Why do transmission congestion contract auctions cost ratepayers money? Evidence from New York

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Job market paper

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Abstract

Transmission congestion contracts are derivative products that pay the holder a future electricity price difference between two locations. The availability of a variety of locations specified in these derivatives can benefit electricity retailers and generators, allowing them to effectively buy or sell electricity at the price of different locations to their own. However, these derivatives have proven controversial because financial traders have consistently earned trading profits of $600m a year from holding these derivatives across the four largest U.S. electricity markets. These products are typically issued via regular auctions, with payouts of the issued derivatives funded by ratepayers, who in turn receive the auction revenues. Under the multi-product auction mechanism, I show that traders that buy products that retailers and generators do not purchase can improve the liquidity of other products offered in the auction. Using data on the New York market to investigate the sources of the trading profits, I find that retailers purchase derivatives in large bundles at prices equal to their expected payouts. Conversely, financial traders typically purchase derivatives in small bundles between locations that physical firms do not tend to buy. Financial traders earn profits when they are the first to buy a previously illiquid product, where they effectively receive a transfer from ratepayers for this service.

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“Across the nation, investment funds and major banks are wagering billions on [transmission congestion contracts], as they chase profits in an arcane arena that rarely attracts attention... The utilities and power companies suggest they cannot win against trading outfits that employ math specialists, often called ‘quants,’ to spot lucrative opportunities. With transmission contracts, there are tens of thousands of tradable combinations.”


Transmission congestion contracts, or TCCs, are derivative contracts that pay the difference between electricity prices at two locations at a specified future period. Like many derivatives, the availability of such contracts can benefit physical firms (electricity retailers and generators in this case). An electricity retailer, which must buy electricity at a fixed location to serve its customers, can buy a TCC to change its future spot price exposure to that of a different location. In the electricity market of New York state, there are 450 locations where electricity can be purchased. This means that 449 TCCs are available that pay price differences between each of these locations and that of the retailer. The retailer can search among the 449 other locations for where it believes it can source its electricity most cheaply and buy the corresponding TCC to effectively pay the electricity price at that location. Such behavior can potentially lower the wholesale energy costs of a retailer. In addition to retailers, electricity generating firms that supply electricity to wholesale markets can participate in markets for these products. Like retailers, generators can derive benefits from TCCs by using them to manage price differentials between their location and where they would like to sell their output. Finally, financial traders participate in the markets, with the motive to acquire derivatives at prices less than their eventual payout. Competition amongst profit-seeking traders can cause price signals for derivatives to converge on the expected payouts of the products, and aid physical firms in their long-term energy procurement process.¹

TCCs are auctioned in all formal electricity markets in the United States. The payouts of the issued derivatives are effectively funded by electricity customers, who in turn receive the auction revenues.² In New York, this has meant auctions for every bilateral combination of the 450 locations – over 100,000 products.³ In TCC auctions, as the opening quote highlights, financial traders can earn large trading profits in these notoriously complex, multi-product auctions, totaling $600m annually across four major US markets.⁴ Market monitors are concerned by these large trading profits earned by participants in TCC

¹See Jha and Wolak (2013) for a demonstration of how financial traders can improve the efficiency of the physical underlying market for the case of electricity.
²Transmission ratepayers, which consists of firms that buy electricity in the wholesale market, fund the auctions.
³450 locations allows for 450*449 = 202,050 directional location pairs or 101,025 unique location pairs.
⁴Sum of the yearly averages of the following: New York: Paid out $3,760m (to all firms) and received $2,905m from 1999-2015 (author calculation). California: Payments of $970m to non-physical participants (banks and energy traders) and auction payments of $450m from 2012-2015 (CAISO Department of Market
auctions, because TCC profits result in transfers from ratepayers (CAISO Department of Market Monitoring, 2016).

The primary objective of this paper is to examine the sources of trading profits in TCC auctions and to understand whether financial trader participation is likely to improve market performance. Understanding the sources of trading profits will identify why the auctions are resulting in large transfers from ratepayers to TCC holders. Further, if potential barriers to eroding these profits can be identified, their removal would end concerns related to these wealth transfers.

To accomplish these objectives, I first present a stylized model of an electricity network and compute electricity market prices and TCC auction outcomes. I show how auctions for these products may benefit physical firms and how financial trader participation may improve market performance. In standard exchange settings, financial traders can improve the liquidity of a derivative product by offering counterpositions to bids and offers. Under the TCC auction mechanism, equilibrium prices and quantities for each product are interdependent and determined simultaneously. I show that when traders buy products that are not typically purchased by physical firms they can provide a service by doing so, improving liquidity and price signals on other products. The results from the theoretical examples are used to guide the empirical portion of the paper where I compile data on 16 years of derivative prices, payouts and firm-level trading positions in the New York TCC market.

TCC products are defined by the two locations specified in the price difference payout and the time horizon of the payouts. In the time dimension, electricity markets are hourly and TCCs are available covering payments for every hour over 1-, 6- or 12-months. In the location dimension, products are either: 1) nodal products that pay the difference between two locations or 2) zone-indexed products that pay holders the difference between regional price indexes. I find that retailers, generators and traders purchase zone-indexed derivatives, but only generators and traders purchase nodal derivatives. Retailers, who account for 16% of derivative expenditures, purchase their products in large bundles and at actuarially fair prices that on average equal derivative payouts. Generator owners, who account for 33% of derivative expenditures, earn trading profits on nodal products, but not zone-indexed products. A large portion of their derivative purchases do not appear related to their physical operations. Financial traders account for the remaining 51% of derivative expenditures, purchase a wide variety of products, and receive most of the trading profits in this market. Like generators, traders only earn systematic profits on nodal, but not zone-indexed products. However, traders make most of their trading profits by purchasing the products that physical firms do not buy.

To investigate why competition between financial traders is not sufficient to erode trading profits, I study whether trading profits persist on the same products over time.

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Monitoring, 2016). Mid-continent (MISO): Paid out $3,453m (to all firms) and received $3,037m from 2013-2015 (MISO, 2015, and various issues). Pennsylvania and surrounds (PJM): Profits to non-physical participants (banks and energy traders) of $904m from 2013-2015 (PJM, 2015, and various issues).
Specifically, I measure derivative price responses across the auctions that take place at regular intervals. I also examine the profitability of derivatives that were liquid or illiquid in the prior auction. The main empirical finding is that the majority of the compensation financial traders receive is earned from being the first firm to purchase previously illiquid products. Following the public revelation of a purchase of a derivative by a profitable firm, the price for that same product appreciates by approximately 10% in the subsequent auction and the profitable opportunity is eroded. This quick adjustment of prices on the same products across auctions suggests that payout premiums are not solely due to the presence of a risk premium, an opportunity cost of capital or some other fixed cost to participation.

Based on these findings, I argue that profitable traders improve price signals, but also that they are unable to persistently profit on the same derivative products. To earn systematic profits, they must consistently identify profitable opportunities amongst the derivative products that have been relatively illiquid in previous auctions. Anecdotes suggest a major barrier to eroding total trading profits could be the cost for new entrants to develop a technology that can identify successful trading strategies in these auctions. The auctions are notoriously complex, where TCC payouts and the auction allocations are determined in part by physical transmission constraints in the electric network. Successful firms consistently update their models and aggressively enforce non-disclosure agreements with ex-employees. The persistence of total trading profits over 16 years and the protection firms place on their trading technologies suggest that if regulators wish to reduce the transfers of wealth from electricity customers to TCC holders, waiting for future trader entry may not achieve this goal. Policy modifications may be required. I discuss the tradeoffs inherent to modifications such as eliminating the markets or modifying the set of products offered.

Regulators weighing whether to keep, eliminate or modify auctions of TCCs can use the findings of this study to help examine the possible policy tradeoffs. Despite not performing a formal welfare calculation, I show which products are purchased by the physical and financial firms, emphasizing that the majority of trading profits are earned by financial traders that purchase the products that are typically not purchased by physical firms. The stylized model highlights the potential value of these actions. The discussion of the paper expands on these tradeoffs.

The paper is organized as follows: Existing studies on TCC markets and financial trader participation in electricity markets are reviewed in section 1. A description of the product, the auction mechanism and the role of financial traders is in section 2, followed by a description of the New York setting in section 3. Data sources are described in section 4, followed by the empirical analysis. Section 5 describes the positions taken by firms and the trading profits they earn across different product types. Section 6 investigates why trading profits have not eroded over time by describing the persistence of trading profits. Section 7 then discusses the policy relevance of the findings.
1 Existing results on TCC performance and forecasting advantages in TCC markets

Prior empirical work on transmission congestion contracts (often referred to as financial transmission rights, FTRs; or congestion revenue rights, CRRs) has established that the full set of TCC derivatives are not priced actuarially fairly (Bartholomew, Siddiqui, Marnay, and Oren, 2003; Hadsell and Shawky, 2009; Adamson, Noe, and Parker, 2010). The reasons behind the rejection of efficient market hypothesis tests in this setting have not been extensively studied.\(^5\) I study the products different firms purchase in this market, with close reference to the incentives of different firms to buy different products.\(^6\)

Existing theories for systematic trading profits in TCC markets have emphasized that the design of the derivatives provide an opportunity for generators to leverage their electricity market power. Bushnell (1999) and Joskow and Tirole (2000) show that firms with market power in wholesale electricity markets can directly influence the payouts of the derivatives through their downstream actions, with the incentive to do so increasing in the quantities of the derivative held. If contract formation required willing counterparties, the market might fail if counterparties are worried about taking opposite positions to a firm that can influence the contract payout. With TCC auctions, the firms that can influence derivative payouts should be able to purchase these products and earn a trading profit. Empirical work by Birge, Hortaçsu, Mercadal, and Pavlin (2017) found evidence consistent with downstream manipulation by a firm that was investigated by the Federal Energy Regulatory Commission (FERC) in the MISO electricity market. However, the extent and economic significance of such actions are not thoroughly studied, with the case study in Birge et al. containing a small set of overall trades.\(^7\) An extension to the analysis in this paper examines an implication from a theory of electricity market power that allows firms to influence derivative prices, whereby derivative payouts should increase at the margin with the size of the firm’s derivative position. I do not find evidence suggesting this mechanism is a major source of trading profits.

Finally, previous work on financial trader participation in electricity price derivatives

\(^5\)Zhang (2009) studies asymmetric information in the New York TCC market by deriving comparative statics from a theoretical model.

\(^6\)Toole (2014) and CAISO Department of Market Monitoring (2016) describe the trading profits in TCC auctions for some different firm types. For more general exchange settings, see Gray (1961) for a case study where trader motives were recorded, showing settings where larger participation by speculators improves market efficiency. See Gray (1966) for a discussion regarding how large derivative trading profits can lead to poor outcomes for exchange traded derivative products. See Black (1986) for a broad summary regarding derivative product design and firm participation in derivative exchanges.

\(^7\)The manipulation under investigation was in a virtual market, where financial traders can offer supply in the day ahead market and close out their position in the real-time market. The virtual market trades in question totaled $390,000, compared to $1b of positions taken annually in the MISO market for financial transmission rights (the products equivalent to the TCCs studied in this market). Birge et al. further examine whether similar behavior is widespread but are impeded by the anonymity of firm identities.
has been confined to virtual bidding markets, not TCC markets. Introducing financial trader participation to day-ahead markets can improve day-ahead price convergence to realized real-time prices (Saravia, 2003; Jha and Wolak, 2013; Birge, Hortaçsu, Mercadal, and Pavlin, 2017). This implies that some traders are able to earn a trading profit, with Jha and Wolak providing evidence suggesting that improved price signals resulting from trader participation led to more efficient electricity production in the Californian market. Arce (2013) and Creswell and Gebeloff (August 14, 2014) describe the operations of financial traders to provide insight into how they can identify profitable strategies in TCC markets. The mechanism for setting wholesale electricity prices and TCC auction prices are large nonlinear problems that have constraints related to the transmission capacities throughout the network. Both articles indicate that the profitable trading firms in this market devote firm resources toward obtaining derivative payout forecasts from a proprietary network model with the goal to uncover a profitable trading strategy. A difficulty in empirically identifying information advantages is that the outcome in models that have well informed firms earning payouts greater than the prices paid (see Wilson, 1967) can be also be caused by factors other than private information advantages. For example, the existence of a common risk premium, opportunity cost of capital or fixed costs to participation providing entry barriers could prevent prices reflecting the expected payout of a derivative. I am able to examine price responses across the sequential auction structure of TCCs, exploiting a unique information revelation structure that includes the identity of the firms taking on derivative positions in order to illustrate the potential for some firms to possess private forecasting advantages on some products.

2 TCC prices, TCC payouts and the role of financial traders

This section provides a theoretical platform for the subsequent empirical analysis by describing how electricity prices and transmission congestion contract (TCC) prices are derived in a network model. Understanding the relationship between wholesale electricity prices and transmission constraints is required to both understand the TCC auction mechanism, and how financial traders can earn profits and improve market performance. The primary result is that financial traders can improve the liquidity of all TCC products available in the network by purchasing the products that are not used by physical firms.

A transmission congestion contract between location $i$ and location $j$ in hour $h$ pays the holder:

$$LMP_{j,h} - LMP_{i,h}$$

where $LMP_{i,h}$ is the electricity price at location $i$ in hour $h$. This payout is a price swap, where if the value is negative the holder must pay money. Earning realized trading profits

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8 Examples of studies of private information advantages with similar empirical consequences are found in oil drainage tract auctions (Hendricks and Porter, 1988) and insurance (Chiappori and Salanie, 2000).
in TCC markets requires a firm to buy (sell) the derivative for less (more) than its eventual payout.

Although in practice TCCs cover 1-, 6- or 12-months of hourly payouts and can be purchased between any of the 450 locations in the New York market, this section will consider a one-period setting with three locations to introduce the fundamental concepts behind TCC markets.

2.1 Determining wholesale electricity prices

All formal wholesale electricity markets in the US use locational marginal prices (LMPs) to set prices at different locations in the network each hour of the day. The prices that determine TCC payouts are LMPs in the day ahead electricity market. In the context of this study, the LMPs in the day-ahead market can be considered the spot market.  

Electricity market operators collect offers to supply electricity from generator owners. They then set LMPs at every location (or node) in the electricity grid to minimize the as-offered cost of supplying electricity, subject to network constraints and supply meeting demand. Due to transmission line constraints, this can mean that a cheap offer of electricity at a generating location will not be taken up if it can not be delivered by the transmission network to a consumption location conditional on the composition of supply and demand throughout the network. In such cases prices between regions affected by this congestion will diverge and a higher cost source will be called upon in the congested regions.

To demonstrate how congestion influences prices in electricity markets, consider the network configuration, supply offers and demand in the market specified in figure 1. This example builds on Oren (2013) and will be used throughout the section. Here, there are three locations in the electricity market, connected by a transmission loop. All locations have generators, but only location \( k \) has consumers. The transmission line between \( i \) and \( j \) is able to accommodate flow up to a maximum capacity of 100MW, while the line between \( i \) and \( k \) has a capacity of 400MW. For strictly illustrative reasons, the remaining \( j \) to \( k \) line is unconstrained and there are no line losses from transmission.  

1500MW of electricity is demanded inelastically at \( k \), with the following offers to supply electricity:

- Generators at \( i \): 2000MW at $80/MWh
- Generators at \( j \): 2000MW at $100/MWh
- Generators at \( k \): 2000MW at $200/MWh

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9Electricity markets have a day-ahead market and a real-time market. Day-ahead markets are run one day in advance to a given delivery hour. When production or demand varies from the day-ahead production allocations during the delivery hour, the real-time market determines which power plants will increase or decrease their production to balance supply and demand in the system.

10Resistance on each line is assumed equal and there are no transmission losses built into the solutions.
Figure 1: A three-node electricity network and example equilibrium

(a) Supply offers, demand and transmission constraints

(b) Equilibrium

Figure (b) displays the solution to the program described in equation (1). To calculate flows on each line (the numbers inside the transmission lines), Kirchhoff’s circuit laws are applied to this stylized network with no transmission losses. The formula is described in text, with the implication being that \( \frac{1}{3} \) of supply at \( j \) flows via \( i \) to \( k \), with the remaining \( \frac{2}{3} \) flowing from \( j \) to \( k \). \( \frac{1}{3} \) of supply at \( i \) flows via \( j \) to \( k \), with the remaining \( \frac{2}{3} \) flowing from \( i \) to \( k \). The body of section 2.1 describes how equilibrium prices (LMPs) are determined.

In a model with no transmission constraints, the optimal market supply is trivial, where the generators at \( i \) produce all of the electricity because it is the cheapest source. However, the transmission limits and the loop flow that occurs in electric circuits constrain the cost minimizing solution. Therefore, the market operator solves the following optimization problem to minimize system as-bid costs:

Objective: \( \min_{Q} 80 \cdot Q_i + 100 \cdot Q_j + 200 \cdot Q_k \)  \hspace{1cm} (1)

Supply = Demand: \( Q_i + Q_j + Q_k = 1500 \)

Transmission constraint \( i \) to \( k \): \( \frac{2}{3} Q_i + \frac{1}{3} Q_j \leq 400 \)

Transmission constraint \( i \) to \( j \): \( -100 \leq \frac{1}{3} (Q_i - Q_j) \leq 100 \)

Generator constraints: \( Q_i \leq 2000, Q_j \leq 2000, Q_k \leq 2000 \)

Solution: \( Q_i = 300, Q_j = 600, Q_k = 600 \)

The objective function minimizes the as-offered cost of supplying electricity. The first constraint is that supply equals demand in the network. The second constraint is the trans-
mission constraint on the $i, k$ line, where flow cannot exceed 400 MW, with the $\frac{2}{3}$ multiplier on $Q_i$ and the $\frac{1}{3}$ multiplier on $Q_j$ due to Kirchhoff’s circuit laws. The third constraint is the transmission constraint on the $i, j$ line, where flow cannot exceed 100 MW, with $Q_i$ and $Q_j$ variables on this line having multipliers that offset each other as counterflows due to Kirchhoff’s circuit laws. The final constraints are the capacities offered by the generators at each location node. The solution is displayed in figure 1. Both transmission line constraints are binding, limiting the generation that can occur at $i$ and $j$.

Locational marginal prices are equal to the increase in the optimized value of the objective function in (1) from withdrawing an extra unit of electricity from the node. The prices for this example are $LMP_i = $80/MWh, $LMP_j = $100/MWh and $LMP_k = $200/MWh.

This three-node example highlights the interdependency of the network problem. Despite the line between $j$ and $k$ being unconstrained, the constraints on the other lines lead to the $LMP_j$ and the $LMP_k$ prices separating, in this case by $100$/MWh.

2.2 Relating network congestion to transmission congestion contracts

Participants in electricity markets face the LMPs at the location where they supply or consume electricity. Therefore, even though generators at $i$ in figure 1 receive $80$/MWh, the retailer at $k$ pays $200$/MWh. Therefore, the cash flows from the market in figure 1 are the following:

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11 Given equal resistance on each line and the loop flow constraints implied by Kirchhoff’s Law, injection of electricity at $j$ and withdrawal at $k$ will have $\frac{1}{3}$ flow via $i$ and the remaining $\frac{2}{3}$ flow directly to $k$. This is because the $i$ route encounters twice the number of lines, therefore twice the resistance, so the $\frac{1}{3}$ and $\frac{2}{3}$ split equates marginal losses meaning that the split ensures electrons take the path of least resistance.

