Strategic Reneging in Sequential Imperfect Markets

Benatia, David and Billette de Villemeur, Etienne

HEC Montréal, LEM-CNRS (UMR 9221), Université de Lille

January 2019

Strategic Reneging in Sequential Imperfect Markets

David Benatia and Étienne Billette de Villemeur*

January 11, 2021

Abstract

This paper investigates the incentives to manipulate sequential markets by strategically reneging on forward commitments. We first study the behavior of a dominant firm in a two-period model with demand uncertainty. Our results show that sequential markets may be a source of inefficiencies. We then test the model's predictions using occurrences of reneging on long-term commitments in Alberta's electricity market. We implement a machine learning approach to identify and evaluate manipulations. We find that a dominant supplier

*Benatia: HEC Montréal, 3000 Chemin de la Côte-Sainte-Catherine, Montréal, Québec, H3T 2A7, Canada (e-mail: david.benatia@hec.ca); Billette de Villemeur: LEM-CNRS (UMR 9221), Université de Lille, 3 rue de la Digue, 59000 Lille, France (e-mail: etienne.de-villemeur@univ-lille.fr). We would like to thank Co-Editor Leslie Marx and two anonymous referees for their helpful comments and suggestions which contributed to substantially improve the paper. In addition, we would like to thank David Brown, Philippe Choné, Arnaud Dellis, Xavier D'Haultfœuille, Laurent Linnemer, Derek Olmstead, Pierre-Olivier Pineau, Steve Puller, Mar Reguant, Charles Séguin, Bert Willems, and participants to seminars at CREST, HEC Montréal, UQAM, Université de Montréal, Montréal Environment and Resource Economics Workshop, and conferences organized by the Société Canadienne de Science Économique, the Canadian Economics Association, and the IAEE. This research is supported by a grant of the French National Research Agency (ANR), "Investissements d'Avenir" (LabEx Ecodec/ANR-11-LABX-0047), and received financial support from the Chair in Energy Sector Management (HEC Montréal) and the Canadian Energy Economics Association.

increased its revenues by \$35 million during the winter of 2010-11, causing Alberta's electricity procurement costs to increase by above \$330 million (20%).
Keywords: Imperfect Commitment, Market Manipulation, Market Power, Electricity Markets
JEL Codes: D43, L12, L51, L94

1 Introduction

"Contracts are like hearts, they are made to be broken".[1] Failures to fulfill contractual obligations are indeed frequent. As parties recognize the risk of a contract "breach", they write clauses to protect themselves against certain contingencies but can hardly consider them all. In sequential markets, a contract breach may occur for legitimate reasons as, say, a shortage may force a supplier to renege on its promise to deliver some goods at a given date. Yet, insufficient penalties (or imperfect penalty schemes) imposed in case of such contingencies give rise to a moral hazard problem by leaving space for parties to renege on their commitments for strategic reasons. This moral hazard problem can have significant consequences in terms of efficiency and welfare distribution, especially in markets where prices are very sensitive to unexpected supply or demand shocks.

In this paper, we first develop a theoretical framework to analyze the behavior of a dominant firm facing a competitive fringe in a two-period model with imperfect commitment and demand uncertainty. Unlike in most the literature on sequential markets, we find that a spot price premium can arise in equilibrium, because of the imperfect commitment problem. Second, we leverage machine learning to test our model's predictions and investigate manipulations using a rich dataset about Alberta's electricity market in Canada. The empirical analysis focuses on alleged occurrences of strategic reneging disguised under claims of "emergency outages" of power plants

[1] So is reported to have said Ray Kroc, the fast-food tycoon who built the McDonalds empire.

under long-term contracts. Third, we estimate the welfare consequences of imperfect commitment in this market. A dominant supplier is found to have caused Alberta's electricity procurement costs to increase by above \$330 million from November 2010 to February 2011. The firm earned an extra \$35 million in revenues. Rival suppliers also greatly benefited from the price increases, of up to +\$950 per megawatt hour (MWh) in some instances.

Our theoretical framework aims at investigating how imperfect commitment interacts with market power in a sequential setting. We show that the decision to renege crucially depends on the residual demand. A less elastic residual demand causes the manipulation to have a larger price impact, while larger demand realizations increase the volume of spot sales which implies more leverage. The key prediction is that the dominant supplier will modify both its forward and spot supply strategies upon anticipating a profitable reneging opportunity. Our theory shows that the exercise of market power and strategic reneging can be *strategic substitutes* or *strategic complements*, depending on market conditions. We can nevertheless establish predictions about the direction and size of the supply shifts. These predictions provide guidance to detect strategic reneging, collect indirect evidence of potential misconduct, measure its consequences, and thus assess the need for regulatory intervention.

In our model, the monopolist competes against a competitive fringe over two periods to supply a homogeneous good at a particular delivery time. Demand is random and assumed to be perfectly inelastic.[2] The residual demand curve is nevertheless elastic in both periods due to the presence of the fringe. In the first period, a share of the expected demand is allocated through forward contracts. The realized demand net of these commitments is supplied in the second period on the spot market, where both production and consumption take place. We assume away arbitrage

[2]This is a quite reasonable assumption for electricity markets, where end-users are rarely faced with real-time prices. Moreover, relaxing this assumption would not alter our qualitative results. In particular, having an inelastic demand simplifies our analysis but is not required for strategic reneging to occur.

opportunities across time so as to restrict attention to the consequences of imperfect commitment. The strategic reneging of commitments on the forward market weakens competition on the spot market to enhance the firm's overall profitability.[3] More precisely, by reducing its own output committed at forward prices, the firm increases the net demand in the spot market because the withdrawn output must be (at least partly) replaced in equilibrium. The residual demand curve is hence shifted which results in a spot price increase.[4] Strategic reneging is found to reduce the forward price premium, and can even induce price-convergence in equilibrium. We thus offer a new rationale of why the latter is no indication of market efficiency.

We test our model predictions and investigate the consequences of imperfect commitment in an application to Alberta's electricity market (Canada). This market provides several advantages to study strategic reneging. First, incentives to suppliers are relatively simple in the Alberta's electricity market. Market outcomes are settled through a real-time auction, and there is no day-ahead auction (Olmstead and Ayres, 2014). Second, the market structure consists of a few large suppliers and many small firms, and market power execution is relevant as documented by Brown and Olmstead (2017). Third, the availability of firm-level bid data allows us to reconstruct residual demand functions and to test the theory. Fourth, the Alberta Market Surveillance Administrator (MSA) accused an incumbent supplier of market manipulations through strategically timed "emergency outages" of power plants subject to long-term forward contracts, in several instances from November 2010 to February 2011.[5] This case thus offers a rare opportunity to investigate strategic reneging empirically.

In our empirical analysis, we interpret these strategic outages as a type of strategic reneging on long-term forward commitments and evaluate their

[3] Carlton and Heyer (2008) defines this as extensive conduct in opposition to extractive conduct, e.g. the exercise of unilateral market power.

[4] Throughout this paper, we use "reneging" to refer to the act of not satisfying one's forward commitments to deliver some output.

[5] We focus on this case study that has been already thoroughly investigated in order to avoid spreading erroneous accusations.

economic impacts. The compelling evidence collected in AUC (2015) makes clear that TransAlta's traders and plant operators collaborated to time outages. The report reveals that the firm had implemented a trading strategy that involved to coordinate forced outages of power plants under long-term contracts, and optimize spot and forward strategies. The strategy also involved wind farms, under similar long-term fixed-price contracts, reducing output during periods of high wind to inflate wholesale prices.

Our empirical investigation uses a sample of hourly observations containing firm-level bids, plant-level production and market outcomes from November 2010 to March 2011. The analysis first documents evidence that the events coincided with high demand and low wind output periods. Although no evidence is found that TransAlta's wind production was reduced for strategic reasons during the outages, our results suggest that the firm strategically curtailed wind power during high demand periods more generally. Second, we show that the firm has optimized its supply strategies accounting for its private information about the outage timing. To do so, we leverage hourly firm-level bid data to predict supply and residual demand functions using a multivariate extension of the least absolute shrinkage and selection operator, or lasso (Simon, Friedman and Hastie, 2013). By predicting counterfactual strategies during reneging events (assuming outages did not occur) we are able to identify strategy shifts, compute counterfactual market outcomes, and therefore evaluate the manipulations. We find deviations of the firm's strategies in the spot market during the outages that are consistent with our model's predictions. By making use of its informational advantage regarding the outage timing, the firm's bids reveal its intent to manipulate. Those deviations provide a red flag for regulators to detect potential misconducts early on, and intervene sooner. Bidding strategies reflecting this inside information indeed deliver indirect proofs of intent, which, as we argue, can be helpful for prosecution.

We finally use counterfactual strategies to estimate the welfare consequences. The official investigation found a welfare harm of $100 million, and a $56 million settlement was made between TransAlta, the alleged manipulator, and the regulatory authority. This settlement included \$27 million for gains disgorgement, \$4 million in regulatory fees and the rest in penalties. As we show in this paper, accounting for equilibrium effects yields much greater estimates of welfare impacts and manipulations gains. We estimate that strategic reneging delivered nearly \$35 million in extra revenues to the firm in five months. Other firms also benefited substantially from the increased spot prices. Ultimately, the corresponding harm to society is estimated above \$330 million. This represents a 20 percentage point increase in total energy procurement costs in the province.

Finally, our paper provides both theoretical arguments and empirical evidence for the fact that, although long-term contracts are often considered as way to limit the exercise of market power (AUC, 2015), they also create incentives for market manipulations with harmful consequences.

Related literature. This paper is related to the strands of economic literature on sequential markets, market manipulations and market power in electricity markets. First, our framework draws from the durable good monopoly model of Coase (1972) which identifies a commitment problem. There is also a large literature in economics studying the role of various factors in the formation of price spreads between sequential markets (Weber, 1981; McAfee and Vincent, 1993; Bernhardt and Scoones, 1994). We focus on the role of imperfect competition, as in Allaz and Vila (1993) who show that sequential markets always improve efficiency. In contrast, we do not assume perfect arbitrage across markets and introduce an imperfect commitment problem. We find that, in the presence of market incompleteness, sequential markets offer a source of market manipulations and inefficiencies.

Our paper is related to Ito and Reguant (2016) who study arbitrage in sequential markets under imperfect competition and show that the conjunction of limited arbitrage and market power generates a forward price premium. We contribute to this literature by showing that the opposite result, i.e. a spot price premium, can arise in expectations because of imperfect commitment. We also complement their important insight about price convergence not being a reliable metric for assessing the degree of competition. In our setting, price convergence can arise because of multiple market failures: imperfect competition and imperfect commitment.

Second, this paper is related to the literature on market manipulations. Ledgerwood and Carpenter (2012) present a general framework of market manipulations with examples taken from financial and commodity markets. Strategic reneging can be interpreted as a form of loss-based manipulation in their framework. One of our main theoretical predictions is in line with the general insight, found in the finance literature, that traders receiving an inside information will re-optimize their strategy (Imkeller, 2003). Recent cases of electricity market manipulations often involve financial derivatives and transmission-related strategies (Birge et al., 2018; Lo Prete et al., 2019; AUC, 2012). Evidence of strategic timing of "emergency" outages of plants during tight market conditions also exist in European markets (Bergler, Heim and Hüschelrath, 2017; Fogelberg and Lazarczyk, 2019). We document similar evidence for Alberta and show that bid data can deliver further evidence of intent to manipulate, and allow for a precise market impact assessment.

Third, there is a large literature on market power in the electricity industry. Borenstein, Bushnell and Wolak (2002) and Puller (2007) study the California electricity market, where suppliers scheduled plant maintenance during peak periods as a way to exercise market power. In our application, we focus on "emergency" maintenance of plants under forward contracts used as a manipulation device to extend unilateral market power in the spot market. There is also a prolific amount of research about the role of forward contracts to mitigate market power. Although forward contracts are generally expected to be welfare-enhancing (Bushnell, Mansur and Saravia, 2008; Green and Le Coq, 2010), they may yield anti-competitive outcomes when firms are asymmetric (de Frutos and Fabra, 2012), or exacerbate intertemporal market power distortions (Billette de Villemeur and Vinella, 2011). This paper shows evidence that incomplete forward contracts can create incentives to dominant players for market manipulations with harmful consequences.

Fourth, there is a growing empirical literature using machine learning methods in microeconomic applications. Burlig et al. (2019) use causal inference for evaluating the gains of energy efficiency investments in K-12 schools in California. More precisely, they use a lasso approach as a way to construct the counterfactual energy consumption of each school assuming no investment had taken place. Benatia (2020) studies the COVID-19 pandemic's consequences for electricity markets. He uses a shallow neural network to predict the counterfactual electricity demand in France during the first round of containment measures. In a related application, Graf, Quaglia and Wolak (2020) use a deep neural network to obtain counterfactual predictions of electricity market outcomes in Italy. To the best of our knowledge, our paper is the first to use an empirical strategy based on machine learning in the context of a strategic game.

Finally, strategic reneging is not limited to the supply side,[6] it can also occur outside electricity markets and take various forms. For instance, a company can schedule deliveries and cancel them at the last minute to withhold pipeline capacities,[7] or it can refuse to honor a particular contract clause in order to foreclose competition.[8] Alternatively, the firm may force its competitors to renege on their contracts,[9] or even renege as a means

[6]Faced with large electricity demand reductions caused by the pandemic in spring 2020, French distributors reneged on their regulated forward contracts, claiming force majeure, hence transferring their losses to the historical producer (Benatia, 2020).

[7]Marks et al. (2017) argue that electricity price spikes in New England have been caused by two companies regularly restricting natural gas capacity by "routinely ordering day-long large deliveries, then sharply reducing those orders at the last minute". By reneging on scheduled deliveries, the authors argue, the firms were able to withhold pipeline capacity, inflate gas prices and yield artificially high electricity prices. Yet after due investigation, regulators have ruled that the companies followed normal industry practices and that there was no matter for prosecution.

[8]An antitrust investigation of the EU Commission has accused Gazprom to have strategically hindered importations of gas to Poland from neighbouring regions during the gas crisis of 2009. Gazprom has allegedly reneged on its obligations to accommodate changes of gas delivery points, the only way to import gas to Poland at that time, so as to ensure that "Russian gas would not compete with Russian gas" and that Poland had "no choice but to cover the gas shortage by acquiring from Gazprom" (EUC, 2018).

[9]In a historical case of commodity prices manipulation in the U.S., two potatoes

to disseminate misleading information.[10] Although our paper is built in reference to precise market manipulations in a specific context, namely that of Alberta' power market, we argue that the lessons learned extend much beyond.

The model is presented in Section 2. The application to Alberta's electricity market is developed in Section 3. Section 4 concludes the paper. All proofs and additional empirical results are collected in the Appendices.

2 Model

A dominant supplier is facing a fringe of competitive firms in a sequential market with stochastic demand.[11] We first present the general setup, and develop the benchmark case (without reneging), before to study the case with reneging and discuss the results.

2.1 The Setup

Let us consider a sequential market organized in two periods. The forward market takes place in period 1 and the spot market occurs in period 2. Both production and consumption take place in period 2. Final demand is a random variable A realized in period 2, and which distribution $F(\cdot)$ is supposed to be known. Demand is observable and perfectly inelastic to prices in the spot market. In period 1, buyers choose to contract an exogenous share $\alpha > 0$ of the expected demand $E(A)$ through forward

producers were forced to default on their deliveries because of the scheme of a competitor which withheld all rail cars with phony deliveries, "leaving 1.5 million pounds of potatoes rotted because they could not be shipped out of Maine" (Markham, 1991).

[10] "Spoofing" that refers in financial markets to the posting and immediate reneging of quotes on electronic trading platforms is an observed practice that artificially increases trading activity and temporarily inflates the stock price (Hewitt and Carlson, 2019).

[11] The main insights would be unchanged under an alternative modeling of imperfect competition.

commitments.[12] They hence buy $A - \alpha E(A)$ in the spot market.[13] For clarity, we assume that arbitrage across markets is not possible.[14]

A dominant supplier competes against a competitive fringe on the supply-side. Let Q_t and q_t be the quantities sold by the dominant firm and the fringe, respectively, in period $t \in \{1, 2\}$. For each player, the total quantity produced is denoted $Q = Q_1 + Q_2$ and $q = q_1 + q_2$, respectively. To gain intuition, we specify linear marginal cost functions as $C(Q) = Q/B$ for the monopolist and $c(q) = q/b$ for the fringe. The hypothesis of price-taking behaviour implies that the fringe's supply in period 1 is $q_1 = bp_1$, while, because the whole production takes place in period 2, $p_2 = (q_1 + q_2)/b$ so that $q_2 = b(p_2 - p_1)$.

2.2 Sequential Markets under Uncertainty

Residual demand. In period 1, the demand $\alpha E[A]$ is covered. The residual demand faced by the monopolist is $D_1(p_1) = \alpha E[A] - bp_1$, meaning that in equilibrium

$$Q_1 = \alpha E[A] - bp_1 \tag{1}$$

must hold. Similarly, the equilibrium quantity sold on the spot market by the monopolist must be such that

$$\begin{aligned} Q_2 &= A - \alpha E[A] - q_2 \\ &= A - \alpha E[A] + b(p_1 - p_2). \end{aligned} \tag{2}$$

[12]Making α endogenous requires assumptions about the risk aversion of buyers and their degree of coordination. In order to remain general, we opted for not introducing such assumptions and offering results that are valid for any α. Some additional results are discussed in the Appendix. In electricity markets, $\alpha E(A)$ represents the forward obligations of load serving entities.

[13]Buyers sell back their extra commitments in the spot market if $A < \alpha E(A)$.

[14]Most of the literature consider at least some degree of arbitrage between spot and forward prices (Ito and Reguant, 2016). We assume away arbitrage because i) we have in mind long-term physical commitments, and ii) it would require the introduction of additional assumptions while only affecting the level of demand above which reneging is profitable, hence not providing additional insights.

In words, spot market sales depend on the difference between realized demand A and total forward commitments $\alpha E[A]$, as well as the difference between forward and spot prices $p_1 - p_2$, which corresponds to the fringe's adjustment on the spot market.

