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

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Abstract

Transmission congestion contracts are derivative products that electricity retailers can use to change their future wholesale electricity price exposure to a different location. U.S. Congress is concerned by large financial trader profits in auctions for these derivatives because the payouts are funded by ratepayers, not willing counterparties. I study firm-level positions in New York to investigate the causes of this concern. I find that some financial traders earn systematic profits when they buy illiquid products, improving liquidity and price signals on these and related products. Given that electricity retailers buy so few of these products, the value of trader actions is discussed.

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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.”


Regulators have long wondered whether financial trader profits in commodity markets are purely transfers from producers and consumers of the underlying product.\(^1\) Ideally, financial traders can improve market liquidity, future price signals, and ultimately, overall market efficiency. The restructuring of wholesale electricity markets has introduced opportunities for purely financial participants, accompanied by concerns that their profits represent costly wealth transfers away from the physical participants that buy and sell wholesale electricity. In this paper, I study the sources of persistent profits that traders have earned in New York's transmission congestion contract market.

Transmission congestion contracts, or TCCs,\(^2\) are derivative contracts that pay the difference between wholesale electricity prices at two locations for a specified future time 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. For example, in the New York Independent System Operator (NYISO) wholesale market, there are 450 locations where electricity can be purchased. This means that 449 TCCs are available that pay a price difference between each a given location 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. Like retailers, electricity generating firms can derive benefits from TCCs by using them to effectively sell their output at a price of a different location to their own. Finally, financial traders participate in the markets, with the motive to acquire derivatives at prices less than their eventual payout. Competition among 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.\(^3\)

\(^1\)See Chapter 10, Baer and Woodruff (1929) for an early list of concerns regarding trader behavior in commodity exchanges.

\(^2\)TCCs are often referred to as financial transmission rights, FTRs; or congestion revenue rights, CRRs.

\(^3\)Introducing financial trader participation to day-ahead electricity markets has been shown to improve day-ahead price convergence to realized real-time prices (Saravia, 2003; Jha and Wolak, 2015). See Jha and Wolak for a demonstration of how financial traders have improved the production efficiency of the physical underlying market.
TCCs are auctioned in all formal electricity markets in the United States. The payouts of the issued derivatives are effectively funded by electricity customers, not a willing counterparty.\textsuperscript{4} In New York, periodic, multi-product auctions offer every bilateral combination of the 450 locations – over 100,000 products.\textsuperscript{5} As the opening New York Times quote highlights, financial traders have consistently earned large trading profits in these notoriously complex auctions, totaling $600m annually across four major US markets.\textsuperscript{6} Market monitors are concerned by these large trading profits earned by participants in TCC auctions, because TCC profits result in transfers from ratepayers (CAISO Department of Market Monitoring, 2016). In November 2017, the U.S House of Representatives Subcommittee on Energy convened with the aim to, “take a hard look at whether [TCC] trading makes sense and answer this question: Does financial trading make the electricity markets more efficient, and in turn, result in benefits to consumers?”\textsuperscript{7}

The objectives of this paper are to examine the sources of trading profits in TCC auctions, the persistence of the trading profits, and to understand whether financial trader participation is likely to improve market performance in this setting. 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 improve liquidity and price signals on other products.

The results from the theoretical examples are then used to guide the empirical portion of the paper where I compile microdata on 16 years of derivative prices, payouts and firm-level trading positions in the New York TCC market to examine the different types of products firms purchase and the persistence of trading profits. To organize the analysis of

\textsuperscript{4}Transmission ratepayers, which consists of firms that buy electricity in the wholesale market, receive the auction revenues and therefore benefit from lower TCC holder profits, all else equal.

\textsuperscript{5}450 locations allows for 450*449 = 202,050 directional location pairs or 101,025 unique location pairs.

\textsuperscript{6}Sum 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 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).

\textsuperscript{7}Passage from the Opening Statement of the Honorable Fred Upton, United States House of Representatives Subcommittee on Energy (November 29, 2017).
the rich variety of products, I classify each derivative into groups based on 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 where a power plant is located or 2) zone-indexed products that pay holders the difference between regional price indexes, which are the prices that retailers face in the spot market.

I find that retailers, generators and traders purchase zone-indexed derivatives, but only generators and traders purchase nodal derivatives. Retailers usually bid on less than 1% of the products that generators and traders bid on in each auction but account for 16% of total derivative expenditures. Retailers purchase their products in large quantities, for long terms, 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.

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. 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 88% of the financial trader profits are 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 can improve price signals and liquidity, 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.8

A major barrier to eroding overall trading profits could be the cost for new entrants to develop a technology that can identify successful trading strategies in TCC auctions. These multi-product auctions are complex, where TCC payouts and the auction allocations are determined in part by physical transmission constraints in the electricity network. Anecdotes

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8These findings extend prior observations that TCCs are not priced actuarially fairly (Bartholomew, Siddiqui, Marnay, and Oren, 2003; Hadsell and Shawky, 2009; Adamson, Noe, and Parker, 2010; Olmstead, 2018).
describe successful firms consistently updating their models and aggressively enforcing non-disclosure agreements with ex-employees. Alternate explanations do not appear to explain the majority of trading profits, such as profits being derived from exploiting market power in the energy market (theorized in Bushnell, 1999; Joskow and Tirole, 2000), or from manipulative actions by traders (demonstrated in a case study for the MISO electricity market in Birge, Hortaçsu, Mercadal, and Pavlin, 2017).  

The persistence of systematic 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. Therefore, policymakers want to see a more efficient electricity market and consumer benefits attached to the systematic profits being earned – I show that the trader profits are largely found on purchases of previously illiquid, nodal products. Theoretically, such purchases are likely be accompanied with liquidity benefits, and empirically, the market updates price expectations for these products in subsequent auctions. I use these findings to highlight some of the tradeoffs that accompany proposals to eliminate or reduce the set of derivative products offered at ratepayer-funded auctions. Greater product offerings allow greater flexibility in the procurement strategies of physical firms, but given that most of these products are not utilized by electricity retailers then it also offers more opportunities for trader profits and associated transfers from ratepayers.

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

1 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

\begin{itemize}
\item Traders can submit “virtual bids” in the electricity market that may influence the payouts of their derivative holdings.
\end{itemize}
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 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.

1.1 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.\(^{10}\) 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. This can mean that a cheap offer of electricity at a generating location might not be taken up if extra supply at that location will violate a line capacity constraint somewhere in 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.\(^{11}\) 1500MW of electricity is demanded inelastically at \( k \), with the following offers to supply electricity:

- Generators at \( i \): 2000MW at $80/MWh

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\(^{10}\)Electricity 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.

\(^{11}\)Resistance on each line is assumed equal and there are no transmission losses built into the solutions.
• Generators at $j$: 2000MW at $100/MWh
• Generators at $k$: 2000MW at $200/MWh

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 1.1 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. The market operator solves the optimization problem described in (1) to minimize system as-bid costs, with a description of the constraints to follow.

Objective: \[
\min_{Q} 80 \cdot Q_i + 100 \cdot Q_j + 200 \cdot Q_k
\] (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 transmission constraint on the $i, k$ line, where flow can not exceed 400MW, 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 can not exceed 100MW, 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 $k$ not having a maximum flow rating, the constraints on the other lines lead to the $LMP_j$ and the $LMP_k$ prices separating, in this case by $100$/MWh.

