

Price Formation in Auctions for Financial Transmission Rights

Jeff Opgrand,^a Paul V. Preckel,^b Douglas J. Gotham,^c and Andrew L. Liu^d

ABSTRACT

Financial Transmission Rights (FTRs) are financial derivatives in wholesale electricity markets that are sold in auctions. The revenue collected from FTR auctions is passed through to electricity customers to reimburse them for transmission congestion payments they make in the spot energy market. On average, electricity customers' congestion payments greatly exceed auction reimbursements in electricity markets across the United States. We study the issue of auction revenue deficiency through the lens of Auction Revenue Rights (ARRs), which is the predominant mechanism used in U.S. electricity markets to distribute auction revenue to electricity customers. We demonstrate how the ARR process influences fundamental supply conditions in the FTR auction market and show how divergent auction equilibria emerge under different ARR decision-making regimes. Using market data from PJM, we find empirical evidence that variation in ARR management strategies helps explain differences between an FTR's auction price and its realized ex post value.

Keywords: Financial transmission rights, Electricity markets, PJM, Congestion, Price discovery

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1. INTRODUCTION

Since the passage of FERC Order 888 in 1996, competitive electricity markets have expanded in the United States to serve roughly two-thirds of electricity consumers in the country. The Order encouraged open access to transmission facilities, the divestiture of vertically integrated utilities, and the creation of Independent System Operators to administer competitive markets. A key feature of competitive electricity markets is a location-based pricing system. For competitive market participants, location-based pricing implies location-specific price risk due to potential network congestion that can cause price differences across nodes. The presence of uncertain network congestion inspired the creation of a financial product to hedge locational price differences (Hogan, 1992). In U.S. electricity markets, this financial product is called a Financial Transmission Right (FTR). These financial products are used by market participants to manage exposure to the risk of price differences between two locations on a transmission network.

a Corresponding author. Economist, Office of Energy Policy and Innovation, Federal Energy Regulatory Commission. E-mail: jopgrand@gmail.com. The views expressed in this article are solely the views of the author(s) and do not represent the views of the Federal Energy Regulatory Commission or the United States Government.

b Department of Agricultural Economics, Purdue University. E-mail: preckel@purdue.edu.

c State Utility Forecasting Group, Purdue University. E-mail: gotham@purdue.edu.

d Department of Industrial Engineering, Purdue University. E-mail: andrewliu@purdue.edu.

FTRs are sold in auctions administered by an Independent System Operator. The revenue raised in these auctions is allocated to load-serving entities (LSEs) to reimburse their electricity customers for expected congestion payments they will incur in the energy market. However, recent analysis shows that FTR auctions are persistently profitable for speculators, and that, on average, electricity customers are not fully reimbursed for their congestion payments.¹ One common explanation for the auction revenue shortfall is that the FTR auction process is inefficient (Deng et al., 2010; Olmstead, 2018).² In this paper, we propose an alternative explanation for persistent congestion reimbursement shortfalls, which is the role of trading premiums demanded by auction participants. Essentially, the trading premium of an FTR adjusts the FTR's bid price to account for the market participant's risk aversion and/or transaction costs.

Our main contribution is a conceptual and empirical analysis of the market mechanism used to reimburse electricity customers for their expected congestion payments. This mechanism, called the Auction Revenue Right (ARR) process, gives an LSE a choice between acquiring an FTR at no cost or selling the same FTR in the annual FTR auction and receiving the associated auction revenue. Given that the choices made by LSEs in the ARR process determine fundamental supply conditions in the FTR auction market, we develop a conceptual framework that describes how different auction equilibria emerge under different ARR decision-making regimes. A key insight is that even if the FTR auction market is fully competitive, an LSE selling an FTR through the ARR process may result in a financial transfer from electricity customers to FTR buyers through a buyers' trading premium. One component of the trading premium is a risk premium adjustment due to the extreme difficulty of forecasting the future payout of an FTR.

We test the predictions from our conceptual model using data from the PJM market. PJM is a wholesale electricity market in the eastern United States serving 65 million customers. We study ARR management strategies and outcomes in PJM using publicly available data on auction results, realized network congestion, auction participant classifications, and various other components. We find robust empirical evidence that variation in ARR management strategies helps explain differences between an FTR's auction price and its realized *ex post* value.

Previous studies have examined the efficiency of FTR auctions (Adamson et al., 2010; Deng et al., 2010; Olmstead, 2018) and analyzed the presence of abnormal returns in FTR markets (Baltadounis et al., 2017). While our empirical finding that FTR auction prices diverge from their *ex post* value is consistent with the literature, we differentiate ourselves from these previous studies by focusing on the role of FTR supply (or lack thereof) in determining an FTR's equilibrium auction price.

To explain the role of the ARR process in price formation in FTR auctions, we organize the rest of the paper as follows. Sections 2 and 3 provide an overview of competitive electricity markets as well as a review of the existing literature that examines FTR auction markets. Section 4 provides a conceptual representation of how decisions made in the ARR process influence equilibrium FTR auction outcomes. Sections 5 and 6 describe the data, empirical approach, and results regarding ARR management strategies in the PJM market. Section 7 concludes.

1. The work of the California ISO's Department of Market Monitoring and PJM's independent market monitor highlight this fact and has received attention in their respective ISO/RTO stakeholder processes (California ISO, 2016; Monitoring Analytics, 2017). See also Leslie (2018).

2. Olmstead's description of inefficiency relies on the observation that FTR auction price are on average lower than FTR realized values in Ontario. Deng et al.'s description of inefficiency is related to the formulation of the auction clearing process and hypothesized bid quantities in the auction.

2. INSTITUTIONAL SETTING

Competitive wholesale electricity markets are based on a system of locational marginal prices (LMPs). An independent system operator (ISO) collects offers from generators to produce power and bids from LSEs to consume power and then solves an economic dispatch optimization problem to settle the market. The essence of economic dispatch is that it selects the least-cost, or welfare-maximizing, mix of generation resources to meet electricity demand. Coordination of power flows by an ISO to achieve least-cost dispatch guarantees the transmission network is used most efficiently. Efficient use of the transmission network in a competitive setting cannot be achieved without the coordination of an ISO (or similar entity) because electricity travels according to Kirchoff's Laws, which makes the enforcement of physical property rights to transmission capacity impractical on an interconnected grid.

In an LMP system, generation resources are dispatched in merit order in terms of marginal delivery cost, starting with the cheapest units. When a transmission element reaches its rated carrying capacity, the ISO may have to dispatch a generation resource out of merit order to avoid damaging the transmission element. In the economic dispatch optimization problem, this limiting transmission element is called a binding constraint. In the absence of binding transmission constraints, all LMPs (ignoring losses) will be equal to the same price throughout the network, namely the marginal cost of generation. Whenever there is a binding transmission constraint in the economic dispatch problem, LMPs at each node reflect the opportunity cost of scarce transmission capacity in addition to the marginal cost of generation. In general, prices at load nodes increase and prices at generator nodes that contribute to congestion decrease with a binding transmission constraint.

The nodal price fluctuations faced by market participants due to congestion represent price risk that is ubiquitous in electricity markets. Generators and power utilities often engage in bilateral contracts or purchase futures contracts to mitigate this price risk. However, these contracts are typically settled at a node that is different from the node at which the generator or load settles physical power transactions with the ISO. Market participants must forward contract at nodes different from their own because there are thousands of nodes and forward contracts at each individual node would be too thinly traded. So, after forward contracting for energy, generators and load face locational basis risk that cannot be hedged with bilateral contracts or exchange-traded products. To fill this gap, most ISOs act as counterparty to a hedging product called a Financial Transmission Right (FTR) that can be used as a hedge against locational basis risk.

2.1 Financial Transmission Rights

An ISO sells FTRs in periodic auctions up to three years before the FTR begins generating cash flows. Market participants submit offer 'schedules' into the auction to buy (or sell previously acquired) FTRs. A schedule is a series of bids where each bid includes a source node, a sink node, a MW quantity, a reservation price, and potentially other characteristics (e.g., on-peak hours or off-peak hours, a particular month or season, etc.). Which characteristics are available in a given auction vary by ISO and auction type (e.g., long-term, annual, or seasonal auction). There are no restrictions as to which nodes can be source or sink nodes, nor do source or sink nodes need to correspond to where generators or load physically reside on the network.³ Most ISOs sell both FTR obligations and options. FTR options are unique because they can never have a negative value. The following

3. A recent market reform in CAISO limits which nodes can be used as source or sink nodes.

description and focus of this paper is on FTR obligations because FTR obligations make up the vast majority of the FTR market and are the relevant product type when discussing ARR.

A mathematical programming model whose objective function is to maximize the FTR auction revenue determines auction-clearing prices. To see a mathematical formulation of the FTR auction problem, see Appendix A. The mathematical program that determines cleared transactions in the FTR auction calculates a price for every source/sink combination simultaneously. The auction-clearing price for an FTR is the nodal price difference between the source and the sink determined in the auction:

$$\text{FTR Auction Price} (\$/\text{MW}) = P_{\text{Auction}}^{\text{Sink}} - P_{\text{Auction}}^{\text{Source}}, \quad (1)$$

where $P_{\text{Auction}}^{\text{Sink}}$ is the nodal price at the sink node in the auction, and $P_{\text{Auction}}^{\text{Source}}$ is the nodal price at the source node in the auction.