12 Notice that for this constraint more electricity can be injected at $i$ if more electricity is injected at $j$. This is because electricity injected at $i$ and $j$ and withdrawn at $k$ each have $\frac{1}{3}$ of the electricity flow via the $i, j$ line.

13 See Bohn, Caramanis, and Schweppe (1984) for a detailed explanation of locational marginal pricing and how the prices reflect Lagrange multipliers on the transmission constraints and shift factors. At node $i$, only 300 MW of the 2000 MW offered at $80$ is generated in equilibrium, therefore the marginal cost of withdrawing a unit of electricity at $i$ is $LMP_i = 80$. However, due to the transmission constraints being binding, it is infeasible to inject an extra MW of electricity at $i$ to be withdrawn at either $j$ or $k$. Only 600 MW of electricity offered at node $j$ is utilized in the solution, therefore the marginal cost of withdrawing a unit of electricity at $i$ is $LMP_i = 100$. Again, it is infeasible to inject an extra unit of electricity at node $j$ to be withdrawn at node $k$, therefore the marginal cost of withdrawing a unit of electricity at $k$ is $LMP_k = 200$.

14 Further, electricity does not necessarily flow from low-cost to high-cost nodes. While cheap electricity flows to $k$, the net flow on the $i, j$ transmission line is in the $j$ to $i$ direction, from a higher to a lower cost location.
This section describes how physical firms can use TCCs to change the LMP location they face when buying and selling electricity, and how the merchandising surplus market operators collect in the final line of the above table can be securitized into a set of TCCs.

For the retailer at $k$ to source 1MWh at the location $i$ price, they would need to purchase a transmission congestion contract (TCC) between locations $i$ and $k$ that pays them $LMP_k - LMP_i$. Combining the TCC payout and their spot price $LMP_i$ means that they effectively pay $LMP_i$, the spot price at $i$:

\[
\text{Retailer spot payment: } -LMP_k \\
\text{TCC payout: } LMP_k - LMP_i \\
\text{Net cashflow from spot + TCC: } -LMP_i
\]

Likewise, if a generator at $i$ wishes to sell their electricity to node $k$, they could buy the $i,k$ TCC and combining the TCC payout with their spot payment means that they effectively receive $LMP_k$ for their generated electricity. In sum, a TCC can allow firms to source or sell electricity at the price of a different location to their own.

Further, a TCC can be combined with a forward contract to remove all price uncertainty. Consider the case of a retailer. If suppliers at each location offered a forward price for delivery at that location, the retailer could pick the cheapest procurement strategy before the spot market is run.\(^{15}\) Therefore, with a full set of TCC and forward prices available to a retailer, competition between suppliers may be enhanced and retailers can more efficiently source electricity by picking the supplier that offers the lowest price when combined with the corresponding TCC. This is one potential mechanism for TCCs to improve economic efficiency or lower the costs of procurement for retailers.\(^{16}\)

\(^{15}\)Consider a retailer at node $A$ entering a forward contract to source $x$MWh of power from node $B$. In the spot market, the firm purchases $x$MWh at $A$ to meet its consumption needs but owns $x$MWh at $B$ from its forward position, therefore its cash flows are now exposed to a basis of $(LMP_B - LMP_A)x$. Notice that an $x$ unit transmission congestion contract position exactly matches this basis, therefore an $x$ unit forward contract at $B$ combined with an $x$ unit TCC between $A$ and $B$ removes all price uncertainty for the firm sourcing $x$MWh of electricity from node $B$.

\(^{16}\)Alsac, Bright, Brignone, Prais, Silva, Stott, and Vempati (2004) argue that TCCs provide hedging benefits to firms. Formalizing hedging benefits is not the focus of this paper. See Jha (2017) for a recent
If physical firms demand TCCs to enable them to buy or sell to different prices to their own, the market operator is in an ideal situation to supply the products. At the equilibrium quantities in the running example, the market operator collects a merchandising surplus equal to the payouts of 300 TCCs between \( i \) and \( k \) and 600 TCCs between \( j \) and \( k \), regardless of the realized prices in the day ahead electricity market. In formal electricity markets throughout the United States, market operators securitize the merchandising surplus into TCCs. These TCCs are auctioned and their payouts are funded from the merchandising surplus. By securitizing the merchandising surplus, the market operator provides a platform for trade and to reveal signals regarding future transmission congestion and future price differences between locational marginal prices in the network. The auction will be described in the next section, with the sequence of events and cash flows being:

1. TCC auction
   - Contracts issued, auction revenues collected by market operator

2. Day-ahead electricity market
   - LMPs determined
   - Market operator collects merchandising surplus from transmission congestion

3. Cash flows
   - TCC holders receive payout based on realized LMPs
   - Merchandising surplus + (auction revenues - TCC holder payouts) distributed to lower the transmission service charge paid by transmission ratepayers
     - The zero sum nature of TCC holder profits (the bracketed term) means that it is effectively funded by ratepayers, and TCC holder losses go to ratepayers

The reason TCC holder profits are transfers from ratepayers is due to the transmission service charge market rule. Transmission forms a natural monopoly, with transmission owners regulated to earn a fixed rate of return in exchange for open access to their transmission lines. A cost-splitting formula is developed such that consumers on the wholesale market collectively pay this fixed rate of return less the merchandising surplus and the difference between auction revenues and TCC holder payouts. This fee is a transmission service charge, where lower TCC holder profits means a bigger reduction in this charge and ultimately, lower bills to customers.\(^{17}\)

\(^{17}\)There are further operational and reliability contingencies that transmission owners must meet to earn its return. See section 14.1.2 of NYISO (2010) for a detailed breakdown of the transmission service charge.
2.3 The transmission congestion contract auction and a role for financial traders

The merchandising surplus collected by market operators is stochastic and depends on equilibrium flows in the network. TCC auctions have been designed to allocate a set of TCCs, where the collective payout to TCC holders does not exceed the merchandising surplus. Hogan (1992) proves that a given allocation of TCCs can be funded from the merchandising surplus if the set of contracts are simultaneously feasible. Simultaneous feasibility means that if each $i,j$ TCC of size $q$ resulted in $q$ MW being injected at $i$ and withdrawn at $j$ in the physical electricity network, no transmission constraint in the network would be violated. Consequently, the volume of the TCCs that can be issued between any two locations is dependent on all other TCCs issued in the network and the transmission capacities in the electricity network. This section outlines the simultaneous feasibility constraint, the auction equilibrium and, through a series of examples, will highlight a potential role for financial traders. Financial traders that purchase the TCCs that physical firms do not take up can improve the liquidity of other TCC products and price signals from the auction.

The market operator collects offers to buy and sell each possible combination of TCC, defined by two locations. For example, a bid to buy the $i,j$ TCC means the holder wishes to receive the future cash flow $LMP_j - LMP_i$ from the electricity market. An offer to sell the $i,j$ derivative is the equivalent of a bid to buy the $j,i$ derivative, with the holder of such a contract receiving $LMP_i - LMP_j$. I consider only three products existing, the $i,j$, the $j,k$ and the $i,k$, where selling a product is equivalent to buying a negative quantity $q$. The network configuration and constraints from the running example in figure 1 is replicated in figure 2. For this 3-node network, the auction problem solves the following program for the vector $q$ containing the quantity of each TCC bid that is issued:

\[
\text{Objective: } \max_q \ b \cdot q \quad \text{ (2)}
\]

\[
\text{Simultaneous feasibility } i,k \text{ line: } \frac{2}{3}q_{i,k} + \frac{1}{3}q_{j,k} + \frac{1}{3}q_{i,j} \leq 400 \quad \text{ (3)}
\]

\[
\text{Simultaneous feasibility } i,j \text{ line: } -100 \leq \frac{1}{3}q_{i,k} - \frac{1}{3}q_{j,k} + \frac{2}{3}q_{i,j} \leq 100 \quad \text{ (4)}
\]

\[
\text{Bid quantity constraints: } \bar{q} \cdot 1(\bar{q} \leq 0) \leq q \leq \bar{q} \cdot 1(\bar{q} \geq 0) \quad \text{ (5)}
\]

where $b$ is the bid price vector for each bid in the $q$ vector and $q_{a,b}$ is the sum of all allocated TCCs issued between $a$ and $b$. The auction equilibrium maximizes the as-bid valuations for financial traders.

\[\text{For example, a 10 unit contract from } i \text{ to } j \text{ implies a 10MW injection of electricity at } i \text{ and a 10MW withdrawal of electricity at } j. \text{ If the implied injections and withdrawals of all contracts is not feasible given the assumed transmission capacities of the grid, then payouts to the set of TCC holders may exceed the merchandising surplus, a funding shortfall. See Hogan (1992) or appendix B for more technical details.}\]
the TCC allocations, subject to the simultaneous feasibility constraint. Notice the tradeoffs between the quantities of \( i, k, j, k \) or \( i, j \) contracts that can be issued. The simultaneous feasibility constraint in (3) has each additional unit of a contract type reducing the amount of other types that can be issued. However, the simultaneous feasibility constraint in (4) dictates that if more \( i, k \) or \( i, j \) TCCs are issued, it allows extra \( j, k \) TCCs to be issued.\(^{19}\)

Therefore, depending on which constraints are binding, bidding on a particular product can improve liquidity of another product. Derivative prices, \( p_{i,k}, p_{j,k}, p_{i,j} \) are set such that all bids above the price are cleared and that they are transitive, meaning that \( p_{i,k} = p_{i,j} + p_{j,k} \), given that the payouts for the \( i, k \) derivative is equal to the sum of the payouts of the \( i, j \) and \( j, k \) derivatives.

Given the complexity of the auction, in order to demonstrate how financial traders may profit and influence auction performance, equilibrium outcomes will be described for five examples of bids, displayed in table 1. These cases are:

1. Ideal allocation: TCC prices and quantities match realized flows in the electricity market. Merchandising surplus if fully securitized.

2. Under allocation: Low demand for one product reduces the liquidity of other products.

3. Trader liquidity 1: Traders buying a TCC with low demand can earn a profit and improve the liquidity of other products.

4. Trader liquidity 2: Traders buying a TCC that is never used in the procurement strategies of physical firms can earn a profit and improve the liquidity of other products.

5. Trader competition: Competition among traders on a product not used by physical firms can restore price efficiency on all contracts in the network.

**Example 1 - an “ideal” solution**

Example 1 displays the TCC auction solution for the program described in equations (2)-(5) with bids for 2000 \( i, k \) derivatives at $120 per unit, 600 \( j, k \) derivatives at $100 per unit, and no bids on the \( i, j \) product.\(^{20}\) These bids could reflect the physical suppliers of energy at nodes \( i \) and \( j \) wanting to use TCCs to sell at node \( k \) prices. The solution to the auction problem has 300 \( i, k \) TCCs and 600 \( j, k \) TCCs being issued. Assuming that the subsequent electricity market outcomes are as described in figure 1, the TCC quantities are equal to the quantities of generation at \( i \) and \( j \). The equilibrium TCC prices are

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\(^{19}\)The constraint includes \( \frac{2}{3} (q_{i,j}) \) because a 1MW injection at \( i \) and a 1MW withdrawal at \( j \) means adding \( \frac{1}{3} \) MW flow on the \( i, j \) line and removing \( \frac{1}{3} \) counterflow from the \( i, j \) line. See Deng, Oren, and Meliopoulos (2004) for the generalized auction problem.

\(^{20}\)The objective function is max \( 120 \cdot q_{i,k} + 100 \cdot q_{j,k} \), where \( q_{i,k} \) is the allocation to the \( i, k \) bidder and \( q_{i,j} \) is the allocation to the \( i, k \) bidder.
Table 1: Example TCC auction bids, allocations, prices and cash flows

<table>
<thead>
<tr>
<th></th>
<th>Example 1</th>
<th>Example 2</th>
<th>Example 3</th>
<th>Example 4</th>
<th>Example 5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bids</strong></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>$i,k$ TCC:</td>
<td>2000 @ $120</td>
<td>30 @ $120</td>
<td>30 @ $120</td>
<td>30 @ $120</td>
<td>30 @ $120</td>
</tr>
<tr>
<td>$j,k$ TCC:</td>
<td>600 @ $100</td>
<td>600 @ $100</td>
<td>600 @ $100</td>
<td>600 @ $100</td>
<td>600 @ $100</td>
</tr>
<tr>
<td>$i,j$ TCC:</td>
<td>No bids</td>
<td>No bids</td>
<td>No bids</td>
<td>2000 @ $10</td>
<td>2000 @ $10</td>
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<td></td>
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<td>2000 @ $20</td>
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<td><strong>Equilibrium</strong></td>
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<td>$i,k$ TCC:</td>
<td>$q_{i,k} = 300$</td>
<td>$q_{i,k} = 30$</td>
<td>$q_{i,k} = 30$</td>
<td>$q_{i,k} = 30$</td>
<td>$q_{i,k} = 30$</td>
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<tr>
<td>$j,k$ TCC:</td>
<td>$q_{j,k} = 600$</td>
<td>$q_{j,k} = 330$</td>
<td>$q_{j,k} = 600$</td>
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<tr>
<td>$i,j$ TCC:</td>
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<td>$q_{i,j} = 0$</td>
<td>$q_{i,j} = 0$</td>
<td>$q_{i,j} = 435$</td>
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<td></td>
<td>$p_{i,k} = $120</td>
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<td><strong>Cash flows</strong></td>
<td></td>
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</tr>
<tr>
<td>(a) Auction revenues$^a$</td>
<td>$96,000$</td>
<td>$36,600$</td>
<td>$93,000$</td>
<td>$67,650$</td>
<td>$72,300$</td>
</tr>
<tr>
<td>(b) Realized merch. surplus (assumed)$^b$</td>
<td>$96,000$</td>
<td>$96,000$</td>
<td>$96,000$</td>
<td>$96,000$</td>
<td>$96,000$</td>
</tr>
<tr>
<td>(c) TCC holder payouts (assumed)$^c$</td>
<td>$96,000$</td>
<td>$36,600$</td>
<td>$96,000$</td>
<td>$72,300$</td>
<td>$72,300$</td>
</tr>
<tr>
<td>(d) TSC reduction$^d$</td>
<td>$96,000$</td>
<td>$96,000$</td>
<td>$93,000$</td>
<td>$91,350$</td>
<td>$96,000$</td>
</tr>
<tr>
<td>(a) + (b) - (c)</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Simultaneous feasibility (Implied transmission flows)$^e$</strong></td>
<td>400</td>
<td>130</td>
<td>400</td>
<td>365</td>
<td>365</td>
</tr>
<tr>
<td>$i,k$ line</td>
<td>400</td>
<td>130</td>
<td>400</td>
<td>365</td>
<td>365</td>
</tr>
<tr>
<td>$i,j$ line</td>
<td>-100</td>
<td>-100</td>
<td>-100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

(a): The sum of the quantities of each TCC type issued multiplied by the price. (b): From the example day-ahead market in figure 1, the difference between the prices retailers pay and generators get paid in that market. (c): From the equilibrium auction quantities of each TCC type in the auction and the realized prices the example day-ahead market in figure 1, with $LMP_i = 80$, $LMP_j = 200$ and $LMP_k = 200$. (d): As explained in the cash flow description, the transmission service charge reduction is the amount that transmission ratepayers effectively gain under the given auction and day-ahead market scenario. (e) The simultaneous feasibility constraints are shown in equations (3) and (4).

$p_{i,k} = $120, $p_{i,j} = $20, $p_{j,k} = $100$, exactly equal to the realized LMP price differences between these locations.$^{21}$

$^{21}$The price solution is not unique in this case, where $p_{i,k} = $120 − $x$, $p_{i,j} = $20 − $x$, $p_{j,k} = $100 − $x$ would also be feasible. The solution in the stylized examples in this section chooses prices among the feasible price
Figure 2: A three-node electricity network and example TCC auction equilibrium

(a) Transmission constraints  
(b) TCC auction equilibrium, Example 1

Figure (b) displays the solution to the problem described in section 2.3, Example 1. The implied flows are from Kirchhoff’s laws assuming that 600MW are injected at $i$ and withdrawn at $k$, and 300MW are injected at $j$ and withdrawn at $k$. Refer to the text to examine the cash flows associated with the TCC positions.

**Example 1 implications:** In situations where there are many bids on TCCs between generation and consumption locations, the simultaneous feasibility constraints on the auction process ensure that the equilibrium quantities of contracts match the realized net flows in the market. This includes a zero quantity being issued on the $i,j$ product, with the $i,j$ price pinned down by the bids on the other products. When the issued contracts match the realized net flows in the market, the merchandising surplus is fully securitized. Finally, when TCC prices equal realized TCC payouts, transmission ratepayers are not transferring wealth to TCC holders.

**Example 2 - an “under allocation” solution**

Example 2 replicates Example 1 with an adjustment that only 30 $i,k$ TCCs are demanded in the auction. TCC prices do not change, however, the simultaneous feasibility constraint in equation (4) would be violated if 600 $i,k$ TCCs were to be issued, resulting in equilibrium quantities of the $j,k$ TCC falling to $q_{j,k} = 330$, with $q_{i,k} = 30$ and $q_{i,j} = 0$.

**Example 2 implications:** Reduced demand on a given TCC product can reduce the liquidity of other TCC products, due to the simultaneous feasibility constraints imposed by the auction mechanism.\(^{22}\) The implied transmission flows from the quantities of issued contracts uses less transmission than in the first example.\(^{23}\) Therefore, contracts are under

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\(^{22}\)The reduced demand for the $i,k$ derivative decreases the counterflows on the constrained line under the simultaneous feasibility constraint (equation 4), with the consequence being that 600 $j,k$ TCCs contracts can no longer be issued.

\(^{23}\)If these flows were actually the realized quantities in the day-ahead electricity market depicted in
allocated and the merchandising surplus is not fully distributed to TCC holders. However, given that TCC prices match the realized LMP differences, transmission ratepayers still have their transmission service fee reduced by the same amount as in Example 1.

Example 3 - trader profits from liquidity provision
Example 3 replicates Example 2, but adds a financial trader that is willing to buy 2000 \(i,k\) products at a price of $110. The equilibrium allocation returns to that in example 1, with 300 \(i,k\) TCCs and 600 \(j,k\) TCCs being issued, so the trader participation on the \(i,k\) product increased the liquidity of the \(j,k\) product.\(^{24}\) However, prices change to \(p_{i,k} = \$110, p_{i,j} = \$10, p_{j,k} = \$100\). Assuming the realized payouts are derived from the electricity market in figure 1, the \(i,k\) derivative holders are buying the products for $10 less than the realized contract payout. Therefore, TCC holders earn trading profits of \(10 \cdot 300\), and consequently, transmission ratepayers receive \(10 \cdot 300\) less than what they received in Example 1.

