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Abstract

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Keywords

organized energy markets, locational pricing, financial transmission rights

Disciplines

Economics | Energy Policy

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Research Paper

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 procure financial transmission rights (FTRs) to hedge against grid congestion charges, while third-party speculators attempt to capture a return with these extremely volatile contracts. This paper develops a novel methodology for estimating the systematic risk of individual FTRs and detecting the presence of abnormal returns among these financial instruments. The prevalence of congestion paths with abnormal returns could be used by policy experts as an efficiency measure when assessing the performance of FTR markets. Being the only organized energy market in the Western Interconnection, California has implemented a version of FTRs officially known as congestion revenue rights (CRRs). This paper applies the proposed methodology to all auctioned CRRs from 2009 to 2015. Our analysis identifies the paths that exhibit persistent abnormal returns, with the majority of them being positive. We also compare the patterns of risk and abnormal returns between on-peak and off-peak CRRs, and find no significant differences.

Keywords: financial transmission right (FTR); congestion revenue right (CRR); hedging; transmission; congestion; electricity market.

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1 INTRODUCTION

Restructured wholesale electricity markets in the United States serve hundreds of millions of consumers every day. Consisting of complex links between generators, energy suppliers, transmission owners, financial intermediaries and system operators, this market is becoming strained as demand for electricity expands while the underlying infrastructure of the grid ages. Although 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 interruptible power flows of renewable energy and connecting distributed energy resources to the grid will be among primary factors affecting system-wide fluctuations in power flows. As a result, energy suppliers will face ever-increasing exposure to the risks associated with the transmission grid functionality as well as congestion that, if not managed properly, could lead to higher costs, lower profits and large losses.

In many power markets, energy is traded at points on the power grid known as nodes. Each node has an associated price called the locational marginal price (LMP). This price is 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, so the differences in LMPs at any given point in time are due to their congestion and loss components. As demand for energy increases at a particular location, power lines servicing the area approach their rated capacity and, as a result, the price of congestion at the associated node starts rising. Consequently, this causes the respective LMP to increase 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 in the day-ahead (DA) electricity markets. It settles off the differences between DA LMPs. We particularly focus on California's markets for FTRs, which are known officially as congestion revenue rights or simply CRRs.

To better grasp the concept of an FTR, consider 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 accepting a loss. A loss could 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 their 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 scenario, 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 directly depends on the difference between the respective congestion charges. 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 (eg, 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 individual FTRs and evaluating the performance levels of FTR markets. To do this, we build on the capital asset pricing model (CAPM) approach of Sharpe (1964) and Lintner (1965).

The proposed methodology is applied to publicly available data on all CRRs acquired in annual and monthly auctions in the California Independent System Operator's (CAISO's) region.[1] Both on-peak and off-peak contracts were included in the analysis. CAISO 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 neighboring states are less developed relative to interconnected regional markets. Theoretically, this could contribute to higher price volatility. In our study, we find that persistent CRR profitability appears to be unusually widespread. Interestingly, CAISO's Department of Market Monitoring has noted that, for many years, the CRR auction revenues were lower than the payments to the auctioned CRR holders; it even questioned the rationale for continuing the CRR auctions in their current form (CAISO 2016).

In Section 2, we review the relevant literature. In Section 3, we build a framework for evaluating the performance of an FTR/CRR. Section 4 applies our analytical framework to the existing CRR markets in California. Section 5 reports our empirical findings. Section 6 concludes the paper.

[1] A large number of CRRs are also distributed at no cost to certain market participants such as load serving entities (LSEs), ie, utilities that provide power to the final consumer. The intention is to provide means for hedging against unpredictable grid congestion in energy spot markets.

2 RELATED LITERATURE

Since the proposal of FTR formulation (Hogan 1992) and its early criticism (see, for example, Oren *et al* 1995), little research has been conducted to categorize observed returns in FTR markets. However, academic research has explored other relevant FTR topics. Initially, researchers were concerned with the potential use of FTRs to curb or exert market power (Stoft 1999; Bushnell 1999). Joskow and Tirole (2000) investigated the use of FTRs 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 with PTRs and concluded that PTRs are better suited to regulating market power via reallocation of rights. More recently, Henze *et al* (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 allocative efficiency upon simple price-cap regulation and caused relatively lower investment.

When ISOs started implementing auction-based markets for FTRs (Ma *et al* 2002), the auction design came under intense scrutiny. Studies suggested that FTR auction markets were inefficient. Even after controlling for risk aversion among bidders, the unexplained differences between FTR prices and their expected values persisted (Adamson and Englander 2005). Deng *et al* (2010) argued that those differences could be partially explained by the low number of bids in an auction, implying that frequent reconfiguration auctions or liquid secondary markets were needed to reduce inefficiencies.

