Market Power and Renewables: The Effects of Ownership Transfers*

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Abstract

The introduction of renewable energy sources (RES) in an electricity market changes the shape of the system's supply curve. In a perfectly competitive market, this causes a downward pressure on equilibrium prices called the merit order effect (MoE). However, when introducing or transferring RES assets to firms with market power, effects on inframarginal rents are ambiguous and depend on the share of RES capacity in the firms' portfolios. We quantify this effect empirically in the Ontario electricity market by finding equilibria under different counterfactual scenarios of RES ownership transfers and expansions. First, we identify the effect of market power in isolation by keeping the system's capacity fixed, but we transfer RES capacity from the fringe (competitive) to firms with market power. These transfers yield increases in prices of up to 24% relative to average wholesale prices. Then, in order to measure the interaction of market power with the MoE, we introduce new RES capacity to the system by giving it to different players with varying levels of market power. We find that, following a net expansion of RES capacity of 5% relative to total capacity, wholesale prices decrease by up to 30% in the case of perfect competition. However, if capacity is assigned to the largest firm the decrease in prices is only 7%. These findings suggest that the MoE can be largely mitigated by market power, hence the key importance of the nature of the owner of new capacity when designing uniform incentives for RES adoption.

JEL codes: L13, L94, Q42, Q48

Keywords: Renewable energy sources, market power, merit order effect, wholesale electricity prices.

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1 Introduction

Over the past few years, electricity markets around the world have seen important changes in their energy portfolios as new sources have been introduced (e.g. wind and solar) and others have been retired or penalized through taxes (e.g. non-refurbished nuclear plants and coal plants). These changes continue nowadays as a number of incentives to curb the greenhouse gas emissions associated with the production of electricity have either been put in place (e.g. production subsidies such as feed-in-tariffs (FiT) and mandates such as renewable portfolio standards (RPS)) or in other cases been dismantled.[1] Although some of the consequences of these policies have been studied, little is known about the effects of these mechanisms in the presence of market power and under different market structures.[2]

In this paper we quantify the net result on wholesale electricity prices of two opposite effects: market power and the merit order effect (henceforth MoE). The latter occurs when there is an expansion of the amount of renewable energy sources (RES): in that case, the system's supply curve shifts to the right and its intersection with the demand curve occurs at a (weakly) lower price than before the expansion. However, partial ownership of RES from firms with market power may counteract the MoE. In fact, as we show theoretically, the best response for firms with market power is to reduce production from conventional sources, which has a positive effect on market prices. We find upper bounds of these effects throughout a series of simulations using an equilibrium model for the Ontario electricity market. First, we quantify the market power effect on its own by measuring the effect on market prices when holding the system's capacity constant and changing the ownership structure. Second, we compare this effect to the MoE by expanding net capacity and allowing different firms to hold the additional capacity. By simulating uniform incentives for the adoption of RES across different ownership structures, we show that allowing market participants with high

[1] In Ontario, more than 700 renewable energy contracts that were signed under the Green Energy Act have been terminated since 2018. In the U.S., there is an ongoing discussion on potential amendments to the Clean Power Plan. In Australia, the carbon tax regulation from 2011 was repealed in 2014.

[2] Different tax and subsidy policies in electricity markets have been empirically studied by Borenstein [2012], Fowlie et al. [2016], Gowrisankaran et al. [2016], Knittel et al. [2015], Leslie [2018], Preonas [2017], and Reguant [2018]. Transfers of public services have also been the objective of research to understand the role of market power in the presence of subsidies (see Polyakova and Ryan [2019]).

market power to hold an increasing fraction of RES capacity mitigates the MoE in a way such that wholesale prices do not decrease significantly (about 7% drop in prices, relative to our baseline Cournot simulation). On the other hand, introducing RES through firms that cannot exercise market power would decrease wholesale prices by large amounts (in the order of 30% in the perfectly competitive case). These simulation results demonstrate that the wholesale price savings that final consumers would receive depend crucially on who owns this additional RES capacity, hence the importance of the ownership structure and market power in the design of uniform incentives for RES adoption.

The effect of market power on prices is one of the main takeaways in the theoretical work of Acemoglu et al. [2017] for the case of symmetric firms and symmetric portfolio compositions. In the presence of market power and a more diversified portfolio (provided an initial low share of RES), strategic firms partially internalize the shift of the supply curve caused by the MoE by decreasing output from their conventional generation sources, thus effectively shifting their individual bid curve to the left and causing an upward pressure on prices. Brown and Eckert [2018] expand on this by allowing for asymmetric amounts of RES in the firms' portfolios[3] and Genc and Reynolds [2019] allow for asymmetric strategic firms.[4]

Our paper continues this line of work by providing a simulation-based analysis of the effect from RES ownership transfers and expansions on wholesale electricity prices. RES transfers and expansions arise in current markets due to the different incentives to adopt RES such as RPS and FiTs. Moreover, the long-term existence of such incentives is threatened in several places around the world, implying a risk of even more ownership transfers. One possibility is that payments cease to exist for FiTs and the idle capacity from non-strategic players gets transferred to the strategic players.[5] The effect of these policies on wholesale prices is an open empirical question. To the best of our knowledge, our work is the first to empirically simulate the effects of portfolio changes from RES additions and transfers on the wholesale electricity

[3] However, both firms start with no RES at the moment of the procurement auction.

[4] Their empirical results confirm that prices decrease by approximately 1% when investment for wind capacity quadruples. We discuss further below how we differentiate from their empirical work.

[5] The current debate in Ontario, where our data come from, is the elimination of incentives for the adoption of RES. See https://business.financialpost.com/commodities/energy/boralex-invenergy-ontario-clean-power-projects-hit-by-ford-1 .

market. One of the advantages of our work is that, by using actual market data, we simulate the effects of transferring or introducing RES in the presence of asymmetric firms, and at different levels of correlation between RES output and load. From an economics perspective, our paper also contributes to the literature by confirming some theoretical results on the interaction of diversification and market power in electricity markets. From a regulatory perspective, our results contribute to environmental policy analysis by quantifying hidden or ambiguous price effects from the introduction of large-scale renewable sources into the electricity production mix.

As Fowlie et al. [2016] point out, since the seminal work of Buchanan [1969] regarding the effect of taxes to correct for externalities on market outcomes in the presence of market power, only a small number of empirical studies have quantified these interactions in the context of pollution taxes.[6] We contribute to this strand of the literature by focusing on the impacts on wholesale electricity prices had the market structure changed. Specifically if the ownership distribution were different. Recent examples of changes in the market structure in the electricity sector have taken place in Western Australia (Leslie [2018]), in the U.S., with a series of restructuring cases from utilities into investor-owned companies (Knittel et al. [2015]) and because of the retirement of coal-powered plants (Kim [2019]) or in Denmark, where the company Ørsted changed its portfolio composition from 17% to 80% RES in 2017.[7] Ownership transfers are also observed in electricity markets: for example, the German company RWE acquired E.ON's and innogy's RES assets in 2019 to become the third-largest firm in Europe by RES capacity.[8]

Although the exact impact of expanding RES is most likely market specific, we believe we can extract general qualitative impacts from the study of a particular market. We choose the case of Ontario and its Independent Electricity System Operator (IESO) to answer these questions. This market has a similar structure to other North American markets such as CAISO, PJM, MISO, and NYISO that have been also the object of other market power studies (see for instance Joskow [2019] where it is recognized that the Alberta and Ontario

[6] See for instance Knittel et al. [2015], Leslie [2018], and Preonas [2017].

[7] https://orsted.com/en/Explore/Business-Transformation

[8] https://news.rwe.com/en/brussels-paves-the-way-for-one-of-the-biggest-transactions-in-germanys-indu

electricity markets are similar to those bid-based markets in the U.S.). Some European electricity markets also share large similarities with the Ontario market (wholesale market, nuclear-dominant, with increasing amounts of renewables). Among them, Germany is the closest, Belgium, and the UK are similar as well.

We model the market following the methods developed by Borenstein and Bushnell [1999] and Bushnell et al. [2008], and more recently by Brown and Eckert [2016]. In particular, the first paper introduces an industry marginal cost curve expressed as a step function that can be fully characterized using engineering parameters and fuel prices. Then, they separate producers into two categories: strategic and non-strategic (price-takers) firms. The former have the capacity to influence the hourly equilibrium price because of their importance in the market or because of their atypical cost structure (e.g. low start-up costs); the latter are firms that own very small nameplate capacities or that have long-term contracts with the system operator or with downstream firms (therefore they have negotiated prices much before the spot price is formed). This second category of firms is important to the specific case of Ontario as a large proportion of producers belong to this category. The other two papers refine those estimation techniques by exploring the consequences of forward contracts and the use of different instrumental variables.

The presence of imports and exports in the Ontario system implies that firms face a different demand than just the domestic one. Following Bushnell et al. [2008], we account for this by estimating a net exports supply function and add it to the domestic demand to get the residual demand that firms face. We estimate this model using data from multiple and publicly available sources. We use weather data from the National Oceanic and Atmospheric Administration (NOAA), hourly production, demand and capacity data from the Independent Electricity System Operator (IESO), firm-level aggregate capacities from financial statements and fuel spot prices from public databases. We use actual production data from wind and solar sources and these are the only RES sources we consider.[9]

Expanding on the stylized theoretical Cournot competition models in Acemoglu et al.

[9]There is also a tiny fraction of biomass used in the system, but we shall neglect it. Therefore, throughout the paper, we shall use the terms RES and non-dispatchable sources interchangeably.

[2017], Brown and Eckert [2018], and Genc and Reynolds [2019], we add a competitive fringe to the model, and show that their results also hold in this extended setting. However, we warn that this result holds under strong market assumptions such as symmetry among the firms.[10] This provides a natural motivation for our analysis as only an empirical analysis can shed light on more realistic configurations, otherwise intractable to solve analytically. In particular, we provide a framework to study RES capacity changes regardless of the degree of asymmetry among the competitors.

We estimate a detailed model of the Ontario electricity market to run simulations that consist of finding the new hourly equilibrium prices under different allocations of RES among market participants using the reaction functions estimated from the data. Our results show that, by keeping the total amount of RES constant in the system, transfers of that capacity from the fringe into the strategic firms give place to positive increases in prices of up to 24% relative to average prices and they increase with the amount of RES capacity transferred. These effects are net of the MoE because there are no additions to the system's RES capacity. As the strategic firms' portfolios include higher shares of RES, equilibrium prices increase by greater amounts. In other words, the expansion of the strategic firms' portfolios from adding RES capacity yields to more expensive electricity, contrary to the effects from a simple MoE. Finally, when we add RES capacity to the entire system following current policy guidelines in Canada, the MoE and market power combined yield lower prices relative to the equilibrium outcome with no added RES. We show that there can be a decrease of up to 30% under perfect competition but only around 7% when the largest firm is the owner of the new capacity.

The rest of the paper is structured as follows. In section 2 we describe the institutional framework of the Ontario electricity generation market and the data used to estimate electricity demand and supply functions. In section 3, we present the model and estimate the demand function. In section 4 we present the goodness-of-fit of our model as well as the main results. Using these results, we simulate and discuss different counterfactuals in section 5. We conclude in section 6.

[10] This is also the case in the literature mentioned earlier.

2 Policy Environment and Data

We use data from Ontario to run our simulations because there are three main changes in the Ontario energy policy stage that are common to other electricity markets around the world. First, in December 2016 the government of Ontario ran the last period of applications for FiT incentives, which, even though they do not directly affect large producers, are aligned with the public perception regarding the Global Adjustment fees.[11] [12] Second, the government of Ontario recently introduced legislation to scrap the Green Energy Act arguing that it caused retail electricity prices to increase. And third, a number of market participants and think-tanks support even stronger measures and argue for the cancellation of already-approved FiT contracts and other subsidies.[13] This creates a strong possibility of a reshuffling of assets in which either new entrants or large firms will acquire the assets that undergo financial distress. While these debates happen in Ontario, federal policies and guidelines are still in effect and call for RES capacity expansions in the coming years.

