# An Empirical Investigation of Speculation in the MISO Financial Transmission Rights Auction Market

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## Abstract

Although financial transmissions rights (FTRs) are intended to allow physical participants in electricity markets to hedge the locational price risk associated with their bilateral contracts, both physical participants and speculators take part in FTR auctions. While speculators likely increase the liquidity of FTR auction markets, physical participants and ultimately ratepayers bear the cost of the profits made by speculators. Given the regulated nature of physical participants in contrast to the largely unregulated speculators, it is hypothesized that speculators in FTR auction markets are obtaining substantial profits at the expense of physical participants. This study details a statistical model for characterizing market participants in the Midwest Independent System Operator (MISO) FTR auctions as either speculators or physical participants. Estimates of the total profit made by speculators and measures of the liquidity provided by speculators in FTR auctions are then determined. A sensitivity analysis is used to provide reasonable bounds for these estimates. The best estimates determined in this analysis show speculator profits of 152% of total market profits, equal to $283 million over three years, with speculator transactions accounting for 74% of total market transactions on a megawatt basis.

## Introduction

Most wholesale electricity markets use financial instruments known as financial transmission rights (FTRs) to both enable bilateral contracting and allocate transmission congestion payments. The combination of FTRs and bilateral contracts allows market participants to hedge both temporal and locational price risks. FTRs are therefore an integral part of deregulated wholesale electricity markets.

FTR auction markets do not require participants to have physical assets in the electricity market. This opens the possibility for market participants to speculate in FTR markets. Some amount of speculation is likely present in FTR markets due to differing incentives between two types of market participants, hereafter classified as physical participants and speculators. Physical participants include many state regulated entities whose profits are limited by state public utility commissions. If they made profits through speculation in FTR markets, retail electric rates would likely be lowered at the next rate case to maintain total profits at a constant level. As regulated physical participants would not get to keep the profits and would need to explain any losses from FTR speculation to state regulators, physical participants have limited incentive to speculate in FTR markets. Additionally, some physical participants, such as Wisconsin utilities, are not permitted to speculate in FTR markets.[1]

Speculators, which are often unregulated entities such as financial institutions, have different incentives. Speculators have fewer constraints on their market activities and are therefore free to keep all profits without the need to justify any losses that result from speculative activity to a regulatory body.

This difference in incentives potentially gives speculators an advantage in FTR auction markets. Any resulting FTR market distortions detract from the market's intended purpose of hedging physical participants' bilateral contracts against locational price risk from transmission congestion. This study investigates the hypothesis that speculator profits in FTR markets produce substantial monetary transfers from physical participants to speculators.

A common argument in favor of speculation is that speculators perform a large share of total market transactions, thereby contributing to market liquidity. Since ratepayers ultimately pay for profits made by speculators, it is important that customer advocates and regulators understand the patterns of transactions made by speculators and the amount of profits made through FTR speculation. Regulators can then balance the liquidity benefits provided by speculators against the profits extracted from FTR markets. Inordinately large speculator profits may indicate a need to reform FTR markets or replace FTRs with a different system entirely.

There is a substantial amount of academic discourse on FTRs. Sarkar and Khaparde (2008) provide a summary of FTR research, including an in-depth discussion of the hedging capability of FTRs, the conditions necessary for revenue adequacy, and the processes for obtaining FTRs. Kumar et al. (2005) present a detailed bibliography of FTR research from the beginning of FTR development through proposed future innovations. The Midwest Independent Service Operator (MISO), provides both an overview and in-depth description of the business practices for FTRs.[2,3]

Several studies have been conducted on FTR market economics. The most relevant to this work are studies that focus on FTR market efficiency. Efficiency in this context refers to the ability of the market to correctly price FTRs. In a perfectly efficient market, FTR prices would precisely equal FTR value such that non-risk averse participants would make zero profit. Note that market efficiency is a different, but related, topic from the problem of characterizing FTR speculation considered in this study. An efficient market could potentially have a high level of speculation and an inefficient market could be free of speculation.

Early work in this area from Siddiqui et al. (2003) investigates the efficiency of the New York ISO (NYISO) transmission congestion contract (TCC) market. TCCs in NYISO are functionally equivalent to FTRs in MISO. Using spring 2000 to fall 2001 data, an ordinary least squares (OLS) model is created to determine how well the prices paid for TCCs correlate with the TCC values. The study assumes full TCC funding and does not split participants into speculator and non-speculator groups. The study finds significant deviation from an efficient market with unreasonably high risk premiums for TCCs. This is attributed to low market liquidity due to the large number of possible TCCs, the constraints necessary for revenue adequacy, and the complex interactions between the TCC and energy markets. Additionally, realistic system considerations such as line losses and contingency planning make it difficult to obtain an efficient market.