A more recent study by Mount and Ju (2014) proposed an econometric framework for evaluating the efficiency of a market for FTRs. This framework was applied to three transmission congestion contracts (TCC), which are FTR equivalents in the state of New York. The authors' approach relied on the comparison of the ex ante expected returns and the paid market prices. They concluded that there was a lack of evidence for consistent TCC underpricing but acknowledged the limitations of their study, since they looked at only one TCC auction from summer 2006.

Although the auction-based FTR markets were criticized for being inefficient, their ability to provide financial services, ie, hedges against potential losses, in restructured energy markets has been widely acknowledged (Mendez and Rudnick 2004; Kristiansen 2004; Siddiqui *et al* 2005). But problems do emerge when the market liquidity is low. Siddiqui *et al* (2005) reported that TCC markets did not appear efficient at hedging complex positions, causing excessively high risk premiums paid by TCC buyers. The authors also note the lack of learning by market participants in using TCCs.

Sarkar and Khaparde (2008) provided a comprehensive summary of the evolution of FTRs over time. More recently, Rosellón and Kristiansen (2013) presented a systematic overview and gathered expert discussions on a wide scope of FTR topics.

A few recent studies (Jha and Wolak 2014; Li *et al* 2014; Hogan 2016) have focused on the performance of another financial instrument in wholesale electricity markets, which is commonly known as convergence bidding or virtual bidding. This also settles off a difference between LMPs, except that, in this case, one LMP is from the DA market and one is from the real-time (RT) market. Unlike FTRs, which are auctioned on separate and purely financial market platforms, the virtual bids are integrated into physical wholesale markets and have a direct impact on the price formation of wholesale electricity. The above studies have provided arguments and empirical evidence suggesting that the presence of convergence bidding improves the efficiency of DA and RT markets. Jha and Wolak (2014) and Li *et al* (2014) focused specifically on virtual bidding in CAISO markets.

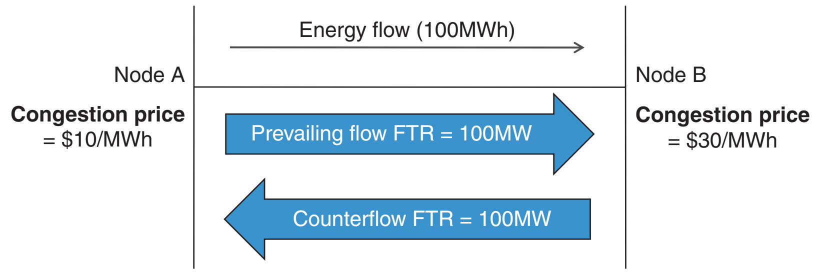
Given that FTR markets have been around for quite some time now, it is surprising that technical approaches to assess highly volatile FTR returns are still largely under-explored. Following CAISO (2016), which reported that for every dollar paid to CRR holders only 46 cents were collected in auction revenues, Harvey (2017) used the comparison of CRR auction revenues and DA market payouts to conclude that most CRRs are purchased not as hedge instruments but rather as risky financial investments. This insight adds to our motivation to develop a CAPM-type approach for evaluating individual CRRs and their risk levels. In addition, Harvey (2017) suggested potential sources for consistent CRR undervaluation, leaving the question “What qualifies as an undervalued CRR?” largely unanswered. Our paper focuses on examining the existing profile of FTR returns in CAISO by suggesting a novel methodology to categorize them. More specifically, we estimate the systematic risk of individual CRRs and explicitly identify paths with persistent abnormal returns, which then could be further scrutinized for isolating specific causes of underpricing as well as overpricing. The prevalence of such paths could be used as another efficiency measure for the performance of FTR markets.

3 A FINANCIAL TRANSMISSION RIGHT VALUATION MODEL

3.1 Measuring an FTR return

Let us look at an example to better understand how FTRs/CRRs work. Consider two hypothetical nodes: node A and node B. In Figure 1, if node A has a congestion price of \$10 and node B has a congestion price of \$30, then the prevailing flow FTR from source A to sink B, ie, in the same direction as the energy flow, is worth \$20 per megawatt hour (MWh). If the market clearing price, which represents the cost of

FIGURE 1 An FTR example.



Prevailing flow FTR credit: 100MWh × ($30/MWh − $10/MWh) = $2000. Counterflow FTR charge: 100MWh × ($10/MWh − $30/MWh) = −$2000.

acquiring an FTR in an auction, is less than $20, the FTR would yield a profit. The counterflow FTR from source B to sink A, ie, in the opposite direction to the energy flow, would require the FTR holder to make a $20/MWh congestion payment to the ISO. For this FTR to make a profit, its holder would need to receive a credit of more than $20 during the auction, ie, the FTR price would need to be less than −$20. If the expenses paid out to the ISO are greater than the collected revenue from the ISO, the FTR holder will experience a loss.

