Renewable Expansion and Strategic Behavior in Restructured Electricity Markets

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Abstract

The expansion of renewable energy is reshaping price formation and strategic behavior in restructured electricity markets. This paper quantifies the impact of wind and solar on wholesale prices, market power, and generator profitability. Using data from Alberta's electricity market, I construct an hourly cost-based competitive benchmark from unit-level marginal costs and decompose price effects into cost and markup components. I find that renewables lower average wholesale prices, but their effects on prices and market power are heterogeneous throughout the day. Wind reduces prices and markups in most hours, with larger impacts during high-demand periods. Solar, however, exhibits asymmetric effects. It reduces midday prices and markups but increases them during some morning and evening hours, creating new opportunities for strategic behavior. Counterfactual capacity scenarios indicate that renewable expansion shifts value from energy to flexibility. Inframarginal rents for renewables and baseload combined-cycle units fall, while scarcity rents concentrate into fewer hours, favoring fast-ramping units and storage. These findings demonstrate that adding renewable supply does not, by itself, eliminate market power. Robust market design and flexible resources are essential to keep decarbonizing grids competitive and reliable.

Keywords: Electricity markets, Renewable energy, Market power, Resource adequacy.
JEL Codes: Q41, Q42, L94, L13, Q48.

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1 Introduction

The rapid expansion of variable renewable energy sources, wind and solar in particular, has led to growing concern about their implications for electricity market performance. While the near-zero marginal costs of these generation types exert downward pressure on wholesale prices, weather-driven variability fundamentally reshapes supply dynamics and complicates price formation in restructured electricity markets. Market restructuring was intended to deliver efficient prices and adequate investment by relying on competition rather than cost-of-service regulation. However, the unique characteristics of electricity markets create opportunities for the exercise of market power that can undermine the price benefits of renewables. Understanding how renewable integration affects price formation and competition is therefore essential for designing efficient markets and ensuring the energy transition supports economy-wide decarbonization.

This paper examines how the large-scale deployment of wind and solar affects wholesale electricity prices, market power, and the profitability of generators. To understand these effects, I develop a theoretical framework using a dominant-firm model with a competitive fringe. Under perfect competition, zero-marginal-cost renewables owned by price-taking fringe firms reduce net demand (demand minus renewable generation) and lower the market price. This is the standard merit-order effect. Under imperfect competition, however, the price effect of renewables can be decomposed into a competitive channel that affects system marginal costs and a markup channel that captures how the dominant firm adjusts its strategy in response to the altered residual demand. Understanding this markup response speaks directly to consumer welfare. If renewables reduce markups, consumers benefit beyond the direct price reduction from lower marginal costs.

In a parametric case with linear marginal costs, I show that an increase in fringe-owned renewables lowers both prices and markups and amplifies the competitive price decline. This occurs because adding zero-marginal-cost supply steepens the residual demand facing the dominant firm, so raising prices requires withholding more quantity, which makes strategic withholding less attractive. However, real-world complexities such as nonconvex costs and operating constraints (e.g., start-up costs, ramp-rate limits, and capacity limits) create intertemporal linkages that can generate nonmonotonic price patterns across hours. When renewable output patterns create predictable tight capacity periods, such as during solar's morning and evening ramps, the scarcity of available conventional capacity increases the profitability of

withholding. During these hours, the dominant firm faces less competitive pressure and stronger incentives to exercise market power, which can increase markups. These competing effects make the markup response an empirical question. I test these predictions using data from Alberta's electricity market between 2021 and 2024.

Alberta is one of the few jurisdictions globally to retain a fully restructured, energy-only market design, with limited market-power mitigation and minimal interconnection to neighboring systems. During the study period, policies already in place drove wind and solar capacity from 11% to 32% of total installed capacity, predominantly developed by small, non-strategic producers. This transition coincided with the expiry of long-term power purchase arrangements (PPAs) at the end of 2020, which effectively increased market concentration and the scope for exercising unilateral market power (Brown et al., 2023).[1] Alberta thus provides a valuable setting for identifying strategic effects that may be muted in more regulated jurisdictions. The analysis, in turn, offers relevant insights for other liberalized markets with high renewable penetration and market-power concerns, including Australia, New Zealand, and parts of Europe.

I develop an empirical framework that quantifies the cost and strategic consequences of wind and solar expansion. Using an hourly regression approach, I estimate the overall impact of renewable generation on observed wholesale prices, a cost-based competitive benchmark constructed from unit-level marginal cost estimates, and markups above this benchmark. This decomposition separates price impacts into changes in fundamental costs (the competitive channel) and shifts in markups (the strategic channel). Following recent literature, I allow renewable generation to affect market outcomes beyond the contemporaneous hour, capturing spillovers across the day.[2] I then quantify the implications for operating profits and long-run investment signals.

Quantifying the overall effects of renewable expansion on wholesale electricity prices, I find that an additional 1 GWh of daily wind generation reduces average prices in Alberta by about $3.30/MWh, with the largest effects concentrated in high-demand hours. The impact of solar generation, however, is notably asymmetric across the day: while a 1 GWh increase in daily solar output depresses midday prices by $7.12/MWh, it increases prices by an average of $5.05/MWh during the morning and

[1] In Alberta's early-2000s restructuring, PPAs temporarily separated ownership of certain power plants from control of their market bids ("offer control"), granting third-party buyers the right to set offer quantities and prices. Upon expiry, control reverted to the original owners. See Section 3.

[2] Bushnell and Novan (2021) first applied this approach to the analysis of California.

evening ramp periods. These price increases are unique to solar's diurnal pattern and contrast with wind generation, which exhibits more variable and less predictable output patterns.

Decomposing the price changes into cost and markup components reveals how competition responds to renewable output. I find that 40% of wind's price reduction and 30% of solar's midday price reduction come from lower markups, which is consistent with pro-competitive effects of low-cost generation. For the morning and evening price spikes associated with solar, about 33% of the increase is due to higher markups, suggesting that solar's intermittency creates new, predictable opportunities for firms to exercise market power. The results also show that large solar output leads to higher marginal production costs from less efficient thermal units that set prices during these hours.

Beyond immediate price effects, I find that renewable integration threatens the financial viability of conventional generators, with peaker plants initially facing greater impacts. As renewable generation erodes their revenues, these flexible units must increasingly rely on volatile early morning and evening hours to recover their costs. However, with further renewable penetration, baseload generators and renewables themselves face the greatest impact as average prices decline and price volatility increases, while flexible assets can better maintain viability by capitalizing on frequent price spikes. This increased price variation also creates stronger incentives for investment in energy storage technologies (Ketterer, 2014). Yet the welfare implications of storage deployment depend critically on ownership structure (Andrés-Cerezo and Fabra, 2023).

My results imply that adding zero-marginal-cost generation is not a remedy for market power. On the contrary, the findings show that certain types of renewable integration can reshape the competitive landscape in ways that create new opportunities for the exercise of market power. This suggests that market monitoring and mitigation measures remain critical even in decarbonizing electricity systems. The results also underscore the rising economic value of flexibility. As the grid becomes dominated by intermittent resources, price volatility during ramp periods increases, which creates strong market signals for investment in assets that can respond quickly, such as energy storage, demand response, and flexible thermal plants. Market designs must therefore be robust enough to properly value and incentivize these flexible resources to ensure both system reliability and competitive outcomes.

Related Literature. This paper contributes to several strands of literature on renewable energy integration in wholesale electricity markets. First, it contributes to a literature documenting that wind and solar generation depress wholesale prices via the merit-order effect (e.g., Sensfuß et al., 2008).[3] A key limitation of much of this work, however, is that it implicitly treats the supply curve of conventional generators as fixed, often abstracting from how strategic firms might alter their operational decisions and bidding strategies in response to renewable entry (Fabra, 2021). I show that such strategic responses can significantly change both the magnitude and the hourly distribution of price effects.

Second, this paper builds upon the growing literature on renewable integration under imperfect competition that emphasizes renewable ownership and compensation design. Prior work shows that when dominant firms hold mixed portfolios of conventional and renewable assets, they can profitably withhold thermal output to sustain higher prices, offsetting the downward pressure from low-marginal-cost renewables. By contrast, renewables owned by smaller, non-dominant (fringe) firms exert a pro-competitive effect by increasing supply and lowering prices (Ben-Moshe and Rubin, 2015; Acemoglu et al., 2017; Genc and Reynolds, 2019; Bahn et al., 2021; Butner, 2018).

A complementary strand demonstrates that renewable pricing and compensation mechanisms shape bidding incentives and the intensity of competition (Fabra and Imelda, 2023; Brown and Eckert, 2020). In particular, revenue-stabilizing instruments such as corporate power purchase agreements or fixed-price Feed-in Tariffs (FITs) hedge spot-price risk and weaken incentives for strategic withholding.[4] The recent expansion of renewables in Alberta, which has been dominated by fringe-owned assets financed through such contracts, provides a unique opportunity to study this pro-competitive channel in a real-world setting.

Third, this paper contributes to evidence on the spillover effects of renewable generation that extend beyond contemporaneous price impacts (Bigerna et al., 2016; Bushnell and Novan, 2021; Jha and Leslie, 2025). Bushnell and Novan (2021) find that solar capacity growth in California depresses midday prices but raises evening prices. Jha and Leslie (2025) find that distributed solar in Australia similarly raises evening

[3]For comprehensive overviews of earlier findings and methodologies, see Würzburg et al. (2013) and Tarufelli et al. (2022), and the more recent Europe-focused review by Bublitz et al. (2017). This framework is also central to quantifying renewables' impact on emissions; see Cullen (2013), Kaffine et al. (2013), and Novan (2015).

[4]For an overview of compensation approaches, see Council of European Energy Regulators (2018).

prices, attributing the effect entirely to market power rather than higher costs. My setting differs in two important ways. First, unlike California where wind growth was limited, I study a system where both wind and solar have grown substantially. I show that significant wind expansion suppresses prices without generating comparable price spikes, demonstrating that the asymmetric effects are technology-specific rather than a general feature of renewable integration. Second, whereas Jha and Leslie (2025) attribute evening price increases entirely to market power, I find that evening price effects also reflect higher marginal production costs from less efficient thermal units setting prices.

Finally, this paper informs the debate on long-run investment incentives in markets with high renewable penetration. A central question is whether energy-only markets can remain viable (Antweiler and Muesgens, 2021) or require supporting mechanisms like capacity payments to ensure resource adequacy and sustained investment (Bushnell et al., 2017; Fabra, 2021; Llobet and Padilla, 2018; Fabra, 2018; Brown and Reichenberg, 2021). While lower wholesale prices from renewables benefit consumers, they also reduce revenues for both thermal and renewable generators (Newbery et al., 2018; Liski and Vehviläinen, 2017; Gowrisankaran et al., 2016; Bushnell and Novan, 2021; Karaduman, 2021; Antweiler and Muesgens, 2021; Hirth, 2013; Prol et al., 2020). For renewable generators, the concentration of output during periods of low prices, when other renewables are also producing, creates a cannibalization effect that erodes marginal revenues as penetration increases. This paper contributes empirical evidence on the shifting profitability of different thermal technologies and utility-scale wind and solar energy in an energy-only market.

The paper proceeds as follows. Section 2 develops a theoretical framework for understanding renewable integration under imperfect competition. Section 3 describes the institutional context and data. Section 4 outlines the empirical methodology. Section 5 presents the main results on price effects and strategic behavior. Section 6 discusses policy implications and concludes.

2 Theoretical Framework

To motivate the empirical analysis, I adopt a stylized dominant-firm model with a competitive fringe, tailored to wholesale electricity markets. The supply side comprises a large, strategic firm with market power and a competitive fringe. This fringe, which includes both smaller thermal generators and a growing fleet of non-strategic

renewable assets, is assumed to supply power at marginal cost. The demand side is characterized by a highly inelastic short-run demand curve, as most consumers are insulated from real-time price signals. Given this steep residual demand, the dominant firm strategically sets the market-clearing price to maximize its profits. This price-setting framework is particularly relevant for uniform-price auctions common in wholesale electricity markets.

The framework provides a theoretical basis for decomposing the total price impact of increasing renewable supply into a competitive channel, driven by changes in marginal costs, and a strategic channel, reflecting the dominant firm's optimal response to its altered residual demand. I solve the static model and derive testable predictions regarding how each channel responds to renewable supply expansion. Throughout, I abstract from uncertainty and treat electricity as a homogeneous good. In addition, I focus on short- to medium-run price formation while the thermal capacity is fixed.

2.1 Setup

Let $A > 0$ denote perfectly inelastic market demand. Let $R_f \geq 0$ denote exogenous, must-run renewable supply measured in energy units with zero marginal cost. I assume renewables are owned by a non-strategic fringe and supplied inelastically (i.e., R_f does not respond to market conditions). The fringe's non-renewable *conventional* supply is also price-taking with aggregate cost $C_f(q_f)$, where $C_f'(q_f) > 0$ and $C_f''(q_f) > 0$. The dominant firm has cost $C_d(q_d)$ with $C_d'(q_d) > 0$ and $C_d''(q_d) > 0$.

2.2 Equilibrium Characterization

Given the price-taking fringe's competitive supply $Q_f(\cdot)$ (formal derivation provided below) and renewable supply R_f, the dominant firm faces residual demand

$$Q_d(p; R_f) = A - R_f - Q_f(p),$$

so $Q_d'(p) = -Q_f'(p) < 0$, and $Q_d''(p) = -Q_f''(p)$. Assume $Q_d(p; R_f) > 0$ on the relevant price range.

The dominant firm chooses the price p it is willing to accept on its marginal unit, taking $Q_f(\cdot)$ as given:

$$\max_p \;\; \pi(p; R_f) = p\, Q_d(p; R_f) - C_d\big(Q_d(p; R_f)\big).$$

The first-order condition (FOC) is

$$\pi_p(p; R_f) = Q_d(p; R_f) + \Big[p - C_d'\big(Q_d(p; R_f)\big)\Big] Q_d'(p) = 0.$$

Let $q_d^* = Q_d(P^*; R_f)$ denote the dominant firm's optimal quantity and P^* the equilibrium price. A sufficient second-order condition for a local maximum (evaluated at $p = P^*$) is

$$\pi_{pp}(P^*; R_f) = 2Q_d'(P^*) + \Big[P^* - C_d'\big(Q_d(P^*; R_f)\big)\Big] Q_d''(P^*) - C_d'''\big(Q_d(P^*; R_f)\big) \left(Q_d'(P^*)\right)^2 \; < \; 0.$$

Given the FOC and the maintained assumptions $Q_d'(P^*) < 0$ and $C_d'' > 0$, the SOC is satisfied whenever the residual demand is weakly concave at P^*—i.e., $Q_d''(P^*) \leq 0$.

2.3 Perfect Competition Benchmark

Under perfect competition, all suppliers price at marginal cost and the market clears at P^C:

$$A \; = \; R_f \; + \; Q_f(P^C) \; + \; S_d(P^C),$$

where $S_d(\cdot)$ is the dominant firm's *competitive* supply. On the interior where inverse marginal costs exist, let $q_f^C(p)$ and $q_d^C(p)$ denote the quantities satisfying $C_f'(q_f^C(p)) = p$ and $C_d'(q_d^C(p)) = p$. Then

$$Q_f'(p) = \frac{1}{C_f'''\big(q_f^C(p)\big)} > 0, \qquad S_d'(p) = \frac{1}{C_d'''\big(q_d^C(p)\big)} > 0.$$

2.4 Price Decomposition Framework

Let $\bar{P}$ be the consumers' maximum willingness to pay for electricity. With perfectly inelastic demand, consumer surplus at price P is

$$CS(P) = \int_P^{\bar{P}} A \, dp = A\,(\bar{P} - P).$$

Hence, the change in consumer surplus from moving from perfect to imperfect competition is

$$\Delta CS \; = \; CS(P^C) - CS(P^*) \; = \; A\,(P^* - P^C).$$

Therefore, the price component of the change in consumer surplus due to strategic behavior can be defined as the difference between the market price under the dominant

firm case, P^*, and the competitive price, P^C. I define this as a market-wide markup M where:

$$M = P^* - P^C$$

It is instructive to distinguish this markup from the dominant firm's own price-cost margin. The markup captures two distinct effects. This can be seen by decomposing it as follows:

$$M = \underbrace{(P^* - C_d'(q_d^*))}_{\text{1. Firm's price-cost margin}} + \underbrace{(C_d'(q_d^*) - P^C)}_{\text{2. Cost difference due to quantity reduction}}$$

The first term is the firm's own markup over its marginal cost at its chosen strategic output level, q_d^*. The second term reflects the cost difference arising from its decision to withhold quantity. Since a firm with market power restricts output relative to the competitive level ($P^C = C_d'(q_d^C)$ and $q_d^C > q_d^*$) and marginal costs are increasing ($C_d'' > 0$), this second term is negative. The market-wide markup, M, therefore reflects the firm's ability to price above its own cost and the price impact of operating at a different point on its marginal cost curve. As such, it is a convenient measure for quantifying the total effect of strategic behavior on consumers' welfare.

