Improving FTR Markets with Better Product Design: Contract Tenor, Market Thickness, and Efficiency

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Abstract

Financial transmission rights (FTRs) are an important class of contracts in decentralized energy markets. This paper explores how market operators' contract design choices affect the efficiency of FTR allocation. With shorter contract tenors, generators and electricity customers can obtain better hedging portfolios for anticipated deliveries. However, short contracts can directly or indirectly reduce market thickness in the FTR auction, leading to welfare losses. In order to understand the significance of this tradeoff I build and estimate a stylized empirical model of the Midcontinent ISO (MISO) FTR allocation mechanism. Relative to a counterfactual with longer contracts, MISO's current contract design reduces welfare losses from congestion risk by \$2.4M, or about 1% of total welfare, at firms' estimated risk preferences. Net auction proceeds fall by 20% and total welfare by 26% or more, highlighting the value of careful contract design. However, the sign of the welfare effect reverses for reasonable alternative risk preferences.

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 physical transmission capacity increases the cost of contracting between wholesale producers and their customers, disincentivizing investment in generation assets. FTR markets are intended to alleviate this friction by enabling firms to hedge against congestion risk, among other purposes.

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 a standard FTR contract vary widely.

Formally, an FTR is a forward contract on network congestion between two nodes during a specified time period. One particularly important dimension of an FTR is its *granularity* (or tenor) at the time of allocation.

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Table 1: FTR Contract Granularities

Market	Period	Time-of-Use	Mkt Size ($M)
SPP	1-, 2-, 4-month	Peak/Off-Peak	1,334
ERCOT	1-month	Peak WE/WD, Off-Peak	1,289
MISO	3-month	Peak/Off-Peak	1,240
PJM	1-year	Peak/Off-Peak	1,014
NYISO	6-month, 1-year	24 Hr	317
CAISO	3-month	Peak/Off-Peak	250
ISO-NE	1-year	Peak/Off-Peak	40

In some markets, standard contracts are as short as a month, and only encompass narrowly defined times of use (e.g., peak hours on weekends). In other markets, contracts are much longer, and may not be subdivided by time of use. Table 1 summarizes FTR contract granularity for each of the seven US ISOs.

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 more effective hedging portfolios. On the other hand, excessively short (or long) contracts can undercut competition between speculators in the ISO's FTR auction, leading to soft prices. Load firms are the residual claimants on auction revenues, and therefore suffer losses from uncompetitive auctions.

This paper considers how an ISO should design FTR contracts when these forces conflict. 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 enter and compete to purchase "residual" FTRs in an auction. In reality, the extent of competition may 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.

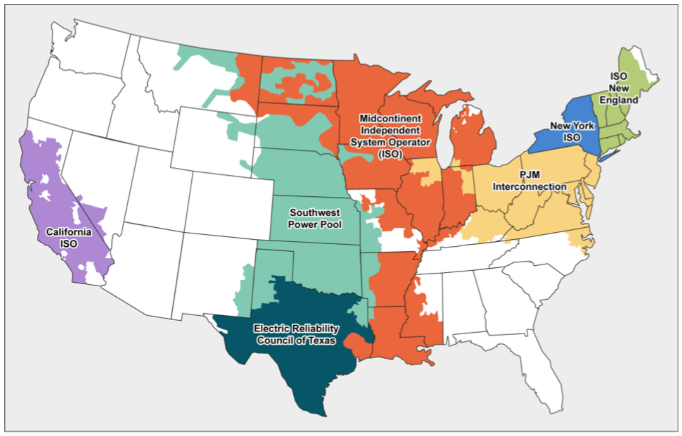
In order to quantify the tradeoff between auction revenue and hedging flexibility, I study the Midcontinent ISO (MISO) FTR market in detail.[1] Currently, MISO allocates 3-month FTR contracts by default, with separate contracts for peak and off-peak hours. I build and estimate a simple structural model to understand whether MISO could obtain a better outcome in terms of welfare by adopting an annual contract design instead. 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 little attention in economics.

I find that auction revenues from speculators are 20-30% lower under the status quo than under this alternative contract design, depending on speculators' participation costs. Load firms' risk exposure is reduced significantly, but not sufficiently for 3-month contracts to be welfare improving at firms' estimated risk preferences. For reasonable alternative risk preferences, however, these effects are reversed. Together, these results help to rationalize the continued use of long-tenored standard contracts in heavily-traded FTR markets such as PJM and NYISO, as well as the lack of convergence to a standard contract granularity across ISOs more generally.

The remainder of this section provides additional background on financial transmission rights and clarifies

[1]The geographic footprints of the seven ISOs (including MISO) are depicted in Figure 1.

Figure 1: US ISO Footprints



the contribution of this paper. Section 2 develops a simple theoretical model to illustrate the tradeoffs associated with contract granularity. Section 3 describes the MISO FTR market in detail. Sections 4 and 5 discuss the empirical model and estimation strategy, respectively. Sections 6 and 7 present the model estimates and the counterfactual analysis.

1.1 Related Literature

A significant body of empirical work analyzes patterns in FTR auction prices and attempts to draw conclusions about the efficiency of FTR auctions. For example, Siddiqui et al. (2003) find evidence of high risk premia in the NYISO TCC market. Olmstead (2018) finds evidence of informational inefficiency in the Ontario FTR market. Leslie (2021) studies the role of speculators in the NYISO TCC market. Another strand of literature attempts to estimate reduced form models of FTR prices using conventional asset pricing frameworks such as CAPM (Baltadounis et al., 2017) or options pricing (Patino-Echeverri and Morel, 2006). None of these analyses derive a structural model of FTR prices, and thus none can easily be extended to predict prices or other market outcomes under alternative product designs or other policy interventions.

Another body of research formulates and in some cases provides numerical simulations of equilibrium models of energy markets that include FTRs. Alderete (2005) considers FTR auction environments with market power, as well as environments with multiple auction rounds and multiple contract periods, among other issues. 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 (2021) link the availability and tenor of FTRs to project finance. Unlike these papers, I do not explicitly model the ISO's economic dispatch problem or market participants strategic behavior in domains outside the FTR allocation. Although the model I present lacks these features, it has a unique and easily computed equilibrium even when the number of nodes is large, making estimation and counterfactual simulation much more straightforward.

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), Babayigit 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 evaluates the role of financial participants in deregulated electricity markets more broadly. Jha and Wolak (2019) find evidence that financial traders improve price discovery and market efficiency in CAISO. In contrast, Birge et al. (2018) find conflicting evidence in MISO. In their study, financial traders manipulate day ahead energy prices in order to influence the value of their FTR positions. This type of behavior falls outside the scope of my analysis.[2] Mercadal (2022) finds that financial traders in MISO reduced generator's market power.

