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# Procurement Auctions for Regulated Retail Service Contracts in Restructured Electricity Markets

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# Procurement Auctions for Regulated Retail Service Contracts in Restructured Electricity Markets

by

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**Abstract**

A challenge in setting regulated rates for default retail electricity products is the presence of both price and quantity uncertainty faced by the default retail provider. To address this challenge, regulators have been increasingly employing competition via full-load (load-following) auctions to value the costs associated with this uncertainty. In a full-load auction, firms bid to supply a fixed percentage of the regulated utility's hourly demand at a fixed price. In this paper, we develop a model of break-even pricing of electricity forward products. We use this model to evaluate the performance of full-load auctions in Alberta, where the largest regulated retail provider adopted such auctions in December 2018. We find that the winning full-load bids exceed break-even levels, but that the difference falls over time. This reduction coincides with an increase in the number of bidders active in the full-load auctions. Our paper highlights the importance of sufficient participation for the success of full-load auctions and the potential role for competitive markets in determining the value of risk faced by regulated retail providers.

**Keywords**: Electricity, Forward Contracts, Regulation, Procurement Auctions
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# 1 Introduction

Jurisdictions worldwide have restructured their electricity markets to introduce competition into settings previously controlled by vertically integrated regulated monopolies. In addition to permitting competition at the wholesale level, many regions now have some degree of competition at the retail level with the objective of lowering costs and enhancing customer choice of differentiated retail products (Woo et al., 2014, Borenstein and Bushnell, 2015). In general, the introduction of retail competition is often coupled with the development of a regulated default product.[1] After restructuring, in a number of jurisdictions consumers would automatically be placed on the default product, and would remain on this product until they chose to switch to a competitive provider.

The rate charged for the default product is an important policy question. Regulators must balance the competing objectives of encouraging consumers to transition to a competitive provider and avoiding a high degree of market power during the transition phase. Notably, while default products are often introduced as a temporary measure, in many cases they have become key features of the retail market.[2] Low default rates may impede the development of the competitive segment of the market, while high rates may permit the exercise of high degrees of market power; see Blumsack and Perekhodtsev (2009) and Littlechild (2018) for a detailed discussion. As a result of these competing objectives, regulated proceedings and hearings to determine these rates can be controversial and drawn-out.

A key question regarding the provision of default service and the determination of rates is how the default provider should procure energy for its retail customers, and how the cost of that energy should be passed on through retail rates. Different approaches have been taken across jurisdictions, and procurement methods have evolved over time.[3] In general, default providers procure financial forward contracts in advance to cover their expected demand. In some jurisdictions, these financial forward contracts are crude in nature, and are either flat contracts which specify a price for a fixed quantity in every hour of the month, or peak contracts which specify a price for a fixed quantity in all peak hours of the month (e.g., from 7:00 AM to 11:00 PM).[4]

As a result of the uncertainty in demand and the crude nature of these contracts, the default provider will find in a particular hour of the month that its forward contract coverage exceeds or is less than its retail demand obligations. If its forward obligation exceeds its realized retail demand, the excess is sold at the wholesale (spot) market price, while if it has too little it faces spot market prices for the shortfall. Because of a positive correlation between spot prices and demand, the result is that default providers generally are selling their excess forward market quantity when prices are low and purchasing additional energy when prices are high. Consequently, default providers face

[1] See Littlechild (2018) for a detailed discussion of default retail products in U.S. residential electricity markets.

[2] Examples include Alberta Canada (Brown and Eckert, 2018), Australia (Esplin et al., 2020), and New York (Littlechild, 2018).

[3] Procurement and rate setting for default products is discussed in detail in Littlechild (2018).

[4] Section 2 provides a detailed summary of these financial forward contracts.

both price-risk associated with wholesale price volatility and quantity-risk associated with the variability in their demand obligations which is enhanced by the crude nature of forward contracts it uses to cover these obligations. Default product providers are compensated for these costs by passing them through to retail rates. This compensation is often determined via regulation leading to considerable controversy over its value.

In contrast, some jurisdictions attempt to employ market mechanisms to determine default rates and the magnitudes of price and quantity-risk compensation. In particular, a number of states, including Connecticut, Massachusetts, Maryland, New Jersey, Ohio, and Pennsylvania employ full-load or load-following auctions,[5] in which firms (e.g., generators) sign fixed-priced forward contracts that represent a percentage of the default product provider's realized retail load (Loxley and Salant, 2004; NERA, 2017; Littlechild, 2018). Under such contracts, the associated costs of supplying uncertain demand are borne by the holders of the full-load contracts. Hence, in principle the costs associated with providing the default service obligation are priced into these products. The winning bids in these auctions are then used to set retail rates.

Full-load procurement auctions have been recently deployed in Alberta Canada, where as of July 2021 45% of residential customers are signed up to the default rate known as the Regulated Rate Option (RRO) (MSA, 2021c). RRO rates were previously set by passing through the cost of procuring the financial forward flat and peak products, plus a regulatory-determined compensation called the Commodity Risk Compensation (CRC), in addition to other adders. In 2018, Alberta's largest RRO provider, EPCOR, transitioned away from setting its retail rates through regulation-set rules and premia to setting rates using full-load auctions (AUC, 2018).

Coincident with this change, EPCOR's RRO rate increased relative to those of RRO providers for other regions who did not transition to full-load auctions.[6] Figure 1 plots the difference between the EPCOR residential RRO rate for the Edmonton region and the RRO rates of two other RRO providers, ENMAX and Direct Energy, over the period from January 2017 to August 2021. The vertical line corresponds to April 2019, representing the first month for which EPCOR's rates were determined using the full-load auctions.

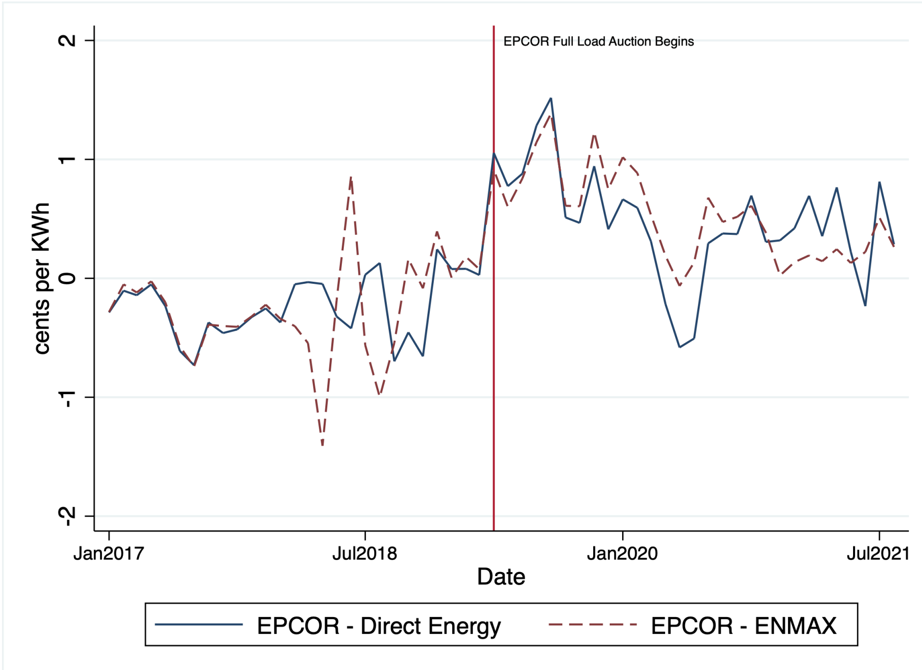
As illustrated in Figure 1, coincident with the introduction of these full-load auctions in April 2019 was an increase in retail rates in EPCOR's service area, relative to the service areas of Direct Energy and ENMAX. To give context to the magnitude, the average price in EPCOR over the sample period was 6.5 cents per kWh. Over the period before April 2019, on average the EPCOR price was -0.24 cents per kWh below the Direct Energy price, but 0.48 cents per kWh above it starting in April 2019. Hence, EPCOR RRO rates increased relative to Direct Energy RRO rates by 0.74 cents per kWh, representing 11% of the average EPCOR RRO rate.

In this paper, we develop a model to evaluate the performance of EPCOR's full-load procurement

[5]These have also been referred to as load-slice or full-requirements auctions.

[6]As will be discussed in more detail below, ENMAX, the second largest RRO provider, eventually adopted full-load auctions, with December 2020 being the first month to reflect bids from these auctions.

Figure 1: EPCOR RRO Rates for Edmonton Minus Direct Energy and ENMAX Rates




auction. This allows us to understand the reason for the increase in EPCOR's RRO rates, relative to those of the other default providers. We consider two primary explanations, both related to the conversion from a regulation-set CRC to the use of a full-load auction to price these costs. The first possibility is that regulatory proceedings result in compensation that is "too low", with pressure from consumer groups leading to inadequate compensation for providers. Alternatively, the increase in EPCOR's rates could be the result of a lack of competition in the full-load auctions.

To distinguish between these explanations, we employ data from EPCOR's procurement auctions from December 2018 to April 2021, along with data on RRO rates, forward contracts, and spot prices. Our first question is whether winning bids in the full-load auctions, and the differences between these bids and those of conventional flat products, simply reflect the additional demand uncertainty inherent in full-load products. To do this, we develop a theoretical model of break-even pricing where risk-neutral firms compete to supply the RRO forward contracts. This modeling framework relies on forecasts of expected wholesale prices and EPCOR demand levels and their covariance. We employ empirical methods to estimate these variables.

We find that the full-load prices from EPCOR's auctions exceed break-even levels by 7% on average, a margin not observed in flat and peak products. We demonstrate that the large differences between the full-load and flat prices cannot be explained by the additional cost associated with bearing the quantity uncertainty that arises in the full-load product. We find that the difference between the full-load and flat prices decreases over time, controlling for differences in the underlying cost of these products. Because EPCOR's full-load price determines its commodity risk compensation, we find that this compensation exceeds the level that would arise using our estimated break-even prices. Further, EPCOR's risk compensation exceeds the regulatory-determined risk compensation for another large RRO provider by a considerable margin.

We then investigate whether the difference between realized and break-even full-load prices can be explained by market structure, and in particular the number of bidders for the full-load contracts. We find that full-load contracts attract fewer bidders per contract than the flat and peak products. However, we find that the number of bidders per unit being auctioned off nearly doubles over our sample period. Further, the market concentration of winning bidders for the full-load product decreases over our sample. These observations coincide with the reduced difference between the cost-adjusted flat and full-load market-clearing prices.

Our findings are consistent with a high degree of market concentration when EPCOR's full-load auction was initially introduced. However, as time progressed, the number of bidders increased leading to a closer alignment of full-load and flat prices, after controlling for the underlying cost differences of these products. Our results highlight the importance of ensuring there are a sufficient number of bidders competing to supply default retail products.

We consider additional explanations for these findings. First, we extend our model and empirical analysis to incorporate risk aversion, and find that risk aversion does not explain the difference between the cost-adjusted full-load and flat prices. Second, we discuss the possible role that learning could have played on RRO auction outcomes.

To the best of our knowledge, our paper is the first to empirically analyze the transition to default rates set through full-load auctions. Several articles have provided detailed descriptive analyses of observed prices and patterns in full-load auctions in several U.S. jurisdictions (Loxley and Salant, 2004; LaCasse and Wininger, 2007; Castro et al., 2008). However, these studies do not utilize a formal model to analyze the performance of these auctions. We provide a contribution to this literature by developing a theoretical and empirical framework to evaluate the performance of full-load auction outcomes used to set default retail rates.[7]

There is a growing literature that documents the design and role of default service products. Tschamler (2006), Blumsack and Perekhodtsev (2009), and Littlechild (2018) describe the transition from regulated markets to those with retail competition that is often coupled with regulated default service products. These articles provide important institutional details and patterns, but do not formally assess the mechanisms used to determine the prices for these regulated products.

Several recent studies analyze how regulated retail products interact with the broader competitive retail electricity market. Brown and Eckert (2018) utilize data from Alberta to analyze the market structure of competitive retailers and how these firms adjust their prices in response to changes in the RRO price. However, their study does not analyze the performance of the RRO auction that determines the RRO price and consider a period where the full-load product did not exist. Esplin et al. (2020) analyze the impact of a recently deployed regulated default offer in Australia

[7]Eakin and Faruqui (2000) develop a related break-even analysis for flat/peak and full-load products. However, the authors do not apply their model to real-world retail market data.

that serves as a price-cap for competitive retailers' prices on retail market outcomes. Unlike our setting, the default offer is determined by either estimating the cost of operating as a retailer using a "cost-stack" approach or based on the distribution of offers by competitive retailers.

More broadly, our analysis contributes to the literature that analyzes the performance of the electricity sector which has transitioned from a regulated to a competitive setting in a number of jurisdictions (Davis and Wolfram, 2012; Cicala, 2015; Borenstein and Bushnell, 2015; Cicala, 2022). The prior literature has documented improved generation unit efficiency (Davis and Wolfram, 2012), reduced labor and fuel costs (Cicala, 2015), and reduced cost due to more efficient arbitrage across regional markets (Cicala, 2022). However, there is a large literature that has demonstrated that restructured wholesale electricity markets are also vulnerable to market power (e.g., Borenstein et al. (2002), Bushnell et al. (2008), and Brown and Olmstead (2017)). While our question is unique by focusing on the determination of the price of default retail products in a restructured market, we parallel the findings in this literature by providing evidence that suggests that market power can erode the potential benefits of market competition.

The remainder of this paper proceeds as follows. Section 2 provides an overview of the RRO in Alberta and EPCOR's RRO Auctions. The data used in the paper are described in Section 3. Our theoretical model of break-even pricing is described in Section 4, and Section 5 outlines the empirical methodology. Results are presented in Section 6. Section 7 provides extensions to our main analysis to investigate alternative explanations for our findings. Section 8 concludes.

