and emissions). However, which price mechanisms may lead to more efficient results in a given market has not been clearly

[1] Global warming might be responsible for the current extreme weather changes causing unprecedented floods and droughts, and hence directly impacting production and services in several sectors. As the weather is an important factor of electricity demand, it can change electricity consumption behavior. In Ontario, coal plants have been phased out to reduce air emissions.
[2] Examples include the California, Texas, and Ontario markets.

addressed mainly due to market design issues, and the difficulties associated with allocation of fixed costs of operations in the industry.

To create price responsiveness in the retail sector, regulatory agencies have implemented several pricing methods such as time-of-use prices, multi-tier prices, and wholesale market clearing prices. For instance in the US, only one percent of households are subjected to time-varying rates and one percent of this one percent are on dynamic pricing rates.[3] In Ontario, Canada time-of-use pricing was initially implemented for the retail market in mid-2005 and gradually extended with smart meter installations. Several recent studies analyze the impact of forms of static and/or dynamic time-varying pricing methods applied to residential and small commercial/industrial customers. In this literature, a number of studies have extended the work of Vickrey (1971) and Chao (1983) to incorporate the efficiency gain analysis and price responsiveness predictions for pilot projects run in certain cities/states/provinces.[4] Price elasticity estimates in this literature are distributed over a large interval and highly variable depending on the rate structures and locations.[5]

The price elasticity of electricity demand studies have mainly investigated price responsiveness of residential (and small industrial and business) customers who essentially face some fixed regulated rates.[6] In contrast, research incorporating wholesale customers subjected to real-time

[3] See Faruqui et al. (2014). Charging wholesale prices to retail customers is an example of dynamic pricing.

[4] Examples include Wolak (2011), and Faruqui et al. (2014), among others. See also Ryan et al. (2006) who examine residential energy (oil, gas, electricity, and wood) demand in Ontario using annual data for the period 1962-1989.

[5] For old studies, see Taylor (1975) who provides a detailed summary of econometric research on demand for electricity and mainly reviews residential demand models. In a recent study, Reiss and White (2005) estimate a household electricity demand model for assessing the effects of rate structure change in California. They find that a small fraction of households respond to price changes, and the price elasticities range from 0 to -2. Related to the price response of residential demand, Bushnell and Mansur (2005) estimate the impact of lagged residential prices on consumption and find that elasticity of demand equals -0.1 in San Diego, California.

[6] Taylor (1975) criticizes residential demand models and explains the difficulties associated with demand function specifications due to the fixed charges and price schedules stemming from different consumption blocks. He points out that these pricing features create non-analytical demand functions which render the validity of econometric estimates of price elasticity of demand questionable. See also Heshmati (2013) for a recent survey of electricity demand models using reduced-form formulations.

market prices is rare[7]. In this paper we focus on demand response of wholesale customers to hourly changing market prices. The wholesale customers/buyers are comprised of large industrial firms, regional electricity distribution companies, dispatchable loads and exporters who are the key players on the demand side and face highly volatile real-time market prices.

In this paper, we utilize an hourly Ontario wholesale electricity market data set of over 35,000 observations for each variable including firm/generator and market level outputs, costs and prices. An advantage of using Ontario market data is that we observe actual hourly outputs and available capacities of generators right after the market clears. Using this disaggregated data set, we initially assess the competitiveness of the Ontario market and calculate market power measures: the Residual Supply Index (RSI), and the Lerner index (LI) using hourly generator and market level data. We then model competition in the Ontario market as a capacity constrained Cournot model and solve it to derive the theoretical relationship between the RSI and LI. Using this relation and the computed hourly values of these indices we first estimate the wholesale price elasticity of demand over several time intervals in 2007-2008, which are the basis periods. We also extend the study period to include one year before and one year after (2006 and 2009).[8]

There are several distinctive features of this paper. First, we derive a price elasticity measure from a Cournot competition model. The structural modeling framework that we apply is appealing and easier to apply than other methods, which have to use more variables and data points to specify demand and/or supply curves. This could be a daunting task as some market and firm-level data are private and hard to obtain. An advantage of using our approach is that we do not need to model market demand explicitly. For example, we only assume that the market demand curve is downward sloping and differentiable. However, to our knowledge, measurements of price elasticities in the literature are almost exclusively based on reduced-form statistical models using some specific demand functions. Instead of dealing with demand

[7] Total system load/demand analysis was first carried out by Cargill and Meyer (1971) who employed a linear model, in which demand was represented as a linear function of average prices for gas and electricity, real per capita income, time and employment in manufacturing sector. They used monthly observations of 48 data points in the late 1960s, and found that price elasticity was negative and statistically different from zero.

[8] During 2006 natural gas prices started to increase before they hit record levels in 2007 and 2008. Year 2009 corresponds to the economic crisis period (in Canada and elsewhere) during which the North American natural gas spot prices plummeted and demand for electricity went down.

specifications, we show how to use market power indices, which are easily computable due to readily available electricity data sets, to estimate the hourly price elasticity of demand in the short run. Second, in the estimation procedure we tackle the endogeneity issue between the market power indices by introducing an appropriate instrumental variable to obtain consistent and efficient elasticity estimates. Third, while other studies mainly focus on industry and/or residential layers of the sector and use weekly/monthly/yearly aggregated data, we employ detailed hourly generator and market level data to estimate wholesale demand response to hourly market price movements. Fourth, as an application of the model we examine the impact of several counterfactual supply scenarios regarding expansions in interconnection capacity facilitating trade activities. These scenarios are justifiable because transmission investments and hence the volume of trade between the neighboring jurisdictions/countries have been increasing since the opening of wholesale markets. Specifically, we will project the market prices in the case of an increase in import quantities from the adjacent markets in the transmission network. Finally, we discuss how our modeling framework could be used to estimate price elasticities for other goods such as crude oil, gasoline, computers, and cigarettes.

We find that there are a few players who are pivotal and are able to exercise market power in the Ontario market. In all of the generalized method of moments (GMM) and the ordinary least square (OLS) regressions we validate the theoretical negative relationship between the LI and RSI. Using the largest firm's RSI and the various LI measures we estimate price elasticities and find that the wholesale demand is price responsive, but only to a small extent – the price elasticities mainly fall in the range [-0.013, -0.133], and they change over peak and off-peak hours of seasons/years. While we use a structural approach in estimating elasticities these findings are consistent with the broader literature. To check the robustness of our elasticity estimates, we also use the fuel prices as a proxy for the marginal costs in computing the hourly LI. We find that the elasticity figures are similar both qualitatively and quantitatively regardless of whether we employ actual fuel prices or actual dollar amounts spent for each fuel type in the LI calculations.

The organization of the paper is as follows. Section 2 examines the Ontario market structure along with the specifics of the data sets. Section 3 defines the competition model employed in the paper. In Sections 4 and 5 we compute market power indices to determine competitiveness of the market and use these indices to estimate the hourly price elasticity of wholesale electricity demand in several periods of 2007 and 2008. Section 6 extends the study period to include years 2006 and 2009 to examine the impact of important events, and offers a robustness check for the estimated elasticities using an alternative marginal cost formulation. Section 7 proposes an application of the modeling framework to project likely impact of certain supply scenarios. Section 8 relates our results to the broader literature and assesses the extent to which our results can be generalized to other markets. Finally, we conclude the paper in Section 9 with a short discussion of key findings.

2. Market Structure and Data

While there is an hourly market price in Ontario, called the hourly Ontario energy price (HOEP), the market is more a "hybrid" market than a fully deregulated one (see Pineau, 2013). In fact, regulations are common in all electricity markets worldwide. The Ontario market is hybrid in the sense that it has been restructured in a way that there are some behavioral restrictions on demand and supply sides. For example, some end users (such as large industrial customers) directly buy electricity from the wholesale market at the HOEP; others (such as households and small businesses) are subject to regulated rates varying with the usage and the time of the day. On the supply side, some generators, mostly small, (called “exempt and non-market generators”) engage in bilateral contracts with a number of non-market participating end-users. Their power productions are not part of the wholesale supply and those consumers’ demand is independent of the total market demand. In this paper, we will examine market demand (consumers who represent the wholesale demand) and market supply focusing on firms who sell power (over 95% of the total production in Ontario) directly to the wholesale electricity market. Some of generators (mainly owned by the Ontario Power Generation (OPG)) are also regulated in terms of payments. However, the market clearing price in Ontario is obtained (solving “unconstrained” optimization problem by the Independent Electricity System Operator (IESO)) without taking any considerations on the payment schemes, and production and network constraints.

In Ontario, the major player is the OPG which is a crown corporation and operates in power production only. Other power producers (e.g., Brookfield Renewable, Trans Alta, Trans Canada) are privately owned and they are assumed to be profit-maximizers. Even though the OPG is a crown corporation, it is assumed in the literature that it is also a profit-maximizer (see footnote 31), but it transfers its “excess profits” to the treasury after netting the “fair rate of returns” for future investments. On the other hand, some customers may pay a price different than the HOEP depending on the usage. According to the IESO (www.ieso.ca) "consumers who pay the HOEP, or have signed a retail contract, will see their electricity bills also include a line for the Global Adjustment (GA). This charge accounts for the differences between the market price and the rates paid to regulated and contracted generators and for conservation and demand management programs." Note that during our study period the GA was very low and insignificant. Nevertheless, in such a context, our market competition framework (see Section 3) is valid because the price formation process in the Ontario market relies on the solution of the "unconstrained problem" under which power firms submit their profit maximization quantity-price pairs to the system operator who clears the market where aggregate demand intersects aggregate supply without taking any constraints into account.

To measure the wholesale buyers' price responsiveness, we utilize detailed plant and market level data provided by the IESO and the Statistics Canada. The data includes hourly export/import quantities, hourly production and available production capacity of each generator, hourly market clearing prices and demand quantities, technical features of generators (such as heat rates and emission rates) and fuel data (including fuel spot prices, actual money spent on each fuel type, and energy content of the fuel). In computing market power indices we use all of the active generators out of 563 registered ones and apply four years of hourly data to the Ontario market.[9] We map generators to the owners of firms and observe that there are a few dominant firms with many fringe firms in the market. We choose the hours of 2007-2008 as a basis period. We also extend the study to include 2006 and 2009 hourly data to examine the impact of year before and year after events in the market. During 2006 extreme weather events (e.g., heat waves) were recorded, which caused imbalances between supply and demand, and electricity and natural gas prices have started to increase before they have hit the high levels during 2007-2008. In 2009 the global financial crisis has been felt in Canada (the economy

[9] The Ontario market has a pool-based centralized structure in which market transactions are carried out by power producers, distribution companies, and other market participants such as importers and exporters. Per market design the electric power is auctioned in the pool where the price is formed. More details about the Ontario market structure and its evolution is available in Genc and Sen (2008), and Pineau (2013).

contracted consecutively, and the recession started) and the natural gas prices (along with other energy prices) have seen the lowest levels, and demand for electricity has decreased.