The payoff to an FTR is determined in the day-ahead energy market over the time period that the FTR covers. The payoff, called the Target Allocation, is defined as the difference between the congestion components of LMP in the day-ahead energy market for every hour the FTR is a valid obligation (as defined by the contract):

$$\text{FTR Target Allocation} (\$/\text{MW}) = \sum_{t \in T} (P_t^{\text{Sink}} - P_t^{\text{Source}}), \quad (2)$$

where t is the index of hours during which the FTR is a valid obligation as defined by set T , P_t^{Sink} is the congestion component of the LMP at the sink node in hour t , and P_t^{Source} is the congestion component of the LMP at the source node in hour t . At the time of the auction, an FTR's Target Allocation is uncertain. Because the bidder specifies a quantity (in MW) for an FTR contract, the payout for a contract is calculated by multiplying the FTR Target Allocation times the contract quantity.

An FTR is conventionally called 'prevailing flow' if its auction price is positive and 'counterflow' if its auction price is negative. A positive price suggests that net power flows tend to move from the source to the sink as defined by the FTR. A negative price suggests that net power flows tend to move from the sink to the source as defined by the FTR, hence, 'counterflow.' In effect, when a market participant purchases a counterflow FTR, the market participant is paid some amount of money in the auction to hold an FTR that has a negative expected cashflow.

2.2 Auction Revenue Rights

We focus on electricity markets that use "Auction Revenue Rights" (ARRs) to distribute auction revenues to market participants.⁴ An ISO allocates ARRs to LSEs along specific source/sink paths and in specific MW quantities. The source node of an ARR usually corresponds to a generating resource in the LSE's service territory, while the sink node is usually an "aggregate" node type that is an index of load nodes in the LSE's service territory. The holder of an ARR can either claim revenue from the auction or convert the ARR into an FTR. The revenue awarded to an ARR holder in the annual FTR auction is:

$$\text{ARR Auction Revenue} (\$) = Q \times (P_{\text{Auction}}^{\text{Sink}} - P_{\text{Auction}}^{\text{Source}}), \quad (3)$$

4. The ARR system is used by ISO-New England, Midwest Independent System Operator, PJM, and Southwest Power Pool.

where Q is the quantity (in MW) of ARR being claimed as auction revenue and auction prices are calculated as before. In PJM, the annual auction occurs in April and consists of four rounds. There is approximately one week between rounds, with results from one round posted before the start of the next round. The sink and source prices used in (3) are simple averages across the four rounds. If the ARR holder chooses to “self-schedule” their ARRs into FTRs, then the payout for the resulting FTRs (i.e., Target Allocation) is the same as in (2), where the sink node is the LSE’s aggregate sink node and the generator node is the source node.

An ARR holder must choose whether they will claim auction revenue or self-schedule into FTRs before the commencement of the annual auction. Thus, both auction revenue and revenue from FTR holdings are uncertain at the time of the decision. Further, the ARR holder is not able to set a ‘strike price’ or otherwise construct a supply curve for self-scheduling FTRs conditional on the auction clearing price. In other words, the ARRs are offered into the auction with a \$0 reservation price. An ARR holder can diversify their ARR allocation by claiming a fraction of the quantity of an ARR allocation as auction revenue and self-scheduling the remaining fraction as FTRs. When an ARR holder chooses to diversify their auction revenue/self-scheduling decision, the payoff becomes:

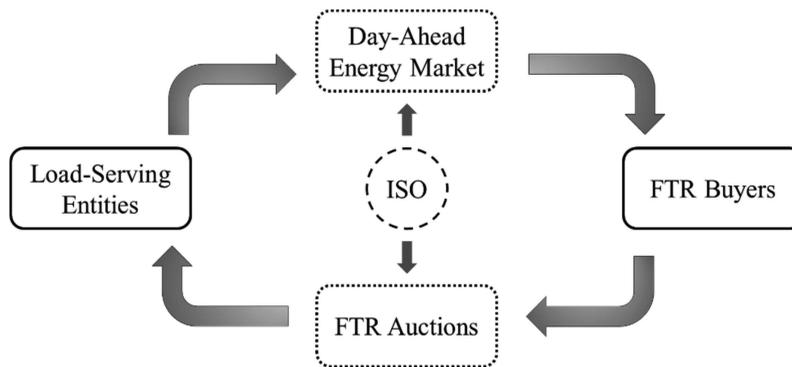
$$\text{ARR Strategy Payoff (\$)} = Q \times \left\{ \alpha \times (P_{\text{Auction}}^{\text{Sink}} - P_{\text{Auction}}^{\text{Source}}) + (1 - \alpha) \times \sum_{t=1}^T (P_t^{\text{Sink}} - P_t^{\text{Source}}) \right\}, \quad (4)$$

where Q is the total quantity of the ARR allocation in MW, α is the fraction of the ARR allocation claimed as auction revenue, and the payoff to the fraction of self-scheduled FTRs is defined as before. Again, note that both components of the payoff (ARR Auction Revenue and FTR Target Allocation) are uncertain when the ARR holder chooses the proportion to claim as auction revenue versus as FTRs.

FTR auctions are peculiar because there are no predetermined products available for bidding. Rather, the ISO auctions off ‘system capability’ that is analogous to transmission capacity. PJM allocates most of the network’s transmission capacity to LSEs in the form of ARRs. The manner in which ARRs are allocated to LSEs or other transmission customers varies across RTOs/ISOs (Bosquez Foti, 2016). In general, ARRs are allocated to market participants who acquire Network Integration Transmission Service or Firm Point-to-Point transmission service through the Open Access Same-Time Information System (Ma et al., 2002). These two types of market participants pay for the construction and maintenance of the transmission system; so, they are allocated ARRs for the purpose of offsetting the expected congestion rent that they incur in the day-ahead energy market.

3. RELATED LITERATURE

This paper contributes to the literature that studies the development and performance of markets for financial transmission rights. Hogan (1992) derived what is now known as the simultaneous feasibility conditions, which guarantee revenue adequacy for FTRs issued by the ISO. The simultaneous feasibility conditions are a set of constraints in the auction revenue maximization problem that require the ISO to respect the network’s transmission limits when issuing FTRs. In practice, the simultaneous feasibility conditions cannot guarantee revenue adequacy because the ISO must use a static ‘snapshot’ of the network for the FTR auction optimization problem. The actual network configuration used for dispatch (and thus for calculating LMPs) is dynamic, changing due to, for example, unforeseen transmission line outages throughout the period when the FTRs are

Figure 1: Flow of Money in an ISO through Congestion and FTRs

Note: From the left: Load-serving entities, on behalf of their electricity customers, pay congestion rent in the day-ahead energy market which flows to FTR buyers. FTR buyers purchased their FTRs in FTR auctions, the revenue from which flows to load-serving entities. The ISO (center) administers both the day-ahead energy market and FTR auctions.

valid financial obligations. For a comprehensive review of FTR auction theory and mathematical formulations, see Rosellon and Kristiansen (2013).

Recent studies of FTR auctions focus on whether the clearing prices in the auction provide unbiased estimates of future congestion charges. Adamson et al. (2010) examine FTR returns in the New York ISO in the earliest years of FTR auctions and find that transactions profits declined as the market matured. Baltadounis et al. (2017) study FTRs in a capital asset pricing model (CAPM) framework where they test whether specific source/sink pairs experience “abnormal” returns relative to the entire market’s returns. Using an *ex post* evaluation of FTR returns in California from 2009–2015, they find that about half of the FTR source/sink pairs studied in California displayed returns statistically different from average market levels (i.e., abnormal returns). The distributions of returns were positively skewed, suggesting that there were more extremely profitable FTR paths than extremely unprofitable paths. Olmstead (2018) studies whether clearing prices in Ontario’s FTR auction are unbiased predictors of congestion. Olmstead finds that auction prices are better predictors of congestion when there are more bidders present in the auction. Leslie (2018) conducts a similar study for the NYISO while controlling for the “firm type” of the bidder; that is, he characterizes each auction participant as a generator, an electricity retailer, or a speculator. He also studies whether the fact that an FTR was purchased in a previous round for a given path helps explain the FTR’s profitability. Leslie finds that FTRs that clear on paths where there are no open positions are more likely to be profitable and suggests that speculators provide liquidity to the FTR auction market.

Our work is also related to the literature that studies the impact that fundamental supply and demand conditions have on forward market risk premiums. In the context of energy markets, Benth et al. (2008) argue that the timing of hedging decisions made by buyers and sellers, along with their levels of risk aversion, impacts the sign and magnitude of the market risk premium in the forward German electricity market. Botterud et al. (2010) study changes in the sign of the market risk premium in the hydro dominated Nord Pool, where reservoir levels and water inflow patterns explain some variation in observed risk premiums.

This study is a contribution to the aforementioned literature because of our rigorous accounting for market supply conditions that precede the commencement of FTR auctions. Decisions made during the ARR process determine where on the transmission network cheap supply is available to FTR bidders. More importantly, we conclude that where and how much cheap supply is

made available through the ARR process impacts equilibrium auction outcomes, as we demonstrate in the following conceptual model.

4. CONCEPTUAL MODEL

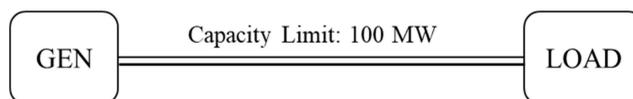
In this section, we develop a conceptual model that describes equilibrium outcomes in FTR auctions under various ARR management strategies. To do this, we consider a hypothetical two-node network where “GenCo” sells power to “LSE” across a transmission line. Using this simple network, we demonstrate the impact that the LSE’s ARR configuration decision has on transmission capacity available to FTR bidders in the FTR auction, and ultimately, the impact that the ARR configuration decision has on electricity customers’ expected payoffs due to the LSE’s ARR management strategies.