Separately, many authors in empirical industrial organization have implicitly or explicitly considered the role of contract design in auction markets. Some examples include: Bajari and Lewis (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. Relatedly, Hendricks and Porter (2015) provide a broad discussion of contract design in oil lease and timber 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 local demand for electricity crosses local supply of electricity 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).

Market operators define and allocate property rights known as *financial transmission rights* 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.[3]

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 collects sufficient congestion revenues to cover FTR payouts (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.

[2]As discussed below, I make the simplifying assumption that FTR payouts are exogenous.

[3]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).

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

2.1 Illustration

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

Firm g has a long term contract to inject electricity at G and withdraw electricity at L. In particular, g plans to use $e_S < K$ units of capacity in the summer, and $e_W < K$ units of capacity 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. Thus, the market operator sets a unit price ρ_G for each unit of capacity injected at G and a 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 price.*

Since individual nodes and lines are small in comparison to the network as a whole, the congestion price π is exogenous from g's perspective. Moreover, 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.

For simplicity, suppose that each season lasts exactly one hour, and that the transmission line between G and L is always fully utilized. Then, over the course of the year, the market operator will collect congestion revenues equal to $R = K(\pi_S + \pi_W)$, where R is a random variable. A financial transmission right (FTR) is a tradeable property right to the future congestion revenues R.

Financial transmission rights are inherently divisible. However, the market operator can choose a standard contract granularity for the initial allocation of FTRs. In this case, there are two possibilities: either the market operator can define *annual* FTRs, which are rights to shares of R, or he can define separate *seasonal* FTRs, which are separate right to summer congestion revenues $R_S = K\pi_S$ and winter congestion revenues $R_W = K\pi_W$.

After choosing a contract granularity the market operator allows g to claim as many FTRs as she would like (up to the amount of transmission capacity K) and then sells any "residual" FTRs on g's behalf in the *FTR auction*. FTRs are valuable to g because they enable g to hedge against her underlying exposure to congestion. Under annual FTR design, g chooses an amount of FTRs $q^* \in [0, K]$ to maximize her expected utility from congestion fees and FTR auction revenues. g's expected utility is:

$$u_g = E\left[U\left(\underbrace{\pi_S(e_S - q^*) + \pi_W(e_W - q^*)}_{\text{net congestion}} + \underbrace{p^*(K - q^*)}_{\text{auc rev}}\right)\right]$$

Cleary, for $q^* \in (0, \min\{e_S, e_W\})$, 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. However, unless $e_S = e_W$, g cannot perfectly hedge against congestion risk. On the other hand, under seasonal FTRs, perfect hedging is feasible. In this case, g can choose separate amounts $q_S^* \in [0, K]$ and $q_W^* \in [0, K]$ for each season, resulting in expected utility:

$$u_g = E\left[U\left(\underbrace{\pi_S\left(e_S - q_S^*\right) + \pi_W\left(e_W - q_W^*\right)}_{\text{net congestion}} + \underbrace{p_S^*\left(K - q_S^*\right) + p_W^*\left(K - q_W^*\right)}_{\text{auc rev}}\right)\right]$$

The case that $q_S^* = e_S^*$ and $q_W^* = e_W^*$ corresponds to perfect hedging. However, in this case, auction revenues are different from auction revenues under annual FTRs, due to both quantity and price effects.

Whether or g prefers the annual or seasonal auction design ultimately depends g's preference for risk and the efficiency of the FTR auction. If g is more risk averse, additional flexibility under the seasonal auction design is more valuable. If auctions are sufficiently competitive that prices are close to the expected value of congestion, a narrower contract design is generally preferable. In practice, however, the seasonal auction could result in worse auction revenues overall, depending on how auction prices are formed. If the benefit of improved hedging is offset by reduced auction revenues, then g will prefer the annual contract design.

In the remainder of the paper, I quantify this tradeoff for the MISO FTR allocation in particular.

3 The MISO FTR Allocation

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

MISO allocates new FTRs once each year. The allocation occurs in two distinct stages: the annual allocation process are 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 to be illiquid after the initial allocation.[4]

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 convertible 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 holder does not self-schedule an ARR, the ARR converts to a claim on auction revenues on the associated FTR path.[5] 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 auction revenues 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 available 3-month contract season (summer, fall, winter,

[4] 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.

[5] Thus, a risk neutral ARR holder prefers to self-schedule whenever the expected auction price is below the expected cost of congestion.

spring) and time 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 simultaneously submit bids (and offers) on all FTR paths that they wish to bid on. 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).[6]

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 firms can explicitly bid for "counterflow" (i.e., negative capacity).[7]

For the typical season-time of use contract period in the period I study there were about 75 active load firms and 50 active "financial" (i.e., non-load) firms.[8] Figure 2 shows the gross volume of FTRs obtained annually by firm type (financial vs. load) and allocation mechanism (self-schedule vs. auction). In aggregate, load and speculator firms each obtain similar gross volumes of FTR capacity. About half of load firm FTRs are obtained via self-scheduling, while half are obtained in the auction. Financial firms are not allocated any ARRs. Thus, financial firms hold about two thirds of the gross volume of FTRs sold in the auction, but only about half of all FTR volume.

Figure 3 reports summary statistics on the average FTR allocation per season-time of use 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. Financial firms obtain FTRs for about 500 source-sink pairs on average, while load firms obtain FTRs for less than 20 source-sink pairs on average. Financial firms typically obtain less than 10 MW on any given path, while non-financial firms obtain more than 50 MW on average. One plausible explanation for these patterns is that financial firms tend to accumulate diversified portfolios (suggesting risk aversion), while risk averse load firms hedge against congestion risk on the specific market paths that correspond to their long term contract obligations.

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. Moreover, since congestion varies considerably across contract periods (for example, being greater in peak periods than off-peak periods), this pattern suggests the marginal costs of bidding are relatively low.

I do not directly observe firms' delivery obligations. However, as is well known, demand for electricity is highly seasonal. Figure 4 presents the average day-ahead forecast load for MISO by region and month. In most regions, 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.

[6] 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.