Electricity demand in Ontario is the highest in the peak seasons of winter and summer than the rest of time and positively correlated with temperature in summer and negatively correlated with it in winter. For example, in 2007 winter the correlation coefficient between hourly demand quantity and hourly temperature was -0.43, and it was 0.43 in summer. In that year, while average hourly demand was 18,779 MWh, it was 19,820 MWh in winter and 19,159 MWh in summer during which the highest temperatures accompanied with the highest demand levels. There was an upward trend for demand for electricity in the following year; however the economic crisis dampened the industrial sector electricity demand: the average hourly quantity demanded increased to 19,454 MWh (by 3.6%) in 2008 before sharply dropped to 17,615 MWh (by 9.5%) in 2009. In terms of distribution of demand by the hour of day, we observe that peak hours correspond to 7am-7pm during which demand for electricity is about 20% higher than the off-peak demand. In both 2007 and 2008, the highest average demand by the hour of day occurred in hour 18 and the lowest happened around hour 3.

There are several large firms in the market which are Ontario Power Generation Inc (OPG), Bruce Nuclear Inc (Bruce), and Brookfield Renewable Energy Inc (Brookfield).[10] Note that these power firms are strictly in the power production business and do not sell natural gas to other power producers and/or gas consumers. The OPG has over 60 generators in its hydroelectric, nuclear, coal, and natural gas fired plants. Using the production characteristics, available capacities, and production costs of these generators, we were able to construct a marginal cost function for OPG for each hour. The total available capacity of OPG generators changes every hour (due to, e.g., generation outages/de-ratings, and regulatory/environmental restrictions); the minimum available total capacity is 12,900 MW, the maximum is 19900 MW, and the average is 16,917 MW per hour in year 2007 during which its average hourly output is 11,966 MWh

[10] Aydemir and Genc (2014) analyze the impact of electricity trade on equilibrium outcomes (such as welfare losses, emissions levels, and productions) using hourly Ontario data between April 2007 and March 2008. They show that the Cournot behavior well represents the strategic interactions and market outcomes in the Ontario market where the dominant firms are OPG, Bruce, and Brookfield, and the rest of the firms are price-taking fringe companies during the study period.

electricity.[11] A bulk of its production comes from nuclear and hydropower stations with the shares 44.2% and 29.6%, respectively. Its total share in meeting market demand is slightly reduced in 2008, but its share of production from nuclear and hydro units is increased. The Bruce nuclear has six nuclear generators with identical heat rates. Total available production capacity from these six nuclear generators changes almost every hour, and its average total capacity is around 4,200 MW with average production near 4050 MW in 2007-8. Brookfield operates hydropower and wind facilities, and a natural gas–fired plant. Its total available capacity for production changes every hour, and is less than 1000 MW in both years. The rest of the firms in the market run hydro, wind, biomass, and natural gas-fired production technologies. These firms are generally small in production capacity and hence they are assumed to be price-taking fringe firms in Aydemir and Genc (2014). However, in the current setting of the paper we do not impose such behavioral restriction on the fringe firms: they could act as strategic or non-strategic, and their behavior does not change our results. They operate many gas-fired generators with different heat and emission rates, and marginal costs, and their sizes are asymmetric: for a given hour available production capacity of a gas generator ranges from 0 to 580 MW. These small firms on average have met on average 8% of the market demand in 2007-2008. Most of their production comes from the high cost natural-gas fired generators. The combined output from hydro and wind comes second, and biomass-fired generation is the third in both years.

Using the firms' actual outputs one can measure the market concentration level via Herfindahl-Hirschman Index (HHI) which is equal to sum of the squared market shares of all firms.[12] Nevertheless the HHI could be a misleading concentration measure in this industry as production from each firm, small or big, might be needed in equilibrium and even a small firm could exercise market power by withholding output. As we utilize hourly production data for each firm and its generators, which are not available for many industries, we believe it is still a worthwhile

[11] The maximum market demand levels are recorded 26,658 MWh and 27,477 MWh in 2007 and 2008, respectively; however the load factor - the ratio of average demand to peak demand- is 0.7 in each year. Utilities, generation firms and the system operators generally prefer higher load factors to lower ones in order to reduce generation costs and maintain system stability.

[12] Formally, $HHI = \sum_i s_i^2$, where $s_i = 100 * q_i/Q$, q_i is the output of firm i, Q is the total market output at a given time (hour).

exercise to compute the hourly HHI at a firm and/or generator level.[13] Nevertheless due to the firm's ownership and operational control over its generators it is more plausible to calculate the market share of each firm by aggregating outputs of all its generators.

When we include all firms (OPG, Bruce, Brookfield and other nine small firms[14]) according to their generator ownership we obtain a 12-firm market structure. We then compute hourly HHI and find that the average hourly HHI in 2007 is 5108 with the summer (June-Aug) average of 5160 and winter (Jan-Mar) average of 5237. On the other hand, in a structure where all fringe firms' outputs are aggregated, we calculate the HHI with the average 5131, and the winter and summer HHI averages are 5265 and 5169, respectively. Although the winter and summer HHI averages are close to the sample mean, the highest levels of HHI are still observed in the peak winter and summer seasons. Consequently, the 4-firm and 12-firm structures lead to the similar HHI properties because the small firms' production shares are low. The high HHI values may suggest the existence of market power in the Ontario market. However, this index does not tell which firm holds how much market power or whether firms actually impact the market prices. Hence, studying other market power measures becomes indispensible to draw conclusions about the magnitude of market power.[15]

3. Modeling Competition

Our modeling framework assumes a Cournot competition in the Ontario wholesale power market where the dominant firms are OPG, Bruce, and Brookfield.[16] There are also nine small firms for

[13] Most of the North American wholesale electricity markets do not release the hourly generator-level production data.

[14] These firms are Trans Alta, Brighton Beach, Northland Power, Trans Canada, Cardinal, Abitibi, GTAA, Tractable Canada, and the rest of the generators are aggregated to form the ninth company.

[15] We also computed the HHI for all hours in 2008 with the 4-firm and 12-firm market structures. We find that the HHI values show similar patterns in both years and are higher in 2008 than in 2007.

[16] Cournot models are commonly used in market power studies in the electricity markets (e.g., Borenstein and Bushnell (1999), Puller (2007), Genc (2012)). Not only they are tractable and implementable, but also some Cournot assumptions are justifiable for electricity markets. A more sophisticated approach would be implementing a supply function equilibrium (SFE) analysis (see, Green and Newbery (1992), Hortacsu and Puller (2008), Genc (2009), Holmberg and Newbery (2010), Genc and Reynolds (2011), and the references therein). However, this approach may be implausible to implement into the Ontario market context as it predicts multiple equilibria and it is harder to compute an SFE with many asymmetric firms and binding production constraints. The main issue is that the capacity constraints have an impact on a firm's profitability of changing its supply function. A firm may find it profitable to change its supply by

which we do not restrict the behavior (they could behave like strategic firms or price-taking competitive fringe). All firms strive to maximize their profits while meeting the total market demand which is differentiable and downward sloping function of the wholesale price p and is denoted $Q_h(p)$.[17]

For a given market price p at hour h, the market demand $Q_h(p)$ represents the total consumption of large industrial customers, exporters, dispatchable loads (who are price responsive), and the regional electricity distribution companies/utilities (who deliver power to residential, business and small industrial customers at the regulated time-of-use prices). Therefore, demand response to market clearing price p directly comes from large industrial customers, exporters, and some designated customers who can adjust their consumption based on the orders of the system operator. Under the current pricing policy, the residential and small industrial/business customers can respond to the regulated tariffs, which are some averages of the past wholesale market prices. If they were exposed to the wholesale prices or some version of dynamic prices which somewhat would reflect the market clearing prices, then they would adjust their consumption in real time. Currently utilities and load distribution companies are directly exposed to market prices, and they bear the price risks on behalf of the residential and business customers.

Each strategic firm i maximizes its profit function for each hour h

(1) $\pi_{i,h} = p_h(Q_h)q_{ih} - c_{ih}(q_{ih})$.

If the fringe firms are price takers then the residual demand for firm i as a function of market price p is $[Q_h(p) - S_h(p) - I_h - q_{-i,h}]$, and $S_h(p)$, I_h are the fringe firms' aggregate supply and

withholding output and bidding up the price, given that its rivals are capacity constrained. The SFE models have mainly focused on local optimality conditions for a firm's supply response to rivals' supply strategies. However, when there are capacity constraints it is important to check for global optimality of a firm's supply response. Rivals' capacity constraints may yield a non-quasi-concave payoff function for which local optima do not in general be globally optimal.

[17] Different than Aydemir and Genc (2014), we let the demand function be as general as possible. Also, they assume an affine demand curve and restrict the small firms to act as price takers.

total imports, respectively. $q_{-i,h}$ is the quantity produced at price p by other dominant firms (-*i*), and $c_{it}(q_{ih})$ is the total production cost function for firm *i* at time h.[18]

If fringe firms are strategic then each strategic firm j, including the dominant firms, maximizes its profit function for each hour as in expression (1), but the residual demand faced by firm j will be equal to $[Q_h(p) - I_h - q_{-j,h}]$, where $q_{-j,h}$ is the total quantity supplied at price p by the rivals of firm j.[19]

Production from each generator is bounded by the hourly available production capacity K_{igh} for firm *i* from a generator *g* at time h.

In constructing a firm's marginal production cost function we take into account of aggregate fuel costs[20], generator characteristics such as heat and emissions rates, and available production capacities of each generator owned by this firm.[21] As an alternative approach we will also use the fuel spot prices directly as an approximation to the marginal production costs for robustness check of the model outcomes in Section 6.

For each generator we compute the marginal cost of production as:

[18] There is no forward market in Ontario due to the market design. All power exchanges are carried out in the pool type real-time market. If there would be forward sales then firm i's profit function would be $\pi_i = p(q_i - x_i) + f x_i - c_i(q_i)$, where *x* denotes forward quantity sold at forward price *f*. Also note that the generators operating in the Ontario market are called "market generators" which do not engage in contracts. The bilateral contracts are carried out by independent producers which are called "exempt and non-market generators" whose power are not part of the wholesale supply and their demand is independent of the total market demand. In addition, no market participant on the production side is part of the retail business. However, some small producers (such as local utilities) who do not sell power into the wholesale market can sell directly to households. That is, vertical integration is not allowed for producers who sell power to the wholesale market by market design.

[19] In the Ontario context, as the firms other than OPG operate near their capacities it does not matter whether we assume other firms behave like competitive fringe with a vertical inverse supply function or behave like Cournot firms choosing their production quantities (at the capacity). In any case, the residual demand faced by OPG is the same.

[20] The data on the amount of fuel consumption, dollar amount spent, and energy content is provided by Statistics Canada (source: Statistics Canada (2009) Electric Power Generation, Transmission and Distribution – 2007, Catalogue no. 57-202-X).

[21] The generator characteristics are provided the Environment Canada: Canadian Module Unit List. It includes inventory of all currently operating (or existing) electric generating units (EGUs) and planned-committed units and their relevant characteristics. The web-link for the reference is http://www.ec.gc.ca/air/default.asp?lang=En&n=D6C16D01-1.

(2) Marginal Production Cost = *Marginal Fuel Cost+ Marginal SO2 emission cost+ Marginal NOx emission cost,* where

Marginal Fuel Cost = Heat rate of generator (in kj/kwh)* Dollar spent on fuel($)/[Total fuel consumption (in ton)*Energy content (in kj/kg)] * a conversion factor = $/MWh.