Monopolist problem. The expected profits of the dominant firm, hereafter referred to as the monopolist, can be written

$$E[\Pi] = p_1 Q_1 + E[p_2 Q_2] - E\left[\int_0^{Q_1+Q_2} C(Q)dQ\right], \tag{3}$$

where the expectation is taken with respect to A, and the prices p_1 and p_2 are determined by the equilibrium conditions (1) and (2). The monopolist maximizes profits by backward induction. Taking forward commitments as sunk decisions, the profit-maximizing spot sales upon observing A are

$$Q_2^\star = \frac{B}{2B+b}A - \frac{B+b}{2B+b}Q_1. \tag{4}$$

In the first stage, the monopolist anticipates its behavior in the spot market and maximizes its expected profits defined in (3). This yields

$$Q_1^\star = \frac{(2\alpha-1)B - (1-\alpha)b}{3B+2b}E[A]. \tag{5}$$

Proposition 1 (Sequential markets under uncertainty) *In equilibrium, the monopolist's forward commitments $Q_1^\star$ and final output $Q_1^\star + Q_2^\star$ decrease with its marginal cost $1/B$ and the slope of its residual demand b. In addition,*

- *(Forward seller) $Q_1^\star \geq 0$ if only if $\alpha \geq \underline{\alpha} = \frac{B+b}{2B+b}$;*
- *(Spot seller) $Q_2^\star \geq 0$ if and only if $p_2^\star \geq C(Q_1^\star + Q_2^\star)$; and,*
- *(Forward premium) $p_1^\star \geq E[p_2^\star]$ if only if $\alpha \geq \underline{\alpha}$;*

In equilibrium, the monopolist's commitments and final output are positively related to the level of demand and its relative competitive advantage.[15] Positive price-cost margins in the spot market are observed when the monopolist is a net seller. Furthermore, there is a forward premium, that is $p_1^\star - E[p_2^\star] > 0$, if and only if the monopolist is a seller in the forward market. This occurs when consumers choose a large enough degree of forward contracting.

In the remaining of the paper, we assume $\alpha > \underline{\alpha}$ so that the monopolist is always a seller in the forward market.

2.3 Strategic Reneging

The monopolist is now given the ability to renege on some of its forward commitments upon observing A. In practice, reneging may occur for legitimate reasons, for instance as a consequence of technical failures, or for strategic purposes. It is nevertheless costly to verify the legitimacy of supply disruptions and thus whether they constitute a contract breach, or even a fraud.

In this paper, we assume the institutional framework to fully ignore the possibility of reneging not being legitimate. This is, of course, an extreme assumption. However, as long as strategic reneging cannot be completely prevented, there will be deviations in equilibrium under imperfect information (Green and Porter, 1984). Those deviations are the main focus of the paper.[16]

Let $\mu \in [0, 1]$ denote the share of commitments that can be reneged upon, because the firm has a "good excuse" to do so. In our application, μ represents the share of contracts tied to specific production assets for which the firm can credibly claim an emergency outage requirement.[17] Those

[15] In addition to being the slope of the residual demand, recall that b is inversely related to the fringe's marginal cost.

[16] An alternative model under asymmetric information would assume two states of the world (true production failure or not) which realizations are unobservable by the principal. We do not pursue in this direction here. In any case, the insights from a more complex model would be unchanged as long as institutions remain imperfect.

[17] In our empirical study of Alberta's electricity market, the firm exaggerated actual technical problems reported by plant operators to substantiate claims of emergency outage requirements. The arrival rate of these technical failures is random and independent

contracts commit the assets to the physical production of μQ_1 in period 2. Let $R \in [0, \mu Q_1]$ denote the "reneged output", i.e. the amount that the monopolist chooses not to produce although initially committed.

The unsatisfied demand R must be served in the spot market.[18] The forward price remains unaffected because it has already been settled. However, reneging affects the price in period 2 as it shifts upward the residual demand curve faced by the monopolist. More precisely, the spot price is now determined by

$$p_2 = \frac{1}{b}\left(A - (Q_1 - R) - Q_2\right). \tag{6}$$

Spot market. Contracts typically account for the possibility of non-delivery. Let τ represent a per-unit deviation penalty that is contractually binding.[19] In period 2, the monopolist solves the profit-maximization problem

$$\max_{Q_2, R} \quad \Pi = p_1(Q_1 - R) + p_2 Q_2 - \int_0^{Q_1 - R + Q_2} C(Q)dQ - \tau R, \tag{7}$$

jointly with respect to Q_2 and R taking Q_1 as given. The profit-maximizing spot sales are now given by

$$Q_2^\dagger = \frac{B}{2B+b}A - \frac{B+b}{2B+b}(Q_1 - R). \tag{8}$$

As long as $Q_1 > 0$, reneging $R > 0$ leads to an increase of the profit-maximizing volume of sales in the spot market $Q_2^\dagger = Q_2^\star + \Delta Q_2$, with $0 < \Delta Q_2 < R$.

of market conditions. The firm can essentially decide whether to take advantage of it.

[18]More generally, this effect could also be the result of reneging in a different market (Marks et al., 2017), or due to the refusal to honor a contract clause (EUC, 2018), or even caused by a scheme forcing some rival firm to default on its delivery obligations (Markham, 1991).

[19]We will see that this linear contract leads to imperfect commitment. In a more general model, the availability of a "good excuse" μ would be random. The optimal τ would hence be determined together with p_1 as functions of the distributions of μ and A, and the cost of auditing.

The commitment problem essentially arises from a contractual failure. A natural solution is to penalize any deviation by $p_2 - p_1$. Doing so makes the firm financially accountable for its deviations, which would prevent any strategic reneging in equilibrium.[20] This penalty can, however, put too much risk on the seller in a situation where actual technical problems are bound to happen. As will be illustrated in the application, contracts unfortunately cannot be expected to be perfect.

Proposition 2 (All-or-nothing strategic reneging) *In equilibrium, taking forward commitments as given, there exists a demand threshold T such that $R = \mu Q_1$ if and only if $A \geq T$, and $R = 0$ otherwise. In addition, T increases with τ and p_1, and decreases with μ and Q_1.*

The volume of commitments to be reneged upon follows an all-or-nothing strategy. It is either profitable to satisfy its contracts and maintain its spot strategy, or to renege as much as possible on commitments and modify its spot strategy to account for this anticipated decision. The most profitable option between the two strategies is determined by the realized level of demand. Demand must be sufficiently large for this conduct to be profitable. Increasing the amount of commitments that can be reneged allows to shift the residual demand further to the right, hence it results in a greater likelihood of a profitable manipulation. Conversely, the larger the cost of the manipulation, the less likely it will be profitable.

Reneging incentives. The optimal strategy can be characterized by comparing the profits obtained in each case. For a given realized demand A, let us denote the ex-post profits in the two cases by,

$$\Pi^{\star}(A) = p_1 Q_1 + p_2^{\star} Q_2^{\star} - \int_0^{Q_1 + Q_2^{\star}} C(Q) dQ, \tag{9}$$

[20]This corresponds to financial forward contracts. Substituting τ by $p_2 - p_1$ in (7) yields $Q_2^{\dagger} - Q_2^{\star} = R$, hence p_2 is unchanged in equilibrium and the problem vanishes. However, in a supply function auction with binding capacity constraints, no finite penalty can fully prevent the strategic reneging of physical contracts when demand is random and inelastic (Benatia, 2018*a*).

when commitments are satisfied, and

$$\Pi^{\dagger}(A) = p_1(1-\mu)Q_1 + p_2^{\dagger}Q_2^{\dagger} - \int_0^{(1-\mu)Q_1+Q_2^{\dagger}} C(Q)dQ - \tau\mu Q_1 \tag{10}$$

when the firm reneges on μQ_1. The latter is profitable for all A such that

$$\Pi^{\dagger}(A) - \Pi^{\star}(A) \geq 0, \tag{11}$$

which yields the profitability condition

$$\Delta p_2 Q_2^{\star} + p_2^{\dagger}\Delta Q_2 + \Delta C \geq (p_1+\tau)\mu Q_1, \tag{12}$$

where $\Delta p_2 = p_2^{\dagger} - p_2^{\star}$ is the price impact, $\Delta Q_2 = Q_2^{\dagger} - Q_2^{\star}$ denotes the strategy shift on the spot market and the cost savings are $\Delta C = \int_{(1-\mu)Q_1+Q_2^{\dagger}}^{Q_1+Q_2^{\star}} C(Q)dQ$.

The condition (12) sheds light on the benefits and losses associated to reneging. On the one hand, the scheme involves incurring the penalty cost τ as well as the opportunity cost p_1 for each reneged unit. On the other hand, it affects the strategic player's profits through two channels.

- First, it affects the (spot) market-clearing price upwards, $\Delta p_2 \geq 0$. This gain corresponds to the intensive margin, that is the increased profit margin on the spot sales. The less elastic the *residual* demand, the larger this effect.

- Second, the spot sales are adjusted upwards, $\Delta Q_2 \geq 0$, which will give more leverage to the manipulation. The less elastic the *residual* demand, the smaller this effect. In any case, because of reneging on the forward market, the firm's total production always decrease hence cost-savings $\Delta C \geq 0$ occur. Both effects are on the extensive margin.

Proposition 3 (Spot strategy) *In equilibrium, if reneging is profitable ($A \geq T$), the monopolist will shift its spot supply to $Q_2^{\dagger} > Q_2^{\star}$ to optimize its profits, total production decreases and, in addition,*

- *(Price impact) $\Delta p_2 \geq 0$ increases with μ, Q_1, $1/b$, and B;*

- *(Strategy shift)* $\Delta Q_2 \geq 0$ *increases with* μ, Q_1, b *and* $1/B$; *and,*

- *(Cost savings)* $\Delta C \geq 0$ *increases with* μ, Q_1 *and* $1/b$, *and the effect of* $1/B$ *depends on the relative cost advantage of the monopolist.*

The elasticity of the residual demand faced by the firm is the key determinant of the strategy shift, the price impact and potential cost savings. In any case, reneging on the quantity supplied on the forward market is associated to an increase in supply on the spot market, hence to a decrease in the exercise of market power. In other words, market power and reneging can be considered as strategic substitutes.

Forward market. In period 1, by assumption, the expected profit maximization program is changed into

$$\max_{Q_1} \quad E[\Pi] = \int_0^T \Pi^\star(A)dF(A) + \int_T^{+\infty} \Pi^\dagger(A)dF(A). \tag{13}$$

For $\mu = 0$, the first-order condition coincides to that characterizing $Q_1^\star$ in the absence of reneging possibility. For $\mu > 0$, because the gains from reneging increases with Q_1, the profit-maximizing forward position will be larger if the monopolist anticipates that reneging will be profitable with positive probability.

Proposition 4 (Equilibrium forward sales) *In equilibrium, upon anticipating a positive probability of profitable reneging, the monopolist will shift its supply of forward contracts to* $Q_1^\dagger > Q_1^\star$*, the extent of which depends on the distribution of uncertainty.*

The monopolist faces a trade-off upon choosing Q_1. In equilibrium, the firm will equalize the expected marginal efficiency loss associated with excessive forward sales with the expected marginal profit associated with spot market manipulation. Upon increasing its forward sales, the monopolist increases both the likelihood of a profitable manipulation $1 - F(T)$ and the profitability of the latter. This comes at the opportunity cost of "overcontracting" when $A \leq T$.

Is there a forward premium? It is worth noting that implementing the manipulative scheme reduces the expected price spread because of its positive effect on spot prices.

Proposition 5 (Equilibrium forward premium) *In equilibrium, there is a forward premium* $p_1^\dagger \geq E[p_2^\dagger]$ *if and only if* $\alpha \geq \overline{\alpha} > \underline{\alpha}$*, and* $p_1^\dagger < E[p_2^\dagger]$ *otherwise. In addition,* $\overline{\alpha} < 1$ *in absence of a forward adjustment, i.e. if* $Q_1^\dagger = Q_1^\star$*.*

The forward premium is decreased by strategic reneging even without anticipatory adjustments in the forward market, i.e. $Q_1^\dagger = Q_1^\star$, because the spot price will be larger in expectations. More importantly, there is a threshold level of forward contracting $\overline{\alpha} > \underline{\alpha}$ below which a spot price premium is sustained in equilibrium. It follows in particular that for $\alpha = \overline{\alpha}$ there is price convergence and the monopolist is a seller in both markets. This convergence exists in our setting *because* the monopolist exerts market power and manipulates the spot price via strategic reneging, and not because of arbitrage and increased competition. This result shows the limit of using price convergence as a metric to measure competitiveness in sequential markets.[21]

Remark that buyers now face a trade-off. Indeed, by increasing forward contracting to hedge against higher spot prices (and volatility) they also provide more room for manipulation to the monopolist. Another lesson drawn from our theoretical model is thus that, while offering an instrument to deal more efficiently with uncertainties, forward markets may actually also introduce additional distortions into market mechanisms.

Discontinuous residual demand. Residual demand functions are seldom linear in the real world. For example, in the application, the observed

[21] This point was already made by Ito and Reguant (2016) in a setup with market power and limited arbitrage. In their setting, more arbitrage leads to more competitive outcomes on average but enlarges the deadweight loss during periods where the strategic player enjoys high market power.

residual demands are step functions because of the multi-unit auction design. We now extend our results by considering (discontinuous) piecewise linear functions. Let the fringe's marginal cost function be modified to $c(q) = q/b + \Delta c$ for $q \geq k$, and be unchanged for $q < k$. The dominant supplier is paid the spot price

$$p_2 = \frac{1}{b}(A - Q_1 - Q_2) + \Delta c, \tag{14}$$

where $\Delta c > 0$ is the step size, if its output is $Q_2 \leq Q_2^k = A - Q_1 - k$. Proposition 6 summarizes the results for the case where the step (the discontinuity jump) is at the left of the profit-maximizing output in the linear setting, i.e. $Q_2^k < Q_2^\star$.

Proposition 6 (Piecewise linear residual demand) *In equilibrium, if the residual demand is a piecewise linear function with a discontinuity at $Q_2^k < Q_2^\star$, there exists a demand threshold $\tilde{A}$ above which it is profitable to trigger the price step Δc by producing Q_2^k instead of $Q_2^\star$. In addition,*

- *(Spot) The threshold $\tilde{A}$ decreases with Δc, and increases with k and Q_1;*
- *(Forward) The firm will also reduce its forward commitments to $Q_1^k < Q_1^\star$; and,*
- *(Reneging) The price step makes strategic reneging profitable for lower values of demand, i.e. there exists $\tilde{T} < T$ above which strategic reneging is profitable for any demand A for large enough values of Δc.*

In the linear setting, strategic reneging always coincides with a positive strategy shift to $Q_2^\dagger$ instead of $Q_2^\star$. The existence of a price step gives rise to a different situation where it is sometimes profitable to renege on commitments and *reduce* output below $Q_2^\star$ to trigger the price step. This occurs for levels of demand smaller than the threshold T characterized in the linear case. The two main implications are that:

- Discontinuous residual demand functions facilitate strategic reneging, because it is now profitable at lower demand levels; and,
- The exercise of market power and strategic reneging can complement each other to create a price impact. Indeed, a negative strategy shift would *not* be profitable *without* reneging.

An additional lesson of our theoretical model is thus that a supply-cut on the spot market coincidental with reneging is not necessarily a proof that the latter is legitimate. It can, instead, reflect strategic manipulations as market power and reneging can also be strategic complements.

2.4 Lessons for Regulation

The model delivers important insights for regulation. Identifying and proving a manipulative behavior is not a trivial task. It entails to provide evidence of the manipulation and the intent to manipulate, as well as the creation of a price impact caused by the alleged manipulation. The evaluation of reneging profitability is key to the identification of strategic manipulations. Let us consider that a firm has strategically reneged on its commitments under (false) claims of a production failure. From (12), the rewards from the manipulation are

$$\left(\Delta p_2 Q_2^\star + p_2^\dagger \Delta Q_2 + \Delta C\right) - (p_1 + \tau)R. \tag{15}$$

The profitability depends on the reneged output R and its associated cost $p_1 + \tau$, the production costs reduction ΔC, the ex-post price $p_2^\dagger$, the strategy shift ΔQ_2, the price impact Δp_2 and the counterfactual sales $Q_2^\star$ assuming reneging had not occurred. In principle, this formula can be used to estimate the disgorgement penalties. Unfortunately, estimates of Δp_2 and $Q_2^\star$ may be the subject of contention. Furthermore, benefiting from a supply disruption or even causing a price impact is not a satisfactory proof of intent to manipulate. Reneging can occur for legitimate reasons and contracts usually account for the possibility of non-delivery.[22] Additional evidence need usually be collected through audits performed ex-post, as in the case of our empirical application.

The auditing costs and limited investigation capacities tend to reduce the scope of regulatory interventions to outright manipulation cases, or following a denunciation. In our application, the strategic manipulations could have escaped the regulator for long, had they not hurt a (large) rival supplier because of its financial position. The theoretical predictions of our model deliver potential red flags and additional proofs of intent which can be helpful to motivate inquiries into more surreptitious cases. According to the model, the occurrence of a reneging event is more likely to be of strategic nature if it coincides with tight market conditions (e.g. peak demand, inelastic residual demand, or low wind output); but also if the firm's strategy on the spot and forward markets differ from usual, and reflects that the supply disruption was anticipated. We argue that, in such case, the observed adjustments constitute indirect evidence of intended market manipulations.

In practice, there are often delays between market closure and the time at which market outcomes are settled. In electricity markets, offer bids must be submitted by market participants several hours before actual production, leaving room for an emergency outage to be declared after market closure. Bids exhibiting a sudden shift before the outage declaration actually *reveals* either its strategic nature, or that the firm concealed information about the upcoming occurrence of a (legitimate) forced outage. In either case, the bids provide a proof of misconduct.

Therefore, the regulator can not only use causal estimates of price impacts, but also obtain estimates of counterfactual strategies in order to evaluate whether further investigation is needed. Even though regulators have been reluctant to prosecute based on statistical inference in the past, they are now increasingly using data for market oversight.[23] We propose to

[22]Reneging under a claim of a technical issue is not legitimate if the claim cannot be substantiated (e.g. the technical failure was exaggerated, or reported later so as to time the non-delivery).

[23]For instance, the FERC's investigation into Constellation's virtual trading activities

collect additional information by leveraging machine learning.

3 Strategic Reneging in Electricity Markets

The theoretical analysis suggests that outages of power plants can be used to disguise strategic reneging in restructured electricity markets. We take advantage of the well-documented market manipulation events that occurred in Alberta's electricity market in 2010-2011 to identify strategy shifts and analyze the impact of reneging. We begin by providing institutional details and data description about the market and the manipulation events. We then develop a preliminary analysis of the events. Finally, we propose an in-depth analysis of the firm's conduct, exhibit additional proofs of intent to manipulate, and account for strategic effects to assess market outcomes and welfare impacts.

3.1 Institutions and Data

The Alberta electricity market. Alberta's electricity system is market-based since 2001. Competition has been introduced on the retail and wholesale segments of the industry, while transmission and distribution remained as regulated monopolies (Olmstead and Ayres, 2014; Brown and Olmstead, 2017). The Alberta Electric System Operator (AESO) is the authority mandated to design and operate the market. The revenues of wholesale suppliers in this market consist almost only on payments collected from the short-run electricity market.[24]

The electricity market is organized as a uniform-price multi-unit procurement auction for each hour of the day. Suppliers submit offer bids one day-ahead of physical production to signal their willingness to produce

in New York's electricity market was initiated following observations of "bizarre price behavior" by the Division of Energy Market Oversight (FERC, 2012).

[24]The Alberta electricity market is an energy-only market, meaning that there are no additional payment to suppliers to ensuring their profitability. In practice, some additional revenues can be obtained from supplying ancillary services to the AESO, such as short-term load balancing.

different amounts of energy. Offer bids can be modified up to two hours before production. Generators must offer their available capacity in the market and can choose prices between \$0 and \$999.99 per MWh. Bids take the form of several price-quantity pairs for each generator. The AESO aggregates them into an industry-level supply function. The market-clearing price is determined at every minute and equals the highest accepted bid price to supply the realized electricity demand. Participants are paid the pool price, which is the time-weighted average price for each hour.