## 2 The Regulated Rate Option and EPCOR's RRO Auction

The restructuring of Alberta's electricity markets, which began in the late 1990s, introduced competition into both the wholesale and retail markets. The wholesale market operates as an hourly uniform-priced auction where generators submit bids that reflect their willingness to supply electricity. The wholesale price is determined where the generators' bids, stacked in order of least-cost, intersect market demand. Unlike many jurisdictions, Alberta has an energy-only market where payments to generators only occur through wholesale and ancillary service markets. Further, there is no location-based pricing; the wholesale market clears at a single price that applies to generation throughout the province.[8]

Alberta has a competitive retail market where retailers compete by offering products with various degrees of price-stability (e.g., variable or fixed). Retailers face wholesale prices to serve their demand obligations and can sign financial forward market products transacted primarily on Alberta's Natural Gas Exchange (NGX) in advance to mitigate their exposure to uncertain wholesale prices. Forward contracts in our setting represent a financial arrangement that secures a pre-specified quantity of electricity at a fixed price. The forward contract is transacted relative to the wholesale (spot) price. If a generator (or financial trader) sells a forward contract to a retailer and the wholesale price exceeds the forward contracted price, the firm pays the retailer holding

[8]For additional details on Alberta's wholesale electricity market, see Brown and Olmstead (2017).

the contract the difference between the spot price and the forward price for the quantity covered under the contract. Alternatively, if the forward price exceeds the spot price, the retailer pays this difference to the seller of the contract. Physical delivery for the quantity specified in a forward contract is not required. However, for expositional ease, in the subsequent discussion we will refer to the seller of a financial forward contract as "supplying" the associated MWhs to the buyer.

At the time of restructuring, the government introduced the Regulated Rate Option (RRO), a regulated default product provided to residential and small commercial and industrial consumers who have not switched to a competitive retailer.[9] While early documents indicate that the RRO was intended as a temporary measure that would be phased out, the RRO continues to exist with approximately 45% of residential sites on the RRO as of July 2021 (MSA, 2021c).

RRO providers vary by region, with each being the sole provider for a particular geographic area; the three largest RRO providers (ENMAX, EPCOR, and Direct Energy) serve approximately 95% of all residential households on the RRO. RRO rates are determined through procedures established through regulatory hearings; rates change monthly. Consumers pay a price per KWh that is constant over the month, as well as a fixed charge.

The rules regarding how rates are determined are contained in each provider's Energy Price Setting Plan (EPSP). New EPSPs are approved by the Alberta Utilities Commission (AUC) through regulatory proceedings approximately every three years. The EPSPs specify the methodology through which the provider procures financial forward products to cover expected RRO retail demand, and the formulas for determining RRO rates. As required in the RRO Regulation, RRO rates are designed to cover the costs of the energy procured through forward contracts, various risks and other costs faced by the provider, and a "reasonable return". RRO rates are determined in advance and there are no adjustments to compensation *ex-post*, for example, if expected and realized costs differ substantially. Procurement methods, and the formulas determining the various components of retail pricing, have varied by provider and over time.

Our analysis focuses on EPCOR, the largest RRO provider. EPCOR is a regulated distribution utility with no generation assets. Since 2011, EPCOR has procured monthly financial forward contracts to cover expected RRO demand through auctions held on Alberta's NGX financial trading platform.[10] Until December 2018, these auctions procured a mix of flat and peak monthly forward contracts, where a flat contract specified a fixed volume for each hour of the specified month, and a peak contract specified a fixed volume for each peak hour, taken to be from 7:00 AM to 11:00 PM. The quantity purchased of each contract was determined by load (demand) forecasting.

Because the amount procured was determined by forecasting, it would typically be below actual load in high demand hours, and above in low demand hours. Further, hours in which EPCOR had underprocured would generally be ones in which demand and prices were high; the opposite

[9]For an overview of retail restructuring in Alberta and the RRO, see also Brown and Eckert (2018).

[10]In contrast, Direct Energy (and ENMAX until September 2020) procure forward contracts under the direction of an Independent Advisor which specifies daily target prices in volumes to the firms' traders.

held in hours in which it had overprocured. When EPCOR procured less than its actual demand, it was exposed to the wholesale price for the remainder. Hence, EPCOR faced both price and quantity risk because of the uncertainty in demand it must serve and the price it faces if its hedged quantities deviate from the forecast. This issue was compounded by the crude shape of the forward contracts being procured, which involved the same quantity for every hour or for every peak hour, and prevented EPCOR from procuring expected load on an hourly basis. As a result, even if there were no uncertainty, EPCOR would have procured too little in the highest demand hours and too much in the lowest demand hours.

Compensation for the fact that the forward quantities chosen were based on forecasted demand and that hedging used crude instruments was included in EPCOR's compensation via an adder called the Commodity Risk Compensation (CRC). Determination of the CRC was based on deterministic formulas and was a contentious aspect of regulatory hearings.

In their 2018-2021 EPSP application, EPCOR proposed replacing formula-based methods of determining the CRC with a market-based auction methodology. In particular, while continuing to procure 50% of expected RRO demand through flat and peak forward contracts, 50% of demand would be covered through full-load contracts. In their proposed full-load auction, providers are (financially) obligated to supply a fixed percentage of EPCOR's realized load in each hour. This means that the full-load product absorbs the variation in the slice of demand covered.[11]

Despite the fact that the full-load product is only used to cover 50% of EPCOR's expected RRO demand, the auction-clearing full-load price determines the energy charge, including the CRC, faced by consumers who sign up for EPCOR's RRO. The general idea of the full-load product is to allow the market to determine the compensation EPCOR should receive for bearing price and demand uncertainty, while also removing the crude nature of the flat and peak instruments because the full-load product tracks variations in EPCOR's demand by construction. In particular, according to EPCOR's 2018-EPSP, its CRC is the difference between the full-load price determined through its auctions, and the average cost of a MWh procured through flat or peak products.[12] The implementation of such auctions was approved by the Alberta Utilities Commission, with the first auction being held in December 2018 for the April 2019 delivery month (AUC 2018).

Under its 2018-2021 EPSP, EPCOR procures flat, peak, and full-load products simultaneously through a series of auctions leading up to each delivery month. Four auctions sessions are held in advance of each delivery month, generally at approximately one, two, three, and four months in advance. During these auctions, EPCOR procures flat and peak products in 5 MW blocks. The

[11] EPCOR procured full-load contracts to cover a portion of its demand obligation over the period 2006 - 2010. However, the industry context was different as these products were quarterly, semi-annual, or annual contracts, and EPCOR self-supplied a portion of its RRO demand via generation assets that were subsequently divested (AUC, 2018). Due to data limitations, these full-load contracts will not be considered in our analysis.

[12] Formally, suppose that the load-following, flat, and peak prices are $p^{LF}, p^{F}$, and $p^{P}$, EPCOR procures volumes $q^{F}$ and $q^{P}$ for the flat and peak products, and that flat and peak products apply for 24 and 16 hours per day. Then, the CRC for EPCOR is computed as $CRC = p^{LF} - \frac{p^{F}\, q^{F}\, 24 + p^{P}\, q^{P}\, 16}{q^{F}\, 24 + q^{P}\, 16}$.

full-load product, covering approximately 50% of EPCOR's expected RRO demand, is procured in strips accounting for a fixed percentage (on average 0.76% during our sample period) of EPCOR's hourly realized load. Auctions follow a descending clock format.[13] Broadly, in each round participants face a price for each product and indicate the quantities of each product they are willing to supply at those prices. If total offers for a product exceed the procurement target for the session, the price is reduced in the next round. This process continues until the willingness to supply equals the procurement target for each product. Methods to ensure auction competitiveness included a cap on the amount that a participant can bid on and win in a particular auction setting.

Importantly, a key focus in the design of the auction format and of the associated AUC hearing was on ensuring that the auction design would encourage participation and yield competitive outcomes (NERA, 2017; AUC, 2018). In particular, concerns were raised by representatives of consumer groups that the set of potential bidders for the full-load product would be limited, and consist primarily of firms with generating capacity. In contrast, EPCOR's experts argued that bidders would include generators, financial traders, and other Alberta retailers. The AUC in its decision concluded that (AUC, 2018, p. 22) "there is a high number of potential auction participants with a physical position, and the number of total potential auction participants should increase when financial entities are considered."

The use of full-load auction prices to determine the CRC was eventually followed by both ENMAX and Direct Energy. ENMAX's first full-load auctions was conducted in September 2020, with December 2020 being the first month to reflect these rates (AUC, 2020). The most recent EPSP for Direct Energy, approved by the Alberta Utilities Commission in February 2021, does not have Direct Energy conducting its own full-load auctions, but uses the EPCOR full-load auction price as an input into the Direct Energy RRO rates (AUC, 2021). The first month to reflect the new pricing formula for Direct Energy was July 2021.

# 3 Data

We use a number of data sets that span the years 2015 - 2021. First, we use data on the RRO market-clearing auction prices for the flat, peak, and full-load products that occurred between December 2018 - April 2021, when the full-load auction was active. Second, we use data on EPCOR's realized and forecasted demand across all customer types. These data will be used to establish a model that represents how market participants form their expectations about EPCOR's demand for future delivery months. Third, we employ data on forward market settlement prices on Alberta's Natural Gas Exchange (NGX).[14] These data will be used to compare forward product prices in EPCOR's RRO auction to the broader forward market. Fourth, we use data that details expected generation unit outages (i.e., total MWs on outage) that were reported to the Alberta Electric System Operator (AESO) for future delivery months. These data will be used in a model

[13]See NERA (2017) for details on the auction format.

[14]The NGX is the primary trading platform for forward market transactions outside of the RRO auctions.

that forms expectations about future spot market prices. These data sets were provided to the authors by the Alberta Market Surveillance Administrator (MSA).

Fifth, EPCOR's customer site counts are available on the MSA's website.[15] These data will be used in forming expectations about EPCOR's expected demand. Sixth, we use data on hourly realized wholesale (spot) market prices from the AESO.[16] Seventh, we employ daily futures crude oil prices traded on the New York Mercantile Exchange and daily Henry Hub futures natural gas prices provided by EIA (2021). Alberta's electricity demand is driven largely by commercial and industrial customers that are often tied to the oil and gas industry.[17] Further, the consideration of expected Henry Hub natural gas prices will provide an exogenous proxy for the cost of natural gas generation in Alberta. Data on expected crude oil and natural gas prices will serve as key inputs into forming expectations about future market outcomes.

Finally, the authors were provided information on the identify of bidders and individual price and quantity bids in EPCOR's RRO auction over the period December 2018 - April 2021. These data will be used in Section 6.2 to analyze how the market structure and degree of competition in EPCOR's RRO auction changed over time.[18]

Table 1 presents summary statistics for a number of the key variables used in our subsequent analysis. Summary statistics for the RRO auction outcomes are for the period April 2019 - March 2021 when EPCOR's RRO auctions with full-load products were operating, all other statistics cover the period November 2015 - March 2021. The RRO auction flat and peak forward prices closely reflect prices arising from the broader NGX forward market. The full-load prices determined in EPCOR's RRO auction, which are not transacted on the broader NGX, are closely aligned with peak prices on average. Table 1 demonstrates that there is considerable variability in the wholesale (spot) market prices and EPCOR demand over our sample period. This variability provides an initial indicator of the price and demand uncertainty faced by suppliers of the full-load product.

Figure 2 presents the average clearing prices for EPCOR's flat, peak, and full-load auctions for each delivery month. Full-load prices have essentially tracked auction prices for the peak product, falling slightly below peak prices, particularly near the end of the sample.[19]

# 4 Model

Our primary objective is to evaluate the performance of the full-load product in the RRO auction. For each auction session, we construct a break-even price for the flat, peak, and full-load products that represents the forward price that would arise if the forward market were perfectly competitive. We use this framework to compare observed full-load prices to the break-even full-load

[15]For details, see https://www.albertamsa.ca/documents/retail-and-rate-cap/retail-statistics/.

[16]Historical Alberta wholesale prices are available at: http://ets.aeso.ca/.

[17]In Alberta, 85% of electricity demand arises from commercial and industrial customers (NERA, 2021).

[18]The data used in Section 6.1 are either publicly available, can be purchased via the NGX, or provided by the Alberta MSA. In contrast, because of the sensitive nature of the data, the data used in section 6.2 were provided to the authors under a non-disclosure agreement and are not publicly available.

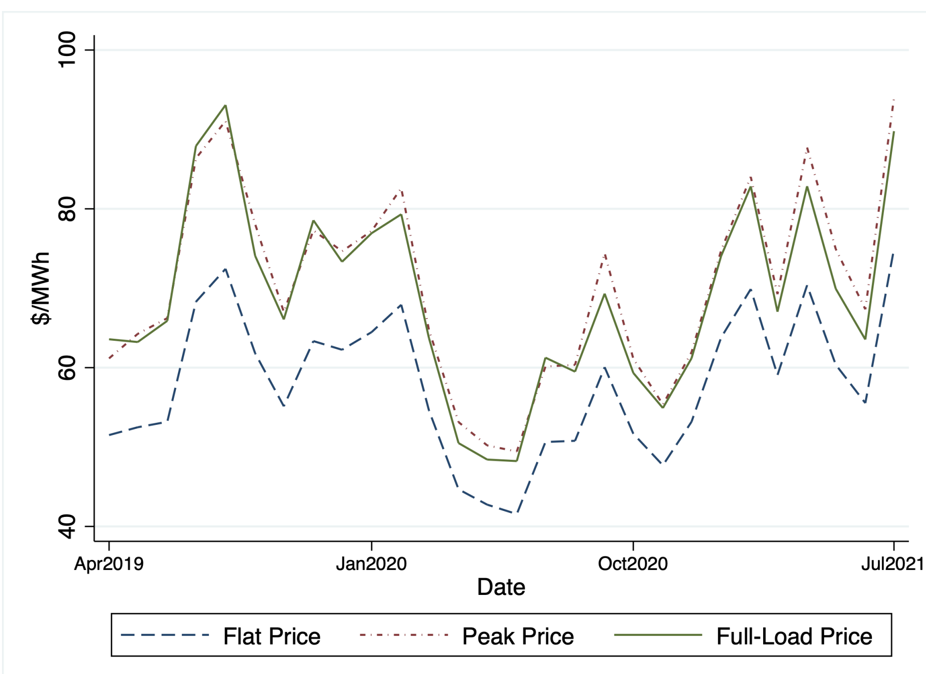
[19]Prices in Figure 2 are unweighted averages of clearing prices in the four auction sessions for each delivery month.

