ESSAYS ON EMPIRICAL ANALYSIS OF MULTI-UNIT AUCTIONS – IMPACTS OF FINANCIAL TRANSMISSION RIGHTS ON THE RESTRUCTURED ELECTRICITY INDUSTRY

A Dissertation

by

HAILING ZANG

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2005

Major Subject: Economics

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Approved by:

Chair of Committee,	Steven L. Puller
Committee Members,	Steven N. Wiggins
	Qi Li
	Stephen W. Fuller
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ABSTRACT

Essays on Empirical Analysis of Multi-unit Auctions

– Impacts of Financial Transmission Rights on the Restructured Electricity Industry. (August 2005)

Hailing Zang, B.S., Fudan University

Chair of Advisory Committee: Dr. Steven L. Puller

This dissertation uses recently developed empirical methodologies for the study of multi-unit auctions to test the impacts of Financial Transmission Rights (FTRs) on the competitiveness of restructured electricity markets. FTRs are a special type of financial option that hedge against volatility in the cost of transporting electricity over the grid. Policy makers seek to use the prices of FTRs as market signals to incentivize efficient investment and utilization of transmission capacity. However, prices will not send the correct signals if market participants strategically use FTRs. This dissertation uses data from the Texas electricity market to test whether the prices of FTRs are efficient to achieve such goals. The auctions studied are multi-unit, uniform-price, sealed-bid auctions.

The first part of the dissertation studies the auctions on the spot market of the wholesale electricity industry. I derive structural empirical models to test theoretical predictions as to whether bidders fully internalize the effect of FTRs on profits into their bidding decisions. I find that bidders are learning as to how to optimally bid above marginal cost for their inframarginal capacities. The bidders also learn to bid to include FTRs into their profit maximization problem during the course of the first year. But starting from the second year, they deviated from optimal bidding that includes FTRs in the profit maximization problems. Counterfactual analysis show that the primary effect of FTRs on market outcomes is changing the level of prices rather than production efficiency. Finally, I find that in most months, the current allocations of FTRs are statistically equivalent to the optimal allocations.

The second part of the dissertation studies the bidding behavior in the FTR auctions. I find that FTRs' strategic impact on the FTR purchasing behavior is significant for large bidders – firms exercising market power in the FTR auctions. Second, trader forecasts future FTR credit very accurately while large generators' forecasts of future FTR credit tends to be biased upward. Finally, The bid shading patterns are consistent with theoretical predictions and support the existence of common values.

Take joy, my King, in what You see.

To my parents

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Second, I wish to thank Professor William Hogan at Harvard University for his kind support of my research. Professor Hogan selected me into the Repsol YPF-Harvard fellow program which provided me with a great opportunity to enrich my knowledge of the electricity industry as well as other energy industries by collaborating with other researchers and people in industry. Not only that, Professor Hogan himself spent hours and hours with me discussing the details of this research, familiarizing me with the most upfront questions in the electricity industry and sharing with me his keen insights about some policy questions.

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CHAPTER I

INTRODUCTION

In the 1980s, several countries initiated electricity industry reforms. The U.S. electricity industry also experiences the transformation from the one that builds upon regulated vertically integrated monopolies to the one that promotes efficient wholesale and retail competition. Most of the restructuring involves the disintegration of generation, transmission and distribution ownership and require open access to the transmission grid. There are several landmarks of policy orders during this transition that is worth mentioning. In 1978, the Public Utility Regulatory Policy Act (PURPA) stimulated independent power plants coming into the sector if they meet certain criteria. The Energy Policy Act of 1992 (EPAct92) further removed some barriers that prevents the entry of independent power plants and initiated the development of an open access regime of the transmission grid. Federal Energy Regulatory Commission (FERC) issued Order 888 in 1996 that implements the open access regime and encourages the formation of Independent System Operators (ISOs) to manage the transmission grid. Paul Joskow concludes the essences of Order 888 as the following: "transmission owners must provide access to third parties to use their transmission networks at cost-based maximum prices, make their best efforts to increase transmission capacity in response to requests by third parties willing to pay for the associated costs, and shall behave effectively as if they are not vertically integrated when they use their transmission systems to support wholesale market power transactions, treating third party transaction schedules on their networks that are supported by firm trans-

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The journal model is Journal of Econometrics.

mission agreements equivalently to their own use of their transmission network."[1] In December 1999, The Commission's Order 2000 promotes the formation of Regional Transmission Organizations (RTOs) over larger regions and ask that transmission owners yield the operation of their transmission to the RTOs. Due to the slow pace of implementation of Order 2000, in June 2002, FERC proposed "Standard Market Design (SMD)" which further emphasized independent transmission provision.

Open access to transmission is a crucial component in the restructuring of the electricity industry. However, how to incentivize transmission investment to relieve bottle-neck constraints on the electricity market is still under discussion. On both the wholesale and retail side of the electricity market, market signals – market prices, are introduced to incentivize investment and consumption. The returns from investment on the wholesale and retail side are mostly decided by "market rates". However, the transmission network typically remians a regulated monopoly until recently and transmission investment is regulated through a regulated rate of return. Following the restructuring of the wholesale market, transmission policies are currently under hot debate as to whether transmission investment decisions should be regulated or be market driven. By using market signals, we allow merchant transmission investors to build capacity based on market incentivized returns. But if we use market-driven forces, the signals provided by the market should be accurate to reflect the actual scarcity or abundance of transmission resources. Otherwise, a biased signal will incentivized over- or under-investment.