Changes in the firms' portfolios composition are already underway in other markets. As we mention in the introduction, in Denmark and Germany there have been fairly recent and ongoing cases of ownership changes of RES assets. Importantly, in the case of Denmark, the overall market capacity remained unchanged, similarly to our first set of counterfactuals.[14]From a technical point of view, the Danish and German cases are embedded in relatively more complex market structures. In fact, Denmark's market has two zonal prices as a part of the Nord Pool whereas Ontario has only one spot market. Germany also has only one spot price but it has more interconnections with surrounding markets than Ontario. Still, we argue that the similarities in terms of current and future policies, as well as the system's portfolio composition make Ontario a good place to carry on with our analysis.[15]

[11] http://www.ieso.ca/sector-participants/feed-in-tariff-program/overview ,

[12] The Global Adjustment consists of additional fees to end consumers to recover the costs of the FiT subsidies.

[13] https://www.fraserinstitute.org/studies/electricity-reform-in-ontario-getting-power-prices-down

[14] https://aleasoft.com/european-electricity-markets-panorama-nordic-countries/

[15] For further details on the Nord Pool market see Lundin and Tangerås [2019] and the references therein.

2.1 Regulatory framework

Many electricity markets are vertically separated into generation, transmission and distribution segments. In these markets (e.g. MISO, NYISO, PJM, ERCOT, IESO, CAISO)[16], the production effort is undertaken by sets of independent producers of electricity that typically own different plants with different technologies. These producers meet in bidding markets usually overseen by an auctioneer entity, the independent system operator. This operator takes all the firm-specific supply curves and constructs a market supply curve by sorting the bids from lowest to highest cost to the system according to the asking prices, this is known in the industry as the merit order. The operator then finds the intersection between the market supply curve and its forecast for demand, which defines the electricity spot price (for each hour). Further details of the functioning on this type of market, and specifically on the Ontario market, are explained later in the paper. Structural changes in these markets can be stylized as competition models where firms have perfect information on the others' marginal cost curves. This is a reasonable assumption since in most markets electricity producers have to comply with administrative forms that reveal to the public their nameplate capacities for different sources and the firms interact every single hour for long periods of time. Since we are mainly interested in wholesale prices, considerations about prices paid by consumers are beyond the scope of this paper.

2.2 Electricity production

Ontario's production system is quite large as its capacity is almost equal to twice the province's average hourly demand. In fact, throughout our main sample (from 2010 to 2012), the average hourly load is equal to 17,751 MWh, while the average available capacity is equal to 28,432 MW.[17] This capacity is composed of five main sources: nuclear energy (around 56% of total production), hydroelectricity (23% and considered in our model as non-RES,

[16]Midcontinent Independent System Operator (ISO), New York ISO, Pennsylvania New Jersey Maryland Interconnection, Electric Reliability Council of Texas, Independent Electricity System Operator (Ontario), and California ISO, respectively.

[17]In the Appendix we show results for a larger sample and discuss the reasons for our choice to concentrate on the 2010-2012 period.

dispatchable source since it is mostly from dams), natural gas (15%), wind power (2-3%) and finally coal (went from 8% of production in 2010 to 3% in 2012, and was later phased out).

Within this total capacity, it is possible to separate production assets in two groups that differ in how they interact with the markets. The first group, named "regulated" assets, produces electricity under a contract that sets a fixed price for generation. There are different types of contracts that imply a guaranteed price. The main one is the specific contract between the Ontario Electricity Board and two companies: Ontario Power Generation (henceforth OPG) and Bruce Power (henceforth Bruce). This contract is the most important as it impacts nearly 15,000 MW of production capacity on average (more than half of Ontario's total capacity). All of Ontario's nuclear capacity falls into this contract, as well as between 40 and 75% of OPG's hydroelectric capacity. The other two types of contracts are Feed-in-Tariffs (FiT and micro-FiT) for production from renewable sources and financial contracts with the Ontario Electricity Financial Corporation (OEFC). The latter type is quite common in electricity markets and can be described as futures contracts on production. Our methodology assumes that all these contracts have the same properties as vertical contracts as described in Bushnell et al. [2008]. In total, these contracts fix the price for approximately 90% of Ontario's total production. Although the fraction of load that is actually traded through the spot market may seem small, this has important consequences for the rest of the market and it is a common feature in other electricity markets.[18] This has for consequence the well-known effect first studied by Allaz and Vila [1993] regarding the consequences of forward contracts on the spot market: the larger the forward commitments, the more aggressive the pricing positions in the spot market.

The IESO licenses more than a hundred electricity producers in Ontario. These companies can be separated in the same way as in Bushnell et al. [2008], by identifying the main firms (or dominant players) and small firms which act as price-takers in the market. Following Genc [2014] we identify three main players in the Ontario market: OPG, Bruce, and Brookfield. These three players hold 80% of the province's total capacity and satisfy, on average, 92% of the hourly demand. All other firms are considered as price-takers. One particularity to

[18] See for instance Potomac Economics [2008].

notice within the group of dominant firms is that all of them hold regulated assets in their portfolio. Bruce even has its whole production guaranteed under contracts with the OEB. Finally, the supply side is also characterized by Ontario's connections with other Canadian provinces and U.S. states. In fact, Ontario's electricity grid is connected to five other regions: Quebec, Manitoba, New York, Michigan, and Minnesota.

2.3 Data

The data used in this paper come from three main sources: market equilibrium data provided by the IESO, meteorological data from the NOAA and production data from the IESO, individual firms' financial statements and cost reports. Our dataset is in the form of hourly variables spanning from May 1st, 2010 to December 31st, 2012.

2.3.1 Market equilibrium data

The market variables extracted from the IESO datasets are the total load, total quantity demanded in Ontario, net exports from each connected region, market prices and available capacity for each generating unit.[19] A summary of the data is provided in Table 1.

Table 1: Descriptive summary statistics of market equilibrium data in Ontario

Year	Avg. hourly demand*	Avg. market price†	Avg. hourly net exports, by region*					
			MB	MI	MN	NY	QC	Total
2010	17,960	37.83	−70	241	10	282	809	1,272
2011	17,616	30.13	−63	441	15	520	233	1,146
2012	17,749	22.82	−26	766	16	658	−203	1,211

Notes: *: in MWh; †: in CAD/MWh. In the last six columns, positive amounts represent exports from Ontario, negative amounts represent imports. Sample period from May 1st, 2010 to December 31st, 2012. MB = Manitoba, MI = Michigan, MN = Minnesota, NY = New York, QC = Quebec connection lines. Note that the fraction of trading amounts within Canada relative to the sum of the absolute value of volumes traded is non-negligible: 62%, 30%, and 16% in each year respectively and using the average hourly flows. Therefore, Ontario prices are not just the outcome of forces from U.S. markets.

[19] Data was obtained openly through the IESO website. The Generator Output and Capability datasets give generator-level capacities, the Inertie Flows datasets provide information on trade flows and finally, the Ontario and Market Demand datasets provide demand data. For more information: http://www.ieso.ca/Power-Data/Data-Directory

2.3.2 Meteorological data

Meteorological data are needed to estimate the net exports supply function for Ontario. From the methodology described in Bushnell et al. [2008], net exports are linked to two types of variables: prices in Ontario and weather conditions (both local and outside the province). NOAA provides hourly temperatures for many major cities in North America.[20] In order to compute the average temperature of each region, we take the population-weighted average over at least 5 major cities in the specified region. Then, we compute the variables Cooling Degree Days (CDD) and Heating Degree Days (HDD).[21]

2.3.3 Electricity generation data

Following the literature mentioned above, in order to find market equilibria, we need to compute cost functions for the market as well as for main players in the industry. Again, the IESO provides a complete, hourly description of electric generation capacity for each different source. However, this capacity is not linked to the asset's specific owner (and even if it was, contracting between firms and regulators would also be needed to assess exact ownership). Therefore, data on asset capacity for the main firms are extracted from financial statements available online (Brookfield Renewable Partners [2012], Bruce Power [2012], Ontario Power Generation [2012]). The capacity for the set of non-dominant players is simply the difference between market capacity and that of the dominant players. We also retrieve from the financial statements the proportion of regulated assets in each firm's portfolio, these data are displayed in Table 7 in the Appendix.

The second piece of information to characterize the cost functions is the marginal cost (MC) of production, which we construct as follows. For any source j among all potential energy sources in Ontario:

$$\mathrm{MC}_j = \text{Variable O\&M cost}_j + \text{Fuel cost}_j \times \text{Heating rate}_j.$$

[20] Data was obtained openly through the National Centers for Environmental Information (NCEI) website. The Climatic Data OnLine (CDO) provides a complete dataset of hourly observations for temperature in most North American cities. For more information: https://www.ncdc.noaa.gov/cdohtml/info.html

[21] HDD are defined as 0 if the day's mean temperature is greater than 65°F and it is equal to (65°F - day's mean temperature) if the mean is less than 65°F. CDD (cooling degree days) are defined similarly but for temperatures above the day's mean, otherwise it is equal to 0.

Where O&M are the operating and maintenance costs. Additional data sources and details on the computation of these marginal costs are provided in the Appendix.

3 Competition Models and their Estimation

In this section we present the theoretical models used to solve for the market equilibria: a perfect competition model and a Cournot duopoly with a non-strategic fringe. Then we explain the relationship between ownership transfers of renewables from non-strategic firms to strategic firms using a stylized model. Finally, we describe the estimation technique for the market demand.

3.1 Competition models

The literature on the particular modeling of electricity markets shows that, under uncertainty, actual market outcomes will lie between Cournot outcomes and perfect competition outcomes (Klemperer and Meyer [1989]). In particular, we should have that $p^{\mathrm{PC}} < p < p^{\mathrm{C}}$ where p stands for the actual market equilibrium price observed in the data and the other two prices represent the perfect competition and the Cournot outcomes, respectively. Empirical work such as in Bushnell et al. [2008] has shown that this insight holds in actual markets. In this paper, we show that this finding can be verified in Ontario as well and use our model to estimate bounds on counterfactual policies.

3.1.1 Perfect competition

In the perfect competition case, all firms act as price-takers and choose the quantity level from their non-RES capacity to be such that the market price is equal to the marginal cost of electricity generation. In this model, without loss of generality, we merge all firms into one such that there is only one supply curve for the market. Note that this supply function is actually a step function with each step being the total capacity of a single generation source, ordered from the lowest to the highest marginal cost. The main difference with the classical optimization problem is that the quantity of renewables is not a decision variable: RES are non-dispatchable.

To solve the model, we write the problem as a mixed complementarity problem (MiCP or MCP) following Ruiz et al. [2014]. Before setting up the model, we introduce some further notations. $\mathcal{J}$ is the set of conventional sources of electricity (non-RES). Renewables will be denoted by the subscript R. Each source has a capacity constraint denoted by $\bar{K}_j$ for conventional sources, with $j \in \mathcal{J}$, and $\bar{K}_R$ for renewables. Both constraints represent the available capacity at each point in time. $P(\cdot)$ is the aggregate inverse demand function and $C(\cdot)$ is the aggregate cost function. Finally, we denote quantities by q_j for conventional sources and q_R for renewables, with $q_R = \bar{K}_R$ because of the non-dispatchable properties of RES. The perfectly competitive equilibrium is given by the intersection of the demand function and the industry's marginal cost curve, which, together with the following capacity constraints:

$$\begin{aligned} q_j \leq \bar{K}_j : \mu_j \quad & (\text{for each } j \in \mathcal{J}) \\ 0 \leq q_j : \lambda_j \quad & (\text{for each } j \in \mathcal{J}), \end{aligned}$$

where μ_j and λ_j represent the dual variables associated with the constraints, gives the following system of equations:

$$\begin{aligned} C'(Q) - P(Q) + \mu_j - \lambda_j = 0 \\ 0 \leq \bar{K}_j - q_j \perp \mu_j \geq 0 \\ 0 \leq q_j \perp \lambda_j \geq 0. \end{aligned}$$

The first equation is the first-order condition derived from the Lagrangian function and Q represents, here and in the following equations, the total output in the market. The second and third equations are the complementarity conditions derived from the constraints. Note that $\perp$ represents the typical slackness conditions (e.g. $q_j \cdot \lambda_j = 0$). Finally, recall that in the perfect competition case, $P'(Q)$ is set to 0 because of the price-taking assumption. This system is then fed into the PATH solver to get the solution, for each individual period separately. The solver is used through the GAMS API for Python 3.6 following Ferris and Munson [2000].