[7] One implication is that FTR auctions are likely more competitive than is sometimes appreciated. For instance, 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

Figure 2: Annual Gross Volume by Firm Type

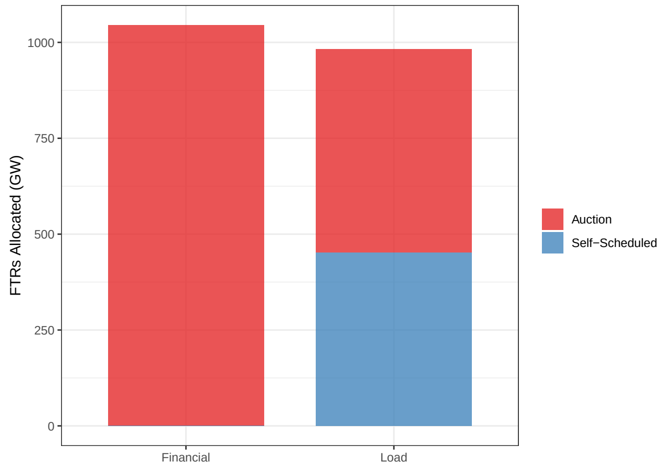


Figure 3: Mean Allocations per Contract Period

	Firm Type	# Firms	# Paths per Firm	MW per Path	Total MW
1	Financial	51.5	497.4	9.4	2681.0
2	Load	74.0	16.9	59.1	905.2

4 Model

This section develops a model of MISO's FTR auction that enables me 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 take the model to data. In the interest of clarity I ignore the distinction between between peak and off-peak hours in this section.

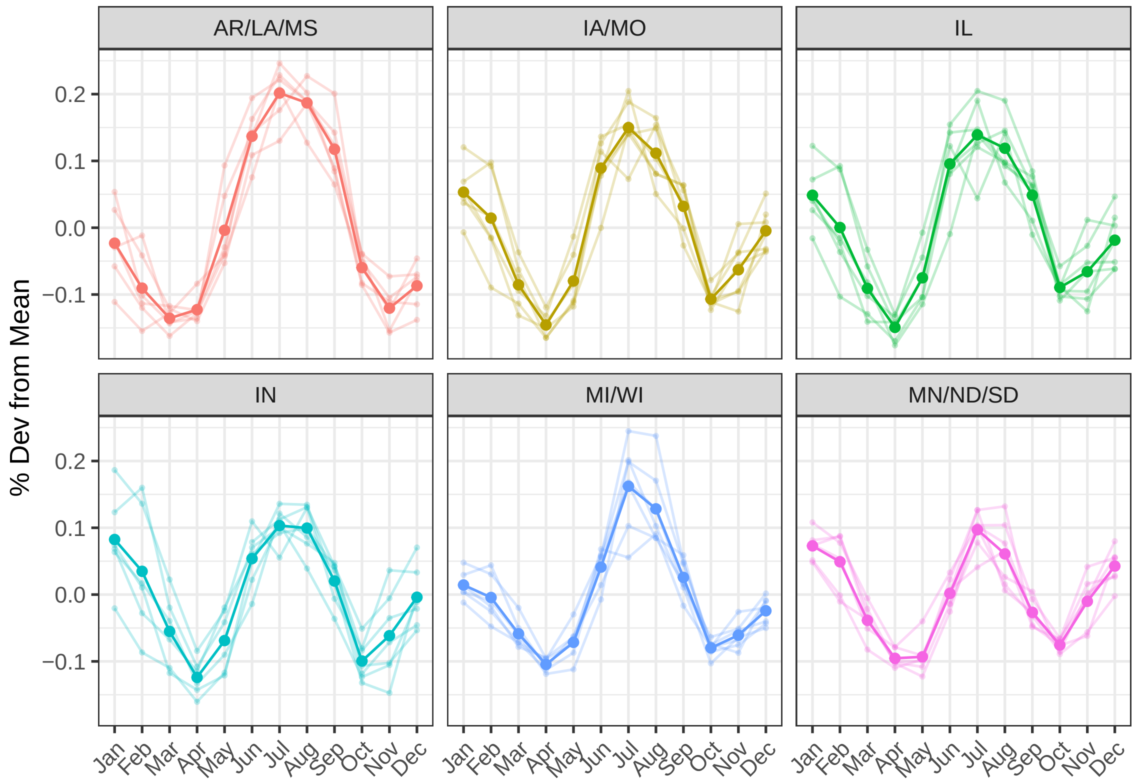
Agents & Timing The agents in the model are the market operator MISO, a collection of asset owning firms G, and a fringe of potential speculators. The agents play a one shot game. MISO first chooses a contract granularity and allocates ARRs to load firms. Next, load firms exercise self-scheduling claims, which are then made public.[9] Afterwards, speculators decide whether to enter the FTR auction. Finally, speculators who have chosen to enter and load firms submit bids and offers in the FTR auction to purchase any residual FTR capacity supplied by the market operator.

path potentially competes against bids on many other paths.

[8]I define a "load" firm as any market participant that submitted a self-scheduling request at some point during the analysis period.

[9]In reality, load firms exercise self-scheduling claims against ARRs during the first round of the auction, simultaneous with bidding. I adopt this alternative timing assumption to reduce the complexity of the model. Without this assumption, speculator entry decisions would be made on the basis of expectations about load firms' likely self-scheduling claims. In the data, it appears that self-scheduling strategies are often easy to predict: many load firms always self schedule 100% of allocated ARRs, while other load firms never self-schedule, suggesting that uncertainty may be small in practice, and hence that little is lost by abstracting from it.

Figure 4: MISO Peak Load by Region & Month, 2013-2019



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.[10] 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 known unitary $N \times P$ matrix of factor loadings, and $\epsilon_s \sim N\left(0, \sigma_e^2 I\right)$ is an error term. Realizations of ν_s and ϵ_s are independent across seasons.[11] 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 $\Sigma_s = A\left\{L\Psi_s L' + \sigma_e^2 I\right\} A'$.

Despite the presence of a strong common values element in this environment, I make the simplifying as-

[10]Formally, row k satisfies $A_{k\cdot} = e_{src_k} - e_{snk_k}$ where e_n is a standard basis vector.
[11]This assumption is fairly mild since congestion events typically do not last more than a few hours (or days in the worst cases).

sumption that agents have no private information about FTR payouts. In practice speculators have heterogenous forecasting skill, and some firms may have private knowledge of future congestion events (such as scheduled outages). Leslie (2021) finds evidence that FTRs purchased in later auction rounds are typically less profitable than those purchased in earlier auction rounds, consistent with the presence of information rents that are dissipated across auction rounds. If all private information is revealed in the first round, then this assumption is innocuous for the second and third auction rounds (and, thus, for the bulk of volume).