Example 3 implications: When demand by physical firms is low for a given product, traders that submit low priced bids for this product can profit and increase the liquidity of other products by doing so. Informally, traders in this example can be considered to have expanded the transmission capacity of the contract network. Their participation has allowed physical firms to buy more of the \(j,k\) product, perhaps aiding market participants in forming expectations about the realized equilibrium to follow in the day ahead market. Formally modeling the benefits derivative liquidity from traders to physical efficiency gains is difficult without imposing further theoretical structure on the model, where TCC contracts influence the behavior of firm strategies in the electricity market.\(^{25}\) Empirically, Jha and Wolak (2013) demonstrate the plausibility that trader participation in electricity markets can lead to better production efficiency in the context of virtual bidding.\(^{26}\)

Example 4 - trader profits from liquidity provision on a different product
Example 4 modifies Example 3 by moving the trader bid on the \(i,k\) product to the \(i,j\) product, bidding $10 for 2000 units. The \(i,j\) product pays differences between generator nodes in this example, so it is unlikely to form a role in any physical firm’s energy procurement strategy. The physical generating firms might not be interested in this product if they want to sell at node \(k\) prices, where the consumers in this market are located. The auction solution allocates 435 of the \(i,j\) TCCs to the financial trader and fully allocates

\[\text{figure 1, production would be inefficient because it would require substitution away from cheaper sources of generation to more expensive sources.}\]

\(^{24}\)The objective function changes to \(\max q_{1} \cdot q_{i,k} + 110 \cdot q_{i,j} + 100 \cdot q_{j,k}\), where \(q_{i,k}\) is the allocation to the 30 unit bidder, and \(q_{i,j}\) is the allocation to the financial trader.

\(^{25}\)As a non-rigorous illustration, strategic generators at \(j\) may be more competitive in their supply if they expect more competitive generation at \(i\), which could be signaled by this new trader-assisted TCC auction equilibrium.

\(^{26}\)The removal of barriers for financial traders to submit virtual bids to day ahead electricity markets is shown in Jha and Wolak (2013) to have lowered total production costs in the Californian market.
the 600 \( j, k \) TCCs demanded\textsuperscript{27} The TCC composition of this solution differs to that in Example 3, but traders still profit at the expense of ratepayers.

**Example 4 implications:** Financial trader participation on products that do not match the injections and withdrawals of electricity in the physical electricity market can still improve contract allocations to physical firms and expand the set of contracts that can be issued. This is because of the simultaneous feasibility constraint (equation 4), where implied flows on one transmission line can free up congestion and allow more flows on different transmission lines, improving the liquidity of the market. Traders can profit in such a scenario, resulting in a smaller reduction in the transmission service charge.

**Example 5 - trader competition improves liquidity and erodes trading profits**

Example 5 adds extra competition to example 4. Suppose competition amongst traders to purchase the potentially mispriced \( i, j \) product induces an extra bid for 2000 \( i, j \) products at a price of $20.\textsuperscript{28} Now, the total allocations for each product are equal to those in example 4, but the extra competition from the trader bid on the \( i, j \) product has resulted in TCC prices adjusting back to be equal to the realized LMP price differences in the electricity market, leaving the collection of TCC holders with zero trading profits.

**Example 5 implications:** Trader competition on TCCs that are not used by physical firms as part of their procurement strategy can both improve the liquidity of the contract market and restore all TCC prices in the network to actuarially fair prices. Therefore, trader competition can reduce trading profits and the consequent transfers from transmission ratepayers to TCC holders.

2.4 Relating the TCC auction examples to empirical questions

The examples in this section showed that firms can profit from TCC auctions and how such profits result in transfers from ratepayers. Different firms might bid on different products, yet trader participation on products not bid on by physical firms can improve the liquidity of other products in the network that physical firms might have placed a bid over. Further, a consequence from the simultaneity and price transitivity is that equilibrium quantities can be zero on some TCCs, despite prices existing for all products.

The empirical portion of this paper will document the products that different firm types purchase, and which products they are able to take profitable positions over. Furthermore, the regular sequence of the auctions in New York (that will be described in the next section) allows us to observe whether trading profits are persistently earned on the same products. We will examine whether financial traders buy the products other firms have not previously purchased and thereby offer liquidity to the auctions, and whether prices update following

\textsuperscript{27}The objective function changes to \( \max_{q} 120 \cdot q_{i,k} + 100 \cdot q_{j,k} + 10 \cdot q_{i,j} \).

\textsuperscript{28}The objective function changes to \( \max_{q} 120 \cdot q_{i,k} + 100 \cdot q_{j,k} + 10 \cdot q_{i,j}^{1} + 20 \cdot q_{i,j}^{2} \), where \( q_{i,j}^{1} \) and \( q_{i,j}^{2} \) are the allocations to the financial traders.
profitable opportunities being realized to erode further profits. This will allow insight into
the situations where derivatives are priced at actuarially fair prices, and do not result in
wealth transfers from ratepayers to TCC holders.

3 Setting: The New York TCC market

This section relates the one-period model in the previous section to the specifications and
format of the New York market, introducing the notation that will be used in the empirical
analysis.

3.1 Defining a derivative and a contract

The average monthly payouts of the derivatives studied in this paper take the following
form:

\[ r_{i,j,T_1,T_2} = \frac{1}{m(T_1, T_2)} \sum_{h=T_1}^{T_2} \left( LMP_{j,h} - LMP_{i,h} \right) \]

\[ \text{Price swap} \] (6)

where \( r \) is the average monthly revenue (or payout) to the derivative holder, \( i \) and \( j \) index
location nodes in a spatial market, \( T_1 \) and \( T_2 \) denote the first and last hour of payments the
derivative covers and \( LMP_{x,h} \) denotes the electricity price per MWh at location \( x \) in hour
\( h \).\(^{29}\) \( m(T_1, T_2) \) is the duration of the derivative payouts in months, either being 1-, 6-
or 12- months and all derivatives start and end on the first and last hour of a calendar month.
The payouts to any derivative holder are not options, meaning that the holder of an \( i,j \)
contract must pay money if \( r_{i,j,T_1,T_2} \) is negative. In finance terminology, \( LMP_{j,h} - LMP_{i,h} \)
is a future spot price swap; in electricity market terminology, \( LMP_{j,h} - LMP_{i,h} \) is the
congestion price difference between a point of injection (POI) \( i \) and a point of withdrawal
(POW) \( j \), with the price being that of the day-ahead market. The price for this derivative
is also standardized to a monthly average, denoted \( p_{i,j,T_1,T_2,t} \), where \( t \) indexes the auction
it was sold in.

Throughout, a derivative will refer to the \((i,j,T_1,T_2)\) financial product with payouts de-

\[^{29}\] \( LMP_{x,h} \) consists of three components, the price at a reference node plus a component that captures
line losses and a congestion component. Line losses tend to be small and transmission congestion contracts
pay the difference in the congestion component of the prices, where \( LMP_{i,h} - LMP_{j,h} \approx CP_{i,h} - CP_{j,h} \)
where \( CP \) is the congestion component of the price.
• Transmission congestion contract from Linden Cogen (POI) to N.Y.C. (POW) for each hour between May 1 2008 - April 30 2009, for 3 units
  – Nodes/locations: $i = \text{Linden Cogen}, j = \text{N.Y.C.}$
  – Start and end hour: $T_1 = 12\text{am May 1 2008}, T_2 = 11\text{pm April 30 2009}$
  – Length: $m(T_2, T_1) = 12$ months
  – Quantity: $q_{i,j,T_1,T_2,f} = 3$

• Purchased at auction for $90,110.07 by J. P. Morgan Ventures Energy Corporation
  – Total contract expenditure: $q_{i,j,T_1,T_2,f} \cdot m(T_2, T_1) \cdot p_{i,j,T_1,T_2} = 90,110.07$
  – Derivative average monthly price: $p_{i,j,T_1,T_2} = \frac{90,110.07}{3 \times 12} = 2,503.06$
  – Firm: $f = \text{J. P. Morgan Ventures Energy Corporation}$

• Locational price differences ($LMP_{POW} - LMP_{POI}$) accrue hourly
  – Total contract payout: $q_{i,j,T_1,T_2,f} \cdot m(T_2, T_1) \cdot r_{i,j,T_1,T_2} = 132,045.15$
  – Derivative average monthly payout: $r_{i,j,T_1,T_2} = \frac{132,045.15}{3 \times 12} = 3,667.92$
  – Derivative average monthly realized profit: $r_{i,j,T_1,T_2} - p_{i,j,T_1,T_2} = 1,164.86$
  – Total contract realized profit: $q_{i,j,T_1,T_2,f} \cdot m(T_2, T_1) \cdot (r_{i,j,T_1,T_2} - p_{i,j,T_1,T_2}) = 132,045.15 - 90,110.07 = 41,935.08$

The remainder of this section outlines the product specifications available for purchase, the firm types that participate in this market and the timing of the auctions and the public release of auction outcomes.

3.2 Derivative specifications available for purchase

A wide variety of transmission congestion contract specifications can be purchased at auction, with the auction sequence described in subsection 3.4. In the $T_1, T_2$ time horizon dimension, all products studied are of 1-, 6- or 12-month duration. 6- and 12-month contracts attract the greatest expenditure by firms (figure 3 (a)). Collectively, holders of all derivative durations earn revenues greater than expenditures from their contract positions, meaning that the auctioneer (the NYISO market operator) collects less from the holders than they pay out. Section 2.2 described how trading profits transfer wealth from electricity ratepayers to TCC holders.

\[\text{Payouts accrue hourly but are paid monthly. Monthly payments were $16,189.50, $33,026.25, $40,237.29, $5,823.54, $1,797.93, $-938.01, $-359.94, $24,155.13, $22,113.6, $852.72, $5,239.23. The negative payout in months 6 and 7 of the contract require the firm to pay money back to NYISO.}\]
Figures (a) and (b) display the sum of $q_{i,j,T_1,T_2,f} \cdot m(T_2,T_1) \cdot p_{i,j,T_1,T_2}$ and $q_{i,j,T_1,T_2,f} \cdot m(T_2,T_1) \cdot r_{i,j,T_1,T_2}$. Sample sizes (number of contracts entered between 1999 and 2015 for each contract grouping) equal to 38,822 for 1-month contracts, 24,412 for 6-month contracts, 14,238 for 12-month contracts, 68,125 for nodal contracts and 9,347 for zone-indexed contracts.

In the location dimension, there are 450 price nodes in the New York grid, resulting in approximately 100,000 $i,j$ derivative specifications available.\textsuperscript{31} A map of the transmission network and these nodes is found in figure 4.

In addition to the price nodes, figure 4 displays 11 price zones. Nodal derivatives pay the difference in the electricity prices at the two nodes. Zone-indexed derivatives pay the difference between two zonal prices ($z_1,z_2$), which are a quantity weighted average of the nodal prices where electricity is consumed in a given zone, with payouts equal to:

$$r_{z1,z2,T1,T2} = \sum_{h=T_1}^{T_2} (LMP^S_{z2,h} - LMP^S_{z1,h})$$

$$= \sum_{h=T_1}^{T_2} \left( \sum_{j \in z2} w_{j,h} LMP^S_{j,h} - \sum_{i \in z1} w_{i,h} LMP^S_{i,h} \right)$$

(7)

Mixed derivatives that pay the price difference between a node and a zone-index are classified as nodal. The example contract in section 3 is classified as nodal, with Linden

\textsuperscript{31}450 locations allows for $450 \times 449 = 202,050$ directional location pairs. Given that $r_{i,j} = -r_{j,i}$ and all other variables share this transitive property, this number is halved to give 101,025 observations. The number of locations is not constant across all auctions, with some nodes being added and removed over the sample window.
Cogen being a node, and N.Y.C being a zone.

There are two important distinctions between nodal and zonal products. First, by construction zonal products are aggregated and therefore the impact of any single nodal price on the zonal price is dampened. Having a forecasting advantage over a given node is necessarily diluted on the zonal product. Likewise, mispricing a given node will result in a smaller pricing error in the zonal product. Second, in NYISO, producers of electricity receive nodal prices whereas consumers of electricity pay the zonal prices described in equation (7) (See Tangeras and Wolak, 2017, for more detail on nodal and zonal prices). Therefore, different firms may demand different products depending on their operations in the wholesale market.

Zonal contracts attract the greatest expenditure (figure 3 (b)), despite having far fewer potential specifications available and many less overall contracts issued. Collectively, holders of both derivative types earn revenues greater than expenditures from their contract positions, however, nodal contract holders receive proportionally larger revenues than their expenditures compared to holders of zonal contracts.

3.3 Participants in the derivative market

130 firms have purchased a TCC in the New York market. This subsection describes three broad firm types (retailers, generators and traders) that participate in this market and will discuss potential motives for their participation. Descriptive statistics on the expenditures
and payouts of the positions entered in the TCC market for each group are in figure 5, and a full list firms and their firm type classifications is in appendix C2.

Figure 5: Contract expenditures and payouts of participants

(a) Total expenditures and payouts

(b) Average expenditures and payouts (restricted to purchases)

(c) Average expenditures and payouts per month and unit of contract (restricted to purchases)

Figure (a) displays the sum of $q_{i,j,T_1,T_2,f} \cdot m(T_2,T_1), p_{i,j,T_1,T_2,f} \cdot m(T_2,T_1), r_{i,j,T_1,T_2}$. Figure (b) displays the average of $q_{i,j,T_1,T_2,f} \cdot m(T_2,T_1), p_{i,j,T_1,T_2,f} \cdot m(T_2,T_1), r_{i,j,T_1,T_2}$. Figure (c) displays the average of $p_{i,j,T_1,T_2} \cdot m(T_2,T_1), r_{i,j,T_1,T_2}$. Sample sizes (number of contracts entered between 1999 and 2015 for each firm type) are 3,295 for the retailers, 59,425 for the generators and 76,905 for the traders.

Average expenditures and payouts are constructed only using contracts purchased for a positive price due to compositional differences in the amount of long and short positions entered by each firm group.
3.3.1 Retailers

Firms that purchase electricity from the New York wholesale electricity market to meet the consumption demands of their customers are classified as retailers. Retailers are often regulated in the prices they can charge to their retail customers and cover large, contiguous geographic areas. In New York, nodes where retailers purchase their electricity have zonal prices. Retailers can profit from minimizing procurement costs in the wholesale market, and their procurement strategy may involve using TCCs.

Overall, retailers receive TCC payouts slightly less than the prices they pay, and retailers are the smallest participant group in terms of total derivative expenditure (figure 5a). However, retailers spend more per contract than other firm groups (figure 5b), and more per derivative month when scaling by the size and duration of a contract (figure 5c). Comparing the magnitudes of figures 5b and 5c, this implies that retailers buy contracts with larger quantities and durations than other firms.

3.3.2 Generators

Firms that own electricity generating plants in New York that are not retailers are classified as generators. These firms supply electricity and may have local market power at the price nodes where their power plants are located. Any market power diminishes at other price nodes.32

Similar to retailers, generators can use TCCs to change their spot price exposure to the price at a different node to where they are located, allowing them to sell to different locations. However, given their ability to influence electricity spot prices via their production decisions, generator participation in the TCC market has been theoretically scrutinized in Bushnell (1999) and Joskow and Tirole (2000). If a generator can influence the payout of a particular derivative, the derivative is worth more in their hands than anyone else. A mechanism to increase a derivative payout held by a generator may be to offer less supply. Such a situation would not be economically efficient if it is a low cost generator and its production is replaced by a higher cost source. As summarized by Bushnell, auctions of TCCs could result in contracts “flowing to those that can abuse them the most.” The implications of these theories are briefly examined in section 5.2.3.

Overall, generating firms received net payouts on their derivative positions of $1,367m, exceeding their net expenditure by $340m from 1999-2015 (figure 5a).

3.3.3 Traders

All remaining firms with no physical interests in the New York electricity market are classified as financial traders. These firms are largely investment banks or energy trading

---

32Market power is related to competitor locations and the capacities of the transmission grid. If transmission capacity was infinite, all power plants throughout the state would compete with an equal degree of market power at all price nodes (and there would be a uniform price).
outfits. In the earlier example contract, J. P. Morgan Ventures Energy Corporation is classified as a trader. I claim that these firms are motivated to make a profit in this market, to buy underpriced products and sell overpriced products. TCC profits solely determine the success of the firm or the TCC division of the firm, whereas TCC profits are only a small portion of total revenues for retailing and generating firms. Section 2.3 demonstrated the potential for traders to improve market allocations and to earn profits in this market.

Overall, trading firms received net payouts on their derivative positions of $1,859m, exceeding their net expenditure by $598m from 1999-2015 (figure 5a).

3.4 The sequence of New York transmission congestion contract auctions

Figure 6: Order of auction vintages and their payout windows

Derivatives of 1 month duration are red, 6 month duration are green and 12 month are blue. The length of the arrow covers the payout period for a derivative. The auctions for each vintage occur in order from the top of the diagram to the bottom.

In New York, a single auction (indexed by \( t \)) allocates a set of TCCs that have a common time horizon, defined by \( T_1 \) and \( T_2 \) in equation (6). Firms can bid to buy, or offer to sell, any of the \( \approx 100,000 \) possible \( i, j \) location pairs with this time horizon. The auction process was described in the section 2.3, with more technical details found in appendix B. The auction generates \( q_{i,j,t,f} \), the positions for each firm on each derivative product. The
prices generated are transitive in the location nodes \( (p_{i,k,T_1,T_2,t} = p_{i,j,T_1,T_2,t} + p_{j,k,T_1,T_2,t}) \)
and the issued contracts (the collection of \( q_{i,j,t,f} \)) are simultaneously feasible.

There are two crucial features of the allocation process that will be utilized in the analysis. As demonstrated in the single period examples, prices are observed for every derivative. Even if a firm is not allocated a contract on a given derivative, a price is set and represents the price at which the market operator would have sold or bought a derivative had bids above or offers below that price been placed. For example, in a three-node system, the \( i,k \) derivative and the \( j,k \) derivative might have had bids placed on them, and given the constraints on the auctioneers problem, this is enough to set a price for the \( i,j \) derivative that did not receive a bid.

Second, the auctions are sequential, providing restrictions on information flows to participants. Figure 6 displays a representation of the auction structure, with the duration of the derivative specified in the horizontal dimension and the order in which auctions occur in the vertical dimension. The 6- and 12-month derivatives either begin in May or November, with each vintage auctioned in three to five tranches. The 1-month derivatives are available for each month of the year, sold in a single auction.\(^{33}\) Information on secondary markets is unavailable, with no formal exchange available, and anecdotal suggestions are that it is non-existent.\(^{34}\)

Figure 7 displays the derivative payouts for every contract purchased by all firms, demonstrating the volatility in derivative payouts for the same \( i,j \) product over consecutive \( T_1,T_2 \) vintages, and that substantial deviations do occur between derivative payouts and derivative prices. This illustrates the opportunity for firms to profit from having a better technology to forecast the payouts of the products. Entering an auction, firms have access to public information on the results of past auctions, but not the bids, which are released 3 months after the fact and with anonymized identifiers placed on the location nodes and the firm identities. For example, every TCC ever issued is publicly available, defined by the node location pair \( (i,j) \), start and end date of payments covered \( (T_1,T_2) \), the firm holding the contract \( (f) \), the number of units in the position \( (q) \),\(^{35}\) and the clearing price per unit \( (m(T_2,T_1) \cdot p_{i,j,T_1,T_2,t}) \). Alternatively, a firm can examine the price outcomes for any location pair derivative from any previous auction \( s \) to get \( m(T_2,T_1) \cdot p_{i,j,T_1,T_2,s} \) - the price at which an \( i,j \) derivative could have been acquired or sold at in auction \( s \). For auctions with payment windows that have elapsed, the payouts that a holder of these derivatives would have received can be calculated, \( m(T_2,T_1) \cdot r_{i,j,T_1,T_2} \).

\(^{33}\)There are occasional auctions for TCCs that cover 24 months of payments, but only 1-, 6- and 12-month auctions have occurred on a consistent schedule each year.

\(^{34}\)This is not to say that similar products are not privately available. Forward contracts (for a single location, not a TCC) are used in wholesale electricity market settings. See Wolak (2007) for just one of many examples of generating and retailing firms entering forward arrangements.