Table 1: Summary Statistics

| | Unit | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| RRO Flat | $/MWh | 55.86 | 8.98 | 34.49 | 77.82 |
| RRO Peak | $/MWh | 67.44 | 12.23 | 39.08 | 98.99 |
| RRO Full-Load | $/MWh | 66.48 | 12.54 | 38.75 | 99.87 |
| NGX Flat | $/MWh | 55.34 | 8.92 | 33.89 | 76.81 |
| NGX Peak | $/MWh | 66.98 | 12.29 | 40.50 | 96.75 |
| Spot Price | $/MWh | 53.99 | 98.22 | 0.00 | 999.99 |
| EPCOR Demand | MWhs | 536.04 | 102.24 | 332.64 | 917.00 |
| Avg. Spot Price (30-Day Lag) | $/MWh | 52.13 | 23.00 | 22.49 | 149.01 |
| Oil Futures Price | $/Barrel | 48.51 | 9.67 | 28.14 | 60.24 |
| Gas Futures Price | $/MMBTU | 3.23 | 0.45 | 2.52 | 4.07 |
| Site Counts | Count | 573,012.86 | 12,023.66 | 555,301.25 | 592,024.50 |
| Expected Outages | MWs | 1,865.88 | 364.98 | 1,107.50 | 2,657.50 |

Notes. All prices are in Canadian Dollars. RRO flat, peak, and full-load prices reflect observed market-clearing prices from EPCOR's RRO auctions. NGX flat and peak are prices from Alberta's NGX market. Spot Price and EPCOR Demand are the observed wholesale price and EPCOR's demand. Avg. Spot Price (30-Day Lag) represents the average wholesale market price over the 30 days prior to EPCOR's RRO auctions. Oil and Gas Futures Price are the daily crude oil and Henry Hub natural gas futures prices. Site Counts are the number of customers served by EPCOR. Expected Outages are the number of MWs that are expected to be on outage for future delivery months. Summary statistics for the RRO outcomes are for the period April 2019 - March 2021, all other summary statistics cover the period November 2015 - March 2021.

Figure 2: Average Clearing Prices by Delivery Month: Flat, Peak, and Full-Load Products




benchmark. In our main analysis, we treat the firms that compete to supply these forward products (i.e., generators, retailers, financial traders) as risk-neutral. As discussed below, we extend our model to include risk-aversion using a mean-variance utility function.

Consider a single RRO procurement auction session that occurs several months in advance of the month covered by the forward market products. There are three products traded: (i) Flat (F), (ii) Peak (P), and (iii) Load-Following (LF). Denote the hour by $t$. The flat and full-load products cover all hours of the month represented by the set $T$ (i.e., 24 hours, 7 days a week). The peak product covers only a subset of hours $T_p \subset T$ (i.e., hours ending 8 to 23, 7 days a week).

Define $q_t^j$ to be the realized quantity committed in period $t$ by signing contract type $j \in \{F, P, LF\}$. For the flat and peak products, this is a fixed quantity (i.e., each flat and peak product represents 5 MWhs). This implies that $q_t^j = q^j = 5$ MWhs for $j = \{F, P\}$. For the load-following contract, supplying a contract "strip" obligates the firm to supply a percentage $\alpha \in (0, 1)$ of EPCOR's realized demand $Q_t$. This implies that $q_t^{LF} = \alpha\, Q_t$.

Define $S_t$ to be the realized spot price in period $t$ (in \$/MWh) and $p_F^j$ to be the forward market price (in \$/MWh) paid to the provider of contract type $j$ set in advance of the wholesale market. Because forward contracts are cleared at the prevailing wholesale (spot) price, the realized payment for the seller (supplier) of the forward contract of type $j$ for each period $t$ is:

$$\pi_t^j \;=\; p_F^j\, q_t^j - S_t\, q_t^j. \tag{1}$$

If $p_F^j \geq S_t$, then the seller of the contract is paid the difference by EPCOR for the quantity ($q_t^j$) covered by the forward contract. Otherwise, the seller of the contract pays EPCOR the difference between the spot and forward price.

The seller of contract $j$ evaluates its payoff over the $t$ periods covered by the forward contract. Consequently, recognizing that the quantity covered by the flat and peak products are time-invariant, (1) implies that the break-even price that yields zero expected payoff for contract $j \in \{F, P\}$ ($\overline{p}_F^j$) is:

$$\sum_{t \in T_j} E\left[\overline{p}_F^j\, q^j - S_t\, q^j\right] \;=\; 0 \qquad \Rightarrow \qquad \overline{p}_F^j \;=\; \frac{1}{|T_j|} \sum_{t \in T_j} E[S_t]. \tag{2}$$

where $|T_j|$ denotes cardinality of the set $T_j$ which represents the hours covered by contract type $j$. (2) demonstrates that the flat and peak break-even prices reflect the average of the expected wholesale prices for the relevant hours covered by the contract.

Characterizing the break-even price for the load-following contract is more complicated. Unlike the flat and peak products, the quantity of electricity covered by the load-following contract depends on EPCOR's realized demand (i.e., $q_t^{LF} = \alpha\, Q_t$). Using (1), the break-even full-load price ($\overline{p}_F^{LF}$) satisfies:

$$\sum_{t \in T} E[\,\overline{p}_F^{LF}\,\alpha\, Q_t - S_t\,\alpha\, Q_t\,] \;=\; 0 \quad \Leftrightarrow \quad \overline{p}_F^{LF} \sum_{t \in T} E[\,\alpha\, Q_t\,] - \sum_{t \in T} E[\,S_t\,\alpha\, Q_t\,] \;=\; 0$$

$$\Leftrightarrow \quad \overline{p}_F^{LF} \;=\; \frac{\sum_{t \in T} E[\,S_t\,\alpha\, Q_t\,]}{\sum_{t \in T} E[\,\alpha\, Q_t\,]} \;=\; \frac{\sum_{t \in T} E[\,S_t\,]\, E[\,\alpha\, Q_t\,] + cov(S_t, \alpha\, Q_t)}{\sum_{t \in T} E[\,\alpha\, Q_t\,]} \tag{3}$$

where the numerator reflects the expected cost of holding a full-load strip of size $\alpha$ and the denominator is the expected quantity covered by the full-load product. Unlike the flat and peak products whose quantities are fixed, the uncertain quantity covered by the full-load product results in expected cost that depend both on the expected spot price and full-load quantity levels and their covariance which is often positive in practice. Compared to the flat product, which covers the same hours, these additional factors are expected to increase the full-load break-even price.

In order to compute the break-even flat, peak, and full-load prices, we need to estimate the expected values of the random variables $Q_t$ and $S_t$ and their covariance. In the next section, we describe our empirical methods for estimating these variables. Appendix A extends our modeling framework to allow for risk-aversion using a mean-variance utility function.

## 5 Empirical Methodology

In this section, we describe our empirical methodology to estimate the expected values of the spot market price $S_t$ and EPCOR demand $Q_t$, as well as the covariance of these random variables. Recall that for each delivery month, there are four RRO auctions where the forward products are traded. The first auction is held approximately four months in advance, followed by the second, third, and fourth auctions which are held approximately three, two, and one month prior to the delivery period, respectively. When firms are forming their expectations about the future delivery month, they are doing so with the information that existed as of the time of the auction.

To formalize this idea with notation, define $m$ to be the delivery month covered by the forward product with $T$ hours of wholesale market transactions. For each delivery month $m$, our objective is to build an empirical model to estimate spot prices $S_{t,m}$ and EPCOR demand $Q_{t,m}$ for all $t = 1, 2, ..., T$ based on information available at time $m - k$ for $k = 1, 2, 3, 4$ (when the RRO auctions are held). We employ a regression analysis to model the properties of these two random variables as follows:

$$Y_{tm} \;=\; \mathbf{X}_{t,m-k}\,\vec{\beta} + \delta_{t,m} + \varepsilon_{t,m} \tag{4}$$

where $Y_{t,m}$ reflects the dependent variables $S_{t,m}$ and $Q_{t,m}$, $\delta_{t,m}$ reflects a set of calendar controls, and $\mathbf{X}_{t,m-k}$ are variables that contain information that form expectations about the level of $Y_{t,m}$ that are known prior to the auction held in month $m-k$. The calendar controls capture systematic time-based variation in prices and EPCOR demand including indicator variables for each month, hour, month-by-hour, day-of-week, and a linear month-year time trend.

For the spot market price regression, $\mathbf{X}_{t,m-k}$ contains four variables that capture information that was available to market participants just prior to when the RRO auction was held that would help form expectations about spot market prices for the delivery month $m$. First, for each hour of the day, we include the average spot price of that hour in the 30 days prior to the day the RRO auction is held. This aims to capture trends in recent spot market prices. Second, we include information on expected generation unit outages (i.e., total MWs on outage) for the delivery month $m$ available just prior to the day the RRO auction was held.[20]

Third, we utilize the New York Mercantile Exchange's daily futures Crude Oil prices for future delivery month $m$ on the morning of the RRO auction. This forward-looking variable captures market expectations about the profitability of oil production, a key industry in Alberta's economy that is often cited as being a driver of electricity demand (e.g., MSA (2021a)). Fourth, we utilize the Henry Hub natural gas price for future delivery month $m$ on the morning of the RRO auction. This variable captures expectations on the cost of natural gas which is a critical input into the cost of electricity generation in Alberta. We utilize the Henry Hub gas futures price because it is exogenous to electricity generation decisions in Alberta. We allow the effect of expected total MWs on outage, oil futures price, and natural gas futures price to vary by peak and off-peak hours reflecting the fact that we expect these variables to have an asymmetric impact on supply and demand conditions in these hours.

For the EPCOR demand regression, $\mathbf{X}_{t,m-k}$ contains three variables. First, we utilize data on the number of customer sites just prior to the RRO auction for all customers types in its delivery area. This variable is a fundamental component of how EPCOR formulates its own demand forecasts for a future delivery month (EPCOR, 2017, Schedule C). Second and third, we include NYME's daily futures Crude Oil price and the Henry Hub natural gas futures price for future delivery month $m$ on the morning of the RRO auction. As noted above, these variables aim to capture the fact that electricity demand is closely linked to the oil and gas industry in Alberta. We allow the effect of the oil and natural gas futures prices on EPCOR's demand to vary by peak and off-peak hour to capture the possible asymmetric effect these variables have on demand conditions throughout the day.

We use the model in (4) to establish out-of-sample estimates of the dependent variables to represent their expected values. More specifically, to estimate the four-month ahead expectations for April 2019, we first estimate the model on a three-year window starting in November 2015 to November 2018. We then estimate the dependent variables out-of-sample based on information available as of December 2018 for four, three, two, and one full months in advance. We move forward a month estimating the model on the window December 2015 - December 2018, then predict the dependent variables out-of-sample as of January 2019 for four, three, two, and one month ahead. This process continues until the end of our sample period and establishes four, three,

[20] This data is available for any day where there was a trade on the broader Alberta NGX market. We take the expected outage measure on the last day where a trade occurred on the NGX prior to the RRO auction.

two, and one-month forward-looking estimates for each of our dependent variables. We chose a three-year window to train the model to balance providing sufficient variation for our model to identify off of, but limit the time window to account for the fact that the market environment changes over time so we want to avoid using data that is too dated.[21]

Next we describe how we establish estimates on the covariance values for our dependent variables. For each month, we multiply the difference of predicted and observed prices by the difference in EPCOR observed and predicted demand. These covariance terms are averaged by hour to give us an hourly covariance measure for each month in our sample.[22]

The aim of this approach is to capture the strong seasonal patterns we observe in the covariance values of these random variables. However, this approach utilizes realized spot prices and demand to compute these measures. We employ several robustness checks to evaluate the sensitivity of our results to this approach. First, we employ an approach that computes the observed hourly covariance measures as above, but average these across all years in our sample at the month level. This approach captures the observed seasonal variation in the covariance measures while relaxing the perfect foresight assumption because an individual hour's value will have a small effect on these measures. The downside with this approach is that it fails to capture changes in the market over time. Further, this approach uses price and demand levels from future months that occur potentially far in advance of the current delivery month.

Second, we estimate the covariance estimates discussed above, but use the values that occurred 11, 12, and 13 months ago. That is, we use the one-year lagged realized values that would have been observed by the firms and one month before and after to smooth out possible outliers associated with an individual month's value. This approach relaxes the perfect foresight assumption on spot prices and demand, while capturing the observed seasonality in these measures.

An alternative approach would be to take observed covariance values for spot market prices and EPCOR demand and build similar regression models to forecast out-of-sample values for these variables in a similar manner to our approach above. However, this approach would not appropriately account for the fact that there is uncertainty in the expected value of the price and demand variables. Rather, this approach would be based on estimating the variation in observed prices (demands) around the observed mean price (demand) level.

For a given delivery month $m$, these methods establish empirical estimates for the expected value and covariances for each of our dependent variables on a four, three, two, and one month

[21] Using the three year window, or a shorter 2.5 year window, we find that our forecasted expected spot prices align with the price expectations arising on the broader Alberta Natural Gas Exchange (NGX). In contrast, we find that shorter time periods result in volatile forecasted expected spot prices that deviate substantially from the broader Alberta NGX forward prices.

[22] More formally, spot prices and EPCOR demand can be thought of as jointly distributed random variables $(S_{t,m}, Q_{t,m})$. We empirically estimate the month-by-hour specific expected value $E[S_{t,m}]$ and $E[Q_{t,m}]$ of these random variables using the regression model in (4). Subsequently, for a given hour $t$ in month $m$, we observe $N$ values on $S_{t,m,j}$ and $Q_{t,m,j}$ for $j = 1, 2, ..., N$. We compute the covariance of these random variables by $\frac{1}{N} \sum_j (\, S_{t,m,j} - E[S_{t,m}]\,)\,(\, Q_{t,m,j} - E[Q_{t,m}]\,)$.

forward-looking basis. For each RRO auction, we utilize these values to estimate the break-even flat, peak, and load-following prices in (2) and (3).

In the results below, we drop two outlier months (January 2020 and February 2021). These two months had extreme unexpected and prolonged periods of cold weather. This caused both prices and demand to be higher than expected (MSA, 2020, 2021b). This yields excessively large values on our variance measures for demand and prices. To avoid having two outlier months drive our quantitative results, we have dropped these months. However, as discussed in the next section, the key qualitative conclusions drawn from our analysis are unaffected by including these months.

# 6 Results

In this section, we present the results of our empirical analysis. We begin by summarizing the results of our regression analyses and the estimated break-even prices. We then investigate possible drivers of our results by investigating changes in the market structure of EPCOR's RRO auction. Finally, we present two extensions to our main modeling framework that consider the role of risk-aversion and experience/learning that could change bidding behaviour over time.

## 6.1 Empirical Results

We first highlight several key observations from the results of our forecasting regressions for spot prices and EPCOR demand. Recall that the motivation for Commodity Risk Compensation and the introduction of the full-load product comes from several observations regarding retail electricity markets: (a) uncertainty regarding hourly load, creating demand risk; (b) a positive correlation between spot prices and retail demand, so that a retailer who has under-procured for a high-demand hour is subject to a high spot price; and (c) the crude nature of flat and peak forward products, which are unable to match daily demand profiles.

