Product Design in FTR Markets: Contract Tenor, Market Thickness, and Efficiency

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Abstract

Financial transmission rights (FTRs) are contracts issued by operators of deregulated energy markets for the purpose of creating firm transmission rights and allocating congestion revenues to market participants. This paper explores how the granularity of FTR contracts affects allocative efficiency, given the incentives of financial participants. With shorter contracts, it is feasible for generators and electricity customers ("load") to obtain better hedging portfolios for anticipated congestion. However, if narrow contracts reduce financial participation, inframarginal financial participants can demand greater risk premia, leading to welfare losses for load firms (who are residual claimants on auction revenues). To quantify this tradeoff I build and estimate an empirical model of financial participation in the Midcontinent ISO (MISO) FTR auction. The model estimates imply that switching from three-month to annual contracts could potentially benefit load firms in MISO by inducing greater competition among financial participants.

1 Introduction

In a decentralized electricity market, scarce transmission resources are allocated by an impartial market operator on the basis of supply and demand. While this market design is believed to bring substantial benefits to consumers, it also introduces a number of inefficiencies. For example, uncertainty regarding the availability of transmission capacity can increase the cost of contracting between wholesale producers and their customers, reducing investment. FTR markets are intended to alleviate this friction by enabling firms to hedge against congestion risk, among other purposes.

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Formally, an FTR is a forward contract on network congestion between two nodes during a specified time period. Market operators in the United States (known as independent service organizations or ISOs) currently issue FTR contracts with a net value of about $5B each year. While the mechanisms used to allocate FTRs are broadly similar across ISOs, the characteristics of typical FTR contracts vary widely.

One particularly important dimension of an FTR is its *granularity* (or tenor) at the time of allocation. In some markets, standard contracts are as short as a month (as in SPP), and only encompass narrowly defined times of use (e.g., peak hours on weekends in ERCOT). In other markets, standard contracts are six months or a year in length, and may not be subdivided by time of use (as in NYISO).

FTR contract granularity affects generators, retailers, and other physical transmission customers on two key margins. When contracts are shorter, the set of feasible FTR portfolios becomes larger, enabling *load firms* to obtain improved hedging portfolios. On the other hand, excessively short (or long) contracts can potentially degrade market thickness in the ISO's FTR auction, leading to soft prices. Load firms are the residual claimants on auction revenues, and therefore suffer from uncompetitive auctions.

This paper considers how an ISO should design FTR contracts to balance the tradeoff between hedging flexibility and auction revenues. Section 2 presents a simple model in which load firms have delivery obligations that vary seasonally. The ISO permits load firms to directly claim FTRs. Potential speculators then enter and compete to purchase "residual" FTRs in an auction. The extent of competition in the FTR auction can depend on factors such as the risk profile of residual FTR capacity and the fixed costs of bidding. Load firms are the residual claimants on auction revenues. Depending on expected auction prices, risk averse load firms may prefer longer FTR contracts even though shorter, more granular contracts enable more precise hedging against congestion risk.

In order to quantify this tradeoff, I analyze the structure and performance of the Midcontinent ISO (MISO) FTR market. Currently, MISO allocates 3-month FTR contracts by default, with separate contracts for peak and off-peak hours. I build and estimate a simple structural model to predict whether consumers would benefit from eliminating 3-month contracts in favor of an annual contract design. Notably, the model features a stylized but tractable model of speculator participation and bidding that distinguishes this paper from prior work. The framework that I develop is potentially useful for investigating other market design questions in FTR markets, which have received limited attention in the economics literature.

The key economic primitives required for evaluating alternative contract granularities include market participants' congestion forecasts, risk preferences, and participation costs.

I combine a stylized model of participation and bidding with FTR auction price data and realized congestion prices to recover these primitives. Notably, I recover market participants' congestion forecasts from variation in observed FTR auction prices, avoiding the need to directly simulate congestion. To do so I exploit the structural linkage between FTR auction prices on electrically related FTR paths to significantly reduce the dimension of the inference problem.

Counterfactual simulations suggest that auction revenues are 20-30% lower under a 3-month contract design than under an annual contract design. Load firms' benefit from reduced risk exposure under a 3-month contract design, but this benefit may not outweigh lost auction revenues unless risk preferences are relatively high. This finding may help to rationalize the continued use of long-tenored contracts in the PJM and NYISO FTR markets.

The remainder of this section provides additional background on financial transmission rights and clarifies the contribution of this paper. Section 2 develops a simple theoretical model to illustrate the tradeoffs associated with contract granularity. Section 3 introduces the MISO FTR market. Sections 4 and 5 discuss the empirical model and estimation strategy, respectively. Sections 6 and 7 present the model estimates and counterfactual analysis.

1.1 Related literature

A significant body of empirical work studies the efficiency of FTR auctions using auction data. Bartholomew et al. (2003) first documented apparent underpricing in the NYISO TCC market. Similar results have been obtained in other FTR markets Olmstead (2018); CAISO (2016). Motivated by these empirical findings, Leslie (2021) analyzes the role of financial speculation in the NYISO TCC market. Other researchers have estimated asset pricing models from FTR returns Baltadounis et al. (2017); Patiño-Echeverri and Morel (2006). In comparison to this literature, I propose a structural empirical model that can be used to predict prices and other market outcomes under alternative product designs and other policy interventions.

Another body of research formulates and in some cases provides numerical simulations of equilibrium models of energy markets that include FTRs. Bautista Alderete (2005) considers FTR auction environments with market power, as well as environments with multiple auction rounds and multiple contract periods, among other concerns. de Maere d' Aertrycke and Smeers (2013) consider a model in which risk averse agents can purchase FTRs in an illiquid financial market. Risanger and Mays (2024) develop a stochastic equilibrium model of project finance that endogenizes FTR trading. Unlike these papers, I do not model cross-market interaction between the FTR market and the energy market. However, the model I propose has a unique and easily computed equilibrium even when the number of nodes is large, greatly simplifying estimation and counterfactual simulation.

Several authors have considered the problem of portfolio construction in FTR markets from the perspective of a single agent (either a load firm or a speculator). Some examples include Acre et al. (2004b), Acre et al. (2004a), Li and Shahidehpour (2005), Babayiğit et al. (2010), Apostolopoulou et al. (2013), and Zheng et al. (2022). This literature does not address the question of how FTR prices arise in equilibrium, the central concern of this paper.

Recent work in economics has evaluated the role of financial participants in deregulated electricity markets, primarily in the context of virtual bidding (a setting which is largely distinct from FTR markets). Jha and Wolak (2023) find evidence that virtual bidding by financial traders improves price discovery and market efficiency in CAISO. Mercadal (2022) finds that virtual bidding by financial traders reduced generator's market power in MISO. In contrast, Birge et al. (2018) finds that financial traders use virtual bidding to influence the value of their FTR positions. This type of (potentially manipulative) behavior falls outside the scope of my analysis.

Separately, many authors in empirical industrial organization have implicitly or explicitly considered the role of product design in auction markets. Some examples include: Lewis and Bajari (2014) who consider the role of deadlines and penalties in procurement auctions; Allen et al. (2022) who analyze the role of contract tenor in Treasury auctions; and Bhattacharya et al. (2022) who study royalties in oil lease auctions. Hendricks and Porter (2015) provide a broader discussion of product design in auctions.

2 Contract tenor and market thickness

Congestion costs are an inherent feature of the design of decentralized electricity markets. Due to the scarcity of transmission capacity, marginal demand for electricity at any particular node in the network cannot typically be satisfied with generation from the next lowest cost producer. When a firm withdraws electricity at a particular node, it pays a *locational marginal price*, which is the price at which the local supply and demand for electricity cross given the current availability of transmission capacity.