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

$$R_i = \frac{\pi_i}{\text{cost}_i} \times 100\% = \frac{\text{revenue}_i - \text{cost}_i}{\text{cost}_i} \times 100\%, \tag{3.1}$$

where π_i is an accumulated net profit or loss from holding the FTR over path i; revenue$_i$ is the associated revenue from congestion (+/−), which originates from the nodal differences of respective congestion prices; and cost$_i$ is the expense of acquiring the FTR in an auction (+/−). Using the above example, if the FTR price was $16, the return would be equal to 25% ($= [(30 \times 100 - 10 \times 100) - (16 \times 100)] \div [16 \times 100] \times 100\%$).

For a path with a positive FTR market clearing price, computing returns is straightforward. However, when the market clearing price is negative, say, −$25 for the counterflow FTR example above, then the calculations using (3.1) may be misleading: the example's return would add up to −20% ($= [(10 \times 100 - 30 \times 100) - (-25 \times 100)] \div [-25 \times 100] \times 100\%$), suggesting a negative return, when, in fact, the path returned a positive profit of $5/MWh. This can be easily resolved if one thinks of the absolute value of the FTR cost as a benchmark for measuring returns. The method for calculating both prevailing flow and counterflow FTR returns is shown in (3.2):

$$R_i = \frac{\pi_i}{|\text{cost}_i|} \times 100\% = \frac{\text{revenue}_i - \text{cost}_i}{|\text{cost}_i|} \times 100\%. \tag{3.2}$$

When profit is divided by the absolute value of the FTR's cost, the rate of return of a counterflow position is computed with respect to the funds spent by the auctioneer. Thus, (3.2) computes the return of the counterflow FTR example above to be equal to 20% ($= [(10 \times 100 - 30 \times 100) - (-25 \times 100)] \div |-25 \times 100| \times 100\%$). The calculation of the rate of return is not altered by this modification for a prevailing flow position.

3.2 Measuring an abnormal FTR return

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 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 risk given the expected return and attempts to maximize the expected return given the variance of returns. The original Sharpe–Lintner CAPM equation can be represented by

$$E(R_i) = R_{\mathrm{f}} + \beta_i[E(R_{\mathrm{MKT}}) - R_{\mathrm{f}}], \tag{3.3}$$

where the assets are indexed by $i = 1, \dots, N$. The model makes two major assumptions:

(1) there is 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 industries. Equation (3.3) 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, β_i, relative to the expected excess market return, $E(R_{\mathrm{MKT}}) - R_{\mathrm{f}}$. 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 original CAPM assumes that an asset's excess return, $E(R_i) - R_{\mathrm{f}}$, can be completely explained by the average value of the market's excess return, $E(R_{\mathrm{MKT}}) - R_{\mathrm{f}}$. 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 α_i. Equation (3.3) can be transformed into the time series regression model shown in (3.4):

$$R_{it} - R_{ft} = \alpha_i + \beta_i[R_{Mt} - R_{ft}] + \mu_{it}, \tag{3.4}$$

where the assets are indexed by $i = 1, \dots, N$ and μ_{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. However, early empirical tests of the model, conducted by Jensen *et al* (1972), Blume and Friend (1973) and Fama and French (1992), provided evidence that intercept terms for many financial assets were statistically greater than zero. The time series regression 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 nonzero Jensen's alpha has been interpreted as the abnormal return of an asset. A positive Jensen's alpha indicates higher than expected overall returns of the asset given its individual systematic risk. Alternatively, negative Jensen's alphas indicate lower than expected returns of the assets while controlling for their own systematic risk levels. Since we are interested in capturing the presence of abnormal returns of FTRs, a modified Sharpe–Lintner CAPM equation, which we name the financial transmission right pricing model (FTRPM), would provide us with alpha, α_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 the 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 a dramatic effect 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 nonconstant variance.

Given these requirements, a type of autoregressive conditional heteroscedastic (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 nonconstant variance of returns as well as 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 heteroscedastic (GARCH) process, which we employ to estimate our time series regression models.

Since the GARCH process aims to account for conditional nonconstant 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 (iid) standardized residuals. We use BDS tests with embedding dimensions two through five and a radius of one standard deviation (using a 99% confidence level) to filter the converged regressions before further analysis.

3.4 Hypotheses and treatments

3.4.1 Abnormal returns of CRR contracts

In a competitive financial market, extremely high returns should not persist from month to month if the system is stationary and participants are able to respond to market signals by adjusting their positions and bidding behavior over time. CRR paths with unusually large returns 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 and well-functioning market, one would expect that abnormal returns would not be present.

3.4.2 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 a seasonal 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, ie, the CRR price from a prompt-month auction. A seasonal contract, which is acquired a 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, consequently, to 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 CRR.[2] 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 also (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) CRRs with abnormal returns when using the FTRPM-M estimation relative to the original FTRPM approach.

3.4.3 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 06:00 to 22:00, Monday to Saturday in the CAISO region. Alternatively, the off-peak CRRs accrue value during the off-peak hours, ie, 22:00 to 06:00, Monday to Saturday, and for twenty-four hours on Sundays and public holidays.