\(^{35}\)Formally, NYISO lists quantity of contracts in megawatts (MW). To avoid a confusion regarding the stock or flow nature of quantity, this paper will not refer to the quantity in MW units, because one TCC pays the MWh price difference between two locations over the duration of the contract \( m(T_2,T_1) \cdot r_{i,j,T_1,T_2,t} \), with \( q \) contracts paying \( q \cdot m(T_2,T_1) \cdot r_{i,j,T_1,T_2,t} \).
4 Data Sources

Data on derivatives and contracts are available to the public at the NYISO TCC website, with mechanical details of the data construction found in Appendix C.

4.1 Contract Data

Contract observations are defined by $i, j, T_1, T_2, f$, the locations and time horizon specified in the derivative contract purchased, the firm that purchased the contract. The key variables are the prices, payouts and quantities of the contract. Data for all contracts are available since the market began in 1999. There are 139,625 contracts in the contract dataset.

4.2 Derivative Data

Derivative observations are defined by $i, j, T_1, T_2, t$, the locations and time horizon specified in the derivative, and the auction $t$ that it was sold in. Each auction $t$ has attached

\[37\text{In the raw data, } i, j, T_1, T_2, f \text{ does not uniquely identify each observation. This is because a firm that bids a step function will get an issued contract for each step that clears at auction. Given that the price per unit is the same, I aggregate these into one observation and add the size of each contract into the single, unique observation.}\]
a common duration window $T_1, T_2$ for all $i, j$ derivatives ($T_1, T_2$ will be dropped in later notation). Derivative data are available for 235 auctions from November 2006 to December 2015.\textsuperscript{38} There are approximately 450 nodes available to be used in a derivative specification each auction, giving approximately 100,000 $i, j$ location pair observations per auction $t$. This gives approximately 23,500,000 $i, j, t$ observations.

The number of derivative observations greatly exceeds the number of contract observations. The auction mechanism sets prices for each derivative in every auction regardless of whether a firm purchased any given derivative (refer to section 2.3). The derivatives studied are restricted to types purchased by firms over the sample window. There are 304,039 unique $(i, j, m(T_1, T_2))$ derivative types, where $m(T_1, T_2)$ is the number of months the derivative spans. The sample is restricted to the 14,969 of 304,039 unique $(i, j, m(T_1, T_2))$ types where a contract was ever issued, giving a sample of 1,151,374 $i, j, t$ derivative observations. Attached to each observation are price and payout per month duration variables $p_{i,j,T_1,T_2,t}$ and $r_{i,j,T_1,T_2,t}$. Both directions of a derivative are not included in the data because it is a duplication with $p_{i,j,t} = -p_{j,i,t}$ and $r_{i,j,t} = -r_{j,i,t}$\textsuperscript{39}.

4.3 Auction bid data

Bidding data is released three months after each auction and lists anonymized identifiers rather than the names of the POI and POW locations and the identity of the firm. I have compiled bid data from 2006-2015. I describe an algorithm for decoding a subset of these identifiers in Appendix C. This subset is used in some descriptions of firm bidding behavior, with the sample outlined at a case-by-case basis in the analysis. The decoded auction data lists all bids as defined by the firm, the product and the auction, with information on the quantity of units demanded and the bid price.\textsuperscript{40}

5 Firm positions and trading profits in TCC auctions

The controversy surrounding TCC auctions is that TCC holders can heavily profit from their position at the expense of ratepayers. This section takes the first step toward understanding which products are purchased by different firm groups, and which are purchased for an eventual profit. Section 5.1 examines the products purchased by firms. Section 5.2

\textsuperscript{38}There are 265 auctions over this time horizon, with 235 having lagged outcomes and realized revenues available for analysis.

\textsuperscript{39}The direction of the derivative is assigned arbitrarily in the direction from the location with the larger identification number to the lower identification number.

\textsuperscript{40}For the decoded locations, market clearing prices can be applied to allocate clearing quantities to participants, and realized revenues can be applied to recover ex-post contract profits. As described in Appendix C, the total profits when split across classes and firms in the auction data are proportional to the total profits from the corresponding period in the awards data. Enough identities are recovered to cover 90% of the contract expenditures and profits from the contract data but only 45% of total contracts. The bid data is more likely to contain locations that are more frequently specified in issued contracts.
then investigates which firms earn systematic trading profits on which products. Profit sources are also investigated for traders that buy less liquid products and for generators that purchase TCCs at locations where they own power plants.

5.1 Participation of firms in TCC auctions

This section describes the types of products firms purchase, the degree of overlap between physical and financial firms purchasing the same products and the types of bids firms place in the market. The aim is to describe whether the auctions are being used by the physical firms that they are intended to benefit, and to investigate whether financial traders are buying products that other firms do not want.

5.1.1 TCC purchases

TCC expenditures are displayed in table 2. Retailers account for 16% of derivative expenditures, generator owners account for 33% of derivative expenditures, and financial traders account for the remaining 51%. Earlier, in figure 5, we saw that retailers on average entered much larger and longer positions, with the retailers entering only 3,295 contracts compared to 59,425 for the generators and 76,905 for the traders. In total dollar figures, retailers take much larger positions on zonal and long duration contracts, whereas generators and traders are more balanced between nodal and zonal contracts.

<table>
<thead>
<tr>
<th>Table 2: Expenditures on TCC contract positions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retailers</td>
</tr>
<tr>
<td>Zonal Nodal 1 month &gt;1 month Round 1 Round &gt;1</td>
</tr>
<tr>
<td>Mean ($)</td>
</tr>
<tr>
<td>Total ($m)</td>
</tr>
<tr>
<td>Generators</td>
</tr>
<tr>
<td>Zonal Nodal 1 month &gt;1 month Round 1 Round &gt;1</td>
</tr>
<tr>
<td>Mean ($)</td>
</tr>
<tr>
<td>Total ($m)</td>
</tr>
<tr>
<td>Traders</td>
</tr>
<tr>
<td>Zonal Nodal 1 month &gt;1 month Round 1 Round &gt;1</td>
</tr>
<tr>
<td>Mean ($)</td>
</tr>
<tr>
<td>Total ($m)</td>
</tr>
</tbody>
</table>

An observation is a contract issued to a firm. Contracts are classified into groups based on the zonal, nodal, 1- month or >1- month characteristics, and whether for the >1- month products they were sold in the first round or a later round. Given positions can be short or long, the absolute value of expenditures is the variable underlying the statistics in the table (|q_{i,j,T_1,T_2,f} \cdot m(T_2, T_1) \cdot p_{i,j,T_1,T_2}|). Sample restricted to the purchases in 2006-2015 where auction round information is available.
The average contract expenditures for retailers are much larger than those for generators and traders. The mean contract purchase for a retailer purchasing a 6- or 12-month contract in a round 1 auction is $966,096, more than 12 times larger than the average for generators and traders. While retailers do purchase derivatives in later rounds, their biggest positions are taken in round 1 of the auctions, suggesting that they do not systematically wait for price guidance and purchase in later rounds. 84% of retailer expenditures are for zone-indexed contracts and 96% are for 6 or 12 month duration contracts. Table A1 replicates table 2 but for contract sizes \( q_{i,j,t,f} \), displaying similar patterns, with a median round 1 retailer purchase of 26 units compared to 4 and 3 for generators and traders. Individually, contract sizes of 3 units would not substantively change aggregate price exposure in the procurement of electricity by major retailers or the sale of electricity by generators.\(^{41}\)

The stylized facts from this section demonstrate that retailers appear to restrict their participation to large purchases of zonal products, whereas generators and traders buy a mix of both zonal and nodal products. The radically different purchase behavior of retailers to generators and traders could be explained by regulatory incentives. The price schedules retailers can charge their retail customers are determined via rate-setting meetings with the public utility commission. There may be some risk to retailers that losses from trading activity not linked to the procurement of energy are not included in the rate base, whereas profits from such activities could lower the rate base.

5.1.2 TCC purchase overlap

The overlapping auction structure depicted in figure 6 shows the potential for a firm to hold an open position on a particular TCC product entering an auction. For example, a firm that buys a 12-month \( i,j \) location pair TCC in round 1 of May 2006 is denoted as holding an open position on the \( i,j \) product for the remainder of the 12- and 6-month auctions in May, every 1-month auction for the following 12 months and the 6- and 12-month auctions in November 2006.\(^{42}\) Table 3 displays the proportion of purchases by retailers, generators and traders made on \( i,j \) products where physical or financial firms held an existing open position.

\(^{41}\)In 2015 Orange and Rockland Utilities, Inc. purchased an average of 655MWh of electricity from wholesale markets each hour and received approximately $75,000 each hour from its customers. In 2015, Consolidated Edison’s New York City retailer averaged approximately 10 times those figures (Consolidated Edison Inc. (2015), pages 20 and 24.). Relating the contract sizes to power plant operation, the Linden Co-generation power plant listed in the earlier contract example had a listed generating capacity of 1034.9MW in 2015. Although there are many small power plants in New York, seldom do they participate in TCC markets (See NYISO (2016) for generator capacities and Appendix C2 for TCC participants).

\(^{42}\)More formally, the open position a firm has over an \( i,j \) derivative entering auction \( t \) is calculated at being the sum of the quantities \( (q) \) of all \( i,j \) TCCs purchased by that firm in prior auctions with windows \( T_1, T_2 \) that cover the start date of payouts in auction \( t \), less the corresponding quantity of all \( i,j \) derivatives sold.
We see that retailers purchased the more liquid zonal products. 95% of their purchases were on products where another physical firm held an open position on the same product entering the auction. Overall, most zonal products purchased by any type of firm had open positions held by at least one other firm entering the auction.

For nodal products, the proportion of purchases on products with existing open positions was lower. Only 33% of financial firm nodal product purchases were on products where physical firms possessed an active open position. Zonal products appear more liquid and from the previous subsection we saw that they attract purchases by all firm types, but nodal products are less likely to attract multiple buyers on the same product. Therefore, returning back to the stylized auction examples in section 2.3, financial firms could be providing liquidity service by buying products not purchased by physical firms.

Table 3: Percentage of TCC purchases on products with existing open positions

<table>
<thead>
<tr>
<th>Zonal purchases</th>
<th>Existing open position held by:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Physical firms</td>
</tr>
<tr>
<td>Retailers</td>
<td>95%</td>
</tr>
<tr>
<td>Generators</td>
<td>87%</td>
</tr>
<tr>
<td>Traders</td>
<td>80%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Nodal purchases</th>
<th>Existing open position held by:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Physical firms</td>
</tr>
<tr>
<td>Retailers</td>
<td>57%</td>
</tr>
<tr>
<td>Generators</td>
<td>48%</td>
</tr>
<tr>
<td>Traders</td>
<td>33%</td>
</tr>
</tbody>
</table>

The figures constructed are the percentage of contracts purchased by the firm type defining the row on i, j products where the firm type defining the column holds an open position over. Physical firms are retailers and generators, financial firms are financial traders. Sample restricted to the purchases in 2006-2015 where auction round information is available.

5.1.3 TCC bid strategies

If firms are willing to both buy or sell a particular derivative depending on the price, then a position on that product is unlikely to form part of an energy procurement strategy. We see in table 4 that retailers submit one-sided bids (they only wish to buy a derivative, they do not simultaneously offer to sell the derivative at higher prices), whereas approximately 15% of generator and trader bids are two-sided. Of the one-sided bids, we see that retailers clear a positive quantity more than half the time, whereas generators and traders are more likely to submit bids out of the money, with only 26% and 20% of their bids clearing a
positive quantity. Further, retailers are more likely to demand large, one-sided positions when compared to the other firm types.

Returning to the example auctions in section 2.3, two-sided bids and low clearing rates could indicate that traders are more likely to offer liquidity on different products, but also that they bid at low prices that often do not clear. Further, generating firms follow the same stylized patterns to traders and it will be shown in section 5.2.3 that only 5% of generator-held contracts have a location specified in the derivative payout where the holder owns a power plant. Many generating firms have trading operations, so their participation in this market may contain a mixture of using the derivatives to sell their electricity to different locations and speculating on profitable positions. Finally, the regulatory incentives explained in section 5.1.1 could explain why retail bids do not follow the same patterns as generators and traders.

Table 4: Bid types and bid clearing by firm type

<table>
<thead>
<tr>
<th></th>
<th>Retailers</th>
<th>Generators</th>
<th>Traders</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Two-sided</td>
<td>1.9</td>
<td>12.6</td>
<td>17.5</td>
<td>15.1</td>
</tr>
<tr>
<td>% One-sided</td>
<td>98.1</td>
<td>87.4</td>
<td>82.5</td>
<td>84.9</td>
</tr>
<tr>
<td>% One-sided bids cleared</td>
<td>55.9</td>
<td>26.1</td>
<td>20.5</td>
<td>22.5</td>
</tr>
<tr>
<td>Total bids</td>
<td>3,109</td>
<td>203,661</td>
<td>226,825</td>
<td>433,595</td>
</tr>
</tbody>
</table>

An observation is a firm bid on a node pair contract in an auction. Bids are classified as two-sided if the firm submits a willingness to buy and sell the contract, and one-sided if it is only willing to either buy or sell. A bid is classified as cleared if part or all of a bid is in the money and the firm is awarded a contract, with the one- and two-sided bids data using all anonymized node locations, with the clearance rates calculated from the node pairs that were decoded.

5.2 Systematic trading profits across firm and product types

Prior work on TCC auctions identified that contract prices were not equal to expected derivative payouts (Bartholomew, Siddiqui, Marnay, and Oren, 2003; Hadsell and Shawky, 2009; Adamson, Noe, and Parker, 2010). A similar analysis to these previous papers that uses the contract data is found in appendix D, which highlights that tests for the efficient market hypothesis can not be rejected for zonal products, but is rejected for nodal products. In this section, I explore the link between derivative product design, the types of firms that profit on each product and whether profits are linked to liquidity provision.

Under the efficient market hypothesis, all prices reflect current information. With free entry of risk neutral firms, this implies that a derivative’s price equals the expected payout of the derivative. Therefore, if each derivative auctioned has some expected payout \( E(r) = \mu \), then its price \( p \) should equal \( E(r) \). Consider a single derivative that is auctioned, and denote \( I = 1 \) when it is purchased by firm \( I \) and \( I = 0 \) otherwise. Then,
\[
E(r|I,p) = p + E(\mu - \beta(t_I)|I = 1) \cdot I
\]

(8)

Deriv. payout
\[
E(r|I=0)
\]
Rent to firm I

In equation (8), \( \beta(t_I) \) is the bid firm \( I \) places when it receives some signal \( t_I \). Under the efficient market hypothesis, conditional on firm \( I \) being awarded the object, \( \beta(t_I) = \mu \). However, if the assumptions of risk neutrality or complete information are violated then it could be that \( \beta(t_I) \neq \mu \) when firm \( I \) is awarded the object. If \( \beta(t_I) > \mu \) when firm \( I \) is awarded the derivative, it could suggest that firm \( I \) values the derivative at more than its expected value, or that it persistently overestimates its value. If \( \beta(t_I) < \mu \) when firm \( I \) is awarded the derivative, it could suggest that firm \( I \) has the ability to purchase the product for less than its expected payout, or that all firms value the derivative at less than its expected value.

This section estimates derivative payouts in a statistical analogue to equation (8). The estimates predict the systematic profits different firm groupings earn from participating in TCC auctions. Denote \( F \) as the set containing the three firm groups: retailers, generators and traders. Each \( i,j,t \) derivative observation contains the following variable on contract allocations for each firm type \( f \in F \):

- \( I^q_{i,j,t,f} \): indicator = 1 if firm type \( f \) was issued an \( i,j \) TCC in this auction.\(^{43}\)

The model to be estimated has the following specification:

\[
r_{i,j,t} = \beta p_{i,j,t} + \sum_{f \in F} \delta_f I^q_{i,j,t,f} + \epsilon_{i,j,t}
\]

(9)

\( p_{i,j,t}, r_{i,j,t} \) and \( I^q_{i,j,t,f} \) are the average monthly prices and payouts, and an indicator function for firm type \( f \) being allocated the contract. Derivative payouts exclude any discount factor.\(^{44}\) The statistical analogue to equation (9) has \( \delta_f \) equal to the difference between the expected payout of the derivative and the market clearing bid when firm \( I \) is awarded the derivative.

Consider the case where \( \beta = 1 \), meaning that the derivative payouts on average equal the derivative price when the product is not purchased. Then, \( \delta_f = 0 \) would imply that when the firm purchases the object, it on average receives a payout equal to the price it paid for the object. If \( \delta_f > 0 \) the firm on average receives a payout greater than the price it pays for the object, and if \( \delta_f < 0 \) the firm receives a lower payout than the price it pays for their derivatives.

\(^{43}\)The indicator is \( I^q_{i,j,t,f} = -1 \) if \( q_{i,j,t,f} > 0 \), the firm type was issued a \( j,i \) TCC in this auction, a position that receives counterpayments to the \( i,j \) derivative.

\(^{44}\)The small payout lengths and monthly payouts mean that applying a discount rate correction has a negligible impact on the results.
To emphasize the nature of the derivative data, whereby prices and payouts exist for each derivative regardless of whether a firm was actually issued a contract on that derivative, note that a retailing firm is issued a contract in 0.2% of observations (\(|I_{i,j,t,RET}| = 0.002\)), with generators and traders each issued contracts for 3% of the derivative observations (\(|I_{i,j,t,GEN}| = 0.031, |I_{i,j,t,TRA}| = 0.033\)).

5.2.1 Estimates of derivative prices and payouts

Table 5 reports the estimates of the parameters in equation (9) for all derivatives and for partitioned samples of the nodal and zonal derivatives. The majority of products available in this market are nodal, but we earlier saw that zonal contracts attract greater total expenditure. The unit of observation is a location pair derivative available in auction \(t\). I estimate the equation using ordinary least squares and cluster the standard errors at a vintage \(T_1, T_2\) level given the transitivity property of prices and payouts.