As a consequence of this design, arms-length and vertically integrated supply commitments from generation assets to electricity customers are subject to significant *congestion risk*, since the price received by the generator at the "source" node generally differs from the price paid by customers at the "sink" node. When congestion is severe, this dislocation in prices can be significant ($100 per MWh or more).

As a result of this market design, market operators accrue large congestion revenue surpluses. Market operators (which are non-profit entities) define and allocate property rights known as *financial transmission rights* both to distribute this surplus and to enable firms to hedge against congestion risk. An FTR is a financial contract that pays the accumulated hourly difference in locational prices between two nodes in the network during a specified period of time. With an appropriate portfolio of FTR contracts, a load firm can perfectly hedge against congestion risk on contractually obligated deliveries that are known in advance. In this way, FTRs enable firms to engage in long term contracting *as if* they owned exclusive physical transmission rights.[1]

FTRs can be allocated directly to firms or sold in an auction. In practice, US ISOs use a combination of direct allocation and auctions. The total quantity of FTRs is intended to correspond to the physical capacity of the system, which ensures that the market operator remains budged balanced (Hogan, 1992). To achieve this objective, the ISO may need to allocate more FTR capacity than load firms wish to claim. Financial speculators are allowed to purchase FTRs in the auction both to absorb this residual supply, and, more generally, to ensure that auction prices are competitive and informative.

The following example highlights a key tradeoff faced by market operators when designing and allocating FTRs.

2.1 Tradeoff between hedging flexibility and auction revenues

Consider two nodes in an electricity grid, G and L, linked by a single transmission line with capacity K:

Suppose firm g has a long term contract to inject electricity at G and withdraw electricity at L. The contract volume is $e_S < K$ in the summer and $e_W < K$ in the winter.

The electricity grid has many nodes and many transmission lines. The market operator determines the price of electricity at each node to balance supply and demand throughout the network. Individual nodes and lines are small in comparison to the network as a whole. Thus, from a local perspective, the market operator sets an exogenous unit price ρ_G for each unit of capacity injected at G and an exogenous unit price ρ_L for each unit of capacity withdrawn at L. When g uses the grid to transmit electricity from G to L, she pays the the market operator the difference in prices $\pi \equiv \rho_L - \rho_G$, which is known as a *congestion*

[1] Unlike in a system of physical transmission rights, however, firms have no incentive or ability to prevent network capacity from being fully utilized in the exercise of market power (Joskow and Tirole, 2000).

price. Suppose π is stochastic and varies depending on the season. The joint distribution of summer and winter congestion costs is $(\pi_S, \pi_W) \sim F$. According to her planned usage, g anticipates paying the market operator congestion fees totaling $\pi_S e_S + \pi_W e_W$ at year end.

If the transmission line between G and L is always fully utilized, then the market operator will collect congestion revenues equal to $R_S = K\pi_S$ in the summer and $R_W = K\pi_W$ in the winter, where R_S and R_W are random variables. A financial transmission right is a tradable property right to a pre-defined share of future congestion revenues $R_S + R_W$.

Financial transmission rights are inherently divisible and can always be divided in the secondary market. However, the market operator can choose a standard contract granularity for the initial allocation of FTRs. In this example, there are two relevant possibilities: either the market operator can define *annual* FTRs, which are rights to shares of $R_S + R_W$, or he can define separate *seasonal* FTRs, which are separate rights to summer congestion revenues R_S and winter congestion revenues R_W.

Assuming g is the only firm with a long term contract on the transmission line, the market operator will allow g to claim as many FTRs as she would like (up to the amount of transmission capacity K) and then sell any "residual" FTRs on g's behalf in the *FTR auction.* Under the annual contract design, g chooses a quantity of FTRs $q \in [0, K]$ to maximize her expected utility from congestion fees and FTR auction revenues:

$$\max_{q\in[0,K]} = E\left[U\left(\underbrace{\pi_S\left(e_S - q\right) + \pi_W\left(e_W - q\right)}_{\text{net congestion}} + \underbrace{p\left(K - q\right)}_{\text{auction rev.}}\right)\right]$$

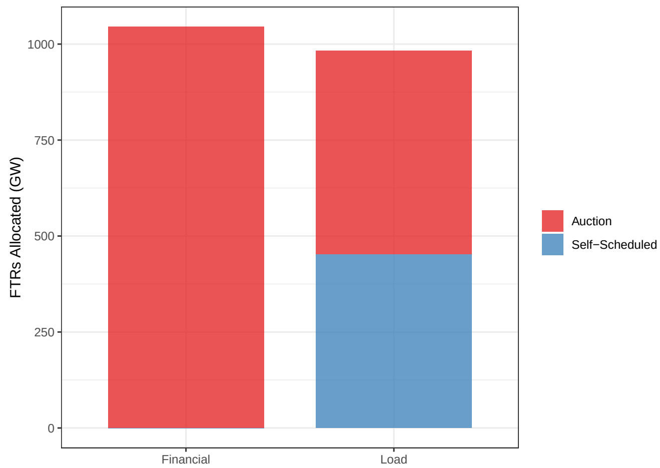
where p is the auction clearing price. Unless $e_S = e_W$, g cannot perfectly hedge against congestion risk. However, for any $q \in (0, \min\{e_S, e_W\})$, g has less exposure to net congestion than she would absent FTRs. If g is risk averse, then this reduction in risk exposure is valuable, and $g$will choose $q^* > 0$ so long as the auction price p is sufficiently low.

The seasonal contract design potentially improves on the annual design by enabling g to perfectly hedge against congestion risk. In this case, g can choose separate amounts $q_S \in [0, K]$ and $q_W \in [0, K]$ for each season:

$$\max_{q_S, q_W \in [0,K]} E\left[U\left(\underbrace{\pi_S\left(e_S - q_S\right) + \pi_W\left(e_W - q_W\right)}_{\text{net congestion}} + \underbrace{p_S\left(K - q_S\right) + p_W\left(K - q_W\right)}_{\text{auc rev}}\right)\right]$$

where p_S and p_K are auction prices. If $e_S \neq e_W$, g can now obtain lower ex post risk exposure than would be possible under the annual contract design. However, if $p_W + p_S \neq p$, auction

Figure 1: Annual gross volume of FTR allocations by firm type



revenues may be lower (or higher) even if $q = q_S = q_W$ such that g attains the same ex post risk exposure. If auction revenues are sufficiently weak under the seasonal contract design, g may prefer the annual contract design despite the loss in hedging flexibility. Ultimately, this depends on g's preference for risk and the efficiency of the FTR auction. In the remainder of the paper, I quantify these forces for the MISO FTR allocation.

3 The MISO FTR allocation

This section describes key elements of the MISO FTR allocation mechanism. The discussion motivates several modeling choices in Section 4.

MISO allocates new FTRs once each year. The allocation occurs in two distinct stages: the Auction Revenue Rights ("ARR") allocation which occurs in March, and the FTR Auction which occurs in April and May. When the process is concluded, FTRs for the subsequent June-May period are fully allocated to market participants and speculators. Resale is possible, but resale volumes are small and FTRs are generally considered illiquid after the initial allocation.[2]

During the ARR allocation, load firms are awarded ARRs on the basis of historical network usage, self-reported long term contracting obligations, and MISO's forecast of network demand. An ARR is a warrant to purchase a given quantity of FTRs on a specific FTR path at a price of zero. Exercising this warrant is known as "self-scheduling." Self-scheduling occurs during the first round of the FTR auction, simultaneous with bidding. If an ARR

[2]Resale can occur via negotiated sale or through monthly re-allocation auctions organized by MISO. Transaction volumes in the re-allocation auctions are significantly smaller than transaction volumes in the annual auctions.

