

# Risk and Abnormal Returns in Markets for Congestion Revenue Rights

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## Abstract

*In organized energy markets that use locational pricing, power generators and energy suppliers use Financial Transmission Rights (FTRs) to hedge against grid congestion charges, while third party speculators attempt to capture a return with these contracts. FTRs are defined between two locations on the power transmission grid, known as a path. These financial instruments accrue their value based on the energy price differential at two ends of a path. Having the only organized energy market in the Western Interconnection, California has also implemented a version of FTRs, officially known as Congestion Revenue Rights (CRRs). This paper investigates the performance of the CRR markets by estimating and analyzing the systematic risk and presence of abnormal returns among these financial instruments. Our analysis identifies the paths with abnormal CRR returns with the majority of them being positive.*

**Keywords:** Financial transmission right, Congestion revenue right, Hedging, Transmission, Congestion, Electricity market

**JEL Classification:** C58, G1, L9, Q4

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<sup>3</sup> The opinions expressed in this paper are the authors' opinions only, and do not necessarily represent the views of the Commission nor of any of the Commissioners. Rimvydas Baltaduonis' work on this research was made possible by appointment as a Visiting Senior Scholar in FERC's Division of Analytics and Surveillance in the Office of Enforcement. The authors would also like to acknowledge two Gettysburg College students – Nathan Blyler and James Myers – for their early work and research assistance on the precursor project titled "Risk and Abnormal Returns in Markets for Financial Transmission Rights."

## **1 INTRODUCTION**

The deregulated electricity markets in the United States serve hundreds of millions of consumers every day. Consisting of a complex grid of generators, transmission lines and system operators, this market is becoming strained as demand for electricity rises while the underlying infrastructure of the grid ages. Though innovations in technology may allow us to tap into new energy reserves in the future and investment in new infrastructure may help to ease this burden, the grid will still have to facilitate an ever increasing flow of energy. The challenge of accommodating sometimes unpredictable renewable energy power flows and linking distant renewable energy sources to the grid will be a primary factor leading to this system-wide increase in the power flow. As a result, energy suppliers will face ever increasing exposure to the risks of transmission grid failure and congestion that, if not managed properly, could lead to higher costs, lower profits and even large losses.

In many power markets, energy is traded at points on the power grid known as nodes. Each node has a price called the Locational Marginal Price (LMP). One may think of this price as the sum of the price of energy, the price of congestion and the price of transmission losses at a particular location. The price of energy is constant at all nodes within a given market. Differences between LMPs are due to the congestion and loss components. As demand for energy rises at a given location, power lines servicing the area approach their rated capacity and as a result, the price of congestion at the associated node rises. Consequently, this causes the respective LMP to rise as well. While the transmission losses will vary by location, generally the largest driver of the variation in LMPs is congestion. This paper examines the use of a financial instrument known as a Financial Transmission Right obligation – hereafter FTR - to avoid potentially extreme congestion charges. We particularly focus on the California's markets for FTRs, which officially are known as Congestion Revenue Rights or simply CRRs.

To better grasp the concept of an FTR, imagine the following example. An energy supplier must transport energy from a generator at point A to consumers located at point B. The energy supplier is locked into a contract and must supply energy to point B even if it would mean taking a loss. A loss would arise due to a difference in the LMPs resulting from congestion between points A and B. On a really hot day, consumers at point B would require more power as a result of the increased air conditioning usage. As the demand for power at point B rises and the flow of energy reaches the capacity of the transmission lines leading to point B, congestion charges begin to accumulate. If the demand is high enough, these congestion charges could be extreme. To hedge against such a situation, an energy supplier could acquire an FTR from point A to point B in a monthly, quarterly or annual auction and be paid an amount that would counter these congestion charges as energy is delivered from point A to point B. That is because the value of an FTR is equal to the difference between the associated congestion charges and its market clearing price, which is set in an auction. While these financial instruments may allow one to hedge against volatile congestion charges, they can also result in very significant losses. The losses from FTR positions can be significant if the power flow unexpectedly changes its usual direction between the locations of interest. This normally happens due to changing physical conditions on the grid (e.g., temporarily down power lines, power plant outages, unexpected weather patterns, etc.). Therefore, a model that properly assesses the risk associated with an FTR and accounts for the dynamic nature of the grid is needed when deciding on bidding strategies for various FTR positions.

The objective of this paper is to build an analytical framework for assessing the performance levels of FTR markets and applying the methodology to California's CRR market. To do this, we build on the capital asset pricing model (CAPM) approach of Sharpe (1964) and

Lintner (1965). This model is then estimated using a generalized autoregressive conditional heteroskedastic (GARCH) process that accounts for the dynamic nature of the power grid.

For our purposes we used publically available data to examine all CRRs acquired in annual and monthly auctions<sup>4</sup> in the California Independent System Operator (CAISO) region. Both On-Peak and Off-Peak contracts were included in this analysis.<sup>5</sup>

“CAISO” is used to refer to the footprint of the regional grid operator in California. It oversees a unique market in that it is the only organized wholesale energy market in the Western Interconnection and it does not border any other regional transmission organization (RTO) or independent system operator (ISO). This regional isolation means that California’s options to trade electricity competitively with the neighboring states are less developed and contributes to higher price volatility relative to the interconnected regional markets. In our study, we find that CRR profitability in California appears unusually persistent.

In the section that follows we review relevant literature. In Section 3, we build a framework for evaluating the performance of a FTR/CRR. Section 4 applies our analytical framework to the CRR markets in CAISO. Section 5 reports the empirical findings. Section 6 concludes our paper.

## **2 RELATED LITERATURE**

Since the proposal of FTR formulation (Hogan 1992), little research has been conducted to study returns in FTR markets. However, academic research has explored other related topics. Initially, researchers were concerned with the potential use of FTRs to exert market power (Oren *et al.* (1995); Stoft (1999); Bushnell (1999)). Joskow & Tirole (2000) investigated the use of FTRs

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<sup>4</sup> A large number of CRRs is also distributed to certain market participants such as Load Serving Entities (LSEs), i.e., utilities that provide power to the final consumer, at no cost. The intention is to provide means for hedging against unpredictable grid congestion in energy spot markets.