3.1.2 Cournot competition

Here we model the market as a Cournot duopoly with a competitive (price-taking) fringe. Two firms ($i \in \mathcal{I}$, where $\mathcal{I}$ is the set of firms) compete à la Cournot while another agent, the fringe (f), takes the price as given. We therefore have three agents, each optimizing their profit function over the quantities of conventional electricity.[22]

Again, we use the MCP framework to solve the model. The fringe player is modeled exactly as the whole market in the perfect competition setting, which is why we omit these equations. A complete characterization of the strategic players' problem is as follows. Denote by $\mathcal{J}_i$ the subset of $\mathcal{J}$ that represents the conventional sources which firm i has access to. For each firm $i \in \mathcal{I}$ we solve the following problem:

$$\max_{\{q_{ij}\}_{j\in\mathcal{J}_i}} P\left(\sum_{j\in\mathcal{J}_i} q_{ij} + \sum_{l\in\mathcal{I}} \bar{K}_{lR} + Q_{-i} + Q_f\right) \cdot \left(\sum_{j\in\mathcal{J}_i} q_{ij} + \bar{K}_{iR}\right) - C_i\left(\sum_{j\in\mathcal{J}_i} q_{ij} + \bar{K}_{iR}\right)$$

$$\begin{aligned} \text{s.t. } q_{ij} \le \bar{K}_{ij} : \mu_{ij} &\quad (\text{for each } j \in \mathcal{J}_i, i \in \mathcal{I}) \\ 0 \le q_{ij} : \lambda_{ij} &\quad (\text{for each } j \in \mathcal{J}_i, i \in \mathcal{I}), \end{aligned}$$

where Q_{-i} is the sum of the outputs of the strategic firms that are not i and Q_f is the total production of the fringe (RES and conventional). This problem yields the following set of conditions, for each firm and each hour:

$$\begin{aligned} C_i'\left(\sum_{j\in\mathcal{J}_i} q_{ij} + \bar{K}_{iR}\right) - P'(Q) \cdot \left(\sum_{j\in\mathcal{J}_i} q_{ij} + \bar{K}_{iR}\right) - P(Q) + \mu_{ij} - \lambda_{ij} = 0 \\ 0 \le \bar{K}_{ij} - q_{ij} \perp \mu_{ij} \ge 0 \\ 0 \le q_{ij} \perp \lambda_{ij} \ge 0. \end{aligned}$$

Altogether with the fringe conditions, we obtain a "square" system of equal number of equations and unknowns.

[22] Recall that the RES we consider here are non-dispatchable and that as mentioned earlier, we are interchangeably using these two terms because the proportion of biomass in the system is negligible.

3.2 Ownership transfers

We begin with a stylized Cournot model inspired by that in Acemoglu et al. [2017] and Brown and Eckert [2018] to show the effect of change of ownership of RES on equilibrium prices.

There are two groups of players in the market: the fringe and the strategic firms. The former does not have any influence on the equilibrium price but the latter does. There is a total capacity of RES in the market of $\bar{K}_{\mathrm{R}}$ and this amount is fixed.[23] The fringe's total capacity consists of a fraction $1-\gamma$ of the total RES capacity plus some thermal capacity $\bar{K}_{f,\mathrm{NR}}$. The strategic firms own the remaining fraction of RES. To simplify the notation we assume that there are n symmetric strategic players in the market, each owning an RES capacity $\bar{K}_{i,\mathrm{R}} = \gamma/n \cdot \bar{K}_{\mathrm{R}}$.

Proposition
With the setting described in the previous paragraph and (i) a demand function $P(\cdot)$ such that $P' < 0$ and $P'' \leq 0$ (ii) a total cost function that is additively separable in non-renewable ($C(\cdot)$) and renewable inputs ($C_R(\cdot)$) and (iii) $C' > 0$, $C'_R > 0$, $C'' > 0$, and $C''_R > 0$, then:

- $\frac{\partial q_{i,NR}}{\partial \gamma} < 0$,
- $\frac{\partial q_{f,NR}}{\partial \gamma} > 0$, *and*
- $\frac{\partial P}{\partial \gamma} > 0$.

The proof is in the Appendix. The assumption $P'' < 0$ is only required to guarantee that some differences in the proof can be given a definitive sign but all that is really needed is that the demand is not too convex.[24] The first result in the Proposition shows that, as strategic firms hold more of the total RES capacity, these firms will decrease their production from conventional sources. At the same time, the fringe will expand its conventional output as it loses RES capacity from its portfolio. Overall, these two effects combined put an upward pressure on equilibrium prices.[25]

[23] This is a reasonable assumption for the Ontario market since there is a surplus of total installed capacity. Later in the paper we run counterfactuals where there is a net expansion of the RES capacity in the system.

[24] P can be convex as long as $(P' + P'' \cdot (q_{i,\mathrm{NR}} + \frac{\gamma \bar{K}_{\mathrm{R}}}{n})) < 0$ for each i. See details in the Appendix.

[25] In Acemoglu et al. [2017] there is an amount $(1-\gamma)\bar{K}_{\mathrm{R}}$ of RES capacity owned by the fringe as well. In their Theorem 1 part 2, their comparative statics show that by increasing γ, prices increase. The authors call

The same characterization for the asymmetric case would require specific assumptions on the way RES and conventional capacities are split among the firms. This observation naturally motivates the use of an empirical analysis to answer the question of whether prices would increase when there are RES transfers from the fringe to the strategic firms.

3.3 Demand estimation

As is typical in the literature, we first assume that domestic demand for electricity in Ontario is perfectly price-inelastic, then we add net exports which we estimate as a function of prices in Ontario (as well as meteorological and calendar variables) to get a price-elastic total (or "residual") demand function. Estimating the net exports supply function is therefore crucial to getting a demand function for our model.

In order to estimate the net exports supply function, we need to choose a functional form. Since we observe both positive and negative quantities and positive and negative prices, we cannot use a log-linear form as used in Bushnell et al. [2008] or Brown and Eckert [2016]; instead, we use a simple linear function. We estimate an individual linear net exports supply function for each region $k \in \mathcal{K}$ connected to the Ontario grid.[26] By separating these regions, we can capture different price elasticities corresponding to different trading behaviors with these regional markets.

Following Bushnell et al. [2008], we estimate the net exports supply function as:

$$
\begin{aligned}
Q_{\mathrm{nx},k,t} = \beta_{0,k} + & \beta_{1,k} \cdot p_{\mathrm{ON},t} + \beta_{2,k} \cdot \mathrm{CDD}_{\mathrm{k},t} + \beta_{3,k} \cdot \mathrm{HDD}_{\mathrm{k},t} + \beta_{4,k} \cdot \mathrm{Weekday}_t \\
& + \sum_{y=2011}^{2012} \psi_{y,k} \cdot \mathrm{Year}_y + \sum_{s \in S} \gamma_{s,k} \cdot \mathrm{Season}_s + \sum_{h \in H} \omega_{h,k} \cdot \mathrm{ToD}_h + \varepsilon_{k,t}
\end{aligned} \tag{1}
$$

where the sets S and H are the sets of seasons and periods of the day, respectively. The most important variables are the net exports to region k at time t, denoted by $Q_{\mathrm{nx},k,t}$ and $p_{\mathrm{ON},t}$ is the spot price in Ontario at time t. CDD and HDD are measures correlated with

this a diversification effect, however the change in prices is not only due to a reshuffling of the capacities of the different technologies in the firm's portfolio, but it requires a physical addition of RES and the market power exercised changes as well. This combination of forces makes it impossible to disentangle a pure diversification effect from the market power effect.

[26] See subsection 2.2 and Table 3 for the list of regions.

the difference between the temperature and a threshold (65°F), as explained in section 2.5. The variables Weekday, Year, Season, and ToD (the period of the day) are all categorical variables. Finally, $\{\beta_{.,.}, \psi_{.,.}, \gamma_{.,.}, \omega_{.,.}\}$ are the parameters to be estimated. The dummy variable for ToD is defined following the IESO classification of hours, as presented in Table 2 below.

Table 2: IESO classification of different periods of the day

Name of the period	**Associated hours**
Night off-peak	8.00 p.m. - 6.00 a.m.
Day peak	6.00 a.m. - 8.00 a.m.
Day off-peak	8.00 a.m. - 5.00 p.m.
Night peak	5.00 p.m. - 8.00 p.m.

Notes: We use the same classification as the IESO, which is public information.

The estimation process described above is not complete without the choice of the instruments. In fact, since we are estimating a market equilibrium, it is affected by both supply and demand shocks. In this setting, we are interested in estimating a supply function, meaning we need to find a "demand-shifter"-type of instrument. The literature gives us two possible choices: domestic weather data (Brown and Eckert [2016]) or domestic demand (Bushnell et al. [2008]). These two instruments are valid as they only affect willingness to pay for imports, without having an effect on the connected regions' capacity to produce energy.

Notice that unlike Genc and Reynolds [2019] (henceforth GR), we allow for endogenous imports and exports in the main specifications and use many more hours of data (23,039 hours) than they do since they only concentrate over a few months (less than a full year of data). GR estimate hourly demand parameters by making their linear demand function to pass through the actual (p, q) equilibrium point for a given level of elasticity. In contrast, we estimate a demand function that can take on weather variables and other market conditions and gives the entire schedule of (p, q) points that are consistent with the historical data. This is the function that enters the first-order conditions. Our elasticity is estimated directly from our data as opposed to taking this value from other market studies. The market conditions not only change the location of the (p, q) equilibrium point, but also the slope of the demand curve. Regarding the supply curve, GR use polynomial functions to model the firms' cost curves. We use directly the step functions using the observed available capacity in each hour.[27]

Table 3 presents the main results. For our equilibrium analysis, we choose to use the regressions from the weather-based instruments since they provide higher R^2 by equation than those obtained from the domestic demand-type instrument. However, we also present those results in Table 9 in the Appendix. The implied inverse demand slopes are -0.0238 and -0.0307, respectively, thus by choosing the former we err on using residual demand functions that are relatively more inelastic but only by a very small amount. Each regression projects net exports through a specific connection line on the market price, weather variables and calendar dummies, as shown in Equation 1.

Table 3: Net exports supply function estimation, using weather-type instruments

Implied inverse demand slope: $\beta = -0.0238$

		First stage		Second stage			
	N	F-stat.	Adj. R^2	Wald-χ^2	R^2	p_{ON}	SE
MB	23,015	210***	0.216	5,700***	0.162	0.382***	0.088
MI	23,015	221***	0.222	12,906***	0.340	6.683***	0.889
MN	23,015	211***	0.219	3,069***	0.123	0.116*	0.060
NY	23,015	215***	0.216	4,895***	-	-18.537***	0.832
QC1	23,015	269***	0.219	12,956***	0.100	-25.001***	0.730
QC2	23,015	-	-	11,613***	0.298	-3.864***	0.214
QC3	23,015	-	-	3,355***	0.024	-0.429***	0.027
QC4	23,015	-	-	3,856***	0.119	-0.455***	0.039
QC5	23,015	-	-	8,628***	0.234	-0.553***	0.042
QC6	23,015	205***	0.221	2707***	-	-0.219***	0.014
QC7	23,015	-	-	2,619***	0.104	-0.015***	0.009
QC8	23,015	-	-	11,342***	0.320	-0.108***	0.013

* , ** and *** represent significance at the 10%, 5% and 1% confidence levels respectively.