A subsequent study by Hadsel and Shawky (2009) comes to a similar conclusion using OLS techniques on 2006 and 2007 NYISO data. This study found that the NYISO TCC market was not efficient, particularly for TCCs between regions with widely differing levels of congestion. Additionally, the study found that the NYISO TCC market "is very volatile but could be extremely profitable for speculators; a significant volume of TCCs is traded by speculators; and participation in TCC markets is thin and may be dominated by a few players." This finding deepens the concerns of potentially excessive speculator profit in the MISO FTR market.

Conversely, the 2008 State of the Market report finds evidence that the MISO FTR market is efficient.[4] The market monitor report contends that the FTR market shows relatively good correlation between FTR prices and payouts.

## Study Overview

The first goal of this study is to create a model that characterizes the FTRs transactions from two subsets of participants in the MISO FTR market: known physical participants and known speculators. It is hypothesized that physical and speculative market participants can be statistically correlated with particular behavior characteristics such as number of FTRs bought and sold, geographic diversity of transactions, and amount and price related data. This model can then be used to classify the third set of unknown participants through the predicted value of their *speculator* variable. Using the characterization of all market participants, the study's goal of estimating the total amount of speculation present in the FTR market and thus the cost to ratepayers in MISO can be accomplished.

To interpret the statistical model used to classify market participants, a description of the available FTR data is first presented. This is followed by a discussion of the statistical analysis strategy, proposed models, and sensitivity analysis. Next, the model results are shown and interpreted. Finally, concluding remarks are presented.

## Data Overview

MISO FTRs are distributed through both an allocation process and an auction. This study focuses solely on the FTR auction. MISO has published both annual and monthly FTR auction results since 2005.[5] Auction data from winter 2006 through spring 2009 were selected for this study due to the initial uncertainties and volatility resulting from substantial market changes in 2006.

Although actual FTR payments are not made publicly available, the value of each FTR can be calculated using the day-ahead LMP data that is publicly available.[6] After determining the value of each FTR, the profit obtained by the FTR holder was determined by the difference between the FTR's value and cost. A negative profit indicates that the FTR holder paid more for the FTR than they received from the FTR's payout.

It is important to note that the FTR value may not actually be paid to the FTR holder if there are insufficient congestion revenues to fully fund all FTRs on an hourly basis. The FTR auction process is designed such that all purchased FTRs will theoretically be fully funded; however, practical issues such as a line going out of service can lead to insufficient congestion revenues to fully fund all FTRs. In these instances, FTR payments are prorated based on the quantity of congestion revenues received by the ISO.

Since hourly prorating factors are not publicly available, the value and profit calculations are approximations of the actual quantities received by market participants.

Since this study is concerned with identifying which market participants are speculating, the FTR data for each market participant was aggregated. Annual auctions split FTRs into three month seasonal blocks and monthly auctions are used to reconfigure FTRs for that month. Therefore, the market "resets" each season. An observation in this study will thus consist of the aggregated FTR data for a single market participant for a single season. A total of 999 such observations are available for the three year period from 2007 to 2009: 277 in 2007, 339 in 2008, and 383 in 2009. Table 1 provides descriptions of the data aggregations used in the study. The theoretical basis for the choice of these data aggregations is provided in the statistical strategy and models section of this paper.

| Aggregation | Description |
|---|---|
| *Speculator* | Binary variable: 1 for speculators, 0 for physical participants. |
| *Geo* | Measure of geographic diversity in FTR transactions between 0 (high diversity) and 1 (low diversity). |
| *Number Transacted* | Sum of number of FTRs bought and number of FTRs sold. |
| *Fraction Buy* | Fraction of total transactions involving an FTR purchase. |
| *Average Amount* | Average megawatt (MW) amount per FTR transacted. |
| *St. Dev. of Amount* | Standard deviation of megawatt (MW) amount per FTR transacted. |
| *Profit* | Difference between the FTR's value and the FTR's cost, summed for all FTRs in the observation (dollars).* |
| * The FTR profit aggregation does not account for prorating due to insufficient congestion revenue. | |