1.2 Relating network congestion to the policy problem and transmission congestion contracts

Participants in electricity markets face the LMPs at the location where they supply or consume electricity. 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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12Given 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 electricity flows take the path of least resistance.

13Notice 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.

14See 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 300MW of the 2000MW 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 600MW of electricity offered at node $j$ is utilized in the solution, therefore the marginal cost of withdrawing a unit of electricity at $j$ to be withdrawn at node $k$, therefore the marginal cost of withdrawing a unit of electricity at $k$ is $LMP_k = 200$.

15Further, 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.
The final line of this table is the *merchandising surplus* that market operators collect from the electricity market. It collects this merchandising surplus because congestion in the system results in the retailer paying more for their energy consumption than the generators are paid for their energy production. In this example, the merchandising surplus is equal to the payouts of 300 TCCs between $i$ and $k$ and 600 TCCs between $j$ and $k$. In all electricity markets, a policy decision must be made for how to distribute this revenue. In formal electricity markets throughout the United States, market operators securitize the merchandising surplus into TCCs in advance of the short-term energy market (described in the next section).

For the retailer at $k$ to source 1MWh at the location $i$ price, they would need to purchase a TCC between locations $i$ and $k$ that pays $LMP_k - LMP_i$. 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.\(^{16}\) Therefore, with a full set of TCC and forward prices available to a retailer, competition between suppliers may be enhanced and retailers can more

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\(^{16}\)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 $B$. 

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<table>
<thead>
<tr>
<th>Entity</th>
<th>Cash flow</th>
<th>Realized cash flow (figure 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retailer at $k$</td>
<td>$- LMP_k \cdot (Q_i + Q_j + Q_k)$</td>
<td>$-200 \cdot 1500$</td>
</tr>
<tr>
<td>Generators at $i$</td>
<td>$LMP_i \cdot Q_i$</td>
<td>$80 \cdot 300$</td>
</tr>
<tr>
<td>Generators at $j$</td>
<td>$LMP_j \cdot Q_j$</td>
<td>$100 \cdot 600$</td>
</tr>
<tr>
<td>Generators at $k$</td>
<td>$LMP_k \cdot Q_k$</td>
<td>$200 \cdot 600$</td>
</tr>
<tr>
<td>Market operator</td>
<td>$(LMP_k - LMP_i) \cdot Q_i + (LMP_k - LMP_j) \cdot Q_j$</td>
<td>$120 \cdot 300 + 100 \cdot 600 = $96,000$</td>
</tr>
</tbody>
</table>
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.\footnote{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 empirical investigation into the risk aversion of electricity retailers.}

To disentangle who loses when an entity profits from their TCC holdings, consider the sequence of events and cash flows in TCC auctions and wholesale electricity markets:

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
     - All else equal, ratepayers benefit from higher auction revenues. The zero sum nature of TCC holder profits (the bracketed term) means that TCC holder profits are effectively funded by ratepayers, and TCC holder losses benefit 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 (TSC), where lower TCC holder profits means a bigger reduction in this charge and ultimately, lower bills to customers.\footnote{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.}
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 and prices in the network (see figure A1). 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 $q\text{MW}$ being injected at $i$ and withdrawn at $j$ in the physical electricity network, no transmission constraint in the network would be violated.\(^{19}\) 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 both 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:

\[
\text{Objective: max } \mathbf{b} \cdot \mathbf{q} \\
\text{Simultaneous feasibility } i,k \text{ line: } \frac{2}{3}q_{i,k} + \frac{1}{3}q_{j,k} + \frac{1}{3}q_{i,j} \leq 400 \\
\text{Simultaneous feasibility } i,j \text{ line: } -100 \leq \frac{1}{3}q_{i,k} - \frac{1}{3}q_{j,k} + \frac{2}{3}q_{i,j} \leq 100 \\
\text{Bid quantity constraints: } \mathbf{q} \cdot 1(\mathbf{q} \leq 0) \leq q \leq \mathbf{q} \cdot 1(\mathbf{q} \geq 0)
\]

where $\mathbf{b}$ is the bid price vector for each bid in the $\mathbf{q}$ vector and $q_{a,b}$ is the sum of all allocated

\(^{19}\)For example, a 10 unit contract from $i$ to $j$ implies a 10MW injection of electricity at $i$ and a 10MW withdrawal of electricity at $j$. 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.
TCCs issued between $a$ and $b$. The auction equilibrium maximizes the as-bid valuations for 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. 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 is fully securitized into TCCs.
2. Under allocation: Low demand for one product reduces the liquidity of other products. Merchandising surplus is partially securitized into TCCs.
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. These bids could reflect the physical suppliers of

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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 per MWh price difference between two locations over the duration of the contract.

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.

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

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<thead>
<tr>
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<th>Example 1</th>
<th>Example 2</th>
<th>Example 3</th>
<th>Example 4</th>
<th>Example 5</th>
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</thead>
<tbody>
<tr>
<td>Bids</td>
<td>2000 @ $120</td>
<td>30 @ $120</td>
<td>30 @ $120</td>
<td>30 @ $120</td>
<td>30 @ $120</td>
</tr>
<tr>
<td>i,k TCC:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></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>
</tr>
<tr>
<td>Equilibrium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i,k TCC:</td>
<td>q_{i,k} = 300</td>
<td>q_{i,k} = 30</td>
<td>q_{i,k} = 300</td>
<td>q_{i,k} = 30</td>
<td>q_{i,k} = 30</td>
</tr>
<tr>
<td>j,k TCC:</td>
<td>p_{j,k} = 600</td>
<td>q_{j,k} = 330</td>
<td>p_{j,k} = 600</td>
<td>q_{j,k} = 600</td>
<td>q_{j,k} = 600</td>
</tr>
<tr>
<td>i,j TCC:</td>
<td>p_{i,j} = $20</td>
<td>p_{i,j} = $20</td>
<td>p_{i,j} = $10</td>
<td>p_{i,j} = $10</td>
<td>p_{i,j} = $20</td>
</tr>
<tr>
<td>Cash flows</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a) Auction revenues$^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>$96,000</td>
</tr>
<tr>
<td>Simultaneous feasibility (Implied transmission flows)$^e$</td>
<td>400</td>
<td>130</td>
<td>400</td>
<td>365</td>
<td>365</td>
</tr>
<tr>
<td>i,k line</td>
<td>-100</td>
<td>-100</td>
<td>-100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>i,j line</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></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 $\text{LMP}_i = 80$, $\text{LMP}_j = 200$ and $\text{LMP}_k = 200$. (d): As explained in the cash flow description, the transmission service charge (TSC) 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).

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
\[ p_{i,k} = \$120, p_{i,j} = \$20, p_{j,k} = \$100, \] exactly equal to the realized LMP price differences between these locations.\(^{23}\)

**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.

![Figure 2: A three-node electricity network and example TCC auction equilibrium](image)

**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 1.3, 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 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.\(^{24}\) The implied transmission flows from the quantities of issued

\(^{23}\)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 sets to also maximize auction revenues.