Figure 2: Mean allocations per contract period by firm type

	Load	Financial
# Firms	74.0	51.5
Gross MW per firm	905.2	2680.2
# paths per firm	16.9	497.4
MW per firm-path	59.1	9.4

holder does not self-schedule an ARR, the ARR converts to a claim on auction revenues on the associated FTR path.[3] Any auction revenues that are not directly owed to the holder of an unconverted ARR are divided between firms pro rata on the basis of unconverted ARR capacity. In this way, the ARR mechanism accomplishes two purposes: it facilitates the direct allocation of FTRs to load firms, and determines how revenues from the sale of "residual" FTR capacity are to be divided between the load firms ex post.

The FTR auction occurs in three consecutive rounds, held about two weeks apart. Each round consists of eight simultaneous auction events, one for each of four 3-month contract seasons (summer, fall, winter, spring) and two times of use (peak vs. off-peak hours). MISO attempts to allocate roughly one third of anticipated network capacity in each auction round. In each round, firms submit bids (and offers) on individual FTR paths. Bids take the form of price-contingent demand or supply schedules with discrete bid points (as in Kastl (2011)). All paths are cleared simultaneously subject to a "simultaneous feasibility" constraint. This constraint ensures that net FTR capacity corresponds to the (anticipated) physical transmission capacity of the network less any self-scheduled FTRs. If the underlying network model were completely accurate, this strategy would guarantee that congestion revenues are sufficient to cover FTR payouts (Hogan, 1992).[4]

The volume of FTRs available on any particular path is not fixed in advance, but is determined endogenously: a bid on one FTR competes with bids on all other FTRs that imply powerflow on overlapping transmission elements at the auction clearing prices. Many combinations of path-to-path FTRs can exhaust network transmission capacity, and capacity can be augmented through "counterflow" bidding (i.e., negative capacity).[5]

[3]Thus, a risk neutral ARR holder prefers to self-schedule whenever the expected auction price is below the expected cost of congestion. Approximately 65% of ARR capacity was self-scheduled in the sample period.

[4]In practice, the market operator does not have perfect foresight with respect to the availability of transmission resources during the coming year (for example, due to unplanned outages), so there are typically shortfalls or surpluses.

[5]Consequently, the fact that most FTR paths receive a small number of bids does not necessarily imply that the scope for market power is large, since a bid on any one path potentially competes against bids on many other paths.

3.1 Data and descriptive statistics

The two primary data sources for the analysis are the bids and results from MISO's annual FTR auctions, and hourly realized congestion. This analysis focuses on 2016, 2017, and 2018 Annual Auctions, in which FTRs were sold for the period June 1, 2016 to May 31, 2019. Additional discussion of the data is provided in Appendix A. In the remainder of this section, I describe key features of the data.

For the typical contract period (season-time of use) in this period there were roughly 75 active "physical" firms (such as load serving entities, generators, and marketers) and 50 active "financial" (i.e., non-physical) firms.[6] For simplicity, I refer to the physical firms as "load" firms, although not all physical firms are load serving entities. Figure 1 shows the gross volume of FTRs obtained annually by firm type (financial vs. load) and allocation mechanism (self-schedule vs. auction). In aggregate, load firms and financial firms each obtained similar gross volumes of FTR capacity. About half of load firm FTR capacity was obtained via self-scheduling, while half was obtained in the auction. Financial firms are not allocated ARRs, and consequently cannot self-schedule. In total, financial firms hold about two thirds of the gross volume of FTR capacity sold in the auction, but only half of all FTR capacity.

Figure 2 reports summary statistics on the average FTR allocation per contract period by firm type. Load firms tend to obtain large volumes of a few FTRs, while financial firms tend to obtain small volumes of many FTRs. On average, load firms obtained 59.1 MW per contract path (i.e., sink-source pairs) on 16.9 contract paths. Financial firms obtained 9.4 MW per contract path on 497.4 contract paths. One plausible explanation for these patterns is that financial firms attempt to accumulate diversified portfolios (consistent with risk aversion), while load firms attempt to offset congestion risk from long term contract obligations on specific contract paths (consistent with risk aversion).

FTRs are expensive and highly risky. Industry accounts suggest that the fixed costs of bidding are large (e.g., Acre (2013)). To accurately price FTRs, firms must develop and maintain complex models of powerflow, which requires significant investments in data, software, and engineering know-how. Consistent with steep fixed costs, financial firms that bid in one of the eight contract periods in a given year nearly always bids in all eight contract periods. In other words, partial entry is relatively uncommon. This may suggest that the marginal cost of participating in an additional contract-period auction is relatively low.

[6] I define a "physical" firm as any market participant that submitted a self-scheduling request at some point during the analysis period. This definition is imperfect. While only firms that hold long-term contracts for physical power are eligible for ARRs, not all physical firms obtain ARRs or engage self-scheduling. Conversely, some firms that are eligible for ARRs may engage in speculative trading.

I do not directly observe firms' delivery obligations. However, as is well known, demand for electricity is highly seasonal. In most sub-regions within MISO's footprint, peak load is about 10% above the annual average in the summer, and 10% below the annual average in the fall and spring. If contract obligations follow a similar pattern, then having seasonal FTRs could significantly reduce firms' exposure to congestion risk.

4 Model

This section develops a model of MISO's FTR auction in order to evaluate alternative contract designs. The key elements of the model are agents' beliefs about congestion, load firms' behavior, and speculators' participation and bidding strategies in the auction market. I discuss these elements in detail before introducing additional assumptions required to estimate the model. For clarity of exposition, I ignore the distinction between between peak and off-peak hours in this section.

4.1 Agents and timing

The agents in the model are the market operator MISO, a collection of load firms G, and a fringe of potential speculators. Timing is as follows:

1. MISO chooses a contract granularity and then allocates ARRs to load firms.

2. Load firms exercise self-scheduling claims, which are then made public.

3. Speculators decide whether to enter the FTR auction. Entry decisions are made public.

4. Load firms and speculators who have chosen to enter bids in the FTR auction.

In reality, steps 2. through 4. occur simultaneously – self-scheduling claims against ARRs are made at the same time as bidding in the first round of the auction, not prior to bidding; moreover, speculators do not know the number of identity of other bidders when making bids. I adopt this stylized timing assumption in order to focus attention on the primary source of uncertainty that market participants encounter: uncertainty regarding congestion.[7]

[7] Without this assumption, speculator participation decisions would be made on the basis of beliefs about load firms' likely self-scheduling activity and competing speculators participation decisions. In the data, self-scheduling strategies appear to be highly predictable: many load firms always self schedule 100% of allocated ARRs, while other load firms never self-schedule, suggesting that there is little uncertainty in practice. With regards to participation, Leslie (2021) shows that speculators face considerable uncertainty over other speculators' participation strategies.

4.2 Congestion forecasts

There are N nodes in the network and K possible FTR paths. Let η_s denote the $N \times 1$ vector of realized (nodal) congestion prices in season s. Then the $K \times 1$ vector of FTR payouts is:

$$\pi_s = A\eta_s \tag{1}$$

where A is a $K \times N$ contract design matrix.[8] Agents have *common information* and *correct beliefs* about η_s. In particular, all agents know the true model of congestion prices, which is given by:

$$\eta_s = \chi_s + Lv_s + \epsilon_s \tag{2}$$

where $\nu_s \sim N(0, \Psi_s)$ is a P-vector of factors (with $P \ll N$), L is a matrix of factor loadings, and $\epsilon_s \sim N(0, \sigma_e^2 I)$ is an error vector. Realizations of ν_s and ϵ_s are independent across seasons.[9] Under these assumptions, the distribution of seasonal FTR payouts is given by:

$$\pi_s \sim N(\mu_s, \Sigma_s) \tag{3}$$

where $\mu_s = A\chi_s$ and $\Sigma_s = A\{L\Psi_s L' + \sigma_e^2 I\} A'$.