4.1 Impact of ARR Configuration on the Supply of Transmission Capacity

The ISO maximizes FTR auction revenue subject to the feasible transmission capacity of the network. In the mathematical formulation of the auction clearing process, transmission capacity is modelled explicitly as the right-hand-side values for each transmission constraint. The majority of the network transmission capacity is allocated to the LSE in the form of ARRs. The LSE determines how much of this transmission capacity is available to bidders at a reservation price of \$0 through their ARR management decision not to self-schedule some of their ARR allocation as FTRs. As the LSE self-schedules more ARRs into FTRs, they are removed from the auction and there is less zero-reservation-price transmission capacity available to other bidders. Transmission capacity (i.e., market supply) beyond the ARR allocation is created either by an FTR holder offering to sell a previously acquired FTR or an auction participant bidding to purchase a counterflow FTR (in the case of ARRs, a counterflow FTR would have a load node as the source and a generation node as the sink).

To demonstrate the effect of an LSE’s ARR configuration decision on the supply of transmission capacity, consider a hypothetical ARR allocation on a simple two-node network with one transmission line that has a maximum flow capacity of 100 MW. GenCo owns cheap generation resources located at one node (the “Gen” node) and the LSE’s electricity customers are located at the other node (the “Load” node). There is also expensive generation located at the Load node, but expensive generation is only dispatched when the transmission line is at its maximum capacity. Thus, whenever the transmission line is at its maximum capacity and the marginal supplier of power is at the Load node, the ISO collects congestion rent from the LSE that is equal to the opportunity cost of scarce transmission capacity.

Figure 2: Two Node Transmission Network



Because the LSE’s electricity customers pay for the transmission line connecting the Gen node and Load node, the LSE is allocated 100 MW of ARRs as compensation for any congestion rent the ISO collects on the transmission line. The LSE chooses what proportion of this 100 MW ARR allocation to claim as auction revenue and what proportion to convert directly into FTRs. For

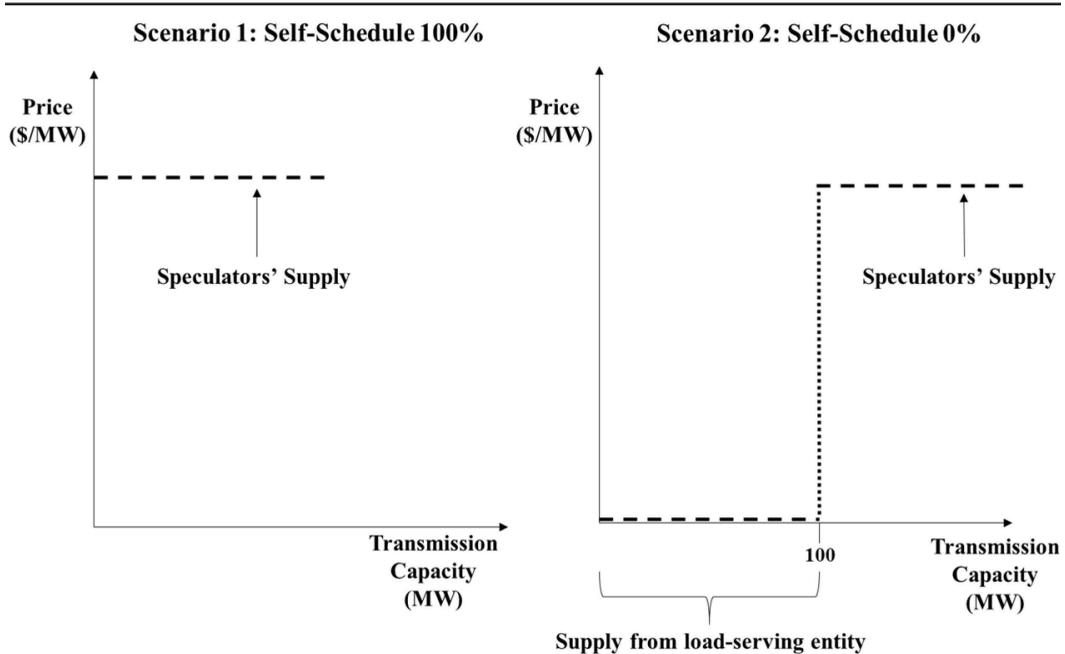
the sake of our example, suppose the LSE is deciding between the two extrema of the ARR management decision: self-scheduling the entire ARR allocation into FTRs (Scenario 1) or claiming the entire ARR allocation as auction revenue (Scenario 2).

Table 1: Hypothetical 100 MW ARR Allocation between Source Node “GEN” and Sink Node “LOAD”

	Self-Scheduled Quantity (MW)	Auction Revenue Quantity (MW)
Scenario 1	100	0
Scenario 2	0	100

Figure 3 illustrates the impact that the LSE’s ARR management decision has on market supply of transmission capacity available to bidders in the FTR auction. In the left frame of Figure 3, the LSE self-schedules its entire ARR allocation into FTRs (Scenario 1). The supply of transmission capacity along the ARR path is composed only of FTR sell offers and counterflow FTR buy bids made by entities other than the LSE (i.e., speculators). Conversely, in the right frame where the LSE claims their ARRs in the form of auction revenue (Scenario 2), the supply curve includes the 100 MW horizontal portion with price \$0 as well as the supply from sell offers and counterflow buy bids. In practice, an LSE may choose a mixed ARR management strategy, for example, self-scheduling 50% of their ARR allocation into FTRs and claiming 50% as auction revenues.

Figure 3: Supply Curve of Transmission Capacity Available to Auction Bidders between GEN and LOAD, with (Scenario 1) and without (Scenario 2) Self-Scheduled FTRs

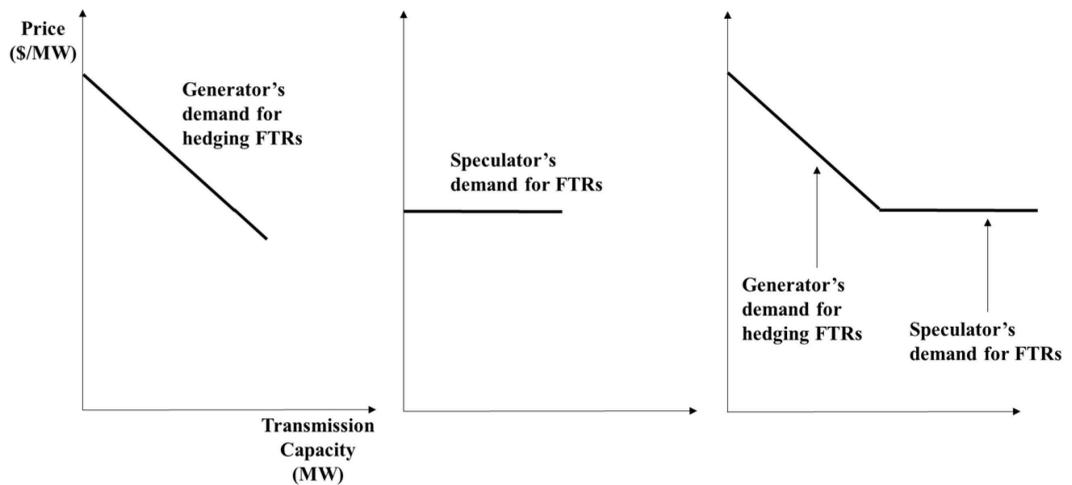


Continuing our example, suppose a generator located at the Gen Node has a forward fixed-price contract for power delivery. The structure of a fixed price contract requires both an agreed upon price and location, which in this case is the Load node. However, the generator conducts

hourly power transactions with the ISO in the day-ahead market that settle at the Gen node. Thus, the generator has not fully hedged its power sales through the fixed price contract. The fixed price contract guarantees the generator price certainty at the Load node but not at the Gen node; so the generator remains exposed to locational basis risk at the Gen Node whenever the transmission line is at maximum capacity. If the generator were to purchase an FTR with the Gen Node as the source node and the Load node as the sink node, the generator would effectively transfer the location of their fixed price contract from the Load node to the Gen node. This is because the FTR reimburses the generator for their congestion charges between the contract node and the node at which they settle daily power transactions with the ISO.

Suppose the generator bids into the FTR auction a demand schedule for FTRs with Gen node as the source and Load node as the sink. The generator competes for FTRs with other auction participants, including financial speculators, who bid for profitable FTRs. Generators and financial speculators have different objectives in the auction, with generators hoping to hedge locational price risk and speculators hoping to reap the benefits of acquiring an FTR for less than it will pay in congestion rents. It seems reasonable to assume that both generators seeking to hedge and speculators are risk averse, and so at least a portion of the generator’s demand curve should be for prices that exceed the speculators’ willingness to pay.⁵ Figure 4 presents stylized demand curves for FTRs between the Gen Node and Load Node. The hedging generator’s demand curve is the leftmost frame, speculators’ demand is the middle frame, and aggregate demand is the right frame.