\(^{24}\)The reduced demand for the \(i,k\) derivative decreases the counterflows on the constrained line under the
contracts uses less transmission than in the first example.\textsuperscript{25} Therefore, contracts are under 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 $110$ (italicized in table 1). 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.\textsuperscript{26} 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.\textsuperscript{27} Empirically, Jha and Wolak (2015) demonstrate the plausibility that trader participation in electricity markets can lead to better production efficiency in the context of virtual bidding.\textsuperscript{28}

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 (italicized in table 1). 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 auction solution allocates 435 of the $i,j$ TCCs to the simultaneous feasibility constraint (equation 4), with the consequence being that 600 $j,k$ TCCs contracts can no longer be issued.

\textsuperscript{25}If these flows were actually the realized quantities in the day-ahead electricity market depicted in figure 1, production would be inefficient because it would require substitution away from cheaper sources of generation to more expensive sources.

\textsuperscript{26}The objective function changes to max $120 \cdot q_{i,k}^1 + 110 \cdot q_{i,k}^2 + 100 \cdot q_{j,k}$, where $q_{i,k}^1$ is the allocation to the 30 unit bidder, and $q_{i,k}^2$ is the allocation to the financial trader.

\textsuperscript{27}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.

\textsuperscript{28}The removal of barriers for financial traders to submit virtual bids to day ahead electricity markets is shown in Jha and Wolak (2015) to have lowered total production costs in the Californian market.
financial trader and fully allocates the 600 \( j, k \) TCCs demanded. 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.\(^{30}\) 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.

### 1.4 Summary of TCC auction examples

The examples in this section showed that firms can profit from TCC auctions and how such profits result in transfers from ratepayers. While the existence of numerous TCC specifications might allow physical firms to change their wholesale price exposure, opportunities for financial firms to profit in TCC auctions might exist such that by taking a position, the financial firm increases the liquidity of other products in the auction. However, under this auction mechanism where price transitivity holds throughout the network, all products will be priced even if the equilibrium quantity is zero. The empirical portion of the paper will study the sources of profits in TCC auctions, their persistence, and their relationship to the liquidity of the product in prior auctions.

\(^{29}\)The objective function changes to \( \max \sum_{q} 120 \cdot q_{i,k} + 100 \cdot q_{j,k} + 10 \cdot q_{i,j} \).

\(^{30}\)The objective function changes to \( \max \sum_{q} 120 \cdot q_{i,k} + 100 \cdot q_{j,k} + 10 \cdot q_{i,j}^{1} + 20 \cdot q_{j,j}^{2} \), where \( q_{i,j}^{1} \) and \( q_{j,j}^{2} \) are the allocations to the financial traders.
2 Setting: The New York TCC market

2.1 Defining a derivative and a contract

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

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

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 \( h \). \(^{31}\) \( m(T_1,T_2) \) 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. 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 defined by equation (6). A contract will refer to a \( q \) unit position purchased on the \((i,j,T_1,T_2)\) derivative by a firm \( f \). The payout of the contract is \( q_{i,j,T_1,T_2,f} \cdot m(T_2,T_1) \cdot r_{i,j,T_1,T_2} \). An example contract follows:

- 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: \( i = \) Linden Cogen, \( j = \) 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: \( q_{i,j,T_1,T_2,f} \cdot m(T_2,T_1) \cdot p_{i,j,T_1,T_2} = 90,110.07 \)

\(^{31}\) \( LMP_{x,h} \) 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.
Derivative average monthly price: 
\[ p_{i,j,T_1,T_2} = \frac{90,110.07}{3 \times 12} = \$2,503.06 \]

Firm: \( f = J.\ P.\ Morgan\ Ventures\ Energy\ Corporation \)

- Locational price differences \((LMP_{POW} - LMP_{POI})\) accrue hourly
- Total contract payout: 
  \[ q_{i,j,T_1,T_2} \cdot m(T_2,T_1) \cdot r_{i,j,T_1,T_2} = \$132,045.15 \]
- 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: 
  \[ q_{i,j,T_1,T_2} \cdot m(T_2,T_1) \cdot (r_{i,j,T_1,T_2} - p_{i,j,T_1,T_2}) = \$132,045.15 - \$90,110.07 = \$41,935.08 \]

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.

### 2.2 Derivative specifications available for purchase

A wide variety of transmission congestion contract specifications can be purchased at auction. In the \( T_1, T_2 \) time horizon dimension, all products studied are of 1-, 6- or 12-months duration. 6- and 12-month contracts attract the greatest expenditure by firms (figure 3 (a)). Collectively, holders of all derivative durations earned revenues greater than expenditures from their contract positions in the NYISO TCC auctions from 1999-2015.

In the location dimension, there are 450 price nodes in the New York grid, resulting in approximately 100,000 \( i,j \) derivative specifications available.\(^3\) 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:

\[
  r_{z_1,z_2,T_1,T_2} = \sum_{h=T_1}^{T_2} (LMP_{z_2,h} - LMP_{z_1,h}) \\
  = \sum_{h=T_1}^{T_2} (\sum_{j \in z_2} w_{j,h} LMP_{j,h} - \sum_{i \in z_1} w_{i,h} LMP_{i,h}) \quad (7)
\]

\(^3\)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.
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.

Mixed derivatives that pay the price difference between a node and a zone-index are classified as nodal. The example contract in section 2 is classified as nodal, with Linden Cogen being a node, and N.Y.C being a zone.

There is a distinction between nodal and zonal products. In the NY-ISO market, producers of electricity receive nodal prices whereas consumers of electricity pay the zonal prices (also known as hub 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.

2.3 Participants in the derivative market

130 firms were allocated a TCC in the New York market between 1999-2015. This subsection describes three broad firm types (retailers, generators and traders)\(^{33}\) that participate
2.3.1 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), meaning that retailers buy contracts with larger quantities and durations than other firms.

2.3.2 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
Figure 5: Contract expenditures and payouts of participants

![Graph showing contract expenditures and payouts of participants](image)

(a) Total expenditures and payouts

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

Figure (a) displays the sum of $q_{i,j,T_2,T_1} \cdot p_{i,j,T_1,x_2} \cdot m(T_2,T_1) \cdot r_{i,j,T_1,x_2}$ and $q_{i,j,T_2,T_1} \cdot m(T_2,T_1) \cdot r_{i,j,T_1,x_2}$. Figure (b) displays the average of $q_{i,j,T_2,T_1} \cdot p_{i,j,T_1,x_2} \cdot m(T_2,T_1) \cdot r_{i,j,T_1,x_2}$ and $q_{i,j,T_2,T_1} \cdot m(T_2,T_1) \cdot r_{i,j,T_1,x_2}$. 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.

Nodes where their power plants are located. Any market power diminishes at other price nodes. 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.” An implication from the theory is examined in section 4.2.3.

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

---

34 Market 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).
2.3.3 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 traders. 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 1.3 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).

2.4 Public information and the sequence auctions

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 1.3, with more technical details regarding the transmission capacity assumptions 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.\(^{35}\)

There are two crucial features of the allocation process that will be utilized in the analysis. As demonstrated in the auction examples in section 1.3, 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, one week apart. The 1- month derivatives are available for each month of the year, sold in a single auction.\(^{36}\) Entering an auction, firms have access to public information on the results of past auctions, but not the

\(^{35}\)The simultaneous feasibility constraint is discussed in further detail in Appendix B, where the rules to account for overlapping time horizons of different products sold at different auctions are explained.