**Table 1: Aggregation Descriptions**

One particularly important variable is the market participant's speculator status. There are two subgroups of market participants with known speculator status: known speculators and known physical participants. Known speculators are primarily financial institutions. Without the ability to generate or distribute electrical energy, these firms are not hedging physical contracts and must therefore be speculating. Known speculators were identified using publically available sources such as company websites. The initial determination of the speculator variable was done in a conservative manner such that only firms that are highly likely to only be speculating are included. Known physical participants consist of Wisconsin utilities, which are not allowed to speculate in FTR markets.[1] A third subgroup of unknown or undefined market participants consists of the remaining market participants for whom *speculator* cannot be reasonably estimated.

A second particularly important variable is *geo*, a measure of the geographic diversity of a market participant's transactions. *Geo* is near one when most of a market participant's FTRs are associated with a common region on the transmission network, and is near zero when the FTRs have wide geographic distribution with little interconnectedness.[7] A qualitative representation of *geo* is given in figure 1.

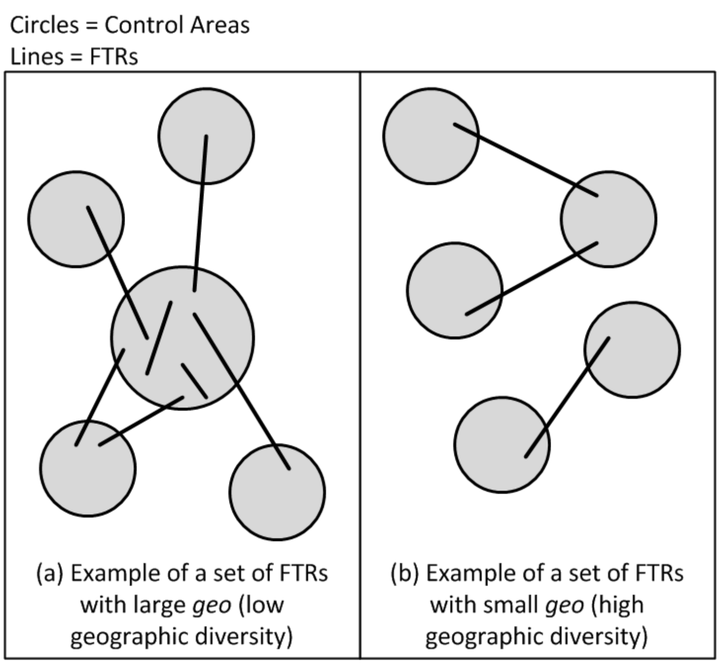


**Figure 1: Illustration of *Geo***

There are 8 known physical (non-speculating) market participants with 66 observations total and 23 known speculating market participants with 181 observations total. Thus, known observations account for 24.7% of the total observations. Descriptive statistics for the relevant data aggregations are presented in table 2.

| | Known Speculators (N=181) | | | Known Physical Participants (N=66) | | | Unclassified Participants (N=752) | | |
|---|---|---|---|---|---|---|---|---|---|
| **Aggregation** | **Mean** | **Min, Max** | **St. Dev.** | **Mean** | **Min, Max** | **St. Dev.** | **Mean** | **Min, Max** | **St. Dev.** |
| *Geo* | 0.312 | 0.126, 1 | 0.189 | 0.915 | 0.202, 1 | 0.163 | 0.756 | 0.117, 1 | 0.314 |
| *Number Transacted* | 641.2 | 2, 3493 | 724.1 | 101.7 | 1, 681 | 126.1 | 198.6 | 1, 4364 | 426.8 |
| *Fraction Buy* | 0.903 | 0, 1 | 0.172 | 0.75 | 0, 1 | 0.31 | 0.820 | 0, 1 | 0.330 |
| *Average Amount* (MW) | 14.35 | 0.506, 150 | 18.12 | 28.2 | 0.47, 102.6 | 23.3 | 32.2 | 0.1, 1058 | 79.9 |
| *St. Dev. of Amount* (MW) | 11.37 | 0, 50.0 | 11.74 | 35.77 | 0, 128.7 | 30.96 | 26.78 | 0, 459.2 | 44.8 |
| *Profit* ($1000) | 571.8 | -2332, 11743 | 1421 | -280.4 | -11305, 8760 | 2890 | 151.3 | -17860, 17817 | 2346 |

**Table 2: Descriptive Statistics for Aggregated Data**

The mean values of *geo*, *number transacted*, *fraction buy*, and *standard deviation of amount*, and *profit* for the unclassified participants fall between the corresponding values for the known speculators and known physical participants. This suggests that the unknown participants are a mixture of speculators and physical participants.