Since on-peak hours are during the time of the day when energy demand is highest, generally, on-peak CRR returns should be more volatile than their off-peak counterparts. When energy demand is high, the variance of grid 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 of LMPs start to diverge. 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 larger congestion price variance during the On-Peak hours, we expect the on-peak CRRs to have a wider dispersion of betas relative to their off-peak counterparts.

4 CALIFORNIA INDEPENDENT SYSTEM OPERATOR'S CONGESTION REVENUE RIGHT MARKET

The CAISO CRR market is one of the smaller markets for congestion contracts in the United States and has historically exhibited low auction revenues relative to the congestion payments made to CRR holders (CAISO 2016). 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).

To study the patterns of returns in this market, we acquired publicly available 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

[2] In the absence of a prompt-month price marker, the actual costs for holding that CRR during that month were substituted.

TABLE 1 The number of market participants that purchased CRRs over time.

	Year						
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Participants	43	41	47	46	56	57	69

to December 2015, which provides us with eighty-one 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. A total of 1 209 521 of the CRRs were contracts that covered on-peak hours of the day, while 1 076 426 covered off-peak hours. In addition, 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 counterflow 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 data set to only those paths where CRR contracts were successfully auctioned for at least thirty months during the period of the study.

In order to estimate our proposed model, represented by (3.4), 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 a one-month constant maturity Treasury bill (T-bill) is used (source: Federal Reserve Bank of St. Louis). 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.

Equation (4.1) shows the calculation of a CRR return for a given path and month, ie, a unique combination of source, sink, peak type (off-peak or on-peak) and month. It follows the general FTRPM framework described above and represents (3.2):

$$R_i = \frac{\text{revenue}_i \times \text{total MW}_i - \sum_{j=1}^{M} \text{cost}_{ij} \times \text{held MW}_{ij}}{|\sum_{j=1}^{M} \text{cost}_{ij} \times \text{held MW}_{ij}|} \times 100\%, \tag{4.1}$$

where R_i is the CRR_i return for the path i across all market participants who held the CRR exposure during the relevant month.[3] The different market participants ($j =$

[3] If no one held the particular CRR during a certain month, the observation of its monthly return was substituted with the monthly return of the market portfolio for the purposes of estimating our time series regressions.

$1, \ldots, M$) have their individual costs (cost_{ij}) and held quantities (held MW_{ij}), which are multiplied individually and then summed to find the total cost of the CRR across all participants. revenue_i is the DA congestion charges ($/MW) that were collected (or paid out) by the CRR holders for that path-month. total MW_i is the sum of held megawatts across all the market participants, given by (4.2)

$$\text{total MW}_i = \sum_{j=1}^{M} \text{held MW}_{ij}. \tag{4.2}$$

One adjustment that was made in calculating CRR return R_i was that if the total cost of contracts for a given path was found to equal $0.00, we replaced it with $0.01. As a cost of a penny is usually very small compared with 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.[4]

In the spirit of the CAPM theoretical framework, we treat the CRR financial market as an isolated economic system and proceed with the calculation of the market portfolio return (R_{MKT}) for a given month using (4.3):[5]

$$R_{\text{MKT}} = \sum_{i=1}^{N} \left(R_i \times \frac{\text{total MW}_i}{\text{total MW}_{\text{MKT}}} \right), \tag{4.3}$$

where total MW_i, as above, is the sum of all held megawatts across the market participants for a given path and total MW_{MKT}, given by (4.4) below, is the sum of all held megawatts for a month across every path ($i = 1, \ldots, N$):

$$\text{total MW}_{\text{MKT}} = \sum_{i=1}^{N} \text{total MW}_i. \tag{4.4}$$

The summary statistics for the returns of CRRs, the market portfolio and a one-month constant maturity T-bill are presented in Table 2. Table 2 shows the high kurtosis and large standard deviations of the CRR returns. These numbers point to significant variance and fat tails in the aggregate distribution of the CRR returns. That is a result of sudden and large congestion charges that accrue during periods of constrained grid conditions. The largest positive return of an individual CRR in our data set is 179 908 576% per month: an extraordinary return for any financial market. The largest loss observed in our data set, −141 153 700%, is also impressive.