The emissions costs are,

Marginal SO2 emission cost = Heat rate of generator (kj/kwh) * SO2 rate of generator (g/MJ) *Price of SO2 emission permit ($/lb) * a conversion factor = $/MWh

Marginal NOx emission cost = Heat rate of generator* NOx rate of generator*Price of NOx emission permit * a conversion factor = $/MWh

The marginal emission cost for a generator will include SO2 and NOx emissions rates (g/MJ) and permit prices, as firms pay for emission certificates of NOx and SO2 gasses.[22] In Ontario diesel, refinery gas, wood and wood waste, landfill gas, coal (lignite, bituminous, sub-bituminous), natural gas, and oil-fueled production technologies release NOx emissions. Among these technologies, only coal (lignite, bituminous, sub-bituminous) plants generate SO2 emissions. Wind, hydropower and nuclear generators are emissions free. Once the total marginal costs for each generator are calculated, for a given cost level we add the available production capacities of generators, which change hourly, to obtain the marginal cost curve for a firm. After obtaining a marginal cost function we fit into a continuous function selected by highest R-square. We approximate the step marginal cost function by a smooth curve for most of the firms. For example, we obtain a quadratic marginal cost function for OPG most of the hours. The marginal cost at zero output is zero because OPG has hydro generators which operate at zero marginal cost (of fuel). Note that for the same day marginal cost function coefficients may change due to hourly changing available capacities of over sixty generators of OPG.

4. Market Power Indices

[22] The cost of CO2 emissions is not part of marginal cost as it is not traded in the Ontario market. More details about the emission costs and the derivation of marginal cost curves are provided in the Appendix A of Aydemir and Genc (2014).

To estimate price elasticities of market demand we first need to compute market power indices (which will show up as equilibrium conditions in the profit maximization problem of each firm). For electricity markets there are several commonly used market power indices which are the Residual Supply Index (RSI) and the Lerner Index (LI).[23] The former includes quantity information such as market demand quantity and firms' production capacities. The latter is a function of prices; mainly market prices and marginal costs.

4.1 Residual Supply Index (RSI)

A practical and commonly used market power index in electricity markets is the Residual Supply Index (RSI)[24], originally developed by the California Market Surveillance Committee (see Sheffrin (2002)), and now being used in other power markets in the world. As a market power measure, the RSI has been used in the US and European electricity markets and examples include Bergman (2005), and Gianfreda and Grossi (2012). The RSI can be calculated for any firm in the market. By definition a firm's RSI equals the ratio of residual market supply capacity (excluding this firm's production capacity) to the market demand quantity at a given time. Therefore, it measures pivotal status of the firm and determines whether this firm's production is needed to meet market demand. The firm facing a positive residual demand is able to unilaterally raise the market price above its marginal cost. As observed in the US and European electricity markets (see London Economics, 2007), a firm's market power measured by the Lerner Index (LI) is inversely related to this firm's RSI: the lower the RSI the higher is the firm's market power. In the situations in which marginal cost information is not readily available, the RSI can be computed to determine the level of market power held by the firm. This paper is different than the above RSI-based studies, as we use these indices to structurally estimate wholesale price elasticity of demand for electricity.

We define firm i's RSI at hour h as,

$RSI_i(h) =$ [Total available market production capacity(h) plus imports(h) minus firm i's production capacity(h)] divided by total market demand(h) = $[K(h) + I(h) - k_i(h)]/D(h)$.

[23] There is another market power index called Pivotal Supplier Index which is a weaker form of the RSI.
[24] The RSI was first designed by the California Market Surveillance Committee. Sheffrin (2002) shows that there is a negative relationship between the RSI and Lerner Index (LI) in the California electricity market in summer 2000.

If the firm i has any bilateral contractual obligations, the total contracted quantity can be subtracted from this firm's available production capacity to calculate the RSI. In the definition of RSI in Sheffrin (2002) and Newbery (2009) it appears that they use the installed capacities of generators.[25] In calculating total production capacity in any hour we only consider the available production capacities of all generators/firms. The available capacity for a generator at each hour indicates the maximum possible production quantity. The treatment of the intermittent technologies such as wind and solar power generators in the RSI calculations is that we discard their production capacities because in reality the production constraints only bind for a few hours in a year in the Ontario market, and therefore we assume that their actual production quantities are equal to their available capacities in each time period in the RSI formulation.[26]

If $0 < RSI_i(h) < 1$, then firm i's production is needed to meet market demand, and hence it is pivotal and has an absolute market power. Otherwise, the rivals of firm *i* can meet the demand.

For the reasons mentioned in Section 2, we model the Ontario wholesale electricity market with 4 firms: OPG, Bruce, Brookfield, and a firm composed by aggregating the output of all the fringe firms. A RSI calculation using all 12 firms would, of course, would yield identical results obtained under four large firms. In Table 1 we present the descriptive statistics of the data used to calculate the RSI. In Table 2 we show the average RSI values of all firms in all hours and peak seasons (winter and summer) of 2007-08.

< Insert Table 1>

Table 2: Average hourly Residual Supply Index (RSI) for all firms in 2007 and 2008 winter, summer, and all hours in the years.

2007	**RSI-OPG**	**RSI-Bruce**	**RSI-Brook**	**RSI-Fringe**
Winter	0.431	1.121	1.278	1.178
Summer	0.461	1.165	1.357	1.271
All hours	0.463	1.147	1.325	1.229

[25] We argue that the relevant capacity measure is not the installed capacity but the available production capacity in a given hour. This is because some portion of the installed capacity is never used or may not be available for production either due to the production specific reasons or transmission constraints.

[26] Another approach would be considering wind and solar production as negative demand. With this assumption, the results would not change as the market share of these renewables is about 1%.

2008				
Winter	0.437	1.138	1.296	1.204
Summer	0.528	1.237	1.426	1.268
All hours	0.516	1.199	1.380	1.232

Table 2 indicates that the lower the RSI the higher is the firm's market power. OPG has a market power and can impact market prices, and it has more market power in winter than in summer. For Bruce and Brookfield the RSI values are higher in high demand-high price summer season than the overall year RSI. All firms have more market power in winter than in summer. A reason for this finding is that in winter there is less water available for hydro production. According to the RSI benchmark of 1.2, which has been applied in the California market (see Sheffrin 2002), a power firm with RSI higher than 1.2 is considered to be competitive. Based on this threshold level all dominant firms have a market power, including Brookfield whose RSI is below 1.2 for 21% of time (1825 out of 8760 hours in 2007), even though its average RSI is about 1.325. This implies that each dominant firm has a market power at least 20% of time.[27]

Compared to 2007, the average hourly RSI values for all firms have increased in 2008. This implies that firms have less market power in 2008. This result also holds for all dominant firms across the winter and summer hours. Finally, it is worthwhile to note that the RSI determines whether a firm has a market power or not based on the quantity information (market demand quantities, imports/exports, and available production capacities). The existence of market power alone does not say how much a firm can influence the market price. Therefore, below we will link existence of market power (RSI) to market power exercise and examine implications of RSI on the price-cost markups.

4.2 Lerner Index (LI)

The Lerner Index (LI) as a market power measure indicates a relative difference between the actual market price and marginal cost price. If the LI is defined for a market (in which marginal cost of the last dispatched generator determis the system or market marginal cost), then it measures the overall market power in the industry. If it is defined for a firm (in which the firm's

[27] OPG is pivotal at all times and its RSI is always less than 1 for all hours.

marginal cost of the most expensive dispatched generator determines the firm's cost), then it measures the firm's ability to raise the market price above and beyond its marginal cost.

Formally, $LI_k = (p - mc_k)/p$, $k = i \text{ or } m,$ where i represents firm i and m denotes market. With LI_i we obtain firm i's ability to raise the market price to p given that its marginal cost of production at the supplied output is mc_i, which can be non-constant and vary with the production level over time. If k refers to market then the LI leads to a measure of market performance and determine how competitive the market is. In this case, marginal cost of the marginal generator/firm (that is the highest marginal cost in the system and hence called the system marginal cost (SMC)) should be determined. In a given hour the marginal output can come from any firm whose output is needed to equilibrate aggregate demand to market supply.

The SMC in any hour is determined as follows. First we compute the marginal production cost of every generator based on the formula (incorporating fuel and permit prices, and heat and emission rates) defined in expression (2). Then we choose the maximum of marginal costs of all active generators in the system producing positive output, which will be denoted by mc_m, in a given hour. This SMC will probably change every hour as the marginal production technology can change from hour to hour depending on supply and demand conditions. Similarly, to calculate firm i's (highest) marginal cost in any hour, we take the maximum of marginal costs of all generators owned by this firm producing positive outputs. Firm i's marginal cost will be denoted mc_i. We exclude back-up generators providing spinning reserve capacity in the system from firm i's production portfolio in calculating its marginal cost mc_i, because the back-up power is priced differently than the wholesale power, possibly higher than the market price depending on the scarcity conditions. When we calculate the system market power LI_m (or the relative markup over the system marginal cost) we observe that a fringe firm with a natural gas plant, which has been called upon for production, has the highest marginal cost in the market for all hours in the study period.

5. Estimating Price Elasticity of Wholesale Demand

This section shows that the market power indices (RSI and LI) are interconnected through the profit maximization problem and the interplay between these indices provides price elasticity estimates. The RSI and LI are dynamic indices and change over time (i.e., hourly) as demand, available production capacity, price, and marginal costs vary.

The price elasticity of market demand indicates wholesale customers' ability to adjust their consumptions with respect to changes in wholesale prices. The magnitude of price elasticities is closely monitored by policy makers, regulators, and market participants, as the wholesale price response will ultimately impact consumption behavior of all types of customers (wholesale customers in the short-run and retail customers in the long-run through regulatory rate changes). While low price responsiveness can harm the consumers' welfare, high price responsiveness can limit market power of power producers and cause productive efficiency by making use of the low-cost production technologies. Moreover, the price elasticity information can be used by both power sellers and buyers to form their offer and bid schedules optimally.

After computing the RSI and the LI for each firm we will estimate price elasticity of wholesale electricity demand in various time periods based on the following quantity choice problem. As in Newbery (2009), firm i maximizes its profit function

$\pi_{i,h}(q) = p_h(Q_h)q_{ih} - c_{ih}(q)$, where Q_h represents the total demand quantity and is equal to the summation of firms' productions and imports in hour h. Note that there is no need to specify a functional form for the inverse demand $p_h(Q_h)$. We only assume that it is downward sloping and differentiable. The quantity demanded at a market price p is $Q_h = Q_h(p)$. The production cost function $c_{ih}(q)$ is convex and differentiable.

The optimum output for an interior solution satisfies

$\frac{\partial \pi_{i,h}}{\partial q_{ih}} = 0 = p_h - c'_{ih} + q_{ih}\,\partial p_h/\partial Q_h$. The terms are re-arranged to obtain

$$p_h - c'_{ih} = -q_{ih}\frac{p_h}{p_h}\frac{Q_h}{Q_h}\partial p_h/\partial Q_h = q_{ih}\frac{p_h}{Q_h}\frac{1}{\varepsilon_h} = (Q_h - k_{-ih})\frac{p_h}{Q_h}\frac{1}{\varepsilon_h} = \left(1 - \frac{k_{-ih}}{Q_h}\right)\frac{p_h}{\varepsilon_h} = (1 - r_{ih})\frac{p_h}{\varepsilon_h},$$

where the second equality comes from the definition of price elasticity $\varepsilon_h = -(p_h/Q_h)\,\partial Q_h/\partial p_h$, and the last equality is based on the definition of RSI for firm i: $r_{ih} = k_{-ih}/Q_h(p_h)$, where $-i$ is referring to all firms other than firm i and k_{-ih} is the total available capacity from all firms but firm i plus imports. Then we obtain the relation between the market power indices:

(3) $\quad LI_{i,h} \equiv \frac{p_h - c'_{ih}}{p_h} = \frac{1-r_{ih}}{\varepsilon_h}$.