\(^{36}\)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.
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.

bids, which are released 3 months after the fact and with anonymized identifiers placed on the location nodes and the firm identities. For example, the prior auction prices for every possible TCC is publicly available, along with the payout if the payout period has been realized. Furthermore, all issued contracts are reported, containing complete information on the TCC specification, the size of the contract and the firm that purchased it.

3 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.

3.1 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.

3.2 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 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. 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 1.3). 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, leaving 1,151,374 $i, j, t$ derivative observations. Attached to each observation are price and payout per month duration variables $p_{i,j,t}$ and $r_{i,j,t}$. 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 $r_{i,j,t} = -r_{j,i,t}$.

3.3 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.

---

38In the raw data, $i, j, T_1, T_2, f$ 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.

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

40For 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
4 Firm participation 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. Section 4.1 examines the participation and purchases of firms. Section 4.2 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.

4.1 Participation of firms in TCC auctions

Figure 7: Unique TCC bids in 12-month auctions, 2006-2015

Figures display the number of unique TCC products (defined by two locations) bid on for each vintage of 12 month TCC products. Vintages are either November to November or May to May, with each vintage auctioned in multiple rounds. The firm type counts in figure (a) include the firms that were decoded from the auction data, described in appendix 8. Otherwise, all firms and all TCC locations are included, regardless of whether the true location was decoded.

Figure 7a shows the number of unique TCC products bid on by retailers, generator owners and financial traders in every 12-month auction since 2007. We see that retailers bid on a tiny portion (less than 1%) of the products that generators and traders bid on. On average, all retailers collectively bid on 7 different TCC specifications for each vintage of 12 month auctions, whereas generators and traders bid on 581 and 1,069 different products. Figure 7b displays the number of firms that place a bid on each TCC that received at least one bid at auction. These charts show that very few of the approximately 100,000 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.
permutations of location-pair derivative specifications are bid on in each auction, with even less products receiving bids from multiple firms.

Despite the small set of products retailers bid on, they are not insignificant in their participation. TCC expenditures are displayed in table 2. Retailers account for 16% of derivative expenditures, with 84% of retailer expenditures on zone-indexed contracts and 96% on 6 or 12 month duration contracts. 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. Individually, the majority of contracts held by generators and traders are for small positions that are tiny relative to the aggregate price exposure faced by major retailers in the procurement of electricity or relative to the sale of electricity by generators.41

Table 2: Expenditures on TCC contract positions

<table>
<thead>
<tr>
<th></th>
<th>Retailers</th>
<th></th>
<th></th>
<th></th>
<th></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>Round 1</td>
<td>Round &gt; 1</td>
</tr>
<tr>
<td>Total ($m)</td>
<td>685</td>
<td>133</td>
<td>34</td>
<td>785</td>
<td>165</td>
<td>620</td>
</tr>
<tr>
<td>Generators</td>
<td>Zonal</td>
<td>Nodal</td>
<td>1 month</td>
<td>&gt;1 month</td>
<td>Round 1</td>
<td>Round &gt; 1</td>
</tr>
<tr>
<td>Total ($m)</td>
<td>901</td>
<td>844</td>
<td>225</td>
<td>1,520</td>
<td>249</td>
<td>1,271</td>
</tr>
<tr>
<td>Traders</td>
<td>Zonal</td>
<td>Nodal</td>
<td>1 month</td>
<td>&gt;1 month</td>
<td>Round 1</td>
<td>Round &gt; 1</td>
</tr>
<tr>
<td>Total ($m)</td>
<td>1,373</td>
<td>1,300</td>
<td>358</td>
<td>2,315</td>
<td>309</td>
<td>2,007</td>
</tr>
</tbody>
</table>

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}|, |x_1, x_2, | , m(T_2, T_1), p_{i,j}|, r_1, r_2|). Sample restricted to the purchases in 2006-2015 where auction round information is available.

Overall, 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, often in small quantities. The radically different purchase behavior of retailers to generators and traders could be explained by regulatory incentives. Retailers face zonal prices in the wholesale market and 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

41The median contract size of 6- and 12-month TCCs is 5 units for generators and 3 for traders. 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.).
are not included in the rate base, whereas profits from such activities could lower the rate base. With generator owners and traders able to keep any trading profits they earn, we see that they are much more likely to bid on and purchase a wide range of products, even in small quantities.

4.2 Systematic trading profits across firm and product types

Prior work on TCC auctions identified that contract prices were not equal to expected contract payouts (Bartholomew, Siddiqui, Marnay, and Oren, 2003; Hadsell and Shawky, 2009; Adamson, Noe, and Parker, 2010; Olmstead, 2018). In this section, I explore the link between derivative product design, the types of firms that profit on each product and whether profits might be linked to liquidity provision or downstream payout manipulation.

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,

\[
\begin{align*}
\bar{r} = (\bar{r} - \beta(t_I) I) I = 1 & \quad \text{Rent to firm } I \\
\bar{r} = \bar{r} + \beta(t_I) I = 0 & \quad \text{Rent to firm } I \\
\bar{r} = \bar{r} + \beta(t_I) & \quad \text{Rent to firm } I
\end{align*}
\]

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). 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.\(^{43}\)

\(^{42}\)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.

\(^{43}\)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.
The model to be estimated has the following specification:

$$r_{i,j,t} - p_{i,j,t} = \sum_{f \in F} \delta_f I^q_{i,j,t,f} + \epsilon_{i,j,t}$$  \hspace{1cm} (9)$$

$p_{i,j,t}$, $r_{i,j,t}$ and $I^q_{i,j,t,}$ are the average monthly prices and payouts, and an indicator function for firm type $f$ being allocated a contract on the derivative. Derivative payouts exclude any discount factor.\textsuperscript{44} Equation (9) has $\delta_f$ equal to the expected difference between the payout of the derivative and the market clearing bid when firm $I$ is awarded the derivative. $\delta_f = 0$ implies 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 that 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.

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 0.1% of observations ($|I^q_{i,j,t,RET}| = 0.001$), with generators and traders each issued contracts for 3% of the derivative observations ($|I^q_{i,j,t,GEN}| = 0.031$, $|I^q_{i,j,t,TRA}| = 0.034$).\textsuperscript{45}

### 4.2.1 Estimates of derivative prices and payouts

Table 3 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.

Retailers are predicted to receive an average payout of $\hat{\delta}_{RET} = $28.49 less per month of contract payments than the price they pay. Generators and traders receiving an extra $\hat{\delta}_{GEN} = $102.12 and $\hat{\delta}_{TRA} = $172.45. However, only for generators and traders are these estimates detected to be statistically different from zero.

Systematic profits are not detected for zone-indexed derivatives, with tests for the predicted premium retailers, generators and traders earn on their zonal positions not being statistically different from 0 at a 5% level. However, systematic profits are detected for generators and traders on nodal derivatives. The average price paid by generators for their nodal derivatives is $804.53$, and using the estimated value of $\delta_{GEN}$ implies an average payout premium to generators of $\frac{102.12}{804.53} \cdot 100 = 12.9c$ per dollar value of the position. The

\textsuperscript{44}The small payout lengths and monthly payouts mean that applying a discount rate correction has a negligible impact on the results.