Analysis of the descriptive statistics reveals a substantial difference in *geo* between groups. Speculators have a low mean value of geo, while physical participants have a mean value of *geo* that is near one. Speculators' individual transactions also tend to be smaller, with less than half the mean value for *average amount* of physical participants. Speculators also have a smaller mean value for *standard deviation of amount*. Additionally, speculators have a positive mean value of *profit*, while physical participants have a negative mean value of *profit.*

## Statistical Strategy and Models

The first goal of the study was to create a statistical model using data from the known physical participants and speculators to identify transaction characteristics that are correlated with speculation. The model was then applied to remaining participants' data to estimate the unknown values of *speculator*. A binary logit model specification is appropriate for this purpose. The cumulative standard logistic distribution function $F(z) = \frac{1}{1+e^{-(z)}}$ is used in all the following models.

Physical participants are expected to hedge their bilateral contracts and therefore have limitations on the FTRs that they purchase. Speculators are likely to act as they would in any market; namely, to maximize their expected profit while minimizing their risk through diversification. It is therefore predicted that speculators will transact large numbers of small quantity FTRs in a wide geographic area, while physical participants will likely transact a relatively smaller number of larger quantity FTRs that have low geographic diversity. Additionally, since speculators are not likely to have externally allocated FTRs, they are more likely to purchase than to sell FTRs in the auction. Physical participants are allocated FTRs and will likely have a more balanced purchase to sales ratio. It also seems plausible that physical participants will have a large standard deviation of amount value since their transactions will likely have widely varying sizes corresponding to the physical reality of the electric system.

By far the best predictor of *speculator* for the known physical participant and known speculator subgroups was the geographic diversity variable *geo*. Speculators almost universally had high levels of geographic diversity (corresponding to low values of *geo*), while physical participants tended to have far lower levels (corresponding to values of *geo* near one). *Geo* will therefore play a key role in the model specifications. The model 1 includes all independent variables expected to be important for predicting *speculator*.

$$\Pr(\text{Speculator}) = F(\beta_0 + \beta_1 \text{ Geo} + \beta_2 \text{ Number Transacted} + \beta_3 \text{ Fraction Buy} + \beta_4 \text{ Average Amount} + \beta_5 \text{ Standard Deviation of Amount})$$

**Model 1: Primary Classification**

A sensitivity analysis is often an important step in statistical studies, and its importance is magnified for this study due to the need to classify the 75.3% of observations that belong to market participants with unknown values of *speculator*. Models 2 and 3 are representative of the many model specifications analyzed in this study that are excluded for brevity. They will provide for the sensitivity analysis.

The strength of *geo* in predicting *speculator* will be demonstrated in model 2 by removing all other independent variables. While omitting the other variables will mean that the coefficient for *geo* is potentially biased, the coefficient values themselves are not the primary interest of this study. Rather, the study focuses on the final results for speculator profit and liquidity. Thus, the relative strength of *geo* vis-à-vis other model variables will be evident if the results of model 2 are consistent with the results of the other models.

$$\Pr(\text{Speculator}) = F(\beta_0 + \beta_1 \text{ Geo})$$

**Model 2: *Geo* Only**

The strength of the *geo* indicator can actually be worrisome since it is known that a low value of *geo* can be misleading for some physical participants that operate in a large geographic region. Therefore, model 3 is proposed as an alternative that does not include *geo*.

$$\Pr(\text{Speculator}) = F(\beta_0 + \beta_1 \text{ Number Transacted} + \beta_2 \text{ Fraction Buy} + \beta_3 \text{ Average Amount} + \beta_4 \text{ Standard Deviation of Amount})$$

**Model 3: No *Geo***

## Model Results and Interpretation

Table 3 provides the results of each model along with the pseudo-$R^2$ fit statistic. Model results are reported as "relative odds ratio (*p*-value)." Positive coefficients indicate that an increase in the corresponding variable increases the odds that the observation came from a speculator, while negative coefficients indicate that an increase in the corresponding variable increase the odds that the observation came from a physical participant.