<sup>5</sup> On-Peak hours are from 6 am to 10 pm Mon-Sat while Off-Peak hours are from 10pm to 6am Mon-Sat and 24 hours on Sunday and Holidays.

and physical transmission rights (PTRs) and argued that both reduce overall welfare by enhancing market power in firms that already control a large part of the market. Kench (2004) conducted laboratory economic experiments to compare FTRs to PTRs and concluded that PTRs are suited better for regulating market power via reallocation of rights. More recently, Henze, Noussair & Willems (2012) studied regulation alternatives for network infrastructure investments in a laboratory setting where one of the treatments employed long term FTRs. The authors concluded that FTRs failed to improve upon simple price-cap regulation and caused relatively lower investment.

When PJM – one of the largest organized energy markets in the world – implemented an auction-based market for FTRs (Ma, Sun & Ott (2002)), the auction design came under intense scrutiny. Studies suggested that FTR auction markets were inefficient. Even after controlling for lagged information and risk aversion among bidders, the unexplained differences in FTR prices remained (Adamson & Englander (2005)). Deng, Oren & Meliopoulos (2010) argued that those differences could partially be explained by the number of bids in a sale implying that the limits on the number of bids could yield even greater inefficiencies in market outcomes. Jullien *et al.* (2012) examined different types of transmission capacity auctions, but none performed well enough to relieve the network economy of inefficiency. Theoretically, an auction-based market can become efficient. However, as Alomoush & Shahidehpour (2000) pointed out, a more liquid secondary market and greater availability of FTRs to all market participants might be needed.

Although the auction-based FTR markets were criticized for being inefficient, their ability to provide financial services, i.e., hedges against potential losses, in restructured energy markets have had more positive reviews. Mendez & Rudnick (2004) argued that a hedging mechanism was needed in markets that employ LMPs because of potentially large financial obligations. They

found FTRs to be the best available hedge in restructured organized markets. This was supported by Kristiansen (2004) who viewed FTRs as a way to increase efficiency in the market by adding incentive for less efficient users to sell their FTRs to more efficient ones. Problems, however, emerge when high transaction costs in the market lowers liquidity, resulting in an excessively high risk premium paid by investors and making market correction unprofitable (Siddiqui *et al.* (2005)).

Mount & Ju (2014) proposed an econometric framework for evaluating the efficiency of a market for FTRs and applied it to three Transmission Congestion Contracts (TCC), which are FTR equivalents in the state of New York. Their approach relied on the comparison of the ex-ante expected returns and the paid market prices. They concluded the lack of evidence for consistent TCC under-pricing, but acknowledged the limitations of their study as they looked at only one TCC auction from 2006 summer.

Given that FTR markets have been around for quite some time now, it is surprising that technical approaches to value highly volatile FTR returns are still largely underexplored. The main focus of the aforementioned studies with an exception of Mount & Ju (2014) is to explore how firms may use FTRs to maximize their profits under various institutional arrangements. The insights from the observations are then used to offer various policy prescriptions. These studies do not look directly at the return profile that firms face in FTR markets. Our paper focuses precisely on studying FTR returns. More specifically, it evaluates the systematic risk of CRRs and identifies paths with abnormal returns.

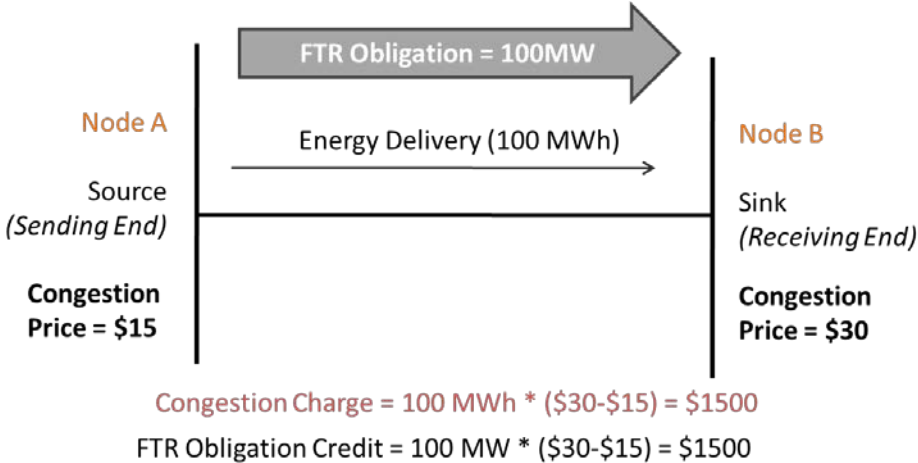
### **3 AN FTR VALUATION MODEL**

#### **3.1 Measuring an FTR return**

Let's look at an example to better understand how FTRs/CRRs work. Consider a hypothetical path between two points, Node A and Node B. In Figure 1, if Node A has a congestion

price of \$15 and Node B has a congestion price of \$30 then the FTR is worth \$15 per megawatt hour (MWh). Since the energy in this example flows from Node A to Node B and the FTR path is from source A to sink B, i.e., in the same direction as the energy flow, this FTR is typically called a prevailing flow position. For a prevailing flow FTR, the market clearing price, which represents the cost of acquiring an FTR in an auction, tends to be positive. However, an FTR may have a negative market clearing price when the FTR path is in the opposite direction of the usual energy flow. This is often called a counter flow position. It means that the bidder will receive a credit for taking on the risk of the counter flow position in the FTR auction. In this case, the FTR will have positive returns if this initial credit is greater than the sum of congestion charges paid out by the market participant. If the amount paid out as congestion charges is greater than the value of the original credit, then the FTR owner will experience a net loss on the position.

**FIGURE 1** An FTR example.



The presence of negative as well as positive FTR market clearing prices creates an interesting dilemma when attempting to calculate the return of the path. If an FTR has a positive market clearing price, then the *return of a prevailing flow FTR* can be computed as:

$$R_i = \frac{\pi_i}{P_i} \times 100\% \tag{1}$$

where  $\pi_i$  is an accumulated profit or loss per MW from holding the FTR over path  $i$  and  $P_i$  is the market clearing price (\$/MW) of the FTR.