The assumption of common information and correct beliefs simplifies the derivation of equilibrium, but excludes much of the richness inherent to the FTR auction. In practice speculators have heterogenous forecasting skill, and some firms may have private knowledge of future congestion events (such as scheduled outages).[10]

4.3 Load firm preferences

In each season s, load firm $g \in G$ is endowed with a vector of contract obligations $e_{g,s} \in \mathbb{R}^{K_g}$ on a subset of FTR paths $K_g \subseteq K$. g has CARA utility with risk aversion parameter λ_g. Thus, if g had no FTRs, g's expected utility (before post-auction transfers) would be:

$$-\mu'_{g,s}e_{g,s} - \frac{\lambda_g}{2}e'_{g,s}\Sigma_{s,g}e_{g,s} \tag{4}$$

[8]This matrix is defined such that $A'_{k\cdot}\eta_s = \eta_{src_k} - \eta_{snk_k}$, where src_k and snk_k are the source and sink nodes of path k.

[9]This assumption is fairly mild since (unanticipated) congestion events typically do not last more than a few hours or days.

[10]Leslie (2021) finds evidence that FTRs purchased in later auction rounds are typically less profitable than those purchased in earlier auction rounds, consistent with an affiliated private values model in which information rents are dissipated across auction rounds.

where $\mu_{g,s}$ and $\Sigma_{s,g}$ are the subvector and submatrix of of μ_s and $\Sigma_{s,g}$ corresponding to K_g. As discussed above, g can obtain FTRs in one of two ways under the status quo: by self-scheduling ARRs, or by bidding in the FTR auction. I assume that g can only obtain FTRs on K_g.[11] If g obtains FTR portfolio $q \in \mathbb{R}^{K_g}$ through self-scheduling and auction purchases, g's pre-transfer expected utility is:

$$W_{g,s}^{0}(q) \equiv \mu_{g,s}'(q - e_{g,s}) - \frac{\lambda_g}{2}(q - e_{g,s})' \Sigma_{s,g}(q - e_{g,s}) \tag{5}$$

Transfers include payments for any FTRs purchased in the auction net of g's share of auction revenues, discussed below.

4.4 Speculator preferences

A speculator who chooses to participate in the auction also incurs a participation cost C_s, which encompasses the fixed and contract period-specific variable costs of speculating on FTRs. All speculators are symmetric. Similar to load firms, speculators have CARA preferences with risk aversion parameter λ_f. Unlike load firms, speculators have no intrinsic exposure to congestion and always bid on the universe of FTR paths.[12] If speculator f obtains FTR portfolio $q \in \mathbb{R}^{K}$ through auction purchases, f's pre-transfer expected utility (excluding any sunk participation costs) is:

$$W_{f,s}^{0}(q) \equiv \mu_s' q - \frac{\lambda_f}{2} q' \Sigma_s \tag{6}$$

In this case, transfers are simply payments for any FTRs purchased in the auction.

4.5 FTR auction

Equilibrium of the FTR auction depends on load firms' self-scheduling decisions and speculators' entry decisions. For the moment, suppose that load firm self-scheduling decisions and speculator entry decisions have already been made: each load firm g is endowed with a vector of self-scheduled FTRs $q_{g,s}^{ss}$, while M_s speculators have sunk the participation cost C_s.

The FTR auction is conducted in three rounds. In round r, g may submit a demand

[11] This restriction is intended exclude the possibility that a load firm's optimal bidding strategy involves speculating on the universe of FTR paths. This type of behavior would be inconsistent with observed purchase patterns discussed above, in addition to being implausible. For instance, Molzahn and Singletary (2011) report that some load firms (including Wisconsin utilities) are explicitly prohibited from speculating on FTRs.

[12] These assumptions are clearly unrealistic, since speculators evidently do not bid on all possible FTRs and do not obtain identical portfolios.

schedule $q_{g,s,r} : \mathbb{R}^{K_g} \to \mathbb{R}^{K_g}$ indicating a quantity of each FTR desired as a function of the clearing price subvector $p_{s,g,r}$.[13] g's accounts for FTRs obtained by self-scheduling or purchased in previous rounds when forming a bid. In particular, g's optimal demand schedule in round r is the solution to:

$$\max_{q_{g,s,r}} \quad W^0_{g,s}\left(q^{ss}_{g,s} + \sum_{i\leq r} q_{g,s,i}\right) - p'_{g,s,r}q_{g,s,r} \tag{7}$$

Similarly, speculator f submits a demand schedule $q_{f,s,r} : \mathbb{R}^K \to \mathbb{R}^K$ indicating a quantity of each FTR demanded as a function of the clearing price vector $p_{s,r}$. Like the load firms, speculators account for purchases in prior rounds, which shift the marginal risk of additional FTRs. Speculator f's optimal demand schedule in round r is the solution to:

$$\max_{q_{f,s,r}} \quad W^0_{f,s}\left(\sum_{i\leq r} q_{f,s,i}\right) - p'_{s,r}q_{f,s,r} \tag{8}$$

The strategic environment for bidders is significantly more complicated than in previously studied multiunit auction environments. To abstract from this complexity, I assume that all load firms and speculators are price-takers. Due to the simultaneous feasibility constraint, a bid on one FTR path can compete for scarce transmission resources (e.g., lines or transformer capacity) with bids on hundreds or thousands of seemingly unrelated FTR paths. In comparison with other multiunit auction environments (such as those studied by (e.g., Hortaçsu and Puller, 2008; Kastl, 2011)), it is challenging to explicitly account for strategic incentives in this environment, particularly given the non-public nature of transmission system details.

Let $F_{s,r}(p_{s,r})$ denote the supply of FTRs sold to speculators in round r (i.e., supply net of demand from load when the equilibrium price vector is $p_{s,r}$). By symmetry, each speculator obtains an identical FTR portfolio in each round. Thus, $q_{f,s,r} = M_s^{-1}F_{s,r}(p_{s,r})$, and the vector of clearing prices is:

$$p_{s,r} = \mu_s - \alpha_s\Sigma_s\left\{\sum_{i\leq r} F_{s,i}(p_{s,i})\right\} \tag{9}$$

where $\alpha_s = M_s^{-1}\lambda_f$ is a risk premia scalar. Note that risk premia in the current round depend on the risk that speculators have accumulated from purchases in prior rounds.

[13] This relaxes the actual auction procedure, in order to simplify the characterization of equilibrium. In reality, g submits a collection of path-specific demand functions $q_{g,s,r,k} : \mathbb{R} \to \mathbb{R}$, one for each path k. Moreover, I do not account for the additional strategic complications that result from discrete bidding.

(9) summarizes important information about the role of risk premia in the auction market. If speculators were risk neutral, then prices $p_{s,r}$ would coincide with the expected level of congestion μ_s. Even if speculators are risk averse, prices $p_{s,r}$ are competed down to μ_s as M_s grows large. The combination of risk aversion and imperfect competition generates risk premia. The sign of the price distortion on any particular path can be positive or negative, depending on the direction of flow as well as on the correlations across paths, with the scale of distortions depending on speculators risk preferences and participation decisions.

4.6 Speculator participation

I assume any speculator who enters bids in all three auction rounds. Speculators enter up until the marginal speculator earns negative expected profits. Relaxing the integer constraint on M_s^*, the risk premia scalar is a simple function of the aggregate market risk borne by speculators:

$$\alpha_s = c_{\lambda,s} \left(\sum_{s \in S_y} \sum_{i \leq R} F_{s,i}^{'} \left(p_{s,i} \right) \Sigma_s F_{s,i} \left(p_{s,i} \right) \right)^{-1/2} \tag{10}$$

where $c_{\lambda,s} = \sqrt{6 \lambda_f C_s}$ is an entry friction parameter and the term in parentheses is the aggregate market risk. See Appendix B.1 for a derivation. (10) further clarifies the nature of risk premia in the auction market. The magnitude of risk premia (which, again, may be positive or negative on any given path) increases with the aggregate risk borne by speculators. However, risk premia are lower when the same aggregate risk can be spread across a greater number of speculators.