| Odds Ratio (p-value) | Model 1: Primary Variables | Model 2: Geo Only | Model 3: No Geo |
|---|---|---|---|
| ***Geo*** | -99.994%** ( < 0.0001) | -99.989%** ( < 0.0001) | |
| ***Number Transacted* (1000)** | -33.0% (0.6872) | | 5995%** (0.0003) |
| ***Fraction Buy*** | -50.11% (0.5486) | | 1868.0%** (0.0005) |
| ***Average Amount* (MW)** | 1.97% (0.1033) | | 1.54% (0.2593) |
| ***Standard Deviation of Amount* (MW)** | -5.11%* (0.0013) | | -6.37%** ( < 0.0001) |
| **Psuedo-$R^2$** | 0.5625 | 0.5396 | 0.3909 |
| * indicates statistical significance at the 95% level, ** at the 99% level. | | | |

### Table 3: Summary of Statistical Models

The strength of the *geo* indicator can be seen in models 1 and 2. In these models, *geo* has a very large effect that is statistically significant at the 99% level. In both models, increasing *geo* from 0 to 1 results in a 99.99% decrease in the odds that the corresponding observation belongs to a speculator. This agrees with the hypothesis that speculators are likely to purchase FTRs in a geographically diverse manner. The strength of the *geo* indicator is reinforced by the results of model 3. Without *geo*, the coefficient for *number transacted* and *fraction buy* differ significantly from model 1, thus demonstrating the importance of *geo*.

Several variables that were predicted to be important were not found to be statistically significant. *Average amount* was not statistically significant in any model. *Number transacted* and *fraction buy* were not statistically significant in model 1. The lack of statistical significance for these variables in model 1 is possibly due to the fact that *geo* is such a powerful predictor of speculation that little variation in *speculator* is left to be explained by the other variables.

## Classification and Overall Results

Each model is calibrated by calculating the values of the coefficients ($\beta_i$) using the known physical participant and known speculator data. These models are then used to classify the unknown observations. A desirable classification would result in histograms of *speculator* that make a "U" shape with the participants forming two clear groups. The results of model 1, 2 and 3 are given in figures 2, 3 and 4, respectively, which show the number of participants as a function of *speculator* probability.