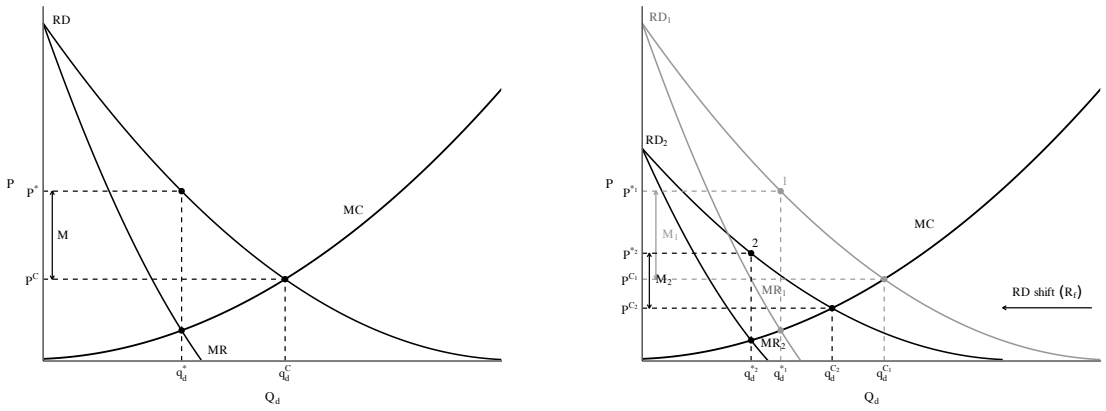
My analysis examines how these components respond to an increase in non-strategic renewable capacity, R_f. Taking the derivative of the identity with respect to R_f yields the central decomposition for my empirical strategy:

$$\frac{dP^*}{dR_f} = \underbrace{\frac{dP^C}{dR_f}}_{\text{Competitive Channel}} + \underbrace{\frac{dM}{dR_f}}_{\text{Strategic Channel}}$$

This equation shows that the total change in the observed price is the sum of the change in the competitive price (the cost or merit-order effect) and the change in the markup (the strategic effect). I separately estimate each of the three terms using the regressions specified in Section 4.

Figure 1 illustrates market outcomes and the decomposition under *cubic total costs* for both the dominant firm and the fringe (hence *quadratic marginal costs*). Panel (a) plots the model when the dominant firm faces inverse residual demand RD after netting out must-run renewables R_f and the fringe's competitive supply. The associated marginal revenue MR intersects the dominant firm's marginal cost MC at

Figure 1. Dominant Firm Equilibrium and Renewable Entry



(a) Baseline (b) Higher Renewable Supply

Notes: Panel (a) depicts the dominant firm's equilibrium. Inverse residual demand (RD), marginal revenue (MR), and marginal cost (MC) determine the dominant firm's output q_d^* and price P^*. The competitive benchmark is given by q_d^C and P^C where the dominant firm's MC meets RD. The market-wide markup is $M = P^* - P^C$ (vertical distance). Panel (b) shows how an increase in must-run renewables R_f shifts RD (and MR) inward, reducing q_d^* and q_d^C and lowering both P^* and P^C. In this calibration, the markup declines ($M_2 < M_1$).

q_d^*, which in turn determines the price P^* on RD. The competitive benchmark price P^C is the price at which the dominant firm's MC intersects RD. The market-wide markup is $M \equiv P^* - P^C$.

Panel (b) shows the effect of increasing R_f, where the inverse residual demand RD shifts inward at every price (must-run supply displaces demand one-for-one), and MR shifts accordingly. This implies (i) a lower optimal quantity q_d^* (the MR–MC intersection moves left), (ii) a lower dominant-firm price P^* (projection to the new RD), and (iii) a lower competitive price P^C (fewer conventional units are required under price-taking supply). In the scenario depicted, both P^* and P^C decline and the markup shrinks from M_1 to M_2.

2.5 Comparative Statics

I now derive the signs and magnitudes of each component through comparative static analysis of the equilibrium conditions. The components of the decomposition can be derived analytically by totally differentiating the relevant equilibrium conditions with respect to the renewable capacity, R_f.

Total Price Effect. The change in the observed market price is derived from the dominant firm's FOC for profit maximization, which implicitly defines P^* as a function of R_f:

$$\pi_p(P^*, R_f) = Q_d(P^*, R_f) + [P^* - C_d'(Q_d(P^*, R_f))]Q_d'(P^*) = 0$$

Totally differentiating this FOC with respect to R_f yields:

$$\frac{\partial \pi_p}{\partial P^*}\frac{dP^*}{dR_f} + \frac{\partial \pi_p}{\partial R_f} = 0$$

Solving for the price change gives the standard Implicit Function Theorem result: $\frac{dP^*}{dR_f} = -\frac{\partial \pi_p/\partial R_f}{\partial \pi_p/\partial P^*} = -\frac{\pi_{pR_f}}{\pi_{pp}}$. The two partial derivatives are:

1. $\pi_{pp} = \frac{\partial \pi_p}{\partial P^*} = 2Q_d'(P^*) + [P^* - C_d'(Q_d)]Q_d''(P^*) - C_d''(Q_d)[Q_d'(P^*)]^2$. This term is negative by the SOC for profit maximization.

2. $\pi_{pR_f} = \frac{\partial \pi_p}{\partial R_f} = \frac{\partial Q_d}{\partial R_f} - C_d''(Q_d)\frac{\partial Q_d}{\partial R_f}Q_d'(P^*)$. Since $\frac{\partial Q_d}{\partial R_f} = -1$, this simplifies to $-1 + C_d''(Q_d)Q_d'(P^*)$. This term is negative.

Substituting these into the expression gives the full derivative for the total price effect:

$$\frac{dP^*}{dR_f} = \frac{1 - C_d''(Q_d)Q_d'(P^*)}{2Q_d'(P^*) + [P^* - C_d'(Q_d)]Q_d''(P^*) - C_d''(Q_d)[Q_d'(P^*)]^2} < 0$$

Competitive Effect. The change in the competitive benchmark price is derived from the market-clearing condition, $G(P^C, R_f) = 0$, where total supply equals total demand:

$$G(P^C, R_f) = A - Q_f(P^C) - S_d(P^C) - R_f = 0$$

Here, $S_d(P)$ is the dominant firm's competitive supply curve (the inverse of its marginal cost). Totally differentiating the market-clearing condition with respect to R_f:

$$\frac{\partial G}{\partial P^C}\frac{dP^C}{dR_f} + \frac{\partial G}{\partial R_f} = 0$$

The partial derivatives are:

1. $\frac{\partial G}{\partial P^C} = -Q_f'(P^C) - S_d'(P^C) < 0$. This is the net slope of excess demand, which is negative.

2. $\frac{\partial G}{\partial R_f} = -1$.

Solving for the price change gives the derivative for the competitive effect:

$$\frac{dP^C}{dR_f} = \frac{1}{-Q'_f(P^C) - S'_d(P^C)} < 0$$

Strategic Effect. The change in the market-wide markup is the difference between the total and competitive price effects. Substituting the fully derived expressions above gives the complete analytical form of the strategic channel:

$$\frac{dM}{dR_f} = \left(\frac{1 - C''_d(Q_d)Q'_d(P^*)}{2Q'_d(P^*) + [P^* - C'_d(Q_d)]Q''_d(P^*) - C''_d(Q_d)[Q'_d(P^*)]^2} \right) - \left(\frac{1}{-Q'_f(P^C) - S'_d(P^C)} \right)$$

The sign and magnitude of this term are ambiguous ex-ante and motivate the empirical investigation. It is also distinct from the change in the firm's own price-cost margin, $M_{firm} = P^* - C'_d(q^*_d)$. The derivative of the firm's margin is $\frac{dM_{firm}}{dR_f} = \frac{dP^*}{dR_f}(1 - C''_d Q'_d) + C''_d$, which has an ambiguous sign based on the opposing effects of a price reduction versus a cost reduction from lower output. My empirical focus on the market-wide markup, M, is motivated by its direct relevance for measuring the total impact on market prices and consumers' welfare.

Parametric Example: Linear Marginal Costs. To illustrate these comparative statics concretely, consider the case where both the dominant firm and fringe have quadratic cost functions with linear marginal costs:

- Dominant firm: $C_d(Q_d) = c_d Q_d + \frac{b_d}{2} Q_d^2$, with marginal cost $C'_d(Q_d) = c_d + b_d Q_d$ and $C''_d = b_d > 0$
- Fringe: $C_f(Q_f) = c_f Q_f + \frac{b_f}{2} Q_f^2$, with marginal cost $C'_f(Q_f) = c_f + b_f Q_f$ and $C''_f = b_f > 0$

The fringe's competitive supply is $Q_f(P) = \frac{P - c_f}{b_f}$, which gives $Q'_f(P) = \frac{1}{b_f}$ and $Q''_f(P) = 0$. The residual demand faced by the dominant firm is therefore $Q_d(P, R_f) = A - R_f - \frac{P - c_f}{b_f}$, with $Q'_d(P) = -\frac{1}{b_f}$ and $Q''_d(P) = 0$.

Under these functional forms, the three derivatives simplify to closed-form expressions:

Total Price Effect. Since $Q''_d(P^*) = 0$, the second-order condition simplifies to $\pi_{pp} = 2Q'_d(P^*) - C''_d[Q'_d(P^*)]^2 = -\frac{2}{b_f} - \frac{b_d}{b_f^2} = -\frac{2b_f + b_d}{b_f^2}$. The cross-partial is $\pi_{pR_f} =$

$-1 + C_d'' Q_d'(P^*) = -1 - \frac{b_d}{b_f}$. Therefore:

$$\frac{dP^*}{dR_f} = -\frac{-1 - \frac{b_d}{b_f}}{-\frac{2b_f + b_d}{b_f^2}} = -\frac{b_f(b_f + b_d)}{2b_f + b_d} < 0$$

Competitive Channel. The dominant firm's competitive supply slope is $S_d'(P^C) = \frac{1}{C_d''} = \frac{1}{b_d}$. Thus:

$$\frac{dP^C}{dR_f} = \frac{1}{-\frac{1}{b_f} - \frac{1}{b_d}} = -\frac{b_d b_f}{b_d + b_f} < 0$$

Strategic Channel. The strategic channel is the difference:

$$\frac{dM}{dR_f} = -\frac{b_f(b_f + b_d)}{2b_f + b_d} + \frac{b_d b_f}{b_d + b_f} = -\frac{b_f^3}{(2b_f + b_d)(b_d + b_f)} < 0$$

These closed-form solutions reveal several key insights. First, both the competitive and strategic channels are unambiguously negative, implying renewable supply reduces both costs and markups. Second, the magnitude of the total price response always exceeds the competitive response:

$$\left|\frac{dP^*}{dR_f}\right| = \frac{b_f(b_f + b_d)}{2b_f + b_d} > \frac{b_d b_f}{b_d + b_f} = \left|\frac{dP^C}{dR_f}\right|$$

This inequality holds because $(b_f + b_d)^2 > b_d(2b_f + b_d)$, which simplifies to $b_f^2 > 0$. The amplification factor, the ratio of the total price response to the competitive price response, is:

$$\lambda \equiv \frac{|\frac{dP^*}{dR_f}|}{|\frac{dP^C}{dR_f}|} = \frac{(b_f + b_d)^2}{b_d(2b_f + b_d)} = 1 + \frac{b_f^2}{b_d(2b_f + b_d)} > 1$$

When marginal cost slopes are equal ($b_d = b_f$), this simplifies to $\lambda = \frac{4}{3}$, indicating that the dominant firm's strategic response amplifies the competitive price decline by 33%. More generally, amplification increases with the relative slope b_f/b_d. A steeper fringe schedule reduces the elasticity of residual demand for the dominant firm, which enhances its market power. This is likely in practice. Dominant firms tend to operate larger, lower-cost units and so have flatter marginal cost schedules than the fringe ($b_d \leq b_f$). This implies $b_f/b_d > 1$, making amplification more common.

2.6 Testable Predictions

The dominant-firm model provides the theoretical predictions for the signs of competitive and strategic components, which I test empirically.

Competitive Channel ($\frac{dP^C}{dR_f}$). An increase in zero-marginal-cost renewables (R_f) unambiguously shifts the aggregate supply curve outward, leading to a lower market-clearing price in a competitive world. Therefore, the expected sign of the competitive channel is negative. This is the standard merit-order effect.

Strategic Channel ($\frac{dM}{dR_f}$). Unlike the competitive channel, the sign of $\frac{dM}{dR_f}$ is theoretically ambiguous. In the parametric example with convex costs (quadratic costs), the model delivers $\frac{dM}{dR_f} < 0$, i.e., markups fall with renewable penetration. However, this hinges on cost curvature and the elasticity of residual demand. With more general cost shapes or binding capacity or network constraints, the sign is an empirical question. The estimation in Section 5.2 identifies this channel from observed price–quantity outcomes to determine which effect dominates in practice.

3 Empirical Setting and Data

I examine Alberta's wholesale electricity market from 2021 to 2024, a period marked by substantial growth in utility-scale renewable capacity. I begin by outlining the institutional and regulatory features of Alberta's electricity market, with particular attention to its evolution in market structure and generation mix. This contextual overview motivates Alberta as a relevant empirical setting for analyzing the market impacts of rising renewable penetration within restructured power markets. I then describe the primary data sources and provide key descriptive statistics on electricity demand, wholesale prices, and renewable generation patterns.

3.1 The Alberta Electricity Market

3.1.1 Market Design and Rules

Before restructuring began in 1996, Alberta's electricity industry was dominated by a few vertically integrated utilities operating under cost-of-service regulation.[5] The restructuring process led Alberta to adopt a competitive energy-only market design,

[5] Daniel et al. (2001) provides the historical context and details of Alberta's market restructuring.

featuring a single, uniform-price, real-time hourly auction. The Alberta Electric System Operator (AESO) administers this market and manages both long-term planning and real-time operations.[6]

In the real-time market, generators submit price-quantity offers in blocks for their available capacity. The market operator uses a least-cost dispatch process that determines the production levels of individual units. Then, all electricity supplied to the grid is paid at a single, uniform clearing price, known as the "pool price." This pool price ranges between \$0 and a cap of \$1,000 per megawatt-hour (MWh).[7]

Alberta's market design rewards only energy delivered and ancillary services. Generators must recover both variable and fixed costs mainly through these market revenues.[8] However, the Market Surveillance Administrator (MSA), which oversees Alberta's electricity market, explicitly allows the unilateral exercise of market power through economic withholding (MSA, 2011, 2020).[9] This practice involves bidding above marginal cost and withholding economically feasible output to raise prices and maximize profits.[10] The argument in favor of this approach holds that market power serves to provide essential investment incentives for generation capacity and maintain resource adequacy.

In Alberta, aside from a price cap of \$1,000/MWh, there are essentially no constraints on strategic bidding.[11] This cap serves as the primary safeguard against extreme price volatility and excessive consumer costs during periods of high demand or supply shortages. This minimal intervention approach, combined with Alberta's limited interconnection with neighboring electricity markets, may amplify the potential for firms' strategic behavior to influence prices.

[6]See Brown et al. (2023) for a recent overview of Alberta's evolving market structure before the expiry of PPAs.

[7]Hourly prices are computed as the time-weighted average of the system marginal price (SMP), which is updated minute-by-minute based on the merit-order curve and prevailing demand. A few exceptions to this process (e.g., pricing under congestion) are omitted for simplicity.

[8]In contrast, many jurisdictions offer capacity payments to compensate generators for system capacity, supplementing energy market revenues; see Joskow (2008) for details of capacity markets.

[9]This framework is currently under review. Following periods of high prices, the AESO is exploring potential mitigation mechanisms, including changes to the offer cap and other market rule adjustments, to address concerns about market power and reliability as the generation mix evolves.

[10]Physical withholding, where firms reduce or under-report available capacity, is likewise relevant but is treated as overtly anti-competitive and is explicitly prohibited by Alberta's regulation (Brown and Eckert, 2017).

[11]This differs from jurisdictions such as CAISO, PJM, NYISO, and MISO, which impose mitigation mechanisms that restrict the extent to which bids can deviate from marginal costs (Graf et al., 2021).

3.1.2 The Energy Transition: 2015-2024

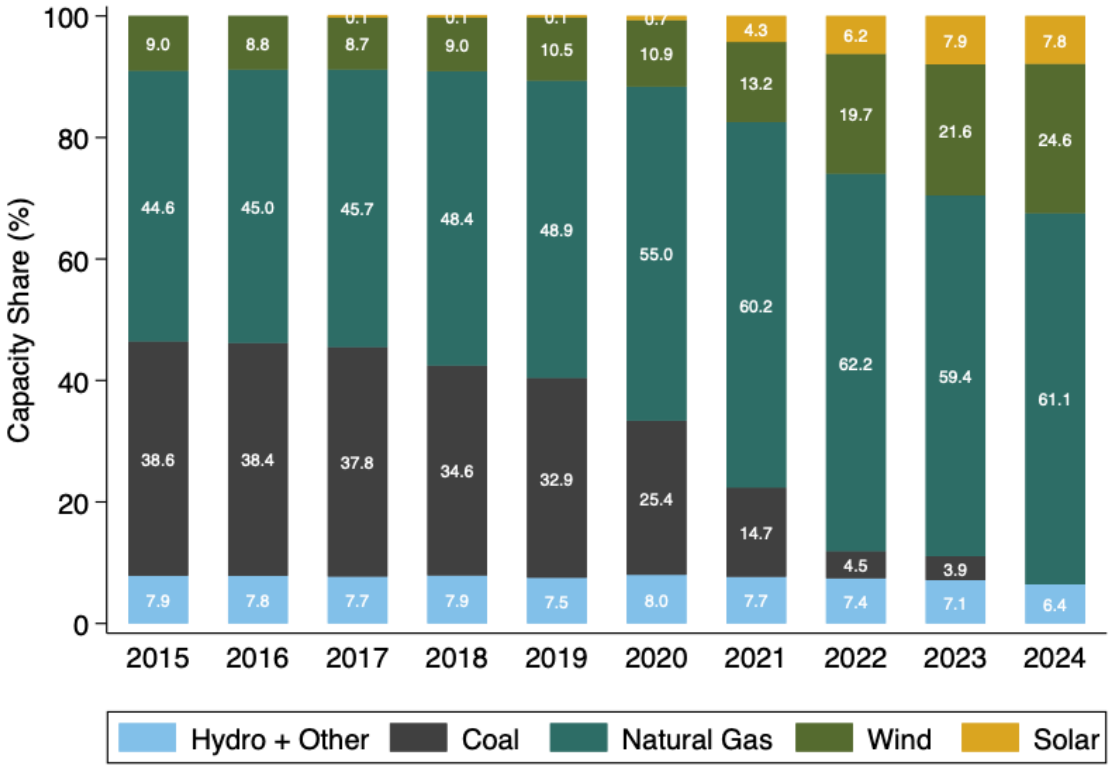
The growth of renewable energy in Alberta's electricity market has been remarkable in recent years, driven by declining technology costs, supportive policies, and a restructured market design that prioritizes competitive procurement. These factors have collectively positioned Alberta as an attractive destination for renewable energy investments, particularly for firms seeking to comply with corporate sustainability targets through power purchase agreements.[12] As shown in Figure 2, wind energy accounted for approximately 9% of Alberta's installed capacity in 2015, while coal and natural gas dominated with nearly 39% and 45% shares. By the end of 2024, however, the energy landscape had shifted dramatically, with wind and solar accounting for over 32% of capacity, while coal generation had been entirely phased out.