4.7 Post-auction transfers

After the auction, each load firm g receives a portion $rev_{g,s}$ of the net auction revenues $\sum_{i \leq R} p_{s,i}^{\prime} \left(\sum_{g \in G} q_{g,s,i} + M_s q_{f,s,i} \right)$ collected by MISO.[14] Accounting for this transfer and any auction payments, g's interim expected utility after the auction is given by:

$$W_{g,s} = W_{g,s}^{0} \left(q_{g,s}^{ss} + q_{g,s}^{auc} \right) - \sum_{i \leq R} p_{g,s,i}^{\prime} q_{g,s,i}^{auc} + rev_{g,s} \tag{11}$$

[14] I do not model the ARR allocation or the self-scheduling decision, so $rev_{g,s}$ is determined exogenously. Appendix D presents an approximate formula for $rev_{g,s}$ which can be used to compute load welfare at the firm level.

where $q_{g,s}^{auc} = \sum_{i \leq R} q_{g,s,i}^{auc}$. Summing over firms, aggregate auction revenues are:

$$\sum_{g \in G} rev_{g,s} = \sum_{i \leq R} p'_{s,i} F_{s,i} \tag{12}$$

where $F_{s,r} \in \mathbb{R}^K$ denotes the vector of net FTR sales to speculators in round r. Note that $F_{s,r}$ can have negative elements.

5 Identification and estimation

This section discusses identification of the key parameters of the model, and how I estimate them.

5.1 Congestion factor model

I construct the factor matrix L appearing in (2) as follows. First, I use the methodology proposed by Zheng et al. (2022) to construct a congestion pattern matrix ΔS. This matrix approximates the power transfer distribution factor (PTDF) matrix which captures the sensitivity of congestion prices at each node to congestion on specific transmission constraints. Unlike the PTDF matrix used by MISO, this approximate matrix can be constructed from publicly available data. In general, the number of transmission constraints that bind in any given year is large. For each auction year y, I use forward selection to extract P columns of ΔS that explain a large share of the variation in hourly congestion prices (where P is small). L is a unitary normalization of the P columns obtained in this fashion. Intuitively, the rows of L capture each nodes' exposure to P key transmission constraints; nodes which similarly exposed to these constraints are assumed to have similar congestion risk profiles. Note that I currently use $P = 75$ factors.

Once L is known, the hourly realized factor vector ν_h can be estimated by regressing the hourly congestion price vector η_h on L. U_y is the (unitary) matrix of eigenvectors of the sample covariance of the estimates $\hat{v}_h$ in year y. I assume that the eigenvectors of Ψ_s in year y correspond to the columns of U. Intuitively, I assume that beliefs about factor covariance are not too dissimilar from the realized factor covariance. Hence, we have:

$$\Psi_s = U_y D_{\lambda_s} U'_y \tag{13}$$

where D_{λ_s} is a diagonal matrix of eigenvalues.

5.2 Pricing model

By construction, the K-dimensional price vector $p_{s,r}$ is a linear function of an N-dimensional shadow price vector $\rho_{s,r}$. If (9) is the true model of FTR prices, then the shadow price vector must satisfy:

$$\rho_{s,r} = \chi_s - \alpha_s \left\{ LUD_{\lambda_s}U'L' + \sigma_e^2 I \right\} A' \left(\sum_{i \leq r} F_{s,i} \right) \tag{14}$$

where α_s is the risk premia scalar from (9). I assume that this equation holds approximately in the data. In particular, I introduce a mean zero error vector $\epsilon_{s,r}$, and assume that:

$$\rho_{s,r} = \chi_s - \alpha_s \left\{ LUD_{\lambda_s}U'L' + \sigma_e^2 I \right\} A' \left(\sum_{i \leq r} F_{s,i} \right) + \epsilon_{s,r} \tag{15}$$

5.2.1 Estimation of the pricing model

I take a two-step approach to estimating the congestion forecast parameters $\theta = \left\{ c_\lambda, \chi_s, \lambda_s, \sigma_{s,e}^2 \right\}$. The procedure is discussed in more detail in Appendix C.

In the first step, I use (15) as the foundation for a least squares-based estimation strategy to recover χ_s and Ψ_s from the observed auction shadow prices. In particular, I find the values of χ_s, $\alpha_s \lambda_s$, and $\alpha_s \sigma_{s,e}^2$ that minimize the squared prediction error with respect to the shadow price vector ρ_r in each auction round, constraining $\alpha_s \lambda_s$ and $\alpha_s \sigma_{s,e}^2$ to be positive:

$$\max_{\chi \in \mathbb{R}, \alpha\lambda \geq 0, \alpha\sigma_e^2 \geq 0} \quad \sum_{r \in R} \quad \left\| \rho_r - \chi + \alpha_s \left\{ LUD_{\lambda_s}U'L' + \sigma_e^2 I \right\} A' \left(\sum_{i \leq r} F_{s,i} \right) \right\| \tag{16}$$

A key observation is that (16) can be re-written as a quadratic program in $\alpha_s \lambda_s$ and $\alpha_s \sigma_e^2$, where $\alpha_s \lambda_s$ and $\alpha_s \sigma_e^2$ are constrained to be positive. This problem can be solved numerically with a quadratic programming solver. In the second step, I estimate c_λ from realized congestion using a minimum distance estimator. The assumptions that firms have correct beliefs implies that:

$$\eta_s \sim N \left(\chi_s, \alpha_s^{-1} \left\{ LUD_{\alpha_s \lambda_s} U'L' + \alpha_s \sigma_e^2 I \right\} \right) \tag{17}$$

Manipulating this expression and substituting in $c_{\lambda,s}$ via (10), we can write:

$$c_{\lambda,s} Z \left(\chi_s, \alpha_s \lambda_s, \alpha_s \sigma_{s,e}^2 \right) \sim N(0, I) \tag{18}$$

where Z is a vector representing the independent components of the realized congestion vector in each season (see Appendix C for details). I assume that $c_{\lambda,s}$ is constant across auction years and estimate it by minimizing the Cramer-Von Mises distance between the empirical distribution of $c_{\lambda,s}\hat{Z}$ and the standard normal distribution, pooling data from all auction events.

This empirical strategy is intended to infer firms beliefs about congestion from the prices paid at the auction, under the assumption that (9) is the true model of FTR prices. Alternatively, one could directly estimate χ_s and Ψ_s using historical congestion prices, similar to how agents might learn these parameters in practice. The simulation approach is perhaps more natural, and several earlier papers have proposed empirical strategies for forecasting FTR payouts which could be adapted to this purpose (Zheng et al., 2022; Acre et al., 2004b,a). However, this approach has significant limitations. For example, agents in the market have access to important sources of information that are not publicly available, such as the PTDF matrix. At best it would be possible to obtain a rough approximation to firms' beliefs using publicly available data, but this would be a difficult task.

5.3 Load firm primitives

I now discuss the load firm risk aversion parameter λ_g and the underlying contract delivery obligations $e_{g,s}$. If g bids in round r of auction s, then the first order condition of (7) is given by:

$$(\mu_{g,s} - p_{g,s,r}) - \lambda_g \Sigma_{g,s} \left(q^{ss}_{g,s} + \sum_{i \leq r} q^{auc}_{g,s,i} + e_{g,s} \right) = 0 \tag{19}$$

This equation has two key implications. First, the differences in a firm's FTR purchases across rounds identifies the risk preference parameter λ_g. To be clear, since beliefs about congestion are fixed across auction rounds, it must be the case that:

$$\lambda_g \Sigma_{g,s} q^{auc}_{s,g,r} = -\left(p_{s,g,r} - p_{s,g,r-1}\right) \tag{20}$$

so that λ_g is identified conditional on $\Sigma_{g,s}$, $a^{auc}_{s,g,r}$, and the auction prices. Intuitively, the correlation between changes in the load firm's risk portfolio and the FTR auction clearing prices reveals the load firm's risk aversion.