Figure 4: Generator and Speculator Demand for FTRs along the GEN to LOAD Path

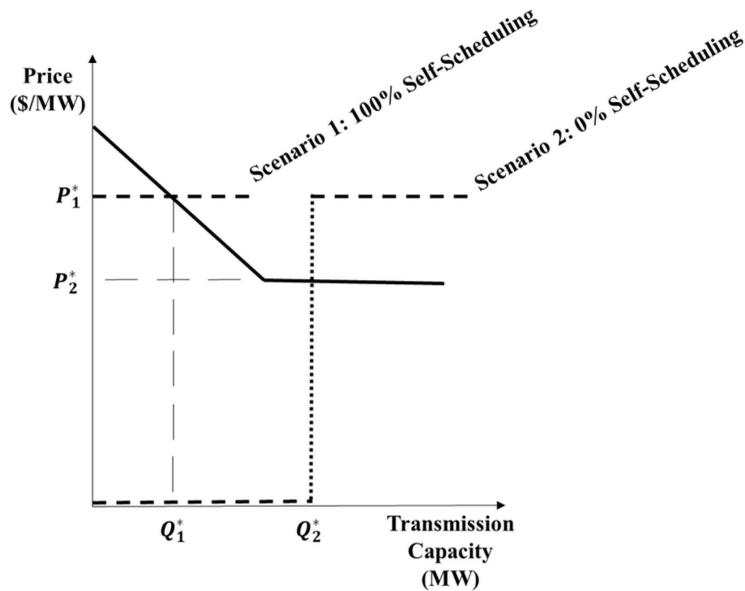


By *not* self-scheduling ARR into FTRs (Scenario 2), the LSE makes transmission capacity available at price \$0 that can be purchased by the generator and speculators. Figure 5 combines the supply curves from Figure 3 and the aggregate demand curve from Figure 4 to depict the influence that the LSE’s self-scheduling decision has on equilibrium prices and quantities for a given ARR/FTR path with fixed hedging and speculation demand. Under Scenario 1 (100% self-scheduling),

5. The generator’s inclination to hedge power sales suggests the generator is risk averse, and thus would be willing to pay a risk premium for some quantity of FTRs above the expected value of the FTR to achieve price certainty. Speculators, as profit maximizers, may or may not be risk averse, but would not be willing to pay any price for an FTR above its expected value. If they are risk averse, they would be willing to pay even less for an FTR. Our stylized example assumes that the generator and speculators have symmetric information regarding the expected value of the FTR.

when the LSE does not make transmission capacity available at \$0, the generator is only able to acquire FTRs by transacting with supply made available by speculators. However, under Scenario 2 (0% self-scheduling), the generator is able to acquire a greater quantity of FTRs at a lower price when the LSE makes transmission capacity available at \$0.

Figure 5: Equilibrium Price and Quantity under Supply Scenarios 1 and 2



Note: Theoretically, transmission capacity is the appropriate unit of analysis for 'quantity' as it relates directly back to the mathematical program that solves the auction problem. Empirically, we do not perfectly observe transmission capacity (either of the system or an individual FTR's impact on transmission capacity) and so have to use FTR quantity (in MW) as a proxy for transmission capacity.

4.2 The Role of Speculators in FTR Auctions

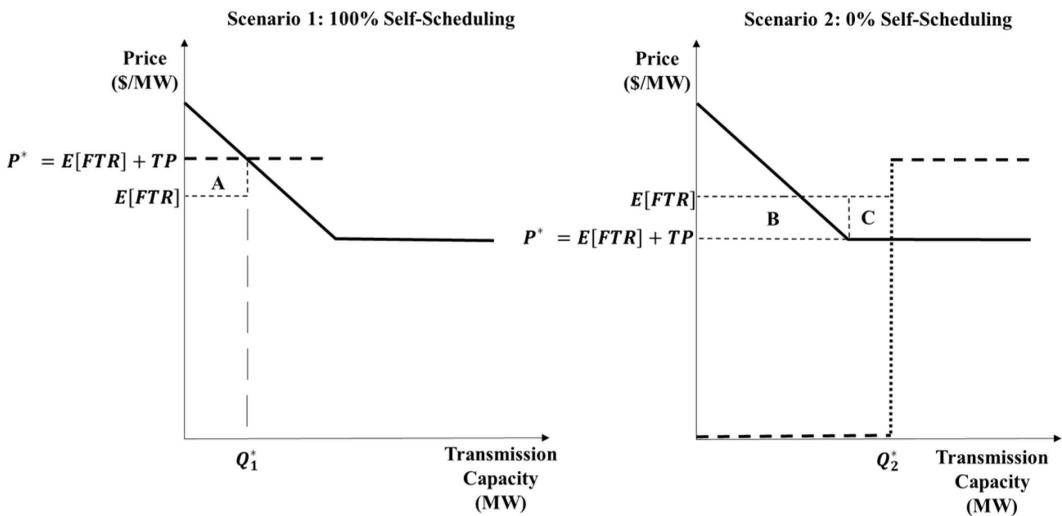
With risk neutral bidders and no transaction costs, market efficiency implies that the equilibrium auction price of an FTR is equal to its expected *ex post* value (conditional on the information available at the time of the auction). However, in this paper and the publications discussed earlier, we observe that FTRs are persistently profitable for financial speculators, suggesting that financial speculators demand a trading premium for holding FTRs. A portion of the trading premium may be a risk premium if the speculators are risk averse. Alternatively, the trading premium may be driven by transactions costs, such as collateral requirements, that are required for auction participants. Further, the cost of developing and executing a trading strategy can also be viewed as a transactions cost. The presence of transactions costs has been studied and identified in other electricity derivative markets (Jha and Wolak, 2020).

When a speculator bids to purchase an FTR, the trading premium *reduces* the speculator's bid price relative to the expected *ex post* value of the FTR. This is regardless of whether the FTR is prevailing flow or counterflow (in expectation). For example, consider an FTR from A→B with an expected *ex post* value of \$40. A speculator's hypothetical trading premium might be \$5; so, the speculator bids \$35 for the FTR. Now, consider a speculator placing a bid to buy the counterflow FTR B→A. By definition, this FTR has an expected *ex post* value of -\$40. If the speculator's magnitude of trading premium is the same for counterflow FTRs as for prevailing flow FTRs, then the

speculator will bid -\$45. In both cases, the trading premium is subtracted from the expected *ex post* value of the FTR.

The right frame of Figure 6 depicts the distribution of expected financial surplus in supply Scenario 2 between the hedging generator and financial speculators. The equilibrium auction clearing price is the expected *ex post* value of an FTR between Gen and Load plus the trading premium (“TP”) demanded by the marginal bidder (i.e., the speculator) for holding a risky asset. As described above, the trading premium is negative, and thus the equilibrium auction price is less than the FTR’s expected value. The hedging generator captures expected financial surplus equal to area B while speculators capture expected financial surplus from area C. This financial surplus is the difference between the revenue the LSE would receive (in expectation) from keeping FTRs themselves and the revenue the LSE receives from the auction by selling the FTRs. Ultimately, this financial transfer is borne by electricity customers who receive credits for ARR auction revenues or FTR revenues on their electricity bills.

Figure 6: Distribution of Trading Premium Rents in Supply Scenarios 1 and 2



Note: The equilibrium clearing price in both scenarios is $E[FTR] + TP$, but TP is positive in scenario 1 and negative in scenario 2. The difference in the sign of TP is driven by whether the financial speculator is the marginal seller (scenario 1) or buyer (scenario 2).

When the LSE does not make cheap transmission capacity available to bidders by self-scheduling the ARRs into FTRs, the hedging generating firm has to pay a trading premium to speculators offering supply (left frame of Figure 6). Here, the equilibrium auction clearing price is the expected *ex post* value of an FTR between Gen and Load plus the trading premium demanded by the marginal bidder (i.e., the speculator) for *selling* a risky asset; hence, the trading premium is positive. The hedging generator has to pay the speculator’s trading premium equal to area A to compensate for the financial participants’ risk and transactions costs associated with supplying transmission capacity. This outcome, where the equilibrium auction price exceeds the expected value of the derivative, is typical in insurance markets where the buyer of insurance compensates the seller of insurance for assuming the buyer’s risk. Note that the auction clearing price and quantity are irrelevant to the LSE in Scenario 1 because the LSE elected to hold FTRs rather than claim auction revenue.

As we have seen, the equilibrium trading premium can be positive or negative. The size of the trading premium depends on the magnitude of risk aversion and transactions costs incurred by

FTR bidders. The sign of the equilibrium trading premium depends on the relative desire of buyers and sellers to hedge. If more buyers hedge (left frame of Figure 6) than sellers, the equilibrium trading premium increases; if more sellers hedge (right frame of Figure 6) than buyers, the equilibrium trading premium decreases and becomes negative. The preceding example considers the extrema of ARR management strategies, i.e., either an entire self-schedule of the ARRs by the LSE or a complete conversion of the ARRs into auction revenues. In reality, LSEs often choose a mix of auction revenue and FTRs from their ARR allocation. From the example, it should be intuitive that moving from 100% self-scheduling to an interior point management point, such as 50% self-scheduling, corresponds to a rightward shift of the supply curve and a (weakly) lower equilibrium auction price.