Policy interventions at both the federal and provincial levels have been instrumental in fostering this growth. In particular, the 2015 Alberta Climate Leadership Plan aimed for a coal-fired generation phase-out by 2030 (a milestone achieved six years ahead of the original target), relying on renewables and natural gas to fill the gap. The provincial Renewable Electricity Program (REP), launched in 2016, facilitated utility-scale renewable procurement through competitive auctions. The program achieved some of Canada's lowest contract prices, procuring 1,360 MW of wind energy (Hastings-Simon et al., 2022). Although the REP concluded in 2019, it had a lasting impact on Alberta's generation mix.

The momentum was further reinforced by a new provincial carbon pricing scheme in 2018, the Technology Innovation and Emissions Reduction Regulation (TIER), and Carbon Offsets and Renewable Energy Credits, which strengthened investor confidence in clean energy projects. The renewable energy expansion has been driven primarily by smaller, independent firms operating outside the legacy utility structure. While generation capacity remains highly concentrated, with the five largest firms, TransAlta, Capital Power, Heartland Generation, ENMAX, and Suncor, controlling on average 60% of the capacity over the sample period, new wind and solar projects are largely developed by a competitive fringe that includes independent power producers, renewable developers, and Indigenous-led partnerships, introducing new dy-

[12]However, recent policy shifts have introduced uncertainty into this trajectory. In 2023, the provincial government imposed a temporary moratorium on approval of new projects, followed by new restrictions on renewable development in certain areas (GOA, 2023b; AUC, 2024). Given the typical 2-4 year timeline from project approval to operation, installations observed through 2024 largely reflect decisions made before these restrictions, though the policy changes may materially affect future investment patterns.

Figure 2. Installed Capacity Share by Technology — Alberta (2015–2024)



Notes: This figure plots the end of year installed capacity share of Coal, Natural Gas, Wind and Solar, and Hydro and other technologies in Alberta's market from 2015 to 2024.

namics into market competition. This latter group's share of installed wind and solar capacity has grown from 45.7% at the end of 2021 to 77.3% by the end of 2024.[13]

Another critical turning point in Alberta's market evolution was the expiry of long-term PPAs at the end of 2020, which had substantial implications for market structure and pricing dynamics. These PPAs, established during Alberta's electricity market restructuring, acted as virtual divestitures to mitigate market concentration and enhance competition by transferring offer control from PPA owners to PPA buyers. While initially allocated to large strategic buyers, most PPAs were transferred to the Balancing Pool, a government entity that offered generation into the market at short-run marginal cost. This shift significantly reduced market power and made market outcomes more reflective of competitive benchmarks. However, when the PPAs expired at the end of 2020, offer control reverted to the original owners, many

[13]Calculations are based on the MSA's Market Share Offer Control (MSOC) dataset (Feb. 12, 2025 release) (MSA, 2025).

of whom were large incumbent generators. This re-concentration of market control led to a substantial increase in the ability and incentive to exercise market power. According to MSA (2025), the share of capacity controlled by the five largest firms in Alberta increased from 57% in 2019 to 70% at the beginning of 2021 and gradually declined to 53% at the end of 2024. Brown et al. (2023) shows that average peak-hour pool prices increased by 120% in 2021 compared to 2020, with nearly two-thirds of this increase resulting from higher markups above marginal cost.

Alberta's rapid shift from a coal-dominated electricity system to one with a growing share of renewable energies highlights how restructured markets, policy incentives, and declining technology costs can align to accelerate decarbonization. However, this transition also introduces challenges for competition, investment incentives, and market reliability. The integration of intermittent renewables, characterized by near-zero marginal costs, fundamentally reshapes supply dynamics, while an energy-only design places greater revenue risk on generators. Alberta's evolving electricity market therefore provides a timely and policy-relevant case study for analyzing competition in wholesale electricity markets under rising renewable penetration and for assessing broader questions of efficient market design in the context of the energy transition.

3.2 Data

The primary data come from publicly available AESO sources from January 1, 2021, to December 31, 2024. These data include hourly records of price and quantity bids by power producers, actual unit outputs, unit availability, asset ownership, market demand, import-supply offers, and available transmission capacity.[14]

To estimate the marginal costs of fossil-fuel generators, I use daily natural gas prices from Alberta's Natural Gas Exchange (NGX) and weekly Powder River Basin (Wyoming) coal prices from the U.S. Energy Information Administration (EIA), combined with thermal efficiency data from CASA (2004). I incorporate operating and maintenance costs for different technologies from EIA (2020, 2024a), along with carbon pricing information from the Government of Alberta publications. For weekends and holidays, I use data from the most recent preceding business day. I convert all monetary values originally reported in U.S. dollars to Canadian dollars using Bank of Canada exchange rates.

I further integrate hourly weather data from major population centers in British Columbia, Alberta, Saskatchewan (Environment Canada), and Montana (National

[14]The datasets are available at: https://www.aeso.ca/.

Oceanic and Atmospheric Administration, NOAA). Finally, to account for interregional trading decisions and neighboring market conditions, I include electricity demand data from the Bonneville Power Administration (BPA, 2024) and Mid-Columbia wholesale peak prices (EIA, 2024b).

Table 1 reports summary statistics for key variables. The sample includes 35,064 hourly observations. The average wholesale price is $117/MWh, with substantial volatility and occasional spikes to the $999.99/MWh cap. Average hourly demand is 9,230 MWh. Wind and solar generate 1,042 MWh and 195 MWh per hour on average, together covering about 13% of the demand. Net imports are small relative to the market demand, consistent with Alberta's limited interties with neighboring markets.

Table 1. Summary Statistics

Variable	**Unit**	**Mean**	**SD**	**Min**	**Max**
Market Price	$/MWh	117.27	177.89	0.00	999.99
Market Demand	MWh	9,230	877	6,864	12,124
Net Imports	MWh	165	466	-1,083	1,022
Wind Generation	MWh	1,042	798	0	3,993
Solar Generation	MWh	195	328	0	1,502
Gas Price	$/GJ	3.08	1.71	-0.25	8.35
Coal Price	$/Short Ton	20.13	5.02	14.33	39.34

Notes: All dollar amounts are in Canadian dollars (CAD).

3.3 Descriptive Evidence

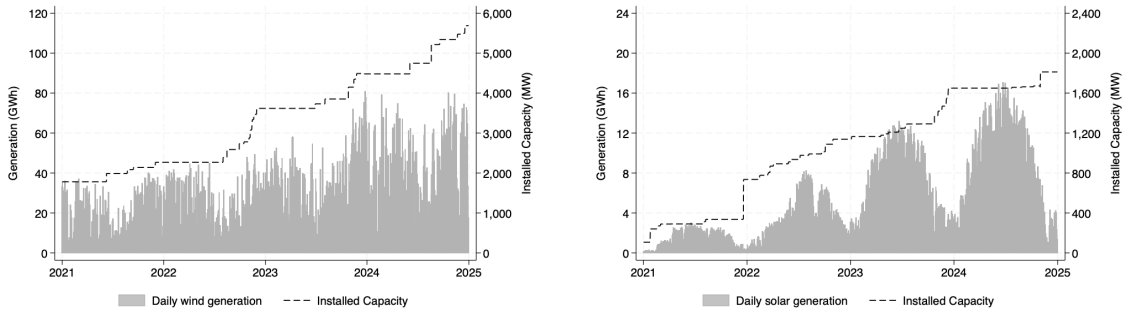
This section documents key features of Alberta's electricity market from 2021 to 2024. During this period, the combined share of wind and solar in installed capacity rose from about 11% to over 32%. Figure 3 shows the scale and timing of this build-out. Panel (a) shows that wind capacity increased from 1,781 MW in early 2021 to 5,688 MW by the end of 2024, with average daily wind generation rising from about 17 GWh to 35 GWh. Wind's average capacity factor during this period was 36%, rising to about 43% in winter.[15]

Panel (b) shows solar capacity growing from 100 MW to 1,800 MW by the end of 2024, with average daily solar generation rising from about 1.3 GWh to 8 GWh.

[15]Capacity factors are energy produced over a period divided by nameplate capacity times the period's hours.

Solar's average capacity factor was about 22%, peaking at about 33% in summer. For context, average daily market demand during this period was about 221 GWh.

Figure 3. Wind and Solar Daily Generation and Installed Capacity

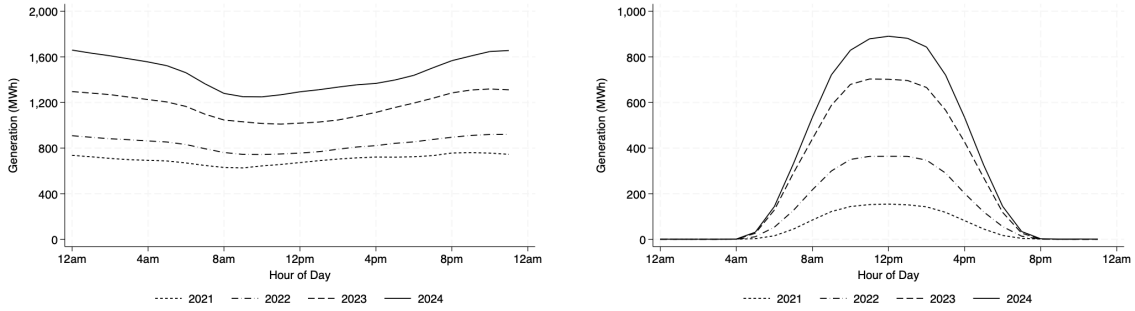


(a) Wind (b) Solar

Notes: Panel (a) plots total daily wind generation (bars) and installed capacity (dashed line). Panel (b) plots total daily solar generation (bars) and installed capacity (dashed line). Values are calculated using hourly data.

Figure 4 shows the diurnal generation profiles of wind and solar during the sample period. The average wind output remains relatively constant throughout the day, with slightly higher values observed overnight and in the early morning hours (Panel (a)). In contrast, solar generation follows the expected bell-shaped curve, with output concentrated during daylight hours (Panel (b)).

Figure 4. Wind and Solar Generation Profiles



(a) Wind (b) Solar

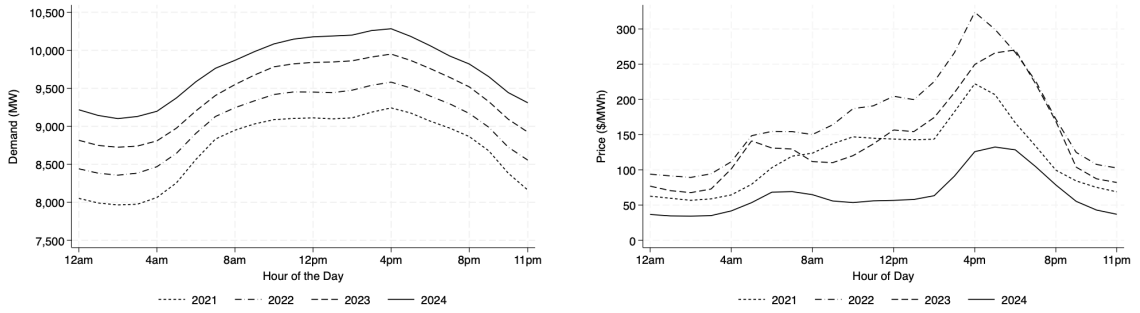
Notes: Panel (a) plots hourly averages of wind generation. Panel (b) plots hourly averages of solar generation. The averages are calculated using hourly data for each calendar year.

Concurrent with this renewable expansion, Alberta experienced the highest popu-

lation growth in Canada, reaching 4% annually in 2023–2024 (GOA, 2024). Figure 5 shows the evolution of average hourly market demand and wholesale prices over this period. Panel (a) shows that demand grew steadily, but its intraday shape remained stable. This mainly reflects the dominance of industrial demand in Alberta, which accounts for 63% of total electricity consumption (CER, 2022).

However, Panel (b) indicates significant changes in the structure of wholesale prices over this period. Prices were exceptionally high in 2022 and 2023, years that also saw higher natural gas prices and lower electricity imports (see Appendix A).[16] Notably, a distinct hourly price pattern emerged in 2023 and became pronounced in 2024, where average midday prices declined while morning and evening prices remained elevated. This pattern likely reflects the growing influence of solar capacity expansion, which generates primarily during midday hours and produces little output during morning and evening ramp periods.

Figure 5. Wholesale Market Demand and Wholesale Price



(a) Wholesale Market Demand

(b) Wholesale Market Price

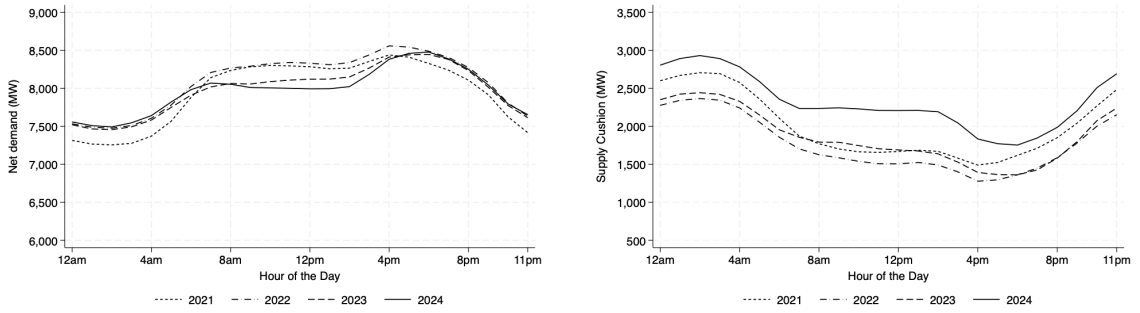
Notes: Panel (a) plots hourly averages of wholesale market demand. Panel (b) plots hourly averages of wholesale electricity price (2024 CAD/MWh).

Figure 6 plots average hourly net demand (market demand minus wind and solar generation) and the supply cushion (total offered available capacity minus market demand) by year. Panel (a) shows that net demand, the residual demand that must be met by dispatchable generation and imports, retained a stable diurnal pattern. Only 2021 had slightly lower off-peak net demand, while both 2021 and 2022 had relatively higher midday net demand compared to 2023 and, to a greater extent, 2024, potentially due to growth in distributed resources during daylight hours.

[16]The decline in imports partly reflected lower exports from British Columbia due to low water levels, higher prices in neighboring markets, and new reliability rules that reduced effective import capacity (MSA, 2023, 2024).

On the other hand, Panel (b) reveals a changing landscape for supply adequacy and market competition. The supply cushion was notably tighter during 2022 and 2023, followed by an expansion in 2024 with the entry of new thermal and renewable capacity.[17] As expected, the cushion is smallest during the evening peak and largest overnight, when demand is low and wind is likely high.

Figure 6. Net Demand and Supply Cushion



(a) Hourly Net Demand

(b) Hourly Supply Cushion

Notes: Panel (a) plots hourly averages of net demand, which is market demand minus wind and solar generation. Panel (b) plots hourly averages of supply cushion, which is the offered available capacity in the market minus market demand.

Motivated by these patterns, Figure 7 examines how concentration among dispatchable in-province suppliers, the units that clear residual demand once wind, solar, and imports are netted, varies by hour and year. Panel (a) shows that, when measured against dispatchable in-province supply (i.e., excluding imports, wind, and solar), the five-firm concentration ratio (CR5) ranged from roughly 52% to 65% across years, with the lowest values at midday and the highest during morning and evening ramp hours.[18]

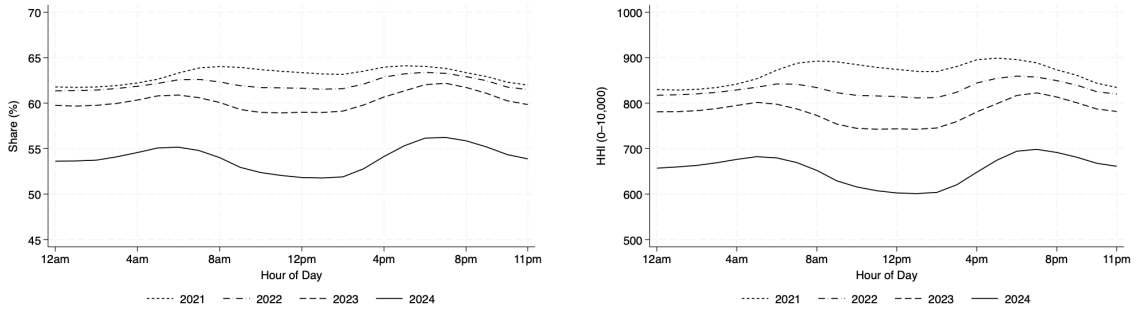
Panel (b) shows the associated Herfindahl-Hirschman Index (HHI), which ranged from about 600 to 900, likewise dipping at midday and peaking in the ramps. Both CR5 and HHI trended downward between 2021 and 2024, consistent with entry and expansion by smaller suppliers. Notably, the midday hollowing out became most pronounced in 2024, consistent with rising solar output that added low-marginal-cost

[17] A significant portion of the new thermal capacity in 2024 came from the commissioning of the 900 MW Cascade Power Project. This combined-cycle plant is owned by a consortium of entities outside the traditional five largest firms in the market.