To illustrate the last point first, Figure 3 presents average hourly EPCOR load, along with the averaged hourly forecasts from the EPCOR demand regressions. Figure 3 illustrates that our forecasts capture hourly patterns in demand well on average. Further, the forward hedge line represents the average load in peak and off-peak hours, as an example of an hourly hedging pattern that can be achieved by purchasing a combination of flat and peak products. As can be seen in Figure 3, this hedging portfolio would under-procure on average in the late afternoon and evening (HE 17 - 21), but would over-procure in early morning (HE 2 - 6) and mid-morning (HE 8 - 11).[23]

Figure 4 plots observed average prices by hour, along with hourly averages of the price forecasts from the spot price forecasting regressions. First, we note that our forecasting approach results in expected spot price levels that closely match the overall level and profile of spot prices throughout

[23]The flat and peak procurement strategy illustrated in Figure 3 is a simplification in that it assumes that EPCOR procures up to its expected average load in flat and peak hours. In practice, it was possible for RRO providers to over-procure peak products in order to reduce commodity risk. For example, according to its 2014-2018 EPSP, EPCOR would procure to the 60th percentile of its average hourly load in peak hours. This followed an initial request to procure to the 75th percentile (AUC, 2015).

Figure 3: Observed, Expected, and Forward Hedged Demand by Hour.

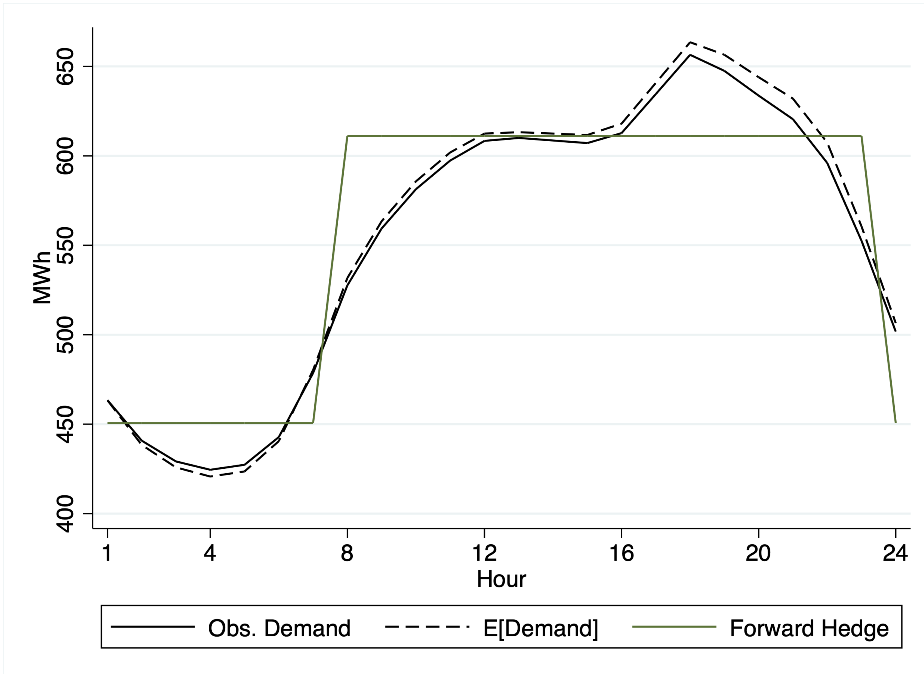
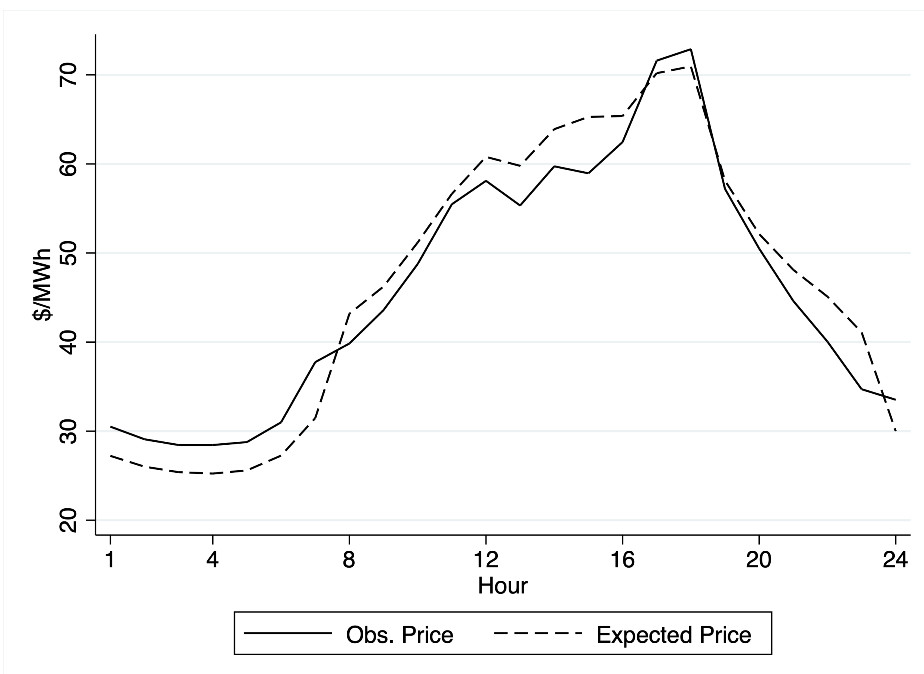



Figure 4: Observed and Expected Prices by Hour.




the day. Second, Figure 4 shows that the hourly pattern in EPCOR load is closely reflected in hourly average spot prices. As a result, under a flat/peak procurement approach, those hours in which EPCOR would be under (over) procured would also be those hours in which the wholesale price is high (low).

We use the estimate wholesale price and EPCOR demand to compute a correlation coefficient between spot price and load for each month. The average correlation coefficient is 0.25 for all hours and 0.28 for peak hours, suggesting a moderate positive correlation between expected spot prices and demand. While the estimated expected demand levels in Figure 3 are close to observed demand on average, the estimated standard deviation in EPCOR's demand at the hourly level is 48.5 MWhs. This demonstrates that holders of full-load contracts face quantity risk when forming expectations about the demand they are obligated to serve when securing a full-load slice.

In addition to observing that our forecast regressions fit observed values well on average, it is also instructive to look at the distribution of parameter values and fit of our price and demand regressions detailed in (4). As discussed in Section 5, we run a large number of regressions because we use these regressions to establish out-of-sample expectations on spot prices and EPCOR demand on a rolling basis. Figures A1 and A2 present box and whisker plots that summarize the distribution of parameter estimates and adjusted R-squared values for the price and demand regressions, respectively. While our objective of these regressions is to establish out-of-sample estimates on expected demand and prices, the distribution of statistically significant coefficient estimates yield the expected signs on average. See Appendix C for a discussion of these results.

Table 2: Average Observed and Break-Even Forward Prices

| Product | Observed | Break-Even |
|---|---|---|
| Flat | 55.86 | 58.20 |
| Peak | 67.44 | 67.07 |
| Full-Load | 66.48 | 61.78 |

Notes. Break-Even represents the estimated risk-neutral break-even flat, peak, and full-load prices from (2) and (3).

Table 2 presents the average observed and estimated break-even forward prices by product in EPCOR's RRO auction. Table 2 demonstrates that the average observed prices are closely aligned with our estimated average break-even prices for the flat and peak products. In fact, the observed flat price is below our risk-neutral estimate suggesting that firms' expectations were for even lower expected wholesale prices across all hours than our estimated values. The fact that firms' expectations appear more aggressive than our model's estimates magnify the concerns over the large observed differences between the observed full-load price and our estimated break-even price for this product. Our results show that the average observed full-load price exceeds our average break-even value by approximately 7%.

To investigate how the full-load price markup above the flat price varies over time (reflecting the added quantity-risk), we compare the full-load and flat prices, controlling for differences in the underlying costs of providing these two forward products. Figure 5 presents the difference between the full-load and flat prices, net of the difference in the two products' break-even prices to control for relative changes in the underlying costs of providing these forward products.[24]

[24]More specifically, using the notation from Section 4, Figure 5 graphs $p_F^{LF} - p_F^F - (\overline{p}_F^{LF} - \overline{p}_F^F) = p_F^{LF} - \overline{p}_F^{LF} - (p_F^F - \overline{p}_F^F)$.

Figure 5: Observed Full-Load Minus Flat Prices, Net of Differences Between Break-Even Prices.

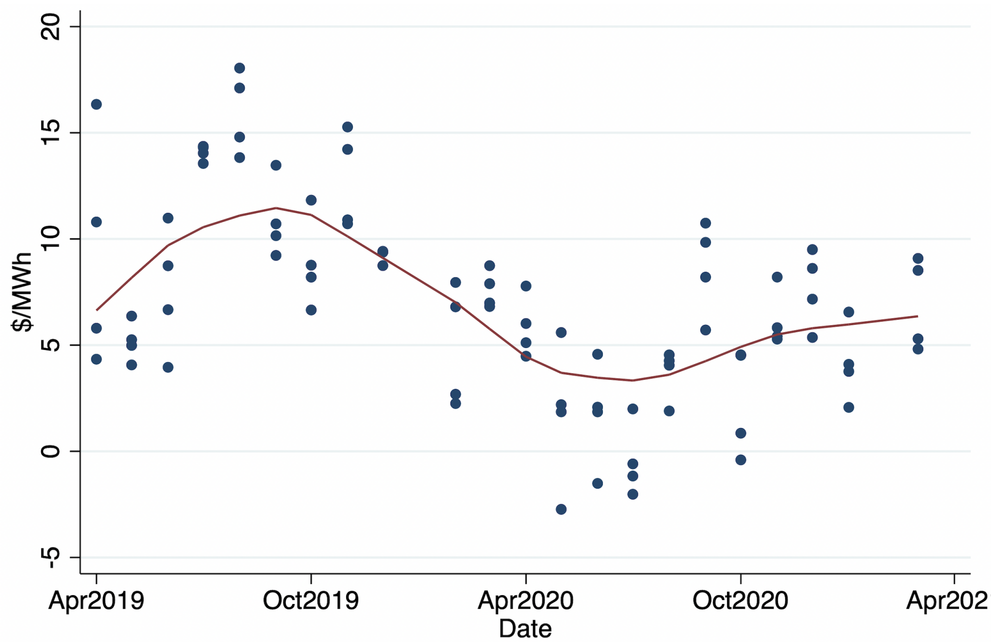



Figure 5 demonstrates that there was a considerable difference between the observed full-load and flat prices, adjusted by differences in their underlying break-even risk-averse prices, at the beginning of our sample. Over our sample period, we observe a considerable reduction in the level of this difference from \$5/MWh to \$19/MWh early in our sample to \$-3/MWh to \$10/MWh near the end of our sample period. More specifically, the average difference is \$7.04/MWh over the full sample. The difference declines from an average of \$9.67/MWh between April 2019 - March 2020 to \$4.41/MWh between April 2020 - March 2021.

These results suggest that while the full-load product has a higher break-even price than the flat product, this price difference is not sufficient to explain the observed differences between these two products. Further, we have documented a considerable reduction in this difference over our sample period. However, a positive difference remains that cannot be explained by differences in the underlying costs of these products.

We can compare the Commodity Risk Compensation (CRC) awarded to EPCOR to the CRC based on the same formula, but using the break-even flat, peak, and full-load prices from our analysis. In addition, we compare our model-estimated CRC values to the actual CRC awarded to Direct Energy through its regulatory hearings. These comparisons allow us to investigate whether regulatory hearings provide sufficient commodity risk compensation, and whether market-based mechanisms are better able to provide appropriate levels of compensation.

Recall from Section 2 that according to EPCOR's 2018-2021 EPSP, its CRC is the difference between the full-load price determined through its auctions, and the average cost of a MWh procured through flat and peak products. Using observed clearing prices, and the volumes of

The line represents the conditional means estimated from a local-linear kernel regression.

flat and peak products procured by EPCOR in its auctions, the average realized EPCOR CRC over our sample period is \$8.49/MWh. In contrast, the CRC values generated using the break-even flat and peak prices is \$1.93/MWh. The average CRC for Direct Energy over the sample period was \$3.10/MWh, suggesting that while Direct Energy's CRC determined through regulatory proceedings also exceeded the break-even benchmarks, it was much closer than the market-determined CRC paid to EPCOR.[25] Further, EPCOR's regulatory-determined CRC for the Edmonton region was \$2.38/MWh on average in the 12 months prior to the implementation of the market-based CRC considered in our analysis.

We run a number of robustness checks to ensure these results are not affected by specific features of our sample period or modeling approach. First, as noted above, we removed January 2020 and February 2021 because these months had unexpectedly large price levels. We analyze the results of our model when these months are included in our analysis. Second, we remove RRO auctions that occurred in March, April, and May of 2020 during the initial wave of the Covid pandemic. In these months, there was considerable uncertainty regarding future wholesale market prices and electricity demand. Third and fourth, as discussed in Section 5, we also compute the covariance measures averaged at the monthly level across all years in our sample and as the average of their observed values 11, 12, and 13 months prior to each RRO auction. These results are presented in order in Tables A2 – A5.[26]

While the precise estimates can vary, these results demonstrate that our qualitative conclusions are robust to these alternative samples and approaches. In particular, we find that the average difference between the cost-adjusted full-load and flat prices demonstrated in Figure 5 are initially large and this margin decreases over our sample period. For each of these robustness checks, our qualitative conclusions regarding the Commodity Risk Compensation, that EPCOR's CRC based on auction-clearing rates is more than double both the regulated CRC given to Direct Energy and the rates based on our model estimated break-even forward prices, persists.[27]

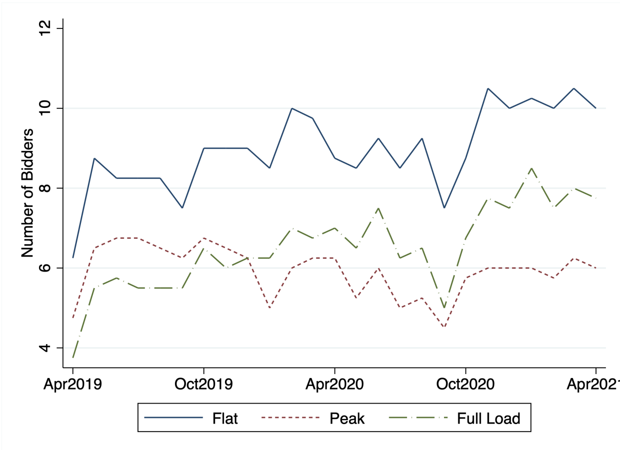
## 6.2 RRO Market Structure Analysis

We will now investigate possible causes for these trends in the data and evaluate if changes in the market structure and degree of competition in EPCOR's RRO auction can help explain the observed patterns. For each product, we document the number of bidders, present concentration ratios, and evaluate the characteristics of the types of bidders participating and winning in EPCOR's RRO auction.