Notes: MB = Manitoba, MI = Michigan, MN = Minnesota, NY = New York, QCx = Quebec connection lines. QC1-QC5 share the same first stage because we use the same regressors across these connection lines. The estimates $\hat{p}$ used in the second stage are therefore the same for QC1-QC5, only the net exports are changing, hence the different second stage results for each line. The same applies to QC6-QC8, but the first-stage includes additional month fixed effects than QC1-QC5 to allow for a more flexible function.

The last step is to recover the aggregate inverse demand function. First, we write total

[27]GR concentrate on expansions of RES capacity whereas in our case we focus on both effects of reshuffling assets while maintaining overall assets constant and expansions. However, unlike GR we trace out the loci of price effects from multiple levels of expansions and to different players (strategic and non-strategic).

demand as a function of the price-inelastic Ontario demand, plus net exports:

$$Q = \bar{Q}_{\text{ON}} + \sum_{k\in\mathcal{K}} Q_{\text{nx},k},$$

Note that we removed the time index t for clarity. Then, we substitute $Q_{\text{nx},k}$ for its estimated counterpart, by aggregating all variables except price into a state-observation specific constant $\hat{\alpha}_k$ and using $\hat{\beta}_{1,k}$ (the estimated coefficients on price from (1)) as the slope to get:

$$Q = \bar{Q}_{\text{ON}} + \sum_{k\in\mathcal{K}} \left[\hat{\alpha}_k + \hat{\beta}_{1,k} p_{\text{ON}}\right] \Leftrightarrow Q = \bar{Q}_{\text{ON}} + \sum_{k\in\mathcal{K}} \hat{\alpha}_k + \left(\sum_{k\in\mathcal{K}} \hat{\beta}_{1,k}\right) p_{\text{ON}}$$

$$\Leftrightarrow p_{\text{ON}} = \frac{-\bar{Q}_{\text{ON}} - \sum_{k\in\mathcal{K}} \hat{\alpha}_k}{\sum_{k\in\mathcal{K}} \hat{\beta}_{1,k}} + \frac{Q}{\sum_{k\in\mathcal{K}} \hat{\beta}_{1,k}}$$

This aggregate inverse demand function is the one that will be used to solve our model throughout our simulations.

4 Baseline Results

In this section, our goal is to assess the performance of our model by comparing simulated prices against the data. Figure 1 shows the time series of simulated and actual prices for the first 240 hours in our dataset. As expected, our model bounds market prices most of the time.[28] This figure also shows that our model captures some cyclicality across days, although it does not fare as well in terms of intra-day cyclicality. A more complete display of how well our model is able to bound market prices is available on Figure 11 in the Appendix. That figure shows the estimated densities of simulated and market prices in a way that supports our claim that observed prices lie between our two competition models. Having a higher goodness-of-fit is challenging. It has been documented that forecasting prices in the IESO is a difficult task, even when using machine learning methods, see for instance Rodriguez and Anders [2004] and Zareipour et al. [2006]. Since our interest is in examining changes in the

[28] Table 8 in the Appendix shows the frequencies of times when the simulated prices bound the observed prices.

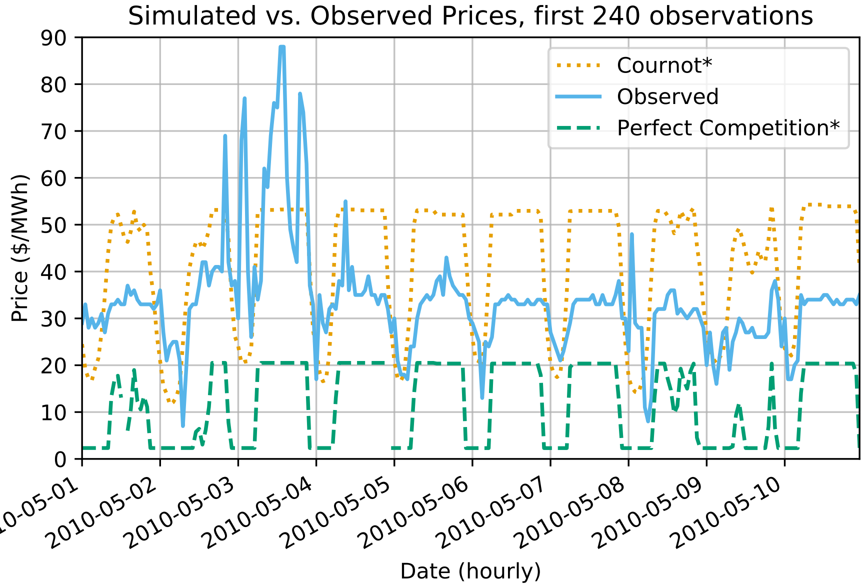
market configuration, we need a structural model that provides a causal interpretation of the parameters that allows us to run counterfactuals.[29]

There are at least three potential explanations for the lack of further accuracy in our simulated prices. First, it is possible that our marginal costs contain measurement error because we are imputing fuel prices from databases that may not reflect accurately the prices faced by the firms. In particular, we use an "average technology" for natural gas and coal, meaning that their marginal cost is the same, regardless of the type of the generator. We use this simplification because the IESO dataset does not provide information on the generator type. Second, it is possible that firms are not fully using their market power. Hortaçsu et al. [2017] document how not all electricity generator companies in ERCOT bid at the optimal levels. Rather, there is a bell-shaped distribution of the levels of sophistication of firms on the way they bid. Not all bid at the profit-maximizing levels. And third, the market solves a problem in which each firm submits step functions with several optimization constraints that do not only include capacity bounds but also transmission and congestion constraints. Since it is unrealistic to attempt to solve such a problem here, we solve for a simplified version and this is why we cannot replicate the exact values of the observed prices but rather we aim to bound these observed prices between two structural models. Nonetheless, we are satisfied by the fact that our model captures two of the most important features of the market: the cyclicality and the responses to demand shocks.

In Figure 2, we plot local constant regressions of simulated and actual prices against a measure of (global) demand intensity, which is defined as the fraction of load relative to the maximum observed load in the sample. The figure shows that actual prices are bounded by the simulated prices more frequently when demand intensity is roughly between 0.55 and 0.85. Outside that interval, actual prices tend to be higher than our Cournot predictions. The cloud of observed prices indicates, however, that most of the observations lie in the interval

[29] We use available capacity given by the IESO, which is an ex-post measure, as the output of the RES. This means that firms do not have that exact information at the time of making the decision, although it is very quick (about one hour after production) and firms must be able to form good forecasts after a while in the market. Therefore, we are implicitly assuming that firms are able to predict their available capacity and the uncertainty about this number is absent from the maximization problem. This way we can concentrate only on the market power effects and not on the ability of the firms to form forecasts.

Figure 1: Simulated vs actual prices



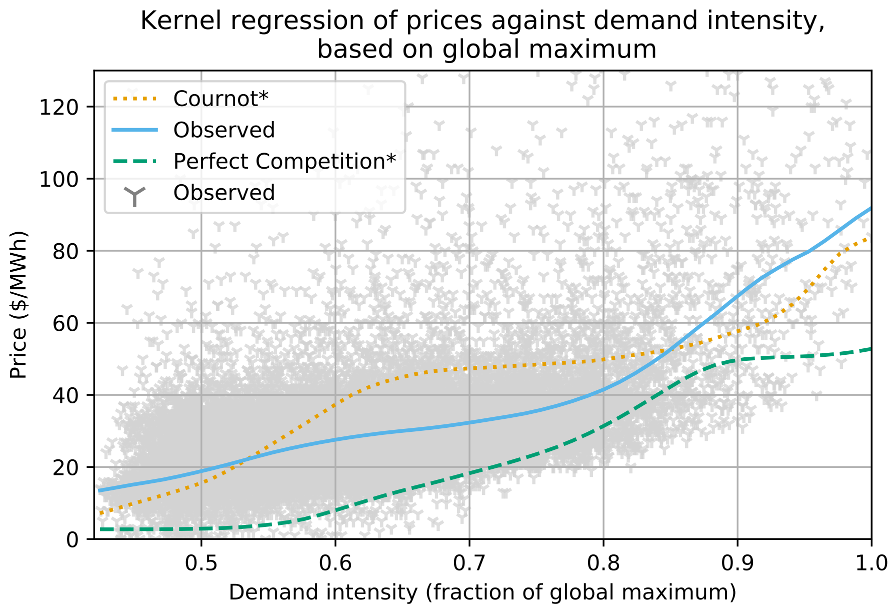
Notes: Time series from the perfect competition and the Cournot simulated prices (simulated prices indicated with the symbol *) and the time series of actual prices for the first part of the sample period.

where our predicted prices bound the market prices. In the Appendix, Figure 12 shows a similar kernel regression but using the demand density conditional on each combination of year-season-peak type. There, actual prices are farther from the Cournot outcomes even at high levels of demand intensity. This observation shows that firms' behavior is more closely represented by a Cournot model when there is high demand, not when demand is only relatively high.

In summary, we have a model that allows us to bound actual prices with a degree of accuracy: the Cournot simulated prices are the upper bound and the perfect competition simulated prices the lower bound.[30] In addition, our model allows us to examine changes in the market structure. As usual, there is a trade-off between goodness-of-fit and the capacity to be able to change our model to reflect changes in the firms' environment. In our series of counterfactuals we simulate both types of prices to conclude that the true outcomes will

[30]Throughout the paper we assume that there is no collusion and therefore our upper bounds are those from the Cournot model. Although there may be tacit collusion sometimes, we are unaware of a collusion case in this market during the time period we used for our estimates and simulations.

Figure 2: Kernel regression on demand intensity



Notes: Horizontal axis represents the fraction of load with respect to the maximum observed load. Gray dots are actual observed prices. The symbol * represents simulated prices.

most likely lie in between those bounds. In some counterfactuals we concentrate on the upper bound only since the perfect competition environment is equivalent to assigning the RES to the fringe.

5 The Effects of RES Ownership Transfers and Expansions

For each time observation, we take a uniform random draw in $[0, 1]$ that represents the fraction of capacity to transfer from the fringe into the two strategic firms. Then, this capacity is split evenly among the two firms.[31] Each time observation is a different combination of state variables and outcomes, by using a uniform random distribution over these observations we attempt to cover as many cases as possible of combinations of factors that affect the outcomes

[31] This limits the exercise of market power over the RES capacity since the two strategic firms are not of equal size. However, we do not want to impose further assumptions on how this capacity is allocated. Later in the paper we present counterfactuals where only one of the firms receives the extra RES capacity.

of our policy experiments.[32]

Even though our equilibrium model takes into account the different states of nature when predicting demand, we present our results segmented by clusters: the load of each day is assigned to one of four groups that classify demand into four different daily profiles. This step does not change the estimation method, it is simply a way to present the results. We use the k-means clustering algorithm, which is an unsupervised machine learning method (see Hastie et al. [2009]). We define an observation as the vector of the 24 demand observations in one day plus an entry equal to the maximum of those 24 numbers.[33] We use different seeds to check for the robustness of the clustering to initial conditions and we settle at four clusters since this is enough to facilitate the visualization of our results. Figure 10 in the Appendix shows that our choice of four clusters does a good job for most hours of the day at separating our sample into non-overlapping distributions of hourly load when comparing the mass of the distribution within one standard deviation from the mean.