[18] Figure A.3 in Appendix A highlights that results constructed relative to total market demand, including imports and non-dispatchable renewables, show a qualitatively similar midday decline and downward trend over time.

generation during daylight hours and reduced the relative share of the largest thermal fleets. Concentration remains comparatively higher in the ramps when solar is low or ramping and demand peaks.

Figure 7. Concentration Measures



(a) CR5 (b) HHI

Notes: Panel (a) plots hourly averages of CR5, the sum of the five largest suppliers' shares of dispatchable in-province supply (excluding imports, wind, and solar). Panel (b) plots hourly averages of HHI, calculated as $\sum_i s_i^2 \times 10{,}000$, where s_i is supplier i's share of dispatchable in-province supply.

Collectively, these patterns suggest that the expansion of renewable energy in Alberta has influenced average price levels, hourly price fluctuations, and competition among suppliers. These patterns motivate my subsequent empirical analysis.

4 Empirical Strategy

My empirical strategy has three stages. First, I estimate the short-run effects of wind and solar generation on wholesale electricity prices. Second, I decompose these effects into cost and strategic channels by comparing observed outcomes with those of a competitive benchmark constructed from generators' estimated marginal costs. Third, I examine medium-run impacts by allowing renewable capacity to adjust and simulating counterfactual scenarios to assess how increased renewable penetration affects the profitability of different generation technologies.

4.1 Short-Run Price Impact of Renewable Generation

To establish a baseline for the short-run price impact of renewables, I estimate the following specification separately for each hour of the day:

$$P_{h,d} = \alpha_{h,m,y} + \beta_h^w \cdot \text{Wind}_d + \beta_h^s \cdot \text{Solar}_d + \boldsymbol{\theta}_h \cdot \mathbf{X}_{h,d} + \varepsilon_{h,d}, \tag{1}$$

where h denotes the hour of day, d the day in the sample, and m and y the calendar month and year. The dependent variable $P_{h,d}$ is the market price of electricity (in \$/MWh). The key explanatory variables are aggregate daily generation from wind (Wind_d) and solar (Solar_d), both measured in GWh. The vector $\mathbf{X}_{h,d}$ includes hourly electricity demand,[19] the daily natural gas price,[20] and quadratic functions of heating- and cooling-degree hours (HDH and CDH).[21] Hour-by-month-by-year fixed effects, $\alpha_{h,m,y}$, flexibly control for seasonal patterns and secular trends. I report Newey–West standard errors with a 7-day lag, which are robust to heteroskedasticity and serial correlation.[22]

The coefficients of interest, β_h^w and β_h^s, measure the average change in the market price for hour h from a 1 GWh increase in daily wind or solar generation. The primary identifying assumption is that, conditional on the controls, daily renewable generation is exogenous to unobserved determinants of hourly prices. This assumption is plausible because short-run renewable output is primarily driven by weather. With hour-by-month-by-year fixed effects, identification relies on day-to-day, weather-driven fluctuations within each month and year, thereby mitigating confounding from capacity growth and long-term trends.[23]

A potential threat to the identifying assumption is curtailment, when the system operator reduces renewable output during periods of oversupply or congestion.[24] In Appendix B.1, I address this by instrumenting realized daily wind and solar generation with AESO day-ahead forecasts published ex ante. The instrumental variables (IV) estimates closely match ordinary least squares (OLS) results and are not statistically distinguishable from OLS by hour, indicating that curtailment does not materially

[19] Demand is internal load served by the wholesale market and excludes behind-the-meter generation by industrial facilities. Results are robust to including behind-the-meter generation.

[20] Natural gas price measure is the Alberta AECO/NGX spot price, which best reflects Alberta generators' local marginal cost of natural gas. Using daily Henry Hub prices from the U.S. EIA yields similar results.

[21] HDH is the number of degrees that an hour's temperature falls below 18.33 °C; CDH is the number of degrees it exceeds this base temperature. Both are centered on their sample means.

[22] Unless otherwise specified, standard errors in all specifications are Newey–West with a 7-day lag to account for heteroskedasticity and serial correlation. Results are robust to alternative specifications, including clustering by day or week of the sample.

[23] When analyzing medium-run impacts in Section 4.3, hour-by-month fixed effects are used to allow the estimates to reflect both exogenous capacity-driven and weather-related variation.

[24] For example, on October 6, 2023, AESO curtailed 165 MW of wind output when Alberta was temporarily disconnected from the Western Electricity Coordinating Council (WECC) (MSA, 2024).

bias the estimated price effects.

I use daily, rather than hourly, renewable generation to capture intertemporal spillovers. An hourly regressor would capture the contemporaneous price effect, whereas a daily variable reflects the supply shock that influences prices throughout the day (Bushnell and Novan, 2021). This methodology is motivated by the operational realities of power markets, where commitment and scheduling protocols, multi-hour constraints, and bidding strategies depend on expected daily net load. In Appendix B.2, I re-estimate the model using hourly wind and solar generation and rescale hourly coefficients to daily-equivalent units based on the average contribution of each hour h to a 1 GWh increase in daily output. Results from the hourly specification are qualitatively similar to those from the daily model.

Finally, my primary specification estimates Equation (1) separately for each hour, allowing all coefficients to vary by hour and capturing heterogeneity across the day. As a complement, I also estimate pooled specifications that constrain the coefficients to be constant across hours to recover a single 24-hour average effect. I estimate these pooled specifications using both daily renewable generation (my main approach) and hourly renewable generation in Appendix B.3.

4.2 Decomposing Price Effects into Competitive and Strategic Channels

To separate cost-driven effects from strategic behavior, I construct an hourly competitive benchmark price, $P^C_{h,d}$, representing the price that would prevail under marginal-cost bidding. This benchmark is derived in two steps. First, I construct a competitive supply curve using estimated unit-level marginal costs and unit availability. Second, I estimate the residual demand curve faced by Alberta generators, which equals inelastic provincial demand net of price-responsive net imports. The benchmark price clears at the intersection of these curves.

I then re-estimate the baseline regression in Equation (1) with two alternative dependent variables. The first is $P^C_{h,d}$, which captures the cost-driven effect of renewable generation (hereafter, the "competitive channel"). The second is the markup, $P_{h,d} - P^C_{h,d}$, which isolates the effect of renewable generation on firms' strategic behavior and the exercise of market power (the "strategic channel"). This decomposition allows me to determine whether renewables reduce prices primarily through lower system marginal costs, lower market power exercise that reduces markups, or both.

4.2.1 Constructing the Competitive Benchmark: Supply

The competitive supply curve is constructed bottom-up from each unit's estimated marginal cost, observed commitment status, and available capacity. In a fully specified competitive model, unit commitment and dispatch would be determined jointly with intertemporal operational constraints (e.g., start-up and no-load costs, minimum up/down times, and minimum stable generation levels). When these nonconvexities are not modeled explicitly, two issues arise. First, observed commitment may be endogenous if firms withhold capacity, tending to bias the benchmark upward by restricting supply. Second, simulating availability from historical outage rates while ignoring dynamic costs and constraints tends to bias the benchmark downward by overstating markups and the feasible operational flexibility of the system (Mansur, 2008; Jha and Leslie, 2025).

My objective is to decompose observed price effects into cost-driven and strategic components, which requires a competitive benchmark that uses the same realized market conditions as observed prices. Simulating optimal unit commitment would introduce operational differences that confound the strategic versus competitive comparison. Given this trade-off, I condition on each unit's observed commitment status in each hour and assume marginal-cost offers. This embeds the dynamic constraints revealed by commitment decisions but not the endogeneity of commitment itself.

The bias of the competitive benchmark is therefore a priori ambiguous. If committed units bid above marginal cost to recover full operating costs, the benchmark can understate the competitive price (overstating markups). Conversely, if capacity is physically withheld, the benchmark can overstate the competitive price (understating markups). However, physical withholding is prohibited by regulation in Alberta and strictly enforced by the MSA, making it less likely in practice. Economic withholding through offer prices remains feasible and is the primary form of strategic behavior I measure. I therefore interpret the benchmark as an approximate lower bound on competitive prices.

I estimate the hourly marginal costs following Brown and Olmstead (2017) and Brown et al. (2023).[25] For most coal and natural gas units, marginal costs consist of fuel costs, environmental costs, and variable operation and maintenance (O&M) costs. Fuel cost, the primary component, is calculated by multiplying a unit's heat rate (a measure of fuel efficiency) by the relevant fuel price.

Thermal units are subject to environmental compliance costs from carbon pricing.

[25] See Appendix C for methodological details.

The marginal environmental cost is estimated as the product of emission intensity (relative to a benchmark) and the carbon price. In January 2020, the TIER carbon pricing policy was implemented in Alberta, requiring facilities to pay \$30/tCO2e on emissions exceeding an industry-wide benchmark of 0.37 tCO2e/MWh, which has declined by 2% annually since 2023.[26] The carbon price increased to \$40/tCO2e in 2021, \$50/tCO2e in 2022, and has increased by \$15/tCO2e annually thereafter. Emission intensity is determined by a unit's heat rate and the fuel-specific emission factor.

Modeling marginal costs for biomass, hydro, and energy storage is challenging because their relevant costs are intertemporal, such as water values, state-of-charge constraints, and fuel or byproduct opportunities. In addition, cogeneration facilities in Alberta typically sell surplus electricity as price takers and often bid at or near zero. I therefore proxy the marginal opportunity costs of these resources with their observed bids.

Finally, at the market level, I shift the supply function to the right by the realized wind and solar output, treating these resources as having zero marginal cost, which is consistent with their observed bidding behavior. The resulting hourly supply curve is stepwise, with blocks ordered from the least to the most expensive available units.

4.2.2 Constructing the Competitive Benchmark: Residual Demand

I next estimate the residual demand faced by Alberta generators. While wholesale electricity demand within the province is largely price-inelastic, net import supply is price-responsive. Firms exporting into Alberta schedule their supply based on expected market prices and must bid at \$0 in the wholesale market, effectively acting as price-takers. If Alberta generators increase prices above competitive levels, net import supply will exceed competitive levels. With higher net imports and perfectly inelastic demand, fewer Alberta generators will operate, resulting in a downward-sloping residual demand curve equal to provincial demand less net imports.

Alberta is a net importer in more than 70% of hours during the sample, with most imports coming from British Columbia (BC). To estimate the net import supply function, I account for Alberta's limited interconnections and the influence of external market conditions, particularly the price at the Mid-Columbia (Mid-C) hub, which competes for electricity from BC. Because the supply relationship can change over

[26] This "good-as-best-gas" benchmark corresponds to the efficiency of Alberta's best combined-cycle natural gas generators.

time, I estimate the function separately for each year using the following log-linear specification:

$$Q_h^{NI} = \beta_{0y} + \beta_{1y} \ln(P_h^{AB}) + \beta_{2y} \ln(P_d^{MidC}) + \gamma_y f(\text{Temp}_h) + \delta_y X_h + \varepsilon_h \tag{2}$$

where Q_h^{NI} represents net electricity imports from neighboring jurisdictions, P_h^{AB} is the Alberta wholesale price, and P_d^{MidC} is the daily quantity-weighted average peak price at Mid-C. The function $f(Temp_h)$ includes quadratic heating and cooling degree days (base 18.33 °C) for Calgary and major cities in bordering jurisdictions (Vancouver, Saskatoon, and Billings) to capture nonlinear temperature effects on demand and supply. Calendar fixed effects X_h control for seasonality and holiday patterns. All coefficients are allowed to vary by year y. Standard errors are Newey-West with a 24-hour lag to account for heteroskedasticity and serial correlation.

Since prices are endogenous, I estimate Equation (2) using two-stage least squares (2SLS), treating both $\ln P_h^{AB}$ and $\ln P_d^{MidC}$ as endogenous. The instruments are log hourly Alberta wholesale demand and log average daily demand at the BPA Balancing Authority in the Northwestern U.S.[27] Wholesale electricity demand is highly price-inelastic, which supports the exclusion restriction that demand shifts the supply curve but does not directly affect import decisions conditional on prices. First-stage diagnostics confirm valid instruments in all years. Detailed results and robustness checks are reported in Appendix B.4.

Finally, I construct the residual demand curve faced by Alberta generators at any price p as:

$$R_h(p) = D_h^{AB} - \widehat{Q}_h^{NI}(p)$$

where D_h^{AB} is provincial demand and $\widehat{Q}_h^{NI}(p)$ is predicted net imports from Equation (2) evaluated at price p. I truncate $\widehat{Q}_h^{NI}(p)$ at the available transmission capacity (import and export limits), yielding a downward-sloping residual demand curve that becomes perfectly inelastic when transmission constraints bind.

[27] This approach is commonly used in the literature (e.g., Mansur, 2007; Bushnell et al., 2008; Brown and Olmstead, 2017; Brown et al., 2023).

4.2.3 Estimating the Competitive and Markup Channels

The Competitive Channel. The first step in the decomposition is to estimate the impact of renewables on the competitive benchmark price, isolating the competitive channel. I re-estimate the baseline model, replacing the observed market price with the competitive benchmark price, $P^C_{h,d}$:

$$P^C_{h,d} = \alpha_{h,m,y} + \gamma^w_h \text{ Wind}_d + \gamma^s_h \text{ Solar}_d + \boldsymbol{\theta}_h \cdot \mathbf{X}_{h,d} + \varepsilon_{h,d}. \tag{3}$$

where γ^w_h and γ^s_h measure the cost effects of wind and solar in the absence of strategic bidding.

The Markup Channel. To quantify the direction and magnitude of strategic responses to renewable generation, I calculate the hourly markup as the difference between the observed market price (P) and the constructed competitive benchmark price (P^C):

$$\text{Markup}_{h,d} = P_{h,d} - P^C_{h,d}.$$

I then regress the markup on daily wind and solar generation, using the same fixed effects and controls as in the baseline model:

$$\text{Markup}_{h,d} = \alpha_{h,m,y} + \delta^w_h \text{ Wind}_d + \delta^s_h \text{ Solar}_d + \boldsymbol{\theta}_h \cdot \mathbf{X}_{h,d} + \varepsilon_{h,d}. \tag{4}$$

The coefficients δ^w_h and δ^s_h measure how daily wind and solar generation affect the markup in hour h. A significantly negative estimate indicates a pro-competitive effect, as markups fall when renewables rise. A zero or positive estimate implies unchanged or increased market power.

4.3 Medium-Run Price and Profitability Impacts

The short-run price effects documented in Section 4.1 establish how renewable generation affects prices conditional on existing capacity. However, the objective is not to identify the effect of transitory renewable fluctuations but rather to characterize how sustained renewable capacity expansion reshapes market fundamentals over time. As capacity grows, the cumulative price impacts may differ substantially from short-run effects due to the changing composition of hours when renewable energy displaces conventional generation. These compositional changes have important implications

for the operating profitability of conventional generators and, consequently, long-run resource adequacy.

To examine these medium-run implications, I allow for changes in the stock of renewable capacity. Following Bushnell and Novan (2021), I employ a two-step approach. First, I re-estimate the price-response relationship from Equation (1) using hour-by-month fixed effects instead of hour-by-month-by-year fixed effects. The identifying variation now reflects both day-to-day weather fluctuations and year-over-year capacity growth. I then use these estimates to predict counterfactual wholesale prices under alternative renewable capacity scenarios and assess how capacity expansion affects the operating profits of different generation technologies.

This reduced-form approach captures the combined effects of renewable capacity growth on prices but does not identify the causal effect of an exogenous capacity shock. Although it is not possible to entirely rule out that some capacity additions responded to market expectations, several features of Alberta's institutional context support a predominantly policy-driven interpretation of the observed capacity expansion. The renewable capacity growth during my sample period was primarily driven by REP auction commitments made years in advance, Alberta's TIER regulation establishing emissions performance standards, and multi-year project development timelines that make capacity highly predetermined relative to contemporaneous price expectations.[28] In addition, I control for key long-run demand and supply drivers of wholesale electricity prices to mitigate spurious-trend concerns.

The analysis is subject to two primary limitations. First, it does not account for revenues from bilateral contracts or ancillary services markets, which together represent approximately 5-7% of total generator revenues in Alberta.[29] While these revenue streams may respond differently to renewable penetration than energy market revenues, spot market revenues constitute the dominant profit driver for conventional generators.

Second, the linear specification used for counterfactual prediction abstracts from

[28] See Section 3.1.2 for institutional details.

[29] In 2024, total forward market trade volumes amounted to 31.2 TWh, approximately 35% of Alberta's internal demand, with bilateral contracts accounting for roughly 6% of this forward market activity (MSA, 2024), implying bilateral contracts covered approximately 2% of total internal demand. Ancillary service revenues constitute approximately 3–5% of total generator revenues (AESO, 2025). Moreover, forward market liquidity has been declining over time, and forward contracts in Alberta are predominantly short-term (over 95% were annual, quarterly, or monthly in 2024) and priced in reference to expected spot market outcomes. This tight linkage between forward and spot prices suggests that the directional effects of renewable penetration are likely similar across both revenue streams.

potentially important nonlinearities in the price-renewable relationship. However, over the range of observed capacity variation in my sample, a linear approximation provides a reasonable first-order characterization of the price response, and results are robust to more flexible functional forms.

4.3.1 Counterfactual Prices

I estimate a specification analogous to Equation (1) with hour-by-month fixed effects, modeling hourly wholesale prices as a linear function of daily solar and wind generation along with controls for hourly demand, daily natural gas prices, and temperature-related variables. I then use this specification to predict counterfactual prices under alternative renewable capacity levels in 2024, the final year of my sample, by varying only the renewable generation terms while holding all other covariates and regression residuals at their observed values in 2024.