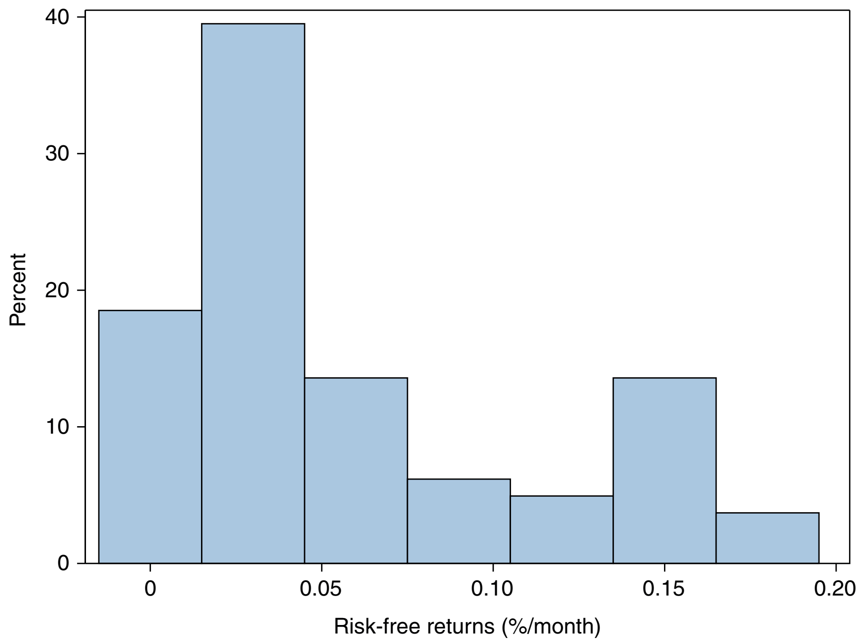
[4] As a robustness check for our findings, we also conducted FTRPM estimations without zero-cost CRR observations. We refer to this estimation treatment as FTRPM-NZ.
[5] Note that CAISO does not auction CRR options, though some entities may be allocated free long-term CRR options to account for particular transmission ownership or contract situations.

TABLE 2 The summary statistics for the monthly returns of market portfolio, one-month constant maturity T-bill and auctioned CRRs.

Monthly return (%/month)	Paths	Obs	Mean	Median	Min	Max	SD	Kurtosis
Market portfolio		81	35 528	10 453	−64 834	267 178	60 967	3.5
One-month constant maturity T-bill		81	0.058	0.040	0	0.180	0.052	−0.410
All CRRs	199 866	852 636	8 352	3.5	−141 153 700	179 908 576	561 946	20 656
On-peak	106 893	439 411	12 686	−4.2	−141 153 700	90 198 044	683 571	6 890
Off-peak	92 973	413 225	3 744	16.5	−36 984 165	179 908 576	393 265	110 816
30+ obs CRRs	3 834	174 199	16 586	−77.9	−141 153 700	179 908 576	884 452	15 553
On-peak	1 911	86 597	22 460	−59.1	−141 153 700	90 198 044	1 008 935	6 337
Off-peak	1 923	87 602	10 779	−91.5	−13 673 436	179 908 576	741 084	41 231
30+ obs CRRs (excess return)	3 834	174 199	16 586	−77.9	−141 153 700	179 908 576	884 452	15 553
Market portfolio (excess return)		81	35 528	10 453	−64 834	267 178	60 967	3.5

SD denotes standard deviation; obs denotes observations.

FIGURE 2 A histogram of one-month constant maturity T-bill returns (%/month).

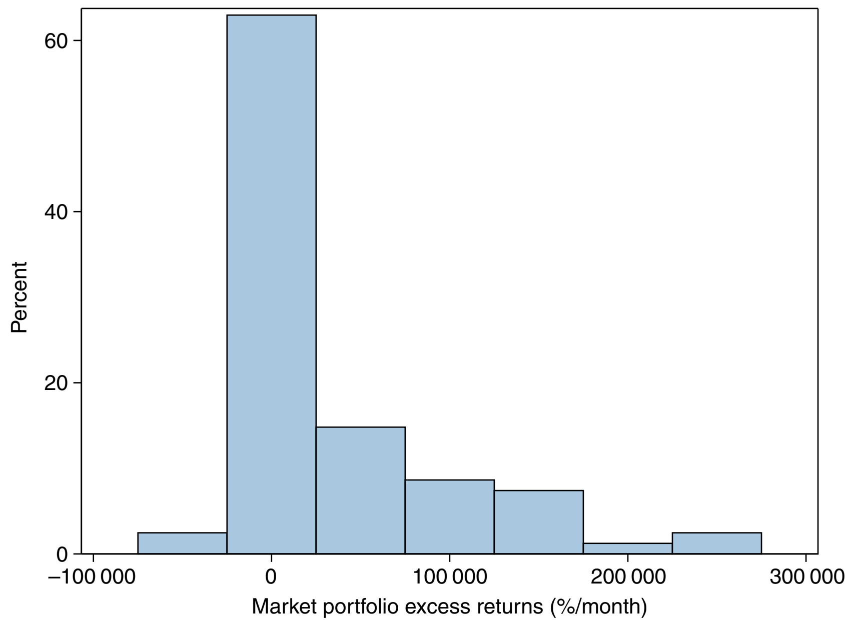


A histogram of one-month constant maturity T-bill returns is presented in Figure 2, and a histogram of the excess return of the market portfolio is shown in Figure 3. A truncated distribution of individual CRR excess returns is depicted in Figure 4. Note that many CRRs have rates of return equal to 100% or -100% per month. These represent the contracts that were auctioned but did not experience congestion in a given month. Therefore, as revenue$_i$ is equal to 0, (4.1) will yield $R_i = -100\%$ for prevailing flow paths and $R_i = 100\%$ for counterflow paths. In Figure 1, this would be equivalent to the congestion prices at both nodes being equal.