Table 5: Estimates of average monthly derivative payouts

<table>
<thead>
<tr>
<th></th>
<th>All (p_{i,j,t} = 1686)</th>
<th>Zonal (p_{i,j,t} = 1667)</th>
<th>Nodal (p_{i,j,t} = 3821)</th>
<th>Nodal (p_{i,j,t} = 1667)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta) ([p_t])</td>
<td>0.93</td>
<td>0.94</td>
<td>0.93</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.09)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>(\delta_{RET}) ([I_{RET,t}^q])</td>
<td>-64.35</td>
<td>-31.69</td>
<td>-57.16</td>
<td>-218.10</td>
</tr>
<tr>
<td></td>
<td>(87.24)</td>
<td>(121.66)</td>
<td>(102.97)</td>
<td>(272.99)</td>
</tr>
<tr>
<td>(\delta_{GEN}) ([I_{GEN,t}^q])</td>
<td>124.48</td>
<td>116.58</td>
<td>125.08</td>
<td>159.13</td>
</tr>
<tr>
<td></td>
<td>(44.52)</td>
<td>(93.20)</td>
<td>(45.33)</td>
<td>(72.63)</td>
</tr>
<tr>
<td>(\delta_{TRA}) ([I_{TRA,t}^q])</td>
<td>207.91</td>
<td>19.61</td>
<td>219.17</td>
<td>333.38</td>
</tr>
<tr>
<td></td>
<td>(46.26)</td>
<td>(124.37)</td>
<td>(45.75)</td>
<td>(61.69)</td>
</tr>
<tr>
<td>(\delta_{OP_{RET}}) ([I_{RET,t}^q \cdot I_{OP_{i,j,t}}^q])</td>
<td>263.39</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(273.04)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\delta_{OP_{GEN}}) ([I_{GEN,t}^q \cdot I_{OP_{i,j,t}}^q])</td>
<td></td>
<td>-55.54</td>
<td></td>
<td>(79.09)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\delta_{OP_{TRA}}) ([I_{TRA,t}^q \cdot I_{OP_{i,j,t}}^q])</td>
<td></td>
<td>-172.35</td>
<td></td>
<td>(65.31)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(N)</td>
<td>1,151,374</td>
<td>10,506</td>
<td>1,140,868</td>
<td>1,140,868</td>
</tr>
<tr>
<td>(N_{A})</td>
<td>235</td>
<td>235</td>
<td>235</td>
<td>235</td>
</tr>
</tbody>
</table>

First 3 columns report estimates of equation (9) and the final column reports estimates of equation (10), using ordinary least squares. Standard errors clustered at a vintage level \(T_1, T_2\) reported in parentheses. All contract prices and payouts are divided by the number of months a contract covers. Summary statistics for the variables used in estimation are found in table A2. \(i, j\) or \(j, i\) direction is arbitrary: \((p_{i,j} = -p_{j,i}, r_{i,j} = -r_{j,i})\).

\(^{45}\)The direction of the derivative data is arbitrary, therefore an observation for the \(i, j\) derivative with \(I_{i,j,t,f}^q = 1\) is equivalent to an observation a \(j, i\) derivative with \(I_{j,i,t,f}^q = -1\).
I estimate the expected payout for nodal derivatives to be $\hat{\beta} = 0.93$ times the purchase price (not statistically different from 1 for a test with a 5% level of significance), with retailers predicted to receive an average of $\hat{\delta}_{RET} = 57.16$ less per month of contract payments and generators and traders receiving an extra $\hat{\delta}_{GEN} = 125.08$ and $\hat{\delta}_{TRA} = 219.17$. However, only for generators and traders are these estimates detected to be statistically different from zero. The average price paid by generators for their nodal derivatives is $804.52$, implying an average payout premium to generators of $\frac{125.08}{804.52} \cdot 100 = 15.5c$ per dollar value of the position. The same calculation for financial trading firms estimates an average payout premium of $\frac{219.17}{1115.36} \cdot 100 = 19.7c$ per dollar.

In contrast to nodal derivatives, I do not detect any firm type earning a payout premium on zonal derivatives. The expected payout for zonal derivatives is estimated to be $\hat{\beta} = 0.94$ times the purchase price (not statistically different from 1 for a test with a 5% level of significance), with tests for the predicted premium retailers, generators and traders earn on their positions not being statistically different from 0 at a 5% level.

To summarize, only generating and trading firms are detected to earn systematic profits on their derivative positions. Further, these firms are only detected to earn realized profits greater than the prices they pay on nodal products. Retailers are not detected to earn trading profits and were earlier shown to largely confine their participation to zonal products. These products are found to be priced efficiently on average, with no firm type detected to be able to systematically take profitable positions on these products.

5.2.2 Extension 1: Are profits linked to liquidity provision?

Realized trading profits in this market were found to exist on nodal, but not zonal products by generators and traders. I now extend the analysis to consider whether payouts differ for positions taken on products that no firms have a current open position. Define the following variable:

- $I_{i,j,t}^{OP}$: indicator = 1 if any firm has an existing open position on the $i, j$ or $j, i$ derivative entering auction $t$

Open positions are defined in section 5.1.2, being non-zero when firms have purchased a TCC in a prior auction with a payout period overlapping with the payout period of the products offered in the current auction. Equation 10 extends equation (9) to allow predicted payout premiums to differ with $I_{i,j,t}^{OP}$:

$$r_{i,j,t} = \beta p_{i,j,t} + \sum_{f \in F} \left[ \delta_f I_{i,j,t,f}^q + \delta_f^{OP} I_{i,j,t,f}^{OP} \cdot I_{i,j,t}^{OP} \right] + \epsilon_{i,j,t}$$

(10)

Here, if $\delta_f^{OP} < 0$, then it will imply that payout premiums for a given firm type’s purchases are on average lower on products where other firms hold an active open position.
entering the auction. The estimates for the sample of nodal contracts are reported in the final column of table 5. We observe that for financial traders, they earn an average realized payout premium of $333.38 per month of contract payout on their TCC purchases when no other firm holds an active open position on the product. However, when any firm holds an open position on a product that a trader purchases, that payout premium is halved, being $333.38 - 172.35 = $161.03 per month of contract payout. These differences are statistically significant at a test size of 5%. Relating this result to the auction examples in section 2.3, it could be the case that when any firm holds an open position on a particular derivative product, competition amongst traders is higher and their ability to earn profits on these products is reduced. Product liquidity and trader profits will be explored in more detail in section 6, which studies the persistence of realized trading profits.

5.2.3 Extension 2: Are generator profits tied to power plant operations?

Existing theories for why TCC auctions may result in systematic trading profits to some firms have predicted that generating firms can earn systematic profits from TCC positions tied to their power plant operations due to their ability to influence downstream electricity prices (Bushnell, 1999; Joskow and Tirole, 2000). In sum, the authors show that if generators can influence the payout of a TCC by exercising market power, the TCC is worth more in their hands than in the hands a firm that does not have this ability. Although the results have emphasized profits, generating firms have also been shown to earn systematic profits in this market. In this extension I investigate the theoretical predictions regarding TCC profits earned by generating firms due to electricity market power.

First, to examine whether the trading profits of generator-held TCCs differ across power plant ownership status, the scaled per derivative per month profit \( r_{i,j,f,t} - p_{i,j,f,t} \) for all contracts ever purchased by generators are regressed on indicator variables \( SZ \) - denoting the firm owns a power plant in the same zone as one of the \( i,j \) locations specified in the derivative, and \( SN \) - denoting the firm owns a power plant at the exact node as one of the \( i,j \) locations specified in the derivative. The data for power plant locations is described in appendix C. Only 1,219 of the 23,951 generator held contracts included in the estimates have a location specified in the payout where the holder owns a power plant. 3,832 contracts have a location specified in the payout which is in the same zone as a power plant owned by the holder. The estimates are:

\[
\begin{align*}
\hat{r}_{i,j,f,t} - \hat{p}_{i,j,f,t} &= 187.2 - 22.6 \ Z_{i,j,f,t} + 37.2 \ N_{i,j,f,t} \\
&= 187.2 - 22.6 \ (56.7) + 37.2 \ (182.0)
\end{align*}
\]

The estimates show that for the 23,951 derivatives purchased at a positive price by generating firms at generating nodes, there is no average profit differential associated with
a firm’s power plant ownership at a node specified in the derivative contract.\footnote{The sample is the 23,951 contracts issued to generating firms at generating nodes for a positive price, with prices and payouts standardized by the length of the contract. Standard errors are clustered at a vintage level (all contracts with the same $T_1$ and $T_2$).}

I next extend equation (9) to investigate an implication from the theories in Bushnell (1999) and Joskow and Tirole (2000) that derivative payouts are increasing in the size of the position held by a generator. To demonstrate, consider the TCC that pays the difference between the spot market electricity price at location $i$ and location $j$ at a given period of time. Assume competition at location $i$ is perfectly competitive, whereas firm $f$ has market power at location $j$ and chooses $Q_E$, its quantity to supply the market. With the stylized assumptions that the firm: faces no capacity constraints; has a fixed marginal cost $c$; faces a known residual demand curve at location $j$ of $LMP_j(Q_E) = \alpha - \beta Q_E$; and holds $Q_{POST}^{i,j,f}$ TCCs paying $LMP_j - LMP_i$, then the firm’s profit maximization problem and optimal behavior is as follows:

$$\max_{Q_E} LMP_j(Q_E)Q + (LMP_j(Q_E) - LMP_i)Q_{POST}^{i,j,f} - c(Q_E)$$

First order condition: $0 = LMP_j'(Q_E)Q + LMP_j(Q_E) + LMP_j'(Q_E)Q_{POST}^{i,j,f} - c'(Q_E)$

$$Q_E = \frac{\alpha - \beta Q_{POST}^{i,j,f} - c}{2\beta}$$

$$LMP_j = \frac{\alpha + \beta Q_{POST}^{i,j,f} + c}{2}$$

Here, we observe that the firm withholds more output in the physical market with more contracts $Q_{POST}^{i,j,f}$, and that $LMP_j$ is increasing in the contracts held by the firm. Therefore, the financial asset that pays $r_{i,j} = LMP_j - LMP_i$ is equal to $r_{i,j} = \frac{1}{2} \cdot (\alpha + \beta \cdot Q_{POST}^{i,j,f} + c) - LMP_B$ in the stylized example, being $\frac{\beta}{2} \cdot Q_{POST}^{i,j,f}$ more valuable if held by the firm than by a different participant.

To investigate whether derivative payouts are related to the size of firm derivative positions, equation (9) is extended as follows:

$$r_{i,j,t} = \beta p_{i,j,t} + \sum_{f \in F} \delta_f \beta_i^{i,j,t,f} + \sum_{f \in F} \beta_f Q_{POST}^{i,j,t,f} + \epsilon_{i,j,t}$$

\footnote{Given the overlapping auction structure shown in figure 6, this value totals all contracts on the $i,j$ derivative with overlapping payouts to the product sold in auction $t$. $Q_{POST}^{i,j,t,f}$ is negative if the firm type has a positive $i,j$ position.}

\hfill (11)
estimates of this model are displayed in appendix D2, with $\rho_f$ not detected to be different from zero for any firm type on nodal contracts and the $\hat{\delta}_f$ estimates similar to those in table 5. Regardless, the point estimate $\hat{\rho}_{GEN} = 0.17$ is small, where at average open position holdings for generator-won derivatives ($Q_{GEN,t}^{POST} = 24.72$), the predicted increase in the derivative payouts is estimated to be \( \frac{0.17 \times 24.72}{804.52} \times 100 = 0.5c \) per dollar value of the position. This premium represents a small fraction compared to the 15.5c predicted premium collected on all contracts of any size won by generating firms implied by the $\delta_{GEN}$ value.

To summarize, I find no evidence that generator trading profits systematically differ with either the product being tied to locations related to their power plant operation or with the size of their open positions. Although in theory TCCs are more valuable in the hands of those that can generate value for them, it is plausible that regulatory rules that allow market operators to withhold TCC payouts if they determine that a firm exploited their contract position via market power could deter such action from occurring on large scale,\(^{48}\) or that this estimation technique is not statistically powerful enough to detect such actions.\(^{49}\)

6 The persistence of trading profits in TCC auctions

Figure 8 plots total TCC profits to participants and the number of participants from 1999-2015. While the previous section detected that generating and trading firms earned systematic profits on nodal contracts, figure 8 shows that these profits have not eroded over time. For each of the 16 years of auctions, profits from nodal contracts have been positive, whereas zonal contract profits appear centered around zero. This is despite a steady year-to-year increase in the number of firms that were observed to purchase at least one contract over the sample window.

In this section I investigate the persistence of trading profits across products to gain insight as to the barriers preventing trading profits eroding over time and therefore the barriers to removing the transfers of wealth from electric ratepayers to TCC holders. If traders are managing to earn systematic profits by purchasing the products not demanded by physical firms, there may be a barrier preventing other traders from competing for these opportunities. To investigate, I will describe the updating of product prices across auction rounds and vintages and present anecdotal evidence regarding how financial traders formulate their auction strategies. If firms have constant profit margins over the same

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\(^{48}\)Regulations exist to deter such activity, with the Federal Energy Regulatory Commission having jurisdiction to investigate and potentially withhold payments to TCC or virtual traders if they were found to have altered their downstream strategies because of their TCC positions (Alderete, 2013).

\(^{49}\)An ideal test for firms possessing the ability or incentive to perform downstream actions to influence asset payouts would be to estimate the impact TCC positions have on their electricity bidding strategies. Given that such data is not available for this market, the indirect test that $\rho_f = 0$ could only identify marginal changes in derivative payouts with contract holdings, whereas a structural model of electricity bidding strategies may be able to identify inframarginal changes in derivative payouts to firm holdings.
products across auctions, this could indicate the presence of a risk premium, an opportunity cost of capital or some other cost to participation. However, if a firm earns a profit on a particular product and the next time that same product is auctioned the profitable opportunity is removed, some other barrier may exist.

Figure 8: TCC holder profits and participants, 1999-2015

(a) Contract profits
(b) Number of firms

Figure (a) aggregates profits from all TCCs with a start hour in the calendar year. Figure (b) counts the number of firms that were observed to buy at least one TCC in the calendar year.

6.1 Price updating across auctions of the same products

This section examines how derivative prices update following the public revelation of a purchase by a given firm. If a firm systematically profits from their trading positions and markets do not update the prices for these products in subsequent auctions, then the products subject to transfers of wealth from TCC auctions will be identified. However, if a firm systematically profits, then there might be a profitable opportunity for other traders to mimic the positions taken by this firm, or to update their positions on similar products. In such a case we might expect that undervalued derivative prices would appreciate in price and perhaps that profitable trading opportunities on that product cease to exist.

The institutional environment offers a discrete, sequential auction environment for contracts of 6- and 12-months duration (figure 6). Each derivative $d$ is defined by $(i, j, T_1, T_2)$, and denote a given subset of these derivatives as $D$. For each auction round $(ar)$, the following statistic can be constructed:

$$\frac{1}{|D|} \sum_{d \in D} 100 \cdot \frac{p_{i,j,T_1,T_2,ar} - p_{i,j,T_1,T_2,ar=1}}{p_{i,j,T_1,T_2,ar=1}}$$

(12)
The statistic is the mean of the percentage derivative price change in auction round \( ar \) relative to the round one derivative price for products in the set \( D \). The empirical strategy is to estimate the price response of derivatives in subsequent auction rounds following the revelation that a firm was awarded that derivative in the first round of the auction. This is compared with the price response of derivatives that were bid on but not awarded a contract, where there was no public information revelation.

The information structure for the sequential auctions is as follows: Immediately after each auction, the prices for every derivative and the contract awards (including the identity of the firm) are made public. Bids by each firm are not made available to the public in time for the next auction. Therefore, if there is information content attached to the award of a derivative, the price of a derivative should rise after it is revealed that a well-informed firm is awarded that derivative, whereas we may not expect to see such a response after a bid that was below the market clearing price. This is because, for 6- and 12-month derivative auctions, the same set of products with the exact same payout specifications are offered across each round. For comparison reasons, the sample used in this section is restricted to the products observed in the auction dataset, described in Appendix C.

Figure 9: Price paths following purchases or bids and following sales or offers

![Graph](image)

(a) Purchases of derivatives

(b) Sales of derivatives

All series plot equation (12). The purchases chart compares two sets \( D \) of derivatives, those that were purchased by any firm at a positive price in round one to those that were not awarded to any firm but receive a round one bid. The sales chart is analogous to the purchases chart but for negatively priced products. Means and pointwise 95% confidence intervals plotted.

Sample sizes: (a) 2,980 and 9,850. (b) 1,009 and 4,059.

Figure 9 plots the price discovery process for bids and offers as specified in equation (12). The set of derivatives that were purchased by any firm at a positive price in round one are compared to the products that were not awarded to any firm, but received a positive price bid in round one. The sets compared in the second chart are analogous to the first
chart but for sales or offers. The results are consistent with information revelation for positive price purchases – derivative prices appreciate an average 7 to 11% following a round one award. Prices only appreciate 2% for contracts receiving a bid but without an award. Equal but opposite responses are not seen for offers to sell. Derivatives with an offer that does not result in an issued contract look similar to bids with no trade, but when a contract is sold, prices do not rise. A potential explanation for the bid/offer asymmetry is that the sell offers increase the supply of derivatives available and implicitly have the firms taking a position similar to the captive seller, the market operator. If derivatives are priced fairly, then firms should be willing to both buy and sell the product in round 1 of the auction.

Figure 10: Price discovery following purchases or sales, by firm type

All series plot equation (12). The purchases chart compares three sets of derivatives, those that were purchased by any firm at a positive price across the three firm groupings, retailers, generators and traders. The sales chart is analogous to the purchases chart but for negatively priced products, with retailers excluded for sample size reasons. Means and pointwise 95% confidence intervals plotted. Sample sizes: (a) 61, 1,151 and 1,211. (b) 296 and 465.

Figure 10 splits the price dynamics by the type of firm awarded a contract in round 1. In the first chart, the sets of derivatives included are all derivatives that were purchased at a positive price, split by the firm type that purchased that derivative. We see that prices do not respond to retailer awards but do respond to generator and trader awards. The second chart is analogous to the first chart but for derivative sales. Similar patterns are seen to figure 10 when splitting the sample into profitable and unprofitable firms in figure A1.

\footnote{The responses to retailer offers are omitted for sample size reasons. The 95% confidence interval covers - 40% to 20% for the second round.}
Finally, I compare the price responses to generator and trader bids on zone-indexed and nodal contract specifications in figure 11. The market responds more to a nodal contract award than a zonal contract award for both generating and trading firms. This suggests that market expectations update more following a nodal contract purchase than a zonal contract purchase by a generator or trader.

To summarize, in this section I have shown that the market updates derivative prices following the revelation of purchases on some products by some firms, but not all. On average, payout expectations for products only adjust following purchases by generating and trading firms, particularly for nodal products. Given the auctions studied in this section sell the same sets of products one week apart, it is difficult to attribute the systematic trading profits earned in these auctions solely to risk premiums, the opportunity cost of capital or a fixed, per auction cost. The response suggests that firms that purchase a derivative reveal some private information to other participants about the value of the derivative. In the context of the examples in section 2.3, it may be that some of the first round purchases are providing liquidity to the market and resulting in a trading profit, where trader competition in subsequent auctions on related products removes this opportunity. This will be explored in further detail in the next subsection. Unlike traders and generators, retailers tend to only purchase products that attract more participants and are priced actuarially fairly (sections 5.1 and 5.2), therefore the products retailers purchase might persistently
have actuarially fair prices.

6.2 Price updating across auctions with different vintages

This section investigates in further detail why trading profits have not eroded over time. We have seen that generating firms and trading firms earn systematic trading profits, and that after they buy a derivative its price appreciates, diminishing the potential to earn profits on that exact same product in the next auction. This section describes the persistence of trading profits over time. For example, a firm may have some forecasting advantage tied to a single location in the network, in which case they would consistently earn payout premiums for derivative products tied to that location, for multiple $T_1, T_2$ vintages.