4.3 The LSE's Expected Revenue

Recall that the LSE's payoff function for their ARR allocation can be written as the sum of payouts from ARRs claimed as auction revenue and self-scheduled FTRs, weighted by the configuration chosen by the LSE where α corresponds to the fraction of the allocation that is claimed as auction revenue. Because the ARR holder does not know the auction value or FTR value of their ARR allocation at the time they make the configuration decision, both the ARR auction value and the FTR value are random variables. Using our visual aid in Figure 6, we can rewrite the ARR payoff function (equation (4)) and expected payoff function as:

$$\begin{aligned} \text{Expected ARR Payoff (\$)} = \\ Q \times \{ \alpha \times (\mathbb{E}[FTR + TP]) + (1 - \alpha) \times \mathbb{E}[FTR] \}, \end{aligned} \quad (5)$$

The level of congestion over the life of the FTR represents the underlying uncertainty in an FTR's Target Allocation. The underlying uncertainty in the ARR auction revenue, $\mathbb{E}[FTR + TP]$, is the complex interaction of supply and demand bids as well as the market clearing equilibrium trading premium, which could be positive or negative. We demonstrated in our conceptual model that the LSE directly influences this equilibrium auction price through their ARR management decision. Specifically,

$$\frac{\partial \mathbb{E}[TP]}{\partial \alpha} \leq 0, \quad (6)$$

where an increase in α is analogous to shifting the auction market supply curve to the right. In other words, the trading premium is decreasing as we move to the right along the demand curve (note that, in practice, the demand curve is a decreasing step function). In our model, we showed how the trading premium can actually change from positive to negative as α increases. For our example, we can write the LSE's expected payoff for each of the two scenarios where the ARR allocation had a quantity of 100 MW as:

$$\text{LSE's Expected Payoff (\$), Scenario 1 } (\alpha = 0) = 100 \times \mathbb{E}[FTR], \text{ and} \quad (7)$$

$$\text{LSE's Expected Payoff (\$), Scenario 2 } (\alpha = 1) = 100 \times (\mathbb{E}[FTR + TP]). \quad (8)$$

The sign and magnitude of the trading premium is determined by the marginal bidder in equilibrium. In our depiction of Scenario 2, the trading premium is negative, meaning the equilibrium auction price of the FTR is less than its expected value at maturity. We argue that the presence

of FTR bidders' trading premia in conjunction with supply made available through the ARR process explains, at least partially, the observed separation between FTR auction prices and FTR realized values in competitive electricity markets. The following sections investigate the role of ARR management strategies in explaining differences between FTR auction prices and FTR realized values in PJM from 2007–2017.

5. DATA

All of the data used in this analysis were downloaded from the PJM website under the “Markets & Operations” tab. PJM removes most market data from its website once it is a few years old; in such cases we retrieved the formerly public data from the PJM website via an internet archive called The Wayback Machine (Internet Archive, 2019). Our data span the years 2007–2018. Three of PJM's largest transmission zones (AEP, ComEd and Dominion) joined PJM in 2004–2005; so by the time our analysis begins in 2007, these three transmission zones had been fully integrated into PJM.

The basis of our data is the tables of annual ARR allocations⁶ published by PJM. An ARR allocation includes a source node, a sink node, and a quantity (in MW). PJM does not publish the market recipient's name associated with an ARR allocation. The sink node of most ARRs is a load aggregate node, which we classify as the ARR's “region” in our analysis. Most source nodes correspond to a generating station located in PJM. We supplement the ARR allocations with their *Auction Price* in the annual FTR auction, which is calculated as the average value of an FTR along the ARR path across the four rounds of the annual auction; this is consistent with the way PJM compensates ARR holders for their retained ARR allocations. We also include the realized *ex post* value of an FTR along the ARR path, called the *Target Allocation*, which is aggregated from daily files of market results from PJM's day-ahead energy market.

We construct our variable of interest, *Path Capacity*, which is a proxy for how much transmission capacity is available along an ARR path, by taking the difference between the ARR allocation quantity and self-scheduled quantity, in MW, along each ARR path. PJM does not report the quantity of ARRs that are self-scheduled into FTRs along a given path. However, we can infer self-scheduled quantities from the annual auction results data using the following observations. All self-scheduled FTRs are 24-hour products. The majority of FTRs that clear the auction are either on-peak or off-peak products; limiting our search to only 24-hour products substantially decreases the pool of candidate self-scheduled FTRs. Further, the annual FTR auction is conducted in four rounds. PJM makes an equal quantity of “transfer capacity” available in each round. To do this, PJM must clear self-scheduled FTRs in equal quantities across rounds. For example, for a 1 MW self-scheduled FTR from source node A to sink node B, we would observe 0.25 MW clearing from A to B in each round. Furthermore, a self-scheduled FTR is associated with the same participant⁷ in all four rounds. For our example, we would observe the same participant clearing 0.25 MW of a 24-hour product from node A to node B in each round. We can then cross-check our candidate self-scheduled FTR observations with the ARR allocations document to confirm that the candidate corresponds to an actual ARR allocation.

Finally, we construct a variable *Hedging Pressure* to approximate how much of the available transmission capacity is demanded by physical asset owners. Our measure of hedging pressure

6. We do not have ARR allocations for market years 2007 and 2008. For these years, we use the 2009 ARR allocations. We do not believe this is problematic because the ARR allocations do not change dramatically year-over-year from 2009–2018.

7. Participant names are observable in the auction market data, but not the ARR allocation data.

is the FTR quantity, in MW, that clears the annual FTR auction whose source node corresponds to the source node of an ARR allocation. We also require that the purchaser of the FTR be classified as a physical asset owner as defined by PJM (i.e., the member is classified by PJM as a Transmission Owner, Generation Owner, Electric Distributor, or End-use Customer).

Even though we observe many of the same ARR source/sink combinations in successive auctions, we do not treat this as a time series setting. An ARR source/sink combination may appear in successive auctions, yet the underlying definition of the FTR product changes from year to year due to changes to the transmission network. Technically, changes to the transmission network impact the shift factors used in the FTR auction and day-ahead energy market optimization. When the shift factors change, the impact a binding transmission constraint will have on a given source/sink combination in the form of FTR revenue changes. Therefore, we treat the data as a repeated cross section rather than time series because the products are not consistently defined over time.

6. ARR MANAGEMENT STRATEGIES

The conceptual model predicts that, all else equal, claiming an ARR in the form of auction revenue rather than self-scheduling it into an FTR will weakly decrease the equilibrium auction price of the associated FTR. This price decrease is associated with shifting the supply curve of available transmission capacity rightward along the downward sloping demand curve for FTRs. For an LSE, decreasing the auction price of an FTR associated with an ARR allocation is analogous to decreasing revenue received from the ARR allocation. This is problematic for electricity customers because decreased revenue from an ARR allocation means less revenue will be passed through via their electricity bills.

Table 2 presents aggregated (i.e., PJM-wide) data of market results. The column “Total ARR Value” measures the hypothetical value of all ARRs using annual auction clearing prices (equation (3)), whereas the column “Total FTR Value” measures the hypothetical value of all ARRs using market congestion data (equation (2)). Note that these two columns ignore whether an ARR was claimed as auction revenue or converted into an FTR. The third column, “Actual Value,” accounts for whether an ARR was actually claimed as auction revenue or converted into an FTR. In other words, the third column is the value that was actually recovered by LSEs through their ARR management decisions. In total, LSEs incurred a shortfall of more than \$700 million relative to what they would have received if they had self-scheduled all of their ARRs into FTRs. The conceptual model predicts that ARR decision making influences equilibrium auction prices, but not network congestion. Thus, we cannot say that LSEs would have increased their “Actual Value” by

Table 2: PJM-wide Results in the ARR Market (Millions \$)

Planning Period	Total ARR Value	Total FTR Value	Actual Value
2007/2008	\$ 1,675	\$ 1,931	\$ 1,771
2008/2009	\$ 2,326	\$ 1,597	\$ 1,723
2009/2010	\$ 1,273	\$ 765	\$ 925
2010/2011	\$ 1,012	\$ 1,433	\$ 1,253
2011/2012	\$ 951	\$ 718	\$ 812
2012/2013	\$ 560	\$ 605	\$ 564
2013/2014	\$ 494	\$ 1,473	\$ 852
2014/2015	\$ 721	\$ 947	\$ 786
2015/2016	\$ 931	\$ 736	\$ 825
2016/2017	\$ 902	\$ 633	\$ 788
2017/2018	\$ 552	\$ 782	\$ 591
Total	\$ 11,402	\$ 11,624	\$ 10,891

claiming more ARRs as auction revenue; the act of claiming more ARRs as auction revenue could decrease the ARR’s auction price.

The ARR market results displayed in Table 2 conceal important information about the role of ARR management strategies in determining auction equilibria and explaining observed differences between auction prices and realized values. In the next section, we test implications of the conceptual model related to the role of ARR management strategies and hedging pressure on the value of an ARR compared to its realized *ex post* value.

6.1 Empirical Strategy and Results

Table 3 presents summary statistics for the dependent variable *Target Allocation* and independent variables *Auction Price*, *Path Capacity*, and *Hedging Pressure* included in the regressions. On average, an ARR allocation has an auction value of \$4,600 per MW but FTRs associated with ARRs have an average *ex post* value of \$4,848 per MW. This average auction markdown of approximately 5% is consistent with the broad literature showing that FTRs sell for a price less than their realized *ex post* value. The average amount of *Path Capacity* (on a per-round basis) associated with an ARR allocation is 13 MW with a standard deviation of 32 MW, suggesting there is substantial variation in the data. The average level of *Hedging Pressure* on an ARR allocation is less than 50% of the average level of *Path Capacity*, which is consistent with the right frame in Figure 6 of our conceptual model where the supply shift from the ARR management decision overwhelms buyers’ desire to hedge, thus resulting in an equilibrium auction price below the expected value of the FTR.