Load Firms In each season s, load firm $g \in G$ is endowed with a vector of contractual delivery 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 revenue transfers) would be:

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

where $\mu_{g,s}$ is the subvector of μ_s and $\Sigma_{s,g}$ is the submatrix of Σ_s corresponding to K_g. As discussed above, g can obtain FTRs in one of two ways under the status quo: g can obtain a limited quantity of FTRs at no cost by self-scheduling her ARR allocation, or g can purchase (or sell) FTRs in the FTR auction.

In practice, I assume that self-scheduling decisions are made non-strategically. More generally, I do not model the ARR allocation process (which determines the self-scheduling limits).

I assume that g can only obtain FTRs on K_g.[12] If g obtains FTR portfolio $q \in \mathbb{R}^{K_g}$ through self-scheduling and auction purchases, g's expected utility before transfers is:

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

Speculators 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 all K available FTRs. If speculator f obtains FTR portfolio $q \in \mathbb{R}^K$ through auction purchases, f's expected utility before transfers (i.e., the net price of the FTRs) is:

$$W^0_{f,s}(q) \equiv \mu'_s q - \frac{\lambda_f}{2}q'\Sigma_s \tag{6}$$

A speculator who chooses to participate in the auction incurs a participation cost C_s, which encompasses the fixed and variable costs of speculating on FTRs.

The benefit of modeling speculators in this manner is that obtaining counterfactual prices and allocations is straightforward, as demonstrated below. However, it is clearly unrealistic, since speculators evidently do not bid on all possible FTRs and do not obtain identical portfolios.

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

[12] This restriction is intended exclude the possibility that a load firm's optimal bidding strategy involves speculating on many irrelevant FTR paths. As suggested above, this type of behavior would be inconsistent with observed purchase patterns. Moreover, Molzahn and Singletary (2011) report that some load firms (including Wisconsin utilities) are explicitly prohibited from speculating on FTRs. However, the restriction may nevertheless exclude certain reasonable forms of hedging.

entry decisions have already been made: each load firm g is endowed with a vector of self-scheduled FTRs $q^{ss}_{g,s}$, while M_s speculators have sunk the participation cost C_s.

The FTR auction is conducted in a three-round procedure. In round r, g may submit a demand schedule $q_{g,s,r} : \mathbb{R}^{K_g} \rightarrow \mathbb{R}^{K_g}$ indicating a quantity of each FTR desired as a function of the clearing price subvector $p_{s,g,r}$.[13] g's optimal demand schedule in round r will account for any FTRs obtained by self-scheduling or purchased in previous rounds. In particular, g's optimal demand schedule in round r is the solution to:

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

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

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

To abstract from the complexity induced by the auction clearing mechanism, I make a number of simplifying assumptions. First, I assume that all load firms and speculators are price-takers. Second, conditional on participation, speculators participate in all eight auction events (four seasons and two times-of-use). In other words, speculators cannot selectively or partially participate in the auction.

Due to the simultaneous feasibility constraint, the strategic environment for bidders is significantly more complicated than in previously studied multiunit auction environments. The price-taking assumption is necessary since it does not appear to be feasible to account of market power explicitly in this presence of this constraint, at least within the standard paradigm for analyzing multiunit auction environments in industrial organization (e.g., Hortacsu and Puller, 2008; Kastl, 2011).[14]

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 at the equilibrium price $p_{s,r}$). 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 $\alpha_s = \lambda_f / M_s$ is a risk premia scalar. Note that the risk premium depends on the risk that speculators have accumulated from purchases in prior rounds.

[13] This slightly relaxes the actual auction procedure, in order to simplify the characterization of equilibrium. In reality, g submits a collection of path-specific demand functions $q_{g,s,r,k} : \mathbb{R} \rightarrow \mathbb{R}$, one for each path k.

[14] For one thing, the MISO market model is not publicly available. Even if it were, constructing the residual supply curve on a given path when the full set of bids is known can only be done by repeatedly solving MISO's market clearing problem (a high dimensional mixed integer programming problem, given the constraints). This is likely to be very challenging, even before accounting for the fact that (in reality) firms face uncertainty over rivals bidding strategies, and many firms bid simultaneously on many paths. Even under exogenous participation, an equilibrium may not exist without further restrictions, since equilibrium results for multiunit auctions generally require the presence of three or more bidders, but many FTR paths attract fewer than three bidders. Nevertheless, it may be possible model market power in the more stylized environment that I consider here (with complete participation and symmetric speculators) using the methods surveyed in Rostek and Yoon (2020). I leave this for future work.

(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. Similarly, if infinitely many speculators entered the market, prices $p_{s,r}$ would be competed down to μ_s. 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 the risk aversion parameter and the entry rate.

Speculator Entry Under certain simplifying assumptions, it can be shown that:

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

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 borne by participating speculators. In particular, this depends on the assumption that speculators enter up to a zero profits condition, capacity is divided equally across rounds, and integer constraints on entry are ignored. See Appendix C for a derivation.

(10) further clarifies the nature of risk premia in the auction market: the magnitude of price distortions (which, again, may be positive or negative on any given path) scales with the degree of risk aversion, the magnitude of entry frictions, and the aggregate risk borne by speculators.

This interpretation relies in large part on the absence of uncertainty in the model: speculators perfectly anticipate the supply of FTRs to be purchased, and the number of competing speculators in equilibrium.

Post-Auction Transfers After the auction, g receives a portion of the net auction revenues collected by MISO which I denote by $rev_{g,s}$. Accounting for this transfer, g's welfare (i.e., interim expected utility) after the auction is given by:

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

where $q_{g,s}^{auc} = \sum_{i \leq R} q_{g,s,i}^{auc}$. By extension, the aggregate welfare of all load firms is:

$$W_s = \sum_{g \in G} W_{g,s}^0 \left(q_{g,s}^{ss} + q_{g,s}^{auc} \right) + \sum_{i \leq R} p'_{s,i} F_{s,i} \tag{12}$$

where $F_{s,r} \in \mathbb{R}$ denotes the vector of net FTR sales to speculators in round r. (Note that $F_{s,r}$ can have negative elements.) Moreover, aggregate welfare does not depend on $rev_{g,s}$.[15]

5 Identification and Estimation

In this discussion I explain how the key parameters in the model are identified, and how I estimate them.

[15]Since I do not model the ARR allocation or the self-scheduling decision, $rev_{g,s}$ is exogenous. Appendix C presents a formula for approximating $rev_{g,s}$ which can be used to compute load welfare at the firm level, although I do not analyze firm level welfare in this draft.