The predicted counterfactual price, $\tilde{P}_{h,d}$, is given by:

$$\tilde{P}_{h,d} = \hat{\alpha}_{h,m} + \hat{\beta}_h^w \cdot \widetilde{\text{Wind}}_d + \hat{\beta}_h^s \cdot \widetilde{\text{Solar}}_d + \hat{\boldsymbol{\theta}}_h \cdot \mathbf{X}_{h,d} + \hat{\varepsilon}_{h,d} \tag{5}$$

where $\widetilde{\text{Wind}}_d$ and $\widetilde{\text{Solar}}_d$ represent counterfactual daily generation levels for wind and solar, and all other terms are as defined in Equation (1). I use Newey–West standard errors with a 7-day lag to account for heteroskedasticity and serial correlation. The residual term, $\hat{\varepsilon}_{h,d}$, captures unobserved factors that influenced prices in 2024 but were not included in the model. A critical assumption underlying this approach is that the error term is uncorrelated with the counterfactual changes in renewable generation, that is, the unobserved price determinants would have been the same under alternative renewable capacity scenarios.

I consider two counterfactual scenarios that bracket the observed 2024 capacity levels. First, I simulate a lower-capacity scenario in which wind and solar capacities are held at their average 2021 levels throughout 2024. This backward-looking counterfactual estimates the price impact of the renewable capacity additions that actually occurred between 2021 and 2024, without extrapolating beyond the observed range of generation levels. Second, I simulate a higher-capacity scenario based on AESO's projected 2030 capacity additions, which include an additional 1.6 GW of wind and 1.9 GW of solar beyond 2024 levels (AESO, 2024).[30] This forward-looking

[30]Recent policy developments have temporarily paused new renewable project approvals in Alberta, which may affect the likelihood and timing of these capacity additions (GOA, 2023a). Nonetheless, these projections provide a useful benchmark for understanding potential price im-

scenario requires extrapolation beyond the sample range and should be interpreted with appropriate caution.

To translate counterfactual capacity levels into daily generation, I compute daily capacity factors as the ratio of observed daily generation to installed capacity for each technology. I then apply these observed 2024 capacity factors to the counterfactual capacity levels, implicitly assuming that additional renewable capacity would be sited in similar geographic locations as existing installations and would therefore exhibit comparable generation profiles.[31] In each simulation, I vary wind capacity while holding solar capacity constant, and vice versa, to isolate the marginal price impact of each technology.

4.3.2 Change in Operating Profits

With counterfactual prices determined, I assess how renewable capacity expansion affects the operating profitability of conventional generation technologies and renewables. This analysis connects directly to the literature on renewable "cannibalization" effects, which documents that intermittent renewables tend to generate during hours when they depress their own marginal revenues (Hirth, 2013; Prol et al., 2020; Bushnell and Novan, 2021).

I use a simple static model to calculate the annual operating profits of a hypothetical 1 MW generator that is available to produce whenever the market price exceeds its marginal cost. This assumes generators face no dynamic costs or operational constraints, such as start-up or ramping costs. A generator produces no output when the wholesale price falls below its marginal cost and operates at full capacity when the price is above it. This approach provides an upper bound on operating profitability because it ignores commitment costs and assumes frictionless entry and exit. In practice, some generators stay online even when market prices are below their marginal cost to avoid shutdown and restart costs. Therefore, the model likely understates actual operating losses.

For a generation technology with a marginal cost of c_i, I compute the predicted annual profit under a counterfactual renewable capacity K_R, which can represent either wind (K_W) or solar (K_S) capacity. Given the counterfactual prices $\tilde{P}_t(K_R)$ for each of the 8,784 hours in 2024, the annual profit per MW of installed capacity is:

pacts under increased renewable penetration.

[31] This assumption is reasonable given that wind and solar resources in Alberta are geographically concentrated in the southern regions due to resource quality and transmission access.

$$\text{Profit}\left(c_i, K_R\right) = \sum_{t=1}^{8{,}784} \max\left(\tilde{P}_t\left(K_R\right) - c_i,\, 0\right) \tag{6}$$

This measures the annual revenue net of variable costs that a 1 MW generator would earn by entering and exiting the market in each hour, representing the potential variable profit available to cover fixed costs and generate returns. The marginal cost range c_i is selected to span a broad spectrum of generation technologies, from low-cost renewables ($c_i \approx 0$) to high-cost peaking thermal units ($c_i \approx 150$ \$/MWh), which allows the analysis to characterize how profitability varies across the merit order under different renewable penetration scenarios.

5 Results

5.1 Observed Prices versus the Competitive Benchmark

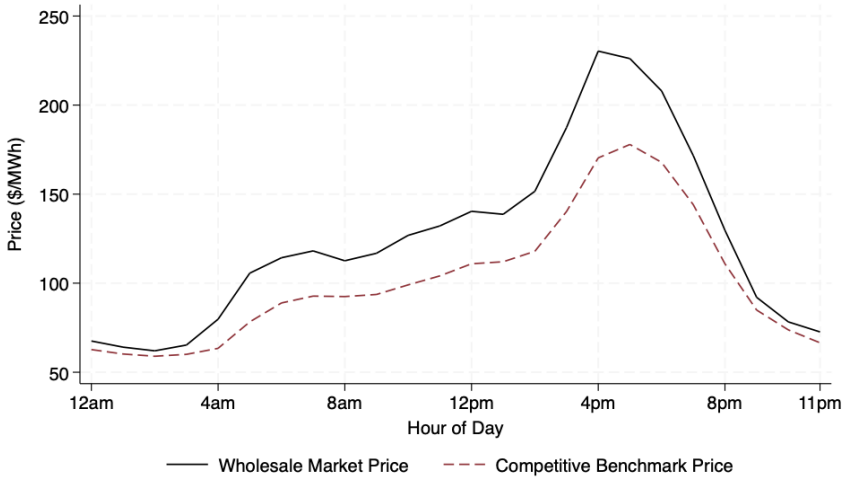
I compare observed wholesale prices to the competitive benchmark (constructed assuming marginal-cost bidding) and examine how they vary across hours and market conditions such as demand level, renewable output, and supply cushion.

Figure 8 shows a persistent gap between observed market prices and the competitive benchmark, especially during peak-demand hours. This pattern is consistent with findings for Alberta in Brown and Olmstead (2017) and aligns with broader evidence from electricity markets: the scope for market power is typically limited off-peak but becomes more pronounced during peak periods, as high demand and more limited transmission or generation capacity concentrate price-setting power among a few dominant suppliers.

Figure 9 presents the relationship between market demand, supply cushion, and prices. Panel (a) shows that both average observed prices and the competitive benchmark are positively correlated with the demand percentile. Furthermore, the gap between observed prices and the benchmark, the markup, generally grows as demand increases. Panel (b) offers a complementary perspective. A lower supply cushion is associated with higher prices and larger markups. In conditions of lowest cushion, both the average price and benchmark reach their highest levels, consistent with scarcity conditions where capacity constraints necessitate the dispatch of high-cost units.

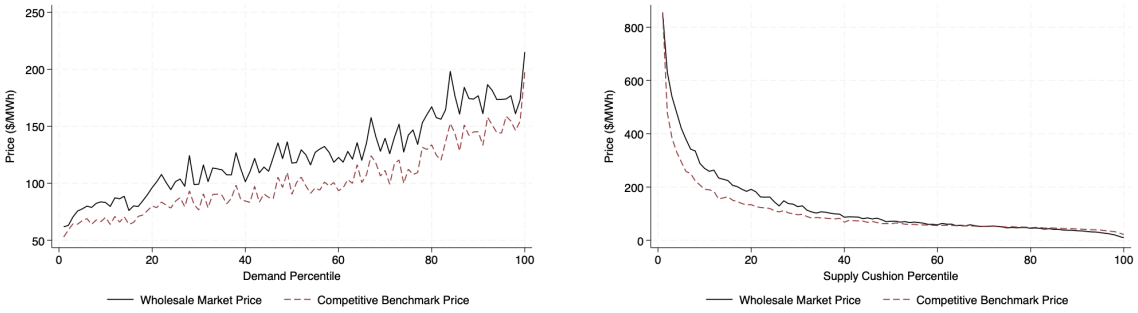
Figure 10 shows average market prices and the competitive benchmark across the distribution of wind and solar generation. Wind and solar percentiles are computed

Figure 8. Observed Market Prices and Competitive Benchmark



Notes: This figure plots the average hourly real-time market-clearing price and the competitive benchmark constructed in Section 4.2 from 2021 to 2024.

Figure 9. Observed Prices and Benchmark by Percentiles of Demand and Supply Cushion



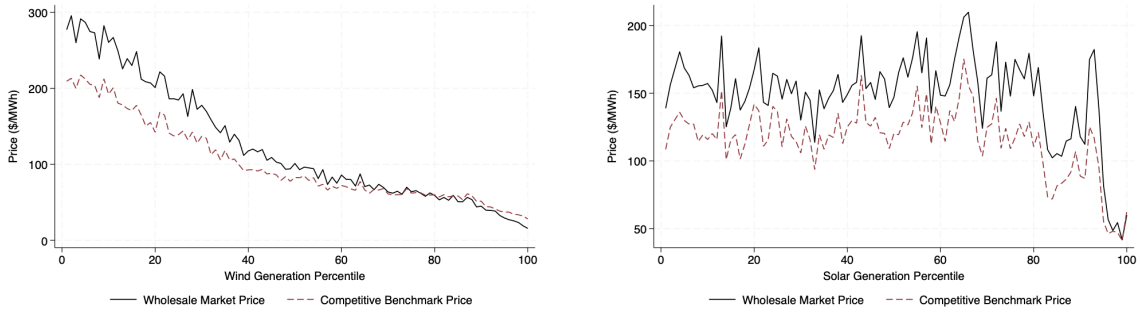
(a) By Market Demand Percentile

(b) By Supply Cushion Percentile

Notes: Each plot shows the average market price and competitive benchmark across 100 percentiles of market demand (Panel (a)) and supply cushion (Panel (b)).

over hours with positive output. For wind, Panel (a) indicates that the price and benchmark decline as output increases, but observed prices remain well above the competitive benchmark at low wind-output percentiles, consistent with the exercise of market power when strategic firms face less competition from low-cost renewable generation. For solar, Panel (b) suggests that prices decline noticeably only at the highest output levels. Otherwise, the relationship between solar generation and prices (both observed and benchmark) is weak. This likely reflects solar's relatively smaller capacity share compared to wind and its more predictable diurnal pattern, which concentrates output during moderate-demand midday hours.

Figure 10. Observed Prices and Benchmark by Percentiles of Wind and Solar Generation



(a) By Wind Generation Percentile

(b) By Solar Generation Percentile

Notes: Each plot shows the average market price and competitive benchmark across 100 percentiles of wind generation (Panel (a)) and solar generation (Panel (b)). Percentiles are computed over positive-output hours.

Overall, deviations of observed prices from the competitive benchmark are largest during high-demand periods, when the supply cushion is small, and when renewable output is low, precisely the conditions when market power is expected to be most pronounced.

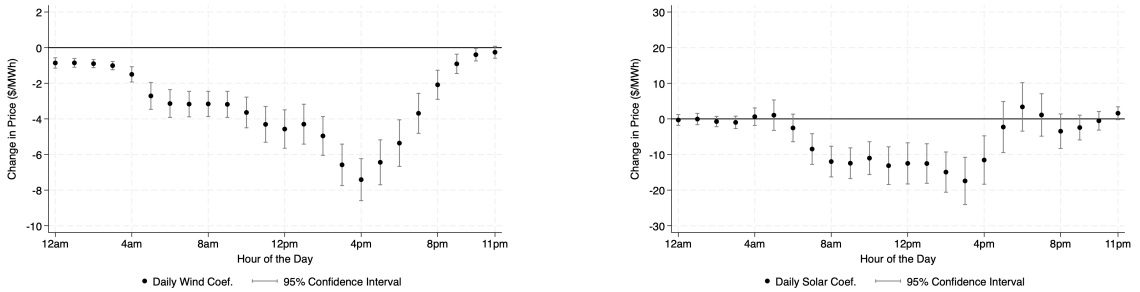
5.2 Short-Run Price Effects

This section reports the primary empirical findings regarding the short-term price impacts of renewable generation.

Total Price Impact Figure 11 plots the hourly point estimates and 95% confidence intervals for β_h^w and β_h^s, which measure the average change in the wholesale electricity

price in hour h resulting from a 1 GWh increase in daily wind or solar generation. The estimates reveal distinct intraday patterns in the price impact of wind and solar generation.

Figure 11. Short-Run Price Effects of Daily Renewable Generation



(a) Wind Generation

(b) Solar Generation

Notes: This figure plots hour-specific coefficients from Equation (1), measuring the price impact of a 1 GWh increase in daily generation. Panel (a) shows the impact of wind generation. Panel (b) shows the impact of solar generation. Bars represent 95% confidence intervals using Newey-West standard errors with a 7-day lag.

For daily wind generation, Panel (a) shows statistically significant price reductions across all hours except 11 PM. At 4 PM, a 1 GWh increase in daily wind output is estimated to lower the market price by \$7.41/MWh, on average. In contrast, during late-night off-peak hours such as 12 AM, the effect is modest, reducing prices by only \$0.86/MWh. These patterns indicate that daily wind generation has its greatest impact during peak-demand hours, even though wind output is generally more abundant overnight. When demand is low at night, the market operates on a relatively flat segment of the supply curve, which results in a smaller price reduction per additional MWh of wind. During periods of high electricity demand, such as the afternoon, the market operates on the upper segment of the supply curve, where marginal costs rise rapidly. As a result, reductions in conventional generation during these hours lead to substantial decreases in market prices.

Panel (b) shows that from 7 AM through 4 PM, the hours that account for 91.3% of daily solar output, a 1 GWh increase in daily solar results in statistically significant reductions in hourly market prices. At 12 PM, for example, a 1 GWh increase in daily solar output is estimated to lower the price by about \$12.17/MWh.[32] At the same

[32]Average price effects of wind and solar in Alberta are broadly consistent with the literature. For a recent review, see Mills et al. (2021), who report that growth in wind and solar has reduced average annual wholesale electricity prices by less than \$3/MWh.

time, the point estimates indicate that higher solar generation is associated with higher prices in some morning and evening hours, although these coefficients are not statistically distinguishable from zero.

Price Impact Decomposition Wind and solar both lower prices, but the magnitude and timing of these effects differ across technologies and hours of the day. I decompose the total price effect into two components. The first is a cost component that captures price changes driven by shifts in the supply curve due to low-cost renewables. I measure this by estimating how renewables affect the cost-based competitive benchmark. The second is a markup component, defined as the difference between observed market prices and the benchmark, which reflects changes in the exercise of market power and pricing above marginal cost. I measure this by estimating the effect of renewables on markups. This decomposition allows me to identify when renewables reduce prices by lowering system costs and when strategic responses amplify, leave unchanged, or offset these gains through changes in markups.

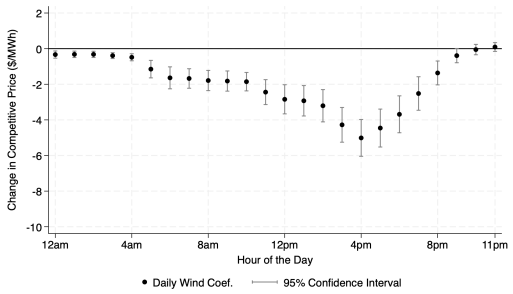
Figure 12 reports coefficient estimates and 95% confidence intervals for each hour of the day from regressions of the competitive-benchmark price (Equation (3)) and the markup (Equation (4)) on daily wind and solar generation.

Referring back to Figure 11, increases in daily wind generation reduce prices across almost all hours, though the magnitude varies by hour. The decomposition shows that both costs and markups decline. For example, at 4 PM, the cost component falls by about \$5.01/MWh (Panel a) and the markup component falls by roughly \$2.40/MWh (Panel b), yielding a total effect of approximately \$7.41/MWh, consistent with Figure 11. On average across hours, daily wind generation lowers prices by \$3.30/MWh, with roughly 60% of this effect operating through the cost component and 40% through the markup component. This highlights wind's substantial disciplining effect on the market power of incumbent firms and its role in strengthening competition.

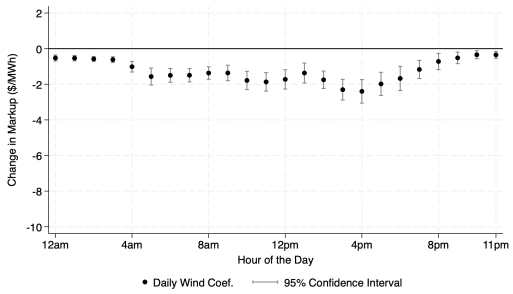
Panels (c) and (d) reveal the channels underlying solar's price effect. At 12 PM, for example, the estimated price decrease of about \$12.49/MWh decomposes into roughly \$8.32/MWh from the cost component and \$4.17/MWh from the markup component. Around midday, abundant solar output lowers the competitive-benchmark price by reducing net demand and shifting dispatch toward lower-cost units, and it intensifies competition among inframarginal units that seek to avoid shutting down, which reduces markups. Although not statistically significant, the point estimates for some

morning and evening hours are positive for the cost and markup components. As solar output falls toward the evening, the ramp is met by higher-cost peaking units and a tighter supply cushion, which raises the cost component and allows remaining suppliers to charge higher markups.