Table 1 provides information with regards to Alberta's market structure and firm characteristics. Production is dominated by coal-fired power plants in Alberta, although it has been slowly replaced by natural gas and some additional wind capacity over the recent years. In 2010-2011, the five largest firms controlled about 70% of market offers while the rest was controlled by a fringe over 20 firms. Wind farms are not included in market shares because they receive fixed price payments irrespective of market outcomes. Offer control differs from capacity ownership because of long-term bilateral contracts between suppliers.[25]

Long-term forward contracts. Power purchase arrangements (PPAs) are long-term contracts of up to 20 years introduced during the restructuring of Alberta's electricity industry in 2000.[26] The primary purpose of the PPAs was to anticipate potential market power issues caused by the concentration of capacity ownership within the hands of incumbent utilities. Before that, 90% of capacity was controlled by TransAlta, ATCO and Capital Power. The contract leaves the ownership and operation of the assets to the owners, but gives buyers the right to sell its production to the electricity market. This is essentially a "virtual divesture" for incumbents. In 2000, PPAs

[25] One caveat of our data is that offer control was not well followed at that time. A few plants are owned by multiple firms, each of which can submit bids for its respective share. Unfortunately, the data does not differentiate the firms behind the bids in these cases. In attempt to account for this issue, we split bids using information on offer controls from MSA (2012).

[26] In the U.S., this type of contracts is generally called power purchase *agreements*, and is used for renewables.

Table 1: Alberta market and firm characteristics

	Market shares (%) 2010-11 to 2011-03	Capacity (%)	Fuel shares (%) 2011	
TransCanada	20.9	4.2	Coal	46.9
ENMAX	18.3	6.5	Natural Gas	36.0
Capital Power	11.8	11.8	Wind	6.1
TransAlta	10.4	36.7	Hydro	6.1
ATCO	8.2	16.2	Other	4.9
Fringe	30.4	24.5		

This table shows market shares of capacity for which a firm can submit offer bids versus capacity ownership by firm (%) as well as capacity shares by fuel type (%). Market shares are calculated as average share of available capacity over total capacity. Capacity shares are based on ownership rather than offer controls. Values for fuel shares are taken from Brown and Olmstead (2017).

were sold in auctions with varying private terms including remunerations for fixed and operating costs, plus a rate of return.

The contracts give the buyer exclusivity to sell the facility's output up to a certain capacity, known as its committed capacity. For obvious reasons, the PPAs include incentives to owners to achieve the committed capacity. These incentives are referred to as availability incentive payments. If available capacity is above a target specified by the contract, then the owner receives this payment. Conversely, if capacity is below the target the owner must pay this amount to the PPA buyer (AUC, 2015). The incentive payment is calculated as a 30-day rolling average of prices times the difference between the actual available capacity and the specified target.

We interpret those contracts as long-term forward commitments tied to some physical capacity. The plants subject to PPAs provide baseload production which is offered at low prices on the energy market by the PPA buyers.[27] The average offer price is between \$2/MWh and \$17/MWh for

[27] Unlike in our model, the energy is sold to a rival firm which, in turn, sells it to the market. Assuming this rival to be a price-taker (or with sufficiently large forward covers) the energy would be offered at price p_1 in the spot market as in our theoretical model. The main results are hence left unchanged. In a strategic setting, reneging would impact a strategic player's cost structure which should further exacerbate the manipulator's market power. This would be an interesting extension.

PPA plants in our sample, and 85% of capacity is offered at $0/MWh. For that reason, they almost always produce up to available capacity. The contract commits the owner to deliver whatever output the buyer might want up to target capacity. In this context, strategic reneging consists in choosing not to deliver the output by reducing available capacity below the contract target, at the cost of incurring the associated penalty. This conduct can be disguised under claims of urgent maintenance needs, which must still be substantiated.

The allegations of market manipulations. The Alberta Market Surveillance Administrator (MSA) accused TransAlta Corporation of market manipulations through strategically timed "emergency" outages of its coal-fired power plants under PPAs in several instances from November 2010 to February 2011. After due investigation, the Alberta Utilities Commission (AUC, 2015) concluded that *"TransAlta unfairly exercised its outage timing discretion [...] for its own advantage and made its own portfolio benefits paramount to the competitive operation of the market"*. In other words, maintenance needs were not urgent and outages could have been delayed to off-peak periods to prevent substantial market impacts. Ultimately, a $56 million settlement was made.

In the fall of 2010, TransAlta identified the complementarity of its supply strategy and forced outages of plants under long-term contracts to increase spot prices. The firm developed the *Portfolio Bidding Strategy* outlined in an (internal) executive summary dated October 21, 2010. The strategy's objective was to enlarge revenues from the spot market by increasing prices when the firm had a net selling position.[28] The main ingredients of that strategy involved to:

1. (Forward & Spot) Optimize the bidding strategy in the spot market and amount of forward contracting;

[28] In addition, the firm considered that the price increase would drive forward prices up. This was expected to create arbitrage opportunities from undervalued forward contracts given the firm's private information about forced outages.

2. (Outages) Coordinate forced outages to optimize market impacts; and
3. (Wind) Have wind farms to reduce output during periods of high wind.

The firm officially started to use this strategy on November 18, 2010. On February 25, 2011, the MSA received a complaint regarding TransAlta's management of outages of its plants under PPAs. The MSA accused TransAlta of timing forced outages on 4 different occasions: November 19-21, November 23, December 13-16, 2010 and February 16, 2011. Details are provided in Table 11 in the Appendix. The evidence collected in AUC (2015) make clear that traders and plant operators collaborated to time the outages. For example, after the event on November 23, 2010, a trader circulated an email stating: *"Operations Manager for Sun 1/2, had called me on [November 22, 2010] afternoon about timing a 150 MW derate [...]. We determined to take [it] during the day for a price impact. [...] This was a great example of the ongoing coordination we have [...] to optimize outages"*.

We interpret strategically timed forced outages of plants under PPAs as a form of strategic reneging on long-term forward commitments. The firm purposefully restrained production from the assets under contracts in order to benefit its portfolio position at the cost of the foregone revenues and contract penalties. Note that the plants were always undergoing actual technical issues although not as urgent as claimed by the firm. In this respect, the urgency of maintenance requirements is difficult to monitor for regulators, rival suppliers and retailers alike. However, as an enforcement matter, the timing of bids accounting for the outage information relative to actual outage declaration is key. This is however not observed in our data.

Data. We use public data shared by the AESO and the MSA.[29] It contains hourly spot prices and loads, as well as generator-level information such as hourly bids, available capacity and dispatch schedules.[30] The data

[29] We are grateful to Derek Olmstead for sharing generator-level bid data.

[30] Bids include domestic generation as well as export and import offers to adjacent regions. At the time, there was no demand-side bidders but some responsive load (about

covers the period where the alleged manipulations took place, that is from November 1, 2010 to March 31, 2011.

This data is aimed at estimating the counterfactual supply strategies during the events, assuming the outages did not occur. For so doing, we train a predictive model of strategic bidding using the observations outside of those events. We carry the estimation separately for the sample of (four) peak hours, from 17:00 to 21:00, and (twenty) off-peak hours. All hourly observations where reneging occurred during the same day are assigned to a "reneging set". This consists of the treatment group, whereas the remaining sample is considered as the control group. We split those remaining observations into a training set and a testing set. The training set is used to estimate the model whereas the testing set is used to evaluate its predictive power. Sample splitting is done randomly so that the training sample has roughly 70% of observations. Table 2 provides summary statistics of the main variables for peak and off-peak hours in each sample. The mean and standard deviations are relatively close between the training and testing samples. Prices are noticeably larger and excess supply is lower during the events.

3.2 Preliminary Evidence of Extensive Conduct

We begin by documenting what features are correlated with the occurrence of the strategic forced outage events. We then investigate whether the firm curtailed wind power production to complement the impacts of the strategic outages. Finally, we show that the firm's bids account for the outage information.

Strategic timing? First, we investigate whether the outages occurred under tight market conditions. We regress a binary variable $\mathbb{1}_t^{outage}$ equal to one in hours during forced outage events on a set of explanatory variables

3% of average demand) including six large users combining 200 MW and one third-party demand-response service provider of 45 MW. We neglect this feature due to insufficient data.

Table 2: Summary statistics

	Training set		Testing set		Events	
	Mean	Std	Mean	Std	Mean	Std
Peak						
Demand: D (GWh)	8.47	0.51	8.38	0.52	8.82	0.30
Price: P (CAD)	129.4	208.6	117.7	197.6	506.0	305.8
Available Cap: K (GW)	9.46	0.41	9.43	0.42	9.55	0.48
Wind TA: W_{TA} (MWh)	141	131	162	140	79	130
Wind Total: W (MWh)	258	218	292	237	138	228
Observations: n	402		154		44	
Off-Peak						
Demand: D (GWh)	7.79	0.63	7.80	0.65	8.10	0.57
Price: P (CAD)	46.2	75.1	46.5	86.0	154.2	256.9
Available Cap: K (GW)	9.21	0.44	9.22	0.45	9.42	0.41
Wind TA: W_{TA} (MWh)	135	129	142	125	69	117
Wind Total: W (MWh)	251	217	263	211	130	204
Observations: n	1991		787		220	

Notes: This table shows descriptive statistics (mean and standard deviation) of the main variables. TA refers to TransAlta, the alleged manipulator.

capturing market conditions. We estimate the following equation by OLS

$$\mathbb{1}_t^{outage} = \beta_0 k_t + \beta_1 LW_t + \beta_2 D_t + \beta_3 dRD_t + \alpha' X_t + u_t, \qquad (16)$$

where controls include the firm's available capacity k_t, a binary variable equal to one during low wind periods LW_t (below 5% of max annual production), system demand D_t, and the slope of residual demand dRD_t.[31] We also include a set of time fixed-effects, denoted X_t, for hours of the day, days of the week and weeks. Table 3 shows the estimation results on the entire sample. To maintain consistency throughout the paper, we choose to report p-values in all tables rather than standard errors. The test statistics used in Section 3.3 obeys non-standard asymmetric distributions (weighted Chi-squares) due to the functional nature of the parameters of interest. Therefore, standard errors do not provide a meaningful way to

[31] The slope is estimated from each hourly residual demand function using an affine specification.

evaluate statistical significance.[32]

Table 3: Strategic timing of forced outages

	(1)	(2)	(3)
Capacity (TransAlta)	0.49	0.51	0.51
	(0.00)	(0.00)	(0.00)
Low wind ($< 5\%$)	0.08	0.09	0.08
	(0.00)	(0.00)	(0.00)
Demand (GWh)		-0.02	-0.02
		(0.10)	(0.11)
RD slope (linear)			-0.04
			(0.13)
Monday	-0.04	-0.03	-0.03
	(0.00)	(0.01)	(0.01)
Tuesday	0.02	0.03	0.03
	(0.04)	(0.01)	(0.01)
Thursday	0.04	0.05	0.05
	(0.00)	(0.00)	(0.00)
12am-8am dummies	$-0.05, -0.04$	$-0.06, -0.05$	$-0.06, -0.05$
	$(0.03, 0.05)$	$(0.01, 0.02)$	$(0.01, 0.02)$
Observations	3598	3598	3598
R^2	0.34	0.34	0.34

Notes: This table shows the estimation results of equation (16). The dependent variable is a binary variable equal to 1 in all hours during strategic outage events. Low wind is a binary variable equal to 1 when wind power generation is below 5% of maximum annual production. All regressions include hour of the day fixed effects, day of the week fixed effects and week fixed effects. In the last row, we report the range of estimates for the hourly dummies between 12am and 8am. The p-values for $H_0 : \beta = 0$ are reported in parentheses. Only statistically significant dummies are reported.

The outage events are found to coincide with tighter market conditions on average. The fixed-effects reveal that outages occurred less often at off-peak hours, and more often on weekdays, hence coincided with higher demand levels. The abundance of seasonal controls may explain the negative sign of demand's coefficient, which is anyway not found to be statistically significant. In addition, the probability to observe a strategic outage is

[32]Inference is discussed further in Section 3.3 and formally detailed in Appendix B.

higher by 8 percentage points during low wind episodes. We also find that the firm's available capacity (excluding PPA plants) was on average larger, which suggests a selling position on the spot market.

Strategic curtailment of wind power? The firm's trading strategy described earlier involved the strategic curtailment of wind farms. We investigate whether this strategy was effectively implemented. To do so, we estimate the following linear model

$$W_t^{TA} = \beta_{ws}' WS + \sum_{j \neq TA} \beta_w^{ij} W_t^j + \beta_D D_t + \sum_{l=1}^{11} \beta_l \mathbb{1}_t^{reneg_l} + \alpha' X_t + u_t \tag{17}$$

where W_t^i denotes firm i's wind power production, $\mathbb{1}_t^{reneg_l}$ is a dummy equal to one for all hours with reneging in day $l \in \{1, ..., 11\}$, and zero in all other hours. D_t denotes total demand. We use wind speed measures WS, from three weather stations located nearby TransAlta's wind farms,[33] and measured output from rival wind farms, W_t^j's, as predictors. We also include hour of the day, day of the week and week fixed-effects. Table 4 reports the results of the estimation and a F-test of the null hypothesis that all coefficients associated with reneging dummies are zero.

The results of the F-test yield no evidence of significant output anomalies from the wind farms owned by TransAlta during the outages investigated by the regulator. It indicates that traders took advantage of low wind power periods, but did not engage in strategic wind curtailment to exacerbate market impacts. However, we find the firm's wind power production to be negatively correlated with total demand. The smaller estimate (column 5) corresponds to an elasticity of wind production with respect to demand of -0.66, after controlling for weather conditions. This result suggests that the firm strategically curtailed wind power during periods of large demand.[34]

[33] TransAlta had seven wind farms, each located between 23 km and 42 km away from their closest weather station.

[34] Due to the inherent difficulty to predict wind power production, a more precise empirical analysis would require more granular weather and wind power data.

Long-term renewable contracts, like feed-in tariffs, do not impose delivery obligations. For this reason, the curtailment of renewable power is a means to "renege" that is always possible and never costly. Therefore, these contracts provide firms with a free market manipulation channel, which should draw attention from regulators and market designers.

Table 4: Strategic wind curtailment

	(1)	(2)	(3)	(4)	(5)
Wind Speed 1	1.29	−0.82	−0.82	−0.81	−0.81
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Wind Speed 2	2.50	0.57	0.57	0.57	0.58
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Wind Speed 3	2.08	0.46	0.48	0.47	0.48
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Wind ENMAX		1.64	1.63	1.64	1.63
		(0.00)	(0.00)	(0.00)	(0.00)
Wind SUNCOR		−0.47	−0.47	−0.52	−0.52
		(0.00)	(0.00)	(0.00)	(0.00)
Demand (GWh)				−12.86	−10.82
				(0.00)	(0.01)
Reneging dummies	No	No	Yes	No	Yes
F-stat			1.48		1.19
$H_0 : \forall l \, \beta_l = 0$			(0.13)		(0.29)
Observations	3555	3555	3555	3555	3555
R^2	0.63	0.83	0.83	0.83	0.83

Notes: This table shows the estimation results of equation (17). The dependent variable is TransAlta's wind power production in MWh. All regressions include hour of the day fixed effects, day of the week fixed effects and week fixed effects. The three wind speed measures are taken from nearby weather stations, for which there are 43 missing values in total. Rivals' wind outputs are also used as controls. P-values for $H_0 : \beta = 0$ are reported in parentheses. The F-test of $H_0 : \beta_l = 0 \; \forall l$ is also reported.

3.3 Machine Learning from Bids about Manipulations

We propose to quantify the strategy shifts during reneging events using a predictive model.[35] We first develop a machine-learning approach to

[35] The title of this section is a reference to Burlig et al. (2019) which inspired our empirical approach.

compute counterfactual strategies which can be used to: identify potential misconducts, derive counterfactual market outcomes, and evaluate welfare consequences. Instead of proposing a structural model, we opt for a predictive model of the firm's strategy under business-as-usual conditions, i.e. in absence of strategic reneging.

Our preference for a predictive approach in this context is motivated by two main reasons. First, the major advantage of the structural approach is to be able to simulate counterfactual outcomes under different structures that have never been observed in practice, such as a prospective change in market design. Our objective is, instead, to predict strategies and market outcomes under business-as-usual conditions, assuming reneging had not happened.

Second, the framework developed in Section 2 provides helpful indications about what to look for in the data. Nevertheless, it lacks too many important elements to be used as a structural model. The structural approach requires imposing behavioral assumptions and choosing an equilibrium concept. The actual game played in Alberta's electricity market is a supply function auction with capacity constraints under uncertainty, making the choice of an equilibrium concept a difficult one. While the Cournot model has been found to apply reasonably well to Alberta (Brown and Olmstead, 2017), it assumes elastic residual functions and quantity strategies that cannot explain the negative supply shifts predicted in Proposition 6. In comparison, the predictive approach does not require an equilibrium concept, works with complex strategy spaces (here supply functions), and can even capture the tendency of some firms to act sub-optimally without imposing behavioral assumptions. This approach also has its limits: it relies on an identifying restriction, which is discussed in due time.

Empirical strategy. Let us denote the observed supply and residual demand functions by S_t and RD_t in hour t. Following our model's notations, let $(S_t^{\dagger}, RD_t^{\dagger})$ and $(S_t^{\star}, RD_t^{\star})$ be the potential outcomes with and without reneging, respectively. However, both potential outcomes $(S_t^{\star}, RD_t^{\star})$ and

$(S_t^\dagger, RD_t^\dagger)$ are never observable for the same hour. We propose to train predictive models for $(S_t^\star, RD_t^\star)$ so as to derive counterfactual estimates during reneging events $(\widehat{S}_t^\star, \widehat{RD}_t^\star)$. These estimates reflect the market conditions that would have prevailed in absence of reneging. The estimated strategy shift is defined as

$$\widehat{\Delta S}_t(p) = S_t(p) - \widehat{S}_t^\star(p), \tag{18}$$

for every price $p \in [0, 999.99]$. It corresponds to the *individual* treatment effect of reneging during "reneging hours" (treatment), and predictions errors during "normal hours" (control).

The (observed) residual demand function is directly impacted by reneging as it makes part of the supply committed at forward prices unavailable. In addition, the function can also be impacted by a reaction from competitors to the supply disruption. The estimated change in residual demand function, that is defined as $\widehat{\Delta RD}_t(p) = RD_t(p) - \widehat{RD}_t^\star(p)$, accounts for both effects. In order to test for the presence of competitors reaction to the supply disruption, we construct an alternative counterfactual residual demand function. The latter assumes that i) no strategic reaction was caused by reneging; ii) the withheld capacity would have been offered at zero prices (as observed in the data).[36] It is defined as $\overline{RD}_t(p) = RD_t(p) + \sum_{r \in \mathcal{R}_t} k_r$, where k_r denotes the capacity which would have been available in absence of reneging by plant $r \in \mathcal{R}_t$, the set of plants which reneged. By construction, in absence of strategic reaction from competitors, $\widehat{RD}_t^\star$ and $\overline{RD}_t$ should be statistically equivalent.