\textsuperscript{45}The direction of the derivative data is arbitrary, therefore an observation for the $i, j$ derivative with $I^q_{i,j,t,f} = 1$ is equivalent to an observation a $j, i$ derivative with $I^q_{j,i,t,f} = -1$.
Table 3: Estimates of average monthly derivative payouts

|            | All $|p_{i,j,t}| = 1686$ | Zonal $|p_{i,j,t}| = 3821$ | Nodal $|p_{i,j,t}| = 1667$ | Nodal $|p_{i,j,t}| = 1667$ |
|------------|----------------|----------------|----------------|----------------|
| $\delta_{RET} [I_{RET,t}^q]$ | -28.49 | -47.17 | 104.35 | -383.17 |
| $\delta_{RET}$ | (135.94) | (152.56) | (182.18) | (355.40) |
| $\delta_{GEN} [I_{GEN,t}^q]$ | 102.12 | 83.36 | 103.61 | 142.27 |
| $\delta_{GEN}$ | (42.17) | (90.68) | (43.61) | (72.27) |
| $\delta_{TRA} [I_{TRA,t}^q]$ | 172.45 | -20.51 | 184.27 | 289.39 |
| $\delta_{TRA}$ | (45.71) | (121.74) | (45.24) | (66.80) |
| $\delta_{OP} [I_{OP,t}^q \cdot I_{i,j,t}^o]$ | 706.35 | | | |
| $\delta_{OP}$ | | | | |
| $\delta_{OP} [I_{OP,t}^q \cdot I_{i,j,t}^o]$ | -65.58 | | | |
| $\delta_{OP}$ | | | | |
| $\delta_{OP} [I_{OP,t}^q \cdot I_{i,j,t}^o]$ | -157.73 | | | |
| $\delta_{OP}$ | | | | |

The first three 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 A1. $i,j$ or $j,i$ direction is arbitrary: $(p_{i,j} = -p_{j,i}, \ r_{i,j} = -r_{j,i})$.

equivalent calculation for financial trading firms estimates an average payout premium of $\frac{184.27}{1113.09} \times 100 = 16.6c$ per dollar.

To summarize, the results add statistical robustness to the observations in figures 3 and 5, that systematic profits are only earned by generators and traders on nodal products. Retailers are not detected to earn trading profits and were earlier shown to largely confine their participation to the zonal products (that are priced actuarially fair).

4.2.2 Extension 1: Are profits linked to liquidity provision?

I now extend the analysis to measure the extent that profits are earned on products frequently purchased by firms or on products that no firm holds a position over. 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. The open position a firm has over an $i,j$ derivative entering auction $t$ is 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
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 \( t \)

Equation 10 extends equation (9) to allow predicted payout premiums to differ with \( I_{i,j,t}^{OP} \):

\[
 r_{i,j,t} - p_{i,j,t} = \sum_{f \in F} \left[ \delta_f I_{i,j,t,f}^q + \delta_{OP} I_{i,j,t,f}^q \cdot I_{i,j,t}^{OP} \right] + \epsilon_{i,j,t} \tag{10}
\]

Here, if \( \delta_{OP}^{f} < 0 \), 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 3. We observe that financial traders earn an average realized payout premium of $289.39 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 289.39-157.73 = $131.66 per month of contract payout. Testing \( \delta_{TRA}^{OP} = 0 \) is rejected at a test size of 5%, and testing \( \delta_{TRA} + \delta_{OP}^{TRA} = 0 \) is also rejected, suggesting that traders earn systematic profits on their purchases, but larger profits are earned when no firm holds an existing open position on the product. Relating this result to the auction examples in section 1.3, 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 5, which studies the persistence of realized trading profits.

4.2.3 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 trader 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.

---

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.
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:

\[
\begin{align*}
  r_{i,j,f,t} - p_{i,j,f,t} &= 187.2 - 22.6 \, SZ_{i,j,f,t} + 37.2 \, SN_{i,j,f,t} \\
  \text{(56.7)} & \quad \text{(82.5)} & \quad \text{(182.0)}
\end{align*}
\]

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.\(^{47}\)

An implication from the theories in Bushnell (1999) and Joskow and Tirole (2000) is 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:

\[
\begin{align*}
  \max_{Q_E} & \quad LMP_j(Q_E) \cdot Q_E + (LMP_j(Q_E) - LMP_i) \cdot Q_{POST}^{i,j,f} - c(Q_E) \\
 \text{First order condition:} & \quad 0 = LMP_j'(Q_E) \cdot Q_E + LMP_j(Q_E) + LMP_j'(Q_E) \cdot Q_{POST}^{i,j,f} - c'(Q_E) \\
 & \quad = -\beta \cdot Q_E + \alpha - \beta Q_E - \beta \cdot Q_{POST}^{i,j,f} - c \\
  Q_E &= \frac{\alpha - \beta \cdot Q_{POST}^{i,j,f} - c}{2\beta} \\
  LMP_j &= \frac{\alpha + \beta \cdot Q_{POST}^{i,j,f} + c}{2}
\end{align*}
\]

\(^{47}\)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 \( T_2 \)).
Here, we observe that the firm withholds more output in the physical market with more contracts $Q_{i,j,f}^{POST}$, 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 $r_{i,j} = \frac{1}{2} \cdot (\alpha + \beta \cdot Q_{i,j,f}^{POST} + c) - LMP_B$ in the stylized example, being $\frac{\beta}{2} \cdot Q_{i,j,f}^{POST}$ more valuable if held by the firm than by a different participant. Further, if a firm otherwise had some other mechanism available to manipulate the payouts of TCCs at the margin as demonstrated in a case study in Birge, Hortaçsu, Mercadal, and Pavlin (2017), we might expect derivative payouts to be increasing in the size of their open position.\footnote{Birge et al. (2017) study the positions of a firm that was investigated by the Federal Energy Regulatory Commission. 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 and influence FTR (TCC) payouts. The virtual market trades in question totaled $390,000, compared to $1b of positions taken annually in the MISO market for financial transmission rights. Birge et al. examine whether similar behavior is widespread but are impeded by the anonymity of firm identities.}

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

$$r_{i,j,t} - p_{i,j,t} = \sum_{f \in F} \delta_f I_{i,j,t,f}^g + \sum_{f \in F} \rho_f Q_{i,j,t,f}^{POST} + \epsilon_{i,j,t}$$  \hspace{1cm} (11)$$

where $Q_{i,j,t,f}^{POST}$ is the number of contracts firm type $f$ holds on the $i,j$ derivative.\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 $t$. $Q_{i,j,t,f}^{POST}$ is negative if the firm type has a positive $i,j$ position.}

The estimates of this model are displayed in appendix D2 (along with a more detailed discussion), with $\rho_f$ not detected to be different from zero for any firm type on nodal contracts and the $\delta_f$ estimates similar to those in table 3. Regardless, the point estimate $\hat{\rho}_{GEN} = 0.04$ is small, where at average open position holdings for generator-won derivatives ($Q_{i,j,t,GEN}^{POST} = 24.72$), the predicted increase in the derivative payouts is estimated to be $\frac{0.04 \cdot 24.72}{804.53} \cdot 100 = 0.1c$ per dollar value of the position. This premium represents a small fraction compared to the 12.9c 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,\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} or that this estimation technique is not statistically powerful enough to detect such...
5 Price discovery and the persistence of trading profits in TCC auctions

With free entry of trading firms, we might expect systematic profits to be eroded over time as other firms mimic the successful firms. However, we see in 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.