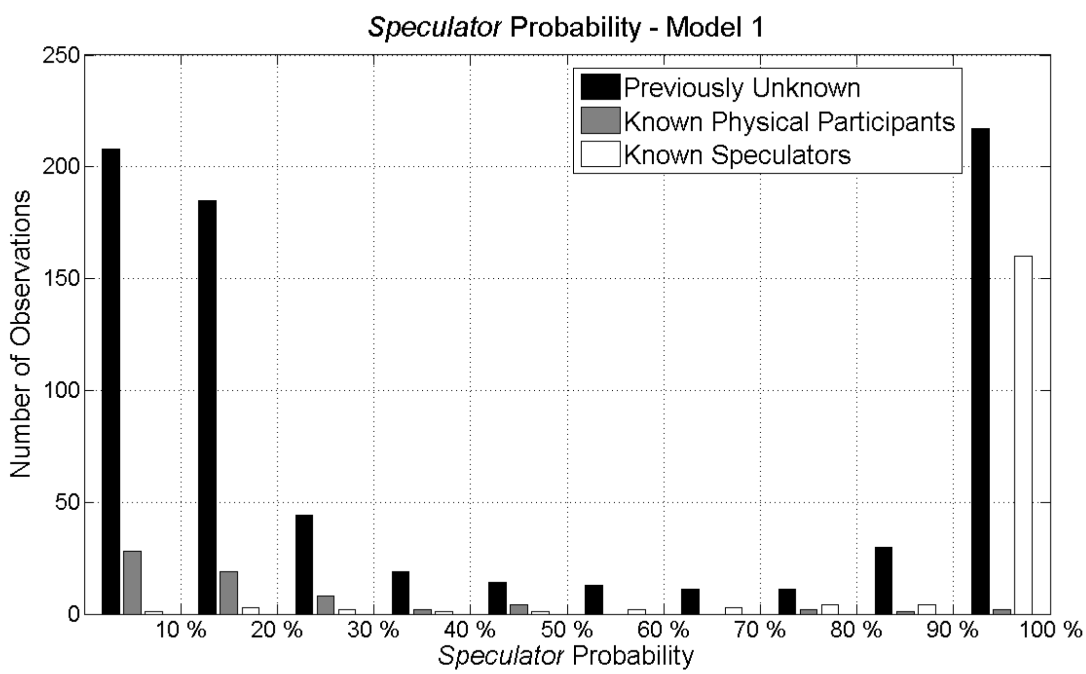


**Figure 2: Results of Model 1 – Primary Classification**

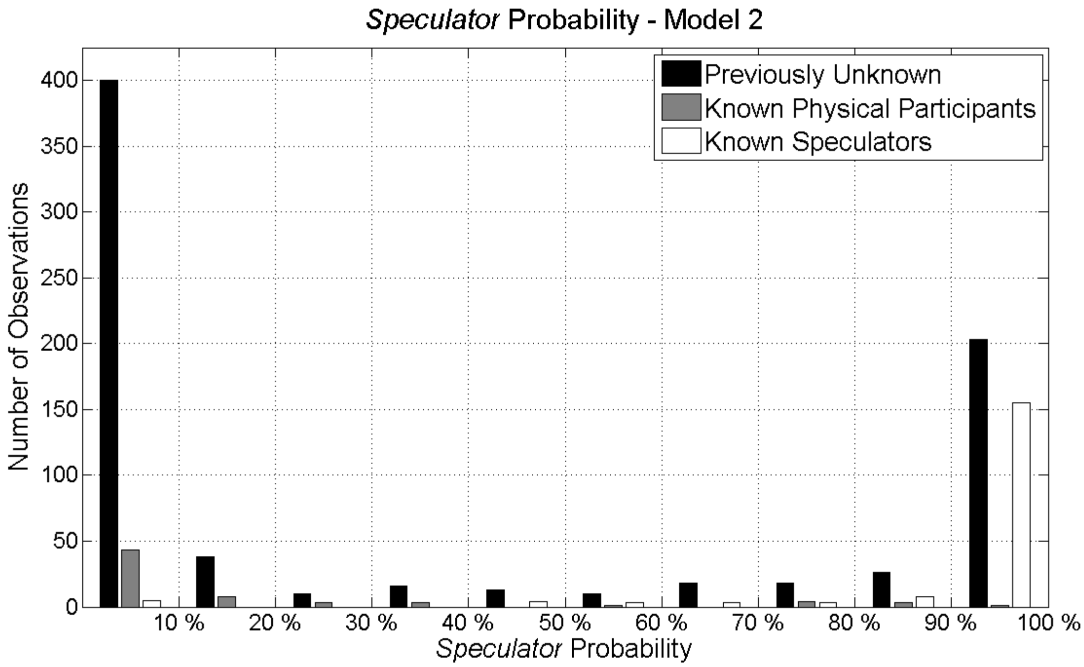


**Figure 3: Results of Model 2 – *Geo* Only**

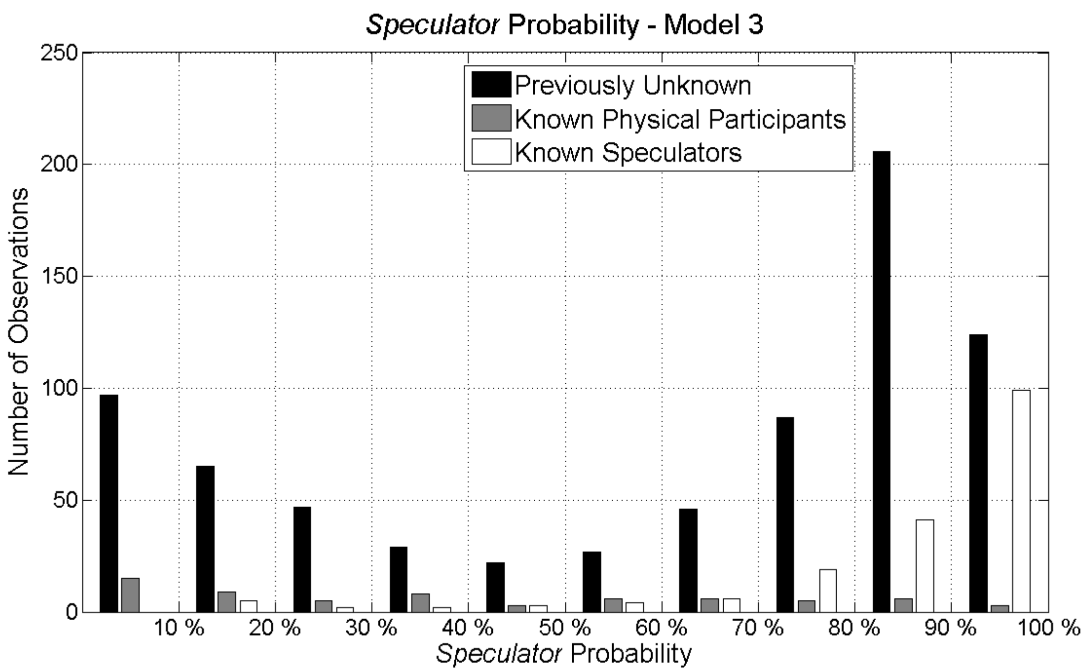


**Figure 4: Results of Model 3 – No *Geo***

Figures 2, 3 and 4 all demonstrate the desired "U" shape. The clustering that occurs in the known speculator and known physical participant groups shows that the models correctly classify the known participants. The fact that the unknown participant groups also form clusters in a "U" shape suggests that the models are applicable to the unknown participants.

The logit models generate a *speculator* probability value for the unknown observations. This probability can be interpreted using an "expected value" method. In this method, the probability returned by the logit model is interpreted as the percentage of a given observation that is speculatory in nature. This interpretation accounts for market participants with multiple intentions for the FTRs transacted in a given three month time period. While some transactions may be for speculation, others may be meant to hedge bilateral contracts. This is likely to be common among deregulated energy marketing companies that often own some physical assets but are free to speculate in FTR markets. Although this is not the way logistic models are typically interpreted (rather than the probability that an outcome occurs or does not occur, the output is interpreted as an estimate of the degree of an outcome), the expected value interpretation of the logit model output is likely to be well aligned with reality.

This interpretation can be implemented using an expected value calculation where the quantities for each market participant are multiplied by the probability returned by the statistical model in order to obtain total market quantities. The results of the expected value method with values given in percentages of total market quantities are shown in table 4.

| | **Model 1: Primary Classification** | **Model 2: *Geo* Only** | **Model 3: No *Geo*** |
|---|---|---|---|
| **Total Number of Speculator Transactions** | 84.1% | 85.1% | 90.0% |
| **Total MW Amount of Speculator Transactions** | 74.1% | 75.7% | 77.0% |
| **Total Speculator Profit** | 151.9% | 148.3% | 148.9% |