We also study the causal effects of reneging on market outcomes, that is price and output deviations. The equilibrium condition, given by

$$\widehat{S}_t^\star(\hat{P}_t) = \widehat{RD}_t^\star(\hat{P}_t), \tag{19}$$

yields the counterfactual price $\hat{P}_t$ as well as the corresponding firm's output $\widehat{Q}_t^\star = \widehat{S^\star}_t(\hat{P}_t)$. The output change is defined as $\widehat{\Delta Q}_t = Q_t - \widehat{Q}_t^\star$ and the price impact is $\widehat{\Delta P}_t = P_t - \widehat{P}_t$. If the predictive model performs well, those

[36] As mentioned earlier, 85% of PPA capacity is offered at \$0/MWh.

values should be statistically close to zero except if reneging affects market outcomes. This approach has the desirable feature to account for the firm's own strategic reaction to reneging, in addition to the strategic reactions of its competitors.

Identification. The identification of causal estimates relies on the assumption that the treatment selection conditionally on covariates is as good as random. This assumption holds as long as, conditional on the covariates, the strategic outage decision depends only on random factors, such as the arrival of a "good excuse" to substantiate the needs for urgent maintenance requirements.

This exogeneity assumption might be violated if the data used to estimate the model, i.e. the observations for the "control group", differs in systematic ways from the data when reneging occurs, i.e. the "treatment group". For instance, if reneging occurs partly because some particular rival generator is in maintenance but there is no similar observation in the training sample, then we would lack information about supply strategies in this circumstance and the counterfactual predictions would be biased. It is also possible that the firm's decision to renege depends on market dynamics, such as recent rival bidding behaviors. For instance, Brown, Eckert and Lin (2018) argue that firms in Alberta may be utilizing bidding patterns to communicate with their rivals to increase market prices. If the occurrence of such collusive behaviors is correlated with that of strategic reneging, our counterfactual predictions would suffer from a selection bias.[37]

We claim that the exogeneity restriction holds because the firm was required to substantiate its urgent maintenance needs with an actual technical problem. Table 3 provides evidence in support of this argument. Indeed, a large share of variance is left unexplained which suggests that outage timing largely depend on random factors, such as the occurrence of actual technical failures.[38] Most importantly, the regulatory investigation revealed that

[37]Note, however, that treatment heterogeneity is not an issue here because we seek to calculate individual treatment effects rather than average treatment effects.

[38]This is in line with the findings of Fogelberg and Lazarczyk (2019).

each event was initiated by a plant operator reporting a technical issue, although not urgent, to TransAlta's trading department (AUC, 2015).

Estimation. Let us consider the following functional linear model

$$S_t(p) = \sum_{s=1}^{103} \beta_{k_s}(p) k_s + \beta_Z(p)' Z_t + \alpha(p)' X_t + u_t(p), \tag{20}$$

defined for all p, where $S_t(p)$ is the firm's supply as a function of the price p, k_s is the available capacity of generator $s \in \{1, ..., 103\}$, and Z_t is a set of predictors including market demand, wind production, and import and export capacities. The variable X_t is a set of time dummies for hours of the day, days of the week, and weeks. u_t is a functional error term. While in equilibrium strategies are best-response to each other, our objective is to identify the best exogenous (or more precisely *pre-determined*) predictors of firm-level strategies. Doing so allows to predict equilibrium strategies without solving for an equilibrium, because they will depend on each other through the predictors only. The model does not condition directly upon the strategies of rivals. However, the specification includes the hourly capacity availability of every single generator in Alberta, irrespective of their ownership or control.[39] Therefore, the fact that TransAlta may have partly based its reneging decision on one particular rival generator's availability should not be a threat to identification.

The model parameters are functions defined over the price interval, and thus are infinite-dimensional. In order to reduce the dimensionality,[40] we estimate the multivariate model given by

$$\boldsymbol{S_t} = \sum_{s=1}^{103} \boldsymbol{\beta_{k_s} k_s} + \boldsymbol{\beta_Z' Z_t} + \boldsymbol{\alpha' X_t} + \boldsymbol{u_t}, \tag{21}$$

[39]During hours with reneging, we predict the counterfactual strategies by setting the available capacity k_s of the unavailable plant s to its value in the hour preceding any reneging.

[40]The estimation of the functional model in (20) can be done using the approach of Benatia, Carrasco and Florens (2017) although it would not allow for variable selection.

where the variables are evaluated over an evenly-spaced grid of prices $\{p_1, p_2, ..., p_L\}$ and stacked into vectors of length $L = 52$, denoted by bold variables. For example, $\boldsymbol{S_t} = \begin{pmatrix} S_t(p_1) & S_t(p_2) & ... & S_t(p_L) \end{pmatrix}'$ is a vector of supply quantities evaluated over the price grid. Vectors for variables that do not depend on p in (20) consist of repeated values. $\boldsymbol{u_t}$ is an iid multivariate gaussian error term. The exact same model is applied to the residual supply $RS(p) = \sum_{j \neq TA} S_j(p)$ instead of $S(p)$, which yields the estimate of interest $\widehat{RD}_t(p) = D_t - \widehat{RS}_t(p)$.

The model is estimated on the training set of observations with the multivariate extension of the lasso developed by Simon, Friedman and Hastie (2013).[41] By design, the lasso selects variables that best predict the outcome of interest and shrinks the others to zero. The lasso is a form of penalized regression useful for model selection. In our setting, it is difficult to know what drives the firm's strategy. At the same time, we want to prevent overfitting issues caused by the inclusion of too many variables. The model parsimony depends crucially on the chosen value of a tuning parameter λ. We opt for using 20-fold cross-validation and select the value of λ that minimizes the average mean-squared-errors.

The predicted functions obtained from model (21) are finite-dimensional vectors which are not restricted to be monotone, unlike supply functions. We recover a smooth monotone function for each estimate using the penalized spline smoothing approach of Ramsay (1998). Inference is described in Appendix B. It essentially boils down to testing the null hypothesis

$$H_0 : \widehat{\Delta S}_t(p) = 0, \quad \forall p. \tag{22}$$

The test statistics are derived from weighted Chi-square distributions, with weights that depend on the eigenvalues of the asymptotic covariance operator of the functions $\widehat{\Delta S}_t(\cdot)$. Because these distributions are not symmetric,

[41]More specifically, we use the glmnet package. We also tried using an elastic net regression, that is the combination of $\mathbb{L}_1$ (lasso) and $\mathbb{L}_2$ (ridge) penalties of the parameters, and a neural network. The results were slightly worse in terms of RMSE on the testing set and are thus not reproduced here.

the standard errors are not appropriate to assess statistical significance. It would be possible to use a t-test, but that would only provide a pointwise evaluation of statistical significance. In contrast, we choose to use a (uniform) test which evaluates significance of the entire functions. We compute p-values using an asymptotic approximation and a parametric bootstrap.

Model evaluation. Table 5 shows the main summary statistics of model performance for S and RS in peak hours[42] in the training, testing and reneging set, as well as coverage probabilities for prices and outputs' confidence intervals. The last column reports the associated statistics for $\widehat{RS}$ evaluated against the constructed counterfactual $\overline{RS}$ which assumes no outage and no strategic response.

The model performs well for both S and RS. For instance, the supply prediction exhibits a mean integrated absolute bias of 21.5 MW on the testing set, which corresponds to a mean integrated relative absolute error of 2.5%. The root-mean-integrated-squared-error (RMISE) is also within the same order of magnitude for both the training and testing sets, meaning that overfitting is not a concern. Substantially larger biases and RMISE are observed for the reneging set.

Inference also performs well on the testing set. The rejection rates for the functional test defined in (22) are reasonably close to the nominal size of 5% for both the asymptotic approximation and the boostrap. In addition, we report the coverage probabilities for estimated prices and outputs derived from the pair of functions $(\widehat{S}, RS)$, that is using the observed residual supply, and $(\widehat{S}, \widehat{RS})$, i.e. using the predicted residual supply. For the testing set, 5% level confidence intervals are found to be close to 95%.

The results for the reneging set yield important insights. As expected, the predictions $(\widehat{S}, \widehat{RS})$ differ significantly from their observed values. Since $\overline{RS}$ does not account for the strategic reaction of competitors to the outages, while $\widehat{RS}$ does, their difference provides evidence of strategic reactions from competitors. We find that it is the case in 34% of reneging hours. Finally,

[42]Results are similar for off-peak hours (see Table 13 Appendix).

coverage probabilities for equilibrium outcomes indicate that counterfactual prices and outputs differ significantly from observed ones.

Table 5: Model performance (Peak hours)

	Training set		Testing set		Reneging set		
n	402		154		44		
Parameters	141						
	S	RS	S	RS	S	RS	$\overline{RS}$
MI-. Bias	0.3	-0.2	0.2	6.7	9.7	-423	-41
MI-. Abs. Bias	18.2	45.9	21.5	69.9	41.9	430.6	125.7
MI-. Rel. Abs. Bias	2.1%	0.6%	2.5%	0.9%	4.7%	5.6%	1.5%
RMISE	23.2	64.2	28.0	100.7	51.7	536.2	177.4
Rej. Rate (Asymp.)	0.027	.007	.078	.058	.409	1	.386
Rej. Rate (BS)	.025	.007	.071	.052	.432	1	.341
Zero parameters	24	18					
λ_{CV}	2.770	3.426					
Coverage probabilities	RS	$\hat{RS}$	RS	$\hat{RS}$	RS	$\hat{RS}$	$\overline{RS}$
Price	0.99	0.98	0.96	0.93	0.89	0.05	0.05
Output	0.98	0.97	0.95	0.95	0.84	0.45	0.48

Notes: This table shows statistics of model performance separately for the training set, testing set and reneging set. The reneging set includes all hours for days when reneging occurred. MI refers to Mean Integrated, RMISE refers to the root-mean-integrated-squared-errors. Zero parameters is the number of parameters set to zero by the algorithm (for each of the 52 price values).

Strategic reactions and counterfactual equilibria. We illustrate the results in Figure 1 for November 19, 2010 18:00 and Figure 2 for November 21, 2010 17:00. Observed supply and residual demand functions are shown by the plain lines and counterfactuals are represented by the dashed lines. We also display the 95% highest density region of counterfactual equilibrium outcomes.[43] The model predicts that the supply strategy was increased by about 55 MW in the first example, and reduced by about 70 MW in the second. In the former case (Figure 1), the supply strategy shift had virtually no impact on spot prices but profitability increases thanks to the additional

[43]The bootstrapped distribution is used to estimate highest density regions in order to graph a confidence set for equilibrium outcomes $(\hat{P}_t, \hat{Q}^{\star}_t)$ (Hyndman, 1996).

sales. In the latter case (Figure 2), the price impact would have been only +\$30, instead of +\$360, had the firm not reduced its supply.

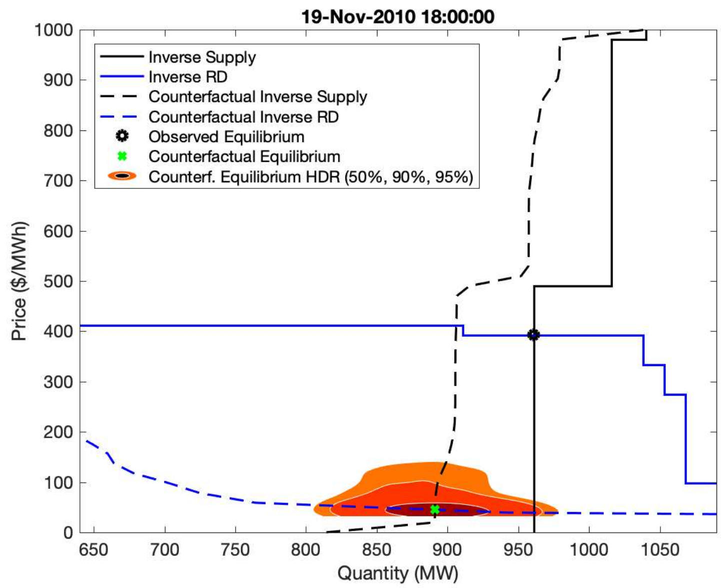

Figure 1: November 19, 2010 18:00

The estimated strategy shifts can be summarized by focusing on the integrated difference between the observed function and its prediction, $\widehat{\Delta S}_t = \int_{\underline{p}}^{\overline{p}} \left(S_t(p) - \widehat{S}_t^{\star}(p) \right) dp$ over different price intervals. This provides information about whether supply offers are modified for low-, middle- or high-range prices, where $\widehat{\Delta S}_l$, $\widehat{\Delta S}_m$ and $\widehat{\Delta S}_h$ denote the difference integrated over the price interval $[\$0, \$150]$, $[\$150, \$500]$ and $[\$500, \$1000]$, respectively. To test the significance of these differences, we calculate the p-values of the functional test defined in (22) for each interval.

Those statistics are reported in Table 6 for peak hours starting at 18:00 and 19:00 during the first day of each of the four identified events. We find evidence that the dominant firm has increased (November 19th and November 23rd), more or less maintained (December 13th), or decreased (February 16th) its supply significantly during the events.

Analogous statistics for the residual demand are reported in Table 14

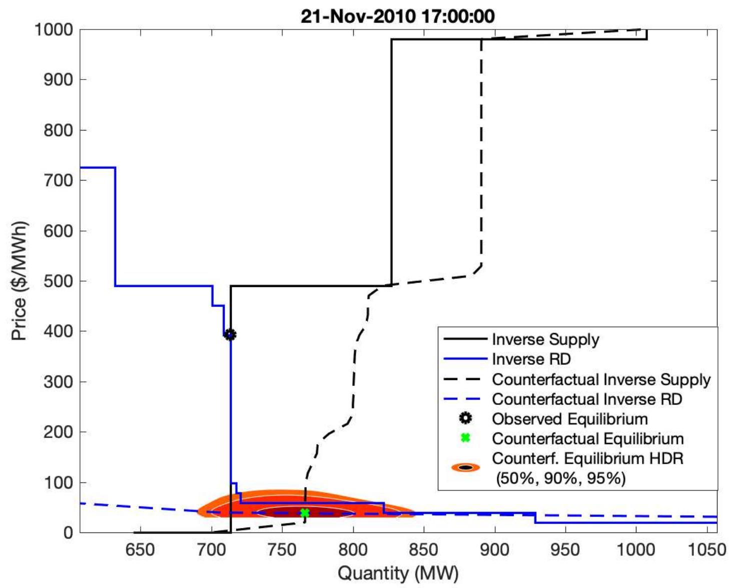

Figure 2: November 21, 2010 17:00

in the Appendix. The integrated difference is now taken between the constructed "naive" counterfactual function and the residual demand prediction, $\widehat{\Delta RD}_t = \int_{\underline{p}}^{\overline{p}} \left(\overline{RD}_t(p) - \widehat{RD}_t^{\star}(p) \right) dp$ over the same price intervals. Those values measure the strategic reaction of rival firms to reneging for low-, mid- and high-range prices. We find that there are no significant deviations in many hours, however for some hours rival firms seem to have strongly reacted to the outages. For example on February 16th, competitors reduced their offers for low and high prices by as much as 300 MW in addition to the outage. Rivals have hence largely contributed to the price jump observed during this event.

The supply and residual demand predictions are used to compute counterfactual market outcomes. Table 7 reports the corresponding price and output impacts of reneging. Price impacts are consistently large, and output impacts are often significant. The latter are positive in many hours and sometimes negative.

Table 6: Estimated supply strategy shifts

	$\widehat{\Delta S_l}$	$\widehat{\Delta S_m}$	$\widehat{\Delta S_h}$	$\widehat{\Delta S_l}$	$\widehat{\Delta S_m}$	$\widehat{\Delta S_h}$
		Nov 19			Nov 23	
18:00	55.7	72.2	55.3	47.7	75.4	58.8
	(0.03)	(0.01)	(0.06)	(0.05)	(0.01)	(0.05)
19:00	55.6	73.3	54.7	55.3	83.4	66.0
	(0.03)	(0.01)	(0.06)	(0.02)	(0.00)	(0.02)
		Dec 13			Feb 16	
18:00	6.3	11.7	5.2	-55.8	-38.2	-62.8
	(0.79)	(0.67)	(0.99)	(0.03)	(0.18)	(0.03)
19:00	34.8	48.4	40.2	-106.1	-60.1	-112.2
	(0.20)	(0.09)	(0.19)	(0.00)	(0.02)	(0.00)

Notes: This table shows estimates of supply shifts for two peak hours during the first day of each outage events. P-values for $H_0 : \widehat{\Delta S}(p) = 0$, $\forall p \in [\$0, \$150]$ ($\widehat{\Delta S_l}$), $[\$150, \$500]$ ($\widehat{\Delta S_m}$) and $[\$500, \$1000]$ ($\widehat{\Delta S_h}$) are reported in parentheses.

Table 7: Estimated price and output impacts

	Nov 19		Nov 23		Dec 13		Feb 16	
	$\widehat{\Delta P}$	$\widehat{\Delta Q}$	$\widehat{\Delta P}$	$\widehat{\Delta Q}$	$\widehat{\Delta P}$	$\widehat{\Delta Q}$	$\widehat{\Delta P}$	$\widehat{\Delta Q}$
18:00	363	69.8	327	77.9	831	46.5	405	13.4
	(0.00)	(0.01)	(0.02)	(0.01)	(0.00)	(0.07)	(0.00)	(0.25)
19:00	183	70.6	208	107.8	364	47.8	785	47.5
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.17)

Notes: This table shows estimates of price and output impacts for two peak hours during the first day of each outage events. Bootstrapped p-values are reported in parentheses.

Testing the model's predictions. Our theoretical model has four testable implications: 1) the magnitude of strategy shifts are positively related to the elasticity of residual demand; 2) price impacts are negatively related to the elasticity of residual demand; 3) output impacts are positively related to the elasticity of residual demand; and, 4) negative supply shifts are profitable only if it is to benefit from a large discontinuity jump in the residual demand function.

To test the first three predictions, we regress $\widehat{\Delta S_t}$, $\widehat{\Delta Q_t}$ and $\widehat{\Delta P_t}$ onto a constant and the slope of residual demand functions. An increase in the slope implies a less elastic function hence smaller strategy shifts, lower quantity cuts and larger price jumps. The first three columns in Table 8 show that the empirical results are in line with those theoretical predictions.

The last prediction follows from Proposition 6. Discontinuous residual demand functions can create incentives to shift the supply strategy to the left so as to reach the discontinuity jump. To test this, we construct a variable *Stepsize*, which measures the size of the price step (in \$) if the firm's strategy is at a discontinuity jump in its residual demand function, and is otherwise equal to zero.[44] The last two columns of Table 8 show regression results of $\mathbb{1}_{\widehat{\Delta S}_t<0}$, a dummy equal to 1 when (integrated) supply shifts are negative, onto a constant, the slope of RD and *Stepsize*.[45] Results show that negative shifts tend to coincide with supply strategies which "target" large discontinuity jumps in the residual demand function.