If traders are managing to earn systematic profits by purchasing a distinct set of products to the 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. By exploiting the unique information revelation structure across sequential auctions, I am able to gain insight on the sources of trading profits and whether price discovery occurs following purchases by profitable firms. If firms have constant profit margins over the same 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. This could represent well informed firms earning payouts greater than the prices paid (see Wilson, 1967) in the first round of an auction, with their information advantage diminished in subsequent rounds after it has been revealed to the market.

5.1 Price updating across auction rounds of the same products

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

\[ \rho_f = 0 \]

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.

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).
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.

That undervalued derivative prices would appreciate in price and perhaps that profitable trading opportunities on that product cease to exist.

The NYISO setting 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:

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

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 (held one week apart) 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
Figure 9: Price paths following purchases or bids and following sales or offers

(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. Sample restricted to derivatives with $p_{i,j,T_1,T_2,ar=1} >$1,000 and where price changes are within a threefold increase or decrease. Means and pointwise 95% confidence intervals plotted. Sample sizes: (a) 2,980 and 9,850. (b) 1,009 and 4,059.

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 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

(a) Purchases of derivatives

(b) Sales of derivatives

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. Sample restricted to derivatives with $p_{i,j,T_1,T_2,ar=1} >$1,000 and where price changes are within a threefold increase or decrease. 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 A2.

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

\[53\] The responses to retailer offers are omitted for sample size reasons. The 95% confidence interval covers -40% to 20% for the second round.
Figure 11: Price discovery process following purchases of zone-indexed or nodal contracts by firm type

All series plot equation (12). Both charts compare two sets $D$ of derivatives, sets that have positive price purchases split by nodal and zonal derivatives. The first chart plots these sets for generating firm round 1 purchases, and the second chart plots the series for trading firm purchases. Sample restricted to derivatives with $p_{i,j,T_1,T_2,ar=1} >$1,000 and where price changes are within a threefold increase or decrease. Means and pointwise 95% confidence intervals plotted. Sample sizes: (a) 193 and 958. (b) 173 and 1,038.

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 participation 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 1.3, 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.

5.2 Price updating across auctions with different vintages

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 poses a puzzle, how have firms been able to systematically earn profits year after year? This section describes the persistence of trading profits on the same products over different vintages. The motivation is that if a firm may have some forecasting advantage tied to a single location in the network, we would expect to see them consistently earn payout premiums for derivative
products tied to that location, for different $T_1, T_2$ 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.\textsuperscript{54} 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 1.3 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.

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 $j$, the opportunity to profit on the $i, j$ product in the next auction disappears. Further investigation 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 (figure A3).\textsuperscript{55}

To summarize, I have shown that financial traders are 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 margins on products that

\textsuperscript{54}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.

\textsuperscript{55}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. Olmstead (2018) observes in Ontario that financial transmission rights are underpriced when less bidders participate and more likely to be actuarially fairly priced when there are many bidders.
Figure 12: Firm contract costs and payouts by past derivative performance

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.

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.
5.3 What barriers prevent competition from eroding systematic trading 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.\footnote{Refer 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.}

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 firms are financial traders Boston Energy Trading and Marketing, DC Energy, DC Energy New York and DC Energy New England, along with two generator owners, Hydro Quebec and EDF Trading North America. 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 EDF and 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 purchase.

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.

6 Policy discussion: Who benefits from ratepayer-funded auctions for 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 actuarially 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 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.

57EDF is classified as a generator owner, even though their trading subsidiary is listed as the TCC trader. They earn substantially less profits than DC Energy and Boston Energy Trading and Marketing, but bid on products that are not tied to their power plant ownership, therefore they might be better considered a financial trader.

58Hydro 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.
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. Concerns from U.S. Congress and market monitors have focused on the distributional aspect of the auctions that appear to be transferring wealth away from ratepayers to TCC holders. Therefore, these policymakers would want to see a more efficient electricity market and consumer benefits attached to the systematic profits being earned.

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, but electricity ratepayers need these actions to facilitate large reductions in retailer procurement costs to benefit from the auction construct. 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, with clear distributional consequences. 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.\footnote{New York, author calculation, California, see CAISO Department of Market Monitoring (2016) and PJM see PJM (2015) and various issues.} 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, policy modifications have been suggested or implemented, each of which would likely reduce trading profits but may also restrict the benefits physical firms derive from TCC markets.

First, there is the option for market operators to disband the auctions and distribute the merchandising surplus it collects from transmission congestion in the short-term energy markets in another manner. 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 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.\(^{60}\) 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. CAISO Department of Market Monitoring (2016) propose that market operators could still facilitate derivative markets for locational price swaps, but have them set up such that contracts are formed only when willing counterparties take opposite positions.\(^ {61}\)

A third policy modification has been implemented in New Zealand. There, following a stakeholder process, a single TCC between two locations was made available, with the remaining merchandising surplus distributed via direct allocation (see Energy Market Services, 2012). 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. Black (1986) gives a summary regarding derivative product design and qualitative predictors for the success or failure of derivatives to be liquid. Derivative payout structures that are at centralized locations or at an index level tend to be more liquid.\(^ {62}\) 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 actuarially 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 removing some profitable opportunities for financial traders will have on their participation.

\(^{60}\)This position is also suggested in CAISO Department of Market Monitoring (2016). The paper contends that transmission ratepayers effectively take counterpositions on TCCs so the auction should be updated such that contracts are only entered by willing counterparties.

\(^{61}\)Whether such derivative markets would be liquid and provide valuable price signals is uncertain. Black (1986) summarizes a large literature discussing why markets for some derivative products fail to exist, while markets for other derivative products are liquid. One feature of liquid derivative markets is that both physical and financial firms participate, with financial traders needing to collect some rents in order to participate.

\(^{62}\)The potential benefits of reducing choice sets in a variety of settings are explored in Levin and Milgrom (2010).
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 purchase. I showed empirically that retailers bid on a tiny proportion of products relative to financial traders. 88% of trader profits are earned by firms that are the first to purchase a previously illiquid product, but that profitable opportunities are 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 tradeoffs 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 from 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. Prior research in the derivative liquidity literature has shown that derivatives designed to pay out at centralized locations or to be more aggregated in their specifications are most likely to exist and be liquid (Black, 1986). Some costs to restricting the product set offered at auction include the loss of flexibility physical firms have in choosing the spot price locations at which they procure or sell their electricity. Some benefits could be the reduction of transfers of wealth and a reduction in the costs of 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 a recent policy change. In 2013, New Zealand introduced auctions for TCC derivatives between two nodes in their electric network. A pre-post study that can measure the realized
physical costs from electricity generation in this market may build upon the description of profit sources in this paper to provide further insight into the physical efficiency impacts from such a policy.