Table 3: Summary Statistics for the Variables Included in the ARR Management Regressions

	Target Allocation	Auction Price	Path Capacity	Hedging Pressure	Total ARR	Self-Scheduled
Units	\$/MW	\$/MW	MW	MW	MW	MW
Obs	9,618	9,618	9,618	9,618	9,618	9,618
Mean	4,881	4,600	13	6	24	12
St. Dev	17,255	15,997	32	30	52	38
Min	(350,548)	(310,819)	0	0	0.03	0
Max	126,655	143,768	409	738	939	530

Our objective is to test whether the quantity of transmission capacity available to bidders in the FTR auction accounts for part of the variation between ARR auction prices and their associated FTR’s *ex post* realized values. To do this, we estimate a set of equations of the general form:

$$\begin{aligned}
 \text{Target Allocation}_{i,j,k} = & \gamma \text{AuctionPrice}_{i,j,k} + \theta \text{Path Capacity}_{i,j,k} \\
 & + \mu \text{Hedging Pressure}_{i,j,k} + \lambda_{j,k} + \varepsilon_{i,j,k},
 \end{aligned}
 \tag{9}$$

Each ARR allocation (our unit of observation) *i* is associated with a region *j* and a year *k*. The vector $\lambda_{j,k}$ captures region-year fixed effects and $\varepsilon_{i,j,k}$ is the error term. Identification of θ , our main coefficient of interest, comes from the region-year fixed effects which capture the impact of unanticipated congestion events that impact all FTRs in a given region and year. Examples of unanticipated congestion events include weather shocks (e.g., “Polar Vortex”) or unplanned outages of transmission lines or generators. The main concern with the use of region-year fixed effects is its potentially strong correlation with our variable of interest *Path Capacity*. This concern arises from the fact that, in some regions, *Path Capacity* is quite high or low for all ARR allocations in a given region and year. In short, the region-year fixed effect may capture some of the variation we are inter-

ested in, which is the effect of *Path Capacity* on *Target Allocation*. Thus, we also estimate versions of (9) that include year fixed effects rather than region-year fixed effects. Finally, given that *Path Capacity* is our primary variable of interest, we include the results of a regression where we consider an interaction between *Auction Price* and *Path Capacity* and higher order terms of *Path Capacity* as an illustrative example of the nonlinear impact of *Path Capacity* on *Target Allocation*. We report the results of these four regressions in Table 4.

One concern with our empirical strategy is potential non-stationarity of the FTR auction data. Thus, we conduct two types (i.e., Levin-Lin-Chu and Harris-Tzavalis) of panel unit root tests on the variables *Auction Price*, *Target Allocation*, *Path Capacity*, and *Hedging Pressure*. We use panel data methods because our data consists of hundreds of ARR paths per auction, with data on 11 auctions over time. In both tests, we reject the null hypothesis of data non-stationarity for all variables. The fundamental difficulty with any test for data stationarity in our setting is the short time dimension, so the results of the stationarity tests must be interpreted with caution. Along similar lines, we did not find evidence of structural change within the data in the years following the financial crisis.

Table 4: Regression Results Estimating the Impact of Available Transmission Capacity on FTR Target Allocation

VARIABLES	Dependent Variable: FTR Target Allocation			
	(1)	(2)	(3)	(4)
Intercept	872.40*** (162.7)	-527.04*** (52.72)	4,890*** (1,749)	-720.28*** (153.83)
Auction Price	0.83*** (0.02)	0.87*** (0.08)	0.84*** (0.06)	0.86*** (0.08)
Path Capacity	17.87*** (3.31)	12.66** (5.56)	16.63*** (5.31)	45.38* (23.80)
Hedging Pressure	-4.53 (3.60)	-3.68 (5.19)	-4.69 (4.96)	-2.93 (5.23)
Auction Price × Path Capacity				6.81E-04 (9.63E-04)
Path Capacity ²				-0.38 (0.23)
Path Capacity ³				7.9E-04 (5.2E-04)
Year FE	NO	NO	YES	NO
Region-Year FE	NO	YES	NO	YES
N	9,618	9,618	9,618	9,618
Adj. R ²	0.59	0.67	0.61	0.67

Notes: Regression 1 reports Pooled OLS with heteroskedastic-robust standard errors.

The interpretation of the intercept depends on the arbitrarily selected fixed effect suppressed from the regression. Standard errors are clustered at the region-year level. In Regression 4, *Auction Price x Path Capacity*, *Path Capacity*², and *Path Capacity*³ are jointly significant at the 5% level using an F-test.

*** p<0.01, **p<0.05, *p<0.1

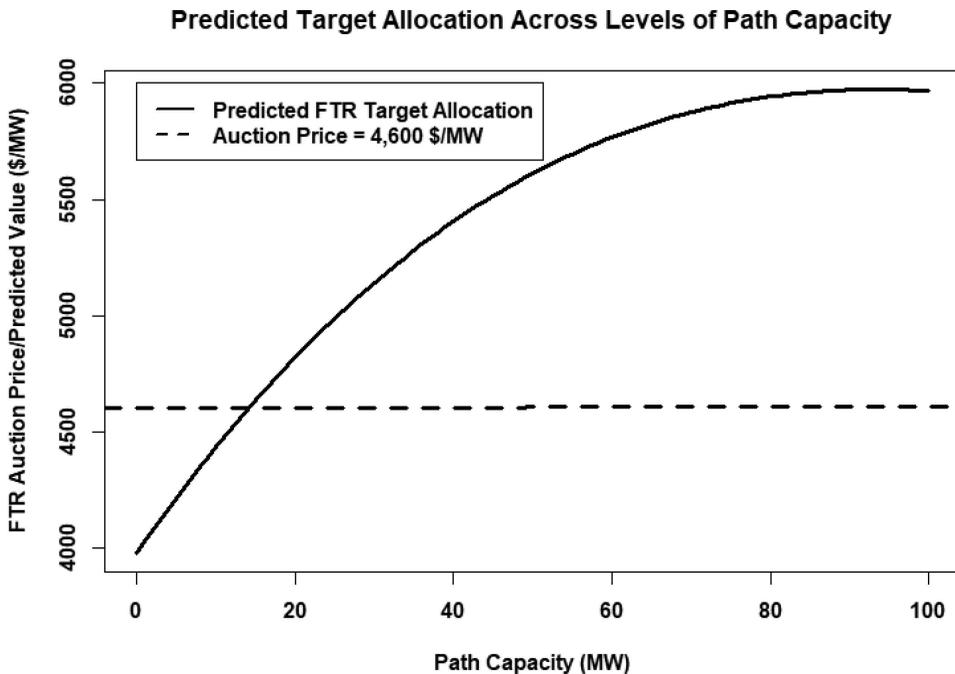
In all four regressions, *Path Capacity* is statistically significant, suggesting that *Path Capacity*'s positive impact on *Target Allocation* is invariant to the combination of fixed effects or confounders used in the analysis. The coefficient estimate of *Path Capacity* is numerically smaller and the adjusted R-squared is larger in the regressions that use Region-Year fixed effects, suggesting that these more granular fixed effects play a larger role in explaining variation in *Target Allocation* than the simple Year effects. In each regression, *Hedging Pressure* has the sign predicted by the conceptual model, but it is not statistically significant. Finally, despite the individual lack of significance of

the interaction and higher order terms in Regression 4, we find, using an F-test, that the interaction and higher order terms of *Path Capacity* are jointly significant.

An intuitive way to interpret the *Path Capacity* variable is to consider a choice between two FTRs, each along an ARR path, and where each was sold in the annual auction for \$100 per MW. The only distinguishing characteristic given regarding the FTRs is how much *Path Capacity* had been available in the auction along each path. Suppose that one of the FTRs was located on an ARR path that had 0 MW of *Path Capacity*, and the other was located on a path that had 100 MW of *Path Capacity*. Which FTR should a profit maximizing investor choose? Our results suggest the investor should choose the FTR along the path that had 100 MW of *Path Capacity* because it has a predicted value (using the results of regression 1) of \$1,787 per MW greater than the FTR on the path with 0 MW of *Path Capacity*. The reason for this difference in expected profitability, as suggested by our conceptual model, is that the trading premium included in the auction price of the FTR sold on the path with 100 MW of *Path Capacity* is smaller than the trading premium included in the auction price of the FTR sold on the path with 0 MW of *Path Capacity*.

To electricity customers, the financial cost or benefit of the LSE configuring an ARR as auction revenue is the difference between the auction revenue and the realized value of the FTR that would have been passed through to the customer. Using the results of Regression 4, Figure 7 illustrates the increasing foregone FTR revenue as the LSE claims an increasing quantity of the ARR allocation as auction revenue. Here, moving left to right is analogous to increasing in the conceptual model, where more transmission capacity is being made available to bidders in the auction. We fix the auction price of the FTR at \$4,600 per MW, which is the mean of *Auction Price* in our data. Notice at a *Path Capacity* level of 0 MW, the predicted value of the FTR is less than its auction price. This is consistent with the conceptual model, which shows that when the LSE does not make

Figure 7: Change in the Predicted Value of an FTR on an ARR Path as Transmission Capacity Increases, Holding Auction Price Constant (Results from Table 4 Regression 4)



transmission capacity available through the ARR process, FTR buyers have to pay FTR sellers a trading premium in order to take on the risk of making the FTR available. The FTR buyers' trading premium is decreasing in quantity (i.e., aggregate FTR demand is downward sloping), raising the expected value of the FTR relative to the auction price of the FTR as the quantity of cheap transmission capacity made available by the LSE increases.

6.2 Some Auxiliary Measures

We considered several alternative specifications as robustness checks on the models reported above, and present and discuss some results here. First, we disaggregate our variable of interest, *Path Capacity*, into two distinct variables, *Total ARR* and *Total Self-Scheduled*. Recall that the variable *Path Capacity* is measured by calculating *Total ARR* – *Total Self-Scheduled*. This robustness measure is meant to confirm that an increase in the size of an ARR award (holding self-scheduling constant) increases the expected value of an FTR on the ARR path, and that increasing the quantity of self-scheduled FTRs (holding the quantity of ARRs on the path constant) decreases the expected value of an FTR on the ARR path.

Table 5 reports the results of the robustness checks using *Total ARR* and *Total Self-Scheduled* as independent variables with two different levels of fixed effects. The two new disaggregated variables have the sign predicted by the conceptual model. *Total Self-Scheduled* can be interpreted as the decrease (in \$/MW) in the predicted value of an FTR as the quantity of ARRs self-scheduled into FTRs increases. *Total ARR* can be interpreted as the increase in the predicted value (in \$/MW) of an FTR on an ARR path when the available transmission capacity on the path increases. Using the Wald test, we cannot reject the hypothesis that the coefficient on *Total ARR* is equal to the negative of the one on *Total Self-Scheduled*.