Data and Sample Period 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.

Congestion Factor Model I construct the factor matrix L as follows. First, I use the methodology proposed by Zheng et al. (2022) to construct a congestion pattern matrix ΔS that captures the sensitivity of congestion prices at each node to shadow prices on all N_c physical transmission constraints in the network that were binding at some point during the analysis period. This matrix approximates the power transfer distribution factor (PTDF) matrix that MISO uses to enforces the simultaneous feasibility constraint, but can be constructed from publicly available data. In general, $N_c \gg N$. I therefore perform dimension reduction to extract P columns of ΔS that explain a large share of the variation in hourly congestion prices observed during auction year y. For this purpose I implement a custom forward selection algorithm that accommodates the hourly congestion price data. 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, and nodes that are similarly exposed to these constraints are assumed to have similar congestion risk profiles.

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. I estimate ν_h for each hour and then compute the sample covariance matrix $\frac{1}{H}\sum_h (\hat{\nu}_h - \bar{\nu}_h)(\hat{\nu}_h - \bar{\nu}_h)'$. U is the matrix of eigenvectors of this matrix.

Furthermore, I assume that the eigenvectors of Ψ_s correspond to the eigenvectors U of the sample covariance matrix of the hourly factor realizations during year y. Intuitively, I assume that beliefs about factor covariance are not too dissimilar from the realized factor covariance. Hence, we have:

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

where U is a known, unitary matrix and D_{λ_s} is a diagonal matrix of eigenvalues.

Pricing Model By construction, the K-dimensional price vector $p_{s,r}$ is a linear function of an N-dimensional shadow price vector $\rho_{s,r}$. (In particular $p_{s,r} = A\rho_{s,r}$ where A is the contract design matrix.) If (9) is the true model of FTR prices, then the shadow price vector must satisfy:

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

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 term $U_{s,r}$, and assume that:

$$\rho_{s,r} = \chi_s - \alpha_s \left\{ L\Psi_s L' + \sigma_e^2 I \right\} A' \left(\sum_{i \le r} F_{s,i} \right) + U_{s,r} \tag{15}$$

Moreover, by (13), we have:

$$\rho_{s,r} = \chi_s - \alpha_s \left\{ LUD_{\lambda_s} U'L' + \sigma_e^2 I \right\} A' \left(\sum_{i \leq r} F_{s,i} \right) + U_{s,r} \tag{16}$$

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

In the first step, I use (16) 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:

$$\max_{\chi \in \mathbb{R}, \alpha\lambda \geq 0, \alpha\sigma_e^2 \geq 0} \quad \sum_{r \in R} \left\| \rho_r - \chi + \alpha_s \left\{ LUD_{\lambda_s} U'L' + \sigma_e^2 I \right\} A' \left(\sum_{i \leq r} F_{s,i} \right) \right\| \tag{17}$$

A key observation is that $LUD_{\lambda_s} U'L'A' \left(\sum_{i \leq r} F_{s,i} \right)$ can be rewritten as $S_r \lambda_s$ for a known matrix S_r, making it possible to reformulate the problem as a quadratic program in $\alpha_s \lambda_s$ and $\alpha_s \sigma_e^2$. Since $\alpha_s \lambda_s$ and $\alpha_s \sigma_e^2$ are constrained to be positive, I solve this problem numerically with a quadratic programming solver.

In the second step, I estimate c_λ from realized congestion via minimum distance. The assumptions that firms have correct beliefs implies that:

$$\eta_s \sim N \left(\chi_s, \alpha_s^{-1} \left\{ LUD_{\alpha_s \lambda_s} U'L' + \alpha_s \sigma_e^2 I \right\} \right) \tag{18}$$

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

$$c_{\lambda,s} Z \left(\chi_s, \alpha_s \lambda_s, \alpha_s \sigma_{s,e}^2 \right) \sim N(0, I) \tag{19}$$

where Z is a vector representing the independent components of the realized congestion vector in each season at the first stage estimates. I obtain an estimate of $c_{\lambda,s}$ 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. Note that $c_{\lambda,s}$ is assumed to be constant across auction years.

Intuitively, this approach 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. The natural alternative approach would be to directly estimate χ_s and Ψ_s using historical congestion prices, similar to how agents might learn these parameters in practice. 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 complete market model and forward looking outage schedules. 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 in its own right.

Load Firm Primitives I now discuss identification of 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:

$$\left(\mu_{g,s} - p_{g,s,r}\right) - \lambda_g \Sigma_{g,s} \left(q^{ss}_{g,s} + \sum_{i \le r} q^{auc}_{g,s,i} + e_{g,s} \right) = 0 \tag{20}$$

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

$$\lambda_g \Sigma_{g,s} q^{auc}_{s,g,r} = -\left(p_{s,g,r} - p_{s,g,r-1}\right) \tag{21}$$

which identifies λ_g conditional on $\Sigma_{g,s}$. Intuitively, the correlation between changes in the asset owners risk portfolio and the FTR auction clearing prices reveals the asset owners' risk aversion.

A second observation is that (20) identifies $e_{g,s}$, since:

$$e_{g,s} = q^{ss}_{g,s} + \sum_{i \le r} q^{auc}_{g,s,i} - \lambda_g^{-1} \Sigma_{g,s}^{-1} \left(\mu_{g,s} - p_{g,s,r}\right) \tag{22}$$

provided that $\Sigma_{g,s}$ is invertible and λ_g is known.

In practice μ_s and Σ_s are estimated with error, and firms bidding strategies are not perfectly described by (7) in all cases. Consequently, estimation strategies directly based on (21) and (22) are likely to deliver extremely noisy estimates. To mitigate this issue, I obtain a point estimate of λ_g by introducing a mean zero error term $u_{s,g,r}$ to (21) and running a (robust) regression. To improve precision I assume λ_g is identical for all firms, although this is not required. In case there are systematic sources of bias, I also consider other plausible values of λ_g when discussing the results.

In comparison, $e_{g,s}$ is more difficult to estimate robustly, since $e_{g,s}$ necessarily differs across firms and may be high dimensional. In the current draft I estimate $e_{g,s}$ with $\hat{e}_{g,s} = q_{g,s} + \sum_{i \le r} q^{auc}_{g,s,i}$, which is biased according to (22) 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 5 presents the second stage estimate of $c_{\lambda,s}$ as well as the implied point estimates for α_s in each year of the sample period and the point estimate for λ_g. (In the current draft, I do not provide standard errors.) Recall that $c_{\lambda,s} = \sqrt{6\lambda_f C_s}$ and that $\alpha_s = \frac{\lambda_f}{M_s}$. 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 revenues of about \$1M per year at the median.[16] Therefore, suppose that $M_s \approx 50$ and $C_s \approx \$1M$. Then the point estimate of $c_{\lambda,s} = 3.06$ implies that

[16] That is, FTR payouts exceed the portfolio purchase price by about \$1M. Since auction prices and realized congestion prices are observed, it is easy to calculate firm profits.