In practice μ_s and Σ_s are estimated with error. Since estimating the inverse of the congestion risk matrix Σ_s is challenging, second step estimation based on (20) and (21) is likely to deliver numerically unstable estimates. To mitigate this issue, I obtain a point

Figure 3: Estimated risk premia coefficients

$c_{\lambda,s}$	3.06
α_s	
2016	1.57×10^{-7}
2017	2.03×10^{-7}
2018	1.45×10^{-7}
λ_g	1.00×10^{-7}

estimate of λ_g by introducing a mean zero error term $\xi_{s,g,r}$ to (20) and running a (robust) regression. To improve precision I assume λ_g is identical for all firms.

(19) also identifies the contractual obligation vector $e_{g,s}$, since:

$$e_{g,s} = q_{g,s}^{ss} + \sum_{i \leq r} q_{g,s,i}^{auc} - \lambda_g^{-1} \Sigma_{g,s}^{-1} \left(\mu_{g,s} - p_{g,s,r} \right) \tag{21}$$

and λ_g is identified by (20). In comparison to risk preferences, $e_{g,s}$ is much more difficult to estimate robustly, since $e_{g,s}$ necessarily differs across firms and may be high dimensional. In light of this challenge, I estimate $e_{g,s}$ with $\hat{e}_{g,s} = q_{g,s} + \sum_{i \leq r} q_{g,s,i}^{auc}$, which is biased according to (21) but does not generate extreme point estimates.

6 Estimates

This section presents the key parameter estimates and discusses model fit.

6.1 Key estimates

Figure 3 presents the estimates of the entry parameter $c_{\lambda,s}$ and load firm risk aversion parameter λ_g as well as the implied point estimates for the risk premia scalar α_s in each year of the sample period. For the purpose of exposition, suppose that $M_s \approx 50$ and $C_s \approx \$1M$.[15] Then the point estimate of $c_{\lambda,s} = 3.06$ implies that $\lambda_f \approx \frac{1.6}{C_s} \approx 1.6 \times 10^{-6}$, which means that a speculator would demand \$0.80 to accept a 50-50 lottery to win or lose \$1,000. On the other hand, the mean point estimate for α implies that $\lambda_f \approx \frac{1.7 \times 10^{-7}}{M_s} \approx 3.4 \times 10^{-9}$, which is much smaller. The point estimate for λ_g falls between these two extremes.

[15] Since the model of FTR speculation is highly stylized, I do not attempt to estimate M_s or C_s from the data. However, it is useful to observe that there are about 50 speculators per year, and that speculators earn trading profits of about \$1M per year at the median.

6.2 Model fit

Figure 6a shows that, for a typical auction event, the pricing model explains over 99% of the variation in nodal clearing prices $\rho_{s,r}$. This simply reflects the fact that, although the model is identified, it has a large number of degrees of freedom. To partial out the effect of the poorly estimated χ_s vector, Figure 6b shows the R^2 coefficient from a de-meaned version of (15):

$$\rho_{s,r} - \bar{\rho}_s = -\alpha_s \left\{ LUD_{\lambda_s}U'L' + \sigma_e^2 I \right\} A' \left(\sum_{i \leq r} F_{s,i} - \frac{1}{R} \sum_{r \leq R} \sum_{i \leq r} F_{s,i} \right) + \epsilon_{s,r} - \bar{\epsilon}_s \tag{22}$$

The estimated parameters explain 15-30% of the de-meaned nodal price variance in most auction events, shown in the figure. This suggests that the model does a reasonable job of explaining price differences across auction rounds, despite its simplicity.

Next I consider how well the estimated model predicts realized congestion. Figure 6c presents the distribution of $\hat{Z}$ for each auction event at the estimated value of $c_{\lambda,s}$. The distribution is presented as a boxplot, with the top and bottom of each box corresponding to the 25%- and 75%-tiles of the empirical distribution. For comparison, the red lines indicate the 25%- and 75%-tiles of the standard normal distribution. This provides suggestive visual evidence that the estimated Ω_s matrix provides reasonable model fit for most auctions in the sample.

7 Contract tenor and welfare

In this section I perform a counterfactual exercise to quantify the tradeoff between narrow and coarse contract designs. Before doing so, I first present additional assumptions underlying this counterfactual.

7.1 Annual contract counterfactual

Suppose that FTR contracts were only available on an annual basis (with separate contracts for peak and off-peak hours). Since realizations of ν_s and ϵ_s are independent across seasons, the distribution of annual FTR payouts is:

$$\pi_y \sim N(\mu_y, \Sigma_y) \tag{23}$$

where $\mu_y = \sum_{s \in S_y} \mu_s$ and $\Sigma_y = \sum_{s \in S_y} \Sigma_s$. Under the annual design, g is only be able to self-schedule and bid on an annual basis, even though its delivery obligations vary seasonally.

Load firm g's welfare is now:

$$W_{g,y} = \sum_{s \in S_y} W^0_{g,s}\left(q^{ss}_{g,y} + q^{auc}_{g,y}\right) - \sum_{i \le R} p'_{g,y,i} q^{auc}_{g,y,i} + rev_{g,y} \tag{24}$$

where $q^{ss}_{g,y}$ is the quantity self-scheduled by g, and $q^{auc}_{g,y}$ is the quantity purchased in the auction by g, and $rev_{g,y}$ is g's share of the auction proceeds. The expected utility term $W^0_{g,s}$ is the same as in (5), and therefore depends on $e_{g,s}$. Total auction proceeds from financial speculators are:

$$\sum_{g \in G} rev_{g,y} = \sum_{i \le R} p'_{y,i} F_{y,i}$$

where $F_{y,i}$ is the vector of annual FTRs sold to speculators in auction round i.

A speculator who chooses to participate submits bids for all available auction periods and all contract rounds. In this case, there are two contract periods (for peak and off-peak contracts). I assume that potential speculators incur a participation cost C_y to bid on annual contracts. Under these assumptions, the counterfactual clearing price vector is:

$$p_{y,r} = \mu_y - \alpha_y \Sigma_y \left\{ \sum_{i \le r} F_{y,i} \right\} \tag{25}$$

where

$$\alpha_y = c_{\lambda,y} \left(\sum_{i \le R} F'_{y,i} \Sigma_y F^s_{y,i} \right)^{-1/2} \tag{26}$$

and $c_{\lambda,y} = \sqrt{6\lambda_f C_y}$ is the entry friction parameter. These expressions are the annual contract analogues of (9) and (10), respectively.

7.1.1 Counterfactual self-scheduling and capacity

Since agents do not make self-scheduling decisions strategically, the model does not make a prediction regarding $q^{ss}_{g,y}$. In general, I do not have access to sufficient information about the underlying market model to determine whether any particular allocation is feasible aside from allocations that I observe.[16] For the purpose of the counterfactual I assume that g's counterfactual self-schedule vector coincides with its winter self-schedule vector under the status quo. That is, $q^{ss}_{g,y} = q^{ss}_{g,win}$. In addition, since (7) is not likely to deliver precise

[16] For example, the mean of the annual allocations is not guaranteed to be feasible.