8 Acknowledgments

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References


Appendix A: Additional figures and tables

Figure A1: Derivative payouts, lagged payouts and prices

(a) Payouts and payouts in previous vintage
(b) Payouts and prices

Figures plot $r_{i,j,t}$ against $r_{i,j,t-1}$ and $p_{i,j,t}$ for all contracts entered from 1999-2015. 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. The line in red plots the values where the y-axis is equal to the x-axis.
Table A1: Summary statistics of the location-pair-auction \((i, j, t)\) derivatives studied

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(p_{i,j,t})</td>
<td>Price and payout of derivative</td>
</tr>
<tr>
<td>(r_{i,j,t})</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>1686 1842</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>3215 4004</td>
</tr>
<tr>
<td>(q_{i,j,t,RET})</td>
<td>Number of derivative units</td>
</tr>
<tr>
<td>(q_{i,j,t,GEN})</td>
<td>at auction</td>
</tr>
<tr>
<td>(q_{i,j,t,TRA})</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.02 0.18 0.23</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>1.29 3.16 3.62</td>
</tr>
<tr>
<td>(I_{i,j,t,RET}^q)</td>
<td>Indicator = 1 if allocated</td>
</tr>
<tr>
<td>(I_{i,j,t,GEN}^q)</td>
<td>contract at auction</td>
</tr>
<tr>
<td>(I_{i,j,t,TRA}^q)</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.001 0.031 0.034</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>0.031 0.174 0.182</td>
</tr>
<tr>
<td>(Q_{i,j,t,RET}^{POST})</td>
<td>Size of open position</td>
</tr>
<tr>
<td>(Q_{i,j,t,GEN}^{POST})</td>
<td></td>
</tr>
<tr>
<td>(Q_{i,j,t,TRA}^{POST})</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.85 2.06 2.03</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>20.46 24.74 18.61</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 \(T_1\).
Figure A2: Price discovery following purchases or sales, by profitable and unprofitable firms

![Graphs showing price discovery](image)

(a) Purchases of derivatives

(b) Sales of derivatives

All series plot equation (12). The purchases chart compares two sets 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.
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.
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).

NYISO pays the generators their nodal price for what they inject and NYISO receives from loads (firms that buy wholesale electricity) 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 \( P_{\text{Auction},i} \) for node \( i \). Therefore, the equilibrium price of the \( i,j \) derivative in the notation of the paper is \( p_{i,j} = P_{\text{Auction},j} - P_{\text{Auction},i} \). 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.
Figure B1: A three node network

- 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 $20*(LMP_j - LMP_i)$ will be awarded a contract if the bid price is greater than $p_{i,j} = P_{Auction,j} - P_{Auction,i}$.

- 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 $k$. Applying Kirchhoff’s laws to this setting, twice as much flow from $j$ to $k$ will occur relative to $j$ to $i$ to $k$. Applying the results in Hogan (1992) to derive the inequalities that must be satisfied for a TCC configuration to be able to be funded from the merchandising surplus in the three node example of figure B1 case, assuming no $i,j$ products are available, gives:

$$\frac{2}{3}q_{i,k} + \frac{1}{3}q_{j,k} \leq 300$$

$$\frac{1}{3}q_{i,k} + \frac{2}{3}q_{j,k} \leq 220$$

$$-100 \leq \frac{1}{3}(q_{i,k} - q_{j,k}) \leq 100$$

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 
var 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. Trans-
mision 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 NY-
ISO (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. This section details the con-
struction of the derivative and contract datasets, which are closely related and have com-
mon 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 \(q_{i,j,t,f}\), \(Q_{i,j,t,f}^{POST}\) and \(I_{i,j,t,f}^q\) 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, power plant ownership information from NYISO (2016) is attached to each node. For the contract dataset, an observation 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 cover almost all of contract expenditures.

   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 almost all of contract expenditures and profits made.

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% (38,370/136,768). 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 cannot 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 945, than the 55,000+ of the generators and traders, but have a higher conversion rate of bids to contracts of 50% compared with approximately 27%. For the purposes of the analysis in section 5.1 and the change in the number of bidders in section 5 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>Auction Data</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>489409</td>
<td>136798</td>
<td>38370</td>
<td>$ 2692.2 m</td>
<td>$ 454.7 m</td>
<td>16.9 %</td>
</tr>
<tr>
<td>Zone-indexed</td>
<td>202957</td>
<td>21825</td>
<td>5955</td>
<td>$ 1291.8 m</td>
<td>$ 139.5 m</td>
<td>10.8 %</td>
</tr>
<tr>
<td>Nodal</td>
<td>286452</td>
<td>114973</td>
<td>32415</td>
<td>$ 1400.4 m</td>
<td>$ 315.1 m</td>
<td>22.5 %</td>
</tr>
<tr>
<td>1 month</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</td>
<td>117091</td>
<td>35896</td>
<td>9939</td>
<td>$ 1113.1 m</td>
<td>$ 241.9 m</td>
<td>21.7 %</td>
</tr>
<tr>
<td>12 month</td>
<td>102786</td>
<td>29461</td>
<td>7003</td>
<td>$ 1232.9 m</td>
<td>$ 137.4 m</td>
<td>11.1 %</td>
</tr>
<tr>
<td>Retailers</td>
<td>1254</td>
<td>945</td>
<td>471</td>
<td>$ 325.3 m</td>
<td>$ 16 m</td>
<td>4.9 %</td>
</tr>
<tr>
<td>Generators</td>
<td>193880</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>218139</td>
<td>59951</td>
<td>15569</td>
<td>$ 1030.3 m</td>
<td>$ 266 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>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Awarded contracts data</th>
<th>N bids</th>
<th>Expenditures</th>
<th>Profits</th>
<th>ROI</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td></td>
<td>$ 3056.8 m</td>
<td>$ 502.5 m</td>
<td>16.4 %</td>
</tr>
<tr>
<td>Zone-indexed</td>
<td></td>
<td>$ 1712.5 m</td>
<td>$ 142.5 m</td>
<td>8.3 %</td>
</tr>
<tr>
<td>Nodal</td>
<td></td>
<td>$ 1344.3 m</td>
<td>$ 360 m</td>
<td>26.8 %</td>
</tr>
<tr>
<td>1 month</td>
<td></td>
<td>$ 380.1 m</td>
<td>$ 102 m</td>
<td>26.8 %</td>
</tr>
<tr>
<td>6 month</td>
<td></td>
<td>$ 1277.2 m</td>
<td>$ 245.4 m</td>
<td>19.2 %</td>
</tr>
<tr>
<td>12 month</td>
<td></td>
<td>$ 1399.5 m</td>
<td>$ 155.1 m</td>
<td>11.1 %</td>
</tr>
<tr>
<td>Retailers</td>
<td></td>
<td>$ 469.5 m</td>
<td>-32.8 m</td>
<td>-7 %</td>
</tr>
<tr>
<td>Generators</td>
<td></td>
<td>$ 1077.7 m</td>
<td>$ 207.9 m</td>
<td>19.3 %</td>
</tr>
<tr>
<td>Traders</td>
<td></td>
<td>$ 1509.6 m</td>
<td>$ 327.5 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. Footnotes describe discretionary categorization decisions. 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 New York electricity market are classified as traders, who are assumed to speculate with the motive to make profits from trading. 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.63


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).64

63Toole (2014) classifies firms into “speculator”, “hedger” and “unknown” categories, analyzing the types of derivatives these groups are more likely to purchase. The main difference between my list and that of Toole is that generating firms tend to fall into the hedging category in Toole’s analysis.