Note that the equilibrium condition in expression (3) is obtained under a number of assumptions. The first one is the Cournot behavior by a large firm. As we explain in Section 3 that this assumption is common in the electricity market studies and moreover Aydemir and Genc (2014) show that a quantity competition setting model of dominant firms with fringe structure predicts the market outcomes with high accuracy in the Ontario market: their Cournot model generates actual market prices and outputs with 94.4% and 96% accuracy, respectively. Second, using the definition of RSI the expression (3) implies that in equilibrium all firms but firm *i* operate at their available production capacities. This initially seems a strong assumption and needs a justification. Observe that the relation in (3) can technically be calculated for any firm *i*; however we find from the production data that the largest firm is OPG which meets about 60% of the market demand. Therefore, it is plausible to assume that firm *i* is referring to OPG.[28] Note that if firm *i* is pivotal so that r_{ih} is less than 1, then firm *i* can profitably burgeon the market price above the marginal production cost of its most expensive dispatched generator. Indeed, as explained in section 4.1 and also exhibited in Table 1 that OPG is the only firm whose RSI is always less than one. Also the expression (3) is obtained under the assumption of interior solution, but this holds true because the OPG's production constraints never bind in any hour during the study period as observed in the actual data. Moreover, the second largest firm is Bruce Nuclear who only operates nuclear stations and always produces near its available production capacity, and OPG and Bruce combined provide about 91% of the total production in the market.[29] Given that OPG and Bruce provide the bulk of total production and their available production capacities are close enough to their total market capacities, our RSI calculations for OPG are realistic. Indeed, the RSI values for other firms only indicate their potential market

[28] In calculating OPG's market power index $LI_{OPG,h}$ we first compute marginal costs of all generators owned by OPG. Then based on the real time hourly productions of OPG we pinpoint the most expensive OPG generator, which gives $c'_{OPG,h}$. For a given hour we use the spot market price and the marginal cost of the most expensive OPG generator to calculate the hourly $LI_{OPG,h}$. The type and/or the name of the most expensive dispatched OPG generator changes from hour to hour.

[29] The average capacity utilization rates of Bruce Nuclear are 97.2% in 2007 and 97.4 % in 2008. In those years OPG and Bruce on average provided 91.4% and 91.9% of the total market productions, respectively. Also, their combined available production capacity is on average 86.8% of the total market capacity in 2007. In 2008, it has dropped a bit to 83.3% of the total available market capacity due to the new production investments by solar and wind generators, whose productions are intermittent.

power, but in essence those values do not correctly measure their market power because their rivals' production constraints do not bind and hence RSI becomes relevant measure for the largest firm only. Consequently, the assumption that in equilibrium OPG operates below its available capacity and Bruce runs near its capacity is justified, and hence the relation between the market power indices provided in (3) is validated in the Ontario market context.[30] As we explain below this expression is also used by London Economics (2007) to explore the extent to which various electricity companies exercise market power in the European electricity markets. Their results were interpreted by Newbery (2009) who argued that the coefficient of the RSI refers to demand elasticity (see Newbery, 2009 pp. 9-10).[31]

It is clear from the above analysis that there is no need to explicitly define a market demand function to measure the wholesale price responsiveness. The competition model directly provides price elasticity as a solution of the equilibrium outcome using the market power indices. The market demand represents all wholesale customers who pay hourly changing electricity prices called the hourly Ontario energy prices (HOEP) p_h. They include large industrial customers, regional electricity distribution companies, and others (e.g., exporters and dispatchable loads).

In (3) the LI is linearly decreasing in RSI. For any hour we can rewrite firm i's LI as

$$(4) \quad LI_{i,h} \equiv \frac{p_h - c'_{ih}}{p_h} + \frac{smc_h - smc_h}{p_h} = \frac{p_h - smc_h}{p_h} + \frac{smc_h - c'_{ih}}{p_h},$$

where smc_h denotes the system marginal cost which is equal to the marginal cost of the last dispatched generator or the marginal generator clearing the market. By definition, the system market power index can be measured by the system/market LI, which equals $LI_{smc,h} = (p_h - smc_h)/p_h$ at hour h. From the expression (4) $LI_{i,h} > LI_{smc,h}$ if $smc_h > c'_{ih}$, and $LI_{i,h} = LI_{smc,h}$

[30] The profit maximization behavior is assumed for OPG although it is a crown-corporation. We do not observe its actual objective function directly, but the findings in Aydemir and Genc (2014) provide a proof of profit maximization behavior for OPG. Therefore, like other researchers (e.g., Green and Newbery, 1992) we assume that all power producers strive to maximize profits non-cooperatively. The companies like OPG transfer their "excess profits" to the treasury after netting the "fair rate of returns" for future investments.

[31] Nevertheless, we note that the equation in (3) should be cautiously treated and underlying assumptions should be justified before (3) is utilized to measure market power and/or estimate price elasticity. As pointed out by a referee, when the supply elasticity of competitors matters, as in the SFE framework, the price elasticity of demand estimation based on (3) should be carefully interpreted. The applicability of this approach for other electricity markets needs further investigation.

if $smc_h = c'_{ih}$.[32] That is, a firm's LI is always higher than the system LI unless this firm is the marginal producer.

Using the definition of $LI_{smc,h}$ we rewrite the relationship between $LI_{i,h}$ and $LI_{smc,h}$ as

$$\frac{1-r_{ih}}{\varepsilon_h} = LI_{i,h} = LI_{smc,h} + \frac{smc_h - c'_{ih}}{p_h}.$$

The first equality is due to the profit maximization problem and the second stems from the definitions of $LI_{i,h}$ and $LI_{smc,h}$. We then rearrange the terms to obtain

$$(5) \qquad LI_{smc,h} = \frac{1}{\varepsilon_h} - \frac{smc_h - c_{ih}}{p_h} - \frac{r_{ih}}{\varepsilon_h}$$

which indicates the theoretical relationship between the system market power index and firm i's residual supply index. Using the data on $L_{smc,h}$ and r_{ih} we intend to run the regression

$$(6) \qquad LI_{smc,h} = \alpha + \beta r_{ih} + e_h \,,$$

where e_h is an error term.

Note that we essentially run the same regression as in the report by London Economics, but with temperature as an instrument, to show importance of the endogeneity issue and how OLS results will differ from GMM estimation with the instrument.

London Economics (2007) provides a detailed market power analysis using the LI and RSI for several European electricity markets.[33] Without justifying whether the expression (3) is valid for the European market power firms, they run regression (6) with OLS assumption to test the

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[32] Note that by definition $smc_h \geq c_{ih}$.

[33] Contrary to London Economics (2007) which focuses on a few firms in a given country, we carefully compute the marginal costs of every generator in the system employing flexible marginal cost formulations. Also, London Economics computes and uses the RSI values in regression (6) for several firms in a market (4 largest firms in Germany and the UK, 2 largest firms in Netherlands, etc). But this may not be a feasible exercise without justifying whether the equilibrium conditions for (3) (e.g., measuring the level of asymmetry in the market and checking whether production constraints are binding or not) are satisfied. Therefore, their regression estimations may be unreliable.
Also, different than London Economics, we focus on the policy implications of our findings and project market prices using our elasticity predictions to be able to assess the likely impacts of some supply scenarios stemming from transmission capacity expansions.

relationship between these indices (see also Arnedillo, 2011 for a critique of London Economics methodology and findings).[34] However, we argue that their regressions are biased and inconsistent due to the endogeneity issue between the LI and the RSI. This is because their error term in (6) will be correlated with the RSI, as both are functions of the price. Therefore, the RSI should not be directly used as a right hand side variable. We find an independent variable (an observable demand shock) that is instrumented for the RSI. Since the RSI is a function of demand that changes with respect to weather conditions, we propose temperature as an instrument, which is simple yet effective variable as we show below. The choice of temperature[35] helps us overcome the endogeneity issue and we use it in the GMM estimation procedure to obtain robust coefficients for the regressions incorporating the indices.

The data also exhibits heteroscedasticity and serial auto correlations. For example, in the sample ACF plots we observe that the RSI exhibits strong seasonal pattern and the LI has a weak positive first-lag correlation and quickly vanishing serial correlations. After splitting data into four seasons, we still find seasonality and the persistency of the RSI which is the strongest in winter followed by summer. Also, the RSI shows slightly faster decreasing serial correlations in fall than in spring. When we plot the sample ACF for RSI data in winters, we observe some seasonality in off-peak hours but almost no cyclical patterns in peak hours. In other seasons we also observe the same patterns. When we plot the sample ACFs for LI in four seasons, we find that the LI exhibits stronger serial correlations in summer and fall peak hours. Consequently, the data analyses indicate that the LI and RSI have short period memories, although the RSI exhibits seasonality. However, the GMM estimation procedure together with appropriate instrumental variable and variance-covariance matrix addresses these issues and provides reliable coefficient and standard error estimations.

To tackle the endogeneity issue and verify that temperature is a valid instrument, we do two tests. First, we calculate the hourly (smc-c')/p, the second term in expression (5), for the entire sample. In this formulation smc is the marginal cost of the marginal generator clearing the market, p is the market clearing price (HOEP), and c' is the OPG's marginal cost of the last

[34] Arnedillo (2011) mainly argues about the flaws in the RSI calculations, the markup estimations, and the regression specifications in London Economics (2007).
[35] Temperature is an exogenous shock to demand and impacts market outcomes.

dispatched generator. Then we calculate the correlation between (smc-c')/p and temperature. [36] The results are as follows: the correlation coefficient is -0.02978 in 2006, it is equal to -0.01663 in 2007, it is 0.01292 in 2008, and -0.00182 in 2009. Due to near zero correlation coefficients, we conclude that temperature is orthogonal to (smc-c')/p. That is, the error term in (6) is independent of the instrumental variable. In theoretical prediction (5) the first two terms correspond to the error term in regression (6) in which we have added an intercept term. Second, we show that temperature does not influence the LI beyond the influence of the RSI. After we run OLS between the RSI and temperature, we obtain the residuals, and then measure the correlation between the residuals and the LI. We find that the residual term is almost perpendicular to the LI, because the correlation coefficient between the LI and the residual term is -0.03516 for the entire sample (2006-2009). This test has intended to explore the correlation between the instrument and the dependent variable once the influence of the RSI has been accounted for.[37] In other words, it explores the validation of the instrument and makes sure that temperature is perpendicular to the error term in (6). Consequently, the results of these two tests justify the orthogonality condition required for a valid instrument.

As we instrument temperature for the RSI, we measure the sample correlation and find that the correlation is significant with p-value of Pearson's correlation test close to zero. Specifically, in 2007 summer (including all hours of June, July and August) and winter (covering all hours of January, February and March) correlations are -0.226 and 0.451, respectively. In 2008, it is -0.589 in summer and -0.432 in winter. This indicates that the temperature[38] is an important instrumental variable for representing the RSI. To compare the model outcomes we report both OLS and GMM estimates.