To examine the persistence of profits, each awarded contract is classified into a quartile based off of the profitability of the underlying $(i,j)$ derivative to the contract for the previous $(T_1, T_2)$ vintage.\footnote{\textsuperscript{51}For example, all contracts covering November 1 2008 to April 30 2009 have their derivative profits from November 1 2007 to April 30 2008 calculated $(r_{i,j,t-1} - p_{i,j,t-1})$. For six and twelve month derivatives, the $t - 1$ values are for the same $i,j$ pair for the derivative beginning 12 months earlier. For one month auctions, this is for the derivative beginning one month earlier.} Within this vintage of contract, each contract location-pair is then classified as being in one of the following five categories:

- 1-4: Quartiles 1-4 in derivative profit in previous auction of the $(i,j)$ derivatives that were purchased

- N/A: Zero quantity of the $(i,j)$ location-pair derivative was purchased by any firm in the previous auction

The N/A category is substantial. We observed in the three node auction example in section 2.3 that not every $i,j$ derivative has non-zero TCC allocations at auction. Unsurprisingly, given the 100,000s of potential specifications available, many of them are not purchased each auction. Figure 12 displays the contract costs and payouts by firm type for contracts in each of the five categories as defined by the outcome for the contract in the previous vintage. It is apparent that a large portion of TCC purchases by generating and trading firms were for $(i,j)$ derivatives that were not purchased by any firm in the previous vintage. These previously untraded, or low liquidity, contracts make up 88% of financial trader profits. The 3-node example in section 2.3 showed that electricity flow on transmission lines is a function of the whole network equilibrium. Therefore, changes to the network equilibrium may issue contracts between locations that previously did not have contracts or had contracts issued in the opposite direction. Real-world network changes can arise due to planned and unplanned outages that may impact flows and the profitability of TCCs, and it may be that profitable opportunities arise when the network flow equilibrium changes across auctions.
A smaller, but not insubstantial portion of industry profits are earned by generators and traders on previously poor performing derivatives, suggesting there may be some overreacting to poor performance. Statistical support for the figures is found in table D2, where the efficient market hypothesis is rejected for lagged quartile 1 and the not previously traded contract groups. Therefore, if a firm takes a profitable position on a derivative between locations \(i\) and \(j\), in the auction for the next vintage of products, the opportunity to profit on the \(i, j\) product disappears.

Figure 12: Firm contract costs and payouts by past derivative performance

(a) Retailing firms
(b) Generating firms
(c) Financial trading firms

Figures plot the total contract costs and contract payouts for derivatives purchased by the specified firm group. Sample is restricted to derivatives traded since 2007, where derivative prices is available. Quartile groupings are determined by the quartile ranking of issued contracts with a common time horizon, for the per unit of derivative profits in the previous vintage, as defined in the paper body.
To investigate why the same derivatives are not persistently profitable, figure 13 presents the change in the average number of bidders and auction clearing price for each category of derivative based on its performance in the previous vintage.\textsuperscript{52} The figure shows that the market responds to poor performing contracts with less bidders on that specific location pair and lower prices, with higher performance contracts attracting more bidders and higher prices in the subsequent auction.\textsuperscript{53} For the set of issued contracts on derivatives that did not have a cleared contract in the previous vintage, it appears somewhat mechanical that the average number of bidders increases between rounds.

Figure 13: Dynamics of prices, payouts and bidder numbers by past derivative performance

(a) Derivative prices

(b) Number of bidders

Samples are restricted to derivatives issued at a positive price since 2007. Quartile groupings are determined by the quartile ranking of issued contracts with a common time horizon, for the per unit of derivative profits in the previous vintage, as defined in the paper body. “N/A” denotes a derivative with a contract issued, but no contracts were issued for that POI/POW location pair in the previous vintage. Prices and payouts are scaled by the length of the contract. The number of bidders sample is restricted to the derivatives that were decoded by the algorithm discussed in Appendix B.2. Hypothesis tests with equality of means under the null are rejected at a 5\% level of significance for all variables and groups, with the exception of lagged quartile 3, number of bidders.

To summarize, I have shown that financial traders are in large part compensated for being the first firm to purchase a contract on a derivative that was not purchased in previous auctions. After a contract has been purchased and revealed to be profitable, it appears that the public learns the given product was underpriced and accurately adjusts their payout expectations in the subsequent period. The market is able to close the profit

\textsuperscript{52}The sample for measuring the number of bidders is restricted to products where the specified locations were decoded from the auction data, outlined in Appendix C.

\textsuperscript{53}The mechanism behind these patterns is not definitive, it may be that when an asset performs poorly it is because of more bidders or higher prices.
margins on products that firms hold, but profit margins exist when a firm is the first to buy a product that was not purchased by a firm in the previous auction.

To identify profitable opportunities, firms may need to possess a forecasting technology for illiquid derivatives that did not have a contract issued in the prior period. Therefore, a regulator’s objective of designing the auction to facilitate price discovery might be working, where markets respond to some form of information revealed by some firms purchasing a contract. However, the compensation traders receive via realized trading profits from buying these less liquid products is essentially a wealth transfer from ratepayers.

6.3 How are trading firms earning systematic profits?

I have shown that traders do not persistently profit on the same derivative products. Following their purchases, market prices update in subsequent rounds to eliminate the opportunity for further profits on that product. To earn systematic profits, traders must consistently identify a new set of mispriced derivative products each auction. Although this paper does not uncover how these mispriced derivatives are identified, this section relates the empirical findings to anecdotes regarding financial trader operations.

Arce (2013) describes the existence of both sunk and ongoing resources being devoted to active trading in TCCs. The mechanism to set electricity prices and TCC auctions are nonlinear, constrained optimization problems. Therefore, a microfounded forecasting strategy requires an understanding of the physics behind electricity networks. Some traders build proprietary electricity network models that can generate prices from different inputs of demand, supply and transmission capacities. The forecast inputs are consistently updated as private information is acquired or public data is released from past electricity markets and TCC markets, along with planned transmission and generator outages. Price forecasts are then used to form a bidding strategy. Arce claims that TCC traders must be competent in each of physics, computing and economics, and also require a high tolerance for tedium. It usually takes between 12 and 24 months of training for an analyst to become competent.

Given the costs involved in developing and maintaining a proprietary black box to trade in TCCs, trading firms must earn some trading profits to continue participating. These costs could be representing a barrier to TCC profits eroding. Furthermore, Creswell and Gebeloff (August 14, 2014) describe an additional difficulty of being able to enter the market, with the most profitable trading firm in New York, DC Energy, requiring non-disclosure and non-compete agreements with their employees. DC Energy has demonstrated their preparedness to enforce these agreements.54

Appendix D3 reports estimates of systematic trading profits at a firm level. Given that the number of issued contracts is more sparse at a firm level, the estimates have low power but 4 major firms are detected as earning systematic trading profits in this market. The

54Refer to Creswell and Gebeloff (August 14, 2014) for a description of a lawsuit filed by DC Energy against an ex-employee that moved to a company that began to trade in TCCs soon after.
firms are financial traders Boston Energy Trading and Marketing, DC Energy New York and DC Energy New England, along with a generator owner, Hydro Quebec. Together, these firms account for 17% of contract expenditures and 50% of contract profits in the whole market. Given 130 firms have ever participated in the market, this concentration of profits suggests these are firms more adept to identifying profitable opportunities. Further investigation into these firms reveals that Hydro Quebec almost exclusively purchased contracts with a point of injection at the import/export node between Quebec and New York, whereas the profitable trading firms buy products across all price nodes in the network, consistent with the predictions and the earlier findings that traders profit from buying the products physical firms do not demand.\textsuperscript{55}

Taking the empirical results and the trader anecdotes together, it appears that profitable financial traders must have some technology to identify profitable trading opportunities among products that were not purchased in previous auctions. Once they act on these opportunities, there are enough participants in the market who update their expectations for the payout of that derivative to erode any further profits that can be made on that product. Therefore, to continue to earn trading profits these firms must update their models of future electricity prices to uncover new opportunities for trading profits without other firms replicating their trading strategy.

7 Policy discussion: Who benefits from transmission congestion contracts?

Three firm groups participate in TCC auctions, with electricity ratepayers the fourth, non-participating stakeholder group. Retailers were shown to have purchased predominantly zonal products in large quantities and due to regulatory incentives might prefer to abstain from taking speculative positions on contracts that are not linked to their procurement strategies. On average, retailers pay fair prices for their derivatives.

Generators were shown to mostly purchase derivatives unrelated to their physical operations. Unlike retailers, generators purchase both zonal and nodal contracts that are offered at auction. On average they earn systematic profits from their trading positions. Therefore, generators may benefit from some of the derivatives that allow them to sell electricity to different locational prices to their own, but they also receive benefits simply

\textsuperscript{55} Hydro Quebec provides an interesting case study as the only firm with systematic profits in the TCC markets that limits their participation to a single local node. In DC Energy, LLC v. HQ Energy Services, DC Energy (DC) took a counterposition to Hydro Quebec (HQ). DC unsuccessfully accused HQ of manipulating prices at the Quebec export node, where the day-ahead electricity price frequently dropped below long term averages to $0/MWh for periods when HQ held TCCs with payouts decreasing in the Quebec price (Cramton, 2007). An observer might speculate that the otherwise information-rich DC Energy and their subsidiaries (accounting for $212m of the $860m TCC profits observed in this dataset) took a position based on a model of TCC payout forecasts, where it might not have taken the position if it had known that HQ, endowed with an operational information advantage, would take the opposite position.
by profiting from their positions.

Financial traders have no physical interests that can be enhanced by holding a TCC. Like generators, traders purchase both zonal and nodal contracts that are offered at auction and do not always purchase large quantities. Traders have no reason to participate in these markets if they are unable to earn trading profits, which I have shown they are able to do systematically. Under the TCC auction mechanism, trader purchases on products with low demand can improve the liquidity of other products in the auction and potentially improve price signals.

While all three firm types appear to benefit from the existence of TCC auctions, transmission ratepayers effectively fund the trading profits earned by generating and trading firms. TCC auctions allocate the merchandising surplus market operators receive from transmission congestion in the spot market to TCC holders, with the auction proceeds used to lower ratepayer bills. Given the magnitude of trading profits earned by generators and traders, the electricity customers that ultimately bear the transfer associated with TCC holder profits would require trader participation in these auctions to facilitate large reductions in procurement costs to benefit from the auction construct.

It is difficult to claim that transmission ratepayers benefit or lose out from trader participation in the TCC auctions without a formal welfare analysis. The results present a case that traders buy many of the products that physical firms do not purchase, and provide price discovery on previously illiquid products. The social value of these services is unclear. Further, there are plausibly other costs or benefits attached to the existence of this market. From a broader welfare perspective, planners might also consider the resources financial traders use when obtaining their forecasts and trading strategies, and the administrative costs of running the auctions.

The magnitude of the regulator’s problem is substantial. TCC profits earned by financial trading firms totaled $600m from 1999-2015 in New York, $420m in California from 2012-2015 and $904m in the PJM market from 2013-2015. This study has shown that in New York, TCC profits are systematic and have not diminished over time. It is unclear that future entry of traders will occur to increase the auction revenues and consequently lower electricity customer bills. To this end, three policy modifications have been proposed or implemented, each of which would likely reduce trading profits but may also restrict the benefits physical firms derive from TCC markets.

First, CAISO Department of Market Monitoring (2016) calls for the auctions to be disbanded. Eliminating the auctions would of course eliminate derivative trading profits, the consequent transfers of wealth and any costly investment in information traders incur via their participation. However, as shown by the participation of retailers in New York’s TCC market, the benefits to physical firms from having products available to source or sell electricity to different locations would be lost by disbanding the auctions, along with any

\[56\] New York, author calculation, California, see CAISO Department of Market Monitoring (2016) and PJM see PJM (2015) and various issues.
benefits tied to the price guidance provided by the auctions.

Second, this proposal is extended by Bushnell and Wolak (2005) who propose directly allocating the merchandising surplus to retailers as a collection of derivatives. If retailers hold a collection of TCCs, it may facilitate greater competition among suppliers – retailers that hold a TCC between their location and that of the supplier and enter a forward contract with a supplier have certainty regarding their procurement costs and pick from the cheapest option. The revenues they collect from their remaining TCC holdings could be used to lower the cost base they can recover from their retail customers.

A third policy modification has been implemented in New Zealand. There, following a stakeholder process, a single TCC between 2 locations was made available, with the remaining merchandising surplus distributed via direct allocation. Although this necessarily reduces the ability for firms to source or sell their electricity to different locations via these particular auctions, it could increase liquidity at these locations and remove the complexity of the auction. In New York, the set of 11 zone prices (55 TCC combinations) received greater expenditure on TCCs than the 100,000 TCC combinations available between price nodes, with retailers restricting their participation to zonal products. Further, zonal products were consistently purchased, priced fairly and were not subject to large TCC holder profits. It is left for further work to evaluate a proposal that restricts the set of products offered in New York to zonal products. Considerations include the lower participation costs from a simpler auction, the loss of product choice for firms to manage locational price differentials and the impact of removing profitable opportunities for financial traders will have on their participation, market liquidity and price signals. In the New York setting, all zonal and nodal contracts collect bids and are issued simultaneously. Therefore, trader participation on zonal products may be a spillover from their interest in finding profitable trading strategies on nodal products.

8 Conclusion

To justify their participation in derivative markets, financial traders must earn trading profits. In markets for transmission congestion contracts, trader profits have attracted regulatory attention because TCCs are auctioned and TCC holder profits are effectively funded by transmission ratepayers. In this paper I have described, using simple models of TCC auctions, the potential for financial traders to improve auction outcomes by purchasing the derivative products retailers and generators do not want to purchase. I showed empirically that financial traders purchase many of the products that physical firms do not purchase, and earn trading profits from these actions. The majority of trader profits are earned by firms that are the first to purchase a previously illiquid product, but that

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58 The potential benefits of reducing choice sets in a variety of settings are explored in Levin and Milgrom (2010).

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profitable opportunity is quickly competed away in subsequent auctions. This pattern has persisted for 16 years in the New York market, suggesting that there is a barrier to more trading firms being able to spot the initial profitable opportunity and in turn erode the trading profits earned in this market.

Regulators need to decide how to distribute the merchandising surplus collected by operators of formal wholesale electricity markets. These revenues accrue when transmission lines get congested, where consumers of electricity in importing regions pay more than the payments suppliers of electricity in exporting regions receive. Every formal electricity market in the United States distributes these revenues as transmission congestion contracts that are sold at auction. These contracts pay the holder future locational price differences in electricity prices and the auction revenues are used to lower transmission ratepayer bills. The merchandising surplus could be used for other purposes than to fund TCC holder payouts. The results of this paper highlight the trade offs that regulators need to weigh up when considering the modifications to the distribution rule. The current auction paradigm results in financial traders earning large trading profits form the auctions and were shown to effectively be compensated for providing liquidity and price convergence on products that were illiquid in previous auctions. Understanding the social value of this service will help identify whether the current policy is socially beneficial.

If regulators wish to revise their policy to reduce large wealth transfers from electricity ratepayers to derivative holders, they could consider a direct allocation policy for the merchandising surplus from transmission congestion, or a restriction on the products offered at auction. Some costs to modifying the existing policy include the loss of flexibility physical firms have in choosing the prices at which they procure or sell their electricity. Some benefits could be the reduction of transfers of wealth and costs in information acquisition. It is left as further work to investigate whether modifications to the derivative product set offered at auction will improve economic outcomes. To this end, there are opportunities to study two recent policy changes. In 2013, New Zealand introduced auctions for TCC derivatives between two nodes in their electric network. In 2014, the Southwest Power Pool introduced auctions for TCC derivatives in a manner more similar to New York, with many products available. Pre-post studies that can measure the realized physical costs from electricity generation in these markets may build upon the description of profit sources in this paper to provide further insight into the physical efficiency impacts from these policies.
References


Table A1: Sizes of TCC contract positions purchased

<table>
<thead>
<tr>
<th></th>
<th>Retailers</th>
<th></th>
<th>Generators</th>
<th></th>
<th>Traders</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Zonal</td>
<td>Nodal</td>
<td>1- month</td>
<td>&gt; 1- month</td>
<td>Zonal</td>
<td>Nodal</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>Round 1</td>
<td>Round &gt; 1</td>
<td>Round 1</td>
<td>All</td>
<td>Round 1</td>
</tr>
<tr>
<td>Mean $q_{i,j,t,f}$</td>
<td>33</td>
<td>12</td>
<td>13</td>
<td>27</td>
<td>9</td>
<td>11</td>
</tr>
<tr>
<td>Median $q_{i,j,t,f}$</td>
<td>17</td>
<td>2</td>
<td>2</td>
<td>11</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>$\sum q_{i,j,t,f}$</td>
<td>37,913</td>
<td>25,309</td>
<td>22,993</td>
<td>40,229</td>
<td>133,206</td>
<td>390,980</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>Round 1</td>
<td>Round &gt; 1</td>
<td></td>
<td>All</td>
<td>Round 1</td>
</tr>
<tr>
<td></td>
<td>Zonal</td>
<td>Nodal</td>
<td>All</td>
<td>Round 1</td>
<td>Traders</td>
<td></td>
</tr>
<tr>
<td>Mean $q_{i,j,t,f}$</td>
<td>24</td>
<td>7</td>
<td>13</td>
<td>9</td>
<td>24</td>
<td>9</td>
</tr>
<tr>
<td>Median $q_{i,j,t,f}$</td>
<td>8</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>$\sum q_{i,j,t,f}$</td>
<td>184,133</td>
<td>490,773</td>
<td>378,761</td>
<td>296,145</td>
<td>37,354</td>
<td>258,791</td>
</tr>
</tbody>
</table>

An observation is a contract issued to a firm. Contracts are classified into groups based on the zonal, nodal, 1- month or >1- month characteristics, and whether for the >1- month products they were sold in the first round or a later round. $\sum q_{i,j,t,f}$ is the total of all contracts entered. Sample restricted to the purchases in 2006-2015 where auction round information is available.
Figure A1: Price discovery following purchases or sales, by profitable and unprofitable firms

All series plot equation (12). The purchases chart compares two sets $D$ of derivatives, those that were purchased by any firm at a positive price across, split by firms that earned positive and negative profits over the sample window. The sales chart is analogous to the purchases chart but for negatively priced products. Means and pointwise 95% confidence intervals plotted. Sample sizes: (a) 2,638 and 342. (b) 984 and 85.
Table A2: Summary statistics of the location-pair-auction \((i,j,t)\) derivatives studied

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
<th>Mean</th>
<th>Std. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(p_{i,j,t})</td>
<td>Price and payout of derivative</td>
<td>1686</td>
<td>3215</td>
</tr>
<tr>
<td>(r_{i,j,t})</td>
<td></td>
<td>1842</td>
<td>4004</td>
</tr>
<tr>
<td>(q_{i,j,t,RET})</td>
<td>Number of derivative units allocated at auction</td>
<td>0.03</td>
<td>1.31</td>
</tr>
<tr>
<td>(q_{i,j,t,GEN})</td>
<td></td>
<td>0.18</td>
<td>3.16</td>
</tr>
<tr>
<td>(q_{i,j,t,TRA})</td>
<td></td>
<td>0.22</td>
<td>3.61</td>
</tr>
<tr>
<td>(Q_{i,j,t,RET}^{POST})</td>
<td>Number of derivative units in open position after auction</td>
<td>0.85</td>
<td>20.46</td>
</tr>
<tr>
<td>(Q_{i,j,t,GEN}^{POST})</td>
<td></td>
<td>2.06</td>
<td>24.74</td>
</tr>
<tr>
<td>(Q_{i,j,t,TRA}^{POST})</td>
<td></td>
<td>2.03</td>
<td>18.61</td>
</tr>
<tr>
<td>(I_{i,j,t,RET}^q)</td>
<td>Indicator = 1 if allocated contract at auction</td>
<td>0.002</td>
<td>0.047</td>
</tr>
<tr>
<td>(I_{i,j,t,GEN}^q)</td>
<td></td>
<td>0.031</td>
<td>0.174</td>
</tr>
<tr>
<td>(I_{i,j,t,TRA}^q)</td>
<td></td>
<td>0.033</td>
<td>0.18</td>
</tr>
</tbody>
</table>

1,151,374 \(i,j,t\) observations in each cell. The absolute value of each variable is reported because the location direction a derivative enters the model is arbitrary. \(p\) and \(r\), the derivative price and payout, are divided by the length of the contract. \(RET, GEN\) and \(TRA\) aggregate all allocations to retailing, generating and trading firms into a single firm grouping. Open position refers to derivatives held on an \(i,j\) derivative that has a payout window that covers \(T_1\).