Figure 5: Risk Parameter Estimates

$c_{\lambda,s}$	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}

$\lambda_f \approx \frac{1.6}{C_s} \approx 1.6 \times 10^{-6}$, which means that a speculator would demand \$0.80 to accept a 50-50 lottery to win or lose \$1,000.[17] 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.

6.2 Model Fit

Figure 7a 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 7b shows the R^2 coefficient from a de-meaned version of (16) at the estimated parameters, as follows:

$$\rho_{s,r} - \bar{\rho}_s = -\alpha_s \left\{ LUD_{\lambda_s} U' L' + \sigma_e^2 I \right\} A' \left(\sum_{i \leq r} F_{s,i} - \frac{1}{R} \sum_{r \leq R} \sum_{i \leq r} F_{s,i} \right) + U_{s,r} - \bar{U}_s \tag{23}$$

The estimated parameters explain 15-30% of the de-meaned price variance in most auction events, shown in the figure. This suggests that the risk premium model does a reasonable job of explaining price differences across auction rounds, despite its simplicity. Note that I currently use $P = 75$ factors.

Next I consider how well the estimated model predicts realized congestion. Figure 8 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 (and by extension, α_s) at least has the correct order of magnitude, although there is some variance in the quality of model fit.

7 Counterfactual

Finally I perform a counterfactual exercise to quantify the tradeoff between narrow and broad contract designs. I first present the key assumptions underlying this counterfactual before discussing the results.

[17] In comparison, Bolotnyy and Vasserman (2019) find that firms bidding on construction projects would demand \$23 for the same lottery. It is reassuring that I find an estimate of similar magnitude, but smaller, since the financial speculators in my setting are presumably less risk averse than the non-financial firms in their setting.

7.1 Annual FTR Contracts

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:

$$\pi_y \sim N\left(\mu_y, \Sigma_y\right) \tag{24}$$

where $\mu_y = \sum_{s \in S_y} \mu_s$ and $\Sigma_y = \sum_{s \in S_y} \Sigma_s$. (Thus, the counterfactual congestion forecasts are already estimated.)

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. Aggregate speculator welfare is now:

$$W_y = \sum_{g \in G} \sum_{s \in S_y} W^0_{g,s}\left(q^{ss}_{g,y} + q^{auc}_{g,y}\right) + \sum_{i \leq R} p'_{y,i} F_{y,i} \tag{25}$$

where $q^{ss}_{g,y}$ is the quantity self-scheduled by g and $q^{auc}_{g,y}$ is the quantity purchased in the auction. The expected utility term $W^0_{g,s}$ is the same as in (5), and therefore depends on $e_{g,s}$. The second term represents net auction revenue from speculators in the counterfactual auction.

I assume that potential speculators incur a participation cost C_y to bid on annual contracts. If the variable costs associated with bidding on a single annual contract are lower than the variable costs of bidding on four separate monthly contracts, then we might expect $C_y \leq C_s$. If variable costs are small, then $C_y \approx C_s$.

Just like under the status quo, a speculator who chooses to participate submits bids for all available auction periods (in this case, there are two such periods, for peak and off-peak contracts.)

Under these assumptions, the counterfactual clearing price vector is:

$$p_{y,r} = \mu_y - \alpha_y \Sigma_y \left\{\sum_{i \leq r} F_{y,i}\right\} \tag{26}$$

where

$$\alpha_y = c_{\lambda,y}\left(\sum_{i \leq R} F'_{y,i} \Sigma_y F^s_{y,i}\right)^{-1/2} \tag{27}$$

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

Counterfactual Allocations & Capacity Since agents do not make self-scheduling decisions strategically, the model does not make a prediction regarding $q^{ss}_{g,y}$. 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 predictions about load firms bidding strategies (for the reasons highlighted 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 month" is motivated by the patterns in Figure 4 – peak load is close to its annual average during the winter. In a similar spirit, I assume that $F_{y,r} = F_{win,r}$. The major advantage of this approach is that it ensures that the counterfactual allocation is feasible. 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.[18] A disadvantage is that the total allocation of FTRs could change significantly if the switch from 3-month to annual contracts led significant changes in bidding behavior on the quantity margin. This consideration is relevant in practice, but falls outside the scope of the current model.

Bidding Costs In order to compare outcomes under the status quo and the counterfactual, I also need to know the ratio of participation costs C_y/C_s. This parameter 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

This section considers how welfare changes under the counterfactual. I begin by separately discussing the effects of increased congestion exposure and the change in auction revenues collected from speculators.

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 9 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).[19] 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 aggregate change in expected congestion is positive, as indicated in Figure 10. The effect is larger in magnitude than the associated disutility from increased risk (at the estimated value of λ_g).

At the same time, changes in auction proceeds collected from speculators affect welfare. Auction proceeds (or revenues) change for three reasons, as summarized in Figure 11. First, the supply vector of FTRs sold to speculators is necessarily different, resulting in an increase in revenues even at the status quo prices.[20] Next, as the supply vector changes, aggregate market risk increases, leading to increased risk premia and decreased prices at the status quo entry level. Finally, increased risk premia induce more speculators to enter, competing away any profits and driving up prices. When entry is less costly (in the case that $C_y = \frac{1}{4}C_s$), this last response is stronger. Even in the case that $C_y = C_s$ (as is likely the case in practice), however, the net change in auction proceeds is large and positive.

Figure 6 considers the overall change in welfare. The first three columns show the three major components of speculator welfare discussed above: expected congestion payments due to the misalignment between q and e, the welfare loss from uncertainty about congestion, and net auction proceeds from speculators. These

[18] For example, the average allocation $\frac{1}{|S_y|}\sum_{s\in S_y}\left\{\sum_{g\in G}\left(q^{ss}_{g,s} + \sum_{r\in R} q^{auc}_{g,s,r}\right) + \sum_{r\in R} F_{s,r}\right\}$ is not guaranteed to be simultaneously feasible.

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

[20] This is necessarily the case, since MISO now only specifies one capacity vector instead of four.