Table 5: Results of Alternative Specifications

VARIABLES	Dependent Variable: FTR Target Allocation	
	(1)	(2)
Intercept	-515.9*** (56.6)	4,857*** (1,754)
Auction Price	0.87*** (0.07)	0.84*** (0.06)
Total ARR	10.89* (5.84)	14.67** (5.85)
Total Self-Scheduled	-8.03 (6.60)	-12.51 (8.00)
Year FE	NO	YES
Region-Year FE	YES	NO
N	9,618	9,618
Adj. R ²	0.66	0.61

Note: All standard errors are clustered at the region-year level.

*** p<0.01, **p<0.05, *p<0.1

One limitation to our analysis is the extent to which *Path Capacity* does not perfectly measure transmission capacity along an ARR path. As described earlier, electricity travels according to the path of least resistance creating the phenomenon of loop flows. Our measure of *Path Capacity* does not capture the impact of loop flows. That is, the self-scheduling decision along an ARR path will impact the availability of transmission capacity along a neighboring ARR path, yet it is impossible to say how impactful loop flows are for a given ARR path because we do not have access to

the network parameters. We hope to have partially alleviated this concern by clustering our standard errors at the region-year level because standard errors may be correlated at the region-year level due to loop flows (Cameron and Miller, 2014).

We consider two additional checks for mismeasurement of *Path Capacity*. First, we aggregate the data to the region level and estimate Pooled OLS again using the aggregated data. Second, we construct a new variable that measures, for a given ARR allocation, how much transmission capacity exists in its region apart from its own transmission capacity. We then re-estimate regression 2 in Table 4 while including this new variable that controls for excess transmission capacity in a region. In each of these scenarios, the coefficient on *Path Capacity* remains positive and statistically significant.

6.3 Patterns in ARR Management Strategies

In Appendix B, we provide a descriptive analysis of patterns in ARR management strategies across space and time in PJM. The ARR management strategies employed by LSEs appear to be persistent (i.e., they do not change drastically year-over-year) and appear to be linked to state-level market regulation. For ARR allocations whose source node is located in a retail choice state, the predominant strategy is to claim the auction revenue from an ARR rather than self-schedule it into an FTR. This observation could be related to the decoupling of generation from load in most retail choice states, which decreases an ARR's effectiveness as a hedging mechanism.

6.4 Discussion

We find empirical evidence that the quantity of transmission capacity available to FTR bidders on an ARR path is a determinant of FTR profitability, and correspondingly, is a determinant of electricity customers' expected revenue. This finding is robust to numerous specifications. This result is critical because LSEs decide how much transmission capacity is available through the ARR process, which determines how much auction revenue electricity ratepayers will receive. The results also suggest that when the LSE does not make transmission capacity available in the auction, the auction price of an FTR *exceeds* the expected value of the FTR. This is consistent with both our conceptual model and the normal functioning of markets that include deterministic prices for uncertain payoff streams, such as insurance markets.

7. CONCLUSION

Regulators are increasingly concerned about the effectiveness of FTR auctions to reimburse electricity customers for their congestion charges. We hypothesize that FTR bidders demand a trading premium to compensate for taking on risky returns and/or transaction costs, and that on the margin this trading premium creates a separation between an FTR's price at auction and its expected *ex post* value. In many competitive electricity markets, FTR auction revenues are returned to electricity customers through a process of Auction Revenue Rights where the value of an ARR is determined in an FTR auction. We show that the ARR management strategies employed by LSEs have a consistent first-order effect on the value of an ARR. Specifically, when an ARR holder increases the quantity of transmission capacity available to bidders in the auction (rather than directly converting the ARR into an FTR), the ARR holder effectively shifts the transmission capacity supply curve to the right. This decreases the value of the associated ARR. Electricity customers suffer financially when ARR values decrease because there is less revenue passed through on their electricity bills.

The result that FTR auction prices diverge from their expected *ex post* value is consistent with the literature on FTRs, in particular with Deng et al. (2010). However, we argue that transaction costs and asset risk associated with purchasing FTRs are the primary mechanism by which this price divergence occurs, as opposed to a fundamental flaw in the auction clearing mechanism and bounded FTR bid quantities described by Deng et al.

One of the objectives of the ARR process is to provide LSEs with a tool to hedge against congestion risk. Another concern related to this study is the LSE's exposure to congestion risk depending on whether they claim ARRs as auction revenue or convert them into FTRs. In theory, if the LSE converts all of their ARRs into FTRs, then their net expected return on congestion expenditures plus FTR revenue is mean zero with zero variance; that is, the LSE's FTR portfolio perfectly offsets congestion payments.⁸ When the LSE claims their ARRs as auction revenue, the LSE remains exposed to risky congestion charges in the day-ahead energy market. In PJM, approximately 70% of ARRs are claimed as auction revenue, suggesting that electricity customers may be exposed to the bulk of uncertain congestion events that occur in the energy market.

The magnitude of the trading premium associated with ARRs could be partially mitigated by changing both the ARR product structure and the auction in which ARRs are sold. Currently (in PJM), ARRs are full year products that have to be claimed as auction revenue or self-scheduled into FTRs during the annual FTR auction. A full-year ARR could be disaggregated into seasonal ARRs that are sold, or self-scheduled, during the monthly FTR auctions. The benefits of this change would be twofold: 1) the products would be shorter term and market conditions would be more well-known in the monthly auctions than during the annual auction, which should shrink the trading premium demanded at the margin; and 2) LSEs would be able to self-schedule FTRs or claim auction revenue based on their seasonal risk preferences, rather than having to make the decision for a full year.

This paper focuses on competitive electricity markets that use an ARR process, but the conceptual framework also applies to markets that have do not have this mechanism. Most, or even all, ISO/RTOs auction off some amount of "excess capacity" (including PJM) that is neither allocated to LSEs in the form of ARRs nor directly allocated to LSEs in the form of FTRs. For example, CAISO allocates some FTRs directly to LSEs and then sells the remaining transmission capacity in FTR auctions. By default, this excess capacity is marketed in CAISO's FTR auctions with a reservation price of \$0; hence, the supply curve used in these markets is analogous to that in the right frame of Figure 6. To our knowledge, all empirical studies confirm that FTRs in regions without an ARR process, including CAISO, are on average sold for prices below their *ex post* value, which is consistent with our conceptual model.

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APPENDIX A

In this appendix, we present a mathematical formulation of the optimization model used to settle FTR auctions, which closely resembles the formulation in Deng et al. (2010). We augment that formulation to include self-scheduled FTRs to illustrate the impact that the ARR process has on transmission capacity available to other bidders in the auction. We then provide an explicit example of the ARR impact on transmission capacity using Scenarios 1 and 2 of our conceptual model described in Section 4.

A.1 FTR Auction Optimization Program

Consider a transmission network composed of the set $i = \{1, \dots, N\}$ nodes and the set $k = \{1, \dots, K\}$ transmission lines. The normal line rating of transmission line k is denoted by L_k . The shift factor matrix for the network is denoted by $f_{k,i}$, where the k, i^{th} element refers to the impact of a 1 MW injection at node i on line k . We simplify our formulation by ignoring sell offers, emergency transmission constraints, losses, and other details such as hour types (e.g., on-peak vs. off-peak hours).

FTR auction participants submit a bid to purchase an FTR which consists of four elements: 1) a source node i ; 2) a sink node j ; 3) a maximum quantity $q_{i,j}$; and 4) a bid price $p_{i,j}$. Thus, a bid is defined by the indexed pair $(p_{i,j}, q_{i,j})$. The set of all bids submitted to the auctioneer is denoted by Ψ . If there is no bid for a particular source/sink pair, then $q_{i,j} = 0$ for that pair. Table 1 summarizes the nomenclature used in the mathematical formulation of the FTR auction model.

We augment the optimization model to include FTRs that are allocated to LSEs through the ARR process. Intuitively, transmission capacity needs to be “reserved” for self-scheduled FTRs to ensure that the self-scheduled FTRs are simultaneously feasible with the FTRs that are sold in the auction. We incorporate the ARR process into the optimization model using two parameters, $A_{i,j}$ and $\alpha_{i,j}$. $A_{i,j}$ refers to the quantity (in MW) of an ARR allocated to an LSE from source i to sink j , while $\alpha_{i,j}$ refers to the proportion of the ARR allocation between source i to sink j that is claimed as auction revenue by the LSE (i.e., not self-scheduled as an FTR).

The objective function of the auction is to maximize bid-based revenue generated by the bids that clear the auction. The load balance constraint ensures that total injections into the network equal total withdrawals while the simultaneous feasibility conditions ensure that the set of cleared bids and self-scheduled FTRs respect the physical limitations of the transmission network.