We observe large differences between OLS and the GMM estimations, because i) the regressor (The RSI) is correlated with the error (the unobserved supply shocks) in OLS; ii) the temperature impacts RSI through demand (high correlation figures are reported, and the findings in the literature suggest that temperature is one of the determinants of demand), but not the other

[36] This method is suggested by an anonymous referee.
[37] This procedure is in the spirit of Hausman (1978) test for endogeneity.
[38] We use hourly dew point temperature in Celsius obtained by the Environment Canada. It is more accurate temperature measure than a simple air temperature as it takes into account of humidity. We apply the city of Toronto temperature as a representative temperature in Ontario province, as the largest portion of population dwells in Toronto and in its neighborhood (where the big industries are located).

variables (such as capacities) in the RSI formula; iii) temperature does not impact the LI directly (temperature is orthogonal to LI); iv) the endogeneity issue appears to be important as the instrumental variable has a significant impact after all.

Table 3 presents the estimation results for the model in (6) using OPG's RSI and the system LI for various time intervals in 2007. We mainly focus on the most important peak seasons and their peak and off-peak hours to differentiate consumption behavior across time. As expected peak seasons and peak hours are associated with high demands, high productions, high temperatures (low in winter), and high prices in a year as clearly observed in Table 1, it becomes important to distinguish price responsiveness of wholesale customers across these time periods. In all regressions peak seasons are summers and winters, and peak hours correspond to 7am-7pm weekdays, and the off-peak times incorporate the remaining hours including weekends and holidays for all years.

In Table 3 we report the regression results for all hours and subsamples covering peak hours only, off-peak hours only, summer and winter hours, and their peak and off-peak hours in 2007. We obtain different price responsiveness as consumption profiles change depending on the time of the day and the season of the year related to weather and production conditions.[39]

< Insert Table 3>

The results in Table 3 demonstrate that almost all regression coefficients are highly significant mostly with p values less than 0.01. At the 5% level, the RSI coefficients are significantly different from zero for all time intervals except the peak hours of 2007 by the GMM estimation method. In these regressions standard errors are calculated using HAC variance-covariance.[40] Comparing the OLS to the GMM estimates indicates that the magnitudes of coefficients, their

[39] As pointed out by a referee, the marginal costs are probably underestimated without the ramping and switching costs, especially during hours of higher ramping. Higher costs should decrease the observed mark-ups, which should result in lower coefficient ($\hat{\beta}$) of the RSI. Since the elasticity is equal to the inverse of ($\hat{\beta}$), the elasticities reported in the paper are probably just a bit underestimated without those costs.

[40] For all GMM regressions we use the Stata command "ivregress GMM" along with the option "wmatrix(hac nw opt)", where HAC lags and WMat Lags are chosen by the Newey-West method and the HAC VCE uses Bartlett kernel with the optimum lags. In all OLS estimations we use the option "vce(hc3)" to correct the standard errors.

significance levels, and hence the elasticity estimates can be very different from each other. Also, the Table indicates that temperature is an appropriate explanatory variable in estimating the RSI as we obtain significant RSI coefficients. Moreover, the sign of the RSI coefficient $\hat{\beta}$ is always negative for all time intervals in all regressions, confirming the theoretical prediction in (5) and implying that as the RSI increases (that is firm's market power reduces) the price-cost markup goes down (that is market becomes more competitive). Therefore, we can conclude that the RSI is a useful measure of market power and can be used to explain the variation in the system LI.

The slope term $\hat{\beta}$ in Table 3 is in the range of [-48.6, -7.5]: the lowest is obtained during the summer off-peak times and the highest is observed in all hours of 2007. The economic implication of this outcome is that as the inverse of this slope gives rise to the price elasticity of demand estimation, we can conclude that the wholesale customers' demand response to price changes is the lowest in summer off-peak hours with elasticity -0.0206, which is smaller (in absolute value) than the summer peak-hours elasticity of -0.0544. In this year the overall price elasticity for all hours is -0.133. Moreover we observe that the price responsiveness is higher in peak seasons/hours than in off-peak seasons/hours.[41] This result is expected as higher consumptions occur in peak times. In Table 7 we report the elasticity estimates in that we see a clear upward trend from (all/peak/off-peak) summer hours to the corresponding winter hours. Comparing elasticity magnitudes over the peak seasons indicates that the consumer price responsiveness is lower in summer than in winter for all time intervals (peak, off-peak, and all). This result may occur due to a substitution effect. For example, when the weather is cold in winter some of the consumers facing high electricity prices can switch to the substitutes of electricity such as wood/natural gas/fuel-oil fired heaters for space heating. In the summer time, however, when the weather is too hot there are no alternatives to air conditioning. We also observe that peak time price elasticity is higher than the off-peak time price elasticity for all seasons. As the peak hour wholesale prices are higher than off-peak prices some large industrial customers may react to those high prices and shift their productions to the off-peak hours to benefit from low prices (and sometimes they face negative prices during midnight).

[41] We have also performed GMM regression estimations for off-peak seasons (fall and spring), but for the sake of brevity we do not report the results. We obtain this pattern throughout all study periods in all years.

Note that in Table 3 (and in other tables that follow) we observe how elasticities change over time. To our knowledge, researchers (e.g., see Borenstein and Bushnell, 1999, and Aydemir and Genc, 2014, and the references therein) in general fix the price elasticity by either using a constant elasticity demand function or assuming an invariable elasticity in affine demand functions. However, our findings suggest that the price elasticity is not constant, at least in the electricity context, and shows great variance over the hours/seasons/years and hence we argue that it is more appropriate to apply variable elasticities in the economic models involving simulations and/or calibrations to obtain practical market predictions.

We also test for the expression (6) whether the parameters α and β are statistically different from each other. We theoretically expect them to be different, therefore our null hypothesis and the alternative will be

(7) $H_0: \alpha = \beta$ and $H_1: \alpha \neq \beta$.

In Table 3 we find that the coefficient of the RSI is higher in absolute value than the intercept term and the hypothesis testing confirms that the magnitudes of these terms are indeed statistically different from each other.

Next we examine the interplay between the market power indices to quantify the wholesale demand response to hourly price movements in 2008 using the GMM estimation method. Similar to the regression results in 2007, in all regressions reported in Table 4 the coefficients are significant (except the regression encompassing all peak hours of 2008) at the 1% level and the intercept terms are always less than the slopes (in absolute value). We also validate the theoretical negative relationship between the LI and RSI in all regressions: the coefficients of the estimated RSI are negative.

< Insert Table 4>

The RSI coefficients in Table 4 are in between [-98.3, -18.1] implying that the elasticity estimates are in the interval of [-0.055, -0.010], which are also reported in Table 7. Comparing winter hours to summer hours in 2008 indicates that wholesale consumers' price responsiveness is higher in winter than in summer for all sub-periods of these seasons. This is the same result we find in 2007. We also estimate lower price elasticities in 2008 than in 2007 for the entire samples (all hours) and sub-samples (peak/off-peak hours and peak/off-peak seasons). This finding may be explained by using the definition of price elasticity: the consumption quantities are higher in 2008 than in 2007 for each study period but the market prices corresponding to those periods are on average near each other in both years, as it can be seen in Table 1.

To sum up, we find that price elasticity of demand is inelastic but the wholesale customers show different price responsiveness over the hours of the day and seasons of year. The small price elasticity figures mainly stem from the low number of wholesale customers who can adjust their consumptions with respect the variations in the HOEP. Among the wholesale customers the distribution companies (who deliver electricity to end-users such as households and small businesses at the regulated price) are not able to respond to the prices, but at certain degree industrial customers, exporters, and dispatchable loads[42] are. In this case a natural question arises: why do these wholesale customers barely respond to high prices? The reasons we offer are as follows: *a*) there are large fixes costs of industrial operations associated with turning on/off the production units, hence while they are running it may become infeasible to cease the production as a response to high prices; *b*) the large industrial firms' labor force is generally on shift basis, and in the real time workers cannot be shifted to another time slot while they are working; *c*) production process is continuous and harder to shift to other hours due to the commitments in the output deliveries; *d*) exporters have commitments to deliver a predetermined amount of power (as exports get scheduled two hours before wholesale market clears) to the neighboring jurisdictions, and their commitments prevent them to effectively respond to high prices; *e*) weather conditions may hinder dispatchable loads to reduce their consumptions due to, for instance, a lack of alternative energy resources at a given time. However, adjustments in the operational and managerial decisions such as timings of productions and logistics, planning of labor shift schedules and employee vacation entitlements, and substitution over the production technologies can be achieved for longer time horizons such as weeks, months, or years. Due to

[42] A dispatchable load receives instructions from the system operator regarding how much to reduce its consumption in the case of market price exceeding certain levels. One clear benefit of being the dispatchable load is that it can participate in the operating reserve market and receive stand-by payments. See the role of dispatchable loads in the Ontario market at http://www.ieso.ca/imoweb/marketsAndPrograms/disp_loads.asp

these flexibilities in the longer horizon, high price responsiveness is expected in the seasonal or year round elasticities. Indeed, this is what we obtain in our estimations in Tables 3 and 4.

6. Extensions

In the previous section we have performed all regressions by deleting the obvious outliers in the data where out of about nine-thousand observations there were about twenty near zero or zero market prices that lead to the LI values either too big or undefined. We will take into account of those extreme LI values and then estimate the price elasticity. To deal with the zero prices, we converted them to arbitrarily small positive numbers. We do not exhibit the all regression tables here for the sake of brevity[43], but we report the range of elasticities we obtain using the instrumental variable GMM estimation technique. Specifically, we find that the price elasticities range in [-0.146, -0.020]; the lowest is observed in the summer and the highest is obtained when all hours of 2007 is considered. This is the range closer to the interval of [-0.133, -0.0206] we obtained when the extreme LI points were omitted in the regressions reported in Table 3. Essentially, the main difference occurs in obtaining the upper bound of price elasticity estimation. Using all data points in 2008 we find that the price elasticities are in the interval of [-0.059, -0.015], while with the omitted extreme LI points we find the range of elasticities in [-0.055, -0.010], as reported in Table 4. Consequently, our elasticity estimations are robust to inclusion of abnormal data points in the study periods.

In subsection 6.2 we also extend the analysis to cover two more years and perform robustness check to investigate whether our elasticity estimates would be valid in the extended years (2006 and 2009) during which certain events, such as severe weather conditions, the collapse of natural gas prices and the global economic crisis, occurred.

6.1 Robustness Check Using Alternative Marginal Cost Formulation

In what follows, we consider a different approach to compute the LI. Specifically, as the marginal supplier is a natural gas-fired generator during the study period we will use natural gas spot prices for computing the system market power index. To investigate whether our elasticity

[43] They are available upon request from the author.

estimates are robust we will compare elasticity estimates in Section 5 to the ones obtained through LI computations based on the Henry Hub natural gas spot prices.