Figure 6: Counterfactual Speculator Welfare ($M)

	Scenario	Load Congestion	Load Risk	Speculator Revenue	Load Welfare	Breakeven lambda_g
1	status quo	0.0	−0.0	158.3	158.3	NA
2	Cy/Cs=1.00	17.9	−2.4	199.6	215.1	2.47e−06
3	Cy/Cs=0.25	17.9	−2.4	225.0	240.4	3.53e−06

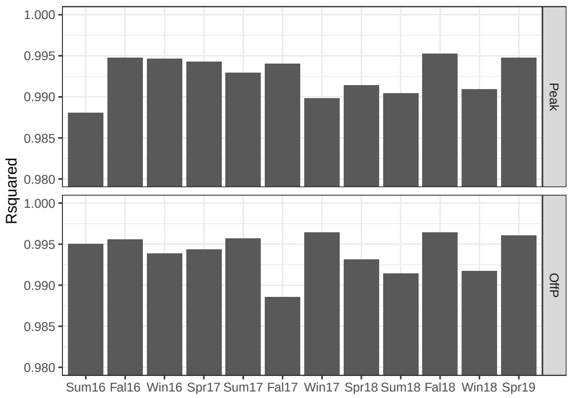
three columns are summed in the "Load Welfare" columns. In both counterfactuals, auction revenues and positive FTR payouts lead to an increase in welfare, despite the loss in welfare from increased risk. However, this conclusion is sensitive to the estimate of λ_g. The final column in Figure 6 indicates the level of risk aversion for which the welfare loss in the second column 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

Financial transmission rights play an important role in decentralized energy markets. Efficient FTR markets are important for incentivizing investments in generation assets. I study the effect of contract design in FTR markets. The ISO must balance firms hedging needs against the need to attract a thick market of speculators to absorb residual FTR capacity. I build and estimate a model to explore this tradeoff in the context of the MISO FTR allocation mechanism. With longer contracts, auction proceeds increase substantially, benefitting load firms, but opportunities to hedge risk are restricted, harming load firms. I find that the welfare losses from increase exposure to congestion risk are relatively small, but this result is sensitive to the estimated risk aversion parameter.

Figure 7: Pricing Model Fit

(a) Raw Prices



(b) De-meaned Prices

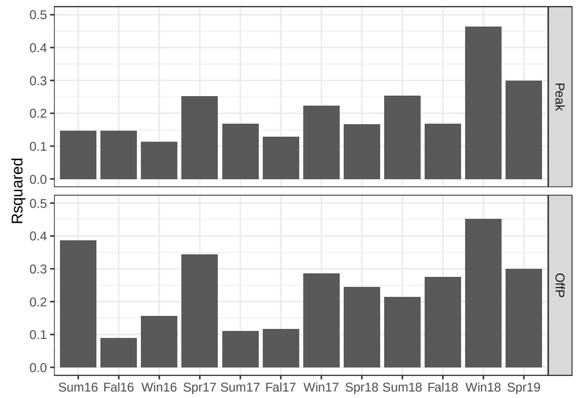


Figure 8: Congestion Forecast Fit

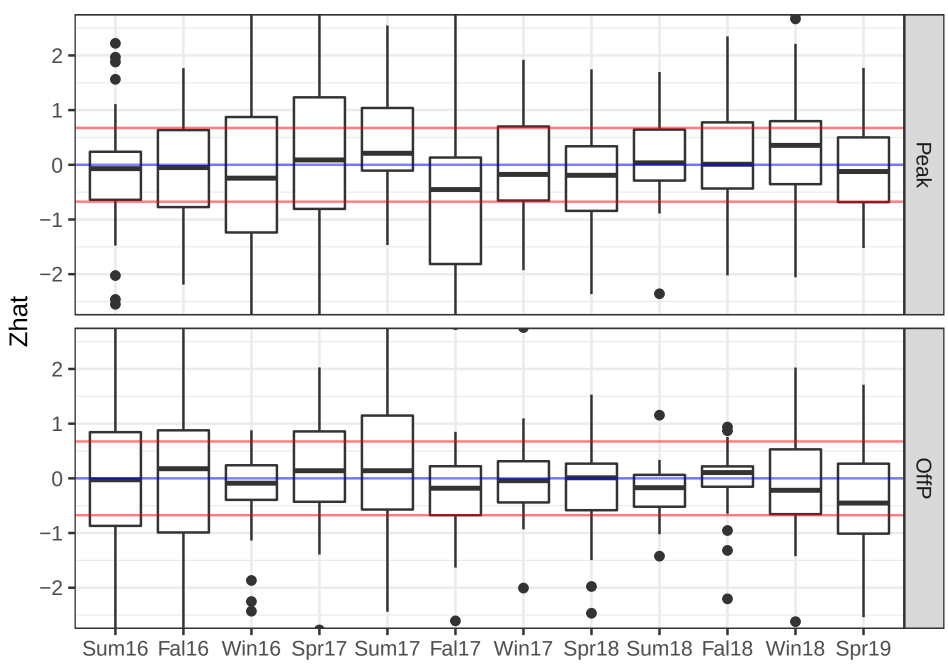


Figure 9: Change in Congestion Exposure by Firm

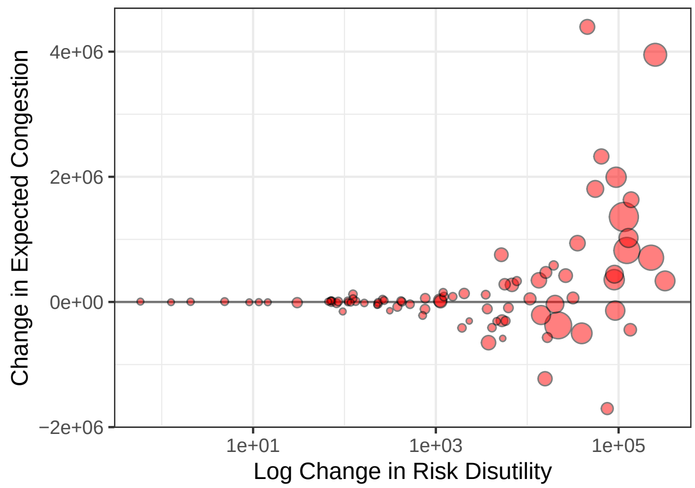


Figure 10: Welfare Change from Congestion Exposure ($M)

	scenario	expected congestion	risk disutility
1	status quo	0.0	−0.0
2	counterfactual	17.9	−2.4

Figure 11: Change in Auction Proceeds ($M)

	scenario	supply	prices	entry	Cy=Cs	Cy=0.25Cs
1	status quo	old	old	old	158.3	158.3
2	–	new	old	old	212.6	212.6
3	–	new	new	old	185.0	185.0
4	counterfactual	new	new	new	199.6	225.0

A Data & Sample Construction

This section describes the procedure used to prepare the analysis dataset. All data sources used in the analysis are 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 the bidding data, bidders are identified by an asset owner ID. In the auction results, firms are identified by a market participant ID. MISO does not provide a crosswalk. Therefore, I manually construct a crosswalk by comparing bids with allocations. There are frequently multiple asset owner IDs associated with the same market participant ID.
- 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 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 addition to the purposes described in the text. 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.