5.1 Isolating the effect of market power

Figure 3 presents the results from transferring RES assets from the fringe to the strategic players as described above. We show the mean effect on prices (counterfactual minus baseline) by quantile of the distribution of ownership transfers. The price differences are obtained using the prices from the new equilibrium after the ownership transfer and the equilibrium using our model before any ownership transfers. The figure shows the results by cluster. The impact on prices is positive or zero for all percentages of ownership transferred which means that counterfactual prices are *higher* than the ones in the initial equilibrium. Relative to the average price over the sample period, the maximum price change (6$/MWh) is equivalent to a 20% increase. These price changes are more pronounced as the amount of RES transferred is larger. This can seem at first in contradiction with the merit order effect of suppressing prices. However no additional RES have been added to the system since there has only been

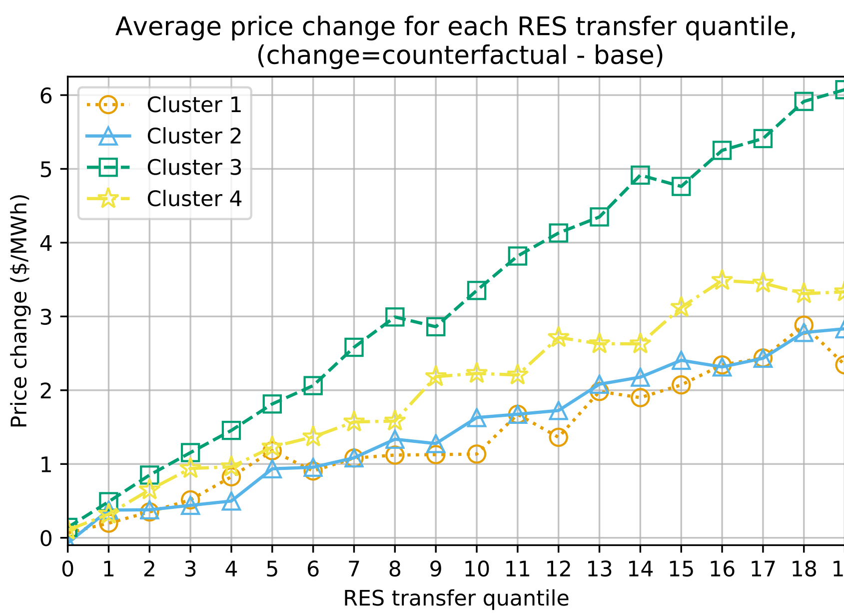
[32]Location may also play a role but we assume that the expansion of RES occurs uniformly over the same locations that existed in 2012. Policies to incentivize the adoption of RES may cause a misallocation of RES if those incentives are not a function of the geographical location (see for example Lamp and Samano [2019].)

[33]Callaway et al. [2018] use this technique to split their data.

a transfer of RES from one type of owner to another. Therefore, the supply curve has not been shifted to the right but upwards due to the exercise of market power over the RES that before was owned by the fringe. Figure 3 also shows that prices almost monotonically increase with the quantile of ownership change for all demand clusters.

Interestingly, for the highest demand level (cluster 1), price changes are the smallest. The opposite occurs with the cluster of the lowest demand level (cluster 3). This phenomenon shows that when the individual marginal cost function gets shifted to the right, its intersection with a high demand curve still occurs at a point not too far from the profitable price level. However, when the new marginal cost curve intersects a low demand curve, it is possible that the new intersection occurs at a very low marginal cost and the firm internalizes this by exercising a significant amount of market power.

Figure 3: Price differences by quantiles of ownership changes



Notes: Mean effect on prices (counterfactual minus baseline) by quantile of the distribution of ownership transfers. The price differences are obtained using the prices from the new equilibrium after the ownership transfer and the equilibrium using our model before any ownership transfers. The figure shows the results by clusters.

5.1.1 The effects from changes in the portfolio composition

Next, we look into the price effects as a function of the concentration degree of the firm's portfolio. We choose to measure the degree of the portfolio composition by using the Herfindahl index (HHI), which is defined as the sum of the squares of the shares of each of the different technologies in the portfolio. The higher the HHI, the more concentrated the portfolio. By construction, the HHI is bounded between 0 and 1. During our sample period, the portfolio concentrations are as in the first line of Table 4. Observe that Brookfield does not have a very diversified portfolio.

Figure 4 and Figure 5 show the price differences (counterfactual minus baseline) relative to the change in the firm's portfolio HHI, which we define as $HHI_{\text{counterfactual}} - HHI_{\text{baseline}}$. Note that this difference in portfolio concentration is negative because by adding RES into the firms' portfolios at very low initial levels of RES shares, $HHI_{\text{counterfactual}}$ decreases relative to the initial amount of concentration. For those random draws close to zero, the amount of RES transfer is negligible, and therefore, the HHI does not change, which in turn implies that counterfactual prices should be almost identical to the actual prices. This can be seen at the right of the two figures. Then, as the amount of RES increases, the difference in HHI becomes more negative (a lower quantile in the distribution of HHI changes) and this is associated with higher equilibrium prices for all the clusters and for both firms. This is a direct confirmation that even though the firms are receiving a low marginal cost production technology, they internalize the shift to the right of the supply curve by decreasing output from thermal sources to counteract the MoE. Notice also that similarly to the results on the amount of ownership transfers, the cluster that contains the highest (lowest) demand levels is

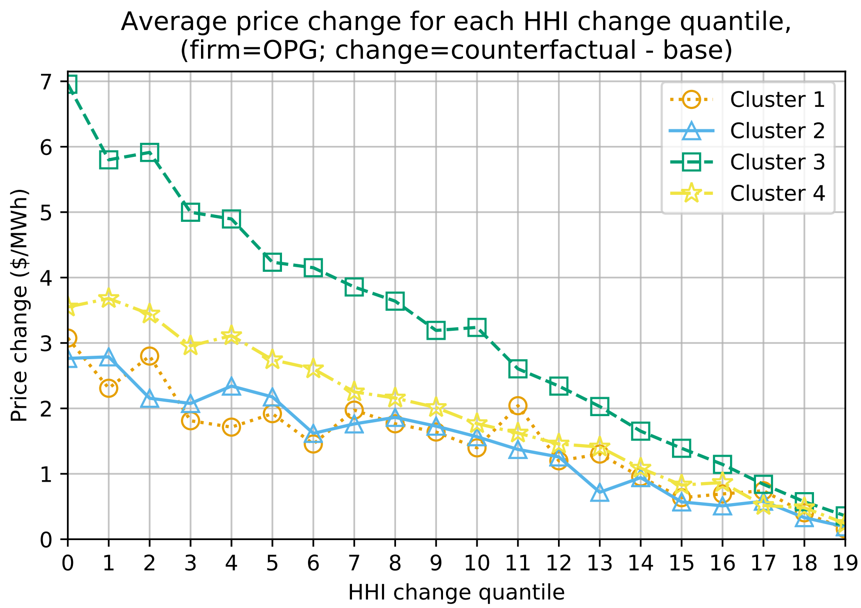
Table 4: Average portfolio concentrations in Ontario

	Market	Fringe	OPG	Brookfield
HHI before adding RES	0.2661	0.3655	0.3529	0.9033
HHI after adding RES	0.2471	0.3294	0.2817	0.5431
Total Capacity (MW)	28,432	19,414	9,462	758

Notes: The Herfindahl index (HHI) is defined as the sum of the squares of the shares of each of the different technologies in the portfolio. Values close to zero represent highly diversified portfolios. Values close to 1 represent highly concentrated portfolios.

the least (most) affected. Relative to the average prices in the sample period, the maximum observed price increase for OPG is about 24% and for Brookfield 23%.

Figure 4: Quantiles of price differences and HHI: OPG



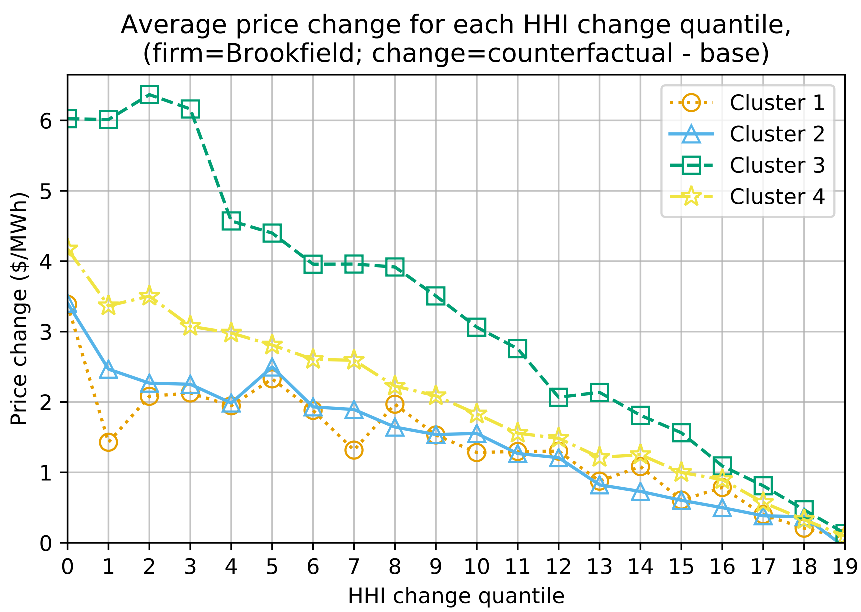
Notes: Horizontal axis represents the change in the degree of portfolio concentration for OPG. Quantiles to the left correspond to negative changes in the HHI. This difference is negative because by adding RES into the firms' portfolios, the new HHI *decreases* (portfolio is more diversified given the initial low levels of RES) relative to the initial amount of concentration.

5.2 The effects from a net expansion in RES

Despite the fact that the Ontario system has an excess of capacity installed relative to average load, the IESO projects an addition of 5,000 MW of wind capacity into the system by the end of 2022.[34] Inspired by this projection, we run a series of counterfactuals in which we add that same amount of wind capacity to the system taking into account that demand grows at an annual rate of 1%.[35] Therefore demand is blown up by the factor $1.01^{(2022-2012)}$. Following studies of the Ontario market, we use a capacity factor for wind of 30%, which gives an

[34] IESO [2017].
[35] Government of Canada https://www.nrcan.gc.ca/energy/electricity-infrastructure/about-electricity/7359

Figure 5: Quantiles of price differences and HHI: Brookfield



Notes: Horizontal axis represents the change in the degree of portfolio concentration for Brookfield. Quantiles to the left correspond to negative changes in the HHI. This difference is negative because by adding RES into the firms' portfolios, the new HHI *decreases* (portfolio is more diversified given the initial low levels of RES) relative to the initial amount of concentration.

effective capacity of 1,500 MW.[36] We leave the rest of the capacity fixed at the 2012 levels. This is plausible since during that period of time, the system went through a coal phase-out program that ended in 2014 and a few additions of other thermal capacity.[37]

The expansion of RES requires an increase of the thermal capacity to comply with the IESO reliability requirements.[38] These requirements are largely based on those established by the North American Electric Reliability Council (NERC) and the Northeast Power Coordinating Council (NPCC). According to the IESO, this requirement translates into operating reserves equivalent to the system's first and half of its second largest generation units' capacities. Notice that this requirement does not take into account the intermittency from RES and therefore, the operating reserves do not change with this increase in wind capacity.[39] In our data, the average proportion of unused capacity in the system is 37% which is significantly larger than the 28% that corresponds to the capacity of the largest and half of the capacity of the second largest plant when added together. Moreover, note that this figure corresponds to whole plants and not generators, as indicated in the guidelines. Therefore, not allowing for an expansion in the system's thermal capacity is a reasonable assumption.