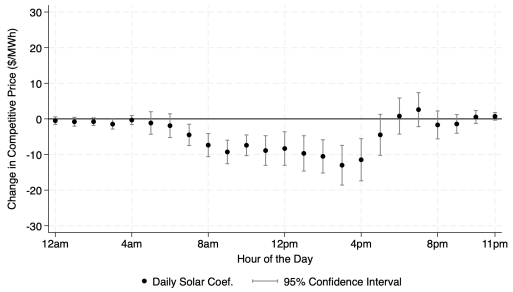
Figure 12. Short-run Price Impact Decomposition: Cost vs. Markup Channel



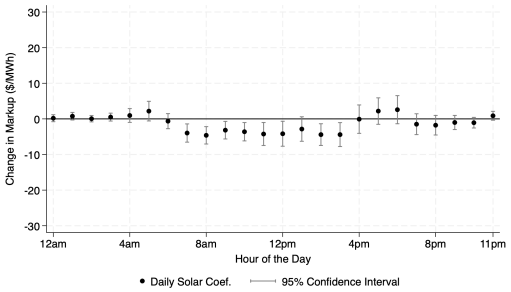
(a) Wind: Cost Component



(b) Wind: Markup Component



(c) Solar: Cost Component



(d) Solar: Markup Component

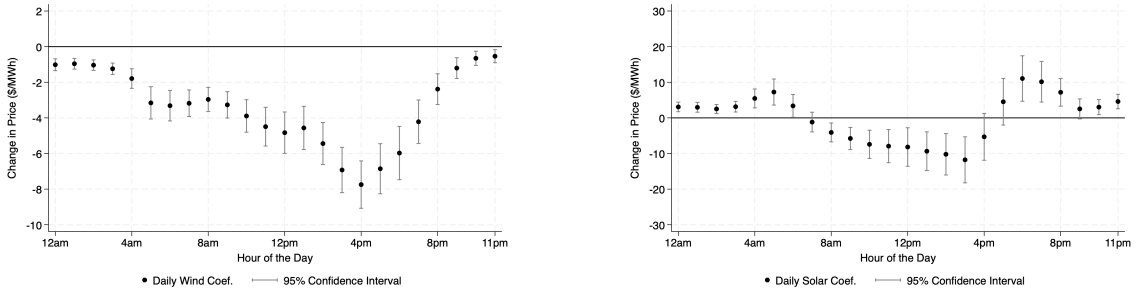
Notes: Panels plot estimated coefficients and 95% confidence intervals by hour of day, showing the effect of a 1 GWh increase in daily renewable generation. The top row displays the impacts of daily wind generation. The bottom row displays the impacts of daily solar generation. Panel (a) and Panel (c) display the cost component, defined as the effect on the competitive benchmark price. Panel (b) and Panel (d) display the markup component, defined as the effect on the difference between the observed price and the competitive benchmark. Confidence intervals are based on Newey-West standard errors with a 7-day lag.

5.3 Impact of Renewable Expansion on Profitability

5.3.1 Medium Run

Figure 13 summarizes the medium-run effects of daily wind and solar generation on hourly wholesale prices. The estimates come from Equation (1) with hour-by-month fixed effects, so they reflect both day-to-day weather shocks and year-over-

Figure 13. Medium-run Price Effects of Daily Renewable Generation



(a) Wind Generation

(b) Solar Generation

Notes: The figure plots hour-specific coefficients from Equation (1), estimated with hour-by-month fixed effects as described in Section 4.3. Coefficients measure the effect of a 1 GWh increase in daily renewable generation on hourly wholesale prices. Panel (a) shows the impact of wind generation. Panel (b) shows the impact of solar generation. Bars indicate 95% confidence intervals based on Newey-West standard errors with a 7-day lag.

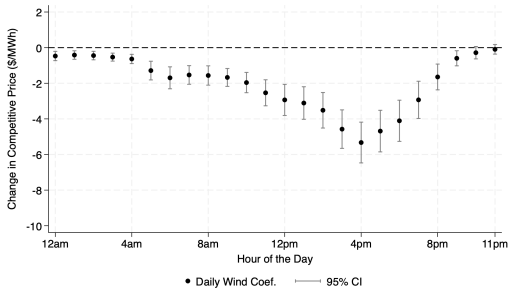
year capacity growth during 2021–2024. Panel (a) shows that higher daily wind generation is associated with statistically significant price reductions in every hour. The magnitudes of these coefficients are quantitatively similar to those from the short-run specification.[33] This similarity indicates that, after accounting for seasonality and controls for fuel costs, demand, and temperature, the marginal price effect of wind remained stable despite the expansion of installed wind capacity from about 1,781 MW to 5,688 MW during 2021–2024.

Panel (b) shows that the medium-run effect of solar is highly uneven across the day. During the daylight hours that account for the vast majority of daily solar output, a 1 GWh increase in daily solar leads to statistically significant price reductions from hour 8 to 15. Compared to the hour–by–month–by–year specification in Panel (b) of Figure 11, the hour–by–month specification delivers somewhat weaker midday price suppression but larger and statistically significant effects during the morning and evening hours. This pattern is consistent with year-over-year solar capacity growth reinforcing an emerging "duck-curve": additional solar continues to depress midday prices, but also contributes to higher morning and evening ramps, so that a growing share of price movements attributed to solar occurs in hours when solar output itself is low.

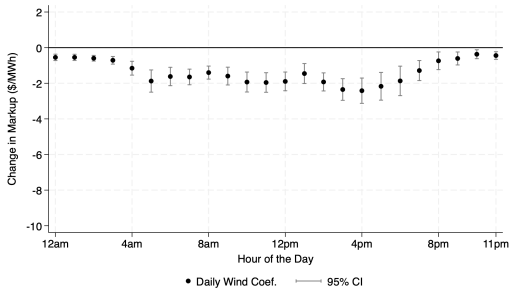
Figure 14 decomposes the medium-run price effects into cost and markup com-

[33]For each hour, two-sided tests using Newey–West standard errors with a 7-day lag fail to reject equality between the short-run and medium-run estimates.

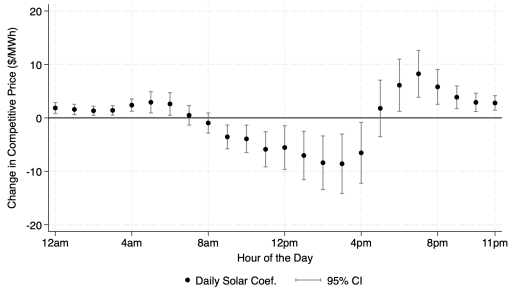
Figure 14. Medium-run Price Impact Decomposition: Cost vs. Markup Channel



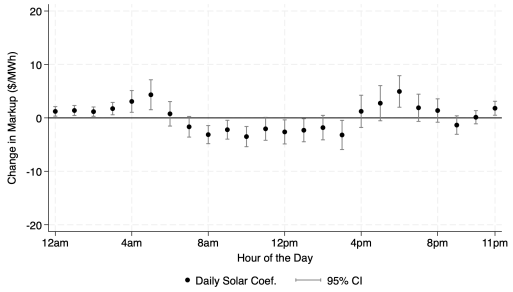
(a) Wind: Cost Component



(b) Wind: Markup Component



(c) Solar: Cost Component



(d) Solar: Markup Component

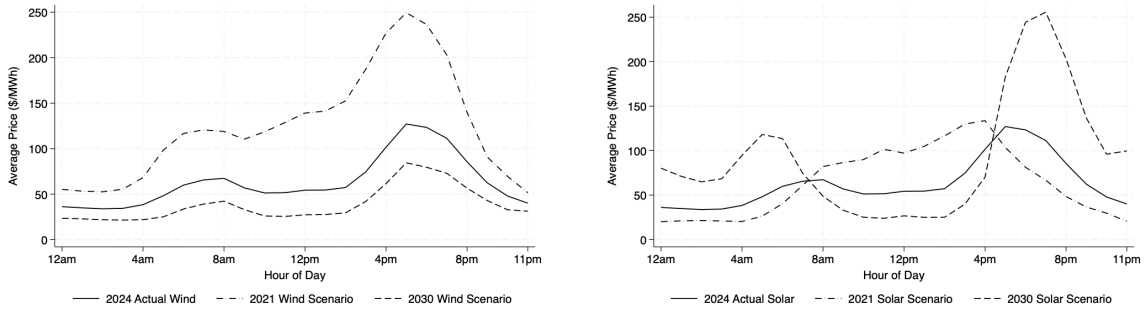
Notes: Panels plot estimated coefficients and 95% confidence intervals by hour of day, showing the medium-run effect of a 1 GWh increase in daily renewable generation. The estimates are based on Equation (3) for the cost component and Equation (4) for the markup component, both estimated with hour-by-month fixed effects. The top row displays the impacts of wind generation. The bottom row displays the impacts of solar generation. Panel (a) and Panel (c) show the cost component, defined as the effect on the competitive benchmark price. Panel (b) and Panel (d) show the markup component, defined as the effect on the difference between the observed price and the competitive benchmark. Confidence intervals are based on Newey-West standard errors with a 7-day lag.

ponents. Referring back to Figure 13, daily wind generation lowers prices across almost all hours. Panels (a) and (b) show that both the competitive benchmark and the markup fall. At 4 PM, for example, the cost component decreases by about \$5.33/MWh and the markup component decreases by roughly \$2.42/MWh. This implies a total effect of about \$7.75/MWh, which matches the medium-run estimate in Figure 11. On average over the day, a 1 GWh increase in daily wind generation reduces prices by about \$3.40/MWh, with roughly 60 percent of this effect coming from lower system marginal costs and 40 percent from lower markups. In the medium run, wind capacity growth therefore reduces both costs and the scope for high markups, and it does so most strongly during high-demand hours.

Panels (c) and (d) show the corresponding decomposition for solar. At 6 PM, for example, the estimated price increase of about \$11.05/MWh decomposes into approximately \$6.10/MWh from the cost component and \$4.95/MWh from the markup component. Around midday, abundant solar output lowers the competitive-benchmark price by reducing net load and shifting dispatch toward lower-cost units. It also intensifies competition among inframarginal units seeking to avoid shutting down, which reduces markups. As solar output falls toward the evening, the ramp is met with higher-cost peaking units and capacity becomes tighter, raising the cost component and enabling remaining suppliers to charge higher markups.

5.3.2 Counterfactual Price Dynamics

Figure 15. Actual and Counterfactual Average Hourly Wholesale Prices



(a) Impact of Wind Expansion

(b) Impact of Solar Expansion

Notes: Panel (a) plots actual and predicted average wholesale prices by hour of day in 2024 under two wind capacity scenarios: 2021 capacity (1.96 GW) and the AESO's projected 2030 capacity (6.4 GW). Panel (b) reports the same for solar under 2021 capacity (0.3 GW) and projected 2030 capacity (3.6 GW).

To analyze the medium-run consequences of renewable expansion for operating profits, I use the price model developed in Section 4.3 to predict how 2024 prices would have differed under the renewable capacity levels of 2021 and those projected for 2030 by the AESO. Figure 15 plots the resulting hourly average price profiles.

For wind, Panel (a) shows that holding capacity at its 2021 level raises prices relative to the 2024 baseline at every hour. The effect is strongest in the evening peak, where average prices reach about $250/MWh. This pattern is consistent with a system that relies more often on higher-cost thermal units and higher market power exercise when wind capacity is lower. Under the projected 2030 wind capacity scenario, predicted prices are lower across the day. Off-peak prices remain below about $50/MWh on average and peak prices remain below about $100/MWh.

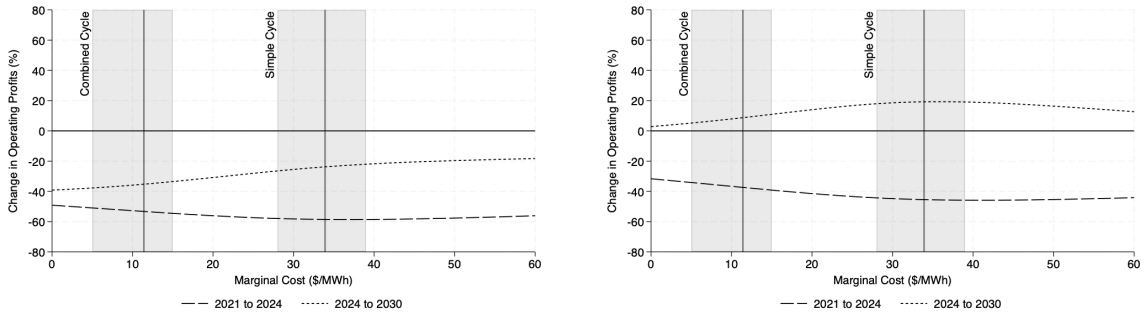
Solar affects both the level and the intraday shape of prices. Panel (b) shows that with 2021 solar capacity, midday prices are consistently higher than under the 2024 baseline, since the system continues to depend more heavily on conventional generation during daylight hours. Under the 2030 solar scenario, predicted prices fall from about 8 AM to 4 PM as abundant solar output displaces higher-cost units. As solar output declines into the late-afternoon peak, the system increasingly relies on a smaller set of dispatchable generators. The resulting scarcity conditions produce evening price spikes that exceed $240/MWh around 6 PM. This familiar "duck-curve" pattern illustrates how higher solar penetration can lower daytime prices while concentrating high prices into a narrower set of ramp hours.

5.3.3 Impact on Generator Profitability

To quantify the distributional effects of renewable expansion across generation technologies, I calculate changes in annual operating profits for units with marginal costs ranging from $0/MWh to $60/MWh under counterfactual renewable-capacity scenarios. Figure 16 displays the percentage change in 2024 profits relative to the 2024 baseline under two counterfactuals: (i) wind and solar capacity fixed at their 2021 levels; and (ii) the 2030 renewable-capacity scenarios projected by the system operator.

Panel (a) shows that the expansion of wind capacity unevenly erodes the profitability of conventional generators. As wind capacity rises from 1.9 GW (2021) to 4.9 GW (2024), a representative combined-cycle (CC) unit with marginal cost of about $11.4/MWh experiences a 53% decline in operating profits, while a simple-cycle (SC) peaker with marginal cost of about $33.9/MWh sees a 58% reduction.

Figure 16. Change in Operating Profits



(a) Impact of Wind Expansion

(b) Impact of Solar Expansion

Notes: This figure shows the percentage change in annual operating profits for power generators under two scenarios: (i) 2024 actual capacities relative to 2021, and (ii) 2030 renewable capacity scenarios relative to 2024. Profits are calculated for hypothetical generators with marginal costs between \$0 and \$60/MWh. Shaded vertical bands mark the interquartile range (25th–75th percentile) and mean estimated marginal cost of natural gas combined-cycle (CC) and simple-cycle turbine (SC) units.

Under the projected 2030 wind capacity of 6.4 GW, the distribution of losses shifts. Relative to 2024, CC profits fall by an additional 39%, whereas SC profits decline by about 24%. The burden of additional wind capacity therefore gradually shifts from higher-cost peakers toward lower-cost baseload and mid-merit units.

Solar capacity changes have a more non-monotonic effect on profits. Panel (b) indicates that the increase in solar capacity from 0.3 GW (2021) to 1.8 GW (2024) reduces profits for both CC and SC units, similar to wind. CC units experience about a 37% decline and SC peakers about a 45% decline. By contrast, further expanding capacity from the 2024 level to 3.6 GW by 2030 raises profits for higher-cost generators relative to 2024. In this scenario, peaker units benefit from the pronounced evening price spikes in Figure 15, which concentrate scarcity rents into a smaller number of hours. These additional rents partly offset lost mid-day revenues and reverse some of the earlier profit losses for high marginal cost generators, while profits for low-cost units remain depressed.

Taken together, the medium-run simulations suggest that renewable growth lowers average wholesale prices while increasing the value of flexibility. The short-run decomposition shows that wind reduces both costs and markups, and the counterfactuals indicate that additional wind capacity shifts the entire price profile downward, eroding inframarginal rents for low-cost thermal units and renewables. Solar deepens midday price reductions but steepens morning and evening ramps. When flexibility is

limited, this tightens capacity during ramp hours and concentrates scarcity rents into a small set of periods. These patterns suggest that continued renewable expansion will favor investment in flexible resources and storage, increase the importance of forward contracting and transmission expansion, and raise resource-adequacy questions in an energy-only design where cost recovery depends on a small number of high-price hours.

6 Conclusion

The rapid expansion of renewable energy is fundamentally reshaping restructured electricity markets. This paper combines theory and evidence to show how wind and solar affect both price formation and investment incentives. I first develop a dominant-firm model with a competitive fringe that separates the total price effect of fringe-owned renewables into a competitive channel and a strategic channel. I then bring this framework to unit-level data from Alberta's energy-only market, construct an hourly cost-based competitive benchmark, and use this benchmark to decompose observed price effects into cost and markup components. Finally, I link these short-run effects to medium-run changes in wholesale prices and operating profits across generation technologies under alternative renewable capacity scenarios.

I find that renewable integration creates striking asymmetry across technologies and time. Wind consistently reduces both prices and markups in most hours, with approximately 40% of wind's average price reduction stemming from markup compression. This indicates strong pro-competitive effects that go beyond the direct merit-order effect. Solar expansion, however, shows a very different pattern across the day. It reduces midday prices and markups, with roughly 30% of the decline coming from lower markups, but increases prices during morning and evening ramp periods. About one-third of these ramp-hour price increases reflect higher markups. This pattern shows that solar's predictable output profile creates systematic opportunities for the exercise of market power.

Counterfactual capacity scenarios reveal that continued renewable expansion fundamentally changes the distribution of profitability across generation technologies. Average wholesale prices decline, which benefits consumers in the short run. At the same time, changing price dynamics shift value from energy to flexibility. Inframarginal rents fall for both renewables themselves, due to cannibalization effects, and baseload combined-cycle units. Scarcity rents become more concentrated and

volatile, and increasingly accrue in a small number of hours that favor fast-ramping generation and energy storage. Initially, high-cost peaking plants face the greatest revenue erosion as renewable generation reduces the frequency of high-price hours. With further renewable penetration, baseload units face increasing challenges because of sustained lower average prices.

These findings have important implications for electricity market design and policy. First, adding zero-marginal-cost renewable supply does not automatically eliminate market power. The competitive effects of renewable integration depend critically on the mix of renewable technologies and on how their output interacts with capacity constraints. Market power monitoring and mitigation remain necessary as the grid decarbonizes. Second, the results highlight the growing importance of flexibility. As intermittent renewables comprise a larger share of the generation mix, price volatility increases and value shifts toward assets that can respond quickly to changing conditions. Whether energy-only markets can provide adequate investment incentives for flexible capacity remains uncertain. The concentration of scarcity rents into fewer, more volatile hours may not be sufficient to support the fixed cost recovery of resources that are essential for managing renewable intermittency and maintaining system reliability.