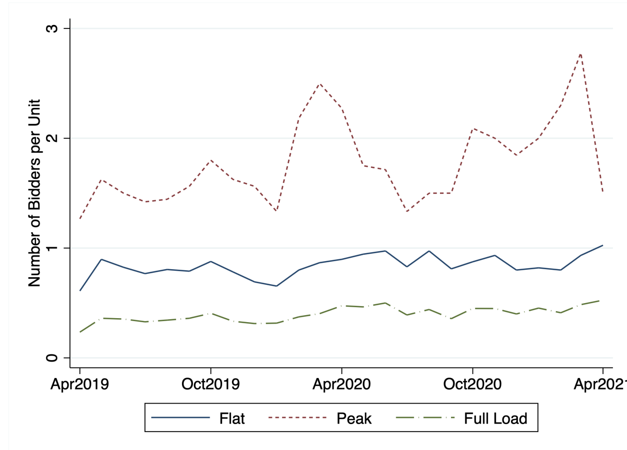
[25] Considering only the years 2020 and 2021, EPCOR's average CRC was \$6.77/MWh when using observed RRO auction prices. The CRC that arises by using our estimated break-even prices is \$2.21/MWh. In comparison, Direct Energy's average CRC for this period was \$3.41/MWh. Hence, the large difference between EPCOR's CRC based on observed clearing prices and those based on break-even prices, or compared to the observed CRC paid to Direct Energy, is not simply the result of the high full-load prices observed when the full-load auction was first introduced.

[26] In each table, we also present the results for our model extension that includes risk-aversion. This extension is discussed in detail in Section 7.1.

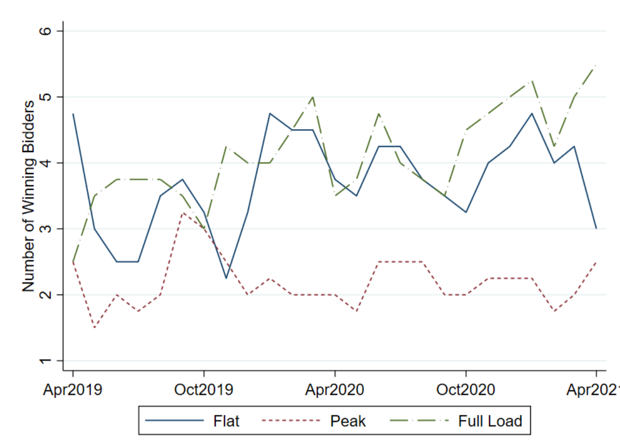
[27] See Table A6 and the associated discussion in the Appendix for detailed results on the CRC calculation.



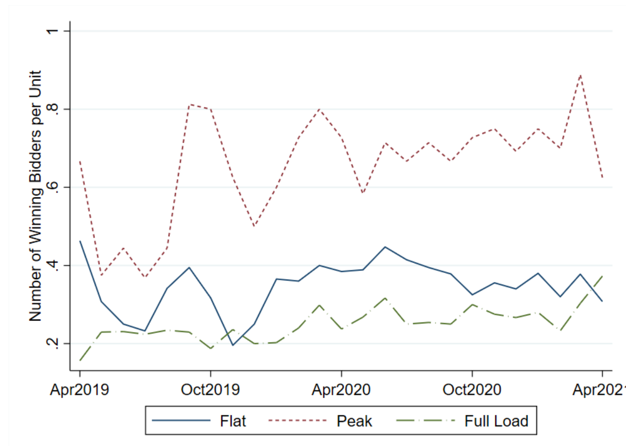

(a) Number of Bidders




(b) Number of Bidders per Unit




(c) Number of Winning Bidders




(d) Number of Winning Bidders per Unit

Figure 6: Number of Bidders by Product

Figure 6 illustrates how the number of bidders competing for each product and number of winning bidders vary over our sample period.[28] We also divide these variables by the number of units being sold for each product to appropriately frame the relative degree of competition for each product. Figure 6(a) demonstrates that the flat product has the largest number of bidders with an average of 9.1. Alternatively, the full-load and peak products averaged 6.7 and 6 over our sample period, respectively. There is a considerable increase in the number of bidders competing to supply the full-load product, increasing from an average of 3.75 in the first delivery month to 7.8 near the end of our sample.[29] The increase in the number of bidders competing to supply the full-load product is consistent with the observed reduction in the full-load markup in Figure 5

[28]In Appendix C, Figure A3 presents the average number of active bidders per unit by auction round for each product, providing insight into how the number of bidders varies as EPCOR's descending clock auction progressed.

[29]NERA (2017) documents evidence on the number of bidders competing to supply full-load products in Maryland, New Jersey, and Ohio. The number of bidders ranges from 2 to 7 for 5 out of the 7 utilities listed. This is in line with the number of bidders in our setting. The remaining two utilities have a considerably higher number ranging from 8 to 17. However, the number of units being auctioned off are not provided so we cannot normalize the number of bidders as we do in our analysis.

suggesting the full-load auction is becoming more competitive over time.

Figure 6(b) shows that the number of bidders per unit is highest for the peak product followed by the flat and then full-load products. This ranking is driven in part by the fact that there is an average of 3.5 peak product units, 10.6 flat units, and 16.3 full-load units being procured per auction over our sample. This suggests that the full-load product has the lowest relative degree of competition. While it is hard to observe in Figure 6(b), it is important to note that the number of firms competing for the full-load product per unit has more than doubled from 0.23 in the first delivery month auctions to 0.49 on average near the end of our sample. This continues to suggest that there has been enhanced competition for the full-load product over our sample period.

Figure 6(c) demonstrates that the flat and full-load products have the highest number of winning bidders with an average of 3.75 and 4.20, respectively. The number of winning bidders in the full-load auction has increased from an average of 2.5 in the first delivery month to 4.8 near the end of our sample. Figure 6(d) demonstrates that when normalized, the flat and full-load products have 0.36 and 0.26 number of average winning bidders per unit over our sample. Consistent with the increase in the number of bidders, the average number of winning bidders per unit for the full-load product has increased from 0.16 in the first delivery month to 0.30 near the end of our sample. These results are consistent with enhanced competition for the full-load product leading to additional firms competing and winning the full-load product.

Looking at the number of winning bidders for each product does not provide information on the concentration of contracts won among those bidders. To address this, Table 3 reports the four firm concentration ratios (CR4) for each product, aggregated to the level of the delivery year; for example, the first column reports the combined percentage of contracts won by the four largest firms for each product from April to December 2019. Notably, Table 3 indicates that for months in 2019 for which all three products were auctioned, full-load products had a CR4 of 95%, which was substantially higher than those of peak (82%) and flat (77%) products. In subsequent years, concentration of the three products converged to approximately 85% in 2021.[30]

Table 3: Four Firm Concentration Ratios (%) by Product and Year

| Product | 2019 | 2020 | 2021 |
|---|---|---|---|
| Peak | 82 | 87 | 85 |
| Flat | 76 | 73 | 85 |
| Full-Load | 95 | 88 | 86 |

Finally, we evaluate the configuration of bidders by type and how bidder characteristics change over our sample period. When the full-load auction was being debated, there were considerable concerns over whether or not there is a sufficient pool of competitors willing to compete to supply the full-load product. In particular, it was argued that only firms with generation assets would

[30]Table A7 in the Appendix presents analogous results using the Herfindahl-Hirschman Index (HHI). The HHI demonstrates the same general pattern as the CR4, with higher concentration in the full-load product initially and a reduction in the full load product's concentration by 2021.

participate in teh full-load auctions, and that financial traders are unlikely to compete effectively against generators who have a distinct advantage of managing the risk of holding a full-load product.[31] Stakeholders advocating for the full-load product noted that financial traders can hedge the risk of the full-load product by signing other financial forward products. In addition, it was suggested that retailers are likely to find the full-load product to be attractive because they are used to managing the risk of such a product which has many similarities to signing a customer with uncertain demand to a fixed-priced contract (NERA, 2017; AUC, 2018).

Table 4: Percentage of Bidders and Contracts Won by Product and Bidder Type

| Product | Type | % of Bidders | % of Contracts Won |
|---|---|---|---|
| **Flat** | Generators | 41.16 | 59.87 |
| | | (4.67) | (27.81) |
| | Retailers with RRO | 17.74 | 5.84 |
| | | (1.44) | (6.88) |
| | Financial Traders | 41.10 | 34.28 |
| | | (4.19) | (26.60) |
| **Peak** | Generators | 34.56 | 63.74 |
| | | (8.56) | (23.65) |
| | Retailers with RRO | 24.08 | 5.83 |
| | | (3.71) | (8.27) |
| | Financial Traders | 41.36 | 30.43 |
| | | (10.77) | (24.13) |
| **Full-Load** | Generators | 36.61 | 50.73 |
| | | (5.79) | (10.97) |
| | Retailers with RRO | 20.09 | 29.54 |
| | | (7.68) | (10.15) |
| | Financial Traders | 43.30 | 19.73 |
| | | (5.03) | (11.63) |

Notes. Standard deviations are in parentheses. "Financial Traders" contains 6 companies that specialize in financial trading in energy markets. "Generators" contains 5 companies that own generation assets in Alberta. "Retailers with RRO" contains 2 companies that are retailers in Alberta that also offer the RRO product in their respective jurisdictions.

To investigate these questions, we define three types of bidders: Generators, Retailers, and Financial Traders. We observe two retailers that actively participate in EPCOR's auction. These retailers also provide the RRO product in their respective jurisdictions so we label this type as Retailers with RRO.[32]

Table 4 provides the percentage of bidders and contracts won by product and firm type over our sample period. The configuration of bidders is similar across all three products. Financial traders and generators make up the majority of bidders. Importantly, we observe all three types

[31] For details, see Section 6.1.1 in AUC (2018).

[32] One of these two retailers is a vertically integrated that also owns generation units. However, to ensure anonymity, we are unable to provide the market shares of these two individual retailers separately.

of firms competing to supply the full-load product. This suggests that concerns raised during the regulatory hearing regarding the lack of participation by financial traders were not realized.

However, by looking only at the percentage of bidders by type, we are missing the intensity to which bidders of certain types compete to supply each individual product. Table 4 presents the % of contracts won by firms of each type. The flat and peak products have similar configurations, the majority of contracts are won by generators followed by financial traders and then a small percentage are won by retailers with RRO products.

Alternatively, for the full-load product, while generators continue to have the highest market share, retailers with RRO products have the second highest percentage of contracts won. Compared to the flat and peak products, retailers win a considerably larger amount of the full-load product. This high market share may be driven by the logic outlined above that retailers will find this product attractive given its similarities to the risk entailed with signing customers to retail service contracts. However, it is important to note that the relatively high percentage of contracts won by retailers is driven by a single retailer, while a number of generators and financial traders supply the full-load product. This raises some concerns over the strength of the incentives that retailers face to compete to supply the full-load product more broadly.

In summary, our analysis demonstrates a sizable divergence between the full-load price and its break-even benchmarks. We demonstrate that this difference has decreased considerably over time. This decrease coincides with a sizable increase in the number of firms competing to supply the full-load product. Further, we provide evidence that financial traders and retailers are interested in supplying the full-load product, alleviating concerns raised by stakeholders that generators would have an advantage when competing for this unique and new product.

# 7 Extensions

In this section, we consider additional possible explanations for our findings that full-load prices exceed estimated break-even prices in a way not observed for the flat or peak products.

## 7.1 Risk-Averse Preferences

One potential explanation for why we observe a full-load price that exceeds our estimated break-even price is the presence of risk-aversion among the suppliers of the RRO products. This can put upward pressure on the break-even full-load price in particular because it entails both price and quantity uncertainty. We adjust our model used to characterize the break-even flat, peak, and full-load prices to allow the suppliers to be risk-averse. We utilize a mean-variance utility function. The formal model and derivations can be found in Appendix A, along with a discussion of how risk aversion affects our empirical approach and how the risk aversion parameter is estimated. Intuitively, the introduction of risk aversion in the model results in an additional premium in the break-even prices of all three forward products. While the risk premia in flat and peak forward prices reflect simply the variance of spot prices over the relevant hours, the risk premia in full-load prices also incorporates the additional uncertainty in load.

A detailed discussion of the results with risk aversion can be found in Appendix B. In general, the estimated average risk margins, which reflect the difference between the risk-averse and risk-neutral break-even prices, are small and range from \$0.56/MWh for flat contracts to \$0.81/MWh for peak contracts. The estimated average risk margin for full-load contracts is \$0.64/MWh, which is greater than the flat risk margin as expected, but less than the risk margin for peak contracts. Importantly, the observed full-load price is \$4.06/MWh higher than the estimated risk-averse break-even full-load price on average. This suggests that risk-aversion explains only a small portion of the difference between the observed and risk-neutral full-load break-even price. Further, the estimated additional risk-premium in the full-load product for carrying the quantity risk, which is represented by the difference in the risk margins for the full-load and flat product, is small and comes in at only \$0.08/MWh on average.

To provide a comparison to our estimated risk-margins, we compute the *ex-post* (realized) forward market premium. More specifically, we compute the difference between the observed forward price and spot market prices. For the realized flat (peak) risk premium, we compute the difference across all hours (only using peak hours). This approach has been commonly employed in the empirical literature to estimate forward risk-premia in electricity markets (e.g., Redl and Bunn (2013)).[33] This literature emphasizes the importance of having a longer time-series of data to estimate realized forward risk-premia. Consequently, we utilize forward market transactions on Alberta's NGX over the period January 2017 – April 2021. We find that the average realized risk-premium for flat and peak products are \$2.02/MWh and \$3.55/MWh. These premia represent 3% to 5% of the observed average price levels for these products. While these numbers are larger than the estimates using our empirical methodology, they continue to show relatively modest risk-premium values for the flat and peak products.[34]

The model with risk aversion was re-estimated under the various robustness checks discussed in Section 6.1; see Appendix B for a detail discussion. While the quantitative values vary, the finding that the cost-adjusted differential between the full-load and flat prices is initially large and decreases over time remains. These results continue to show that there is a differential between the full-load and flat prices that cannot be explained by the underlying cost of these products.