Table 8: Strategy shifts, market impacts, and residual demand (Peak hours)

	$\widehat{\Delta S}$	$\widehat{\Delta Q}$	$\widehat{\Delta P}$	$\mathbb{1}_{\widehat{\Delta S}<0}$	$\mathbb{1}_{\widehat{\Delta S}<0}$
RD slope (linear)	−79.21	−44.02	379.46	0.71	
	(0.00)	(0.03)	(0.00)	(0.00)	
Stepsize				0.06	0.09
				(0.05)	(0.01)
Observations	44	44	44	44	44
R^2	0.33	0.10	0.22	0.35	0.14

Notes: This table shows regression results of five models, where the dependent variables are: strategy shifts, output impacts, price impacts, and a dummy equal to one if strategy shifts are negative. *Stepsize* measures the size of the price step when supply and residual demand intersect at a discontinuity jump, and is equal to zero otherwise. P-values for $H_0 : \beta = 0$ are reported in parentheses.

[44] This feature occurs relatively often in our data, suggesting that the firm has much information about its residual demand.

[45] Similar results are obtained for off-peak hours (see Table 15 in the Appendix). As a falsification test, we run the same regressions using the testing set and find that those variables are, as expected, no more significantly correlated with the predicted changes (see Table 16 in the Appendix).

3.4 Evaluating the Impacts

Firm-level impacts. The firm-level hourly gross gains from reneging are defined as

$$\widehat{\Delta\Pi}_t = P_t Q_t - \widehat{P}_t \widehat{Q}_t^{\star}, \tag{23}$$

and, as $\widehat{\Delta\Pi}_{\times} = \widehat{\Delta\Pi}_t / \widehat{P}_t \widehat{Q}_t^{\star}$ in relative terms. Those gains result directly from reneging, i.e. from the outage-induced displacement of the residual demand function, but also indirectly through the firm's supply strategy shift and the possible strategic reactions of its competitors.

We isolate the direct effect of reneging on revenues. To do so, we estimate equilibrium outcomes based on counterfactual residual demand functions accounting for reneging but assuming no strategic reaction. These functions are obtained as before. We train separate models specified like (21) to predict the supply functions of plants under PPAs (see Table 17 in the Appendix). The counterfactual residual demand of interest is then defined as $\widetilde{RD}_t^{\star} = D_t - (\widehat{RS}_t^{\star} - \sum_{r \in \mathcal{R}_t} \hat{S}_t^r)$, with $\mathcal{R}_t$ being the set of plants under outage in t. The counterfactual equilibrium $(\widetilde{P}_t, \widetilde{Q}_t^{\star})$ is determined by the condition $\widehat{S}_t^{\star}(\widetilde{P}_t) = \widetilde{RD}_t^{\star}(\widetilde{P}_t)$. The direct gains from reneging are hence given by $\widetilde{P}_t \widetilde{Q}_t^{\star} - \widehat{P}_t \widehat{Q}_t^{\star}$, whereas indirect gains are $P_t Q_t - \widetilde{P}_t \widetilde{Q}_t^{\star}$.

Table 9 reports the results for peak and off-peak hours aggregated by event, and the share of direct gains from reneging. The firm's total gains from manipulations during peak hours are evaluated at almost \$15 million, and \$20 million for off-peak hours. Direct gains from reneging makes the bulk of those revenues (80%). However, strategic responses generated about 70% of revenues during the first event.[46] This result confirms that strategic bidding can exacerbate substantially the market impacts of reneging. Therefore, neglecting strategic effects can lead to greatly underestimate market impacts.

These estimates abstract from financial forward contracts, potential cost savings related to output changes, and outage costs. Cost changes, which

[46]The gains were sizable in many hours. For example, at 18:00 on November 19, 2010, the manipulation generated extra revenues of above 350,000\$, an increase nearly nine times larger than the counterfactual hourly revenue.

Table 9: Profitability of the manipulations

	$\widehat{\Delta\Pi}$	$\widehat{\Delta\Pi_\times}$	$\widehat{\Delta\Pi}$	$\widehat{\Delta\Pi_\times}$	$\widehat{\Delta\Pi}$	$\widehat{\Delta\Pi_\times}$	$\widehat{\Delta\Pi}$	$\widehat{\Delta\Pi_\times}$
Peak	Nov 19-21		Nov 23		Dec 13-16		Feb 16-18	
Gains (M$)	2.26	×5.1	0.98	×0.6	6.21	×13.8	5.05	×1.4
Reneging	25%		104%		78%		106%	
Off-Peak								
Gains (M$)	0.22	×0.2	1.22	×1.9	4.12	×2.9	14.75	×2.9
Reneging	76%		72%		52%		80%	
Total								
Gains (M$)	2.48	×1.5	2.19	×1.0	10.33	×5.6	19.80	×2.3
Reneging	30%		85%		67%		87%	

Notes: This table shows the gross gains from manipulations for peak and off-peak hours in each event. The values for hourly gains are expressed in 1,000$. Reneging represents the share of gains caused by reneging alone (direct gains) the remaining share is associated with the equilibrium effect (indirect gains from strategic response of both the firm and its rivals). $\widehat{\Delta\Pi_\times}$ denotes the relative change.

are probably small here, could be accounted for using the estimates from Brown and Olmstead (2017). However, forward contracts can substantially reduce those gains if a large share of the firm's output is committed to be supplied at forward price. Data on forward contracts being difficult to obtain, we neglect this aspect.[47] Outage costs consist in the foregone revenues from reneged commitments and penalty charges, which could be calculated if one had detailed information on the contractual arrangements. However, the firm would have had to shut down the plant for maintenance anyway, although at off-peak to avoid large market impacts. The firm would have incurred some costs anyway due to the design of availability incentive payments.

Welfare impacts. Short-run demand being inelastic, the only impact of strategic reneging on total welfare results from the inefficiencies on the supply-side. More expensive production units are used instead of cheap coal-fired plants under outage, which undermines the system efficiency and

[47] Hortaçsu and Puller (2008) propose a method to estimate forward positions from marginal cost estimates and bid functions.

brings up prices. However, this cost inefficiency is likely to be small, because reneging affects only a tiny fraction of total supply. We hence choose to focus only on the "redistributive" impacts of the outages, which corresponds to the transfer from buyers to sellers given by

$$\widehat{T}_t = \left(P_t - \widehat{P}_t\right) D_t, \tag{24}$$

and $\widehat{T}_{\times t} = \widehat{T}_t / \widehat{P}_t D_t$ in relative terms. It corresponds to a transfer from retailers/consumers to producers in absence of financial forward contracts. In their presence, the total is unchanged but gains and losses are distributed differently. For example, *Capital Power*, the supplier whose complaint initiated the investigation for market manipulations, made considerable financial losses because of its net buying position in the spot market during several of the events.

The direct effect of reneging on this transfer is defined by $\left(\widetilde{P}_t - \widehat{P}_t\right) D_t$. The remaining part of the transfer, $\left(P_t - \widetilde{P}_t\right) D_t$, is generated by the strategic responses to reneging.

Table 10 reports the transfers for each event for peak and off-peak hours. The manipulations caused total power procurement costs to increase by roughly \$135 million for peak hours and \$200 million for off-peak hours over the period. This corresponds to an increase of 20 percentage points in 5 months. We find nonetheless that the impacts on procurement costs vary substantially across hours and events. The direct effects of reneging is large (79% of total transfer), albeit the strategic component is also sizable in some cases.

The share of the surplus $\hat{T}_t$ that the firm was able to capture during the events is sometimes well above its market share – which is around 10%. For example, on November 23, the firm captured up to 25% of the windfall producer revenues. By making use of its informational advantage, the firm increased markedly its supply to profit from the large price increase caused by reneging. Conversely, the firm may find profitable to reduce its market share when doing otherwise would make reneging ineffective. For example, the firm captured only 8% of the surplus at 17:00 on November 21 (Figure 2).

Table 10: Welfare impacts

	$\widehat{T}$	$\widehat{T_\times}$	$\widehat{T}$	$\widehat{T_\times}$	$\widehat{T}$	$\widehat{T_\times}$	$\widehat{T}$	$\widehat{T_\times}$
Peak	Nov 19-21		Nov 23		Dec 13-16		Feb 16-18	
Transfer (M$)	21.8	×4.6	7.7	×0.5	58.0	×12.4	46.3	×1.3
Direct effect	27%		110%		81%		101%	
Off-Peak								
Transfer (M$)	1.84	×0.1	12.3	×1.8	40.0	×2.7	145.7	×2.9
Direct effect	88%		86%		72%		81%	
Total								
Transfer (M$)	23.7	×1.3	20.0	×0.8	97.9	×5.0	192.1	×2.2
Direct effect	33%		92%		76%		85%	

Notes: This table shows the transfer caused by the manipulations for peak and off-peak hours in each event. The values for hourly gains are expressed in 1,000,000$. "Direct effect" represents the share of the total transfer caused by reneging alone, the remaining share is associated with the strategic response. $\widehat{T_\times}$ denotes the relative change.

It turns out that neglecting strategic effects can lead to vastly under-estimated market impacts, not only by failing to account for a large share of the impacts, but also by using the wrong reference point.[48] We evaluate TransAlta's undue profits from manipulations at $35 million, a figure that is "only" 30% larger than the disgorgement penalty set by the regulator. In contrast, the estimated "welfare impact" of AUC (2015) amounts to around $100 million, less than one third of our estimate. The $56 million settlement covers only 17% of the latter. The remaining $274 million, which consist in windfall revenues to suppliers who benefited from the manipulation, will never be recovered by ratepayers.

These estimates only quantify the most important consequences. An aspect not considered here is the reshuffling of the energy mix. Outages

[48]In our notations, the impacts are measured by comparing the outcomes by the supply-residual demand pair with reneging, $(S_t(1), RD_t(1))$, to those without reneging, $(S_t(0), RD_t(0))$. Neglecting strategic effects leads to consider outcomes generated by a deviation as a reference point. For instance, AUC (2015) use $(S_t(1), RD_t(1)+R)$ instead of $(S_t(0), RD_t(0))$.

can be expected to have reduced CO2 emissions because the old coal-fired power plants were substituted by gas units. Strategic wind curtailment would have the reverse effect.

More importantly, as the theory shows, the ability to strategically renege has impacts on futures contract prices, and in turn on spot prices through equilibrium effects. These impacts can be difficult to quantify empirically, and even more so due to the inherent lack of data on financial forward contracts. Our model predicts that forward prices must have increased in response to expectations of higher spot prices caused by the manipulations. Yet, the model establishes that part of the price discrepancy created by the firm's conduct may remain in equilibrium. A spot price premium might even had prevailed in equilibrium over the long run, had the firm been able to continue this strategy. Evidence show that TransAlta's traders noticed that (month-ahead) forward prices for March 2011 increased by 30% above expectations, reflecting the impacts of the strategic outages (AUC, 2015). Those overvalued forward contracts were seen as another trading opportunity. The firm planned to take a net buying position on the spot market, then reverse its outage and bidding strategies to maintain spot prices as low as possible. In absence of regulatory intervention, the firm would have optimized its informational advantage about forced outages by alternating these two strategies over time.

Even though we account for strategic behaviours in the spot market, our analysis neglects the general equilibrium effects, such as the consequences for forward markets. Our figures should hence be seen as lower bounds of the harm resulting from reneging.

4 Conclusion

We study incentives to manipulate sequential markets arising from imperfect commitment. We show how a supplier with market power would modify its supply strategy upon anticipating a potentially profitable deviation to its commitments. Our model provides guidance for the detection of potential misconducts related to strategic reneging. In an application to Alberta's electricity market, we confirm our theoretical predictions and estimate that this commitment problem had harmful welfare consequences for consumers. Albeit long-term contracts were primarily implemented in the province to mitigate potential market power issues, they created powerful incentives to manipulate markets. We are convinced that the downside of sequential markets that we evidence constitutes a serious issue beyond this specific case.

Our analysis shows that strategic reneging can take various forms. The findings suggest that the firm strategically curtailed wind power during episodes of large demand. This illustrates how long-term renewable contracts, like feed-in tariffs, provide firms with a free channel for undue profits. The extensive use of long-term contracts without delivery obligations, as means to support the development of intermittent renewables, will lead to similar issues if contracts are concentrated within the hands of otherwise large suppliers. This stresses the importance of facilitating renewable investment from entrants rather than incumbent firms, and of the centralization of both wind forecasts and dispatch by the system operators.

We argue that these issues can occur beyond electricity markets. The method outlined in this research is a step towards the development of tools for the detection of market manipulations. It is obviously not specific to the electricity sector. It also illustrates how theoretical models and machine learning methods can complement each other for regulatory purposes. We claim that, with all its limits, the implications of this research should extend largely to all markets that are somehow interrelated (not necessarily through time) and subject to imperfect commitment.

References

Allaz, Blaise, and Jean-Luc Vila. 1993. "Cournot Competition, Forward Markets and Efficiency." *Journal of Economic Theory*, 59(1): 1–16.

AUC. 2012. “Application for Approval of a Settlement Agreement between the Market Surveillance Administrator and TransAlta Energy Marketing Corp, Decision 2012-182, July 3, 2012.” *Alberta Utilities Commission*.

AUC. 2015. “Market Surveillance Administrator Allegations against TransAlta Corporation et al., Mr. Nathan Kaiser and Mr. Scott Connelly, Phase 1, Decision 3110-D01-2015, July 27, 2015.” *Alberta Utilities Commission*.

Benatia, David. 2018*a*. “Essays in Econometrics and Energy markets.” *PhD Thesis, University of Montreal*.

Benatia, David. 2018*b*. “Functional Econometrics of Multi-Unit Auctions: an Application to the New York Electricity Market.” *Working Paper*.

Benatia, David. 2020. “Ring the Alarm! Electricity Markets, Renewables, and the Pandemic.” *USAEE Working Paper*.

Benatia, David, Marine Carrasco, and Jean-Pierre Florens. 2017. “Functional Linear Regression with Functional Response.” *Journal of Econometrics*, 201(2): 269–291.

Bergler, Julian, Sven Heim, and Kai Hüschelrath. 2017. “Strategic Capacity Withholding through Failures in the German-Austrian Electricity Market.” *Energy Policy*, 102: 210–221.

Bernhardt, Dan, and David Scoones. 1994. “A Note on Sequential Auctions.” *American Economic Review*, 84(3): 653–657.

Billette de Villemeur, Etienne, and Annalisa Vinella. 2011. “Long-term contracting in hydro-thermal electricity generation: Welfare and environmental impact.” *Utilities Policy*, 19(1): 20–32.

Birge, John R., Ali Hortaçsu, Ignacia Mercadal, and J. Michael Pavlin. 2018. “Limits to Arbitrage in Electricity Markets: A Case Study of MISO.” *Energy Economics*, 75: 518–533.

Borenstein, Severin, James B. Bushnell, and Frank A. Wolak. 2002. "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market." *American Economic Review*, 1376–1405.

Brown, David P., and Derek E.H. Olmstead. 2017. "Measuring Market Power and the Efficiency of Alberta's Restructured Electricity Market: An Energy-only Market Design." *Canadian Journal of Economics/Revue Canadienne d'Économique*, 50(3): 838–870.

Brown, David P., Andrew Eckert, and James Lin. 2018. "Information and Transparency in Wholesale Electricity Markets: Evidence from Alberta." *Journal of Regulatory Economics*, 54(3): 292–330.

Burlig, Fiona, Christopher Knittel, David Rapson, Mar Reguant, and Catherine Wolfram. 2019. "Machine Learning from Schools about Energy Efficiency." *NBER Working paper.*

Bushnell, James B., Erin T. Mansur, and Celeste Saravia. 2008. "Vertical Arrangements, Market Structure, and Competition: An Analysis of Restructured US Electricity Markets." *American Economic Review*, 98(1): 237–66.

Carlton, Dennis W., and Ken Heyer. 2008. "Appropriate Antitrust Policy towards Single-Firm Conduct." *Economic Analysis Group Discussion Paper No. EAG*, 08–2.

Carrasco, Marine, Jean-Pierre Florens, and Eric Renault. 2014. "Asymptotic Normal Inference in Linear Inverse Problems." *Handbook of Applied Nonparametric and Semiparametric Econometrics and Statistics*, 73(74): 140.

Coase, Ronald H. 1972. "Durability and Monopoly." *The Journal of Law and Economics*, 15(1): 143–149.

de Frutos, María-Ángeles, and Natalia Fabra. 2012. "How to Allocate Forward Contracts: The Case of Electricity Markets." *European Economic Review*, 56(3): 451–469.

EUC. 2018. "COMMISSION DECISION of 24.5.2018 relating to a proceeding under Article 102 of the Treaty on the Functioning of the European Union (TFEU) and Article 54 of the EEA Agreement Case AT.39816 – Upstream Gas Supplies in Central and Eastern Europe. Date: 24/05/2018." *European Union Commission. Antitrust Procedure. Council Regulation (EC) 1/2003.*

FERC. 2012. "Constellation Energy Commodities Group, Inc., 138 FERC ¶ 61,168. March 9, 2012."

Fogelberg, Sara, and Ewa Lazarczyk. 2019. "Strategic Withholding through Production Failures." *The Energy Journal*, 40(5).

Graf, Christoph, Federico Quaglia, and Frank A. Wolak. 2020. "(Machine) learning from the COVID-19 lockdown about electricity market performance with a large share of renewables." *Journal of Environmental Economics and Management*, 102398.

Green, Edward J., and Robert H. Porter. 1984. "Noncooperative Collusion under Imperfect Price Information." *Econometrica*, 87–100.

Green, Richard, and Chloé Le Coq. 2010. "The Length of Contracts and Collusion." *International Journal of Industrial Organization*, 28(1): 21–29.

Hewitt, John R, and James B Carlson. 2019. *Securities practice and electronic technology.* Law Journal Press.

Hortaçsu, Ali, and Steven L. Puller. 2008. "Understanding Strategic Bidding in Multi-unit Auctions: a Case Study of the Texas Electricity Spot Market." *The RAND Journal of Economics*, 39(1): 86–114.

Hyndman, Rob J. 1996. "Computing and Graphing Highest Density Regions." *The American Statistician*, 50(2): 120–126.

Imkeller, Peter. 2003. "Malliavin's Calculus in Insider Models: Additional Utility and Free Lunches." *Mathematical Finance*, 13: 153–169.

Ito, Koichiro, and Mar Reguant. 2016. "Sequential Markets, Market Power, and Arbitrage." *American Economic Review*, 106(7): 1921–57.

Ledgerwood, Shaun D., and Paul R. Carpenter. 2012. "A Framework for the Analysis of Market Manipulation." *Review of Law & Economics*, 8(1): 253–295.

Lo Prete, Chiara, William W. Hogan, Bingyuan Liu, and Jia Wang. 2019. "Cross-product Manipulation in Electricity Markets, Microstructure Models and Asymmetric Information." *The Energy Journal*, 40(5).