For a path with a positive FTR market clearing price, computing returns is straightforward. However, if the market clearing price is negative, then the above equation provides an inaccurate picture of the actual return. For example, in a prevailing flow position, if the final profit is \$10 and the market clearing price is \$20, the rate of return for the month is 50 percent. But imagine a counter flow position with the final profit of \$10 and the market clearing price of -\$20. The negative market clearing price indicates a credit of \$20. This means that, if we calculated the return of the counter flow position in the same manner as the prevailing flow, the return would be \$10 divided by negative \$20, which would misleadingly appear as a negative return (i.e., -50%), when, in fact, the return was positive. This can be easily resolved if one thinks of the absolute value of the market clearing price as a benchmark for measuring returns. The method for calculating both prevailing flow and counter flow FTR returns is shown in Equation 2:

$$R_i = \frac{\pi_i}{|P_i|} \times 100\% \quad (2)$$

When profit is divided by the absolute value of the FTR's market clearing price, the rate of return of a counter flow position is computed with respect to the funds spent by the auctioneer. The calculation of the rate of return is not altered by this modification for a prevailing flow position.

### **3.2 Measuring abnormal return of an FTR**

The CAPM framework, detailed below, provides grounds for analyzing the returns of traded financial assets. This approach could be a reasonable starting point for investigating FTR returns as well. CAPM was first developed by William Sharpe (1964) and Lintner (1965). The



model assumes that investors are risk averse and that they choose “mean-variance-efficient” portfolios. This means that the individual investor tries to minimize the return volatility given the expected return and attempts to maximize the expected return given the volatility of returns. The original Sharpe-Lintner CAPM equation can be represented as:

$$E(R_i) = R_f + \beta_i[E(R_M) - R_f] \quad (3)$$

where the assets are indexed by  $i=1, \dots, N$ . The model makes two major assumptions: 1) complete agreement among investors about the joint distribution of the asset returns from time  $t-1$  to time  $t$  and 2) both borrowing and lending can take place at a risk free rate. Note that the model does not require the assets to generate their returns in perfectly competitive markets. That certainly would not be the case for many FTRs as some previous literature suggests. The equation above simply states that the expected return  $E(R_i)$  on any asset  $i$  will be equal to the risk free interest rate,  $R_f$ , plus a risk premium,  $\beta_i$ , relative to the expected excess market return,  $E(R_M) - R_f$ . Beta can be interpreted as the sensitivity of the asset return to fluctuations in the overall market and therefore represents the systematic risk inherent in the asset.

Jensen (1968) argued that the Sharpe-Lintner equation could naturally be estimated using a time-series regression. He noted that the CAPM above assumes that an asset’s excess return,  $E(R_i) - R_f$ , can be completely explained by the average value of the market’s excess return,  $E(R_M) - R_f$ . This implies that in a time series regression an intercept term would have to equal zero for each asset. This intercept term became known as “Jensen’s alpha” or  $\alpha_i$ . Equation 3 can be transformed into a time-series regression model shown in Equation 4:

$$R_{it} - R_{ft} = \alpha_i + \beta_i[R_{Mt} - R_{ft}] + \mu_{it} \quad (4)$$

where the assets are indexed by  $i=1, \dots, N$  and  $\mu_{it}$  represents an error term that satisfies  $E(\mu_{it}) = 0$  and is serially independent.

As noted by Jensen, under the Sharpe-Lintner assumptions the intercept point, alpha, should equal zero. Thus, a cross-sectional regression should yield an estimate of the intercept that would not be statistically different from zero. But early empirical tests of the model, conducted by Douglas (1968), Miller & Scholes (1972), Blume & Friend (1973), Jensen *et al.* (1972), Fama & MacBeth (1973) and Fama & French (1992), provided evidence that intercept terms for many financial assets were statistically greater than zero. The cross-sectional regression test by Fama & Macbeth (1973) and time series tests by Gibbons (1982) and Stambaugh (1982) have provided support for rejecting the theory that the excess return per unit of beta is the expected return of the market portfolio minus the risk free rate. Since then, the non-zero Jensen's alpha has been interpreted as the abnormal return of an asset. Given that we are interested in capturing the presence of abnormal returns of FTRs, a modified Sharpe-Lintner CAPM equation, which we name Financial Transmission Right Pricing Model (**FTRPM**), would provide us with alpha,  $\alpha_i$ , as an indicator for the existence of abnormal returns.

### 3.3 Estimating the model

The physical nature of the transmission grid creates a challenge for econometric modeling of FTR returns. Over time, power markets evolve as a result of new transmission lines being added and old ones being taken down. Other factors such as temporarily down lines, power plant outages and seasonal weather patterns also have dramatic impacts on grid conditions. These factors influence congestion patterns on the grid that can persist for weeks, months and even years. Therefore, when modeling FTR returns, an estimation process must account for conditional non-constant variance.

Given these requirements, a type of autoregressive conditional heteroskedastic (ARCH) process for the estimation of the model's parameters is advantageous over the ordinary least squares (OLS) estimation, which assumes constant variance. The ARCH process was first introduced by Engle (1982) as a means to account for the non-constant variance of returns as well as for movement between periods of high and low volatilities in financial markets. Bollerslev (1986) built on Engle's work with the introduction of a generalized version of ARCH known as a generalized autoregressive conditional heteroskedastic (GARCH) process, which we employ to estimate our proposed regression models.

Since the GARCH process aims to account for conditional non-constant variance, the remaining residuals of a well fitted GARCH model should be independent. The Brock-Deschert-Scheinkman (BDS) test, described in Brock et al. (1996), gives an indication of the adequacy of the GARCH model by testing the null hypothesis of independent and identically distributed standardized residuals. We use the BDS tests with embedding dimensions two through five and a radius of one standard deviation (using 99 percent confidence level) to filter the converged regressions before further analysis.

### **3.4 Hypotheses and Treatments**

#### *Abnormal returns of CRR contracts*

In a competitive financial market, abnormally high returns should not persist from month to month because participants are able to respond to persistent market signals and adjust positions and bidding behavior over time. CRR paths with abnormally large returns (positive *alphas*) should attract more demand in consecutive monthly auctions. Because CAISO limits the amount of megawatts available on any given path, participants must outbid each other to win awards. This would cause the clearing price of a CRR to rise leading to a decrease in the CRR return. Likewise,

CRR paths with abnormally negative returns should experience lower participation making them cheaper to obtain and thus eliminating persistent negative returns. Over time, persistent gains or losses should diminish. Therefore, in a competitive market, one would expect that abnormal returns would not be present.