Thus far we have employed the marginal cost formulation in expression (2) to compute the marginal costs of all generators in the system and hence obtained the hourly LI values. Indeed these marginal costs are representing the average variable costs of productions because we use the financial data on the total amount of money spent for each fuel type; therefore we intrinsically assumed that the average variable cost equals the marginal cost. In this section we will relax this assumption and directly use fuel prices as a proxy to the marginal costs. Because the marginal production technology is the natural-gas fired generator(s) for all hours of years 2007-2008, we can use the Henry Hub natural gas spot prices as an opportunity cost of burning fuel. The Henry Hub prices are reference prices and the major firms with the natural gas fired generators in the North America are concerned with or subject to these prices. In Canada there are two natural gas markets which are Intra-Alberta and Dawn Hub. However, only Henry Hub and Dawn Hub prices are relevant for the Ontario power producers. The Dawn Hub is located in Ontario and is the smallest of all as it is a secondary market. However, large volume natural gas buyers such as OPG are subject to the Henry Hub prices which are always less than the Dawn Hub prices. Historically, the Intra-Alberta prices are the lowest but Alberta's natural gas is mainly sold to the US markets. When analyzing the Henry Hub prices we find that the correlation coefficient between daily Henry Hub natural gas prices and Ontario wholesale electricity prices are 0.15 and 0.09 in the years 2007-8, resp. Also, the OLS regressions between daily power prices and natural gas prices are statistically significant.

Once we collect the daily Henry Hub spot prices, we convert them into the hourly prices by assuming that the daily price is uniform across hours of the day. Originally natural gas prices are in \$/MMBtu, and using the marginal generators' heat rates and a conversion rate (from GJ to MMBtu) we transform the natural gas prices into \$/MWh to make it the same unit with electricity. Using these hourly prices we calculate the system LI and run the GMM regressions from the system LI to the OPG's RSI in 2007 and 2008 during which natural gas prices were higher than the previous and subsequent years.

< Insert Table 5>

In Table 5 we report the results of OLS and GMM regressions for 2007 using the Henry Hub natural gas spot prices. All OLS regression coefficients are biased, significant, and different from the GMM results. Comparing price elasticity estimates in Tables 3 and 5 shows that the elasticity figures are similar in nature whether we use Henry Hub prices or actual dollar amounts spent for fuel in the LI calculations. The elasticity estimates in winter, winter peak, and winter off-peak periods in 2007 are all significant at 1% level and are close to each other and around -0.107. The summer price elasticities show small discrepancies in magnitude and are in the interval of -0.039 and -0.016. Moreover, the elasticities in summer are always lower than the ones in winter periods.

In Table 6 we present the regression results for 2008. The price elasticities fall into the interval (-0.051, -0.006) with the lowest one observed in the summer off-peak time and the highest occurred in winter peak time. A comparison of the elasticity estimates in Tables 4 and 6 displays some similar price response characteristics. For example, the winter elasticities are in the range of (-0.051, -0.0156) when the average variable fuel prices are used in the LI computations (in Table 4), and it is in between (-0.051, -0.0150) when the Henry Hub prices are directly used (in Table 6). The summer elasticity figures present some minor differences across the tables. However, when we compare the elasticity intervals in both tables, we observe that they are in the similar range. Therefore, we conclude that our elasticity estimates in Tables 3 and 4 are robust to the choice of marginal cost formulation and one can simply use the natural gas spot prices directly in computing the LI, if the natural gas generators are the marginal technologies at all times, as is the case in the Ontario market. This, on the other hand, confirms that our marginal cost formulation in (2) would be very useful in case the marginal production technologies alter over the hours and their fuel prices are not readily available.

In Table 7 we summarize the price elasticity estimates for wholesale demand using both marginal cost formulations, based on the actual fuel spending in formula (2) and the opportunity cost of the marginal generator, in years 2007-2008. We find that a) demand responses to price changes show variations over times of days/seasons/years; b) price elasticities are negative, small, significant, and consistent with the findings in the literature; c) it is important to disaggregate the data into seasons and sub-periods of those seasons (peak, off-peak) to correctly pinpoint and differentiate the customers' price responses; d) using different system marginal cost formulations do not change the results qualitatively and quantitatively (i.e., elasticity estimates are about the same order of magnitude), and indeed during some seasons (e.g., winter 2008) and their sub-periods the elasticity estimates are almost identical. These findings have some economic and policy implications. First, as the wholesale customers show different price responsiveness during different periods of time regulators or policy makers may design dynamic market rules and/or dynamic pricing methods so as to increase welfare gain. For example, it is clear from Table 9 that summer, summer peak, and summer-off peak price elasticities are the lowest. Therefore, regulators may choose lower price cap in summer than in winter. Second, simulation-based or market modeling papers in the literature (that we mentioned earlier) assumes a constant elasticity. From this paper we learn that customers' behavior change over time and therefore fixing the price elasticities may result in imprecise market outcome predictions.

< Insert Tables 6 and 7>

6.2 Extending Time Periods: Measuring Price Elasticities in 2006 and 2009

To test whether the range of our price elasticity estimates would be valid for other years we consider one year before (when extreme weather conditions occurred and natural gas prices started to increase before they hit the record levels in 2007-08) and one year after (when the natural gas prices collapsed in connection with the economic crisis and new gas field discoveries, including shale gas).

First we estimate price elasticities in the periods of 2009, during which the global economic crisis has affected almost all countries, including Canada. In this year average Henry Hub natural gas daily spot price dropped to \$3.94/MMBtu from \$8.86 in 2008 and \$6.97 in 2007. We run the OLS and GMM regressions and find that the RSI coefficients are all negative and significant with the OLS procedure and mostly insignificant with the GMM method. However, only during the peak hours of winter 2009, the price elasticity estimate of the GMM is significant and equals -0.049 which is smaller (in absolute value) than the elasticity of -0.051 in 2008, which is smaller than the elasticity of -0.087 in 2007. In other periods of 2009, the relationship between the market power indices is weak. We argue that this structural break between the market power indices mainly happened due to the economic crisis along with the new wind generation investments and productions, which led to anomalies on the market outcomes. First, the market clearing prices (HOEP) happened to be negative for 351 hours (or 4% of time) in 2009. These negative prices indeed disturb the definition of the LI as a measure of market power. Because, with the negative prices the LI values take positive numbers, which in turn suggests market power even though the prices are non-positive and electricity producers actually pay to the customers to sell electricity at these negative market prices. Therefore, the computed LI values with the negative prices distort the interplay between the LI and the RSI and lead to some insignificant relations between them. To resolve this issue, we will closely examine the peak seasons and their sub-periods of 2009 by deleting the outliers (i.e., negative prices) and then will show that the coefficients of the RSI values are in fact significant and negative, and the elasticity estimates are in the usual range. Second, we also observe that there are several periods during which spot prices are "very low" and in between [0, 1), which cause very high values for the LI because the mark-up is divided by a smaller number. Those low price levels also distort the LI values. Third, while due to the economic crisis electricity consumption decreased (the average quantity demanded went down about 10% from 2008 to 2009), the available production capacities increased in 2009 by 5% from a year earlier level, mainly due to the new generation investments and green technology capacity additions. This caused higher than usual RSI values for all firms, including OPG. Consequently, the distorted LI values together with the structural changes in the market led to the insignificant relations between the market power indices in many sub-periods of 2009.

In what follows we show that the usual relations between the market power indices are reinstated when the periods of negative prices and the periods of "very low" prices are excluded from the regressions. In Table 8 we report the GMM results with and without those outliers during the winter and summer periods. Note that the negative prices mostly occur during the off-peak periods, and by including them to the regressions we obtained insignificant RSI coefficients as reported on the last columns of Table 7. However, when we run the GMM regressions without the negative prices, for example during the winter off-peak periods (deleted 66 negative and very low price periods out of 1414 observations), we find that the RSI coefficient is -20.74 with the HAC standard error 6.92, which implies that the RSI coefficient is significant at 1% level. This translates to the price elasticity of -0.048 in 2009 winter off-peak. During the summer off-peak period, we observe both negative prices and very low prices in the interval of [0, 1), and when we delete the data observations encompassing those price levels (which occurred 85 hours out of

1436 hours) we obtain that the coefficient of RSI is significant at the 2% level with the coefficient of -56.05 and the HAC standard error of 23.94. This implies the GMM price elasticity estimate of -0.0177 during the summer off-peak hours of 2009. Consequently, comparing Tables 4 and 8 indicates that the price elasticities are higher during the economic crisis in 2009 than ones in previous year for all seasons and their sub-periods (except winter off-peak times where elasticity figures are about the same in both years).

< Insert Table 8>

Next we examine the relationship between the market power indices in 2006 during which North America has experienced extreme weather events (mesoscale convective systems, severe thunderstorms, deadly heat waves, and hence large power outages) according to the National Climatic Data Center's Climate Extremes Index[44]. Year 2006 was the second most extreme year after the weather conditions observed in 1998. In Table 9 we present the OLS and GMM price elasticity estimates during the summer and winter seasons of 2006 without deleting the negative prices and small price levels. Similar to the results in 2007-2008, the OLS estimates are significant, but different than the GMM estimates. Specifically, the RSI coefficients are significant for summer and winter seasons and during their off-peak periods. The significant RSI coefficients are in the interval of [-37.58, -5.67] by the GMM method, which translates into the price elasticity of [-0.027, -0.176]: the highest price responsiveness found during all hours of winter, and the lowest price elasticity predicted during all hours of summer in 2006. That is elasticity figures are smaller in summer than in winter hours. This is the same result we obtained for 2007 and 2008. Also, the predicted interval of price elasticities in 2006 is very close the elasticity estimates ranged [-0.021, -0.133] in 2007. When elasticity intervals are compared for all years we conclude that price elasticities slightly decreased over the years covering 2006-2008. For the sake of brevity, we do not report the GMM estimates when negative and small price periods are discarded from the whole sample in 2006. However, due to the reasons mentioned in the analysis of 2009, we would clearly expect improved RSI coefficients in terms of magnitudes and significance levels when those extreme observations in 2006 were excluded.

< Insert Table 9>

7. An Application: Using the RSI and LI to Project Market Prices

[44] http://www.ncdc.noaa.gov/extremes/cei/

In this section we will show that these indices can easily be used to project market prices with respect to changing market supply conditions. As an example, we will examine the impact of three counterfactual supply scenarios facilitating expansions in the interconnection capacity and hence causing more trade activities between the adjacent power markets. Specifically, we will project market prices in the case of increase in imports (coming from New York, Michigan, Minnesota, Manitoba, and Quebec markets). In these supply scenarios we will consider actual import levels increased by 10%, 25% and 50%, respectively, during the first 24 hours of winter (January 1th) 2008.[45] These scenarios are reasonable because i) transmission investments and hence the volume of trade have been expanding since the opening of the Ontario wholesale market; ii) the percentage import increases corresponds to small increments in the total supply; for example, 25% import increase covers about 2% of the market demand during the highest demand hours.

We will first estimate the change in the system Lerner Index resulting from a change in imports, and then back out the implied price from the LI for each hour. Specifically, we do the following for each import scenario (*x*=0.1, 0.25, 0.5):

i) run the GMM regression in expression (6) with the existing hourly RSI, LI, and temperature values to estimate the coefficients $\alpha_1, \ \beta_1$;

ii) for a given import scenario x compute the corresponding hourly RSI $r_{opg,h} = (K_h + (1+x)\, I_h - k_{opg,h})/N_h$, where K_h is the total available capacity in the system, $k_{opg,h}$ is the OPG's total available capacity, I_h is the total actual imports, and N_h is the load quantity at hour h ;

iii) run OLS from $r_{opg,h}$ to temperature and compute the estimated hourly residual supply index $\hat{r}_{\ opg,h}$;

iv) compute the predicted prices using the formula $\hat{p}_h = \frac{smc_h}{1-(\alpha_1+\beta_1\hat{r}_{\ opg,h})}$, $h = 1,2, \ldots, T$ implied from the expression (6).