64Hydro 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.

Traders: 330 Fund I LP; AC Energy, LLC; Amber Power, LLC; Appian Way Energy Partners East, LLC; Aquila Energy Marketing Corp.; BJ Energy LLC; Black Oak Capital LLC; BNP Paribas Energy Trading GP; Boston Energy Trading and Marketing LLC; BP Energy Company; Cargill Power Markets, LLC; Centaurus Energy Master Fund, LP; Citadel Energy Products LLC; Citadel Energy Strategies LLC; Citigroup Energy Inc.; Credit Suisse Energy LLC; DB Energy Trading LLC; DC Energy LLC; DC Energy New England, LLC; DC Energy New York, LLC; DTE Energy Trading Inc; E.ON Global Commodities North America LLC; Emera Energy Services, Inc; Enron Power Marketing; ENTEGRA CAPITAL MANAGEMENT LP; Entergy-Koch Trading, LP; EPIC Merchant Energy L.P.; EPIC Merchant Energy NY LP; Franklin Power LLC; Galt Power Inc.; GRG Energy LLC; J Aron and Company; J. P. Morgan Ventures Energy Corporation; KFW Energy Trading, LLC; Lighthouse Energy Trading Co., Inc.; MAG Energy Solutions Inc.; Merchant Energy Group (MEGA); Merrill Lynch Capital Services, Inc.; Merrill Lynch Commodities, Inc.; Midwest Energy Trading East LLC; Morgan Stanley Capital Group, Inc.; Nalcor Energy Marketing Corporation; Northern States Power Company; Ocean Power LLC; Old Lane Commodities, LP; OPD Energy LLC; Orthogonal Energy, LLC; Petra Technical Consultant Group, LLC; PG&E Energy Trading; Powerex Corporation; Pythagoras Global Investors LP; Quark Power LLC; RAM Energy Products LLC; RBC Energy Services LP; Royal Bank of Canada; Saracen Energy East LP; Saracen Energy West LP; Saracen Energy, LP; Saracen Power LP; Sempra Energy Trading LLC; SESCO Enterprises LLC; SIG Energy, LLLP; Silverhill Ltd., GP for Power Fund LPs.; Solios Power LLC; Split Rock Energy LLC; TransAlta Energy Marketing (U.S.) Inc.; Twin Cities Power, LLC; TXU Energy Services; Viridian Energy NY, LLC; Vitol Inc.; Williams Power Company Inc.

New York Power Authority (NYPA) is a publicly owned generator owner but does not have a standard profit maximization objective function. For the analysis of auction positions in this paper, NYPA’s classification is irrelevant as they never purchased a TCC at auction, with their only positions existing from grandfathered TCCs.
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; Hadsell 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:

\[ q_{i,j,t,f} \cdot (T_2 - T_1) \cdot (r_{i,j,t} - p_{i,j,t}) = \alpha + \epsilon_{i,j,t} \tag{D1} \]

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.\(^{66}\) 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

\(^{66}\)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 restricted to issued contracts.
67 month duration contracts. 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 \( r = E(r) + \epsilon \), 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 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>( \hat{\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.

Table D2 further extend the tests of the efficient market hypothesis for partitions of contracts by the performance of that derivative in the previous auction. Outlined in section 5.2, 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.

**Appendix D2: Derivative payouts and downstream actions**

Table D3 displays estimates of the equation reported in section 4.2.3:

\[
 r_{i,j,t} - p_{i,j,t} = \sum_{f \in F} \delta f I^0_{i,j,t,f} + \sum_{f \in F} \rho f Q_{i,j,t,f}^{POST} + \epsilon_{i,j,t}
\]

This result is invariant to aggregating or disaggregating 6- or 12-month products.
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>( (6,807) ) ( (2,614) ) ( (3,612) ) ( (16,035) ) ( (4,656) )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></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>( (6002) ) ( (6913) ) ( (6422) ) ( (7276) ) ( (32,016) )</td>
<td>6002</td>
<td>6913</td>
<td>6422</td>
<td>7276</td>
<td>32,016</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.

Table D3: Estimates of average monthly derivative payouts

|                      | All $|p_{i,j,t}| = 1686$ | Nodal $|p_{i,j,t}| = 1667$ | Zonal $|p_{i,j,t}| = 3821$ |
|----------------------|-----------------|------------------|------------------|
| $\delta_{RET}$ $[P_{RET,t}]$ | 4.37            | 130.89           | -60.73           |
|                      | \( (117.24) \)  | \( (174.67) \)  | \( (137.35) \)  |
| $\delta_{GEN}$ $[P_{GEN,t}]$ | 96.95           | 103.07           | 3.40             |
|                      | \( (42.93) \)   | \( (44.66) \)   | \( (101.65) \)  |
| $\delta_{TRA}$ $[P_{TRA,t}]$ | 170.26          | 184.69           | -85.01           |
|                      | \( (46.67) \)   | \( (46.89) \)   | \( (137.25) \)  |
| $\rho_{RET}$ $[Q_{POST,RET,t}]$ | -0.26           | -0.24            | -0.33            |
|                      | \( (0.22) \)    | \( (0.20) \)    | \( (0.33) \)    |
| $\rho_{GEN}$ $[Q_{POST,GEN,t}]$ | 0.24            | 0.04             | 1.08             |
|                      | \( (0.19) \)    | \( (0.15) \)    | \( (0.59) \)    |
| $\rho_{TRA}$ $[Q_{POST,TRA,t}]$ | 0.03            | -0.02            | 0.42             |
|                      | \( (0.31) \)    | \( (0.38) \)    | \( (0.55) \)    |
| N                    | 1,151,374       | 1,140,868        | 10,506           |
| $N_A$                | 235             | 235              | 235              |

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 A1. $i,j$ or $j,i$ direction is arbitrary: $(p_{i,j} = -p_{j,i}, r_{i,j} = -r_{j,i})$.

Comparing the estimates of table D3 to table 3, 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
firms performing 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 $\hat{\rho}_{GEN} = 0.04$ 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 $\frac{0.04 \times 24.72}{804.52} \times 100 = 0.1c$ per dollar value of the position. This premium represents a small fraction compared to the 12.9c predicted premium collected on nodal contracts of any size won by generating firms implied by the $\delta_{GEN}$ value.

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 suggest that if virtual market manipulation is captured by the marginal increase in payouts from increasing firm open positions then it is estimated to be at most 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

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

Here, $F$ is the set of all 130 firms ever observed to buy a TCC. Figure D2 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 D1 displays the aggregate profits and aggregate expenditures incurred by each firm in the data, with the six major firms that are detected to earn systematic profits ($\delta_f > 0$) at a 10% test size marked on the chart.\footnote{The coefficients in figure D2 show that some richness in the heterogeneity is lost by collapsing firms} The six major firms observed to have statistically detectable values of $\delta_f$
greater than zero, consistent with the collection of information rents, are EDF Trading North America, Boston Energy Trading and Marketing, Hydro Quebec, DC Energy, 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 D1: 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.
Figure D2: Estimates of payout premiums by firm

(a) All point estimates

(b) All point estimates with 95% confidence intervals not covering zero.

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.