*Actual Costs versus Prompt-Month Price as a Marker for the CRR Cost*

Since a market participant could potentially buy a long dated contract on a given path at an annual auction and then sell it back at a monthly auction to other market participants or even back to the ISO itself, we use the actual volume-weighted CRR prices when measuring the monthly path returns and estimating our FTRPM regressions. However, one may argue that a more fitting way to capture the market value of a CRR would be to use the latest available market price, i.e., the CRR price from a prompt-month auction. A seasonal contract that is acquired long time before the month of interest will be priced with a larger uncertainty in mind. As the month of interest approaches, conditions that create congestion are easier to predict and therefore value. Therefore, as a robustness check for our findings, we also conducted the same FTRPM estimations by using prompt-month prices rather than the actual costs for each held CRRs. We refer to this estimation treatment hereafter as FTRPM-M. A prompt-month price should reflect not only more available information relative to an annual auction price but potentially more competition too. Participants who cannot lock their financial capital for extended periods of time such as arbitrageurs or short term hedgers may see value in joining a monthly CRR auction. Therefore, one would expect fewer (if any at all) CRRs with abnormal returns when using the FTRPM-M estimation relative to the original FTRPM approach.

### *Risk of On-Peak versus Off-Peak CRRs*

The CRRs accrue value by the hour as congestion prices fluctuate at each node. The On-Peak CRR positions accrue value during On-Peak hours, which are from 6AM to 10PM Monday-Saturday in the CAISO region. Alternatively, the Off-Peak CRRs accrue value during the Off-Peak hours, i.e., 10PM to 6AM Monday-Saturday and 24 hours on Sundays and Holidays.

Since On-Peak hours are during the time of the day, when energy demand is highest, On-Peak CRR returns should be more volatile than their Off-Peak counterparts. When energy demand is high, the volatility of congestion charges is higher too, since more energy must be transported across the grid increasing the likelihood of congestion. As the grid approaches its transmission capacity constraints, the congestion prices become positive. Therefore, On-Peak CRR returns should face more uncertainty than the Off-Peak positions when many congestion prices are simply equal to zero. Due to this higher congestion volatility during the On-Peak hours, we expect the On-Peak CRRs to have higher betas than their Off-Peak counterparts and a wider distribution of betas relative to the Off-Peak CRRs.

## **4 CAISO'S CRR MARKET**

The CAISO CRR market is one of the smaller markets for congestion contracts in the U.S. and has historically exhibited an unusual returns profile relative to other markets for congestion contracts. Also, where some markets have over a hundred participants, CAISO has a consistently smaller participant pool, though the number has been growing in recent years (Table 1).

**TABLE 1** The number of market participants that purchased CRRs overtime.

<b>Year</b>	<b>2009</b>	<b>2010</b>	<b>2011</b>	<b>2012</b>	<b>2013</b>	<b>2014</b>	<b>2015</b>
Participants	43	41	47	46	56	57	69

To study the patterns of abnormal returns in this market, we acquired data produced by CAISO that includes information on CRR market clearing prices and accumulated monthly revenues. Our data for all CRR holdings spans from April 2009 to December 2015, which provides us with 81 monthly periods, 2,285,947 CRR contracts and a total of 852,636 monthly observations across 199,866 paths. 1,110,926 of these contracts were awarded at monthly auctions while 1,175,021 were awarded at seasonal auctions. We converted these seasonal contracts to individual monthly positions for the purposes of our study. 1,209,521 of the CRRs were contracts that covered On-Peak hours of the day while 1,076,426 covered Off-Peak hours. Additionally, while some contracts were written to benefit holders when congestion exists in the prevailing direction of electricity flow, 1,088,779 contracts in our analysis were counter flow contracts. Finally, 1,095,843 contracts across 30,247 paths were not auctioned and were instead given to LSEs to hedge the consumer against price volatility. Since these particular contracts were not awarded via markets, they were excluded from our analysis. To estimate the regressions, we further limited our dataset only to those paths where CRR contracts were successfully auctioned for at least 30 months during the period of the study.

In order to estimate our proposed model, represented by Equation 4, we calculate individual CRR returns, assume a monthly risk free rate of return, and calculate market portfolio returns for each month in the study. For the risk free rate,  $R_f$ , the monthly return of One-Month Constant Maturity Treasury Bill is used.<sup>6</sup> The risk free rate is subtracted from the individual CRR returns to obtain the excess CRR returns, which are used as the dependent variable in the individual CRR regressions.

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<sup>6</sup> Source: the Federal Reserve Bank of St. Louis

Equation 6 shows the calculation of a CRR return for a given path and month, i.e., unique combination of source, sink, peak type (Off-Peak or On-Peak) and month. It follows the general FTRPM framework described above and represents Equation 2:

$$R_i = \frac{Revenue_i * TotalMW_i - \sum_{j=1}^M Cost_{ij} * HeldMW_{ij}}{\left| \sum_{j=1}^M Cost_{ij} * HeldMW_{ij} \right|} \times 100\% \quad (6)$$

where  $R_i$  is the CRR<sub>*i*</sub> return for the path across all market participants who held the CRR exposure during the relevant month. The different market participants ( $j=1, \dots, M$ ) have their individual costs ( $Cost_{ij}$ ) and held quantities ( $HeldMW_{ij}$ ), which are multiplied individually and then summed to find the total cost of the CRR across all participants.  $Revenue_i$  is the day-ahead congestion charges (\$/MW) that were collected by the CRR holders for that path-month.  $TotalMW_i$  is the sum of held megawatts across all the market participants, given by Equation 7:

$$TotalMW_i = \sum_{j=1}^M HeldMW_{ij} \quad (7)$$

One adjustment that was made in calculating CRR return  $R_i$  was that if the total cost of contracts for a given path were found to equal \$0.00, we replaced it with \$0.01. Because a cost of a penny is usually very small compared to a profit/loss of thousands of dollars, this alteration maintained the large returns in those instances while preventing indeterminate values that would have resulted from the division by zero.