## 7.2 Experience

An additional possible factor that could help explain the initial large margin between full-load and flat prices, and its subsequent decline (see Figure 5), is that auction participants were

[33] Pena and Rodriguez (2022) provide a detailed summary of this literature and highlight the empirical caveats that come with employing *ex-post* prices to measure the forward premium. The authors note that this literature finds a wide range of estimates on the *ex-post* forward premium ranging from negative, zero, to large positive values.

[34] If we use forward market prices and transactions that occurred on EPCOR's RRO auction over our sample period (which represents a shorter time-series of data), the *ex-post* forward premium is \$1.20/MWh and \$2.77/MWh. The estimates are closer to those that arise from our model, but remain higher than our estimates.

initially uncertain about how to bid on a new product, and how to account for quantity-risk in their bids. According to this explanation, firms would initially submit conservative bids due to this uncertainty, but bid more aggressively after they have learned more about the product. It is also possible that firms would chose to not submit any bids initially in the full-load auction. This explanation is fundamentally linked with the concerns that the full-load auctions were initially heavily concentrated, but they became more competitive over time.

Note first that auctions for flat and peak products were conducted by EPCOR since at least 2011, so that by the introduction of the full-load auctions, suppliers would be familiar with valuing these products and bidding in these auctions. Experience with flat and peak products would also come from the forward market more broadly. Hence, an experience/learning explanation for the initially high full-load prices would need to be based specifically on the introduction of quantity risk. While some potential bidders may lack experience in valuing full-load products, such experience could be present among existing retailers in Alberta and elsewhere, along with firms supplying full-load contracts in other jurisdictions.[35] In addition, as noted in Section 2 footnote 11, EPCOR procured full-load products to cover a portion of its demand between 2006 - 2010 (AUC, 2018). This suggests some experience with full-load auctions may have existed in the province when EPCOR's 2018 full-load auctions were introduced. Finally, we note that even by the end of our sample, the margin between observed and break even full-load prices remains positive.

It is possible, however, that the initial high full-load auction prices may be the result of asymmetric information and experience when the full-load product was introduced. Breaking down the results in Table 4 by year indicates that retailers involved in the RRO in other Alberta regions accounted for 36%, 28% and 24% of contracts won in 2019, 2020 and 2021 respectively. Given that these firms would be expected to have the most initial experience regarding the valuation of Alberta retail load, this downward trend is consistent with an informational advantage at the introduction of the full-load product that dissipates as other providers gain more experience.

# 8 Conclusion

Regulators have increasingly been employing full-load auctions as a method of valuing the price and quantity risk inherent in default retail electricity provision and to set default rates. While it has been understood that the effectiveness of these auctions depends on sufficient participation, the literature assessing the performance of full-load auctions has been limited and largely descriptive.

In this paper we presented a model of break-even pricing for flat, peak, and full-load forward electricity products. We apply this framework to winning bids from EPCOR's full-load auctions in Alberta, where such auctions replaced regulatory price-setting mechanisms. We find that winning full-load bids in these auctions exhibit a margin over break-even prices, even allowing for risk-aversion, that is not observed in the winning bids for flat and peak forward contracts.

[35] Online documents indicate that certain firms supplying full-load products in EPCOR's auctions also supply similar products in New Jersey; see Bates White (2022).

We demonstrate that the observed market-determined risk compensation provided to EPCOR far exceeds the risk compensation that would arise at break-even prices via our model, as well as the regulatory-determined risk compensation for another large RRO provider during the same period.

The margin between observed and break-even full-load prices declines over our sample period as participation in the full-load auctions increased, with the number of bidders per full-load unit doubling from the beginning to end of the sample period. In general, our paper highlights the importance of sufficient participation for the success of full-load auctions and the potential for regulated rates determined through full-load auctions to exceed those determined through a regulatory process until the auctions have attracted a sufficient number of bidders.

In addition, our paper highlights that different types of participants may be expected in full-load auctions compared to auctions for other forward electricity contracts. As anticipated by EPCOR's experts, full-load auctions may be expected to attract bidders beyond those bidding on flat and peak products, and who may have particular expertise in evaluating quantity risk and the interaction of retail price and quantity; this particularly includes electricity retailers. Results from EPCOR's auctions suggest that the relative attractiveness of these products to such bidders could have the potential to create dominant firms, at least initially.

Our analysis leaves several fruitful directions for future research. One question raised by the above discussion is the role and incentives of regulated retail providers as bidders in the full-load auctions of other regulated providers. For example, instead of introducing its own full-load auctions, Direct Energy's most recent EPSP bases its RRO rate on the winning bids from EPCOR's auction (AUC, 2021). The effect of this change on Direct Energy's participation and bidding in other full-load auctions is a subject of future research.

A second direction for future research is a structural analysis of bidding in EPCOR's full-load auctions. Results in the current paper suggest that winning bids in these auctions exceed break-even levels. To understand this result further would require a structural model of bidding in these auctions, and an analysis of specific bids.

Third, our analysis abstracts from the impact of the full-load auction and its role in determining the regulated default product price on the broader competitive retail market. The regulated retail product serves nearly 45% of residential sales as of July 2021 (MSA, 2021c). Consequently, the pricing of the default product may impact the pricing decisions of competitive retailers. Fourth, while we discuss the potential role of experience and how it could explain our findings, we are unable to formally estimate the degree of learning and separate this from the impacts of market concentration on RRO auction outcomes. Future research that develops a structural model to evaluate the relative weight of these interrelated factors is warranted.[36]

[36]Dorazelski et al. (2018) develop an equilibrium framework to evaluate the effects of learning in a procurement auction setting. Similar methods could be employed in our context to formally quantify the role of learning in the full-load auctions.

# Appendix

## A Model with Risk-Aversion

We adjust our modeling framework to include risk-averse preferences. We employ a mean-variance utility function to represent preferences of the sellers that compete in the auction. This has been utilized broadly in the asset pricing and economics literature as a model of risk-aversion. For example, see Bessembinder and Lemmon (2002), Willems and Morbee (2010), and Aid et al. (2011). The expected utility of signing the forward contract type $j$ covering period $t$ is:

$$U_t^j \;=\; E[\pi_t^j] - \frac{A}{2}\, V(\pi_t^j) \tag{5}$$

where $A \geq 0$ is the risk-aversion parameter, $E[\,\cdot\,]$ represents expected value, and $V(\,\cdot\,)$ is the variance.

Recognizing that the quantity covered by the flat and peak products are time-invariant, (1) and (5) imply the break-even flat product price ($\overline{p}_F^F$) that yields zero expected utility over the $t$ periods covered by the contract is:

$$U^F \;=\; \sum_{t \in T} \left\{ E\left[\overline{p}_F^F\, q^F - S_t\, q^F\right] - \frac{A}{2}\, V\left(\overline{p}_F^F\, q^F - S_t\, q^F\right) \right\} \;=\; 0$$

$$\Rightarrow \quad \overline{p}_F^F \;=\; \frac{1}{|T|} \sum_{t \in T} \left\{ E[S_t] + \frac{A}{2}\, q^F\, V(S_t) \right\}. \tag{6}$$

where $|T|$ denotes cardinality of the set $T$. Similar calculations reveal that the break-even peak product price ($\overline{p}_F^P$) is:

$$\overline{p}_F^P \;=\; \frac{1}{|T_p|} \sum_{t \in T_p} \left\{ E[S_t] + \frac{A}{2}\, q^P\, V(S_t) \right\}. \tag{7}$$

(6) and (7) demonstrate that the presence of risk-aversion (i.e., $A > 0$) imposes a premium on these products that depends on the variance of spot market prices. This reflects the exposure to price-risk associated with the forward product because the financial contract is settled based on the difference between the pre-specified forward price and the realized spot price.

Using (1) and (5), the utility from purchasing a load-following forward product is defined by:

$$U^{LF} \;=\; \sum_{t \in T} \left\{ E[\, p_F^{LF}\, \alpha\, Q_t - S_t\, \alpha\, Q_t\,] - \frac{A}{2}\, V(\,[\, p_F^{LF} - S_t\,]\, \alpha\, Q_t\,) \right\}. \tag{8}$$

Using (8), the break-even full-load price ($\overline{p}_F^{LF}$) satisfies:

$$\sum_{t\in T} \left\{ E[\,\overline{p}_F^{LF}\,\alpha\,Q_t - S_t\,\alpha\,Q_t\,] - \frac{A}{2} V(\,[\,\overline{p}_F^{LF} - S_t\,]\,\alpha\,Q_t\,) \right\} \;=\; 0$$

$$\Leftrightarrow \quad \overline{p}_F^{LF} \sum_{t\in T} E[\,\alpha\,Q_t\,] - \sum_{t\in T} E[\,S_t\,\alpha\,Q_t\,] - \frac{A}{2} \sum_{t\in T} V(\,[\,\overline{p}_F^{LF} - S_t\,]\,\alpha\,Q_t\,) \;=\; 0. \tag{9}$$

The first term in (9) reflects the expected revenue in the forward market. The second term reflects the expected cost of the full-load product that has to be paid back at the prevailing spot market price ($S_t$). The third term reflects the variability in the payoff from holding a full-load product which now arises due to uncertainty in both the revenue ( $\overline{p}_F^{LF}\,\alpha\,Q_t$) and cost ($S_t\,\alpha\,Q_t$).

Since $S_t$ and $Q_t$ are dependent random variables and $\alpha$ and $p_F^{LF}$ are constants, the variance term in (9) can be written as:

$$\begin{aligned} V(\,[\,p_F^{LF} - S_t\,]\,\alpha\,Q_t\,) \;=\; V(\,p_F^{LF}\,\alpha\,Q_t - S_t\,\alpha\,Q_t\,) \;&=\; (p_F^{LF})^2\,(\alpha)^2\,V(Q_t) + \alpha^2\,V(S_t\,Q_t) \\ &\quad -2\,p_F^{LF}\,(\alpha)^2\,cov(Q_t, S_t\,Q_t). \end{aligned} \tag{10}$$

Using (10) and setting (9) equal to zero implies the break-even full-load price satisfies:

$$\sum_{t} \left\{ E[\,p_F^{LF}\,\alpha\,Q_t - S_t\,\alpha\,Q_t\,] - \frac{A}{2} V(\,[\,p_F^{LF} - S_t\,]\,\alpha\,Q_t\,) \right\} \;=\; 0$$

$$\begin{aligned} \Leftrightarrow \quad & p_F^{LF}\,\alpha \sum_{t} E[\,Q_t\,] - \alpha \sum_{t} E[\,S_t\,Q_t\,] \\ & \qquad -\frac{A}{2} \sum_{t} V(\,[\,p_F^{LF} - S_t\,]\,\alpha\,Q_t\,) \;=\; 0 \end{aligned}$$

$$\begin{aligned} \Leftrightarrow \quad & p_F^{LF}\,\alpha \sum_{t} E[\,Q_t\,] - \alpha \sum_{t} E[\,S_t\,Q_t\,] \\ & -\frac{A}{2} \sum_{t} \Big( (p_F^{LF})^2\,(\alpha)^2\,V(Q_t) + \alpha^2\,V(S_t\,Q_t) - 2\,p_F^{LF}\,(\alpha)^2\,cov(Q_t, S_t\,Q_t) \Big) \;=\; 0 \end{aligned}$$

$$\begin{aligned} \Leftrightarrow \quad & p_F^{LF}\,\alpha \sum_{t} E[\,Q_t\,] - \alpha \sum_{t} E[\,S_t\,Q_t\,] - \frac{A}{2}\,(p_F^{LF})^2\,(\alpha)^2 \sum_{t} V(Q_t) \\ & \qquad -\frac{A}{2}\,\alpha^2 \sum_{t} V(S_t\,Q_t) + A\,p_F^{LF}\,(\alpha)^2 \sum_{t} cov(Q_t, S_t\,Q_t) \;=\; 0 \end{aligned}$$

$$\Leftrightarrow \quad p_F^{LF} \sum_t E[\,Q_t\,] - \sum_t E[\,S_t\,Q_t\,] - \frac{A}{2}\,(p_F^{LF})^2\,\alpha \sum_t V(Q_t)$$

$$-\frac{A}{2}\,\alpha \sum_t V(S_t\,Q_t) + A\,p_F^{LF}\,\alpha \sum_t cov(Q_t, S_t\,Q_t) \;=\; 0$$

$$\Leftrightarrow \quad -\frac{A}{2}\,(p_F^{LF})^2\,\alpha \sum_t V(Q_t) + p_F^{LF}\left(\sum_t E[\,Q_t\,] + A\,\alpha \sum_t cov(Q_t, S_t\,Q_t)\right)$$

$$-\frac{A}{2}\,\alpha \sum_t V(S_t\,Q_t) - \sum_t E[\,S_t\,Q_t\,] \;=\; 0$$

$$\Leftrightarrow \quad H_2\,(p_F^{LF})^2 \;+ H_1\,p_F^{LF} \;+ H_0 \;=\; 0$$

where

$$\begin{aligned}
H_2 &\equiv\; -\frac{A}{2}\,\alpha \sum_t V(Q_t) \\
H_1 &\equiv\; \sum_t E[\,Q_t\,] + A\,\alpha \sum_t cov(Q_t, S_t\,Q_t) \\
H_0 &\equiv\; -\frac{A}{2}\,\alpha \sum_t V(S_t\,Q_t) - \sum_t E[\,S_t\,Q_t\,] \\
&=\; -\frac{A}{2}\,\alpha \sum_t V(S_t\,Q_t) - \left(\sum_t E[\,S_t\,]E[\,Q_t\,] + cov(Q_t, S_t)\right). \qquad (11)
\end{aligned}$$

We solve for the break-even $p_F^{LF}$ using the quadratic equation in (11). In particular, we need to expand the expressions $cov(Q_t, S_t\,Q_t)$ and $V(S_t\,Q_t)$ further in order to utilize the spot market and EPCOR demand regressions detailed in Section 5 to compute their values. To do so, we characterize several general statistical properties. Suppose $X, Y, u, v$ are all dependent random variables. Using equation (11) in Bohrnstedt and Goldberger (1969):

$$\begin{aligned}
Cov(XY, uv) \;=\;& E[X]\,E[u]\,Cov(Y, v) + E[X]\,E[v]\,Cov(Y, u) \\
&+E[Y]\,E[u]Cov(X, v) + E[Y]\,E[v]Cov(X, u) - Cov(X, Y)\,Cov(u, v) \\
&+E\Big[\,(x - E[X])\,(Y - E[Y])\,(u - E[u])\,(v - E[v])\,\Big] \\
&+E[X]\,E\Big[\,(Y - E[Y])\,(u - E[u])\,(v - E[v])\,\Big]
\end{aligned}$$

$$
\begin{aligned}
&+E[Y]\,E\Big[\,(X-E[X])\,(u-E[u])\,(v-E[v])\,\Big] \\
&+E[u]\,E\Big[\,(X-E[X])\,(Y-E[Y])\,(v-E[v])\,\Big] \\
&+E[v]\,E\Big[\,(X-E[X])\,(Y-E[Y])\,(u-E[u])\,\Big]. \qquad (12)
\end{aligned}
$$