Figure 4: Annual contract counterfactual welfare bounds ($M/year)

	Lo Cost	Hi Cost
Δ Load Welfare	56.8	82.2
exp. congestion	17.9	17.9
risk disutility	-2.4	-2.4
auction proceeds	41.4	66.7
Breakeven λ_g	2.47e-06	3.53e-06

predictions about load firms' bidding strategies (for the reasons discussed in the previous section), I assume that $q^{auc}_{g,y,r} = q^{auc}_{g,win,r}$, regardless of the counterfactual clearing price. My choice of winter as the "reference season" is motivated by the fact that peak load is closer to its annual average during the winter than in other seasons. In a similar spirit, I assume that $F_{y,r} = F_{win,r}$.

7.1.2 Bidding costs

If the variable costs of bidding on a single annual contract are lower than the variable costs of bidding on four separate monthly contracts, then we would expect $C_y \leq C_s$. If variable costs are small, then $C_y \approx C_s$. The ratio of participation costs C_y/C_s is unidentified. However, it is reasonable to assume that $1 \leq C_y/C_s \leq 4$. This can be understood in the following way. Suppose that bidders incur a constant marginal cost for each available contract tenor, such that total marginal costs are four times higher under 3-month contracts. If this marginal cost is zero, then $C_s = C_y$. On the other hand, if this marginal costs accounts for the total cost of bidding under the status quo, then $C_s = 4C_y$.

7.2 Results

Under the annual contract design, load firms are more exposed to congestion: firms now hold too many FTRs in some seasons and too few in others. This affects aggregate welfare through two channels. First, there is a change in firms' expected congestion payments, which can be positive or negative. Second, the risk associated with congestion exposure is weakly increased. Figure 7 shows these two effects for each load firm. The y-axis indicates the change in expected congestion (in levels) while the x-axis indicates the disutility from congestion risk (in logs).[17] Many firms now have positive expected congestion – these firms expect to receive more in FTR payouts than they will spend on congestion costs. Indeed, the expected

[17]The size of each circle indicates the gross volume of the firm's counterfactual FTR portfolio.

Figure 5: Decomposition of counterfactual auction proceeds ($M)

Supply	Prices	Entry	Counterfactual Lo Cost	Counterfactual Hi Cost
Monthly	Monthly	Monthly	158.3	158.3
Annual	Monthly	Monthly	212.6	212.6
Annual	Annual	Monthly	185.0	185.0
Annual	Annual	Annual	199.6	225.0

congestion increases by $17.9M across all load firms. This effect is larger in magnitude than the associated disutility from increased risk, which is valued at $2.4M for the estimated value of λ_g. This represents an important source of welfare gains for load firms under the annual contract design. At the same time, auction proceeds collected from speculators also increase significantly. Auction proceeds change for three reasons, as summarized in Figure 5. First, a different combination of FTRs is sold to speculators, resulting in an increase in revenues at the status quo prices. Second, as the supply of FTRs changes, the amount of risk held by speculators increases, leading to an increase in risk premia conditional on the status quo entry level. Finally, this increase in risk premia induces more speculators to enter, driving up prices.

Figure 4 considers the overall change in welfare combining these effects. Regardless of entry costs, auction revenues and positive FTR payouts lead to an increase in load firms' welfare. The overall change is decomposed into three effects: expected congestion payments increase due to the misalignment between q and e, disutility from risk increases due to uncertainty about congestion on unhedged positions, while net auction proceeds from speculators increase by a lesser or greater amount depending on the entry cost assumption. However, this conclusion is sensitive to the estimate of λ_g, which affects the severity of the risk disutility. The final row indicates the level of risk aversion for which the welfare loss in the third row would be severe enough to make load firms indifferent between the status quo and the annual contract counterfactual. For reasonable levels of risk aversion, risk disutility would be sufficiently large for the sign of the welfare effect to reverse.

8 Conclusion

FTRs play an important role in decentralized energy markets. I study contract design in FTR markets. The ISO must balance firms' hedging needs against the benefits of a thick market of speculators that can absorb residual FTR capacity. I build and estimate a model to explore this tradeoff in the context of the MISO FTR allocation. With longer contracts, auction proceeds increase substantially, benefitting load firms, but opportunities to hedge risk are restricted. I find that the welfare losses from increased exposure to congestion risk are relatively small, but this result is sensitive to the estimated risk aversion parameter.

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A Data preparation

This section describes the procedure used to prepare the analysis dataset. All data sources used in the analysis were obtained from the MISO website.

MISO reports all bids and offers in the FTR auction as well as comprehensive auction results. The primary files of interest include the FTR Annual Auction Bid and Offer files and the FTR Annual Auction Results files. The Annual Auction Results files include the total volume of FTRs allocated by market participant and FTR path, as well as the nodal shadow prices

Two significant data cleaning steps are required. In order to distinguish FTR allocations to each type of firm, I first map asset owner IDs in the bidding data to market participant IDs in the bidding data. MISO does not provide a crosswalk; therefore, I manually construct a crosswalk by comparing bids with allocations.[18] Second, I infer self-scheduling volumes from the FTR Annual Auction Bid and Offer Files, under the assumption that all self-schedule requests are honored in full and apportioned across rounds according to the procedure described in the relevant Business Practice Manual.

Hourly realized nodal congestion prices are reported in the Day-Ahead Ex Post LMP files. This information can be used to compute the payout associated with a particular FTR. In some cases, the source and sink nodes associated with a given ARR or FTR at the time of the annual allocation are re-mapped to other nodes during the year. If the LMP corresponding to an auction node is not available in the realized congestion data, I replace it with the LMP of the most similar node for which congestion data is available. The "similarity" between nodes is determined by the frequency with which nodes had the same LMP in hours when an LMP was reported for both nodes.

B Model details

B.1 Speculator entry

Let Π_s denote a speculator's profit in auction s when there are M_s entrants. If one third of capacity is sold in each round and each speculator obtains an identical portfolio, then each

[18]There are frequently multiple asset owner IDs associated with the same market participant ID.

speculator f earns profits:

$$\Pi_f\left(M_s\right)=\left(\frac{F_s}{M_s}\right)'\mu_s-\frac{\lambda_f}{2}\left(\frac{F_s}{M_s}\right)'\Sigma_s\left(\frac{F_s}{M_s}\right)-\left(\frac{F_s}{3M_s}\right)'\left(\sum_{r\in R}p_{s,r}\right) \tag{27}$$

And it is straightforward to show that:

$$\sum_{r\in R}p_{s,r}=3\mu_s-\lambda_f M_s^{-1}2\Sigma_s F_s \tag{28}$$

Combining (27) and (28), we have:

$$\Pi_f\left(M_s\right)=\left(\frac{1}{6}\right)\lambda_f M_s^{-2}F_s'\Sigma_s F_s$$

The equilibrium entry level M_s^* satisfies:

$$\Pi_f\left(M_s+1\right)\leq C_s\leq\Pi_f\left(M_s\right)$$

This is the zero profits condition. Relaxing the integer constraint on entry, the equilibrium number of entrants is:

$$M_s=\sqrt{\frac{1}{6}\lambda_f C_s^{-1}}\left(\sum_{s\in S_y}F_s'\Sigma_s F_s\right)^{1/2}$$

and the risk premia scalar is:

$$\alpha=\sqrt{6\lambda_f C_s}\left(\sum_{s\in S_y}F_s'\Sigma_s F_s\right)^{-1/2}$$

C Estimation details

As described in Section 5, I estimate the model in two stages.