In the spirit of CAPM theoretical framework, we treat CRR financial market as an isolated economic system<sup>7</sup> and proceed with the calculation of the Market Portfolio return ( $R_M$ ) for a given month using Equation 8:

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<sup>7</sup> Note that CAISO does not auction CRR options, though some entities may be allocated free longer term CRR options to account for particular transmission ownership or contract situations.

$$R_M = \sum_{i=1}^N \left( R_i \times \frac{TotalMW_i}{TotalMW_M} \right) \quad (8)$$

where  $TotalMW_i$ , as above, is the sum of all held megawatts across the market participants for a given path and  $TotalMW_M$ , given by Equation 9 below, is the sum of all held megawatts for a month across every path ( $i=1, \dots, N$ ):

$$TotalMW_M = \sum_{i=1}^N TotalMW_i \quad (9)$$

The summary statistics of the returns of CRRs, Market Portfolio and One-Month Constant Maturity T-Bill are presented in Table 2. Table 2 shows high kurtosis and large standard deviations of the CRR returns. These numbers point to significant volatility and fat tails in the aggregate distribution of the CRR returns. These are a result of sudden and large congestion charges that accrue during periods of constrained grid conditions. The largest positive return of a CRR in our dataset is 179,908,576% - an extraordinary return for any financial market. The largest loss observed in our dataset, -141,153,700%, is as impressive.

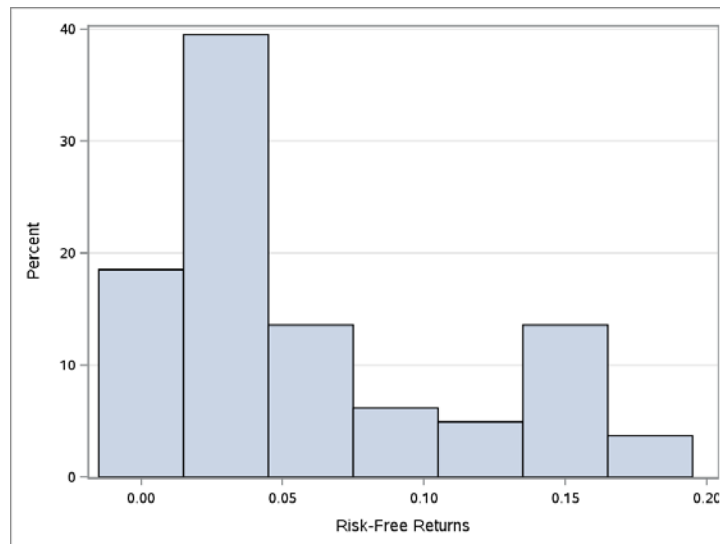
A histogram of One-Month Constant Maturity T-Bill returns is presented in Figure 2 and a histogram of the excess return of the Market Portfolio is shown in Figure 3. A truncated distribution of individual CRR excess returns is depicted in Figure 4. Note that many CRRs have rates of return equal to 100% or -100%. These represent the contracts that were auctioned but did not experience congestion in a given month. Therefore, as  $Revenue_i$  is equal to 0, Equation 6 will yield  $R_i=-100%$  for prevailing flow paths and  $R_i=100%$  for counter flow paths.



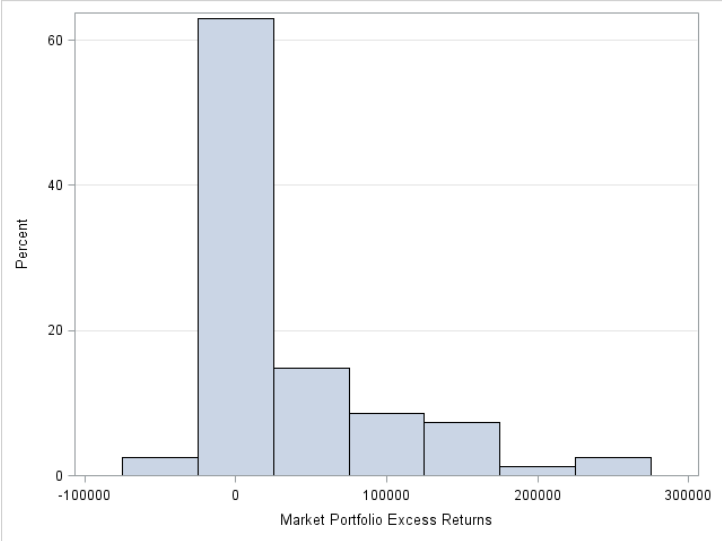
**TABLE 2** The summary statistics for the monthly returns of Market Portfolio, One-Month Constant Maturity T-Bill and auctioned CRRs.

Monthly Return (100%)	Paths	Obs	Mean	Median	Min	Max	Std. Dev	Kurtosis
Market Portfolio		81	35528	10453	-64834	267178	60967	4
One-Month Constant Maturity T-Bill		81	0.058	0.040	0	0.180	0.052	-0.410
All CRRs	199866	852636	8352	3.5	-141153700	179908576	561946	20656
On-Peak	106893	439411	12686	-4.2	-141153700	90198044	683571	6890
Off-Peak	92973	413225	3744	16.5	-36984165	179908576	393265	110816
30+ obs CRRs	3834	174199	16586	-77.9	-141153700	179908576	884452	15553
On-Peak	1911	86597	22460	-59.1	-141153700	90198044	1008935	6337
Off-Peak	1923	87602	10779	-91.5	-13673436	179908576	741084	41231
30+ obs CRRs (excess return)	3834	174199	16586	-77.9	-141153700	179908576	884452	15553
Market Portfolio (excess return)		81	35528	10453	-64834	267178	60778	3