Suppose $X$ and $Y$ are two dependent random variables. It is well documented that:

$$
\begin{aligned}
V(XY) &= E[X^2\,Y^2]-(E[X\,Y])^2 = E[X^2]\,E[Y^2]+Cov(X^2,Y^2)-(E[X]\,E[Y]+Cov(X,Y))^2 \\
&= \big(V(X)+(E[X])^2\big)\,\big(V(Y)+(E[Y])^2\big)+Cov(X^2,Y^2)-(E[X]\,E[Y]+Cov(X,Y))^2\,. \qquad (13)
\end{aligned}
$$

Suppose $X=Y=S_t$ and $u=v=Q_t$. (12) implies:

$$
\begin{aligned}
Cov(S_t^2,Q_t^2) &= E[S_t]\,E[Q_t]\,Cov(S_t,Q_t)+E[S_t]\,E[Q_t]\,Cov(S_t,Q_t) \\
&\quad +E[S_t]\,E[Q_t]Cov(S_t,Q_t)+E[S_t]\,E[Q_t]Cov(S_t,Q_t)-Cov(S_t,S_t)\,Cov(Q_t,Q_t) \\
&\quad +E\Big[\,(S_t-E[S_t])\,(S_t-E[S_t])\,(Q_t-E[Q_t])\,(Q_t-E[Q_t])\,\Big] \\
&\quad +E[S_t]\,E\Big[\,(S_t-E[S_t])\,(Q_t-E[Q_t])\,(Q_t-E[Q_t])\,\Big] \\
&\quad +E[S_t]\,E\Big[\,(S_t-E[S_t])\,(Q_t-E[Q_t])\,(Q_t-E[Q_t])\,\Big] \\
&\quad +E[Q_t]\,E\Big[\,(S_t-E[S_t])\,(S_t-E[S_t])\,(Q_t-E[Q_t])\,\Big] \\
&\quad +E[Q_t]\,E\Big[\,(S_t-E[S_t])\,(S_t-E[S_t])\,(Q_t-E[Q_t])\,\Big] \\
&= 4\,E[S_t]\,E[Q_t]\,Cov(S_t,Q_t)-V(S_t)\,V(Q_t) \\
&\quad +E\Big[\,(S_t-E[S_t])^2\,(Q_t-E[Q_t])^2\,\Big] \\
&\quad +2\,E[S_t]\,E\Big[\,(S_t-E[S_t])\,(Q_t-E[Q_t])^2\,\Big] \\
&\quad +2\,E[Q_t]\,E\Big[\,(S_t-E[S_t])^2\,(Q_t-E[Q_t])\,\Big]. \qquad (14)
\end{aligned}
$$

(13) and (14) imply:

$$
V(S_t\,Q_t) = \big(V(S_t)+(E[S_t])^2\big)\,\big(V(Q_t)+(E[Q_t])^2\big)+Cov(S_t^2,Q_t^2)-(E[S_t]\,E[Q_t]+Cov(S_t,Q_t))^2
$$

$$
\begin{aligned}
= \;& \left(V(S_t) + (E[S_t])^2\right)\left(V(Q_t) + (E[Q_t])^2\right) - \left(E[S_t]\, E[Q_t] + Cov(S_t, Q_t)\right)^2 \\
& +4\, E[S_t]\, E[Q_t]\, Cov(S_t, Q_t) - V(S_t)\, V(Q_t) \\
& +E\Bigg[ (S_t - E[S_t])^2 (Q_t - E[Q_t])^2 \Bigg] \\
& +2\, E[S_t]\, E\Bigg[ (S_t - E[S_t])\, (Q_t - E[Q_t])^2 \Bigg] \\
& +2\, E[Q_t]\, E\Bigg[ (S_t - E[S_t])^2 (Q_t - E[Q_t]) \Bigg]. \qquad (15)
\end{aligned}
$$

Suppose $X = 1, Y = Q_t, u = S_t, v = Q_t$. Using (12) and recognizing that $E[X] = 1$, $E[\, X - E[X]\,] = 0$, and $Cov(X, v) = Cov(X, u) = Cov(X, Y) = 0$ because $X$ is a constant implies:

$$
\begin{aligned}
Cov(Q_t, S_t\, Q_t) \;=\;& E[S_t]\, Cov(Q_t, Q_t) + E[Q_t]\, Cov(Q_t, S_t) \\
& + E\Bigg[ (Q_t - E[Q_t])\, (S_t - E[S_t])\, (Q_t - E[Q_t]) \Bigg] \\
=\;& E[S_t]\, V(Q_t) + E[Q_t]\, Cov(Q_t, S_t) \\
& + E\Bigg[ (Q_t - E[Q_t])^2\, (S_t - E[S_t]) \Bigg]. \qquad (16)
\end{aligned}
$$

We utilize (11), (15), and (16) to characterize the break-even LF price with risk-aversion. In particular, we compute the expected value and variance expressions using our spot market price and EPCOR demand equations detailed in Section 5. To estimate the variance terms, for each month, we compute the squared difference between the predicted and observed price and average these by hour to give us hourly price and demand variances. The objective of this approach is to capture the strong seasonal patterns we observe in the variance values of these random variables. As we discuss in detail in Section 5, this approach utilizes realized prices and demand to compute these measures. We carry out the robustness checks detailed for the covariance term in Section 5 to compute the variance and covariance terms required to solve for the full-load break-even price under risk-aversion detailed in (11). These results are presented in Tables A4 and A5.

In order to compute the break-even full-load product price in (11), we also need to estimate the risk-aversion parameter $A$. We estimate the degree of risk-aversion $A$ of the sellers in EPCOR's RRO auction by utilizing the difference between the market-clearing prices for the flat and peak products. We assume that the flat and peak products trade at their break-even levels. Unlike the full-load product, these products have been traded on the broader financial exchange market (i.e., the NGX) for several decades and the RRO auctions since 2011. To defend this assumption, we compare the RRO flat and peak prices to the prices of these products on the broader financial exchange prior to each RRO auction.[37] The difference between the RRO flat and peak prices and

[37]More specifically, we compare the RRO flat and peak prices to the last traded flat and peak price transactions on

NGX prices are \$0.51/MWh and \$0.54/MWh on average representing a 0.95% and 0.79% difference in the prices, respectively. The minimal difference in prices on these products helps demonstrate the competitiveness of these products on EPCOR's RRO auction.

The general idea behind using the difference between the market-clearing flat and peak products to estimate the risk-aversion parameter is the following. These products are for a fixed quantity (i.e., 5 MWhs) for all days of the month, but differ in the hours they cover. The peak forward product covers hours with a higher expected spot price level and variance.[38] This helps explain the higher price on the peak versus the flat product. Importantly, as shown in (6) and (7), the presence of risk-aversion adds on a premium on the peak and flat products that varies with $A$ and is dependent on the variance of the spot market price. The higher the degree of risk-aversion, the more sensitive the firm will be to the higher spot price variance in peak hours and as a result, the higher the value on the peak price relative to the flat price. We estimate the $A$ parameter that is consistent with the price differential across the flat and peak product, controlling for differences in the expected spot price level and variance covered by the two products.

More formally, using (6), (7), and that the flat and peak products are the same size (i.e., $q^P = q^F$), the difference in the observed peak and flat product prices can be written as:

$$p_F^P - p_F^F \;=\; \frac{1}{|T_p|} \sum_{t \in T_p} \left\{ E[S_t] + \frac{A}{2}\, q^P\, V(S_t) \right\} - \frac{1}{|T|} \sum_{t \in T} \left\{ E[S_t] + \frac{A}{2}\, q^F\, V(S_t) \right\}$$

$$\Rightarrow \quad \left( p_F^P - \frac{1}{|T_p|} \sum_{t \in T_p} E[S_t] \right) - \left( p_F^F - \frac{1}{|T|} \sum_{t \in T} E[S_t] \right) \;=\; \frac{A}{2}\, q^P \left( \frac{1}{|T_p|} \sum_{t \in T_p} V(S_t) - \frac{1}{|T|} \sum_{t \in T} V(S_t) \right) \tag{17}$$

where the first and second terms on the left-hand side reflect the difference between the peak and flat forward prices and the time-weighted expected peak and flat spot prices, respectively. These two terms capture the relative markup of the forward market prices above their respective average expected spot prices. The term on the right-hand side captures the difference in the time-weighted wholesale market price variances. This term captures the relative difference in the exposure to price risk during the peak and flat contract periods.

We utilize data on market-clearing forward prices for the peak and flat products across the various EPCOR RRO auctions in our data set, and empirical estimates on the expected spot price levels and variances (discussed below) to estimate equation (17) via a regression analysis. In particular, the terms on the left-hand side reflect the dependent variable. The independent variable is equal to the difference between the peak and flat time-weighted spot market price variances.

the NGX. We also compared the RRO prices to the quantity-weighted average NGX flat and peak prices for the 15 and 30 days prior to the RRO auction yielding analogous conclusions.

[38] Recall that the flat product covers all hours of the day, while the peak product only covers a subset of hours from 7:00 AM - 11:00 PM. The average ratio of the peak-to-off-peak expected spot price and variance are 1.15 and 1.38, respectively.

The coefficient estimate in the regression equation allows us to back out our estimate on $A$ (i.e., $\widehat{\beta} = \frac{A}{2}\, q^p$).

# B Results Under Risk-Aversion

The average estimated break-even prices under risk aversion, and associated risk margins, are reported in Table A1, along with the average observed prices are risk-neutral break-even prices from Table 2 for comparison.

Table A1: Average Observed and Estimated Break-Even Forward Prices - Risk-Aversion

| Product | Observed | Break-Even | Risk-Averse | Risk Margin |
|---|---|---|---|---|
| Flat | 55.86 | 58.20 | 58.76 | 0.56 |
| Peak | 67.44 | 67.07 | 67.88 | 0.81 |
| Full-Load | 66.48 | 61.78 | 62.42 | 0.64 |

Notes. Break-Even represents the estimated risk-neutral break-even flat, peak, and full-load prices from (2) and (3). Risk-Averse represents the break-even values with risk-aversion for the flat, peak, and full-load detailed in (6), (7), and (11). Risk Margins reflect the risk-averse minus risk-neutral break-even prices.

For each forward product, the estimated (risk-averse) break-even prices exceed the risk-neutral prices. This is driven by the fact that we find a positive risk-aversion parameter $A$ using the methodology detailed in (17).[39] For the flat and peak products, the risk-averse break-even price is larger than its risk-neutral counterpart by \$0.56 and \$0.81 per MWh on average, respectively. These results demonstrate that there is a relatively modest estimated risk margin (premium) for these products. Looking at the full-load product, we also observe a small increase in the estimated break-even price. This yields a risk-margin of \$0.64/MWh on average that lies between the flat and peak risk-margins. Importantly, the observed full-load price is \$4.06/MWh higher than the estimated risk-averse break-even full-load price on average. This demonstrates that risk-aversion explains only a small portion of the difference between the observed and risk-neutral full-load price.

Interestingly, Table A1 demonstrates that the estimated full-load product's observed and break-even risk-averse values lie between the flat and peak products. It is clear from an *ex-ante* perspective that in the presence of risk-aversion, the full-load price would exceed the price of the flat product because it covers the same hours (i.e., all hours of the day) but entails greater risk due to the uncertainty in the quantity covered by the contract. However, it is not clear *ex-ante* that the full-load price would be below the peak price. In fact, Figure 2 demonstrates that the full-load price is closely aligned with and sometimes above the peak price in EPCOR's RRO auctions. The peak product only covers a subset of hours of the day with higher average spot price levels and

[39] More specifically, our estimated $\widehat{A} = 0.00004182$. While this estimated value is small in magnitude, it is important to recognize that this parameter is multiplied by the variance in expected profits (i.e., recall (5)). In our sample, this variance is large in magnitude leading to a non-trivial effect on expected utility.

volatility, but it does not entail the quantity risk associated with the full-load product.[40]

Finally, we can compare the Commodity Risk Compensation awarded to EPCOR to the CRC based on the same formula, but using the risk-averse break-even flat, peak, and full-load prices from our analysis. These results are presented in Table A6. The results parallel those in the risk-neutral setting summarized in Section 6.1. As expected, the CRC values in the risk-averse setting increase when compared to the risk-neutral CRC values. This arises because of the (small) risk-premia. However, the key conclusions remain. The risk-averse CRC values arising from our analysis are considerably below the value observed in EPCOR, and are more closely aligned with Direct Energy's CRC. These results continue to support the evidence from the main analysis that the full-load price determined in EPCOR's auction exceeded the break-even value and resulted in an elevated CRC.

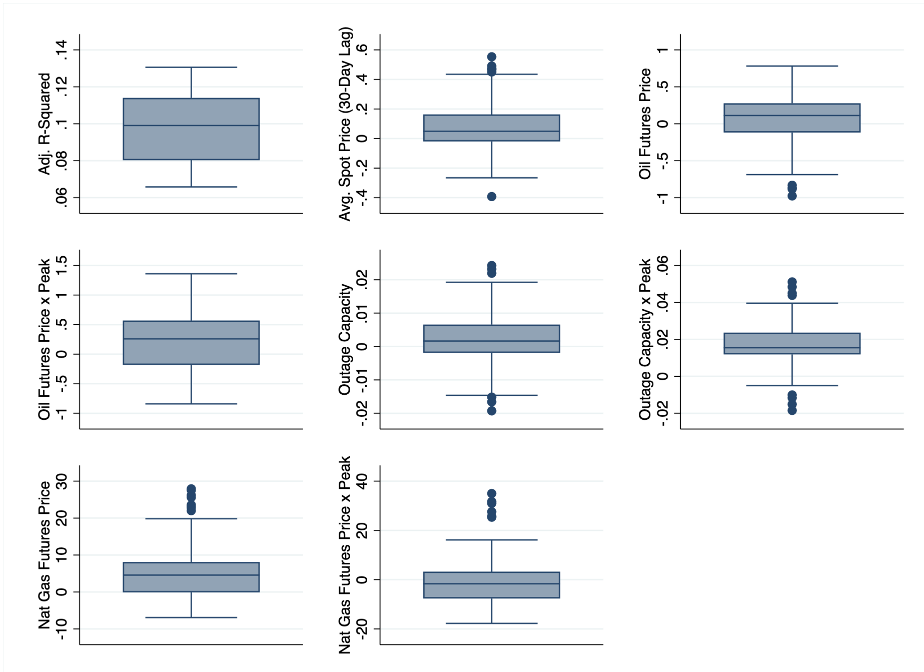
We rerun the robustness checks discussed in our main analysis (see Section 5) in the setting under risk-aversion. First, we include the months of January 2020 and February 2021 which were excluded from the main analysis. Second, we remove RRO auctions that occurred in March, April, and May of 2020 during the initial wave of the Covid pandemic. In these months, there was considerable uncertainty regarding future wholesale market prices and electricity demand. Third and fourth, as discussed in Section 5, we also compute the variance and covariance measures averaged at the monthly level across all years in our sample and as the average of their observed values 11, 12, and 13 months prior to each RRO auction. These results are presented in order in Tables A2 – A5.