5 EMPIRICAL RESULTS

Overall, our GARCH regression results achieved a high convergence rate. All in all, 3678 of 3834 FTRPM regressions converged, yielding a convergence rate of 96%. We then eliminated the paths with estimated regressions that violated error independence, leaving us with 2829 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

FIGURE 3 A histogram of market portfolio excess returns (%/month).



hypothesis of error term independence with embedding dimensions $M = 2, \dots, 5$ and a radius of one standard deviation at a 99% confidence level.[6]

Finding 1

The significance of the market portfolio excess return ($R_{\mathrm{MKT}} - R_{\mathrm{f}}$) in the FTRPM regressions is widespread.

The FTRPM estimated 2290 paths with statistically significant (p-value $\leqslant 0.1$) 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_{MKT} to explain an individual CRR's return volatility.[7] Figure 5

[6] 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%. In the FTRPM-NZ treatment, the respective passing rate for the BDS tests and the regression convergence rate were 96% and 99.5%.

[7] The number of regressions with significant (p-value $\leqslant 0.1$) betas was 1701 paths (64% of analyzed regressions) in FTRPM-M and 3002 paths (88%) in FTRPM-NZ.

FIGURE 4 A histogram of all CRR excess returns truncated at −1000 and 1000 (%/month).

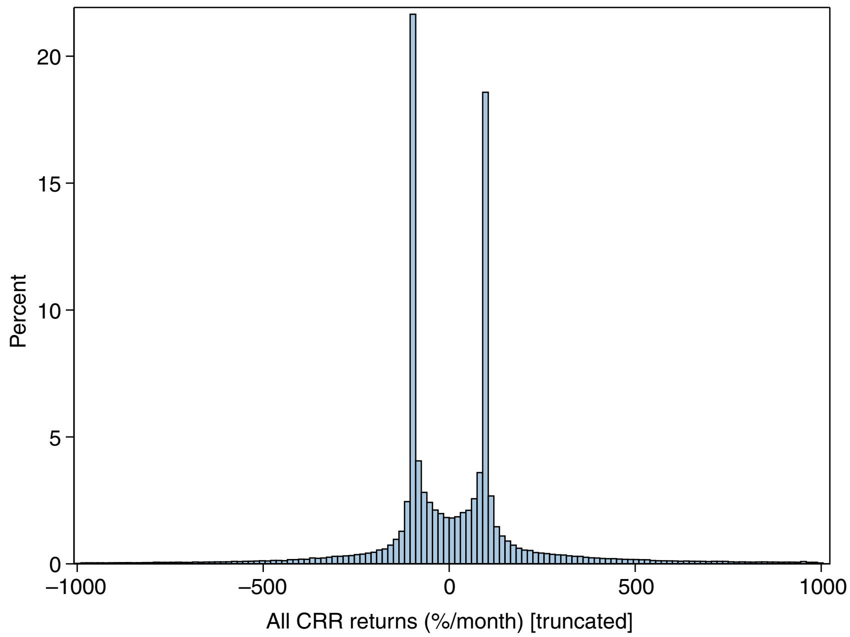
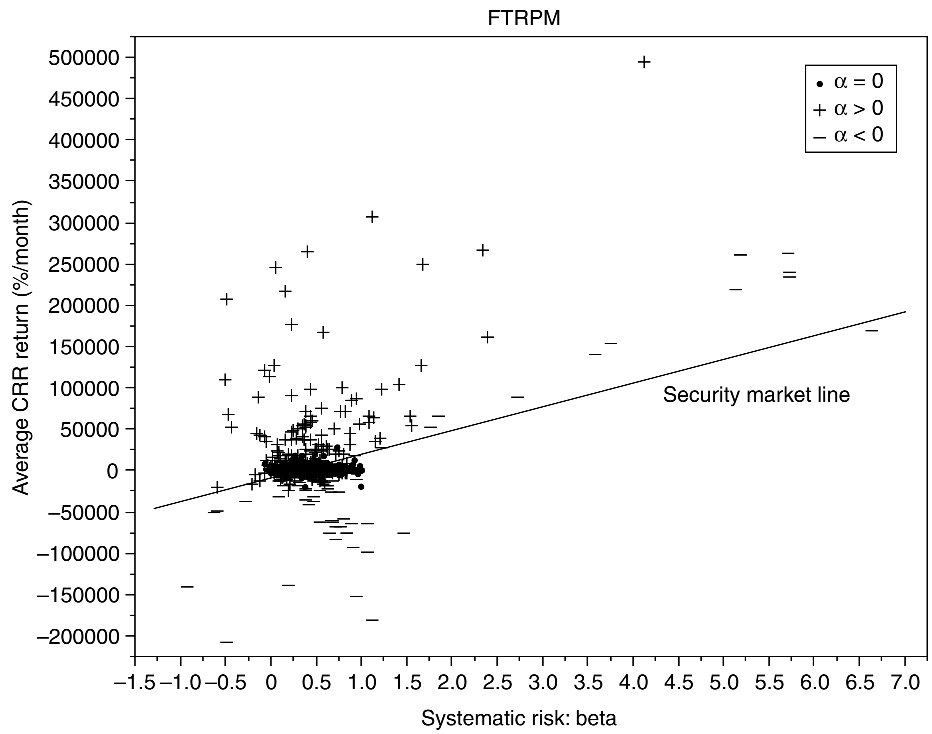


TABLE 3 Summary of BDS test results for the FTRPM regressions.