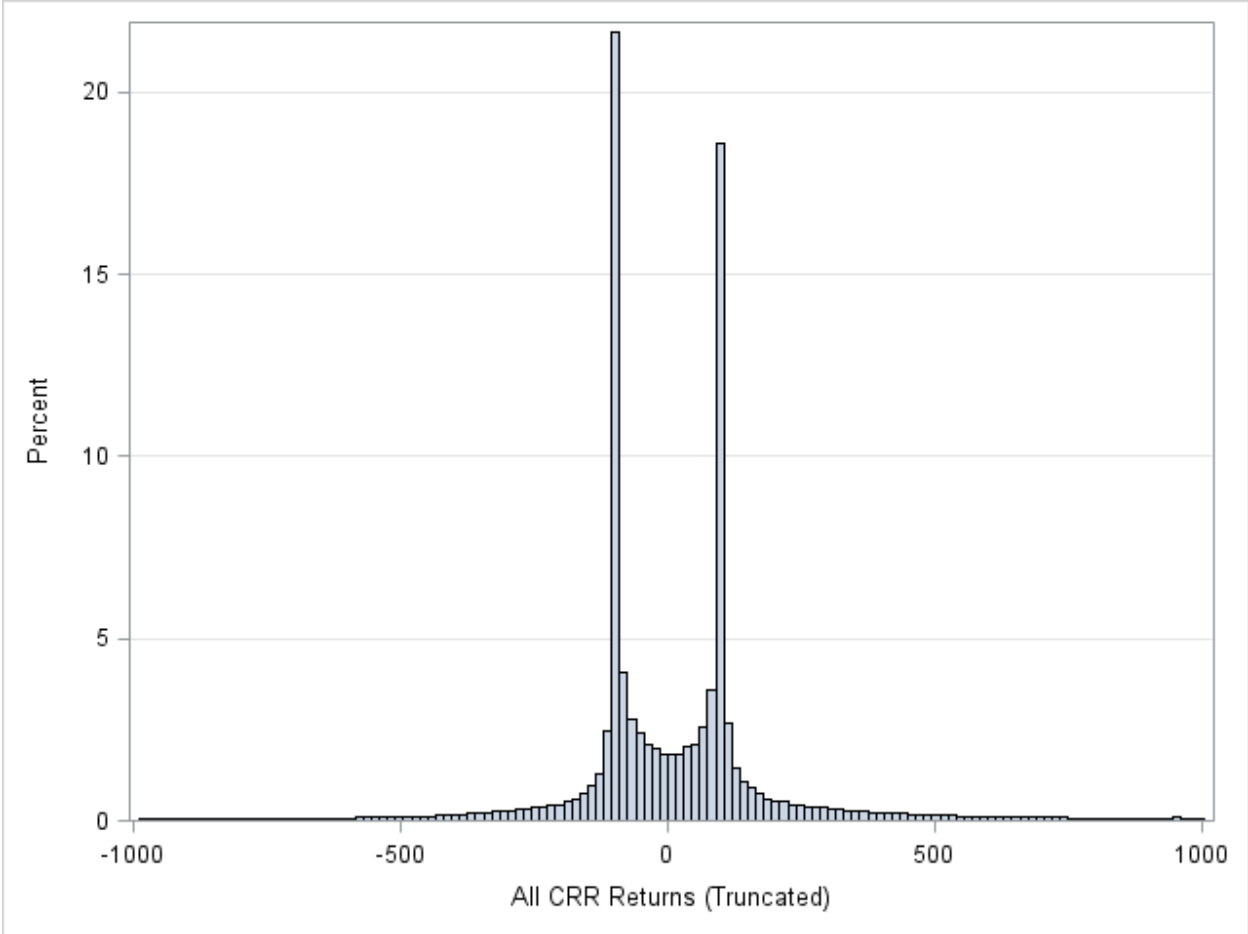
**FIGURE 2** A histogram of One-Month Constant Maturity T-Bill returns (%).



**FIGURE 3** A histogram of the Market Portfolio excess returns (%).



**FIGURE 4** A histogram of all CRR excess returns truncated at -1000% and 1000%.



## 5 EMPIRICAL RESULTS

Overall, our GARCH regression results achieved a high convergence rate. 3,678 of 3,834 FTRPM regressions converged, yielding a convergence rate of 96%. We then eliminated the paths with estimated regressions that violated error independence leaving us with 2,829 paths (77% of the converged regressions) for our further analysis. Table 3 presents the number of paths where the BDS test failed to reject the null hypothesis of error term independence with embedding dimensions  $M=2, \dots, 5$  and a radius of one standard deviation at 99 percent confidence level.<sup>8</sup>

**TABLE 3** Summary of BDS test results for the FTRPM regressions.

<b>BDS Tests</b>	<b>CRRs Passing BDS tests (as % of 3678 Converged Regressions)</b>
M = 2	3,215 (87.4%)
M = 3	3,166 (86.1%)
M = 4	2,986 (81.2%)
M = 5	3,059 (83.2%)
M = 2, 3, 4, and 5	2,829 (76.9%)

**FINDING 1** The significance of the Market Portfolio excess return ( $R_M - R_f$ ) in the FTRPM regressions is widespread.

The FTRPM estimated 2,290 paths with statistically significant ( $p\text{-value} \leq 0.1$ ) beta coefficients for Market Portfolio excess return, which represents about 81% of regressions in the analysis. This suggests that, for the majority of paths, the FTRPM is justified in using  $R_M$  to explain an individual CRR's return volatility. Figure 5 graphs these betas, the measure of systematic risk for each path, against the average CRR return for the market. The majority of paths have betas that fall within the interval of zero and one. The fitted trend line represents an empirical security market