In the first stage, I use realized auction prices to estimate firms' congestion forecasts using a constrained least squares approach. In (16), observe that χ is unconstrained. An analytical expression for χ conditional on $\alpha\lambda$ and $\alpha\sigma_e^2$ is:

$$\chi=\bar{\rho}+\alpha\left\{LUD_{\lambda_s}U'L'+\sigma_e^2 I\right\}A'\bar{F}$$

Therefore (16) can be re-written as:

$$\max_{\alpha\lambda\geq 0,\alpha\sigma_e^2\geq 0}\quad\sum_{r\in R}\quad\left\|\rho_r-\bar{\rho}+\alpha_s\left\{LUD_{\lambda_s}U'L'+\sigma_e^2 I\right\}A'\left(F_r-\bar{F}\right)\right\| \tag{29}$$

To simplify the expression, we can define a constant matrix

$$S_r=\left[\left(F_r-\bar{F}\right)'A\left(LU\right)\otimes\left(LU\right)\right]B$$

where B is a matrix that selects the columns of the full Kronecker product in the term on the left corresponding to the diagonal elements of D_λ. Re-arranging (29) gives:

$$\max_{\alpha\lambda\geq 0,\alpha\sigma_e^2\geq 0}\quad\sum_{r\in R}\quad\left\|\rho_r-\bar{\rho}+\alpha\lambda S_r+\alpha\sigma_e^2 D_r\right\|$$

which is simply a quadratic program with simple inequality constraints. This type of problem can be solved efficiently. I do so using KNITRO's nonlinear least squares solver.

In the second stage, I use realized congestion prices to infer the risk premia shifter c_λ. Once χ, $\alpha\lambda$, and $\alpha\sigma_e^2$ are estimated, an estimate of c_λ can be obtained in the following way. Assume that c_λ implies a unique α parameter for each auction year y in the data, which we can denote α_y. Re-arranging (17) gives:

$$\alpha_y^{1/2}\left(\eta_s-\chi_s\right)\sim N\left(0,LuD_{\alpha\lambda}\left(Lu\right)'+\alpha\sigma_e^2 I\right)$$

And since Lu is unitary, we have:

$$\alpha_y^{1/2}Lu'\left(\eta_s-\chi_s\right)\sim N\left(0,D_{\alpha\lambda}+\alpha\sigma_e^2 I\right)$$

And therefore:

$$\alpha_y^{1/2}D_{\alpha\lambda_m+\alpha\sigma_e^2}^{-1/2}Lu_m'\left(\eta_s-\chi_s\right)\sim N\left(0,1\right)$$

provided that $\alpha\lambda_m+\alpha\sigma_e^2>0$. Substituting (10) into this expression gives (18), where:

$$Z\left(\chi_s,\alpha_s\lambda_s,\alpha_s\sigma_{s,e}^2\right)=\left(\sum_{s\in S_y}F_{s,r}'A'\left\{LuD_{\alpha\lambda}u'L'+\alpha\sigma_{s,u}^2 I\right\}AF_{s,r}\right)^{-1/2}D_{\alpha\lambda_m+\alpha\sigma_e^2}^{-1/2}Lu_m'\left(\eta_s-\chi_s\right)$$

I construct $\hat{c}_\lambda$ as the value of c_λ that minimizes the Cramer-Von Mises statistic of the empirical cumulative distribution function of z values constructed in this manner relative to the standard normal distribution.

D Supplemental material

D.1 Allocation of excess auction revenues

Let $F_{s,r}$ denote the vector of FTRs sold to speculators in round r. Let $K_{g,s}$ denote g's ARR portfolio. Then g receives $r_{g,s} = \sum_{r \leq 3} r_{g,s,r}$, where $r_{g,s,r}$ is defined to be:

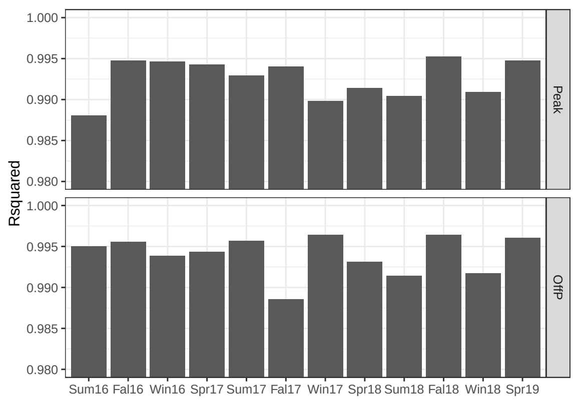
$$r_{g,s,r} = \left(K_{g,s} - q^{ss}_{g,s}\right)' p_{g,s,r} + \left\{ \frac{\|K_{g,s} - q^{ss}_{g,s}\|}{\sum_{g \in G} \|K_{g,s} - q^{ss}_{g,s}\|} \right\} \left(p'_{s,r} F_{s,r} - \sum_{g \in G} \left(K_{g,s} - q^{ss}_{g,s}\right)' p_{g,s,r} \right)$$

where $p_{g,s,r}$ is the subvector of $p_{s,r}$ corresponding to K_g. This allocation rule is similar to the one used by MISO.

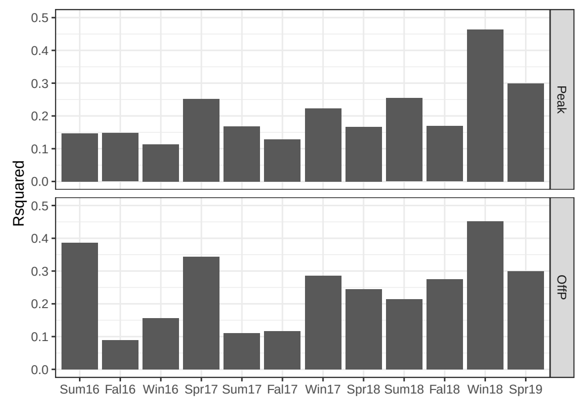
E Additional tables and figures

Figure 6: Pricing and congestion forecast model fit

(a) Raw prices



(b) De-meaned prices



(c) Congestion forecast fit

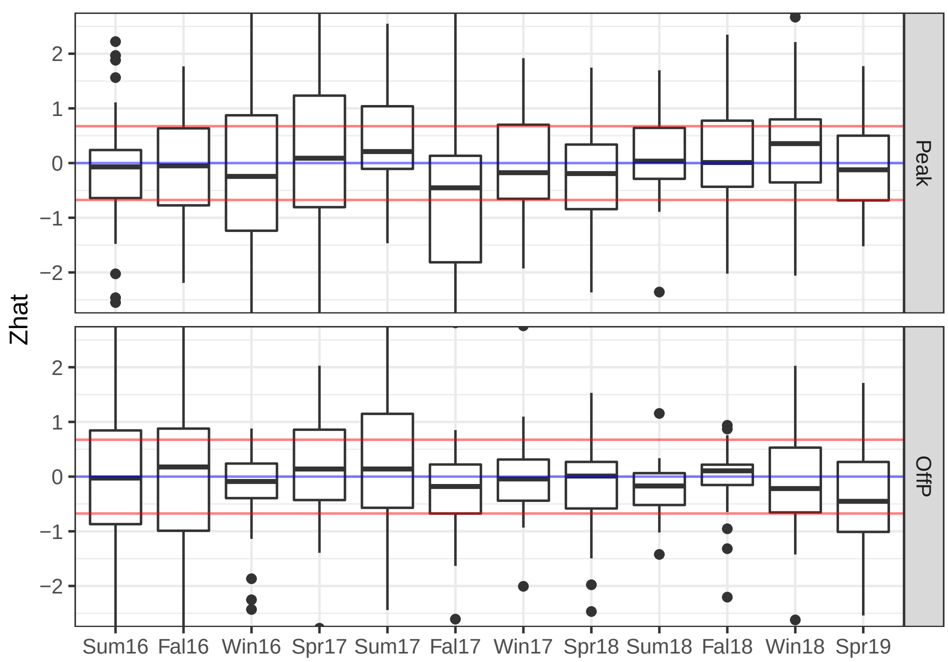


Figure 7: Change in congestion exposure under annual contracts, by firm