Markham, Jerry W. 1991. "Manipulation of commodity futures prices-the unprosecutable crime." *Yale J. on Reg.*, 8: 281.

Marks, Levi, Charles F Mason, Kristina Mohlin, and Matthew Zaragoza-Watkins. 2017. "Vertical market power in interconnected natural gas and electricity markets." *CESifo Working Paper Series.*

McAfee, R. Preston, and Daniel Vincent. 1993. "The Declining Price Anomaly." *Journal of Economic Theory*, 60(1): 191–212.

MSA. 2012. "Market Share Offer Control 2012, June 11, 2012." *Market Surveillance Administrator.*

Olmstead, Derek E.H., and Matt J. Ayres. 2014. "Notes from a Small Market: The Energy-only Market in Alberta." *The Electricity Journal*, 27(4): 102–111.

Puller, Steven L. 2007. "Pricing and Firm Conduct in California's Deregulated Electricity Market." *The Review of Economics and Statistics*, 89(1): 75–87.

Ramsay, James O. 1998. "Estimating Smooth Monotone Functions." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 60(2): 365–375.

Simon, Noah, Jerome Friedman, and Trevor Hastie. 2013. "A Blockwise Descent Algorithm for Group-Penalized Multiresponse and Multinomial Regression." *arXiv preprint arXiv:1311.6529.*

Weber, Robert J. 1981. *Multiple-Object Auctions.* Northwestern University.

A Mathematical Appendix (For Online Publication)

Proof 1 (Proof of Proposition 1) *Solving backward, we consider first the profit-maximization problem of the monopolist in period 2, when uncertainty is resolved. Given* p_1 *and* Q_1*, the problem writes*

$$\max_{Q_2} \quad \Pi = p_1 Q_1 + \frac{1}{b}\left(A - Q_1 - Q_2\right) Q_2 - \int_0^{Q_1+Q_2} C(Q)dQ. \tag{25}$$

The first-order condition is

$$\begin{aligned} \frac{\partial \Pi}{\partial Q_2} = 0 &= \frac{\partial p_2}{\partial Q_2} Q_2 + p_2 - C(Q_1 + Q_2) \\ &= \frac{1}{b}\left(A - Q_1 - 2Q_2\right) - \frac{1}{B}\left(Q_1 + Q_2\right) \end{aligned} \tag{26}$$

and the quantity supplied in period 2 is thus (4)*. Result 2 follows from the first-order condition in* (26) *which can be rewritten* $Q_2^\star/b = p_2^\star - \left(Q_1^\star + Q_2^\star\right)/B$.

In period 1, the expected profit maximization program is given by

$$\max_{Q_1} \quad E[\Pi] = \frac{1}{b}\left(\alpha E[A] - Q_1\right) Q_1 + E\left[\frac{1}{b}\left(A - Q_1 - Q_2^\star\right) Q_2^\star\right] - E\left[\int_0^{Q_1+Q_2^\star} C(Q)dQ\right]. \tag{27}$$

Making use of the envelope theorem, the first-order condition is

$$\begin{aligned} \frac{\partial E[\Pi]}{\partial Q_1} = 0 &= \frac{\partial p_1}{\partial Q_1} Q_1 + p_1 + E\left[\frac{\partial p_2}{\partial Q_1} Q_2^\star\right] - E\left[C(Q_1 + Q_2^\star)\right] \\ &= \frac{1}{b}\left(\alpha E[A] - 2Q_1 - E[Q_2^\star]\right) - \frac{1}{B}\left(Q_1 + E[Q_2^\star]\right), \end{aligned} \tag{28}$$

or equivalently

$$\frac{\partial E[\Pi]}{\partial Q_1} = \frac{1}{b}\left\{\alpha E(A) - \frac{3B + 2B}{2B + b} Q_1 - \frac{B + b}{2B + b} E(A)\right\} = 0. \tag{29}$$

The quantity supplied in period 1 is such that

$$Q_1^\star = \frac{B}{2B+b}\alpha E[A] - \frac{B+b}{2B+b}E[Q_2^\star]. \tag{30}$$

From (4)*, in equilibrium, the monopolist's forward sales are* (5) *which yields the first result, and its total output is*

$$Q_1^\star + Q_2^\star = \frac{B}{2B+b}(A - E[A]) + \frac{(1+\alpha)B}{3B+2b}E[A]. \tag{31}$$

The forward price is

$$p_1^\star = (1+\alpha)\frac{B+b}{3B+2b}\frac{E[A]}{b}, \tag{32}$$

and the spot price is

$$p_2^\star = \frac{A}{b}\frac{B+b}{2B+b} + \frac{E[A]}{b}\left(\frac{B}{2B+b} - \frac{(1+\alpha)B}{3B+2b}\right). \tag{33}$$

The spread between the forward and spot markets depend on the realization of demand and the forward demand $\alpha E[A]$*. It is given by*

$$p_2^\star - p_1^\star = \frac{A}{b}\frac{B+b}{2B+b} + \frac{E[A]}{b}\left(\frac{B}{2B+b} - \frac{(1+\alpha)(2B+b)}{3B+2b}\right), \tag{34}$$

and the expected price spread between the sequential markets is given by

$$\begin{aligned} p_1^\star - E[p_2^\star] &= \left(\alpha - \frac{B+b}{2B+b}\right)\frac{E(A)}{b} - \frac{B+b}{2B+b}\frac{Q_1^\star}{b} \\ &= \frac{(2\alpha-1)B - (1-\alpha)b}{3B+2b}\frac{E[A]}{b}. \end{aligned} \tag{35}$$

yielding Result 3 in the proposition.

Moreover, feasibility requires $Q_1^\star + Q_2^\star \geq 0$ *and* $q_1^\star + q_2^\star \geq 0$*. From* (31)*, the first condition is satisfied if* $F(\cdot)$ *is such that*

$$Pr(A < -\frac{(2\alpha-1)B - (1-\alpha)b}{3B+2b}E[A]) = 0, \tag{36}$$

and the second condition is equivalent to $A - (Q_1^\star + Q_2^\star) \geq 0$ which holds if $F(\cdot)$ is such that

$$Pr(A < \frac{B}{B+b}\frac{(2\alpha-1)B-(1-\alpha)b}{3B+2b}E[A]) = 0. \tag{37}$$

Proof 2 ((Side result) Endogenous α in this context) *Risk-neutral consumers choose α to minimize their total expected expenditures to procure A. This problem is given by*

$$\min_{\alpha} \quad E[TE] = \alpha p_1 E[A] + E\left[p_2\left(A - \alpha E[A]\right)\right]. \tag{38}$$

The optimal share denoted $\alpha^\star$ is characterized by the first-order condition

$$\begin{aligned}\frac{\partial E\left[TE\right]}{\partial \alpha} &= 0 = \left(p_1 + \alpha\frac{\partial p_1}{\partial \alpha} - E[p_2]\right)E(A) + E\left[\frac{\partial p_2}{\partial \alpha}(A - \alpha E[A])\right] \\ &= \frac{1}{b}\left(\alpha E[A] - Q_1 + \alpha E(A) - \alpha\frac{\partial Q_1}{\partial \alpha} - E[A] + Q_1 + E[Q_2]\right)E(A) + E\left[\frac{\partial p_2}{\partial \alpha}(A - \alpha E[A\right. \\ &= \frac{1}{b}\left((2\alpha-1)E[A] - \alpha\frac{\partial Q_1}{\partial \alpha} + E[Q_2]\right)E(A) - \frac{1}{b}E\left[\frac{\partial(Q_1+Q_2)}{\partial \alpha}(A - \alpha E[A])\right]\end{aligned} \tag{39}$$

where

$$\begin{aligned}\frac{\partial Q_1}{\partial \alpha} &= \frac{2B+b}{3B+2b}E(A), \\ E(Q_2) &= \frac{(2-\alpha)B+(1-\alpha)b}{3B+2b}E(A), \\ \frac{\partial Q_1 + Q_2}{\partial \alpha} &= \frac{B}{3B+2b}E(A).\end{aligned} \tag{40}$$

Substituting and rearranging yield

$$\begin{aligned}0 &= \frac{1}{b}\left((2\alpha-1)(3B+2b) - \alpha(2B+b) + B + (1-\alpha)b\right)\frac{E(A)^2}{3B+2b}, \\ 0 &= \frac{1}{b}(2\alpha-1)(2B+b)\frac{E(A)^2}{3B+2b},\end{aligned} \tag{41}$$

which implies that it is optimal for consumers to choose $\alpha^\star = 1/2$. This solution is feasible only if the monopolist produces a positive output, i.e. if

$Q_1^\star + Q_2^\star \geq 0$ *which is guaranteed under the previous feasibility conditions on* $F(A)$*.*

Proof 3 (Proof of Proposition 2) *We first show that the problem admits a corner solution, then characterize the demand threshold* T*.*

Part 1 (Corner solution). *The first-order condition with respect to* Q_2 *is changed to*

$$\begin{aligned} \frac{\partial \Pi}{\partial Q_2} = 0 = & \frac{\partial p_2}{\partial Q_2} Q_2 + p_2 - C(Q_1 - R + Q_2) \\ = & \frac{1}{b}(A - Q_1 + R - 2Q_2) - \frac{1}{B}(Q_1 - R + Q_2), \end{aligned} \tag{42}$$

and thus we have (8)*. The first-order condition with respect to* R *is*

$$\begin{aligned} \frac{\partial \Pi}{\partial R} = 0 = & -(p_1 + \tau) + \frac{\partial p_2}{\partial R} Q_2 + C(Q_1 - R + Q_2) \\ = & -(p_1 + \tau) + \frac{1}{b} Q_2 + \frac{1}{B}(Q_1 - R + Q_2), \end{aligned} \tag{43}$$

However, this condition does not characterize the optimal reneging strategy. The set of first-order conditions does not characterize a maximum because we have $\left(\partial^2 \Pi / \partial Q_2^2\right)^2 = -(2/b + 1/B) < 0$ *and the determinant*

$$\frac{\partial^2 \Pi}{\partial Q_2^2} \frac{\partial^2 \Pi}{\partial R^2} - \left(\frac{\partial^2 \Pi}{\partial Q_2 \partial R} \right) = -\frac{1}{b^2} < 0. \tag{44}$$

To solve this problem, let us consider R *to be fixed at the time of choosing* Q_2*, so that* (8) *holds. Substituting its expression into* (43) *yields*

$$\frac{\partial \Pi}{\partial R} = -(p_1 + \tau) + \left(\frac{1}{b} + \frac{1}{B} \right) \left(\frac{B}{2B + b} A - \frac{B + b}{2B + b}(Q_1 - R) \right) + \frac{1}{B}(Q_1 - R). \tag{45}$$

Differentiating with respect to R gives

$$\begin{aligned}\frac{\partial^2 \Pi}{\partial R^2} &= \left(\frac{1}{b} + \frac{1}{B}\right)\left(\frac{B+b}{2B+b}\right) - \frac{1}{B} \\ &= \frac{B}{b(2B+b)} > 0,\end{aligned} \tag{46}$$

that is the objective function is convex in R, leading to a corner solution. The optimal reneging strategy is an all-or-nothing strategy, i.e. $R^\star = 0$ *or* $R^\star = \mu Q_1$.

Part 2 (Demand threshold). *Reneging is profitable for all A such that*

$$\Pi^\dagger(A) - \Pi^\star(A) \geq 0, \tag{47}$$

which develops into

$$\Pi^\dagger(A) - \Pi^\star(A) = \frac{2(B+b)A - B(2-\mu)Q_1}{2b(2B+b)}\mu Q_1 - (p_1+\tau)\mu Q_1 \geq 0. \tag{48}$$

If $Q_1 > 0$, *then reneging is optimal for all* $A \geq T$, *where*

$$T = (p_1+\tau)\frac{b(2B+b)}{B+b} + \frac{B}{2(B+b)}(2-\mu)Q_1. \tag{49}$$

It is easily checked that this threshold satisfies

$$\begin{aligned}\frac{\partial T}{\partial \tau} &= \frac{b(2B+b)^2}{2B^2 + b(3B+b)} > 0, \\ \frac{\partial T}{\partial \mu} &= -\frac{B(2B+b)}{2(2B^2+b(3B+b))}Q_1 < 0, \ \textit{and}, \\ \frac{\partial T}{\partial Q_1} &= \frac{\partial p_1}{\partial Q_1}\frac{b(2B+b)}{B+b} + \frac{B}{2(B+b)}(2-\mu) \\ &= \frac{-2(2B+b) + B(2-\mu)}{2(B+b)} \\ &= -\frac{(2+\mu)B + 2b}{2(B+b)} < 0.\end{aligned} \tag{50}$$

The development in (48) is obtained from the addition of

$$\Delta p_2 Q_2^\star = \frac{1}{b(2B+b)^2}\left(B^2 A - B(B+b)(1-\mu)Q_1\right)\mu Q_1, \text{ and,}$$
$$p_2^\star \Delta Q_2^\star = \frac{1}{b(2B+b)^2}\left((B+b)^2 A - B(B+b)Q_1\right)\mu Q_1,$$

which yields

$$\Delta p_2 Q_2^\star + p_2^\star \Delta Q_2^\star = \frac{1}{b(2B+b)^2}\left((B^2+(B+b)^2)A - B(B+b)(2-\mu)Q_1\right)\mu Q_1,$$

and from which we finally obtain

$$\begin{aligned}\Delta p_2 Q_2^\star + p_2^\star \Delta Q_2^\star + \Delta C &= \frac{(2(B^2+(B+b)^2+2Bb)A - (2B(B+b)-Bb)(2-\mu)Q_1)}{2b(2B+b)^2}\mu Q_1\\ &= \frac{((4B^2+2b(3B+b))A - B(2B+b)(2-\mu)Q_1)}{2b(2B+b)^2}\mu Q_1.\end{aligned}$$

Proof 4 (Proof of Proposition 3) *The first two results are directly obtained from*

$$\Delta p_2 = \frac{B}{b(2B+b)}\mu Q_1$$
$$\Delta Q_2 = \frac{B+b}{2B+b}\mu Q_1,$$

and the third result follows from the expression

$$\begin{aligned}\Delta C &= \int_{(1-\mu)Q_1+Q_2^\dagger}^{Q_1+Q_2^\star} C(Q)dQ = \int_{\frac{B}{2B+b}(A+(1-\mu)Q_1)}^{\frac{B}{2B+b}(A+Q_1)} C(Q)dQ\\ &= \frac{1}{2B}\frac{B^2}{(2B+b)^2}\left((A+Q_1)^2 - (A+(1-\mu)Q_1)^2\right)\\ &= \frac{B}{2(2B+b)^2}\left(2\mu A Q_1 + \mu(2-\mu)Q_1^2\right)\\ &= \frac{B}{2(2B+b)^2}\left(2A+(2-\mu)Q_1\right)\mu Q_1.\end{aligned}$$

This expression is derived by combining and rearranging the following *expressions:*

$$
\begin{aligned}
Q_1 + Q_2^\star &= \frac{B}{2B+b}(A+Q_1), \\
(1-\mu)Q_1 + Q_2^\dagger &= \frac{B}{2B+b}(A+(1-\mu)Q_1), \\
Q_2^\star &= \frac{B}{2B+b}A - \frac{B+b}{2B+b}Q_1, \ \textit{and,} \\
Q_2^\dagger &= \frac{B}{2B+b}A - \frac{B+b}{2B+b}(1-\mu)Q_1.
\end{aligned}
$$

Proof 5 (Proof of Proposition 4) *The first-order condition is*

$$
\frac{\partial E[\Pi]}{\partial Q_1} = 0, \tag{51}
$$

where

$$
\begin{aligned}
\frac{\partial E[\Pi]}{\partial Q_1} &= \frac{\partial T}{\partial Q_1} f(T)\left(\Pi^\star(T) - \Pi^\dagger(T)\right) + \int_0^T \frac{\partial \Pi^\star(A)}{\partial Q_1} dF(A) \\
&\quad + \int_T^{+\infty} \frac{\partial \Pi^\dagger(A)}{\partial Q_1} dF(A).
\end{aligned} \tag{52}
$$

The definition of T implies $\Pi^\star(T) = \Pi^\dagger(T)$ and the condition becomes

$$
\int_0^T \frac{\partial \Pi^\star(A)}{\partial Q_1} dF(A) + \int_T^{+\infty} \frac{\partial \Pi^\dagger(A)}{\partial Q_1} dF(A) = 0, \tag{53}
$$

The second-order condition is given by

$$
\begin{aligned}
\frac{\partial^2 E[\Pi]}{\partial Q_1^2} =& \frac{\partial T}{\partial Q_1} f(T)\left(\frac{\partial \Pi^\star(T)}{\partial Q_1} - \frac{\partial \Pi^\dagger(T)}{\partial Q_1}\right) \\
&+ \int_0^T \frac{\partial^2 \Pi^\star(A)}{\partial Q_1^2} dF(A) + \int_T^{+\infty} \frac{\partial^2 \Pi^\dagger(A)}{\partial Q_1^2} dF(A).
\end{aligned} \tag{54}
$$

The first term is negative since $\frac{\partial T}{\partial Q_1} < 0$, $f(T) > 0$ *and* $\left(\frac{\partial \Pi^\star(T)}{\partial Q_1} - \frac{\partial \Pi^\dagger(T)}{\partial Q_1}\right) >$

0 *since*

$$\begin{aligned}
\frac{\partial \Pi^{\dagger}(T) - \Pi^{\star}(T)}{\partial Q_1} =& \mu \left[\frac{(2(B+b)T - B(2-\mu)Q_1)}{2b(2B+b)} - (p_1 + \tau) \right] \\
=& - \mu Q_1 \left(\frac{B(2-\mu)}{2b(2B+b)} + \frac{\partial p_1}{\partial Q_1} \right) \\
=& - \mu Q_1 \left(\frac{B(2-\mu) - 2(2B+b)}{2b(2B+b)} \right) \\
=& \mu Q_1 \left(\frac{(2+\mu)B + 2b}{2b(2B+b)} \right) > 0.
\end{aligned} \tag{55}$$

The two last terms of (54) *are negative so the first-order condition characterizes a maximum.*

The integrand of the first term in (53) *can be developed into*

$$\begin{aligned}
\frac{\partial \Pi^{\star}(A)}{\partial Q_1} &= \frac{\partial p_1}{\partial Q_1} Q_1 + p_1 + \frac{\partial p_2^{\star}}{\partial Q_1} Q_2^{\star} - C(Q_1 + Q_2^{\star}) \\
&= \frac{1}{b} \left(\alpha E(A) - 2Q_1 - Q_2^{\star} \right) - \frac{Q_1 + Q_2^{\star}}{B}, \\
&= \frac{\alpha E(A)}{b} - \frac{2B+b}{Bb} Q_1 - \frac{B+b}{Bb} Q_2^{\star}, \\
&= \frac{\alpha E(A)}{b} - \frac{2B+b}{Bb} Q_1 - \frac{B+b}{Bb} \left(\frac{B}{2B+b} A - \frac{B+b}{2B+b} Q_1 \right), \\
&= \frac{\alpha E(A)}{b} - \frac{3B+2B}{b(2B+b)} Q_1 - \frac{B+b}{b(2B+b)} A.
\end{aligned} \tag{56}$$