We present the price projections under these supply scenarios along with the actual market prices in Figure 1, where the curve Invest_10% represents the projected prices when transmission

[45] This time period is arbitrarily chosen. One can choose any time interval to do price projections for a given supply scenario.

investment leads to 10% increase in imports, the curve Invest_25% displays the market price predictions when imports are increased by 25%, and the curve Invest_50% depicts prices when imports are increased by 50% from their current levels on January 1, 2008.[46]

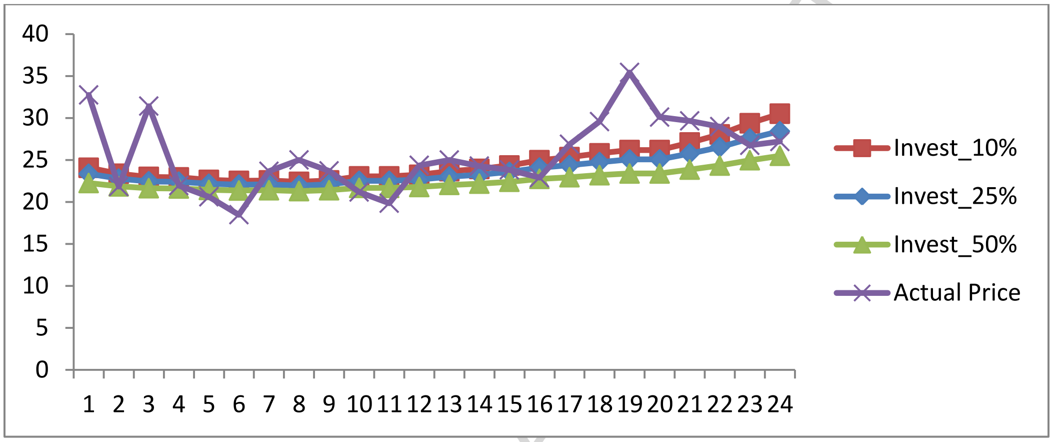

Figure 1: Actual and projected market prices during the first 24 hours of 2008. X-axis hours; Y-axis wholesale prices in $/MWh.

The Figure 1 shows that the average wholesale market prices go down as a result of increased import activities stemming from the transmission capacity expansions. The average prices during these hours are 25.64, 24.60, 23.77, and 22.51 dollars per MWh for the actual market, and the markets with the increased imports x=0.1, 0.25, 0.5, respectively. As expected, the percentage increase in imports causes prices to go down monotonically. This is due to the fact that imports are part of market supply and increased supply reduces the residual demand for OPG, and hence its market power. Also observe that the price volatilities decrease in imports.

8. Discussion and Relation to the Broader Literature

Electricity demand response models were surveyed earlier by Taylor (1975) and most recently by Heshmati (2013). They mainly investigates price elasticities for residential customers. The price elasticity analysis for the industrial or commercial sector is rare principally due to the lack of data availability, nonlinear rate structures, and little potential to consumption reductions. The papers surveyed in this literature formulate demand as some functions of energy prices, income,

[46] When we closely examine the imports activities in the hourly data set of 2007-8 we observe that during the high demand periods both local productions and imports increase to meet the demand. Hence examining the outcomes of increased imports on the market prices is interesting and a valid exercise.

time dependent dummy variables and appliance usages, and then provide elasticity estimates of some reduced form econometric models using time series, panel or cross-section data. They note that these demand models mainly suffer from nonlinearity, endogeneity and simultaneity issues. They report a wide range of price elasticity estimates between 0 to -2 depending on methodology, location, and data type (usually long-run price elasticity is three to four times larger than short-run elasticity).

Different than other studies we focus on real-time aggregate market demand response to hourly spot price movements. We use a competition model to derive the structural interplay between the market power indices through which we estimate price elasticities. There are several advantages of using this approach. First, our methodology can also be used to study price elasticities in other electricity markets, because i) Cournot models are well accepted in modeling electricity markets; ii) electricity markets offer rich and transparent time-series data sets, which can entail calculations of the market power indices RSI and LI. Second, as opposed to the literature we are able to measure demand response to price changes without assuming a specific demand function. Third, we use a simple and robust estimation procedure (GMM) in which an instrumental variable such as temperature data is readily available. In estimation process we take into account of time-dependent factors impacting demand so as to determine demand responses at different times (peak time, off-peak time, seasons, and years).

Note that since all wholesale customers in our study are subject to the same wholesale price (HOEP), we do not differentiate customer types as utilities, distribution companies or industrial buyers. However, the magnitudes of demand responses across the group of buyers can probably be different. Another important feature of this paper is the Cournot assumption and how we derive the market power indices from the largest firm's first order conditions. As shown in Aydemir and Genc (2014), the Cournot assumptions well describe production behavior of firms in the Ontario market. Also in this market, the largest firm captures about 60% of the market share in almost all hours in the study period and the other firms operate near their available capacities. This evidence helps us calculate the RSI accurately.

We begin with crude oil industry which has relations with electricity production process. While the literature for oil market analyses is vast, we will review Cooper (2003) which we believe has an extensive coverage for providing price elasticity estimates in oil industry. Using yearly data

Cooper analyzes price elasticity of demand for crude oil for 23 countries and estimates a log-linear equation (per capita crude oil consumption as a function of real price of crude oil and real GDP per capita) to measure short- and long-run price elasticities of demand for crude oil in 23 countries, mostly in the OECD. He finds that short-run elasticities fall in the interval of -0.026 to -0.109. Also, long-run price elasticities for the G7 countries range from -0.18 to -0.45, which is almost within the bounds of -0.2 to -0.6 estimated by the US Federal Energy Office. First, notice that our short-run elasticity estimates are near the estimates of Cooper. Second, we argue that if the oil production industry would be modeled by a quantity competition model (indeed several papers, e.g., Salant, 1976), and Breton and Zaccour, 1991, use Cournot framework to analyze competition in oil and gas industries) then our approach would be used to estimate price elasticity for oil. One could assume that the OPEC is the largest oil supplier as it supplies about 40% of the production, and calculate daily/weekly/monthly/yearly RSI for OPEC easily, noting that Cooper used yearly data only. Computing the LI would be easier as market price and marginal costs are transparent in the oil industry. After obtaining the market power indices, one can run 2SLS or GMM regressions (where temperature still could be used as an instrumental variable) to estimate demand responses to oil price movements.

Related to the crude oil demand analyses, there are a number of studies investigating demand for automobile fuel. Graham and Glaister (2002) provide up-to-date survey of demand for automobile fuel and report motorists' response to the fuel price changes. They highlight the orders of magnitude of the income, and short- and long-run price elasticities for fuel demand. They report that the short-run price elasticities range from -0.2 to -0.5, and the long-run price elasticities fall in the interval [-0.23, -1.35] in the OECD countries. We first note that there is a high correlation between gasoline and crude oil prices, and there is a high degree of vertical integration between oil productions, distributions, and retail businesses. We argue that the RSI calculations can be performed for all retail suppliers. Also, the LI can be calculated for the market and each supplier. Based on the RSI and the LI relations, price elasticity of demand for gasoline can be calculated. However, the following question arises: is Cournot competition appropriate for describing the competition between the gasoline producers/retailers? A recent OECD report (2013) on competition in road fuel indicates that Cournot competition describes the market behavior in some OECD countries. Therefore, we suggest that our methodology could also be used in demand for gasoline context.

9. Conclusions

Demand for electricity has been growing and this growth can be met directly by generation investments or indirectly by market integrations via transmission investments, and/or demand reductions. If the consumers face regulated tariffs then they will respond little to changes in price movements in the wholesale market. If they are directly exposed to wholesale prices or some versions of dynamic prices then they respond to prices and adjust their consumptions accordingly. In this paper we focus on the wholesale customers and analyze their demand responsiveness to hourly changing wholesale spot prices. We find that our price elasticity estimates are quantitatively closer to ones in the literature although our modeling framework is different and based on a competition model.

In this research, we structurally develop a tractable and useful approach to estimate price elasticity of demand using an extensive high frequency data in a wholesale electricity market. The model uses a Cournot competition framework to model the behavior of wholesale electricity producers then applies an econometric approach to identify the relationship between the market power measures of Lerner Index and Residual Supply Index to estimate price elasticity of wholesale demand. This approach is appealing and easier than its counterparts, which need to use more variables and data points to specify reduced-form demand functions or structurally specify demand and/or supply curves, which could be a daunting task in electricity context. For instance, as opposed to these alternative approaches, we do not need to specify the functional forms of demand and/or supply curves. The literature generally assumes linear or log-linear curves, which could be viewed as restrictive. In our approach demand curve has the regular properties (differentiable and downward sloping). Also there is no need to specify the market supply curve as we assume a Cournot behavior for the power producers, which is more reasonable then a fully competitive structure due to the existence of market power in the wholesale power markets.

We test the inverse relationship between the LI and RSI using the generators' production characteristics, costs, outputs, and capacities along with the Ontario market data including wholesale prices and demand. We use a robust econometric approach and find that this negative relationship is empirically supported for all data sets. We demonstrate how elasticities vary over time and across the peak times and seasons. Even though there is some variation over the periods, our hourly wholesale elasticity estimates are negative, significant and small, and it is in the interval of [-0.013, -0.133] during 2007-2008. Moreover, we illustrate how these market power measures could be used for policy purposes: to determine firms with potential market powers and project market prices with respect to changing supply conditions. Although we have examined supply scenarios involving import increases made possible by the interconnection investments, it is easy to extend the number of supply scenarios to examine their likely impacts on the market outcomes. To name a few, these supply scenarios could include outages in generation sites, power delivery failures in transmission system, or change in the number of firms due to entries or exits, or capacity investments.

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Table 1: Summary statistics of average prices, quantities, trade and temperature data (standard deviation in parenthesis) in 2007-2008. TCap refers to the total available production capacity in which we use actual wind production as available capacity. Price is reflecting the hourly Ontario energy price (HOEP). Price= $/MWh; Temp= Celsius; TCap= MW; Demand, Production, Import, Export = MWh.

	Price	Temp	TCap	Demand	Production	Imp	Exp
2007							
all hours	47.8	4.2	24,669	18,778	17,819	822	1,403
	(24.7)	(10.6)	(1,615)	(2,551)	(2,398)	(516)	(536)
winter	52.6	-7.1	25,329	19,820	18,980	703	1,307
	(23.5)	(7.7)	(1,343)	(2,245)	(2,187)	(465)	(541)
summer	47.3	14.7	25,806	19,161	18,286	713	1,504
	(27.2)	(4.4)	(1,019)	(2,830)	(2,569)	(444)	(520)
2008							
all hours	48.8	4.6	25,955	19,453	18,022	1,288	2,527
	(29.8)	(10.1)	(1,841)	(2,600)	(2,406)	(778)	(896)
winter	49.7	-5.7	25,987	20,570	19,152	1,303	2,473
	(26.1)	(6.5)	(1,346)	(2,216)	(1,996)	(622)	(685)
summer	53.5	15.9	27,421	20,143	18,540	1,448	2,951
	(37.7)	(3.4)	(1,533)	(2,976)	(2,688)	(902)	(922)

Table 3: OLS and GMM regression results for the relationship between LI and RSI in 2007. *i*=OPG. We estimate the expression (5) using hourly 2007 data. n is the number of observations. In the GMM estimation temperature is instrumented for RSI.