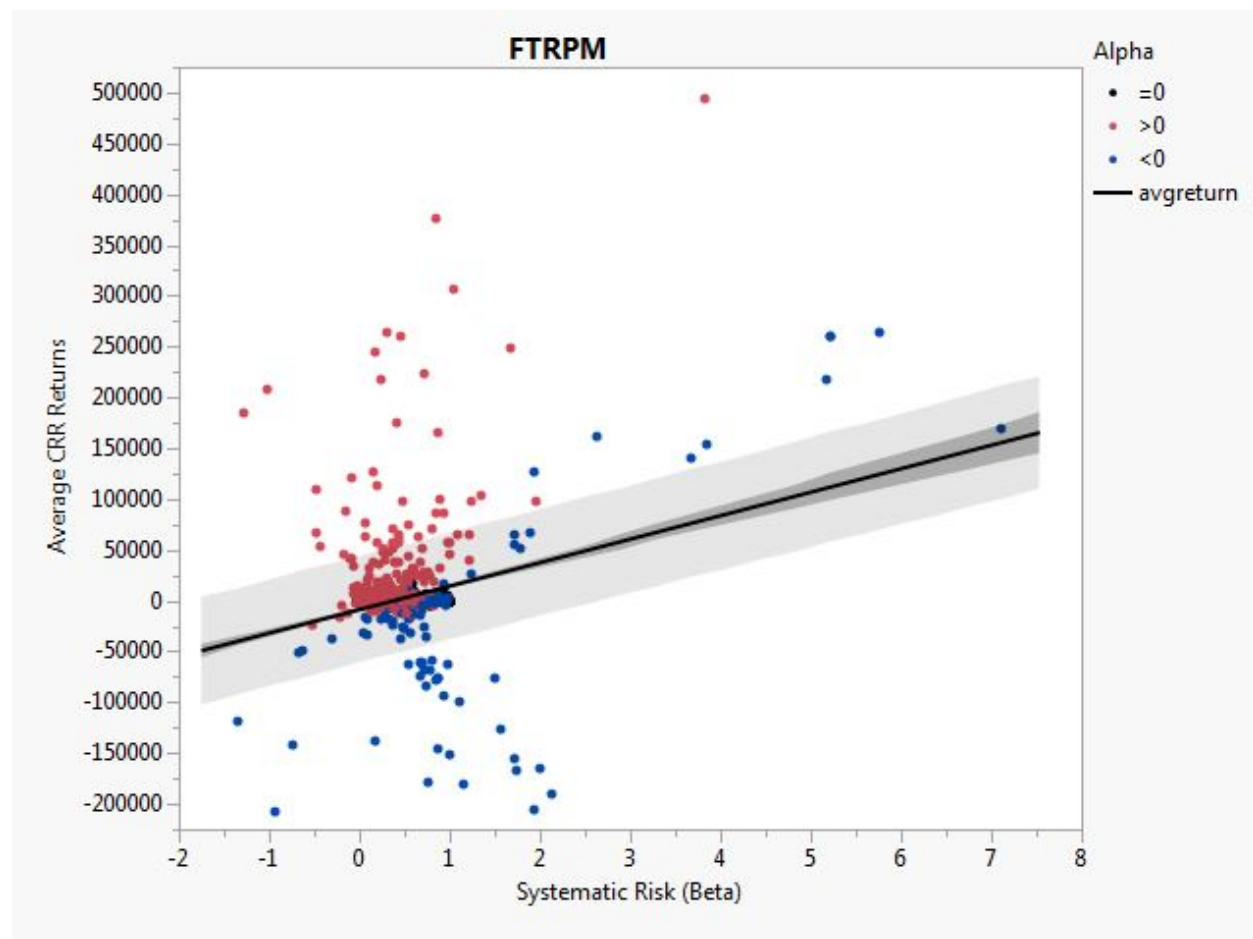
<sup>8</sup> Very similarly, the BDS tests failed to reject the null hypothesis of error term independence for 71% of the converged regressions in the FTRPM-M treatment with the convergence rate being 98%.

line for the estimated CRRs. As CAPM theory would suggest, the trade-off between risk and return is positive.

The number of regressions with significant ( $p\text{-value} \leq 0.1$ ) betas was 1,701 paths (64% of analyzed regressions) in FTRPM-M.

These results reaffirm our use of the CAPM framework to study CRR returns.

**FIGURE 5** An empirical security market line for the FTRPM estimated CRRs.



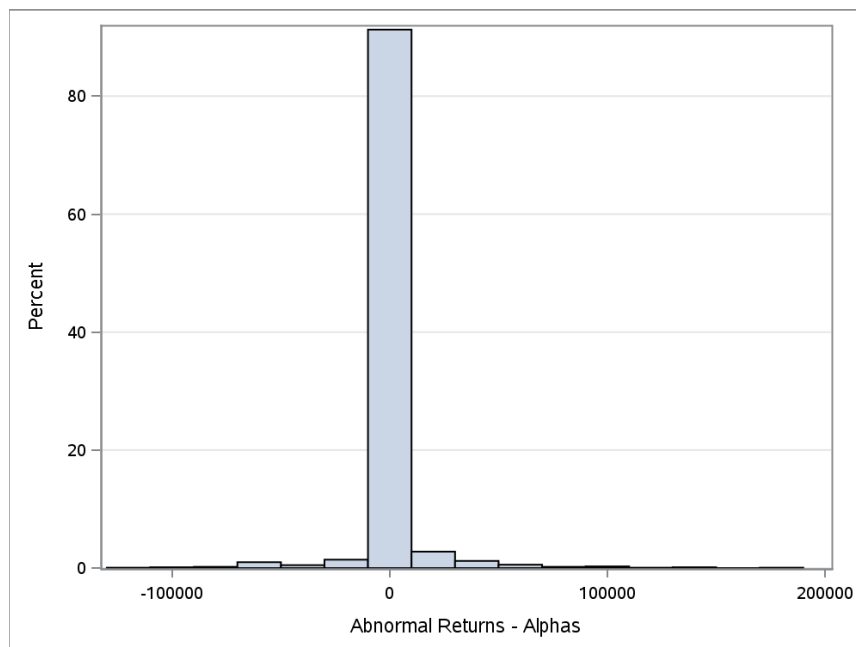
**FINDING 2** The FTRPM identifies paths that exhibit abnormal returns (non-zero *alphas*) with the majority of them being positive.

Recall that the FTRPM predicts that the *alphas* in a competitive market should be zero. The FTRPM regressions identified 1,398 paths that had statistically significant ( $p\text{-value} \leq 0.1$ )

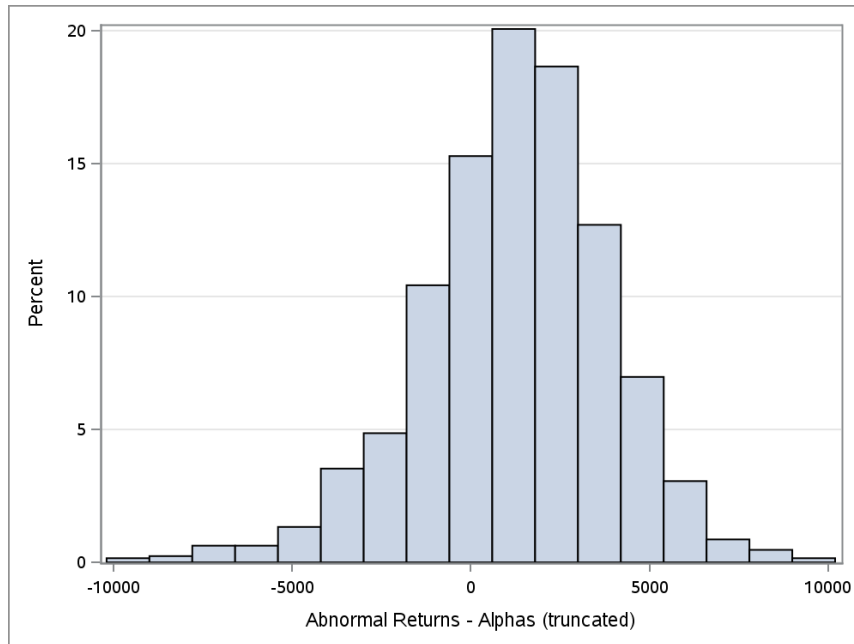
abnormal returns, which represents about 49% of analyzed regressions. Figures 6 & 7 presents the distributions of these abnormal returns estimated with the FTRPM approach. The two figures are identical except Figure 7 truncates the data for a more granular view. The vast majority of significantly different from zero *alphas* are positive. FTRPM estimates 990 paths with positive and 408 with negative abnormal returns. The positive skewness of abnormal returns is also independent of the size (MW) of the auctioned CRR paths.