BDS tests	CRRs passing BDS tests (as % of 3678 converged regressions)
$M = 2$	3215 (87.4%)
$M = 3$	3166 (86.1%)
$M = 4$	2986 (81.2%)
$M = 5$	3059 (83.2%)
$M = 2$, 3, 4 and 5	2829 (76.9%)

graphs these betas – a measure of the systematic risk of each path – against their average returns. The data points are visually differentiated according to the statistical significance and sign of their respective alphas. The solid line represents the security market line, where the intercept is equal to the arithmetic average of the historical risk-free rates and the slope is determined as the arithmetic average of the historical excess returns on the market portfolio. It is noteworthy that the majority of

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



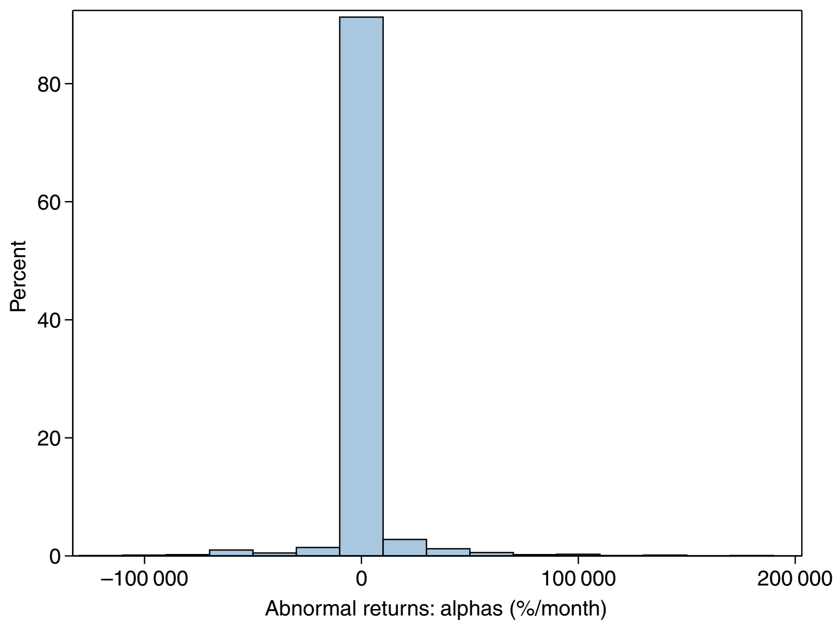
estimated paths have betas that fall within the interval of zero and one, ie, frequently held CRRs tend to have lower systematic risk than the market portfolio. There are only three estimated CRR regressions (0.1% of analyzed regressions) with negative betas that are statistically significant (p-value $\leqslant$ 0.1). The negative betas indicate that the corresponding CRRs tend to do better when the CRR market as a whole declines.

Finding 2

The FTRPM identifies paths that exhibit abnormal returns (nonzero alphas), with the majority of them being positive.

Recall the FTRPM predicts that the alphas in a competitive market should be zero. The FTRPM regressions identified 1398 paths that had statistically significant (p-value $\leqslant$ 0.1) abnormal returns, which represents about 49% of analyzed