Table A1: Notation for FTR Auction Optimization Program

i,j	Index for nodes in set N
k	Index for transmission lines
$q_{i,j}$	Bid quantity (MW) for FTR with source node i and sink node j
$p_{i,j}$	Bid price (\$/MW) for FTR with source node i and sink node j
Ψ	Set of bids entered into the auction, each bid consisting of a source i , sink j , quantity $\overline{q_{i,j}}$, and bid price $p_{i,j}$
q_{ij}	Variable quantity (in MW) from source node i to sink node j
$f_{k,i}$	Change in power flow on line k due to 1 MW injection at node i (i.e., shift factor matrix)
L_k	Normal line rating for transmission line k
$A_{i,j}$	Quantity (MW) associated with an ARR allocation with source node i and sink node j
$\alpha_{i,j}$	Proportion of ARR allocation with source node i and sink node j claimed as auction revenue
C_i	Market clearing price at node i
λ_k	Shadow price on the simultaneous feasibility condition for line k

Objective function

$$\max_{\{q_{i,j} \leq \overline{q_{i,j}}\}} \sum_{i \in N} \sum_{j \neq i} p_{i,j} q_{i,j} \quad (\text{A1})$$

Load Balance:

$$\sum_{i \in N} \left(\sum_{j \neq i} (q_{i,j} + (1 - \alpha_{i,j}) A_{i,j}) - \sum_{j \neq i} (q_{j,i} + (1 - \alpha_{j,i}) A_{j,i}) \right) = 0 \quad (\text{A2})$$

Simultaneous Feasibility Conditions, \forall (k) transmission lines.

$$-L_k \leq \sum_{i=1}^n f_{k,i} \left\{ \sum_{j \neq i} (q_{i,j} + (1 - \alpha_{i,j}) A_{i,j}) - \sum_{j \neq i} (q_{j,i} + (1 - \alpha_{j,i}) A_{j,i}) \right\} \leq L_k \quad (\text{A3})$$

Bid Constraints $\forall i,j$

$$0 \leq q_{i,j} \leq \overline{q_{i,j}} \quad (\text{A4})$$

The clearing price for any source/sink pair on the network (regardless of whether there was a bid for that FTR) is calculated by subtracting the nodal price of the sink from the nodal price of the source. The nodal price C_i for any node i on the network is calculated using the shadow prices determined in the optimization program and the shift factor matrix:

$$C_i = \sum_{k=1}^K f_{k,i} \lambda_k. \quad (\text{A5})$$

A.2 Transmission Capacity in Scenario 1 (100% self-scheduling) and Scenario 2 (0% self-scheduling)

In the conceptual model, the network is a two-node network (Gen and Load) connected by a transmission line with a normal rating of 100 MW. The LSE receives an ARR allocation $A_{Gen,Load} = 100$. We consider two scenarios, one where the LSE self-schedules the entire ARR allocation into FTRs ($\alpha_{Gen,Load} = 0$) and another where the LSE claims the entire ARR allocation as auction revenue ($\alpha_{Gen,Load} = 1$). Using the Load node as the reference bus in the shift factor matrix $f_{k,i}$, the shift factor matrix is simply a 1x1 matrix containing the element 1, which we interpret as a 1 MW injection at the Gen node creates 1 MW of flow on the transmission line Gen→Load. Thus, the simultaneous feasibility conditions in scenario 1 are:

$$-100 \leq 1(q_{Gen,Load} + (1)100 - q_{Load,Gen}) \leq 100 \quad (A6)$$

$$-200 \leq q_{Gen,Load} - q_{Load,Gen} \leq 0 \quad (A7)$$

Treating the self-scheduled FTRs as 100 MW fixed injections and withdrawals at the Gen node and Load node respectively, we see that $q_{Gen,Load} - q_{Load,Gen} \leq 0$, which tells us that there is no “free” transmission capacity from the Gen node to the Load node available to FTR bidders. However, this transmission capacity can still be “created” by bids to purchase FTRs from the Load node to the Gen node (i.e., a counterflow FTR). In scenario 2, the simultaneous feasibility conditions are:

$$-100 \leq 1(q_{Gen,Load} + (1)0 - q_{Load,Gen}) \leq 100 \quad (A8)$$

$$-100 \leq q_{Gen,Load} - q_{Load,Gen} \leq 100 \quad (A9)$$

Here, we see that $q_{Gen,Load} - q_{Load,Gen} \leq 100$, which tells us that there is 100 MW of “free” transmission capacity from the Gen node to the Load node available to FTR bidders. There does not need to be a counterparty in the form of an FTR sell offer or counterflow FTR buy bid in order to purchase this transmission capacity. In the absence of FTR sell offers and counterflow buy bids, this transmission capacity will be sold to the highest bidder(s), with the clearing price equal to the bid price for the 100th MW (i.e., the marginal bid).

APPENDIX B

There are two notable patterns in ARR management strategies across space and time in PJM. First, the proportion of self-scheduled FTRs has been declining over time. At the start of our data, approximately 70% of ARRs were converted directly into FTRs. More recently, only about 30% of ARRs are being converted directly into FTRs. Figure B1 shows the time trend of decreasing percentage of self-scheduled FTRs over the past 10 years.

Second, ARR management strategies can vary greatly across zones, but the management strategy within a zone is relatively persistent. Figure B2 demonstrates the regional variation in ARR management strategies across four of the largest transmission zones (by MW) in PJM for our entire sample period. We see that there is not an absolute strategy in these regions (i.e., no 100% self-scheduling or 100% auction revenue), but the three largest zones have a relatively dominant strategy. Self-scheduled proportions in AEP and Dominion are very high relative to ComEd, whereas PECO is closer to evenly split.

Figure B1: Proportion of ARRs Self-Scheduled as FTRs in PJM

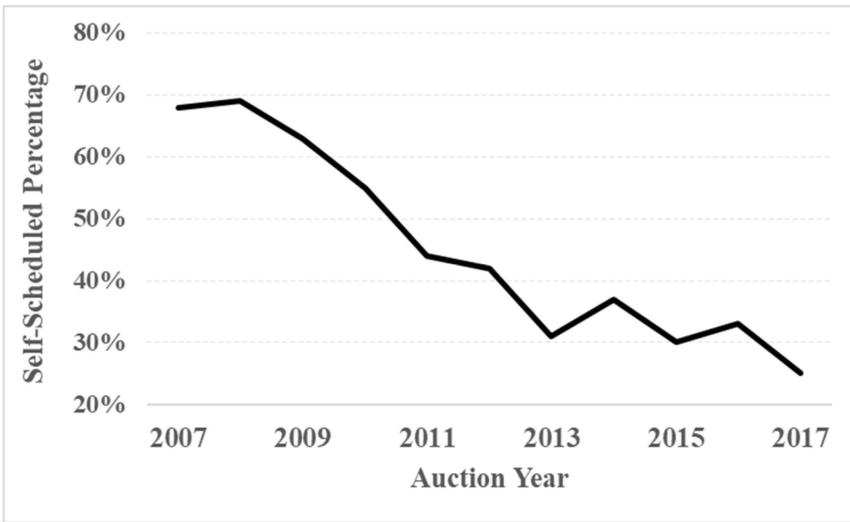
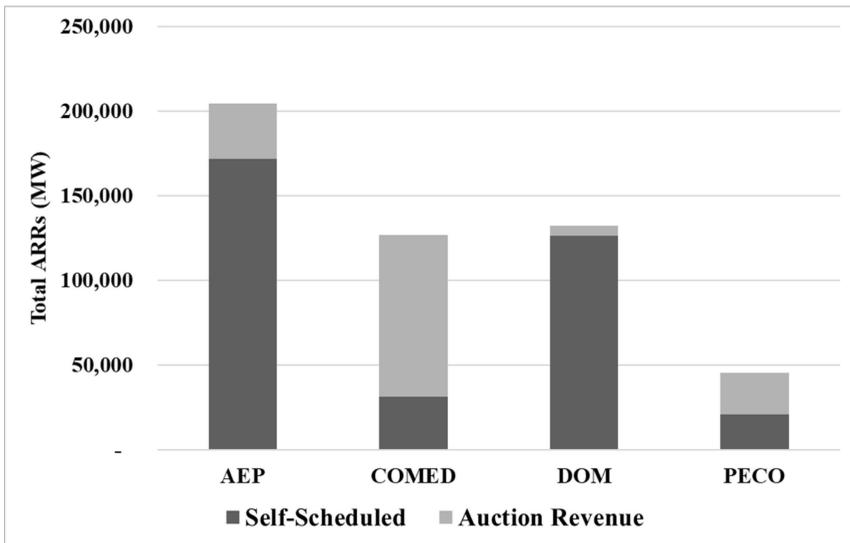


Figure B2: ARR Management Strategies in Selected Transmission Zones, 2007–2018



A final consideration to understanding ARR management strategies is whether there is any qualitative connection between the industrial organization of the electricity industry in the state where an LSE is located and the ARR management strategy employed by the LSE. Notably, almost all ARRs are self-scheduled into FTRs in the Dominion transmission zone of PJM. The Dominion transmission zone is primarily located in Virginia, which is one of the few states in PJM that does not offer competitive retail supply for residential electricity customers. In this case, it makes sense for a vertically integrated utility to self-schedule their ARRs into FTRs because they are responsible for managing both generation costs and electricity customer rates, and an FTR between the two ensures price certainty between the two entities. Table B1 summarizes the percentage of ARRs self-scheduled into FTRs by state for the 2017/2018 planning period, and indicates whether that state is a retail choice state.

Table B1: Percentage of ARRs Self-Scheduled into FTRs by state of ARR source node, 2017/2018 planning period

State	Total ARRs (MW)	Percent Self-Scheduled	Retail Choice State
North Carolina	665	95%	No
Virginia	10,171	90%	No
West Virginia	8,688	56%	No
Michigan	1,338	50%	Yes
Indiana	3,341	44%	No
Kentucky	1,435	39%	No
Ohio	11,721	23%	Yes
Illinois	11,008	11%	Yes
Maryland	5,764	3%	Yes
Pennsylvania	16,997	2%	Yes
Delaware	1,336	2%	Yes
New Jersey	7,341	0%	Yes
Washington, D.C.	297	0%	Yes

Notes: ARR source nodes are mapped to states using data from PJM, while retail choice state information comes from Zhou (2017).



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