While the precise estimates can vary, these results demonstrate that our qualitative conclusions are robust to these alternative samples and approaches. In particular, we find that the average difference between the cost-adjusted risk-averse full-load and flat prices demonstrated in Figure 5 range from \$5.18/MWh to \$7.74/MWh across the full sample in these robustness checks. Further, the finding that this margin falls over the sample is robust to different specifications. Across the robustness checks, we find an average difference of \$7.47/MWh to \$9.55/MWh in the early sample (April 2019 - March 2020) which declines to \$2.89/MWh to \$5.16/MWh in the latter sample period (April 2020 - March 2021). For each of these robustness checks, our qualitative conclusions regarding the Commodity Risk Compensation, that EPCOR's CRC based on auction-clearing rates is more than double both the regulated CRC given to Direct Energy and the rates based on our model estimated risk-averse and risk-neutral break-even forward prices, persists (See Table A6).

[40]Using Table A1, even if we assume the risk-premium on the full-load product is as high as the peak product's risk-premium, the difference between the observed average full-load price and the risk-averse break-even full-load price is sizable at \$3.25/MWh (i.e., the observed full-load price (\$66.48) minus the risk-neutral break-even full-load price (\$62.42) minus the peak risk-premium (\$0.81)).

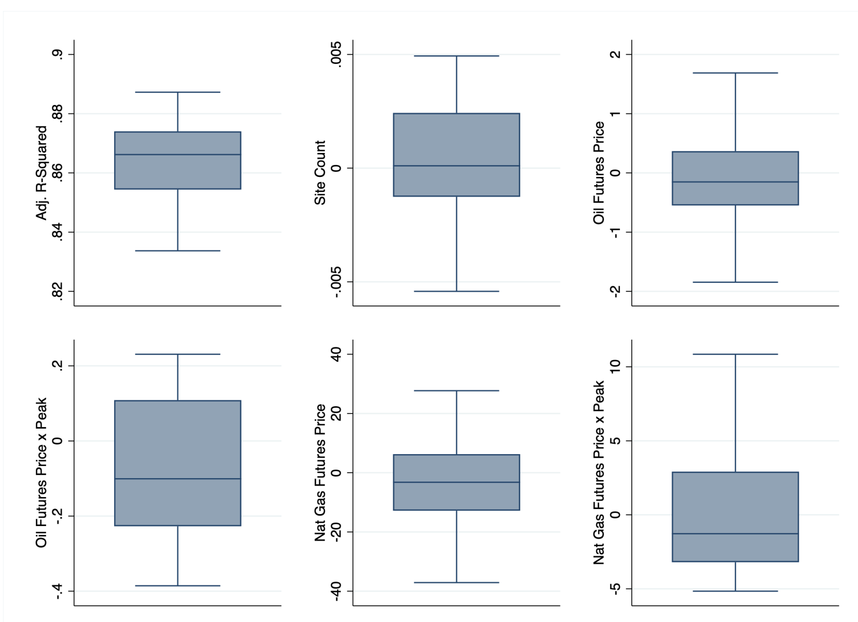
# C Additional Results

Figure A1: Distribution of Key Coefficients from Price Regressions




Notes: The box represents the inner quartile range with the median value being represented by the interior line. The 5th and 95th percentiles are represented by the bottom and top lines. Dots represent outliers.

Figure A2: Distribution of Key Coefficients from Demand Regressions




Notes: The box represents the inner quartile range with the median value being represented by the interior line. The 5th and 95th percentiles are represented by the bottom and top lines. Dots represent outliers.

Figure A1 demonstrates that lagged average spot price, oil futures prices, and natural gas futures prices tend to have a positive effect on spot prices. The effect of oil futures prices are magnified in peak hours. While the coefficients on these variables can be negative in a subset of regressions, we find that these estimates are systematically statistically insignificant. The expected outage capacity variable tends to be statistically insignificant, but when interacted with a peak hour dummy it is often significant and positive taking on the expected sign. The adjusted R-squared value ranges from 0.06 to 0.13. This value is consistent with the high degree of variability observed in hourly prices, and the fact that our regressions aim to establish month-ahead expectations on spot prices using only covariates that were observed months prior to the realization of spot market outcomes. However, as shown in Figure 4, we fit hourly average prices reasonably well.

Figure A2 demonstrates that we fit EPCOR demand quite well with adjusted R-squared values ranging from 0.835 to 0.89. We find that the site count, oil futures price, and the natural gas futures price variables are systematically statistically insignificant and distributed around zero. These findings suggest that EPCOR's demand patterns are primarily driven by seasonal and hourly variation that are picked up by the calendar control variables.

Table A2: Average Observed and Estimated Forward Product Prices - EPCOR's RRO Auction - Including Outlier Months January 2020 and February 2021

| Product | Observed | Break-Even | Risk-Aversion | Risk Margin |
|---|---|---|---|---|
| Flat | 56.80 | 58.66 | 60.83 | 2.17 |
| Peak | 68.54 | 67.35 | 70.47 | 3.12 |
| Full-Load | 67.60 | 63.70 | 66.45 | 2.74 |

Notes. Break-Even represents the estimated risk-neutral break-even flat, peak, and full-load prices from (2) and (3). Risk-Averse represents the break-even values with risk-aversion for the flat, peak, and full-load detailed in (6), (7), and (11). Risk Margins reflect the risk-averse minus risk-neutral break-even prices. Results include outlier months of January 2020 and February 2021.

Table A3: Average Observed and Estimated Forward Product Prices - EPCOR's RRO Auction - Remove March, April, and May 2020 Auctions

| Product | Observed | Break-Even | Risk-Aversion | Risk Margin |
|---|---|---|---|---|
| Flat | 57.63 | 58.94 | 61.03 | 2.10 |
| Peak | 69.79 | 66.94 | 69.97 | 3.03 |
| Full-Load | 68.82 | 62.15 | 64.48 | 2.33 |

Notes. Break-Even represents the estimated risk-neutral break-even flat, peak, and full-load prices from (2) and (3). Risk-Averse represents the break-even values with risk-aversion for the flat, peak, and full-load detailed in (6), (7), and (11). Risk Margins reflect the risk-averse minus risk-neutral break-even prices. Results remove observations that were determined in RRO auctions held in March, April, and May 2020.

Table A4: Average Observed and Estimated Forward Product Prices - EPCOR's RRO Auction - Variance and Covariance Measures Averaged by Month

| Product | Observed | Break-Even | Risk-Aversion | Risk Margin |
|---|---|---|---|---|
| Flat | 55.86 | 58.20 | 58.31 | 0.11 |
| Peak | 67.44 | 67.07 | 67.23 | 0.16 |
| Full-Load | 66.48 | 62.50 | 62.65 | 0.15 |

Notes. Break-Even represents the estimated risk-neutral break-even flat, peak, and full-load prices from (2) and (3). Risk-Averse represents the break-even values with risk-aversion for the flat, peak, and full-load detailed in (6), (7), and (11). Risk Margins reflect the risk-averse minus risk-neutral break-even prices. These results represent the approach where variance and covariance measures are averaged across all years at the monthly level.

Table A5: Average Observed and Estimated Forward Product Prices - EPCOR's RRO Auction - Variance and Covariance Measures (11, 12, 13 Month Lagged)

| Product | Observed | Break-Even | Risk-Aversion | Risk Margin |
|---|---|---|---|---|
| Flat | 55.86 | 58.20 | 59.72 | 1.52 |
| Peak | 67.44 | 67.07 | 69.27 | 2.20 |
| Full-Load | 66.48 | 61.78 | 63.90 | 2.12 |

Notes. Break-Even represents the estimated risk-neutral break-even flat, peak, and full-load prices from (2) and (3). Risk-Averse represents the break-even values with risk-aversion for the flat, peak, and full-load detailed in (6), (7), and (11). Risk Margins reflect the risk-averse minus risk-neutral break-even prices. These results represent the approach where variance and covariance measures are set equal to the average of their realized values 11, 12, and 13 months ago.

Table A6 reports, for our primary specification and for each of the robustness checks reported in Section 6.1, four different measures of average Commodity Risk Compensation over our sample period: the average observed CRC awarded to Direct Energy, the average observed EPCOR CRC using auction-clearing prices for full-load, flat and peak contracts, and the simulated CRCs using the estimated risk-neutral and risk-averse prices for full-load, flat, and peak contracts via our model. While precise magnitudes vary, we find that for all specifications the observed EPCOR CRC using auction-clearing prices substantially exceeds both the CRC awarded to Direct Energy, and the simulated CRCs using risk-neutral or risk-averse break-even forward prices. The simulated CRCs prices fall below Direct Energy's observed CRC for all specifications except for the second row, which includes the outlier months of January 2020 and February 2021.

Table A6: Commodity Risk Compensation - Summary of Results

| Specification | Direct Energy Observed | EPCOR Observed | EPCOR Risk-Neutral | EPCOR Risk-Averse |
|---|---|---|---|---|
| Main Specification | 3.10 | 8.49 | 1.93 | 1.97 |
| Include Outlier Months | 3.17 | 8.69 | 3.45 | 3.86 |
| Remove Covid Months | 3.10 | 8.71 | 1.85 | 2.01 |
| Var-Cov. - Average by Month | 3.10 | 8.49 | 2.65 | 2.68 |
| Var-Cov. - Lagged Window | 3.10 | 8.49 | 1.93 | 2.40 |

Notes. Direct Energy Observed reflects Direct Energy's realized CRC set via regulation. Observed, Risk-Neutral, and Risk-Averse reflects EPCOR's CRC calculated using observed, model estimated risk-neutral break-even, and model estimated risk-averse break-even flat, peak, and full-load prices, respectively. Main Specification represents the results for the model specification reported in the text. Include Outlier Months includes January 2020 and February 2021. Remove Covid Months drops RRO auctions that occurred in the initial wave of Covid. Var-Cov. - Average by Month and Var-Cov. - Lagged Window are our third and fourth robustness checks listed in Section 6.1 that consider alternative methods for computing the variance and covariance measures.

Table A7: HHI by Product and Year

| Product | 2019 | 2020 | 2021 |
|---|---|---|---|
| Peak | 1,937 | 2,535 | 2,575 |
| Flat | 2,174 | 2,083 | 2,481 |
| Full-Load | 2,744 | 2,259 | 2,146 |

EPCOR's RRO auction is a descending clock auction where there is a sequence of rounds and a posted price in each round. The posted price declines until the auction clears where supply and demand are balanced for each product. Consequently, it is informative to not only look at the level on the number of bidders competing, but also how the number of active bidders varies as the auction progresses.

Figure A3 presents the average number of active bidders per unit by auction round for each product. The vertical lines indicate the average number of auction rounds before the auction clears for each product. The number of active bidders can increase as rounds progress because bidders can adjust the quantity they offer in one of the three products upward (e.g., from 0 to a positive number) as the relative prices change across the three products (NERA, 2017).[41]

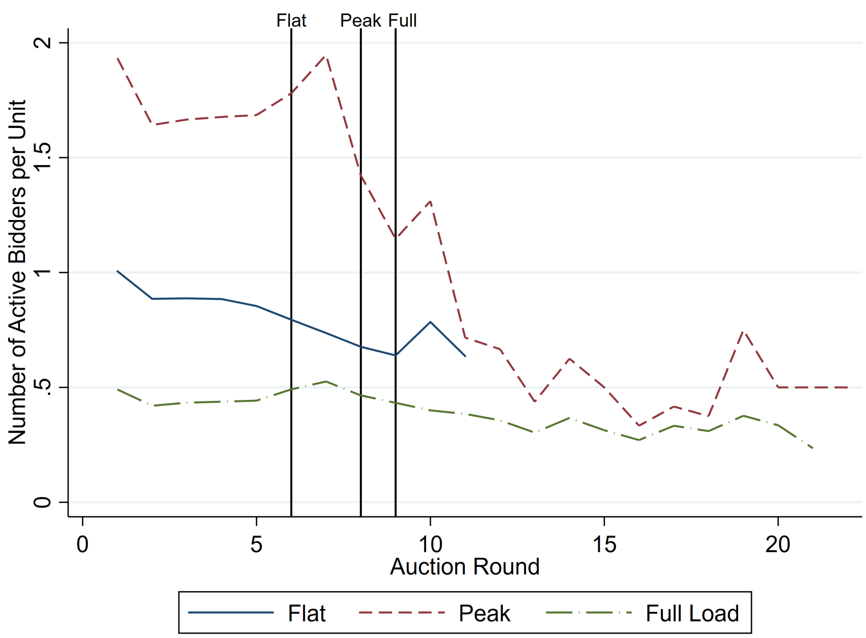



Figure A3: Average Number of Bidders by Auction Round and Product.

Figure A3 demonstrates that the peak product has the most active bidders per unit for all auction rounds followed by the flat and then full-load products. For the flat and full-load products, the number of active bidders are quite stable as the number of rounds progress. There is a larger

[41]In addition, as the number of rounds increase, fewer auctions are "active". As a result, when calculating the average number of bidders in a given round, the averaging is being done over a different sample of auctions. This can cause the average number of bidders to increase as auctions with a lower number of average bidders drop off because the auction ends.

decline in the average number of active bidders per unit for the peak product, but it remains higher for nearly every auction round. The full-load product is typically the last product to clear as its average number of auction rounds before clearing is 9. This contrasts with only 6 rounds for the flat and 8 rounds for the peak product.

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