Third, the asymmetric effects of wind and solar on market power suggest that renewable portfolio composition matters for competitive outcomes, not just total renewable penetration. Policies that incentivize solar development without corresponding investment in flexibility resources or transmission capacity may unintentionally create new opportunities for strategic behavior. Market design reforms, including enhanced scarcity pricing, improved real-time pricing signals, and complementary flexibility markets, are essential to ensure that renewable integration supports both decarbonization and competitive outcomes.

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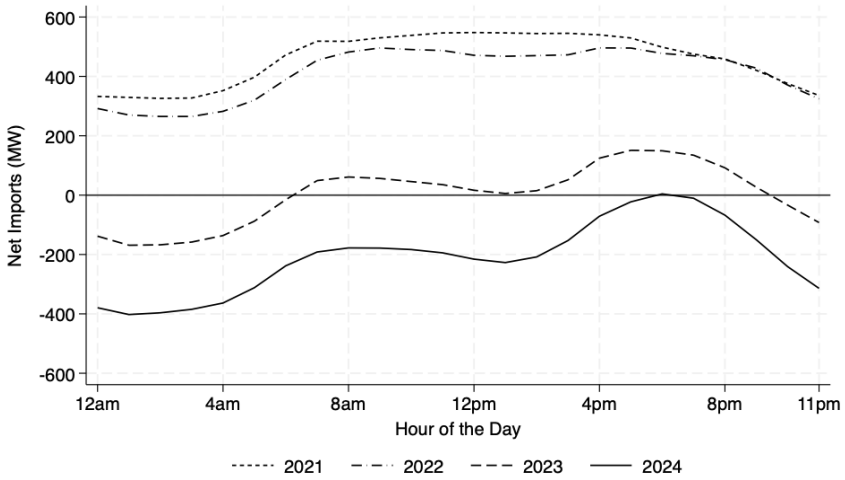
Appendices

A Additional Descriptive Statistics

Figure A.1 indicates that Alberta was a net importer during most hours in 2021 and 2022. Net imports declined substantially in 2023, with midday values approaching zero. In 2024, Alberta transitioned to a net exporter during most daylight hours and recorded minimal average imports during the evening peak. This transition is attributable to increased in-province generation, diminished import incentives resulting from higher neighboring prices, and more restrictive intertie limits (MSA, 2023, 2024).

Figure A.1. Average Hourly Net Imports by Year

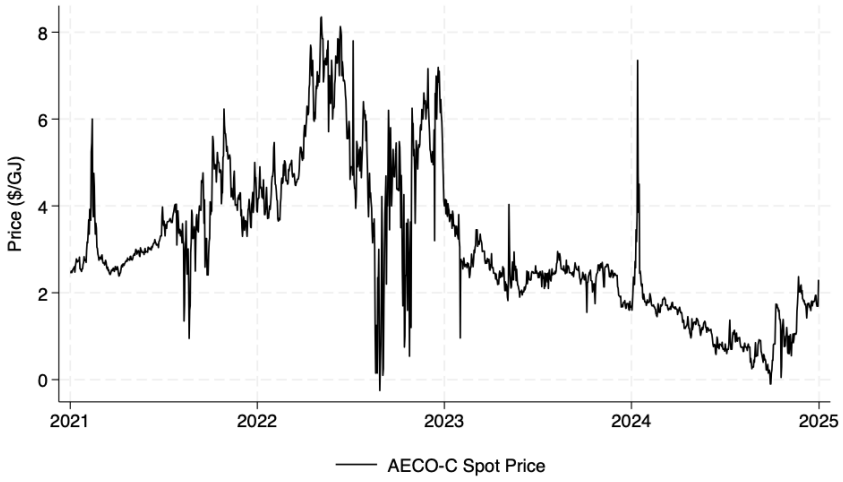


Notes: The lines show average net imports (imports minus exports) in MW by hour of day for each calendar year. Positive values indicate net imports; negative values indicate net exports.

Figure A.2 shows daily AECO-C spot natural gas prices, the Western Canadian benchmark, over the sample period. Prices rose through 2021, peaked in 2022, then fell through mid-2024 before rising again in late 2024. These gas price swings, in turn, contributed to the dynamics of wholesale electricity prices. Electricity prices were higher in 2022 with higher gas spot prices, while average electricity prices were lower in 2024 with lower gas prices.

Figure A.3 presents market concentration measured relative to total market demand, including imports and renewables. The diurnal and inter-annual patterns are consistent with those described in the main text. The CR5 index remains in the mid-

Figure A.2. Daily AECO-C Spot Natural Gas Price



Notes: This figure plots the daily AECO-C spot price ($/GJ).

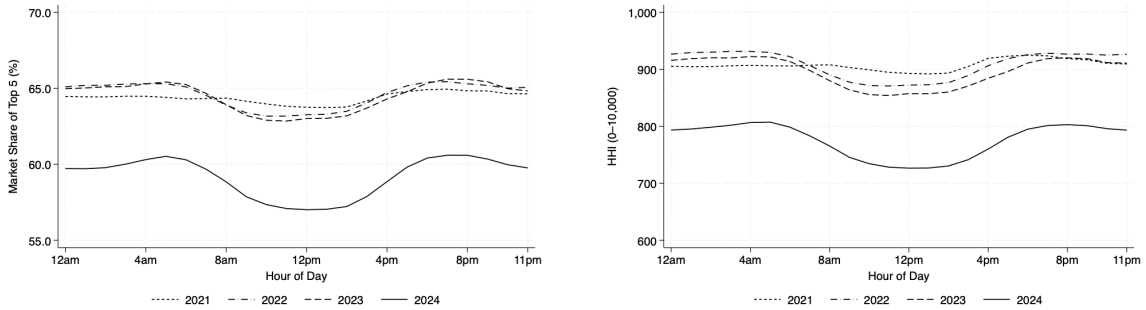
60 percent range from 2021 to 2023 and declines in 2024, showing a midday trough and peaks during morning and evening ramp hours (Panel A.3a). The Herfindahl-Hirschman Index (HHI) displays a similar intraday pattern, with consistently lower values in 2024 compared to previous years (Panel A.3b). These qualitative results are consistent with the patterns observed for dispatchable in-province supply: concentration is lower at midday and higher during ramp periods, and both CR5 and HHI decrease over time. This evidence supports the conclusion that solar expansion reduced market concentration during daylight hours, while evening conditions remained relatively more concentrated.

B Robustness and Extensions

B.1 Curtailment and Forecast Instruments

A potential threat to my identification assumptions is curtailment, where the system operator reduces renewable output during periods of oversupply or congestion. If curtailments are more likely when prices are low (e.g., due to high renewable output or transmission constraints), then regressions of prices on realized renewable generation could be biased toward finding larger price-suppressing effects. To address this concern, I re-estimate the hourly price equations, instrumenting realized daily wind and solar generation with AESO's day-ahead forecasts. These forecasts are published

Figure A.3. Hourly Concentration by Year



(a) CR5 (b) HHI

Notes: Each line plots values by hour of day for each calendar year. CR5 is the sum of the five largest suppliers' shares of supply. HHI is defined as $\sum_i s_i^2 \times 10{,}000$, where s_i is supplier i's share of supply.

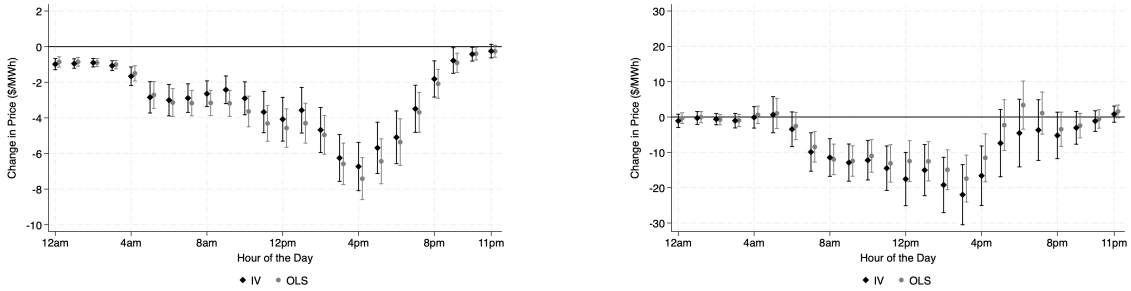
before real-time market outcomes and are therefore predetermined with respect to intra-day price shocks and curtailment decisions, while remaining highly predictive of realized output.[34]

The exclusion restriction requires that day-ahead forecasts affect hourly prices only through their influence on realized generation. This is plausible because forecasts are based solely on meteorological predictions and contain no information about same-day demand shocks, fuel prices, or other factors that directly determine prices. Across all hours $h \in \{1, \ldots, 24\}$, the instruments are exceptionally strong. F-tests of the excluded forecasts are on the order of 10^3, Sanderson–Windmeijer multivariate F statistics are similarly large, and Kleibergen–Paap rk LM tests always reject underidentification ($p < 0.001$). Kleibergen–Paap rk Wald F statistics are likewise very large, alleviating weak-IV concerns.

Figure B.4 compares OLS and IV estimates by hour. For wind (Panel B.4a), IV coefficients are negative and economically significant in every hour and closely track the OLS profile. For solar (Panel B.4b), IV estimates replicate the pronounced midday price suppression. The IV and OLS profiles are quantitatively similar, and hour-by-hour tests show that differences are generally not statistically significant at conventional levels. Overall, IV estimates corroborate the baseline results.

[34] In my setting, detailed curtailment data are limited and reported curtailments are infrequent over the sample period. With hourly curtailment data, one could construct a proxy for available energy by summing realized generation and curtailment and use it as an instrument for realized generation.

Figure B.4. IV vs. OLS Hourly Price Responses to Daily Renewable Generation



(a) Wind (b) Solar

Notes: The figure displays point estimates and 95% confidence intervals from the baseline (OLS) daily specification and the IV specification that instruments daily wind and solar with AESO day-ahead forecasts. First-stage F and Sanderson–Windmeijer F statistics are on the order of 10^3 every hour. Kleibergen–Paap rk LM tests reject the null of underidentification at $p < 0.001$.

The IV estimates closely match the baseline OLS results, with differences of small magnitude and statistically insignificant. Therefore, curtailment-related endogeneity does not materially bias the baseline estimates.

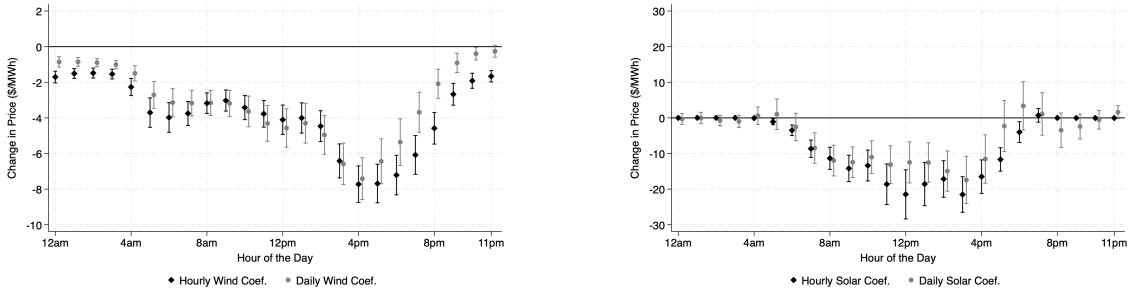
B.2 Daily vs. Hourly Generation Specification

To test the robustness of the daily specification, I re-estimate the model using hourly wind and solar generation, implicitly assuming that renewable generation in one hour has no impact on price formation in other hours. The resulting coefficients are in \$/MWh per hourly MWh and are therefore not directly comparable to the daily results. To place them on the same scale, each hourly coefficient β_h^{hr} is rescaled using the source's typical diurnal profile:

$$\tilde{\beta}_h \;=\; 1{,}000 \times \bar{s}_h \times \beta_h^{hr},$$

where $\bar{s}_h \equiv \mathbb{E}[q_h/Q_d]$ is the average share of daily generation occurring in hour h, q_h is hourly MWh, Q_d is total daily MWh, and 1,000 converts GWh to MWh (so $\sum_h \bar{s}_h = 1$). The scaled coefficients $\tilde{\beta}_h$ can be interpreted as the hourly price impact of a 1 GWh increase in daily renewable generation allocated according to the typical hourly profile, making them directly comparable to the baseline daily estimates. All hourly regressions use the same controls and fixed effects as the baseline, and standard errors are Newey-West with a 7-day lag. Results are presented in Figure B.5.

Figure B.5. Hourly Price Response to Renewable Generation



(a) Wind (b) Solar

Notes: The figure reports point estimates and 95% confidence intervals for the effect of hourly wind (Panel B.5a) and solar (Panel B.5b) generation on the corresponding hourly price ($/MWh per MWh). The (unscaled) hourly coefficients β_h^{hr} are rescaled by multiplying each by the average MWh generated in hour h per 1 GWh increase in daily output for the respective source. The rescaled coefficients $\tilde{\beta}_h$ represent the hourly price impact of a 1 GWh increase in daily generation, distributed according to each source's typical diurnal profile. Results from the daily specification are overlaid for reference.

Panel B.5a shows that wind results are qualitatively similar across the daily and scaled-hourly specifications, with statistically significant price-suppressing effects in all hours. The scaled-hourly estimates are somewhat larger in nighttime hours (approximately 7 PM-4 AM). This is because wind output is typically higher at night, so a 1 GWh increase in daily wind generation translates into larger MWh additions during these hours. Moreover, during high-demand afternoon hours, the market operates at a higher level on the supply curve, where marginal costs rise steeply. Consequently, reductions in conventional output produce relatively large price decreases. Conversely, during low-demand nighttime hours when wind is abundant, the market operates on a flatter portion of the supply curve, and the contemporaneous price impact per MWh of wind is smaller. However, because wind additions are concentrated in these nighttime hours, the scaled hourly estimates—which weight the hourly price effects by the typical wind profile—show somewhat larger nighttime effects than the daily specification, which implicitly spreads the impact across all hours.

For solar (Panel B.5b), both specifications capture the pronounced midday price reductions and are broadly consistent. Hours with negligible solar output have $\bar{s}_h \approx 0$ and thus near-zero scaled effects by construction.

B.3 Pooled Specifications

The main analysis estimates impact on prices in Equation (1), competitive benchmark prices in Equation (3), and markups in Equation (4) separately for each hour of day, allowing all coefficients to vary by hour and capturing heterogeneity in renewable effects across the diurnal cycle. This approach is motivated by the substantial variation in electricity demand, generation mix, and market conditions across hours. For comparison and to provide summary measures of the average impact, I also estimate pooled specifications that constrain the coefficients on wind and solar generation to be constant across all hours.

Tables B1 and B2 report results from pooled regressions using daily and hourly renewable generation variables. Each table presents three outcome variables: observed wholesale prices (columns 1-2), competitive benchmark prices (columns 3-4), and markups (columns 5-6). For each outcome, I present estimates using two alternative fixed effect specifications: hour-by-month-by-year fixed effects (odd columns) and hour-by-month fixed effects (even columns). The hour-by-month-by-year specification corresponds to the short-run analysis, isolating weather-driven variation in renewable output. The hour-by-month specification corresponds to the medium-run analysis, allowing the estimates to reflect both capacity-driven and weather-driven variation.

Table B1 shows that a 1 GWh increase in daily wind generation reduces observed wholesale prices by approximately \$3.06-\$3.31 per MWh, with slightly larger effects under the medium-run specification. The effect operates through both channels: competitive prices decline by \$1.83-\$1.97 per MWh and markups fall by \$1.24-\$1.34 per MWh.

For solar generation, the results reveal more complex dynamics. In the short-run specification (column 1 of Table B1), daily solar generation shows a significant price reduction of \$4.45 per MWh, which can be decomposed into a \$3.49 competitive effect and a \$0.96 markup effect. When accounting for the spillover impact of solar generation across the day, the majority of the observed price reduction operates through the competitive channel rather than the markup channel. However, the medium-run solar coefficients (column 2) become statistically insignificant and positive, indicating that increased solar capacity over time has negligible pooled effects on average prices. This reflects substantial heterogeneity in solar's impact across hours of the day. The hour-specific estimates in Sections 5.2 and 5.3.1 reveal statistically significant price reductions during midday hours when solar generation occurs, but statistically signifi-

Table B1. Effect on Price and Price Components: Daily Renewable Generation

	Observed Price		Competitive Price		Markup	
	(1)	(2)	(3)	(4)	(5)	(6)
Daily Wind (GWh)	−3.06***	−3.31***	−1.83***	−1.97***	−1.24***	−1.34***
	(0.26)	(0.30)	(0.16)	(0.18)	(0.19)	(0.23)
Daily Solar (GWh)	−4.45***	0.93	−3.49***	0.53	−0.96**	0.40
	(1.18)	(1.31)	(0.99)	(1.01)	(0.57)	(0.61)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects:						
HoD × MoY × Year	Yes		Yes		Yes	
HoD × MoY		Yes		Yes		Yes
Observations	35,063	35,063	35,063	35,063	35,063	35,063

Notes: This table reports pooled regression estimates using daily renewable generation, constraining coefficients to be constant across all hours of the day. Columns (1)-(2) use observed wholesale prices ($/MWh) as the dependent variable. Columns (3)-(4) use competitive benchmark prices ($/MWh) as the dependent variable. Columns (5)-(6) use markups (observed minus competitive prices) as the dependent variable. Odd-numbered columns use hour-by-month-by-year fixed effects (short-run specification), while even-numbered columns use hour-by-month fixed effects (medium-run specification). All specifications include controls for hourly market demand, daily AECO natural gas price, and quadratic functions of heating and cooling degree hours. Standard errors (in parentheses) are Newey-West with a 7-day (168-hour) lag. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

cant price increases during some morning and evening ramping hours. These opposing effects offset in the pooled specification and mask the rich within-day dynamics.