Thus, we have

$$\int_0^T \frac{\partial \Pi^{\star}(A)}{\partial Q_1} dF(A) = \left(\frac{\alpha E(A)}{b} - \frac{3B+2B}{b(2B+b)} Q_1 - \frac{B+b}{b(2B+b)} E[A|A \leq T] \right) F(T). \tag{57}$$

The integrand of the second term in (53) *can be developed into*

$$\begin{aligned}
\frac{\partial \Pi^\dagger(A)}{\partial Q_1} &= (1-\mu)\left[\frac{\partial p_1}{\partial Q_1}Q_1 + p_1 - C((1-\mu)Q_1 + Q_2^\dagger)\right] - \mu\tau + \frac{\partial p_2^\dagger}{\partial Q_1}Q_2^\dagger \\
&= (1-\mu)\left[\frac{\partial p_1}{\partial Q_1}Q_1 + p_1 - \frac{1}{b}Q_2^\dagger - C((1-\mu)Q_1 + Q_2^\dagger)\right] - \mu\tau \\
&= (1-\mu)\left[\frac{\alpha E(A)}{b} - \frac{2B + b(1-\mu)}{Bb}Q_1 - \frac{B+b}{Bb}Q_2^\dagger\right] - \mu\tau \\
&= (1-\mu)\left[\frac{\alpha E(A)}{b} - \frac{2B + b(1-\mu)}{Bb}Q_1 - \frac{B+b}{Bb}\left(\frac{B}{2B+b}A - \frac{B+b}{2B+b}(1-\mu)Q_1\right)\right] - \mu\tau \\
&= (1-\mu)\left[\frac{\alpha E(A)}{b} - \left(\frac{2B + b(1-\mu)}{Bb} - \frac{(B+b)^2(1-\mu)}{Bb(2B+b)}\right)Q_1 - \frac{B+b}{b(2B+b)}A\right] - \mu\tau \\
&= \frac{(1-\mu)}{b}\left[\alpha E(A) - \frac{(3+\mu)B + 2b}{(2B+b)}Q_1 - \frac{B+b}{(2B+b)}A\right] - \mu\tau
\end{aligned} \tag{58}$$

Thus, we have

$$\begin{aligned}
\int_T^{+\infty} \frac{\partial \Pi^\dagger(A)}{\partial Q_1} dF(A) =& (1-\mu)\left(\frac{\alpha E(A)}{b} - \frac{(3+\mu)B + 2b}{b(2B+b)}Q_1 - \frac{B+b}{b(2B+b)}E[A|A>T]\right)(1-F(T)) \\
& - \mu\tau\left(1 - F(T)\right).
\end{aligned} \tag{59}$$

Combining and rearranging yields the equivalent expression of the first-order condition

$$\begin{aligned}
&\frac{(1-\mu\left(1-F(T)\right))}{b}\left\{\alpha E(A) - \frac{3B+2B}{2B+b}Q_1 - \frac{B+b}{2B+b}E(A)\right\} + \\
&\frac{\mu\left(1-F(T)\right)}{b}\left\{\frac{B+b}{2B+b}\left(E[A|A>T] - E(A)\right) - \frac{(1-\mu)B}{2B+b}Q_1 - b\tau\right\} = 0.
\end{aligned} \tag{60}$$

From (29), *the first term in* (60) *is equal to zero for* $Q_1^\star$. *Furthermore, we have* $T \leq E[A|A>T]$ *hence the second term between braces admits as minimum bound*

$$\frac{B+b}{2B+b}\left(T - E(A)\right) - \frac{(1-\mu)B}{2B+b}Q_1 - b\tau. \tag{61}$$

Substituting p_1 by its expression into (49) yields

$$T = \alpha E(A)\frac{2B+b}{B+b} - Q_1\frac{(2+\mu)B+2b}{2(B+b)} + \tau b\frac{2B+b}{B+b}, \tag{62}$$

which substituting into (61) and rearranging yields another expression for this bound

$$E(A)\frac{B(2\alpha-1)-b(1-\alpha)}{2B+b} - Q_1\frac{\frac{4-\mu}{2}B+b}{2B+b}. \tag{63}$$

It is easily checked that this bound is positive at $Q_1^\star$. Therefore for any parameter values (provided that $Q_1^\star$ is positive) the solution of (60) will be above $Q_1^\star$.

Proof 6 (Proof of Proposition 5) *The results are easily checked from (35) and its analog under imperfect commitment is given by*

$$\begin{aligned} p_1^\dagger - E[p_2^\dagger] = &\left(\alpha - \frac{B+b}{2B+b}\right)\frac{E(A)}{b} \\ &- \left(\frac{B+b}{2B+b} + \mu(1-F(T))\frac{B}{2B+b}\right)\frac{Q_1^\dagger}{b}. \end{aligned} \tag{64}$$

Assuming further that $Q_1^\dagger = Q_1^\star$, the condition for a forward premium to be sustained, i.e. $p_1^\dagger \geq E[p_2^\dagger]$, simplifies to

$$\left(\alpha - \frac{B+b}{2B+b} - \frac{(1+\mu(1-F(T)))B+b}{2B+b}\frac{B}{3B+2b}\right)\frac{E(A)}{b} \geq 0. \tag{65}$$

Under this assumption, the threshold level of contracting $\overline{\alpha}$ is hence such that

$$\underline{\alpha} < \overline{\alpha} = \underline{\alpha} + \frac{(1+\mu(1-F(T)))B+b}{2B+b}\frac{B}{3B+2b} \leq \underline{\alpha} + \frac{B}{3B+2b} < 1. \tag{66}$$

Proof 7 (Proof of Proposition 6) *Following the specification of the fringe's marginal cost function, let us define $Q_2^k = A - Q_1 - k$ as the dominant player's maximum volume of spot sales such that the fringe marginal cost is $q/b + \Delta c$ (i.e. on the upper segment). The equilibrium condition in the* *spot market is changed to:*

$$Q_2 = A - Q_1 + b\Delta c - bp_2 \text{ for any } 0 \le Q_2 \le Q_2^k,$$
$$Q_2 = A - Q_1 - bp_2 \text{ for any } Q_2 > Q_2^k.$$

Over the interval where $Q_2 \in \left[0, Q_2^k\right]$ *the price is given by*

$$p_2 = \frac{1}{b}\left(A - Q_1 + b\Delta c - Q_2\right)$$

hence the profit function is given by

$$\begin{aligned}\Pi &= p_1 Q_1 + p_2 Q_2 - \int_0^{Q_1+Q_2} C(Q)dQ \\ &= p_1 Q_1 + \frac{1}{b}\left(A - Q_1 + b\Delta c - Q_2\right)Q_2 - \frac{1}{B}\int_0^{Q_1+Q_2} QdQ.\end{aligned}$$

Part 1. Optimal strategy without reneging. *The optimal strategy is given by*

$$\frac{\partial \Pi}{\partial Q_2} = \frac{1}{b}\left(A - Q_1 + b\Delta c - 2Q_2\right) - \frac{1}{B}\left(Q_1 + Q_2\right)$$

so that

$$\overline{Q}_2 = \frac{B}{2B+b}\left(A + b\Delta c\right) - \frac{B+b}{2B+b}Q_1$$

if $Q_2 \le Q_2^k$, *and* $Q_2^\star$ *defined in* (4) *if* $Q_2 > Q_2^k$.

For given values of A *and* Q_1, *we have* $\overline{Q}_2 > Q_2^\star$ *because* $\Delta c > 0$ *although the feasibility conditions dictate that the strategy* $\overline{Q}_2$ *prevails over* $Q_2 \in \left[0, Q_2^k\right]$ *and* $Q_2^\star$ *prevails for "large" values of* Q_2 *(*$Q_2 > Q_2^k$*). Observe that:*

- *If* $Q_2^\star(A, Q_1) < Q_2^k(A, Q_1)$ *then the optimal strategy over* $\left[Q_2^k; +\infty\right[$ *is* Q_2^k *(the profit function is decreasing on* $[Q_2^\star; +\infty[\cap \left[Q_2^k; +\infty\right[$ *).*

- *If* $\overline{Q}_2(A, Q_1) > Q_2^k(A, Q_1)$ *then the optimal strategy over* $\left[0; Q_2^k\right]$ *is* Q_2^k *(the profit function is increasing on* $\left[0; \overline{Q}_2\right] \cap \left[0; Q_2^k\right]$ *).*

There are three cases:

1. If $Q_2^\star < Q_2^k < \overline{Q}_2$ then the optimal strategy is Q_2^k.

2. If $Q_2^\star < \overline{Q}_2 < Q_2^k$ then the optimal strategy is $\overline{Q}_2$.

3. If $Q_2^k < Q_2^\star < \overline{Q}_2$ then we must compare profits for Q_2^k and $Q_2^\star$.

We compare the profits in each case to characterize this case. Let $\Pi^\star$, $Q_2^\star$ and Q_2^k be given as above and define

$$\delta = Q_2^\star - Q_2^k,$$

that can be positive or negative. By definition

$$\begin{aligned} p_2(Q_2^k) &= \frac{1}{b}\left(A - Q_1 - Q_2^k\right) \\ &= \frac{1}{b}\left(A - Q_1 - Q_2^\star - \left(Q_2^k - Q_2^\star\right)\right) \\ &= p_2^\star + \frac{\delta}{b} \end{aligned}$$

if $Q_2 > Q_2^k$. The lower price at the step (at $Q_2^k + \varepsilon$) is thus $p_2^\star + \delta/b$. The upper price is $p_2^\star + (\delta/b) + \Delta c$. The profit obtained with strategy Q_2^k writes

$$\begin{aligned} \Pi^k &= p_1 Q_1 + p_2 Q_2^k - \int_0^{Q_1+Q_2^k} C(Q)dQ \\ &= p_1 Q_1 + \left(p_2^\star + \frac{\delta}{b} + \Delta c\right)(Q_2^\star - \delta) - \frac{1}{B}\int_0^{Q_1+Q_2^\star+\delta} QdQ \\ &= p_1 Q_1 + \left(p_2^\star + \frac{\delta}{b} + \Delta c\right)(Q_2^\star - \delta) - \frac{1}{2B}\left(Q_1 + Q_2^\star - \delta\right)^2 \\ &= p_1 Q_1 + p_2^\star Q_2^\star + \left[\Delta c Q_2^\star + \left(p_2^\star + \Delta c - \frac{Q_2^\star}{b}\right)\delta - \frac{\delta^2}{b}\right] \\ &- \frac{1}{2B}\left[\left(Q_1 + Q_2^\star\right)^2 - 2\delta\left(Q_1 + Q_2^\star\right) + \delta^2\right] \\ &= \Pi^\star + \left[\Delta c Q_2^\star - \left(p_2^\star + \Delta c - \frac{Q_2^\star}{b}\right)\delta - \frac{\delta^2}{b}\right] - \frac{1}{2B}\left[-2\delta\left(Q_1 + Q_2^\star\right) + \delta^2\right]. \end{aligned}$$

It is therefore profitable to choose Q_2^k rather than $Q_2^\star$ if

$$\Delta c Q_2^\star > \delta \left\{ -\frac{1}{2B}\left[2\left(Q_1 + Q_2^\star\right) - \delta\right] + \left[p_2^\star - \frac{1}{b}Q_2^\star + \frac{\delta}{b} + \Delta c\right] \right\}.$$

Since $Q_2^\star$ is optimal we know that it satisfies:

$$p_2^\star - \frac{1}{b}Q_2^\star = \frac{1}{B}\left(Q_1 + Q_2^\star\right)$$

from the FOC in (26) *therefore the previous inequality boils down to:*

$$\Delta c Q_2^\star > \delta \left[\Delta c + \left(\frac{1}{2B} + \frac{1}{b}\right)\delta\right]$$

which yields the condition

$$\Delta c Q_2^k > \left(\frac{1}{2B} + \frac{1}{b}\right)\delta^2. \tag{67}$$

Observe that a negative shift from $Q_2^\star$ to Q_2^k in order to trigger Δc is more likely when Q_2^k is large, Δc is large, δ is small, b is large (RD is less elastic).

Let us denote $W = \Delta c Q_2^k - \left(\frac{1}{2B} + \frac{1}{b}\right)\delta^2$ and differentiate to obtain

$$\frac{\partial W}{\partial A} = \Delta c + \frac{B+b}{Bb}\delta > 0 \tag{68}$$

since $\delta > 0$ when $Q_2^k < Q_2^\star$. Moreover,

$$\frac{\partial^2 W}{\partial A^2} < 0, \tag{69}$$

thus there is a threshold level of demand $\tilde{A}$ such that for all $A > \tilde{A}$ (assuming $\delta > 0$ though), Q_2^k yields larger profits than $Q_2^\star$ and reversely for lower values *of A. This threshold is characterized by*

$$\begin{aligned} W &= \Delta c Q_2^k - \left(\frac{1}{2B} + \frac{1}{b}\right)\delta^2 = 0 \\ \leftrightarrow \Delta c(\tilde{A} - Q_1 - k) &= \left(\frac{1}{2B} + \frac{1}{b}\right)\left(k - \frac{B+b}{2B+b}\tilde{A} + \frac{B}{2B+b}Q_1\right)^2. \end{aligned} \tag{70}$$

Total differentiation and rearrangement yield the relation between this threshold and forward commitments

$$0 < \frac{d\tilde{A}}{dQ_1} = \frac{\Delta c + \frac{1}{b}\delta}{\Delta c + \frac{B+b}{Bb}\delta} < 1. \tag{71}$$

Part 2. Strategy on forward markets. *A complete characterization of the optimal forward strategy requires to solve several cases depending on the distribution of demand. To gain intuition of the effect of discontinuities on the forward strategy, we only focus on a specific case where demand is distributed so that $Q_2^k < Q_2^\star$, i.e. $A < \frac{2B+b}{B+b}k + \frac{B}{B+b}Q_1$. In this case, the expected profit is given by*

$$\begin{aligned} E[\Pi] = &\int_0^{\tilde{A}} \left(p_1 Q_1 + p_2^\star Q_2^\star - \int_0^{Q_1+Q_2^\star} C(Q)dQ\right) dF(A) \\ &+ \int_{\tilde{A}}^{+\infty} \left(p_1 Q_1 + p_2^k Q_2^k - \int_0^{Q_1+Q_2^k} C(Q)dQ\right) dF(A). \end{aligned} \tag{72}$$

Differentiating with respect to Q_1, making use of the definition of $\tilde{A}$ and *applying the envelope theorem yield*

$$\begin{aligned}
\frac{\partial E[\Pi]}{\partial Q_1} &= \int_0^{\tilde{A}} \left(p_1 - \left(\frac{1}{b} + \frac{1}{B}\right)(Q_1 + Q_2^\star)\right) dF(A) + \int_{\tilde{A}}^{+\infty} \left(p_1 - \left(\frac{1}{b} + \frac{1}{B}\right)(Q_1 + Q_2^k)\right) dF(A) \\
&\quad - \int_{\tilde{A}}^{+\infty} \left(\frac{\partial p_2^k}{\partial Q_2} Q_2^k + p_2^k - \frac{Q_1 + Q_2^k}{B}\right) dF(A) = 0 \\
&= \int_0^{+\infty} \left(p_1 - \left(\frac{1}{b} + \frac{1}{B}\right)(Q_1 + Q_2^\star)\right) dF(A) \\
&\quad + \int_{\tilde{A}}^{+\infty} \left(\frac{1}{b} + \frac{1}{B}\right)\delta - \left(p_2^k - \frac{Q_1 + Q_2^k}{B}\right) dF(A).
\end{aligned} \tag{73}$$

The integrand of the second term can be rewritten

$$\begin{aligned}
&\frac{\delta}{b} + \frac{Q_2^\star - Q_2^k}{B} - p_2^k + \frac{Q_1 + Q_2^k}{B} \\
&= -\frac{Q_2^k}{b} - (p_2^k - p_2^\star) - p_2^\star + \frac{Q_2^\star}{b} + \frac{Q_1 + Q_2^\star}{B} \\
&= -\frac{Q_2^k}{b} - (p_2^k - p_2^\star) < 0,
\end{aligned} \tag{74}$$

where the inequality holds for the considered case. Therefore the second integral is negative and it must be that the first integral is positive for the first-order condition (73) *to hold. Following the previous result for* $Q_1^\star$*, it implies that the equilibrium forward commitment is* $Q_1^k < Q_1^\star$ *in this case.*

Part 3. Reneging under non-linear residual demand. *The complete characterization of strategic reneging in this setting involves solving multiple cases. The most interesting case is when reneging would not be profitable without taking advantage of the price jump created by the step function. That is when exerting market power in the spot market and reneging on forward contracts are complementary means to achieve a price impact. We focus on this case by assuming that, for* $A = T$*,*

- $Q_2^\dagger - Q_2^{\dagger k} = \epsilon > 0$*: reaching the step requires to produce less than the optimal amount* $Q_2^\dagger$ *in presence of reneging; and*

- $\Delta c Q_2^k < \left(\frac{1}{2B}+\frac{1}{b}\right)\left(Q_2^\star - Q_2^k\right)^2$: *the strategy $Q_2^\star$ yields larger profits than Q_2^k hence the firm will not take advantage of the price step in absence of reneging.*

The first assumption implies $Q_2^k < Q_2^\star$ because

$$\begin{aligned} Q_2^\dagger - Q_2^{\dagger k} &= k - \frac{B+b}{2B+b}A + \frac{B}{2B+b}(Q_1 - R) \\ &= \left(Q_2^\star - Q_2^k\right) - \frac{B}{2B+b}R. \end{aligned} \tag{75}$$

In words, without reneging reaching the step also requires to produce less than the optimal amount $Q_2^\star$. This assumption is used to focus on the values of demand for which the step is at the left of the optimal output level in both cases. For some A, the increase in profits from combining both reneging and taking advantage of the price step can be written as

$$\Pi^{\dagger k}(A) - \Pi^\star(A) = \Pi^\dagger(A) - \Pi^\star(A) + p_2^{\dagger k}Q_2^{\dagger k} - p_2^\dagger Q_2^\dagger + \int_{Q_1-R+Q_2^{\dagger k}}^{Q_1-R+Q_2^\dagger} C(Q)dQ. \tag{76}$$

Recall that at $A = T$ the firm is indifferent between choosing $R = 0$ and $R = \mu Q_1$. At $A = T$, the above hence simplifies to

$$\Pi^{\dagger k}(T) - \Pi^\star(T) = p_2^{\dagger k}Q_2^{\dagger k} - p_2^\dagger Q_2^\dagger + \int_{Q_1-R+Q_2^{\dagger k}}^{Q_1-R+Q_2^\dagger} C(Q)dQ, \tag{77}$$

where the second term on the right-hand-side is positive under the previous assumptions. It can be developed into

$$\int_{Q_1-R+Q_2^{\dagger k}}^{Q_1-R+Q_2^\dagger} C(Q)dQ = \frac{1}{B}\left(Q_1 - R + \frac{Q_2^\dagger + Q_2^{\dagger k}}{2}\right)\epsilon. \tag{78}$$