We implement three different scenarios: all new RES capacity is owned by the fringe, by OPG or by Brookfield. The HHI change as shown in the second line of Table 4. For each of the scenarios we solve for the Cournot equilibrium prices at each hour. Figure 13 in the Appendix shows the equilibrium prices predicted by our model in each of those scenarios altogether with the simulated prices when there is no expansion in RES for comparison for the first few hours of our sample. When the additional capacity is owned by the fringe, no market power is exercised over that capacity but the overall system supply curve shifts to the right which tends to lower prices. This is exactly what we see in that graph relative to

[36]See `https://canwea.ca/wind-integration-study/key-findings/` and `https://www.ospe.on.ca/public/documents/presentations/wind-and-electrical-grid.pdf`

[37]Notice that Genc and Reynolds [2019] also add new RES capacity into the system.

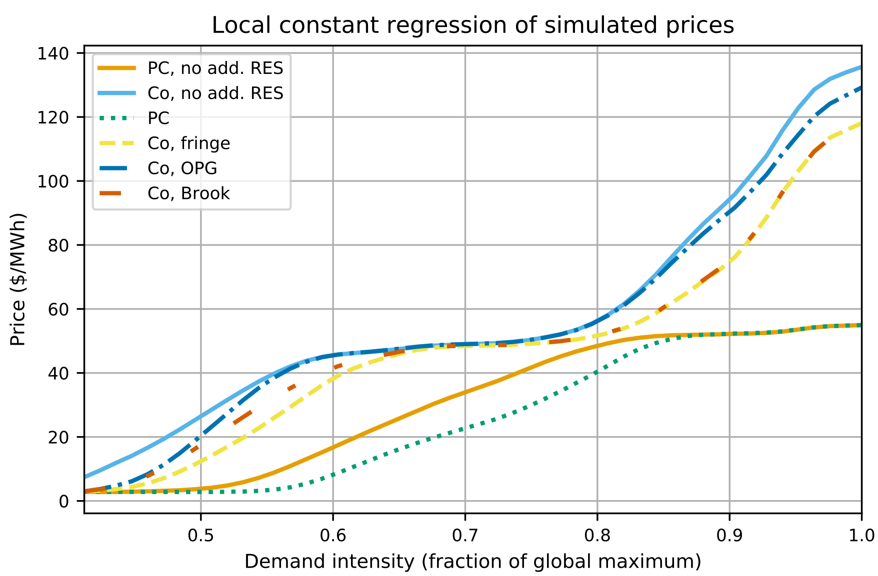
[38]See `http://www.ieso.ca/en/Sector-Participants/Market-Operations/Markets-and-Related-Programs/Operating-Reserve-Markets`

[39]Gowrisankaran et al. [2016] find that when solving for the optimal amount of operating reserves in a social planner problem, that amount is 30.5% on average over the different hours of the time period studied in the no RES penetration scenario and up to 35.2% when there is a 20% increase in solar capacity, whereas the implied NERC requirement was of 23% of total capacity only.

the prices when either OPG or Brookfield own the additional capacity.

The net effect of prices depends on the trade-off between the market power effect from adding RES to the firm's portfolio (upward pressure on prices) and the merit order effect (downward pressure). Figure 6 shows the kernel regressions of simulated prices from each scenario as a function of demand intensity. The highest prices are still those for the Cournot scenario with no RES added, this is the upper bound. When all the additional RES capacity is owned by OPG, prices are very close to the upper bound. Recall that OPG is the largest firm. Then if all the additional RES capacity is owned by the second largest firm, Brookfield, market power only has a noticeable effect for demand intensity levels between 0.5 and 0.8, otherwise it has very similar effects as when giving all the extra RES capacity to the fringe.

Figure 6: Price levels for different market structures and demand intensity levels



Notes: Co = Cournot, PC = perfect competition, Brook = Brookfield. The "no add. RES" are scenarios where only demand was increased but there is no additions of RES. All other cases include both an increase in demand and an increase in RES capacity.

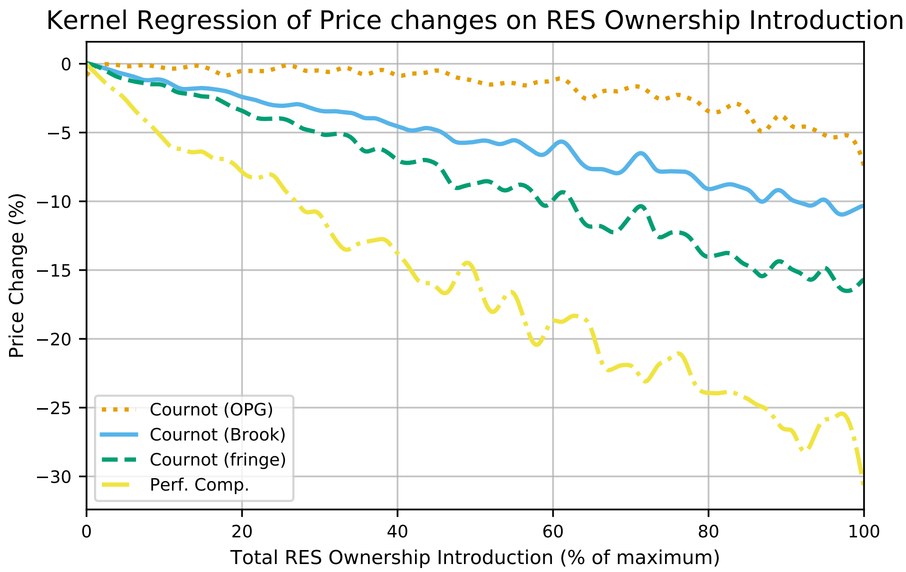
Alternatively, we can measure the net impact on prices for different levels of RES capacity extensions and for different owners of this additional capacity. To do so, we select the owner of the new capacity first, then we assign a random draw from a uniform distribution in $[0, 1500]$ to each of our time observations and give that selected owner the amount given by the random draw. We solve for the new equilibrium for each time observation and we repeat this for each of the main players in the market. Figure 7 shows the upper bound in wholesale price savings (in %) for each type of ownership of the new RES capacity and for different levels of this additional capacity. Figure 6 above is the full analysis for the case of 100% total RES ownership introduction shown at the right of Figure 7. This shows that by providing the totality of the new planned capacity (1,500 MW) of RES to different players, the combined effect of market power (or lack of in the case of perfect competition) and the MoE can be about 3 times larger when the owner is the fringe than when the owner is the largest firm. The horizontal axis of Figure 7 can be thought as different levels of a renewable portfolio standard (RPS) and each curve shows the associated maximum wholesale price change. Ultimately these changes will be passed-through onto final consumers −quantifying this is beyond the scope of this paper− and our results put in perspective the collateral damages of providing incentives to different market participants to own additional RES capacity. Whether an RPS, a FiT, or a subsidy policy is put in place, the recipient of the incentive will have a tangible effect on the resulting equilibrium prices.

6 Conclusion

In this paper we shed light on the still unexplored consequences of RES additions to the electricity producers' generation portfolios and their interaction with the nature of the ownership of RES capacity. We concentrate on two opposing effects: market power and the merit order effect. We find theoretically and empirically that the former puts upward pressure on prices, holding everything else constant. That effect counteracts the widely studied merit order effect. Throughout our series of counterfactuals we show that (i) prices increase when transferring RES capacity from small producers to large producers, (ii) these price increases are larger when the portfolio mix includes higher shares of RES, and (iii) a net expansion of the RES capacity lowers prices by amounts that depend on the size of the firm that acquires the new capacity and by whether the entity can exercise market power or not.

Our results contribute to the long-standing debate on the advantages and disadvantages

Figure 7: Upper bounds on wholesale price savings by ownership structure



Notes: Each line represents the mean change in maximum price savings as a function of the RES expansion level. "Cournot (OPG)" is the scenario where all the new RES capacity is owned by one single firm: OPG. "Cournot (Brook)" is when all the new RES capacity belongs to Brookfield. "Cournot (fringe)" is the case when all the new RES capacity is owned by the fringe but OPG and Brookfield exercise market power over their initial set of assets. "Perf. Comp." is a scenario where there is no market power. The maximum RES capacity expansion is 1,500 MW.

of RES additions in electricity markets. From the economics perspective our paper confirms and quantifies some theoretical results on the interaction of portfolio dilution and market power. From the regulatory and policy analysis perspective, our results suggest a careful analysis on the transfer of RES capacities among market participants and on the nature of the ownership of RES.

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Appendix

Proofs

Proof of the Proposition.

Proof. Profits for the typical strategic firm i are

$$\pi_i = (q_{i,\mathrm{NR}} + q_{i,\mathrm{R}})P(Q) - C(q_{i,\mathrm{NR}}) - C_R(q_{i,\mathrm{R}})$$

where $Q = q_{i,\mathrm{NR}} + q_{i,\mathrm{R}} + Q_{-i} + Q_f$ and Q_{-i} is total output from other strategic firms. The first order condition of the unconstrained problem is:

$$(q_{i,\mathrm{NR}} + q_{i,\mathrm{R}})P'(Q) + P(Q) - C'(q_{i,\mathrm{NR}}) = 0$$

from which we can differentiate with respect to γ:

$$(q_{i,\mathrm{NR}} + q_{i,\mathrm{R}})P''(Q)\frac{\partial Q}{\partial \gamma} + P'(Q)\frac{\partial (q_{i,\mathrm{NR}} + q_{i,\mathrm{R}})}{\partial \gamma} + P'(Q)\frac{\partial Q}{\partial \gamma} - C''(q_{i,\mathrm{NR}})\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} = 0. \tag{2}$$

Observe that by using symmetry of strategic firms, the non-dispatchable properties of RES ($q_{i,\mathrm{R}} = \bar{K}_{i,\mathrm{R}} = \frac{\gamma \bar{K}_{\mathrm{R}}}{n}$) and $Q_f = (1-\gamma)\bar{K}_{\mathrm{R}} + q_{f,\mathrm{NR}}$, where $q_{f,\mathrm{NR}}$ is the output from non-RES in the perfectly competitive fringe, we obtain:

$$\frac{\partial Q}{\partial \gamma} = n\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} + \frac{\partial q_{f,\mathrm{NR}}}{\partial \gamma}. \tag{3}$$

If we substitute this expression into Equation 2 we get:

$$\left[(q_{i,\mathrm{NR}} + q_{i,\mathrm{R}})P''n + P' + P'n - C''\right]\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} + \left[(q_{i,\mathrm{NR}} + q_{i,\mathrm{R}})P'' + P'\right]\frac{\partial q_{f,\mathrm{NR}}}{\partial \gamma} = -P'\frac{\bar{K}_{\mathrm{R}}}{n}. \tag{4}$$

At the same time, the fringe takes the market price as given and solves the equation

$$P(Q) = C'(q_{f,\mathrm{NR}}).$$

By differentiating with respect to γ we obtain

$$\frac{\partial q_{f,\mathrm{NR}}}{\partial \gamma} = \frac{P'n}{C'' - P'}\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} \tag{5}$$

and by substituting this into Equation 4 we obtain:

$$\begin{aligned}
&\Big[(n+1)P' + (q_{i,\mathrm{NR}} + \frac{\gamma \bar{K}_{\mathrm{R}}}{n})nP'' - C'' + (P' + P'')\frac{P'n}{C'' - P'}\Big]\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} = -P'\frac{\bar{K}_{\mathrm{R}}}{n} \\
\iff &\Big[P' - C'' + (P' + P'' \cdot (q_{i,\mathrm{NR}} + \frac{\gamma \bar{K}_{\mathrm{R}}}{n}))n\frac{C''}{C'' - P'}\Big]\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} = -P'\frac{\bar{K}_{\mathrm{R}}}{n},
\end{aligned}$$

which implies that $\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} < 0$ since $P' < 0$, $P'' < 0$, and $C'' > 0$. As a consequence, $\frac{\partial q_{f,\mathrm{NR}}}{\partial \gamma} > 0$.