Appendix B: The NYISO transmission congestion contract auction

NYISO administers transactions in the New York wholesale electricity market. This appendix describes how payments work in electricity markets, and how auctions for transmission congestion contracts operate. Information on the operation of the New York wholesale electricity market and transmission congestion contract market is available in the market rules (NYISO, 2015). A less technical, yet succinct overview can also be found in Toole (2014). For general explanations not specific to NYISO, Alsac, Bright, Brignone, Prais, Silva, Stott, and Vempati (2004) contains a terrific high level summary and Hogan (1992) a more detailed explanation. For the specific New York auction, refer to NYISO (2010).

The day ahead electricity market sets prices at each location node in the New York electric grid. Loads that purchase electricity submit the quantities they wish to withdraw at each node, and generators submit their willingness to supply which is tied to their location node. The market operator solves an optimization problem which sets prices at every node such that the total quantity injected into the grid equals that which is withdrawn at the lowest as bid system cost. This problem has a feasibility constraint, where the capacity of the transmission can not be exceeded. Kirchhoff circuit laws describe how flow...
capacities across transmission lines is a simultaneous problem, where the maximum flow on a particular line will depend on the flows on other lines in the network. Therefore, nodes may have different prices where more expensive generators might run instead of cheaper generators because of the transmission feasibility constraints.

After setting the nodal prices in the wholesale market, NYISO pays the generators their nodal price for what they inject and receive from loads the nodal price where they withdraw. This is the source of NYISO’s merchandising surplus. Hogan (1992) shows that a set of financial transmission rights (FTRs) that is simultaneously feasible in the electric grid satisfies revenue adequacy. This means, that if the set of injections and withdrawals implied by a set of FTRs could feasibly occur given the transmission constraints of the electric grid, the merchandising surplus the market operator collects will be greater than or equal to the payouts the holders of the FTRs will collectively receive.

Each market has idiosyncratic auction rules for FTRs, with NYISO choosing to perform a simultaneous auction for every combination of price swaps in the network. NYISO collects price and quantity bids for locational price difference derivatives from auction participants. Then, it solves a non-linear optimization problem that:

- Sets auction shadow prices at each node to maximize the as-bid value of allocated TCCs.
  - Denote node shadow prices as $P_{Auction,i}$ for node $i$. Therefore, the equilibrium price of the $i,j$ derivative in the notation of the paper is $p_{i,j} = P_{Auction,j} - P_{Auction,i}$. This is the practical mechanism that enforces the transitivity of derivative prices.
  - Firms bid on a POI/POW pair. Bids to buy clear if it is greater than the difference in the node shadow prices.

- Constraint is that all implied injections and withdrawals from the derivatives are feasible in the physical transmission grid, with assumed transmission capacities for the problem released to participants prior to the auction. Further, for zonal bids, fixed injections and withdrawals at specific nodes are assumed, as described in section 19.9.7 of NYISO (2010).
  - A bid for a derivative that pays $20 \times (LMP_j - LMP_i)$ implies that 20 MW is injected at A and is withdrawn at B.
  - If all injections and withdrawals from a set of contracts that would be issued at a given set of auction shadow prices are not feasible given the assumed transmission capacities throughout the electric grid (derived from Kirchhoff’s Law) then the prices and allocation are not a solution to the auctioneer’s problem.

- All bids that are above the auction shadow prices are allocated the contract. So a bid for a derivative that pays $20 \times (LMP_j - LMP_i)$ will be awarded a contract if the bid price is greater than $p_{i,j} = P_{Auction,j} - P_{Auction,i}$. 

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Figure B1: A three node network

- Supplying this contract is the equivalent of bidding on the contract that has the opposite payment, $$(LMP_i - LMP_j)$$. Therefore, this auction is not simply a sale of goods, it can indirectly match other buyers and sellers.

For an example of the constraints on the set of TCCs that can be issued by the market operator, consider the example in Toole (2014) and Oren (2013) in figure B1 where the resistance of each line is equal, but the thermal capacities mean that each has a maximum MW flow that can constrain feasible generation quantities among the nodes.

From node $$i$$, the resistance for electricity to be transported to $$k$$ is twice as large via $$i$$ than direct to $$k$$. Therefore, from Kirchhoff’s laws, twice as much flow from $$j$$ to $$k$$ will occur relative to $$j$$ to $$i$$ to $$k$$. Therefore, how much electricity will flow across each line, which line will be binding, and therefore how many TCCs can be issued with the system operator being able to fund payouts from the merchandising surplus. Hogan (1992) shows that the inequalities that must be satisfied for a TCC configuration to be able to be funded from the merchandising surplus from some configuration of generation and load (consumption) match Kirchhoff’s laws. In the three node example of figure B1 case, assuming no $$i, j$$ products are available, the TCC quantities $$q$$ between each node must satisfy:

\[
\begin{align*}
\frac{2}{3}q_{i,k} + \frac{1}{3}q_{j,k} & \leq 300 \\
\frac{1}{3}q_{i,k} + \frac{2}{3}q_{j,k} & \leq 220 \\
-100 & \leq \frac{1}{3}(q_{i,k} - q_{j,k}) \leq 100
\end{align*}
\]

The feasibility constraint of the TCC auction is modified to allow for contract periods to overlap. Before each auction which may cover 1, 6 or 12 months of derivative payments, the existing contracts and the proportion of the NYISO grid to be auctioned are known. Therefore, existing contracts are factored in to the implied injections and withdrawals from the contracts and the available transmission capacity is scaled to reflect the amount of transmission capacity being released. If 12 month contracts are auctioned off in 4
tranches, these scale factors will be 25%, 50%, 75% and then 100%.

Other practical matters include that transmission capacities are stochastic, they can vary with weather and can have unexpected outages. Therefore, when allocating FTRs, market operators must decide how much capacity to release - release too much and they might have a revenue shortfall, too little and they will maintain a surplus. Over a period of time, NYISO on average is revenue adequate (see Patton, LeeVanSchaick, and Chen, 2016, for a recent annual report covering the wholesale and TCC markets, demonstrating the revenue adequacy of the TCC contract positions for the NYISO), with rules that transmission owners make up or receive any differences from merchandising surplus and FTR/TCC payouts.

The revenues from the TCC auctions are split amongst transmission owners. Transmission owners are regulated to earn a fixed rate of return, given that they form natural monopolies and it is inefficient to have them participate in markets as strategic players. The total revenues they are entitled to receive under the regulated return is calculated, then the TCC auction payments are taken away from that figure, with the remainder paid by transmission ratepayers via a cost-sharing formula outlined in NYISO (2005) and NYISO (2010). Therefore, in effect, the higher the TCC auction payments, the less ratepayers ultimately have to pay transmission owners.

Appendix C: Data construction

All data are available to the public at the NYISO TCC website, http://www.nyiso.com/public/markets_operations/market_data/tcc/index.jsp. However, the assembly task is not straightforward and some classification decisions were at the author’s discretion. This data appendix explains the assembly and the discretionary decisions. Data descriptions and observation counts are in the body of the paper. This section contains the construction of the derivative and contract datasets, which are closely related and have common information merged on to each other. The most complicated data construction used in the analysis is the anonymized auction data, described next, in Appendix C1.

The main data used in this analysis is at a derivative level. The auction prices for these derivatives were collected from the “View nodal prices” link on the NYISO webpage, that lists the shadow prices generated from every auction. These files are appended, with a unit of observation constructed as being a derivative start date \((T_1)\), end date \((T_2)\), auction round \((ar)\), POI \((i)\), POW \((j)\).

The derivative payouts are sourced from the “DAM marginal losses and congestion” link. The unit of observation is constructed as being month-of-sample, POI, POW and the relevant variable is the payout to an \(i,j\) derivative for the sample month. For each observation in the auction prices data, the payouts for the \(T_1,T_2\) window are calculated and merged onto the dataset. Although data for derivative payouts is available since the introduction of the auctions in 1999, the auction prices are only available from late 2006,
therefore the derivative dataset is restricted to derivatives issued at auction between 2006-2015.

A separate but related dataset, containing all contracts issued from 1999 is found at the “Summary Of Transmission Contracts” tab. Each observation contains start date \((T_1)\), end date \((T_2)\), POI \((i)\), POW \((j)\), firm \((f)\), purchase price per MW \((p)\) and quantity in MW \((q)\). Again, payouts are merged on to each observation to give \(r\).

The contract dataset is expanded to form quantity variables that are merged onto the derivative dataset. These variables are derived from the derivative holdings of each firm in the data entering and following each auction. To generate the \(q_{i,j,t,f}, Q_{i,j,t,f}^{PRE}, Q_{i,j,t,f}^{POST}, I_{i,j,t,f}^{PRE}\) and \(I_{i,j,t,f}^{PRE}\) variables in the derivative dataset, each variable is created for each firm, giving each derivative 5*130 extra variables. The values for these variables are described in the body of the text. Of note is that for multi-round auctions, the value entering an auction includes holdings from earlier rounds, but the holdings exiting the auction are common for all observations. This is because when testing for moral hazard, it is total holdings that matter for the incentive to deviate one’s actions, whereas entering an auction, later round outcomes are not in the public information set.

For both the contract and derivative datasets, the type of node is added. That is, from NYISO (2016) and various issues, a node is marked as a generating node if a power plant is located at that node. Further, for the contract dataset, it is marked if the contract holder holds a power plant at a node specified in the contract or in the same zone as a node in the contract.

To summarize, the derivative dataset contains prices and payouts for every derivative available at auction with a unit of observation being derivative start date \((T_1)\), end date \((T_2)\), auction round \((ar)\), POI \((i)\), POW \((j)\). Information attached to each observation includes the price and payout of each derivative (scaled by the length of time the derivative payout covers), the 5*130 variables relating to the holdings entering and leaving each auction for each firm, and indicator variables that list the type of nodes the contract contains (generating/non-generating). The contract dataset only contains issued contracts, with a unit of observation defined as the start date \((T_1)\), end date \((T_2)\), POI \((i)\), POW \((j)\) and firm \(f\). The information contained in the contract dataset include the prices, payouts and quantities of derivatives issued, along with the type of nodes in the contract.

Other information attached to each observation in the contract set, and used to construct aggregated quantity variables in the derivative dataset is the firm-type classification of each firm, described in Appendix C2.

Appendix C1: Decoding the anonymized identities of locations and firms in NYISO’s Transmission Congestion Contract auction data

NYISO publicly releases all bids and offers entered into TCC auctions at http://mis.nyiso.com/public/P-27list.htm. Each auction is for a given start date and end date, with each bid a price/quantity pair. Unlike the contract dataset, each bid/offer has an
anonymized identifier in place of the firm that places the bid/offer and anonymized identifiers in place of the POI and POW. These anonymized identifiers are stable across auctions.

To analyze auction behavior, a large set of the anonymized identifiers have been decoded by combining the information across the publicly available auction and contract datasets. The underlying principle behind the algorithm is to utilize the equilibrium contracts data that contains a market clearing price and quantities sold to each firm for a given location-pair to find bids and offers in the auction data that could generate the same quantity allocations for the given market clearing price.

1. For a given start date, end date and location-pair that has a non-zero equilibrium contract quantity, calculate the number of firms that bought this contract, sold this contract and store the sizes of these contracts and the clearing price $p$

2. In the auction data for that given start date and end date, take a given location-pair (these are anonymized identifiers)
   (a) Calculate the clearing parcels and quantities that are implied by a clearing price of $p$
   (b) Mark the pair as a potential match if the clearing parcels and quantities implied by this price match the equilibrium data
   (c) If one of the bids/offers is equal to the market clearing price, it is a potential marginal bid. Allow the parcel quantity for that bid/offer to be less than the size of the bid/offer when determining if the location-pair is a potential match.
   (d) Iterate to the next location pair in the auction data and continue until all location pairs have been marked as a potential match or otherwise.
   (e) If there is only one potential match, assign the POI and POW listed in the equilibrium contract data to the anonymized identifiers.

3. Iterate to the next location pair in the equilibrium contract data and stop after all observed contract location pairs have had this procedure performed.

For the current draft of this paper, the algorithm is restricted to marginal bids. The algorithm matches 94 of the anonymized location identifiers to actual locations. Although less than half of the locations are decoded, they represent the majority of contracts issued.

The next step of the algorithm recovers firm identities in the auction data.

1. For a given start date, end date and location-pair that both have matches to the anonymized location identifiers, calculate the number of firms that bought this contract, sold this contract and store the sizes of these contracts and the clearing price $p$

2. In the auction data, match the parcel sizes bid/offered that clear at $p$ to clearing quantities observed.
3. If there the parcels are uniquely matched, assign the firm name to the anonymized firm identifier.

For the current draft of this paper, the algorithm matches 49 of the anonymized firm identifiers to the 130 firms that ever won a contract. Although less than half of the firms are decoded, they represent the majority of contracts issued and profits made.

In principle, the algorithm could iterate again at this point to recover more locations and firms given the partial identification recovered at this point.

Table C1 compares the auction data to the awards data to examine the selection of the auction data. When defining a bid as a step function between a unique pair of locations (with a positive price a bid to buy between a POW and POI, a negative price an offer to sell between that POW and POI), the top panel of table C1 shows there are 489,409 bids in the data, 136,798 of which both the POW and POI location identifiers are decoded. Only on the decoded locations can the auction clearing prices and realized revenue information be mapped to each bid. Using this information, the value of the contracts generated between the decoded locations is $2.7 billion, just less than the $3.1 billion total observed in the awarded contract data covering the same period in the second panel of table C1. Comparing the top to the bottom panel gives insight into the selection of the auction data. The auction data only covers 43% (38,370/89,124) of the awarded contracts, but 90% of the expenditure and profit values.

The top panel of table C1 shows that the proportion of bids and offers on locations that were decoded that were successful in winning a contract was 28% (38,370/136,798). Given there were 489,409 bids in total and 89,124 contracts generated, this means that the remaining locations had a 14% (89,124-38,370)/(489,409-136,798)*100 of bids and offers that won a contract. Overall, the data selection for the auction data appears to cover higher value contracts with higher clearing rates. Given the algorithm to decode the auction data relies on matching award data to the auction data, it is vacuously true that locations that do not have awarded contracts can not be decoded and will result in the auction data covering the more liquid locations.

Coverage of the zone-indexed contracts is better than the nodal contracts, with a greater proportion of the retailer awards also seen in the auction data than the generators and retailers. Overall, the returns by contract class are similar in both datasets, but the returns by firm type differ in that retailer returns are higher using the auction data and generator returns are lower. The unknown firm types in the auction data are firms who’s identities were not decoded. To reconcile the retailer and generator return differences, the collective return for the unknown firms of 2% could be explained by having the unknown category contain some of the losing retailers and winning generators.

The patterns in the awards data are broadly seen in the shorter sample of restricted locations observed in the auction data, summarized in table C1. The value of zone-indexed and nodal contracts are roughly equal, but the quantity of nodal contracts are much greater. Shorter duration contracts are more profitable, with traders realizing the greatest profits,
followed by generators and then retailers. Retailers have far fewer bids (defined as a step function on a node pair) at 1,699, than the 115,139 of the generators and traders, but have a higher conversion rate of bids to contracts of 56% compared with 27%. For the purposes of the analysis in section 6.1 and the change in the number of bidders in section 6 across auctions, the derivatives included are less likely to contain illiquid, low price products.

Table C1: Comparing implied awards from auction data with the award data: Costs and returns by contract class, 2006-2015

<table>
<thead>
<tr>
<th>Sample</th>
<th>( N ) bids</th>
<th>( N ) decoded</th>
<th>( N ) contracts</th>
<th>Expenditures</th>
<th>Profits</th>
<th>ROI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Auction Data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All contracts</td>
<td>489409</td>
<td>136798</td>
<td>38370</td>
<td>$2,692.2 m</td>
<td>$454.7 m</td>
<td>16.9%</td>
</tr>
<tr>
<td>Zone-indexed contracts</td>
<td>202957</td>
<td>21825</td>
<td>5955</td>
<td>$1,291.8 m</td>
<td>$139.5 m</td>
<td>10.8%</td>
</tr>
<tr>
<td>Nodal contracts</td>
<td>286452</td>
<td>114973</td>
<td>32415</td>
<td>$1,400.4 m</td>
<td>$315.1 m</td>
<td>22.5%</td>
</tr>
<tr>
<td>1 month contracts</td>
<td>269531</td>
<td>71441</td>
<td>21428</td>
<td>$346.3 m</td>
<td>$75.3 m</td>
<td>21.7%</td>
</tr>
<tr>
<td>6 month contracts</td>
<td>117091</td>
<td>35896</td>
<td>9939</td>
<td>$1,113.1 m</td>
<td>$241.9 m</td>
<td>21.7%</td>
</tr>
<tr>
<td>12 month contracts</td>
<td>102786</td>
<td>29461</td>
<td>7003</td>
<td>$1,232.9 m</td>
<td>$137.4 m</td>
<td>11.1%</td>
</tr>
<tr>
<td>Retailers</td>
<td>3093</td>
<td>1699</td>
<td>958</td>
<td>$326.5 m</td>
<td>$16.1 m</td>
<td>4.9%</td>
</tr>
<tr>
<td>Generators</td>
<td>193879</td>
<td>56491</td>
<td>16309</td>
<td>$859.9 m</td>
<td>$162.9 m</td>
<td>18.9%</td>
</tr>
<tr>
<td>Traders</td>
<td>216301</td>
<td>59197</td>
<td>15082</td>
<td>$1,029.1 m</td>
<td>$265.9 m</td>
<td>25.8%</td>
</tr>
<tr>
<td>Unknown</td>
<td>76136</td>
<td>19411</td>
<td>6021</td>
<td>$476.7 m</td>
<td>$9.8 m</td>
<td>2%</td>
</tr>
<tr>
<td><strong>Awarded contracts data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All contracts</td>
<td></td>
<td></td>
<td>89124</td>
<td>$3,056.8 m</td>
<td>$502.5 m</td>
<td>16.4%</td>
</tr>
<tr>
<td>Zone-indexed contracts</td>
<td></td>
<td></td>
<td>8959</td>
<td>$1,712.5 m</td>
<td>$142.5 m</td>
<td>8.3%</td>
</tr>
<tr>
<td>Nodal contracts</td>
<td></td>
<td></td>
<td>80165</td>
<td>$1,344.3 m</td>
<td>$360 m</td>
<td>26.8%</td>
</tr>
<tr>
<td>1 month contracts</td>
<td></td>
<td></td>
<td>51781</td>
<td>$380.1 m</td>
<td>$102 m</td>
<td>26.8%</td>
</tr>
<tr>
<td>6 month contracts</td>
<td></td>
<td></td>
<td>21775</td>
<td>$1,277.2 m</td>
<td>$245.4 m</td>
<td>19.2%</td>
</tr>
<tr>
<td>12 month contracts</td>
<td></td>
<td></td>
<td>15568</td>
<td>$1,399.5 m</td>
<td>$155.1 m</td>
<td>11.1%</td>
</tr>
<tr>
<td>Retailers</td>
<td></td>
<td></td>
<td>2275</td>
<td>$471.8 m</td>
<td>-32.8 m</td>
<td>-7%</td>
</tr>
<tr>
<td>Generators</td>
<td></td>
<td></td>
<td>39267</td>
<td>$1,077.7 m</td>
<td>$207.9 m</td>
<td>19.3%</td>
</tr>
<tr>
<td>Traders</td>
<td></td>
<td></td>
<td>47582</td>
<td>$1,507.3 m</td>
<td>$327.4 m</td>
<td>21.7%</td>
</tr>
</tbody>
</table>

A bid is a step function between a unique point of injection (POI), point of withdrawal (POW), start date, end date and firm (with a positive price a bid to buy between a POW and POI, a negative price an offer to sell between that POW and POI). All contract data from the auction dataset (the top panel) is for the location identifiers that were decoded and assume that bids less than or equal to the market clearing price are fully cleared. The bottom panel contains the full set of awarded contracts over the period. Contract expenditures sum the absolute value from the initial contract price across the class of contract defined by the row - buying and selling a $1m contract are both listed as a $1m contract. Profits are the sum of the profits for all contract positions. ROI is a modified return on investment for the asset class, equal to the total profits divided by the absolute value of contract expenditures, listed in the preceding two columns.
Appendix C2: Classification of participating firms into firm types

Each firm that participates in these auctions has been classified into three distinct categories based on their core business. First, any firm that purchases wholesale electricity in New York is classified as a retailer. Second, any firm that operates an electric generating facility that is not a retailer is classified as a generator. These two firm types are physical players in the electricity market and may have a hedging motive to participate in auctions for transmission congestion contracts. Third, all remaining firms that have no physical interests in the electricity market are classified as traders, who are assumed to speculate with the motive to make profits from trading. However, the motives of the participants are not definitive, physical players can speculate, and non-physical players may have positions to hedge.