Let us now turn to the first term. We have

$$p_2^{\dagger k}Q_2^{\dagger k} - p_2^\dagger Q_2^\dagger = (p_2^{\dagger k} - p_2^\dagger)Q_2^{\dagger k} - p_2^\dagger(Q_2^\dagger - Q_2^{\dagger k}), \tag{79}$$

where at $A = T$,

$$\begin{aligned}
p_2^{\dagger k} - p_2^{\dagger} &= \frac{1}{b}(T - (Q_1 - R) - Q_2^{\dagger k}) + \Delta c - p_2^{\dagger} \\
&= \frac{k}{b} + \Delta c - p_2^{\dagger} \\
&= \frac{k}{b} + \Delta c - (p_1 + \tau) - \frac{B}{2B + b}\frac{R}{2b} \\
&= \frac{\epsilon}{b} + \Delta c,
\end{aligned} \tag{80}$$

and

$$Q_2^{\dagger} - Q_2^{\dagger k} = k - bp_2^{\dagger} = \epsilon. \tag{81}$$

Making use of these expressions yields

$$p_2^{\dagger k} Q_2^{\dagger k} - p_2^{\dagger} Q_2^{\dagger} = \left(\frac{\epsilon}{b} + \Delta c\right) Q_2^{\dagger k} - p_2^{\dagger}\epsilon. \tag{82}$$

Thus, we have $\Pi^{\dagger k}(T) - \Pi^{\star}(T) > 0$ *if and only if*

$$\left(\frac{\epsilon}{b} + \Delta c\right) Q_2^{\dagger k} - p_2^{\dagger}\epsilon + \frac{1}{B}\left(Q_1 - R + \frac{Q_2^{\dagger} + Q_2^{\dagger k}}{2}\right)\epsilon > 0, \tag{83}$$

which can be rearranged into

$$\begin{aligned}
\Delta c Q_2^{\dagger k} &> \left(p_2^{\dagger} - \left(\frac{Q_2^{\dagger k}}{b} + \frac{Q_1 - R}{B} + \frac{Q_2^{\dagger}}{2B} + \frac{Q_2^{\dagger k}}{2B}\right)\right)\epsilon \\
&= \left(p_2^{\dagger} - \frac{Q_2^{\dagger}}{b} - \frac{Q_1 - R + Q_2^{\dagger}}{B}\right)\epsilon + (Q_2^{\dagger} - Q_2^{\dagger k})\left(\frac{1}{b} + \frac{1}{2B}\right)\epsilon \\
&= \left(\frac{1}{b} + \frac{1}{2B}\right)\epsilon^2,
\end{aligned} \tag{84}$$

where the last equality comes from the definition of ϵ *and the first-order condition for* $Q_2^{\dagger}$. *Therefore, for any* $\epsilon > 0$, *there exists* Δc *such that this condition is satisfied. This condition is not mutually exclusive with* $\Delta c Q_2^k < \left(\frac{1}{2B} + \frac{1}{b}\right)\left(Q_2^{\star} - Q_2^k\right)^2$ *since* $Q_2^k < Q_2^{\dagger k}$ *and* $Q_2^{\star} - Q_2^k > Q_2^{\dagger} - Q_2^{\dagger k}$. *We have shown that there is* $\Delta c > 0$ *such that* $\Pi^{\dagger k}(T) - \Pi^{\star}(T) > 0$ *for some* $\epsilon > 0$.

Now we want to show that $\Pi^{\dagger k}(A) - \Pi^\star(A) \geq 0$ *for all* $A \geq \tilde{T}$ *with* $\tilde{T} < T$. *First, it is easy to show that* $\frac{\partial^2 \Pi^{\dagger k}(A) - \Pi^\star(A)}{\partial A^2} < 0$. *The desired result hence holds if* $\frac{\partial \Pi^{\dagger k}(A) - \Pi^\star(A)}{\partial A}|_{A=T} > 0$. *We have,*

$$\begin{aligned}
\frac{\partial \Pi^{\dagger k}(A) - \Pi^\star(A)}{\partial A} &= \frac{\partial p_2^{\dagger k} Q_2^{\dagger k}}{\partial A} - \frac{\partial p_2^\star Q_2^\star}{\partial A} + \frac{\partial Q_2^\star}{\partial A}\frac{Q_1 + Q_2^\star}{B} - \frac{\partial Q_2^{\dagger k}}{\partial A}\frac{Q_1 - R + Q_2^{\dagger k}}{B} \\
&= p_2^{\dagger k} - \left(p_2^\star \frac{B}{2B+b} + Q_2^\star \frac{B+b}{b(2B+b)}\right) + \frac{B}{2B+b}\frac{Q_1 + Q_2^\star}{B} - \frac{Q_1 - R + Q_2^{\dagger k}}{B} \\
&= p_2^{\dagger k} - \frac{B}{2B+b}\left(p_2^\star - \frac{Q_2^\star}{b} - \frac{Q_1 + Q_2^\star}{B}\right) - \frac{Q_2^\star}{b} - \frac{Q_1 - R + Q_2^{\dagger k}}{B} \\
&= p_2^{\dagger k} - \frac{Q_2^\star}{b} - \frac{Q_1 - R + Q_2^{\dagger k}}{B} \\
&= \Delta c + \frac{k}{b} - \frac{Q_2^\star}{b} - \frac{Q_1 - R + Q_2^{\dagger k}}{B}.
\end{aligned} \tag{85}$$

Furthermore, at $A = T$, *we have* $k = \epsilon + \frac{B+b}{2B+b}T - \frac{B}{2B+b}(Q_1 - R)$, *hence* $k/b = \epsilon/b + p_2^\dagger$. *Substituting into the above yields*

$$\begin{aligned}
\frac{\partial \Pi^{\dagger k}(A) - \Pi^\star(A)}{\partial A}|_{A=T} &= \Delta c + \frac{\epsilon}{b} + p_2^\dagger - \frac{Q_2^\star}{b} - \frac{Q_1 - R + Q_2^{\dagger k}}{B} \\
&> \Delta c + \frac{\epsilon}{b} + p_2^\star - \frac{Q_2^\star}{b} - \frac{Q_1 - R + Q_2^{\dagger k}}{B} \\
&> \Delta c + \frac{\epsilon}{b} + p_2^\star - \frac{Q_2^\star}{b} - \frac{Q_1 + Q_2^\star}{B} \\
&> \Delta c + \frac{\epsilon}{b} \\
&> 0.
\end{aligned} \tag{86}$$

These results characterize the conditions that it is profitable to choose $R > 0$ *and trigger the step by changing output from* $Q_2^\star$ *to* $Q_2^{\dagger k}$. *It is interesting to note that when* $Q_2^\star > Q_2^{\dagger k}$ *the output is reduced when reneging occurs. This happens when* $\epsilon > \frac{B+b}{2B+b}R$.

B Inference (For Online Publication)

We test the null hypothesis formalized in (22) using the Cramer-Von Mises statistic $CVM_S = \int_0^{1000} \widehat{\Delta S}_t(p)^2 dp$. Remark that $\widehat{\Delta S}_t(p) = \hat{u}_t(p)$ is obtained from the vector approximation $\hat{\boldsymbol{u}}_{\boldsymbol{t}}$. This vector is asymptotically distributed as a multivariate normal. Thus, CVM_S asymptotically follows a weighted χ^2 distribution which weights depends on the eigenvalues of the asymptotic covariance of $\widehat{\boldsymbol{u}}_{\boldsymbol{t}}$. We estimate this covariance matrix using the testing set (and not the training set). P-values are computed from an approximate asymptotic distribution.[49] The same approach is used to conduct inference on $\widehat{\Delta RD}_t$.

In addition, we test the null hypotheses

$$H_0 : \widehat{\Delta P}_t = 0, \text{ and,} \quad H_0 : \widehat{\Delta Q}_t = 0. \tag{87}$$

The distribution of those equilibrium values depend non-linearly on the joint distribution of supply and residual demand functions. We propose to use a parametric bootstrap to approximate their distributions. The random draws are taken from the multivariate normal distribution using the covariance of error vectors for supply and residual demand (estimated using the testing set). This aims at accounting for the correlation between the two functions. The procedure is as follows. Separately for each hour t in the sample, we draw 10,000 multivariate normal random vectors $\boldsymbol{u}_{\boldsymbol{t}}^{\boldsymbol{S_b}}$ and $\boldsymbol{u}_{\boldsymbol{t}}^{\boldsymbol{RD_b}}$ to construct $\widehat{S}_t^{\star b}$ and $\widehat{RD}_t^{\star b}$. Then, for each draw we compute the equilibrium price and firm's output $(\hat{P}_t^{b}, \hat{Q}_t^{\star b})$. Finally, we use the quantiles of the bootstrapped distribution to construct confidence intervals, and to compute p-values for the CVM statistics.

[49] A more formal treatment of functional testing procedures is proposed in Benatia (2018*b*) and Carrasco, Florens and Renault (2014).

C Additional Tables (For Online Publication)

Table 11: Timing of strategic outage events

	Date	Time	Facility	Event	PPA Buyer
Event 1	Nov 19, 2010	17:00	Sundance 5	-385 MW	Capital Power
	Nov 22, 2010	03:00	Sundance 5	+385 MW	Capital Power
Event 2	Nov 23, 2010	09:00	Sundance 2	-150 MW	TransCanada
	Nov 24, 2010	00:00	Sundance 2	+150 MW	TransCanada
Event 3	Dec 13, 2010	17:00	Sundance 2	-280 MW	TransCanada
		17:00	Keephills 1	-387 MW	ENMAX
	Dec 14, 2010	16:00	Sundance 6	-401 MW	Capital Power
	Dec 15, 2010	21:00	Keephills 1	+387 MW	ENMAX
	Dec 16, 2010	18:00	Sundance 2	+280 MW	TransCanada
		23:00	Sundance 6	+401 MW	Capital Power
Event 4	Feb 16, 2011	17:00	Keephills 2	-387 MW	ENMAX
	Feb 18, 2011	21:00	Keephills 2	+387 MW	ENMAX

Notes: This table provides a summary of the timing of outage events investigated by the regulator. Most outages/derates lasted about two days. Timing is only indicative as plants gradually decrease/increase output, possibly over a few hours, in order to be fully offline/online.

Table 12: Demand, weather conditions and seasonality

	Demand (GWh)		
Temperature	0.05	Monday	0.32
	(0.00)		(0.00)
Dew Point Temp	−0.08	Tuesday	0.35
	(0.00)		(0.00)
Humidity	0.02	Wednesday	0.38
	(0.00)		(0.00)
Wind Speed	−0.00	Thursday	0.36
	(0.00)		(0.00)
12am-8am dummies	−0.73, −0.29	Friday	0.34
	(0.00, 0.00)		(0.00)
9am to 4pm dummies	0.14, 0.50	Saturday	0.04
	(0.00, 0.00)		(0.01)
5pm to 8pm dummies	0.42, 0.77		
	(0.00, 0.00)		
9pm to 11pm dummies	0.34, 0.61		
	(0.00, 0.00)		
Observations	3555		
R^2	0.87		

Notes: This table shows the estimation results of $D_t = \beta' WEATHER_t + \alpha' X_t + u_t$, where $WEATHER_t$ is a set of weather variables and X_t a set of time dummies for hours of the day, days of the week and week fixed-effects. The dependent variable is total demand. Hours fixed-effects are reported as a range. P-values are reported in parentheses.

Table 13: Model performance (Off-peak hours)

	Training set		Testing set		Reneging set		
n	1991		787		220		
Parameters	157						
	S	RS	S	RS	S	RS	$\overline{RS}$
MI- Bias	.4	$-.3$	.7	$-.1$	-5.4	-328	14
MI- Abs. Bias	17.5	51.6	18.7	53.5	28.6	346.2	91.0
MI- Rel. Abs. Bias	2.2%	.7%	2.4%	.7%	3.6%	4.5%	1.1%
RMISE	23.6	72.1	24.9	74.4	36.2	46.9	132.1
Rej. Rate (Asymp.)	.054	.060	.070	.061	.223	.741	.323
Rej. Rate (BS)	.052	.058	.070	.058	.214	.741	.323
Zero parameters	17	15					
λ_{CV}	.532	2.354					
Coverage probabilities	RS	$\hat{RS}$	RS	$\hat{RS}$	RS	$\hat{RS}$	$\overline{RS}$
Price	.96	.93	.96	.93	.29	.35	.23
Output	.96	.96	.95	.95	.80	.70	.67

Notes: This table shows statistics of model performance separately for the training set, testing set and reneging set. The reneging set includes all hours for days when reneging occurred. In the reneging set, reneging occurred in 71% of hours. Remaining observations are hours before or after the outages during days where reneging occurred in some hours. MI refers to Mean Integrated. RMISE refer to the root-integrated-mean-squared-errors. Zero parameters is the number of parameters set to zero by the algorithm (for each of the 52 price values).

Table 14: Estimated changes in residual demand

	$\widehat{\Delta RD_l}$	$\widehat{\Delta RD_m}$	$\widehat{\Delta RD_h}$	$\widehat{\Delta RD_l}$	$\widehat{\Delta RD_m}$	$\widehat{\Delta RD_h}$
		Nov 19			Nov 23	
18:00	32.8	123.0	194.1	44.5	−125.7	2.2
	(0.07)	(0.18)	(0.04)	(0.20)	(0.34)	(0.58)
19:00	94.7	194.0	269.6	28.2	−145.1	−17.5
	(0.03)	(0.06)	(0.01)	(0.21)	(0.26)	(0.59)
		Dec 13			Feb 16	
18:00	−77.7	−174.6	−141.6	62.2	−68.8	52.9
	(0.25)	(0.13)	(0.21)	(0.32)	(0.64)	(0.72)
19:00	−67.0	−83.9	−91.2	277.9	44.8	378.0
	(0.41)	(0.44)	(0.32)	(0.00)	(0.33)	(0.00)

Notes: This table shows estimates of deviations in residual demand for two peak hours during the first day of each outage events. P-values for $H_0 : \widehat{\Delta RD}(p) = 0, \forall p \in [\$0, \$150]$ ($\widehat{\Delta RD_l}$), $[\$150, \$500]$ ($\widehat{\Delta RD_m}$) and $[\$500, \$1000]$ ($\widehat{\Delta RD_h}$) are reported in parentheses.

Table 15: Strategy shifts, market impacts, and residual demand

	$\widehat{\Delta S}$	$\widehat{\Delta Q}$	$\widehat{\Delta P}$	$\mathbb{1}_{\widehat{\Delta S}<0}$	$\mathbb{1}_{\widehat{\Delta S}<0}$
Peak					
RD slope (linear)	−79.21	−44.02	379.46	0.71	
	(0.00)	(0.03)	(0.00)	(0.00)	
Stepsize				0.06	0.09
				(0.05)	(0.01)
Observations	44	44	44	44	44
R^2	0.33	0.10	0.22	0.35	0.14
Off-Peak					
RD slope (linear)	−59.55	−61.88	205.33	0.85	
	(0.00)	(0.00)	(0.00)	(0.00)	
Stepsize				0.03	0.04
				(0.16)	(0.12)
Observations	220	220	220	220	220
R^2	0.24	0.14	0.04	0.18	0.01

Notes: This table shows regression results of five models, where the dependent variables are: strategy shifts, output impacts, price impacts, and a dummy equal to one if strategy shifts are negative. *Stepsize* measures the size of the price step when supply and residual demand intersect at a discontinuity jump, and is equal to zero otherwise. P-values for $H_0 : \beta = 0$ are reported in parentheses.

Table 16: Strategy shifts, market impacts, and residual demand (Robustness check)

	$\widehat{\Delta S}$	$\widehat{\Delta Q}$	$\widehat{\Delta P}$	$\mathbb{1}_{\widehat{\Delta S}<0}$	$\mathbb{1}_{\widehat{\Delta S}<0}$
Peak					
RD slope (linear)	14.02	8.55	−70.32	−0.19	
	(0.12)	(0.43)	(0.13)	(0.29)	
Stepsize				−0.03	−0.04
				(0.30)	(0.26)
Observations	154	154	154	154	154
R^2	0.02	0.00	0.02	0.02	0.01
Off-Peak					
RD slope (linear)	−5.57	−3.85	−40.93	0.04	
	(0.25)	(0.45)	(0.04)	(0.74)	
Stepsize				0.05	0.05
				(0.10)	(0.10)
Observations	787	787	787	787	787
R^2	0.00	0.00	0.01	0.00	0.00

Notes: This table shows regression results of five models on the testing set, where the dependent variables are: strategy shifts, output impacts, price impacts, and a dummy equal to one if strategy shifts are negative. *Stepsize* measures the size of the price step when supply and residual demand intersect at a discontinuity jump, and is equal to zero otherwise. P-values for $H_0 : \beta = 0$ are reported in parentheses.

Table 17: Model performance (PPA Plants)

	Training set		Testing set		Reneging set	
	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Sundance 2						
MI- Bias	0.8	1.0	1.8	0.5	−76.1	−63.3
MI- Abs. Bias	5.2	4.0	5.7	4.6	78.3	66.6
Mean Avail. Cap	74.9	81.6	97.9	81.4	113.1	121.1
RMISE	9.5	8.3	11.1	9.6	134.8	123.3
Sundance 5						
MI- Bias	0.9	0.8	1.6	0.5	−89.5	−70.4
MI- Abs. Bias	3.5	3.5	4.6	3.9	94.1	73.1
Mean Avail. Cap	386.0	380.9	370.2	376.4	281.7	298.7
RMISE	6.3	7.2	8.4	7.8	171.8	156.7
Sundance 6						
MI- Bias	−0.0	−0.0	−0.1	0.0	−70.0	−69.7
MI- Abs. Bias	0.6	0.7	0.6	0.7	70.9	70.8
Mean Avail. Cap	381.3	376.0	377.8	375.3	224.9	243.5
RMISE	1.6	2.4	1.9	2.6	164.1	163.8
Keephills 1						
MI- Bias	0.0	0.0	0.0	0.0	−66.0	−69.9
MI- Abs. Bias	1.1	0.8	1.1	0.8	67.0	70.6
Mean Avail. Cap	376.6	379.6	382.1	380.2	307.6	313.5
RMISE	2.7	2.7	2.8	2.9	149.9	163.1
Keephills 2						
MI- Bias	0.2	0.1	0.7	0.1	−82.5	−76.2
MI- Abs. Bias	1.4	0.9	2.2	0.9	83.6	77.3
Mean Avail. Cap	357.2	355.6	351.5	351.1	308.0	295.1
RMISE	4.6	4.9	6.0	5.0	136.7	139.4

Notes: This table shows statistics of model performance for supply strategies of PPA plants which reneged. We report statistics separately for the training set, testing set and reneging set. The reneging set includes all hours for days when reneging occurred. In the reneging set, reneging occurred in 71% of hours of off-peak hours. Remaining observations are hours before or after the outages during days where reneging occurred in some hours. Mean Available Capacity in expressed in MW. MI refers to Mean Integrated. RMISE refer to the root-integrated-mean-squared-errors.