Now, we substitute Equation 5 into Equation 3 to get

$$\begin{aligned}
\frac{\partial Q}{\partial \gamma} &= n\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} + \frac{\partial q_{f,\mathrm{NR}}}{\partial \gamma} \\
&= n\Big(1 + \frac{P'}{C'' - P'}\Big)\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} \\
&= n\Big(\frac{C''}{C'' - P'}\Big)\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} \\
&= n\Big(\frac{1}{1 - P'/C''}\Big)\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} \\
&< 0
\end{aligned}$$

since the fraction in parenthesis is between 0 and 1 and $\frac{\partial q_{i,\mathrm{NR}}}{\partial \gamma} < 0$.

Finally, observe that

$$\frac{\partial P}{\partial \gamma} = \frac{\partial P}{\partial Q}\frac{\partial Q}{\partial \gamma} > 0.$$

□

Data sources for marginal costs

Renewable energy sources

Marginal costs for RES, wind and solar sources, are set to 0$/MWh at all times. This follows an assumption that both the Variable Operations and Management (VO&M) costs and energy costs are zero. However, this assumption may not be ideal, in particular for the case of wind power where sources (Navigant [2015]) indicate a positive VO&M cost. This is an innocuous assumption since regardless of the marginal cost for an RES, we treat as non-dispatchable and therefore, they are put in front of the queue of the merit order. Ex-post profits would change if we assumed positive marginal costs. Thus, our profits can be thought as upper bounds of the true ex-post profits.

Natural gas

We follow the NREL Cost Report published by the private consulting firm Black and Veatch in February 2012 [Black & Veatch Holding Company, 2011]. This report identifies three different technologies for electricity production from natural gas: combustion turbine, combined-cycle and combined-cycle with carbon capture. The VO&M costs for these technologies vary between 3.67 US$/MWh and 29.9 US$/MWh (projected as stable for the 2010-2015 period). Concerning marginal cost, the same report states that between 6,705 Btu and 10,390 Btu are needed to produce 1 kWh of electricity. Using historical data on natural gas futures contracts (daily prices) from the Energy Information Administration (http://tonto.eia.gov/dnav/ng/hist/rngc1d.htm), we compute the median energy cost by multiplying the input price and the median conversion rate stated above.

Coal

Using the same methodology as for natural gas, we use estimates from the NREL Report in order to get VO&M costs as well as conversion rates for input transformation into electricity. We use historical data on CME futures from the website Investing.com (https://ca.investing.com/commodities/coal-cme-futures-historical-data) to get daily input prices that we multiply by the median conversion rate.

Hydroelectric

Following the NREL Report, we set the total marginal cost of hydropower at its VO&M rate, which is estimated to be 6 US$/MWh. No energy cost is reported in the study, which is not surprising given the nature of hydroelectric generation.

Nuclear

Once more, we use the NREL Report estimates. For nuclear energy, no VO&M is reported, the conversion rate is of 9.72 MBtu/MWh. Then, we compute total marginal cost using yearly uranium prices as reported by the EIA (https://www.eia.gov/nuclear/data.php).

USD-CAD exchange rates

Finally, since all prices from our data sources on fuel prices are in U.S. dollars, we convert them to Canadian dollars. We use historical data on weekly exchange rates from the website Investing.com (https://ca.investing.com/currencies/usd-cad-historical-data).

Extending the model to additional years

We conducted our main analysis using data from 2010-2012 because that is the most recent fully available data before two structural changes take place in the Ontario market. Here we present the results for years 2013-2015 in addition to our main results for years 2010-2012.

The two changes in the Ontario market are the following.

1. After 2012 there is a change of regime in net exports.

   The column of means clearly shows that Ontario increased on average its level of exports starting in 2013 by approximately 30%. This indicates that the estimates for a supply function of net exports are most likely different for 2013-2015 than those for 2010-2012.

2. After 2012 the frequency and the level of the negative wholesale electricity prices dramatically increased.

   From the table above it is clear that there were more negative prices in 2013-2015 than before 2013. In addition, the average of the negative prices in 2010-2012 is at least between 4 and 10 times larger (in absolute value) than the average for negative prices

Table 5: Net exports in 2010 - 2015. Summary statistics

year	obs.	mean	S.D.	min	max
2010	5,880	1,271	882	$-2,423$	3,870
2011	8,760	1,146	726	$-2,397$	4,607
2012	8,784	1,212	662	$-2,273$	3,694
2013	8,760	1,607	753	$-1,496$	4,095
2014	8,760	1,687	1,038	$-2,834$	4,612
2015	8,760	1,961	1,078	$-2,098$	4,742

Notes: Data from the IESO. All columns in MWh except for year and observations.

Table 6: Negative prices in 2010 - 2015. Summary statistics

year	hours	mean	S.D.	min	max
2010	35	-17.0	27.7	-128.0	0
2011	164	-53.7	46.4	-139.0	0
2012	169	-54.0	43.6	-128.0	0
2013	396	-4.8	9.2	-106.0	0
2014	965	-3.7	5.6	-110.0	0
2015	1,232	-2.5	2.7	-22.0	0

Notes: Data from the IESO. All columns in \$/MWh except for year and hours.

in 2013-2015. To put it in perspective, 2014 and 2015 have more than the equivalent of a whole month of negative prices each.[40] In 2013, the IESO set floor prices for RES at -10 \$/MWh for the first 90% of capacity and -15 \$/MWh for the remaining.[41]

These two points motivate our choice of estimating our model separately for 2010-2012 and 2013-2015. More specifically, we use the same Cournot model but using two different sets of exports supply curves: each one obtained separately by using the period 2010-2012 and another using the period 2013-2015. Counterfactuals are then obtained by using the corresponding exports supply function depending on whether we are solving for the equilibrium under a market structure change in 2010-2012 or in 2013-2015. Then we pool all the results to plot the changes in prices with respect to the amount of RES transfers and with respect to the HHI.

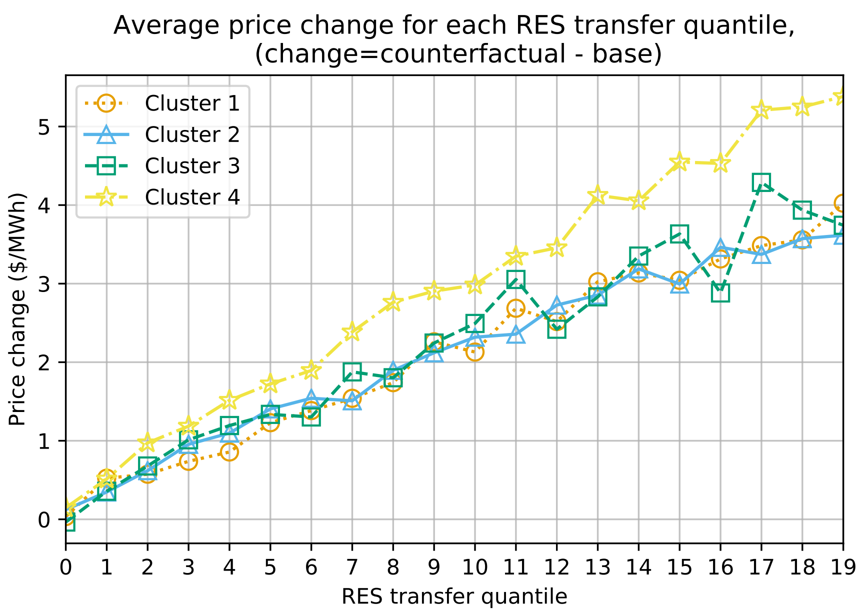
The following graphs are the equivalents of Figure 3 and 5 but for the full sample and they show that our results from 2010-2012 extend to the full sample 2010-2015.

The lack of monotonicity in the last graph is most likely due to the lower goodness-of-fit we obtain for 2013-2015. This seems plausible since we are using the exact same model over

[40]In North America wind blows faster at night. This creates high production periods in wind farms at night, right when demand is the lowest. This negative correlation cannot be easily changed since there is no storage for electricity (at reasonable prices) and wind turbines are difficult to plug and unplug at will. Then, these producers are willing to pay to the IESO in order for it to take the electricity. One would think that this is not a profit-maximizing strategy but the explanation is that there are production subsidies. If for example, at 3 a.m. the equilibrium price is -5 \$ / MWh and the subsidy is 6 \$ / MWh, the net gain from selling that MWh of electricity is 1\$.

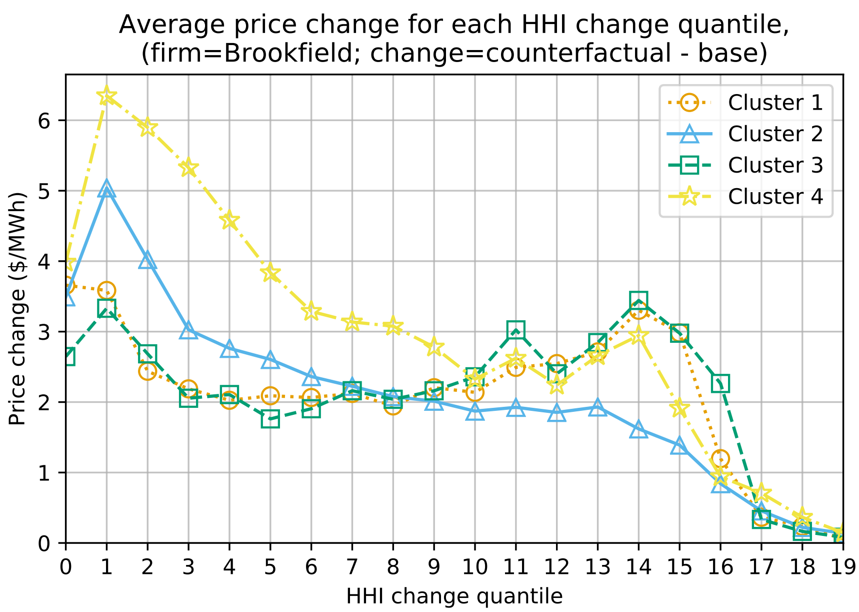
[41]https://www.ivey.uwo.ca/cmsmedia/3776559/the-economic-cost-of-electricity-generation-in-ontario-apr pdf

Figure 8: Price differences by quantiles of ownership change. 2010-2015



Notes: Mean effect on prices (counterfactual minus baseline) by quantile of the distribution of ownership transfers. The price differences are obtained using the prices from the new equilibrium after the ownership transfer and the equilibrium using our model before any ownership transfers. The figure shows the results by clusters. Data period: 2010-2015.

Figure 9: Quantiles of price differences and HHI: Brookfield

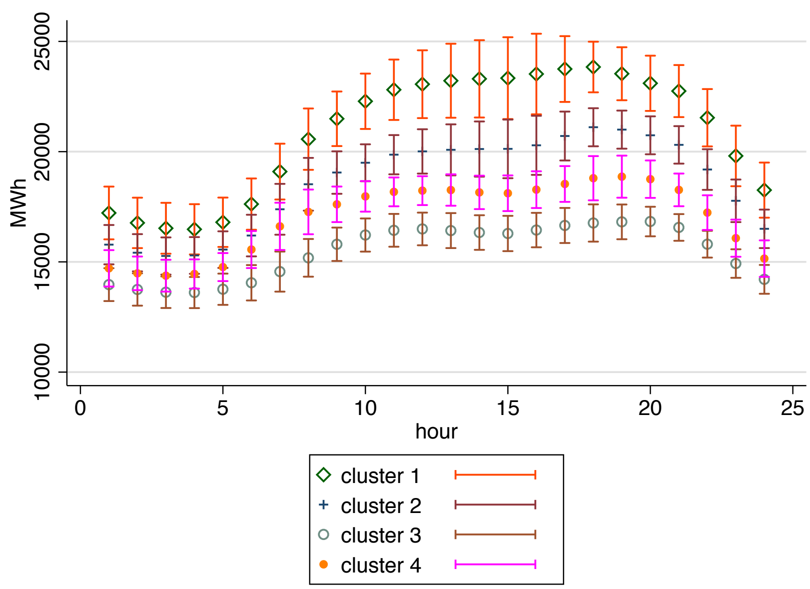


Notes: Horizontal axis represents the change in the degree of concentration in Brookfield's portfolio. Quantiles to the left correspond to negative changes in the HHI. This difference is negative because by adding RES into the firms' portfolios, the new HHI decreases (portfolio is more diversified given the initial low levels of RES) relative to the initial amount of concentration. Data period: 2010-2015.

two different periods of time but in one we have a higher frequency of negative prices than in the other. A possible solution would require a different supply functional form for the second regime (2013-2015). This would lead to comparing or pooling outcomes from two different models for export supply curves. We choose therefore to show in the main results the equilibria obtained using the exports supply function that best fits the data: 2010-2012. This also makes our conclusions consistent relative to one single set of market rules: no price floors for RES. Nonetheless, qualitatively we still get the same reaction in price changes if we used the two sets of parameter estimates (one for each regime).