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

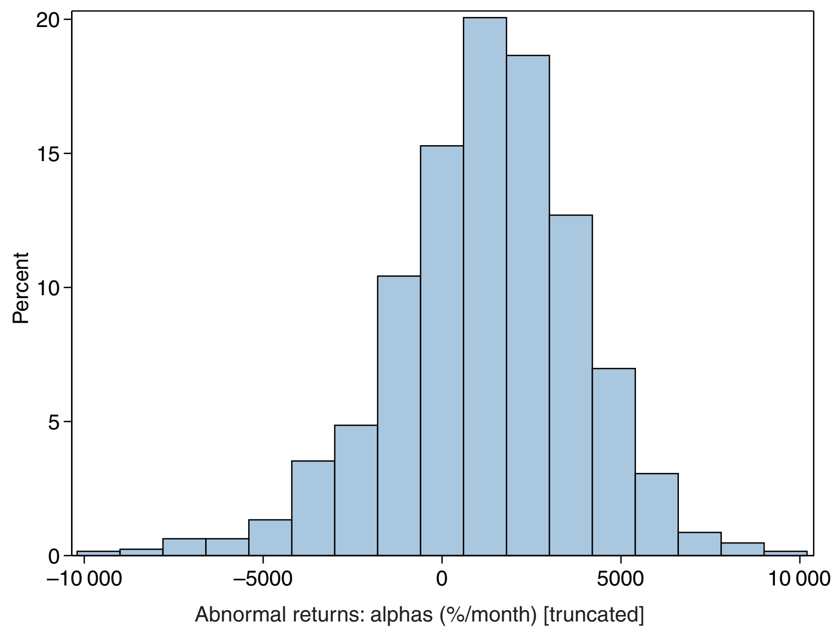


regressions.[8] Figures 6 and 7 presents the distributions of these abnormal returns estimated with the FTRPM approach. The two figures are identical, except Figure 7 truncates the data for a more granular view. The vast majority of significantly-different-from-zero alphas are positive. FTRPM estimates 990 paths with positive and 408 paths 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%

[8] The average profit of all analyzed paths exhibiting abnormal returns is \$43/MWh (standard deviation \$779) versus \$50/MWh (standard deviation \$813) for zero-alpha paths. If we restrict the analysis further to only the CRR paths that individually yield on average at least \$1/MWh in profits, we end up with 1614 such paths, of which 808 (50%) are identified as paths with abnormal returns and an average profit of \$116/MWh (standard deviation \$873), while the average profit of the respective zero-alpha paths amounts to \$128/MWh (standard deviation \$912). These statistics highlight that the CRRs identified as having abnormal returns are not simply an artifact of paths with negligible profit levels.

FIGURE 7 A histogram of the estimated FTRPM abnormal returns (%) truncated at −10 000 and 10 000 (%/month).



of the analyzed regressions. In this case, 371 of those abnormal returns are positive while 159 are negative.[9] These estimates are further discussed in Finding 3.

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 major reduction in the percentage of statistically significant alphas from 49.4% to 20.0%. The statistics from two treatments are summarized in Table 4.

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

[9] FTRPM-NZ identifies 227 paths with abnormal returns, which correspond to 7% of its analyzed regressions. A relatively lower number of the identified paths highlights the contribution of the zero-cost CRRs to the profile of abnormal returns. However, it is noteworthy that removing the zero-cost CRR observations still does not eliminate paths with abnormal returns.

TABLE 4 Number of paths with estimated abnormal returns, ie, nonzero alphas.

Treatment	Converged regressions	Analyzed regressions	Nonzero alphas	% of nonzero alphas
FTRPM	3678	2829	1398	49.40%
FTRPM-M	3744	2648	530	20.00%

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, ie, 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 paths with negative alphas, while off-peak has 503 paths with positive alphas and 216 paths with negative alphas. A total of 257 paths (22.5% of 1141 unique paths with nonzero alphas) exhibit abnormal returns in both the off-peak and on-peak versions of their contracts.

Similarly, results for both on-peak 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, compared with 96% of off-peak betas. Figure 8 contrasts the distributions of off-peak and on-peak betas on a more granular scale.[10]

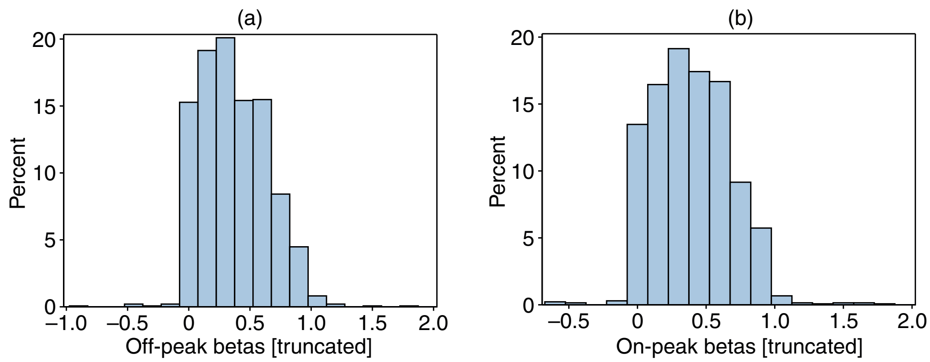
6 CONCLUSION

Given the multibillion-dollar FTR markets 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 tools to assess the performance of FTR markets is key to effective surveillance and advancement of these markets. This paper develops such a tool and then applies it to CAISO markets by examining the return patterns of almost 3000 CRR paths.

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

[10] The estimated FTRPM-NZ profiles of abnormal returns and betas for on-peak versus off-peak paths appear to be similar as well (see Appendix A online).

FIGURE 8 Histograms of the FTRPM beta estimates for (a) off-peak and (b) on-peak CRRs (truncated at −1 and 2).



for both off-peak and on-peak contracts. This finding complements a recent report (CAISO 2016) that presented widespread and persistent underpricing of CRRs. The estimated inefficiencies of CRR markets beg for further studies to uncover their causes and gain insights on potential fixes.

In addition, 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 the proposed analytical framework with the data from other FTR markets would be a useful direction for future research, which could yield valuable market design prescriptions for improving efficiency, competitiveness and transparency in these markets.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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