All classifications were decided by the author, based on web searches of the firm, FERC listings of retailers and NYISO lists of generating plants and their ownership. In many cases, the listed owner of the generator is a subsidiary or parent of a firm listed as the trading entity in the TCC data. In such cases, the classification rule applies to any and all businesses in the conglomerate, so a conglomerate will not have some subsidiaries listed across the different classifications of firms, they will all be contained in one classification.


**Generators:** AES Creative Resources, L.P.; American Electric Power Service Corp.; Bayonne Energy Center, LLC; Brookfield Energy Marketing LP; Bruce Power Inc.; Castleton Commodities Merchant Trading L.P.; Dynegy Marketing and Trade, LLC (DMT); Dynegy Power Marketing, LLC; EDF Trading North America, LLC; EDP Renewables North America LLC; Exelon Generation Company LLC; GDF Suez Energy Resources NA, Inc; GenOn Energy Management, LLC; Hess Corporation; HQ Energy Services (US); Inte-

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59 Hydro Quebec is a peculiar case that has been classified as a generator for two reasons. First, it can purchase electricity for consumption, with the retail operation outside the NYISO. Second, it is a major net exporter to the NYISO.

60 Toole (2014) classifies firms into “speculator”, “hedger” and “unknown” categories, analyzing the types of derivatives these groups are more likely to purchase. The groupings are not highly correlated between my list and that of Toole - generating firms tend to fall into the hedging category in Toole’s analysis.
Appendix D: Additional efficient market hypothesis tests

Appendix D1: Tests using contract data

Previous studies of TCC auctions have tested for the efficiency of prices by testing whether expected payouts were equal to the prices paid for issued TCCs (Bartholomew, Siddiqui, Marnay, and Oren, 2003; Hadseell and Shawky, 2009; Adamson, Noe, and Parker, 2010). The studies use a variety of shorter sample windows than that of this paper. Each paper finds prices are not efficient across all products. This section uses the set of issued contracts and the total contract payouts and prices to perform tests of the efficient market hypothesis,
in line with earlier works. Tests are performed on the full sample and partitions the contracts by characteristic groups. In figure 5 we saw that generating and trading firms earn trading profits in this market. Further, in figure 3 we saw that there were different expenditure and payout ratios across zonal and nodal contracts and different contract lengths.

Table D1 reports estimates of the average realized profit across a variety of contract specifications. The estimating equation is:

$$q_{i,j,t} \cdot (T_2 - T_1) \cdot (r_{i,j,t} - p_{i,j,t}) = \alpha + \epsilon_{i,j,t}$$  \hspace{1cm} (D1)

Testing $\alpha = 0$ is equivalent to testing $p_{i,j,t} = E(r_{i,j,t})$, and is a test of the efficient market hypothesis. Rejection of the null is consistent with the existence of asymmetric information or a rejection of any other maintained assumption for prices to equal expected payouts, including free entry of risk neutral firms and the absence of transaction costs. The estimation approach follows that of previous tests of the efficient market hypothesis in this market (Bartholomew, Siddiqui, Marnay, and Oren, 2003; Hadsell and Shawky, 2009; Adamson, Noe, and Parker, 2010), where a unit of observation is a contract purchased by firm $f$ on an $i,j,t$ derivative, and the sample is restricted to those purchased at a positive price.$^{61}$ Table D1 shows that like the previous literature, the efficient market hypothesis is rejected for all contracts, with an average contract profit of $9,369 on a $77,952 expenditure base, significantly different from zero for a test with a 5% level of significance. However, the efficient market hypothesis can not be rejected for zone-indexed contracts, with the average realized profit of $36,471 per contract (over an average purchase price of $279,244), not significantly different from zero for a test with a 5% level of significance. The hypothesis is rejected for nodal contracts. Comparing the tests by contract duration rejects the null hypothesis for 1 month duration contracts, but fails to reject the null for 6 and 12 month duration contracts.$^{62}$ Separating these products into those sold in the first or a later auction round, we do not reject the efficient market hypothesis, although average trading profits are almost twice as large in round 1.

These disaggregated findings may rationalize why Mount and Ju (2014) are the only study that does not reject the efficient market hypothesis for NYISO’s TCC market. They forecast zonal prices using a VAR model, showing that derivative prices reflect these expected values. The difference is likely due to sample selection, not methodological, because either methodology is valid. If $r$ is the payout realization where $r = E(r) + \epsilon$, tests of the form $r = \alpha + \beta p + \epsilon$ or $r - p = \alpha + \epsilon$ are valid tests of the efficient market hypothesis given that $\epsilon$ is an expectational error.

Table D2 further extend the tests of the efficient market hypothesis for partitions of

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$^{61}$ This test can not be applied to the derivatives dataset defined by $i,j,t$ observations, because a stand must be made on which derivatives are included. Payouts of the $i,j$ derivative are equal in magnitude and opposite in sign negative to the $j,i$ derivative, so including both (or randomly picking the direction) will vacuously fail to reject the null even in the presence of asymmetric information. That is why the sample is
Table D1: Coefficients for efficient market tests, by contract specifications

<table>
<thead>
<tr>
<th>Sample</th>
<th>All</th>
<th>Zonal</th>
<th>Nodal</th>
<th>1 month</th>
<th>&gt;1 month</th>
<th>Round 1</th>
<th>Round &gt; 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>9.369</td>
<td>36.471</td>
<td>5.636</td>
<td>3.300</td>
<td>15.436</td>
<td>24.399</td>
<td>13.675</td>
</tr>
<tr>
<td></td>
<td>(4.142)</td>
<td>(25.594)</td>
<td>(1.462)</td>
<td>(981)</td>
<td>(8.358)</td>
<td>(13.946)</td>
<td>(7.935)</td>
</tr>
<tr>
<td>Mean expenditure ($)</td>
<td>53,978</td>
<td>279,244</td>
<td>22,695</td>
<td>9,325</td>
<td>93,956</td>
<td>91,599</td>
<td>94,419</td>
</tr>
<tr>
<td>N</td>
<td>77,952</td>
<td>9,438</td>
<td>68,514</td>
<td>38,822</td>
<td>38,650</td>
<td>6,347</td>
<td>32,303</td>
</tr>
</tbody>
</table>

Standard errors are clustered at a vintage level (all contracts with the same $T_1$ and $T_2$) in parentheses. The null hypothesis for efficient markets is equivalent to $\alpha = 0$. The unit of observation is a unique contract, defined by location pair $i,j$, auction it was purchased in $t$ ($t$ defines the payout window $T_1$ and $T_2$), and the firm holder $f$. The sample contains all 1, 6 and 12 month contracts issued from 1999 to 2015.

contracts by the performance of that derivative in the previous auction. Outlined in section 6.2, contracts are grouped into the following categories:

- 1-4: Quartiles 1-4 in derivative profit in previous auction of the $(i,j)$ derivatives that were purchased
- N/A: Zero quantity of the $(i,j)$ location-pair derivative was purchased by any firm in the previous auction

The results suggest that systematic profits are only earned on previously poor performing contracts, and those that were not purchased in the previous vintage.

Table D2: Coefficients for efficient market tests, by previous auction performance

<table>
<thead>
<tr>
<th>Prev. auction performance</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>N/A</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha [q_{i,j,t,f}(T_2 - T_1);(r_{i,j,t} - p_{i,j,t})]$</td>
<td>15,263</td>
<td>3,386</td>
<td>-859</td>
<td>5,008</td>
<td>9,023</td>
</tr>
<tr>
<td></td>
<td>(6,807)</td>
<td>(2,614)</td>
<td>(3,612)</td>
<td>(16,035)</td>
<td>(4,656)</td>
</tr>
<tr>
<td>$q_{i,j,t,f}p_{i,j,t}$</td>
<td>70,343</td>
<td>16,071</td>
<td>29,586</td>
<td>121,523</td>
<td>23,536</td>
</tr>
<tr>
<td>N</td>
<td>6002</td>
<td>6913</td>
<td>6422</td>
<td>7276</td>
<td>32016</td>
</tr>
</tbody>
</table>

Standard errors are clustered at a vintage level (all contracts with the same $T_1$ and $T_2$) in parentheses. The null hypothesis for efficient markets is equivalent to $\alpha = 0$. The unit of observation is a unique contract, defined by location pair $i,j$, auction it was purchased in $t$ ($t$ defines the payout window $T_1$ and $T_2$), and the firm holder $f$. The sample contains all 1, 6 and 12 month contracts issued from 1999 to 2015. Q1-Q4 refer to contracts on $i,j$ derivatives that were in the first to fourth quartiles of profits in the previous auction. N/A refers to contracts on $i,j$ derivatives that were not issued in the previous auction.

Appendix D2: Derivative payouts and downstream actions

Table D3 displays estimates of the equation reported in section 5.2.3:

restricted to issued contracts.

62 This result is invariant to aggregating or disaggregating 6- or 12-month products.
\[ r_{i,j,t} = \beta p_{i,j,t} + \sum_{f \in F} \delta_f I_{i,j,t,f} + \sum_{f \in F} \rho_f Q_{e}^{POST} + \epsilon_{i,j,t} \]

Table D3: Estimates of average monthly derivative payouts

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Nodal</th>
<th>Zonal</th>
</tr>
</thead>
<tbody>
<tr>
<td>[</td>
<td>p_{i,j,t}</td>
<td>] = 1686</td>
<td></td>
</tr>
<tr>
<td>[\beta[p_t]]</td>
<td>0.93</td>
<td>0.93</td>
<td>0.94</td>
</tr>
<tr>
<td>[\delta_{RET}[I_{RET,t}]]</td>
<td>-84.41</td>
<td>-62.63</td>
<td>-119.63</td>
</tr>
<tr>
<td>[\delta_{GEN}[I_{GEN,t}]]</td>
<td>113.23</td>
<td>120.93</td>
<td>0.37</td>
</tr>
<tr>
<td>[\rho_{GEN}[Q_{POST}^{GEN,t}]]</td>
<td>0.43</td>
<td>0.17</td>
<td>1.48</td>
</tr>
<tr>
<td>[\rho_{GEN}[Q_{POST}^{TRA,t}]]</td>
<td>0.14</td>
<td>0.08</td>
<td>0.55</td>
</tr>
<tr>
<td>[\rho_{TRA}[Q_{POST}^{TRA,t}]]</td>
<td>(0.08)</td>
<td>(0.09)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>[\delta_{TRA}[I_{TRA,t}]]</td>
<td>(80.20)</td>
<td>(101.98)</td>
<td>(104.67)</td>
</tr>
<tr>
<td>[\delta_{TRA}[I_{TRA,t}]]</td>
<td>(44.24)</td>
<td>(45.83)</td>
<td>(100.51)</td>
</tr>
<tr>
<td>[\delta_{TRA}[I_{TRA,t}]]</td>
<td>(47.15)</td>
<td>(47.33)</td>
<td>(139.58)</td>
</tr>
<tr>
<td>[\rho_{RET}[Q_{POST}^{RET,t}]]</td>
<td>-0.01</td>
<td>0.02</td>
<td>-0.12</td>
</tr>
<tr>
<td>[\rho_{GEN}[Q_{POST}^{GEN,t}]]</td>
<td>(0.24)</td>
<td>(0.23)</td>
<td>(0.28)</td>
</tr>
<tr>
<td>[\rho_{GEN}[Q_{POST}^{TRA,t}]]</td>
<td>(0.23)</td>
<td>(0.17)</td>
<td>(0.53)</td>
</tr>
<tr>
<td>[\rho_{TRA}[Q_{POST}^{TRA,t}]]</td>
<td>(0.31)</td>
<td>(0.37)</td>
<td>(0.54)</td>
</tr>
</tbody>
</table>

Estimates of equation (9), using ordinary least squares. Standard errors clustered at a vintage level \(T_1, T_2\) reported in parentheses. All contract prices and payouts are divided by the number of months a contract covers. Summary statistics for the variables used in estimation are found in table A2. \(i, j\) or \(j, i\) direction is arbitrary: \(p_{i,j} = -p_{j,i}, r_{i,j} = -r_{j,i}\).

Examining the estimates of D3 to table 5, first note that the common \(\delta_f\) coefficients estimated in both specifications are not sensitive to relaxing the restrictions on the \(\rho_f\), size of position parameters. For nodal contracts, a test that \(\rho_f = 0\) for any firm group with a test size of 5% fails to reject that the average marginal effect of increasing a firm’s open position on derivative payouts is zero. I do not claim that these estimates preclude downstream actions to influence derivative payouts, rather I claim that there is no evidence that payouts are increasing in the size of firm open positions. Regardless, the point estimate \(\hat{\rho}_{GEN} = 0.17\) is small, where at average open position holdings for generator won derivatives \((Q_{POST}^{GEN,t} = 24.72)\), the predicted increase in the derivative payouts is estimated to be \(0.17 \times 24.72 \times 100 = 0.5c\) per dollar value of the position. This premium represents a small fraction compared to the 15.5c predicted premium collected on all contracts of any size won by generating firms implied by the \(\delta_{GEN}\) value.
Curiously, for contracts paying at non-generating locations, $\rho_{GEN}$ is detected to be non-zero. Previous sections have shown that zonal contracts appear to be priced fairly and that zonal prices do not update following the revelation of a purchase by a generator or trader, but these coefficients imply that payouts are increasing at the margin for generator open positions, and prices are increasing at the margin with trader open positions. In New York, virtual bidding is available at a zone-index level. Virtual bidding is purely financial, where firms can supply or demand electricity in the day ahead market, where they close out their virtual bid position in the real-time market without consuming or producing any physical electricity.\footnote{See Jha and Wolak (2013) for a summary of virtual, or convergence, bidding. The authors demonstrate the physical efficiency benefits for allowing financial traders to risk arbitrage differences in day-ahead and real-time prices.} Although not the focus of this paper, this finding adds to the empirical work of Birge, Hortaçsu, Mercadal, and Pavlin (2017) that relate TCC positions to virtual bidding behavior in the MISO market. The authors present a case study of a firm found by the Federal Energy Regulatory Commission found to have intentionally lost money in the virtual market to enhance the payoffs from their TCC positions and to turn an overall profit. They suggest that such behavior might be more widespread in the MISO market by showing some other firms lose money in the virtual market. However, the prevalence and economic significance of such strategies has not been extensively studied. The findings in this section do not contradict those in Birge, Hortaçsu, Mercadal, and Pavlin (2017), but in the context of all trading profits, if virtual market manipulation is captured by the marginal increase in payouts from increasing firm open positions then it is estimated to be only a tiny portion of trading profits. Although theoretically TCCs are more valuable in the hands of those that can generate value for them, it is plausible that the ability for regulators to withhold TCC payouts to firms that are found to exploit their contract position via market power or virtual trading deters such actions from occurring on large scale, or that this estimation technique is not statistically powerful enough to detect such actions.\footnote{Regulations exist to deter such activity, with the Federal Energy Regulatory Commission having jurisdiction to investigate and potentially withhold payments to TCC or virtual traders if they were found to have altered their downstream strategies because of their TCC positions (Alderete, 2013).}

**Appendix D3: Firm level estimates**

The derivative payout equation is also estimated at a firm level

$$r_{i,j,t} = \beta p_{i,j,t} + \sum_{f \in F} \delta_f I_{i,j,t,f} + \sum_{f \in F} \rho_f Q_{i,j,t,f} + \epsilon_{i,j,t}$$

Here, $F$ is the set of all 130 firms ever observed to buy a TCC. Figure B3 presents the coefficient estimates of $\delta$ and $\rho$ for each firm in a scatterplot. However, given the large
quantity of coefficients plotted and the absence of any major participants found to have payouts increasing at the margin of the size of their open positions, figure B2 displays the aggregate profits and aggregate expenditures incurred by each firm in the data, with the four major firms that are detected to earn systematic profits ($\delta_f > 0$) at a 5% test size marked on the chart. The four major firms observed to have statistically detectable values of $\delta_f$ greater than zero, consistent with the collection of information rents, are Boston Energy Trading and Marketing, Hydro Quebec, DC Energy New York and DC Energy New England, together, accounting for 17% of contract expenditures and 50% of contract profits in the whole market. The figure shows that a handful of extra firms have also earned positive aggregate profits, but the testing technique did not detect them as systematically earning trading profits. Figure B4 shows that only Hydro Quebec had a profitable trading strategy that was limited to a few locations in the electricity network.

Figure B2: Total contract costs and profits by firm

Aggregate firm values for all 1, 6 and 12 month awarded contracts since 2006. Total contract costs is the sum of the absolute value of each contract position taken by a firm.

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65 The coefficients in figure B3 show that some richness in the heterogeneity is lost by collapsing firms into firm groupings, where a mass of firms appear to not earn systematic profits. Outliers in the coefficient space have low participation rates in terms of the total costs of contracts they purchased.
Figure B3: Estimates of payout premiums by firm

Figure plots firm level estimates of $\delta_f$ (the coefficient on the firm contract indicator variable) and $\rho_f$ (the coefficient on the firm open position variable) as specified in equation (9). Second figure replaces $\delta_f = 0$ or $\rho_f = 0$, if that hypothesis test at a 5% level of significance is not rejected. All markers are weighted by the sum of the total costs a firm incurred when purchasing TCCs over the sample window for the firms included on the chart.

(a) All point estimates

(b) All point estimates with 95% confidence intervals not covering zero.
Figure B4: Number of unique nodes ever specified in a purchased contract

Aggregate firm values for all 1, 6 and 12 month awarded contracts since 2006. Figure only plots the 47 firms that had their anonymized identities in the auction dataset decoded.