FTRPM-M treatment reveals similar patterns. The results identify 530 paths with abnormal returns, which represents about 14% of the converged regressions and 20% of the analyzed regressions. 371 of those abnormal returns are positive while 159 are negative. These estimates are further discussed in Finding 3.

**FIGURE 6** A histogram of the estimated FTRPM abnormal returns (%).



**FIGURE 7** A histogram of the estimated FTRPM abnormal returns (%) truncated at -10,000% and 10,000.



**FINDING 3** Using prompt-month prices rather than actual CRR procurement costs in CRR return calculations significantly reduces the number of paths with abnormal returns.

A comparison of results from FTRPM and FTRPM-M estimations shows a dramatic reduction in the percentage of statistically significant alphas – from 49.4% to 20.0%. The statistics from each treatment are summarized in Table 4:

**TABLE 4** Number of paths with estimated abnormal returns, i.e. non-zero *alphas*.

<b>Treatment</b>	<b>Converged Regressions</b>	<b>Analyzed Regressions</b>	<b>Non-Zero Alphas</b>	<b>% of Non-Zero Alphas</b>
FTRPM	3678	2829	1398	49.40%
FTRPM-M	3744	2648	530	20.00%

This finding suggests that a large percentage of abnormal returns are the result of contracts bought far in advance of the relevant month. The high uncertainty and smaller competition of long-term auctions allow market participants to discount CRR contracts and collect higher returns.

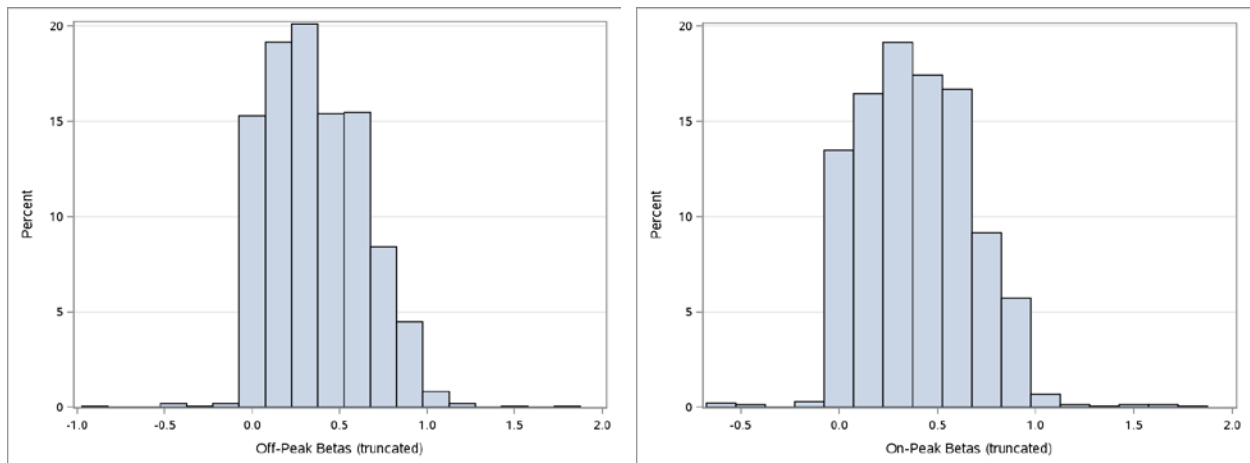
**FINDING 4** The above results are not dependent on the CRR peak type, i.e., Off-Peak and On-Peak.

For the FTRPM, both On-Peak and Off-Peak paths have abnormal returns that skew positive: On-Peak has 487 paths with positive *alphas* and 192 with negative *alphas*, while Off-Peak has 503 paths with positive *alphas* and 216 with negative *alphas*. 257 paths (22.5% of 1,141 unique paths with non-zero *alphas*) exhibit abnormal returns in both the Off-Peak and On-Peak versions of their contracts.

Similarly, results for both On- and Off-Peak CRRs skew positive in the FTRPM-M treatment. It estimates 172 paths with positive *alphas* and 73 with negative *alphas* among On-Peak contracts, while regressions on Off-Peak contracts point to 199 paths with positive *alphas* and 86 with negative *alphas*.

The patterns of the FTRPM estimated betas for On-Peak versus Off-Peak CRRs also appear to be similar. 95% of On-Peak betas fall within the interval of zero and one in comparison to 96% of Off-Peak betas. Figure 8 contrasts the distributions of Off-Peak and On-Peak betas at a more granular scale.

**FIGURE 8** Histograms of the FTRPM beta estimates for Off-Peak and On-Peak CRRs (truncated at -1 and 2)



## **6 CONCLUSION**

Given the size of all the FTR markets (> \$3billion annually) as well as their function providing hedging options and scarcity signals regarding grid resources, it is important to ensure efficient operation of these markets. Having a clear and complete understanding of how FTR markets are organized and operate in different ISOs/RTOs is key to the effective surveillance and advancement of these markets. This paper focused on the CAISO region and examined the patterns of CRR returns.

The main finding of this project is the existence of abnormal returns in the CAISO CRR markets and the consistent skew of those returns in the positive direction for both Off-Peak and On-Peak contracts. This finding compliments a recent CAISO report (2016) that presented widespread and persistent underpricing of CRRs. The noted inefficiencies of CRR markets begs for further studies to uncover their causes and gain insights on potential fixes.

Additionally, the widespread statistical significance of the Market Portfolio excess return throughout our empirical treatments confirms that the theoretical CAPM framework has substance in suggesting that the return of a CRR has a systematic relation to the return of the market portfolio. The analysis also suggests that the risk profile of the estimated CRRs is very similar during both Off-Peak and On-Peak periods.

Validation and testing of these findings with the data from other FTR markets could be a useful direction for future research, which could yield valuable market design prescriptions for improving efficiency, competitiveness and transparency in these markets.

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