**Table 4: Results of Expected Value Method**

All of the models give estimates of speculator profit that are greater than 100%. Although this initially seems paradoxical, it is possible since physical participants tend to lose money in the FTR auction. Conceptually, speculators are able to profit from both the congestion payments made by transmission system users and the monetary losses in the FTR markets that are incurred by physical participants. Since the total market profit is calculated as the sum of each market participant's total profit (some of which is negative), the total speculator profit can be greater than 100% of the total market profit.

While all the models seem capable of predicting *speculator*, model 1 will be used as the primary model ("best estimate" in tables 5 and 6) since it contains all variables hypothesized to be important. Models 2 and 3 will be used for a sensitivity analysis.

While it is not overly concerning if the classifications of some individual market participants vary with different model specifications, stable overall results are desirable. Such stability was observed among all model specifications that did a satisfactory job at classifying the known participants, including models not detailed in this report, as the total amount of profit extracted by speculators was relatively consistent. All three models estimated total speculator profits approximately equal to 150% of total market profit. The measures of liquidity provided by speculators were similarly consistent, with the total speculator transactions all around 85% of total market transactions and around 75% of total market transactions in terms of MW amounts.

The consistency displayed between model specifications can be at least partially explained by the fact that a small number of market participants accounted for a large share of total market transactions. 69.2% of market transactions and 68.2% of market transactions by MW amount were conducted by the top 20 of the 165 total participants (top 12.1%). This suggests that small number of large market participants have consistent categorization. Once these participants are categorized, any differences in participant categorizations that exist between models are relatively insignificant.

Concern that the importance of *geo* could result in misclassification of some physical participants that operate in a geographically diverse manner can be ameliorated with model 3, which does not use *geo*. While model 3 has the worst model fit among the three models considered here, the model still has some predictive power as evidenced by the pseudo-$R^2$ value (0.3909). Since the final value of speculator profit obtained from model 3 is very similar that resulting from the other models, it does not appear that *geo*-based misclassifications are a substantial problem.