Table B2 presents estimates using hourly renewable generation, isolating contemporaneous within-hour effects instead of including daily spillovers. The hourly coefficients are substantially smaller, with $0.10 per MWh of contemporaneous hourly generation for wind and $0.10-$0.15 per MWh for solar. Notably, the per-MWh price impact of solar ($0.15) is 50% larger than that of wind ($0.10), reflecting the timing of generation. Solar generates predominantly during daytime peak demand hours when marginal generators have higher costs and prices are higher, whereas wind generation is more evenly distributed across the day, including overnight low-demand periods when its price impact is muted.

However, the coefficients from hourly renewable generation are not directly comparable to the daily estimates because they measure price effects per unit of hourly generation rather than per unit of daily generation. To facilitate comparison, I rescale the hourly coefficients to daily-equivalent units. Given that a 1 GWh increase in daily generation (1,000 MWh) corresponds to an average increase of $1000/24 \approx 41.7$ MWh per hour, the rescaled hourly wind coefficient of $-\$0.10 \times (1000/24) \approx -\$4.17$ per

Table B2. Effect on Price and Price Components: Hourly Renewable Generation

	Observed Price		Competitive Price		Markup	
	(1)	(2)	(3)	(4)	(5)	(6)
Wind (MWh)	−0.10***	−0.10***	−0.06***	−0.06***	−0.04***	−0.04***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Solar (MWh)	−0.15***	−0.10***	−0.12***	−0.07***	−0.04***	−0.03***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects:						
HoD × MoY × Year	Yes		Yes		Yes	
HoD × MoY		Yes		Yes		Yes
Observations	35,063	35,063	35,063	35,063	35,063	35,063

Notes: This table reports pooled regression estimates using hourly renewable generation, constraining coefficients to be constant across all hours of the day. Columns (1)-(2) use observed wholesale prices ($/MWh) as the dependent variable. Columns (3)-(4) use competitive benchmark prices ($/MWh) as the dependent variable. Columns (5)-(6) use markups (observed minus competitive prices) as the dependent variable. Odd-numbered columns use hour-by-month-by-year fixed effects (short-run specification), while even-numbered columns use hour-by-month fixed effects (medium-run specification). All specifications include controls for hourly market demand, daily AECO natural gas price, and quadratic functions of heating and cooling degree hours. Standard errors (in parentheses) are Newey-West with a 7-day (168-hour) lag. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

GWh of daily generation is broadly consistent with the daily specification estimate of −$3.06 to −$3.31 per GWh.[35] Similarly, the rescaled solar coefficient of −$0.15 × (1000/24) ≈ −$6.25 per GWh aligns with the short-run daily estimate of −$4.45 per GWh. The close correspondence between rescaled hourly effects and daily effects supports the validity of using daily generation variables to capture both contemporaneous and intertemporal price impacts.

The decomposition results for wind are qualitatively similar across both daily and hourly specifications. Renewable generation reduces wholesale prices through both cost reduction (lower competitive prices) and pro-competitive channels (lower markups), with the competitive channel accounting for approximately 60% of the total price effect and the markup channel accounting for 40%. This decomposition is robust to the choice between daily and hourly renewable variables, confirming that the main findings are not artifacts of the temporal aggregation approach. The

[35]This simplified calculation assumes a 1 GWh increase in daily generation is spread evenly across all 24 hours (i.e., each hour's share is 1/24). Because wind and solar have non-uniform diurnal profiles, a more accurate conversion multiplies each hourly estimate by the average share of daily output occurring in that hour. Appendix B.2 implements this rescaling and shows that the main conclusions are unchanged.

hourly generation results show that solar's contemporaneous within-hour effect does reduce prices, with the competitive channel accounting for approximately 70-80% of the decrease and the markup channel for approximately 20-30%. This indicates that when solar is actively generating, it exerts downward pressure on both costs and markups, consistent with the midday results from the hour-specific analysis.

To interpret the economic magnitude of these effects, it is useful to consider the variation in renewable generation observed in the sample. Daily wind generation averages 25 GWh with a standard deviation of 16.5 GWh, while daily solar generation averages 4.7 GWh with a standard deviation of 4 GWh. A one-standard-deviation increase in daily wind generation (16.5 GWh) corresponds to a price reduction of approximately \$50-\$55 per MWh (\$3.06 $\times$ 16.5), representing a substantial 40-45% decrease relative to the sample mean wholesale price of \$125 per MWh. This effect decomposes into a \$30-\$33 reduction in competitive prices and a \$20-\$22 reduction in markups. Similarly, a one-standard-deviation increase in daily solar generation (4 GWh) reduces prices by approximately \$18 per MWh in the short-run specification.

For the hourly specifications, hourly wind generation averages 1,042 MWh with a standard deviation of 798 MWh, while hourly solar generation averages 195 MWh with a standard deviation of 328 MWh. A one-standard-deviation increase in hourly wind generation (798 MWh) reduces prices by approximately \$80 per MWh (\$0.10 $\times$ 798), while a one-standard-deviation increase in hourly solar generation (328 MWh) reduces prices by approximately \$49 per MWh (\$0.15 $\times$ 328). Despite solar's larger per-MWh effect, wind's substantially greater variation (standard deviation of 798 MWh vs. 328 MWh for solar) results in larger total price impacts in practice. These magnitudes confirm that both approaches capture comparable economic effects despite measuring renewable generation at different temporal frequencies. The statistics also confirm that wind generation exhibits substantially greater variation than solar, both within and across days, which explains the more precisely estimated and economically larger wind effects throughout the analysis.

Finally, all estimates use Newey-West standard errors with a 7-day (168-hour) lag to account for serial correlation and heteroskedasticity. Results are qualitatively unchanged and remain statistically significant when using shorter lag lengths or when clustering standard errors by week of the sample.

B.4 Estimation of the Net Import Supply Function

I estimate a price-responsive net import supply function for Alberta at the hourly level, following established methods in the literature (e.g., Mansur, 2007; Bushnell et al., 2008; Brown et al., 2023).

Table B3 reports first- and second-stage results by year. First-stage statistics confirm instrument relevance. For $\ln P^{AB}$, conventional F-statistics range from 75 to 198 and Sanderson–Windmeijer (SW) F-statistics from 151 to 363. For $\ln P^{MidC}$, the conventional F-statistic is weak in 2021 (4.71) but the SW F-statistic exceeds the threshold for multiple endogenous regressors (11.15), and both statistics are stronger in subsequent years. Kleibergen–Paap LM statistics reject underidentification in all years.

Second-stage estimates are stable and economically significant. The semi-elasticity with respect to the Alberta price ranges from 284 to 465 MW, implying that a 1% increase in P^{AB} raises net imports by 284–465 MW. The semi-elasticity with respect to the Mid-C price ranges from –314 to –548 MW. The positive Alberta price effect reflects arbitrage incentives, as higher Alberta prices attract imports. The negative Mid-C price effect captures opportunity cost, as higher Pacific Northwest prices make exporting to WECC more attractive, reducing net supply to Alberta. These estimates imply an upward-sloping net import supply function, which translates into a downward-sloping residual demand curve facing Alberta generators.

The implied elasticities of residual demand (demand less net import supply) at the sample mean range from –0.032 to –0.038 across the four years. These low elasticities reflect Alberta's limited interconnection capacity relative to market size and fall within the range estimated by Brown et al. (2023) (–0.01 to –0.08) for Alberta between 2013 and 2021. For comparison with other North American markets, Bushnell et al. (2008) estimate residual demand elasticities of –0.027 for PJM and –0.168 for New England during the summer of 1999.

As a robustness check, I pool all years (2021–2024) and re-estimate the model with hour-by-month-by-year fixed effects, clustering standard errors by week of the sample. The pooled specification yields coefficients of 485 (SE = 97) for the Alberta price and –405 (SE = 95) for the Mid-C price, both significant at the 1% level. First-stage diagnostics remain strong, with Sanderson-Windmeijer F-statistics of 30 and 25, respectively. These pooled estimates are consistent with the year-by-year baseline results.

Table B3. Instrumental Variables Estimation of Net Import Supply Function by Year

	2021			2022		
Model	First $\ln(P^{AB})$	First $\ln(P^{MidC})$	Second $\ln(Q^{NI})$	First $\ln(P^{AB})$	First $\ln(P^{MidC})$	Second $\ln(Q^{NI})$
$\ln(Q^{AB})$	4.96^{***}	-0.04		5.56^{***}	-0.45^{***}	
	(0.25)	(0.12)		(0.27)	(0.16)	
$\ln(Q^{BPA})$	-0.24	1.35^{***}		-1.42^{***}	1.86^{***}	
	(0.46)	(0.44)		(0.49)	(0.47)	
$\ln(P^{AB})$			317.70^{***}			283.55^{***}
			(23.00)			(26.81)
$\ln(P^{MidC})$			-553.40^{***}			-492.55^{***}
			(186.28)			(160.50)
F-Stat	203.76^{***}	4.68^{***}		206.33^{***}	11.25^{***}	
S-W F-Stat	383.61^{***}	10.79^{***}		195.46^{***}	13.29^{***}	
K-P LM			9.20^{***}			13.09^{***}
	2023			2024		
Model	First $\ln(P^{AB})$	First $\ln(P^{MidC})$	Second $\ln(Q^{NI})$	First $\ln(P^{AB})$	First $\ln(P^{MidC})$	Second $\ln(Q^{NI})$
$\ln(Q^{AB})$	4.61^{***}	0.22^{*}		4.50^{***}	-0.08	
	(0.32)	(0.12)		(0.34)	(0.13)	
$\ln(Q^{BPA})$	0.41	1.74^{***}		-0.18	2.10^{***}	
	(0.66)	(0.42)		(0.61)	(0.41)	
$\ln(P^{AB})$			369.76^{***}			487.50^{***}
			(32.02)			(37.25)
$\ln(P^{MidC})$			-321.54^{**}			-417.16^{***}
			(156.14)			(147.70)
F-Stat	105.01^{***}	10.83^{***}		86.54^{***}	13.11^{***}	
S-W F-Stat	152.62^{***}	20.33^{***}		172.46^{***}	28.59^{***}	
K-P LM			18.59^{***}			26.29^{***}

Notes: This table reports IV estimates of the net import supply function Equation (2). The dependent variable is net imports into Alberta (MW). The endogenous variables are log Alberta price ($\ln P^{AB}$) and log Mid-Columbia price ($\ln P^{MidC}$), instrumented with log Alberta demand ($\ln Q^{AB}$) and log Bonneville Power Administration demand ($\ln Q^{BPA}$). All specifications include month fixed effects and quadratic terms for heating and cooling degree days (HDD/CDD) from Billings, Calgary, Vancouver, and Saskatoon. Standard errors (in parentheses) are Newey-West with a 1-day (24-hour) lag. F-Stat reports the first-stage F-statistic for excluded instruments. S-W F-Stat is the Sanderson-Windmeijer multivariate F-statistic accounting for multiple endogenous variables. K-P LM is the Kleibergen-Paap rk LM statistic testing for underidentification. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B.5 Impact on Competitive Rents

In this section, I quantify the impact of renewables on competitive rents, defined as the infra-marginal surplus earned by dispatched generators. For each hour, the

average competitive rent per MWh is:

$$CR_h = \sum_{i \in \mathcal{I}_h} \frac{q^C_{i,h}}{Q_{Net}} \cdot \left(\widehat{P}^C_h - MC_{i,h} \right)$$

where $\mathcal{I}_h$ is the set of units dispatched under the competitive benchmark (excluding wind and solar), $\widehat{P}^C h$ is the competitive price, $MC_{i,h}$ is the marginal cost of unit i, and $q^C i, h/QNet$ is the unit's share of net demand (Q_{Net}, i.e., market demand minus wind and solar generation). This captures the per-unit average rents that inframarginal units would earn if prices were set competitively and all units bid at marginal cost.

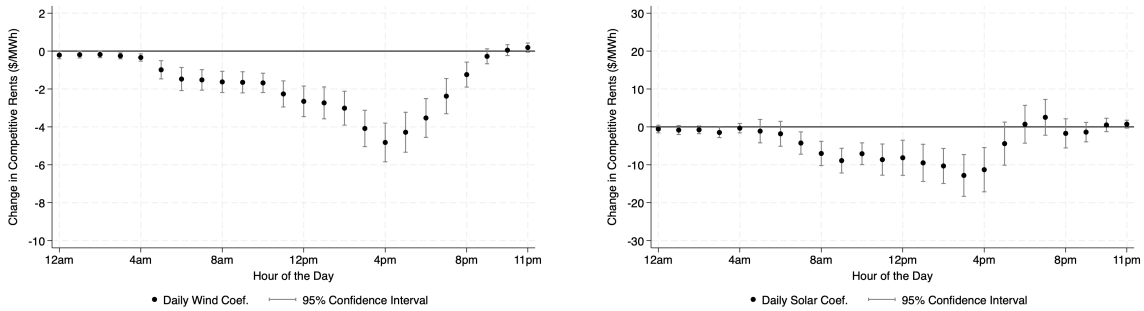
I then regress these rents on renewable generation to evaluate how increased wind and solar output affects infra-marginal profitability under price-taking conditions:

$$CR_{h,d} = \alpha_{h,m} + \phi^w_h \cdot \text{Wind}_d + \phi^s_h \cdot \text{Solar}_d + \boldsymbol{\theta}_h \cdot \mathbf{X}_{h,d} + \varepsilon_{h,d}$$

A negative ϕ^w_h or ϕ^s_h suggests that the merit-order effect of renewables compresses competitive rents. If, however, actual observed rents remain constant or increase while CR declines, this points to growing markups or strategic behavior that offset the competitive pressure from renewables.

As shown in Panel B.6a, wind generation consistently and significantly reduces competitive rents throughout the day, with the largest negative impact again occurring between the afternoon and the evening hours. This reinforces the finding that wind acts as a broad-based competitive pressure, reducing rents above marginal cost for infra-marginal units.

The results for solar in Panel B.6b are again more complex. Solar generation reduces competitive rents during the daylight hours it produces. However, consistent with the price and markup results, an increase in daylight solar is associated with a large and statistically significant increase in the competitive rents earned in the evening, particularly at 6 PM and 7 PM. This finding provides further support for the market concentration hypothesis, where the surviving firms in the less competitive evening market are able to capture a larger surplus. Together, these results provide strong empirical evidence for the theoretical model, demonstrating that solar's unique diurnal profile can fundamentally alter market structure and shift the exercise of market power in subsequent hours.



(a) Wind: Competitive Rents Impact (b) Solar: Competitive Rents Impact

Figure B.6. Hourly effects of wind and solar generation on competitive rents

Notes: Each panel plots hour-of-day specific coefficients with 95% confidence intervals. The estimates come from regressions of hourly competitive rents—the quantity-weighted average of price-cost differences—on daily wind or solar generation.

C Marginal Cost Estimation Details

The estimation of static marginal costs for Alberta's electricity generation technologies is carried out as follows.[36] The province's generation mix is categorized into three groups: renewable energy sources (wind and solar), fossil fuel units (natural gas and coal), and hybrid or niche units (cogeneration, biomass, hydro, and energy storage). For wind and solar units, marginal costs are effectively zero after installation as these technologies do not incur fuel costs and have minimal variable O&M expenses. This is consistent with wind and solar units bidding behavior in the wholesale market, where they consistently bid at \$0/MWh.

For fossil fuel units, the marginal cost (MC) can be determined using the following engineering-based equation:

$$MC = \underbrace{P_{Fuel} \cdot HR}_{\text{Fuel cost}} + \underbrace{P_{Emission} \cdot (EI - \bar{I})}_{\text{Environmental cost}} + \underbrace{\text{Variable OPEX}}_{\text{O\&M cost}}$$

where P_{Fuel} represents the price of the fuel, natural gas or coal, and HR (heat rate) reflects the efficiency of energy conversion for each unit in GJ/MWh. Fuel cost is typically the largest component of marginal cost for fossil fuel generators.

The second term captures the emission-related costs associated with Alberta's carbon pricing framework under the TIER Regulation. Here, $P_{Emission}$ denotes the pre-

[36] This framework follows Brown and Olmstead (2017), Brown et al. (2018), and Brown et al. (2023).

vailing carbon price, EI represents the emissions intensity of the generator (measured in tonnes of CO_2 equivalent per MWh), and $\bar{I}$ is the emissions intensity benchmark set under TIER. The term $(EI - \bar{I})$ measures the generator's emissions performance relative to the benchmark. The final component, Variable OPEX, represents the variable operation and maintenance costs associated with running the generator. These include labor, routine maintenance, equipment wear and tear, and other consumables.

Hybrid and niche units, such as cogeneration, biomass, hydro, and energy storage, have more complex cost structures. Cogeneration facilities, primarily natural gas-fired, generate electricity as a byproduct of industrial processes such as oil sands extraction. These units sell their excess electricity to the wholesale market. They typically bid at \$0/MWh to avoid shutdown costs associated with their industrial processes, although occasional high-priced bids (exceeding \$900/MWh) are observed due to regulatory requirements. Marginal costs for cogeneration are approximated using observed bidding behavior, with more than 91% of bids at \$0/MWh.

Biomass units, often operated by small firms in industries such as forestry, are treated similarly. These units generally bid at \$0/MWh, reflecting operational constraints tied to industrial processes rather than strategic market behavior, and are assumed to behave as price-takers. Hydroelectric units are unique because their marginal costs reflect the intertemporal opportunity cost of water usage. While high-priced bids (\$999/MWh) may occur occasionally due to regulatory requirements or ecological constraints, the majority of hydro bids are at \$0/MWh. Therefore, I assume that hydro units act as price takers and equate their marginal costs to their bids. Given hydro's small share of Alberta's total generation (2.5% on average during the sample period), any bias introduced by relying on bid-based marginal cost estimates is expected to be minimal.