A speculator is defined to be a market participant that does submit a self-schedule request in any period during the sample. This is reasonable since only ARR holders are able to submit self-scheduling requests, and ARRs are allocated on the basis of usage of the physical network. Unfortunately, the distinction between load firms and speculative firms is not always clear. In this case, self-scheduling requests could be submitted by a trading firm on behalf of a physical firm, and firms with physical operations might engage in significant amounts of speculative trading.

B Estimation Details

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

1. In the first stage, I use realized auction prices to estimate firms' forward-looking price signals.
2. In the second stage, I use realized congestion prices to infer the risk premia shifter c_λ

In the first stage I use a constrained least squares approach. The problem is:

$$\max_{\chi \in \mathbb{R}, \alpha\lambda \geq 0, \alpha\sigma_e^2 \geq 0} \quad \sum_{r \in R} \left(\rho_r - \chi + \alpha \Omega A' F_r\right)' \left(\rho_r - \chi + \alpha A \Omega A' F_r\right)$$

Notice that χ is unconstrained. An analytical expression for χ conditional on $\alpha\Omega$ is:

$$\chi = \bar{\rho} + \alpha\Omega A'\bar{F}$$

Therefore the objective function can be re-written as follows:

$$\sum_{r\in R}\left(\rho_r - \bar{\rho} + \alpha\Omega A'\left(F_r - \bar{F}\right)\right)'\left(\rho_r - \bar{\rho} + \alpha\Omega A'\left(F_r - \bar{F}\right)\right)$$

Expanding the expression for Ω gives:

$$\sum_{r\in R}\left(\rho_r - \bar{\rho} + \alpha LUD_\lambda\left(LU\right)'A'\left(F_r - \bar{F}\right) + \alpha\sigma_e^2 A'\left(F_r - \bar{F}\right)\right)'\left(\rho_r - \bar{\rho} + \alpha LUD_\lambda\left(LU\right)'A'\left(F_r - \bar{F}\right) + \alpha\sigma_e^2 A'\left(F_r - \bar{F}\right)\right)$$

This can be written explicitly as a quadratic program in $\alpha\lambda$ and $\alpha\sigma_e^2$. To see this, I first write:

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

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. Then the problem to be solved is therefore:

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

which is a quadratic program with simple inequality constraints, and can therefore be solved efficiently. I solve the problem using KNITRO's nonlinear least squares solver.

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. In particular, recall that for each auction year y in the data, we must have:

$$\alpha = c_\lambda\left(\sum_{s\in S_y} F_{s,r}'A'\left\{LuD_\lambda u'L' + \sigma_{s,u}^2 I\right\}AF_{s,r}\right)^{-1/2}$$

and therefore:

$$\alpha_y^{1/2} = c_\lambda\left(\sum_{s\in S_y} F_{s,r}'A'\left\{LuD_{\alpha\lambda} u'L' + \alpha\sigma_{s,u}^2 I\right\}AF_{s,r}\right)^{-1/2}$$

Since agents beliefs are correct, the distribution of ex post congestion prices η satisfies:

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

where y is the relevant auction year. Re-arranging yields:

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

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:

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

provided that $\alpha\lambda_m + \alpha\sigma_e^2 > 0$. (In practice, $\alpha\lambda + \alpha\sigma_e^2$ may be estimated on the boundary, in which case $\alpha\lambda_m + \alpha\sigma_e^2 = 0$.) Substituting the expression for α_y from above gives the following:

$$c_\lambda \left(\sum_{s\in S_y} F_{s,r}' A' \left\{LuD_{\alpha\lambda}u'L' + \alpha\sigma_{s,u}^2 I\right\} AF_{s,r}\right)^{-1/2} D^{-1/2}_{\alpha\lambda_m + \alpha\sigma_e^2} Lu_m' \left(\eta_s - \chi_s\right) \sim N\left(0, I\right)$$

Therefore c_λ can be estimated under the assumption that the z-scores on the left hand side are drawn from a standard normal distribution. In particular, I construct $\hat{c}_\lambda$ as the value of c_λ that minimizes the Cramer-Von Mises statistic of the ecdf of z values constructed in this manner.

C Supplemental Material

C.1 Model

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:

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

This allocation rule is similar to the one used by MISO in practice.

Speculator Entry Let Π_s denote a speculator's profit in auction s when there are M_s entrants. Then the zero profit condition on speculator entry is:

$$\sum_{s\in S_y} \Pi_s\left(M_s\right) = C_s$$

Formally,

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

Assume that one third of the quantity is allocated in each auction round, so that $F_{s,r} = \frac{1}{3}F_s$. Then:

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

The equilibrium price vector is:

$$p_{s,r} = \mu_s - \alpha_s \Sigma_s \left\{\sum_{r\leq r} F_{s,r}\right\} \tag{28}$$

where $\alpha_s = \lambda_f M_s^{-1}$. Therefore:

$$\begin{aligned}\sum_{r\in R} p_{s,r} &= 3\mu_s - \lambda_f M_s^{-1}\left\{\frac{1}{3}\Sigma_s F_s + \frac{2}{3}\Sigma_s F_s + \frac{3}{3}\Sigma_s F_s\right\} \\ &= 3\mu_s - \lambda_f M_s^{-1} 2\Sigma_s F_s\end{aligned}$$

And:

$$\begin{aligned}\Pi_s &= \left(\frac{F_s}{M_s}\right)' \mu_s - \frac{\lambda_f}{2} M_s^{-2} F_s' \Sigma_s F_s - \left(\frac{F_s}{M_s}\right)' \mu_s + \lambda_f M_s^{-2}\left(\frac{2}{3}\right) F_s' \Sigma_s F_s \\ &= \left(\frac{1}{6}\right)\lambda_f M_s^{-2} F_s' \Sigma_s F_s\end{aligned}$$

So the zero profits condition is:

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

Therefore:

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

Hence:

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

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