The final results are reported in table 5 in percentages of total FTR auction market values. In order to obtain conservative lower bounds, only market participants in the known speculator group were used to calculate the “minimum” column of table 5. These values likely underestimate the actual values by a significant margin, but do provide a lower limit that is as accurate as the designation of known speculators. Best estimate values are obtained from model 1, which contains all the variables believed to be relevant. The maximum value column is obtained for each measure by taking the largest value from any of models. The true values could potentially be larger than the maximum values given in table 6 due to the conservative assumptions used throughout the study. The consistency between the results of different models indicates that other reasonable models would give similar results.

| | **Minimum** | **Best Estimate** | **Maximum** |
|---|---|---|---|
| **Total Number of Speculator Transactions** | 42.7% | 84.1% | 90.0% |
| **Total MW Amount of Speculator Transactions** | 33.8% | 74.1% | 77.0% |
| **Total Speculator Profit** | 56.4% | 151.9% | 151.9% |

**Table 5: Overall Estimates of Speculator Profit and Liquidity in Percent of Total Market Values**

It is important to reiterate the inability to precisely calculate the FTR payments, and thus the profit accrued by their holder, due to the hourly prorating done when congestion revenue is not sufficient to fully fund all FTRs. The accuracy of the total profit made by speculators must be considered in light of monthly average prorating factors that range from 70% to 100%. The total profit made by speculators may have similar levels of error. Since the prorating factor will always reduce total profit, the estimates of speculator profit will be biased upwards. This effect is not as significant when results are presented in terms of percentage of total profit (as in table 5) since all market participants likely experience similar prorating factors. However, it is desirable to determine the dollar values of speculator profits and transaction amounts in order to put these estimates in a relatable context. Therefore, total speculator profit is estimated by multiplying the speculator percentage of total profit from table 5 by the total market profit ($216 million) and by the average prorating factor over the three year time period (86.2%) as shown in table 6. The other values in table 6 are obtained by multiplying the percentages in table 5 by the total market values for the entire three years under consideration (272.1 thousand transactions and 3.50 million megawatts).

| | **Minimum** | **Best Estimate** | **Maximum** |
|---|---|---|---|
| **Total Number of Speculator Transactions (thousands)** | 115.8 | 228.9 | 244.8 |
| **Total MW Amount of Speculator Transactions (millions)** | 1.183 | 2.594 | 2.685 |
| **Total Speculator Profit ($ millions)** | $105.0 | $283.4 | $283.4 |

**Table 6: Overall Estimates of Speculator Profit and Liquidity in Actual Values**

The estimates of speculator profit show that speculators do extract significant profits from the FTR market through monetary transfers from physical participants. As predicted, speculators also provide a significant amount of market liquidity. Speculators make up a large percentage of market transactions when considered on both a number of transaction quantity and MW basis. Therefore, it appears that speculators obtain large profits, but may also provide significant liquidity benefits to the FTR market.

## Conclusion

The results of this study come with several caveats from data limitations. First, as previously discussed, *geo* is not an ideal measure of geographic diversity and could lead to some market participants being misclassified. The results from model 3 at least partially ameliorate this concern. Second, the hourly prorating factors are not available, so actual profit for FTR holders is estimated using the monthly prorating factors. Third, with only 24.7% of observations belonging to known participants, the data for calibrating the models is limited. Finally, any errors made in classifying the known speculators and known physical participants will propagate through the rest of the study. However, the study results were not very sensitive to a variety of statistical model choices or to choices in classifying known market participants, including many variations not explicitly detailed in this study. Therefore, the study results are believed to be robust.

Despite these data limitations, the consistency of the model results and the general agreement of model predictions are very encouraging. While the assumptions are quite conservative (tending to decrease the probability of a speculator classification), the results still indicate significant speculator transactions and profits. While policy recommendations are beyond the scope of this study, the large speculator profits indicate that a strong argument could be made that the MISO FTR auction market is not functioning well for its intended purpose. However, this study also gives credence to the argument of speculator liquidity benefits. It is hoped that this study can contribute some of the information necessary for an enlightened debate on the appropriateness of speculator participation in FTR markets.

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## Endnotes

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[7] *Geo* is a measure of the geographic diversity of a set of FTRs transacted by a market participant. It is calculated by taking the maximum of the total MW amount of FTRs transacted by the market participant associated with each

control area, and then normalizing the resulting value by the total MW quantity of FTRs transacted by that market participant. $Geo = \frac{\max_{Control\ Areas}(Total\ FTR\ amount\ associated\ with\ control\ area)}{\sum_{FTRs} FTR\ amount}$.