Model ($LI_{smc} \sim RSI_i$)

	OLS Estimation			**GMM Estimation**		
2007	Constant1	RSI	R^2	Constant2	RSI	n
All hours	6.156***	-15.302***	0.273	2.557*	-7.521**	8740
	(.205)	(.471)		(1.557)	(3.346)	
Peak hours	2.049***	-5.325***	0.169	-0.080	-0.369	3028
	(0.095)	(0.224)		(1.906)	(4.420)	
Off-peak hours	6.388***	-15.986***	0.233	3.670**	-10.321***	5712
	(0.255)	(0.572)		(1.633)	(3.378)	
Winter	3.568***	-9.544***	0.299	5.145***	-13.203***	2157

	(.331)	(.798)		(.804)	(1.890)	
Winter peak	2.117***	-5.648***	0.201	4.507***	-11.522***	766
	(.167)	(.421)		(.828)	(2.067)	
Winter off-peak	3.472***	-9.495***	0.257	5.395***	-13.823***	1391
	(.433)	(1.019)		(.869)	(1.985)	
Summer	6.776***	-16.838***	0.310	13.860***	-32.213***	2202
	(.383)	(.889)		(3.535)	(7.775)	
Summer peak	4.005***	-9.993***	0.345	7.554***	-18.386***	764
	(.198)	(.473)		(1.952)	(4.653)	
Summer off-peak	6.631***	-16.672***	0.236	21.994**	-48.623**	1438
	(.472)	(1.064)		(9.762)	(20.447)	

Notes: 1) Standard errors are in parentheses. 2) Significance levels are ***p<0.01; ** p<0.05; *p<0.1. 3) All regressions were run using Stata, and all standard errors were corrected for serial correlations with sufficient lags. GMM weight matrix formed by HAC Bartlett with optimum lags.

Table 4: OLS and GMM regression results for the relationship between LI and RSI in 2008. *i*=OPG. We estimate the expression (5) using hourly 2008 data. n is the number of observations. In the GMM estimation temperature is instrumented for RSI.

Model ($LI_{smc} \sim RSI_i$)

	OLS Estimation			**GMM Estimation**		
2008	Constant1	RSI	R^2	Constant2	RSI	n
All hours	8.968***	-21.039***	0.122	7.457***	-18.107***	8764
	(.415)	(.876)		(1.929)	(3.749)	
Peak hours	1.495***	-4.008***	0.054	-2.351	4.023	3036
	(0.230)	(0.504)		(1.640)	(3.405)	
Off-peak hours	8.944***	-21.672***	0.100	10.043***	-23.727***	5728
	(.415)	(.876)		(1.929)	(3.749)	
Winter	9.203***	-23.639***	0.150	21.097***	-50.848***	2181
	(1.065)	(2.540)		(5.641)	(13.016)	
Winter peak	3.314***	-8.993***	0.205	7.737***	-19.550***	768
	(.271)	(.662)		(2.309)	(5.593)	
Winter off-peak	10.034***	-25.801***	0.134	27.235***	-64.281***	1413
	(1.375)	(3.227)		(8.997)	(20.318)	

Summer	18.920***	-40.068***	0.225	37.292***	-74.887***	2200
	(1.287)	(2.597)		(9.740)	(18.446)	
Summer peak	5.411***	-11.763***	0.140	12.912***	-27.321***	756
	(.937)	(2.008)		(4.339)	(9.010)	
Summer off-peak	20.398***	-42.880***	0.184	50.980***	-98.333***	1444
	(1.715)	(3.306)		(15.710)	(28.413)	

Table 5: OLS and GMM regression results of the relation between LI and RSI in 2007 using Henry Hub hourly natural gas prices. *i*=OPG. Regressing Lerner Index on Residual Supply Index: Using OPG's RSI and system market power index LI_{smc}, which is generated by using the hourly Henry Hub natural gas spot prices.

Model ($LI_{HH} \sim RSI_i$)

	OLS Estimation			GMM Estimation		
2007	Constant1	RSI	R^2	Constant2	RSI	n
All hours	6.283***	-16.099***	0.233	-0.361	-1.733	8740
	(0.233)	(0.535)		(2.130)	(4.575)	
Peak hours	1.703***	-4.889***	0.106	-3.523	7.280	3015
	(0.116)	(0.273)		(3.215)	(7.456)	
Off-peak hours	6.404***	-16.609***	0.194	1.147	-5.652	5725
	(0.289)	(0.648)		(2.124)	(4.395)	
Winter	2.428***	-7.385***	0.201	3.289***	-9.382***	2159
	(0.296)	(0.710)		(0.809)	(1.887)	
Winter peak	0.923***	-3.135***	0.058	2.993***	-8.225***	767
	(0.165)	(0.407)		(0.789)	(1.971)	
Winter off-peak	2.044***	-6.796***	0.157	3.386***	-9.819***	1392
	(0.389)	(0.911)		(0.868)	(1.965)	
Summer	7.304***	-18.365***	0.275	18.103***	-41.798***	2201
	(0.460)	(1.067)		(4.879)	(10.720)	
Summer peak	4.538***	-11.494***	0.313	10.470***	-25.515***	762
	(0.294)	(0.704)		(2.657)	(6.343)	
Summer off-peak	7.073***	-18.039***	0.205	29.204**	-64.060**	1439
	(0.570)	(1.282)		(13.374)	(28.005)	

Table 6: OLS and GMM regression results of the relation between LI and RSI in 2008 using Henry Hub hourly natural gas prices. *i*=OPG. Regressing Lerner Index on Residual Supply Index: Using OPG's RSI and system market power index LI_{smc}, which is generated by using the hourly Henry Hub natural gas spot prices.

Model (LI_{HH} ~ RSI_i)

	OLS Estimation			GMM Estimation		
2008	Constant1	RSI	R^2	Constant2	RSI	n
All hours	10.443***	-25.485***	0.091	14.788***	-33.915***	8764
	(0.535)	(1.142)		(3.518)	(6.821)	
Peak hours	0.866***	-3.392***	0.020	1.226	-4.145	3024
	(0.270)	(0.599)		(1.878)	(3.956)	
Off-peak hours	10.067***	-25.782***	0.073	18.376***	-41.335***	5740
	(0.633)	(1.322)		(4.566)	(8.540)	
Winter	9.336***	-24.795***	0.114	20.837***	-51.102***	2182
	(1.387)	(3.304)		(5.863)	(13.512)	
Winter peak	3.420***	-9.894***	0.287	7.481***	-19.543***	756
	(0.238)	(0.569)		(2.202)	(5.264)	
Winter off-peak	10.224***	-27.209***	0.100	27.700***	-66.406***	1426
	(1.844)	(4.328)		(9.653)	(21.808)	
Summer	26.910***	-58.383***	0.194	61.743***	-124.395***	2200
	(1.964)	(3.971)		(18.285)	(34.671)	
Summer peak	7.719***	-17.888***	0.097	20.693**	-44.797***	756
	(1.775)	(3.808)		(8.507)	(17.732)	
Summer off-peak	28.343***	-61.297***	0.154	85.001***	-164.027***	1444
	(2.589)	(4.999)		(29.390)	(53.239)	

Table 7: Price Elasticity of demand estimates in 2007 and 2008 using system marginal costs calculated based on formula in (2), and Henry Hub (HH) fuel prices.

	e_{smc}		e_{HH}	
	2007	2008	2007	2008
All hours	-0.133**	-0.055***	-0.578	-0.029***
Peak hours	-2.7	0.248	0.137	-0.241
Off-peak hours	-0.031***	-0.042***	-0.177	-0.024***
Winter	-0.076***	-0.020***	-0.107***	-0.020***
Winter peak	-0.087***	-0.051***	-0.122***	-0.051***
Winter off-peak	-0.072***	-0.016***	-0.102***	-0.015***
Summer	-0.031***	-0.013***	-0.024***	-0.008***
Summer peak	-0.054***	-0.020***	-0.039***	-0.022***
Summer off-peak	-0.021***	-0.037***	-0.016***	-0.006***

Table 8: The GMM regression results for the relationship between LI and RSI in 2009 with and without the negative prices and "low prices in (0, 1) . *i*=OPG. We estimate the expression (5) using hourly 2009 data. n is the number of observations. In the GMM estimation temperature is instrumented for RSI.

	Model ($LI_{smc} \sim RSI_i$)					
	GMM without – price & (0, 1)			**GMM with all price levels**		
2009	Constant1	RSI	n	Constant2	RSI	n
Winter	13.409***	-22.707***	2091	8.527	-14.445	2157
	(4.826)	(8.164)		(5.335)	(9.029)	
Winter peak	11.411*	-20.395*	743	11.411*	-20.395*	743
	(6.331)	(11.421)		(6.331)	(11.421)	
Winter off-peak	12.599***	-20.740***	1348	7.314	-12.132	1414
	(4.206)	(6.918)		(6.167)	(10.093)	
Summer	26.877***	-43.941***	2115	59.367	-94.043	2204
	(10.911)	(16.686)		(46.035)	(70.578)	
Summer peak	13.003	-23.193	764	55.054	-95.376	768
	(9.017)	(15.299)		(38.662)	(65.500)	
Summer off-peak	36.161**	-56.052**	1351	68.689	-103.495	1436
	(16.556)	(23.942)		(61.431)	(89.083)	

Table 9: OLS and GMM regression results for the relationship between LI and RSI in 2006. *i*=OPG. We estimate the expression (5) using hourly 2006 data. n is the number of observations. In the GMM estimation temperature is instrumented for RSI.

Model (LI_{smc} ~ RSI_i)

	OLS Estimation			GMM Estimation		
2006	Constant1	RSI	R^2	Constant2	RSI	n
Winter	1.072***	-2.987***	0.186	2.387	-5.671*	2160
	(0.073)	(0.156)		(1.641)	(3.338)	
Winter peak	-0.205	0.078	0.001	4.069	-9.261	780
	(0.111)	(0.243)		(7.806)	(17.011)	
Winter off-peak	0.881***	-2.752***	0.158	2.229	-5.405**	1380
	(0.089)	(0.185)		(1.353)	(2.664)	
Summer	2.964***	-7.254***	0.347	17.948**	-37.579**	2206
	(0.151)	(0.322)		(8.100)	(16.339)	
Summer peak	0.409**	-1.277***	0.012	-12.067	26.375	778
	(0.174)	(0.389)		(8.481)	(18.866)	
Summer off-peak	2.816***	-7.118***	0.302	11.661**	-24.211***	1428
	(0.192)	(0.394)		(4.712)	(9.100)	

Highlights

• Demand response to hourly price movements is small and statistically significant.

• Price elasticities exhibit large variations over the times of days/seasons.

• Price elasticities during the economic crisis were higher than a year earlier.

• Our approach can be used to estimate elasticities for crude oil and gasoline.