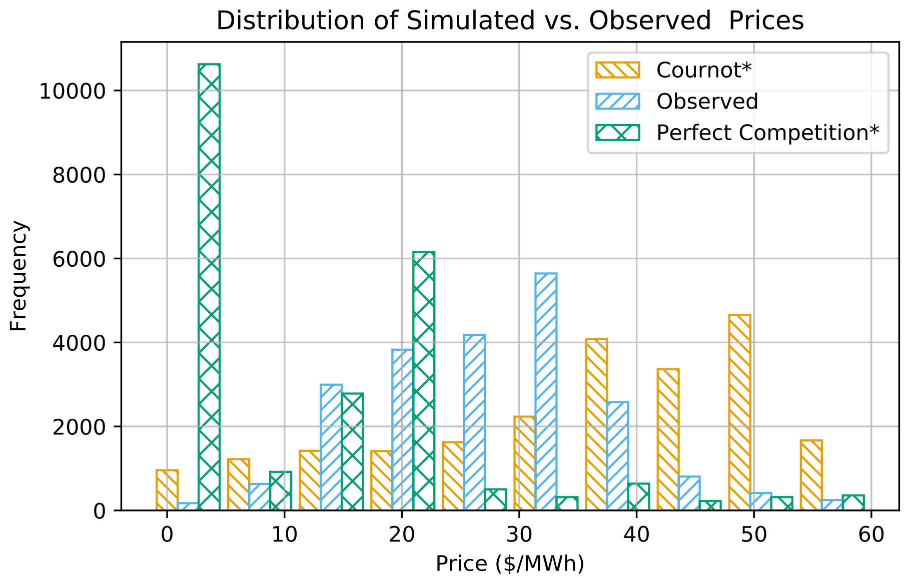
Additional Figures and Tables

Figure 10: Clusters



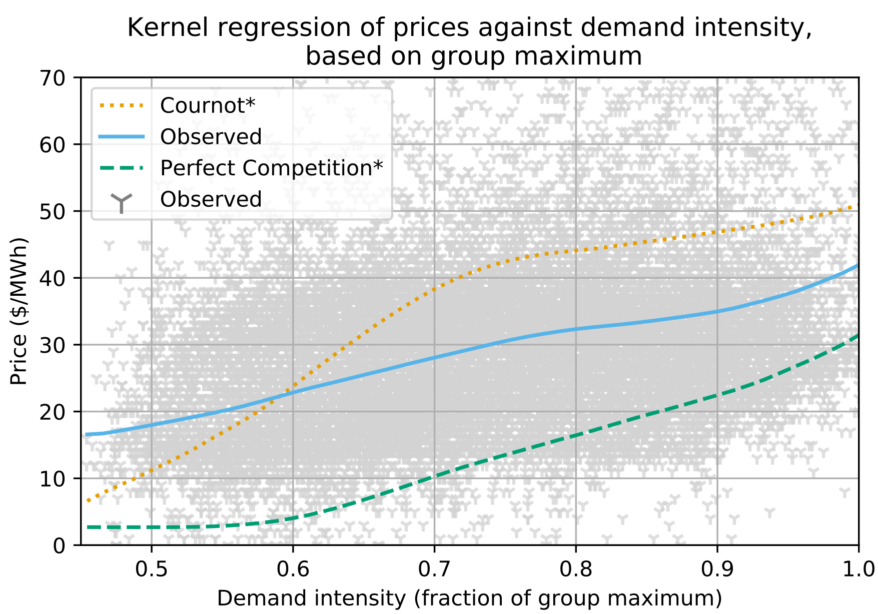
Notes: We use the k-means clustering algorithm, which is an unsupervised machine learning method (see Hastie et al. [2009]). We define an observation as the vector of the 24 demand observations in one day plus an entry equal to the maximum of those 24 numbers. Vertical lines represent $+1$ and -1 standard deviations around the mean.

Figure 11: Distribution of simulated and actual prices



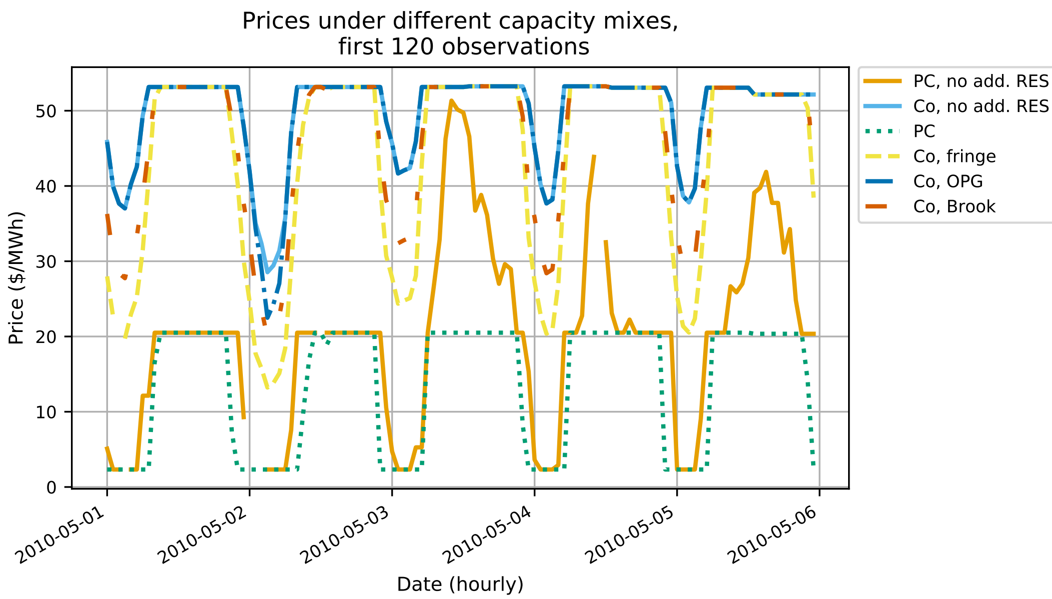
Notes: Histograms of predicted and actual prices confirming that observed prices lie between our two competition models. The symbol * represents simulated prices.

Figure 12: Kernel regression on conditional demand intensity



Notes: Horizontal axis represents the fraction of load relative to its maximum on each combination of year-season-peak type. Gray dots are actual observed prices. The symbol * represents simulated prices.

Figure 13: Counterfactual results, first 120 observations (5 days)



Notes: Co = Cournot, PC = perfect competition, Brook = Brookfield. The "no add. RES" are scenarios where only demand was increased but there is no additions of RES. All other cases include both an increase in demand and an increase in RES capacity. Gaps in the time series represent points where the solver did not find a solution.

Table 7: Description of the three main firms' energy mix, in MW

Firm	Energy source	2010	2011	2012
OPG				
	Nuclear	6,606	6,606	6,606
	regulated	*6,606*	*6,606*	*6,606*
	Hydropower	6,996	6,996	6,996
	regulated	*3,312*	*3,312*	*3,312*
	Thermal*	5,447	5,447	5,447
	regulated	*0*	*0*	*0*
	Total	19,049	19,049	19,049
	regulated	*9,918*	*9,918*	*9,918*
Brookfield				
	Hydropower	1,369	1,369	1,356
	regulated	*648*	*648*	*642*
	Wind	324	324	326
	regulated	*324*	*324*	*326*
	Natural Gas	36	36	47
	regulated	*0*	*0*	*0*
	Total	1,729	1,729	1,729
	regulated	*972*	*972*	*968*
Bruce				
	Nuclear	6,300	6,300	6,300
	regulated	*6,300*	*6,300*	*6,300*
	Total	6,300	6,300	6,300
	regulated	*6,300*	*6,300*	*6,300*

Notes: * Thermal capacity is not separated between coal and natural gas in OPG's financial statements. However, it is stated in the 2012 report that most of it is coal.

Table 8: Frequencies of observed prices that are bounded by simulated prices

year	#obs. within bounds	#obs. in year	%
2010	4,117	5,880	70%
2011	5,612	8,471	66%
2012	5,658	8,688	65%

Notes: The number of observations in the year is the number of hours in that year for which we have data in the domestic and the trading markets. The number of observations within bounds is the number of hours in that year for which the actual price is below the Cournot simulated price and above the perfectly competitive simulated equilibrium price.

Table 9: Net Exports supply function estimation, using market demand instruments.

Implied inverse demand slope: $\beta = -0.0307$								
		First stage		Second stage				
	N	F-stat.	Adj. R^2	Wald-χ^2	R^2	p_{ON}	SE	
MB	23,015	323***	0.289	5,449***	0.087	1.035***	0.063	
MI	23,015	348***	0.288	8,099***	-	24.260***	0.717	
MN	23,015	329***	0.290	2,821***	-	0.964***	0.044	
NY	23,015	341***	0.287	5,625***	-	-18.867***	0.522	
QC1	23,015	587***	0.289	12,705***	-	-29.006***	0.545	
QC2	23,015	-	-	8,962***	-	-8.934***	0.189	
QC3	23,015	-	-	3,521***	0.134	-0.086***	0.018	
QC4	23,015	-	-	4101***	-	-0.882***	0.029	
QC5	23,015	-	-	8,517***	0.176	-0.757***	0.029	
QC6	23,015	402***	0.295	2,904***	0.104	-0.056***	0.009	
QC7	23,015	-	-	2,781***	0.027	-0.121***	0.006	
QC8	23,015	-	-	11,377***	0.313	-0.122***	0.008	

* , ** and *** represent significance at the 10%, 5% and 1% confidence levels respectively.

Notes: MB = Manitoba, MI = Michigan, MN = Minnesota, NY = New York, QCx = Quebec connection lines. QC1-QC5 share the same first stage because we use the same regressors across these connection lines. The estimates $\hat{p}$ used in the second stage are therefore the same for QC1-QC5, only the net exports are changing, hence the different second stage results for each line. The same applies to QC6-QC8, but the first-stage includes additional month fixed effects than QC1-QC5 to allow for a more flexible function.

Table 10: Simulation statistics, by year

	Mean price			Median price		
Year	PC*	Mkt	Cou*	PC*	Mkt	Cou*
2010	17.44	37.83	45.70	19.88	35.00	50.96
2011	12.76	30.14	38.06	8.71	32.00	45.09
2012	11.07	22.82	31.47	2.89	22.00	36.64

Notes: * denotes results from simulation. PC = perfect competition. Mkt = actual prices. Cou = Cournot competition.

Table 11: Predicted and actual prices distributions

	Mean	Median	SD	Min	Max	Decile 1	Decile 10
Before period							
PC*	13.28	10.95	12.47	0.00	60.98	2.56	25.30
Mkt	29.34	29.00	20.87	-139.00	558.00	15.00	42.00
Cou*	37.51	40.12	15.75	0.00	106.75	12.63	54.32

Notes: * denotes results from simulation. PC = perfect competition. Mkt = actual prices. Cou = Cournot competition.