Researchers (Hogan (1992, 2002), Bushnell & Stoft (1996, 1997)) as well as policy makers (for example, FERC's July 2002 Standard Market Design) propose to use Financial Transmission Rights (FTRs) to help market participants hedge against

[1] See Joskow (forthcoming 2005).

price volatilities due to transmission congestions on the wholesale electricity market. Interested market participants can buy FTRs through auctions conducted by grid operators. Brunekreeft (2003) summarized several ways to incentivize merchant transmission investment, one of these is to award the FTR auction revenue to merchant transmission investors. There are already some active merchant transmission investments in the United States market[2] and the investors rely on the FTR auction revenue to justify the benefit of the new transmission investment or the upgrade of the transmission line even if they are not awarded FTR revenues.

Since FTR auction revenue is a market signal to merchant transmission investors, This signal can only be efficient when there is no failure in the markets where FTRs are involved. If FTRs can be strategically employed by market participants to enhance their market power on the wholesale market, then FTR prices (or FTR auction revenues) are not purely reflective of the true valuation of transmission capacity. Following the proposal of FTRs, a lot of discussion has been going on as to whether FTRs would have any impacts on the competitiveness of the wholesale electricity market and whether FTR prices would be efficient in conveying the valuation of marginal transmission capacity. Bushnell(1999), Stoft (1999), Joskow and Tirole (2000, forthcoming 2005) discuss theoretically the impacts of FTRs that would have on the wholesale electricity market. Gilbert, Neuhoff and Newbery (forthcoming) study efficient auction designs for selling FTRs. This dissertation serves to empirically address the question as to whether FTRs are strategically manipulated by market participants who own FTRs and whether FTR prices are affected by such strategic manipulation. These empirical results help policy makers have a better knowledge of FTRs' impact in the real world and use FTRs as a better policy instrument.

[2]The most active one is the transmission interconnection between PJM (Pennsylvania, Maryland and New Jersey) and New York City and Long Island.

The difficulties in studying FTRs' impacts originate from the difficulties in the empirical study of multi-unit auctions. Different from single unit auction, where bidders submit to the auctioneer one price bid, the bids submitted by each bidders in multi-unit auctions are composed of multiple price-quantity pairs. Consequently in multi-unit auctions, the strategy space is much larger than that in single unit auctions. The major difficulty becomes how to handle such large strategy space. Further, there are different formats for multi-unit auctions. One form of multi-unit auction is uniform-price auction where the bidders pay the market clearing price for all the bids awarded; the other form is called discriminatory-price auction, where bidders pay their own awarded bids. An original theory paper by Wilson(1979) collapses all the uncertainties into the uncertainty of market clearing price. Following Wilson, more theory paper about properties of multi-unit auctions emerge, including revenue equivalence comparison (see Back and Zender (1993)) between different formats of multi-unit auctions, equilibrium strategies under different assumptions of valuation distribution structures (see Ausubel and Cramton (2002)), etc. The surging of empirical study of multi-unit auctions starts in late 1990s due to the more frequent practice of multi-unit auctions, for example the spectrum auction, the auctions in the electricity market and Treasury Bill auctions. Wolfram (1998) studies the bids on England and Wales electricity market to test whether two largest suppliers are exercising market power. Hortaçsu (forthcoming) studies the multi-unit auction in Turkish Treasury Bill auction and structurally backs out bidders' valuation by imposing valuation independence. He then use those backed-out valuation to empirically compare revenues under uniform-price and discriminatory-price auctions. Hortaçsu and Puller (2004) use bids on the Texas electricity market to test bidders' bidding behavior and is the closest paper to my first part of the dissertation.

This dissertation is composed of two major parts. In order to test whether

FTR prices are affected by strategic considerations, first we need to ask the question as to whether FTRs are strategically used by market participants. The first part is to empirically test FTRs' impacts on the owners' strategic behavior on the wholesale market. More specifically, since market participants supply power in the deregulated wholesale electricity market through auctions, I ask whether FTRs affect firms' bidding decisions. The wholesale market auction is in the format of multiunit, uniform-price, sealed bid auction. To date, virtually no empirical work has tested the existence and extent of such an issue on the wholesale electricity market. I also conduct counterfactual studies which give policy makers quantitative evidence as to whether the current allocations of FTRs are optimal.

Several researchers (as mentioned above) have made theoretic predictions that the allocation of FTRs can have important effects on the efficiency of the electricity market. Since FTR owners collect FTR revenue when positive congestion costs occur, the FTR revenue comes into the profit maximization decision of the FTR owners. In its simplest form, unit FTR credit[3] equals $P_{import} - P_{export}$, where P_{import} is the price in the import-constrained market[4] and P_{export} is the price in the export-constrained market. A local monopoly owning FTRs in the import-constrained market will have additional incentives to raise the price (P_{import}) in its regional market to increase the unit FTR credit; similarly, a local monopoly owning FTRs in the export-constrained market will have incentives to lower the price (P_{export}) in its own market to increase the FTR credit, *ceteris paribus*.

[3]Unit FTR credit is the "rebate" that the grid operator will pay to the FTR owners on the wholesale market when positive congestion costs occur.

[4]By import-constrained, I mean that the regional market cannot import any more of the electricity due to the binding transmission constraint. Similarly, by export-constrained, I mean that the regional market cannot export any more of the electricity due to the binding transmission constraint.

Based on newly developed empirical methodologies to analyze multi-unit auctions, I derive structural empirical models to test these theory predictions. The empirical methodology is an application of the Wilson (1979) share auction model and the supply function equilibrium model of Klemperer and Meyer (1989). This paper extends the work of Hortaçsu & Puller (2004). By making assumptions on the structure of the bid functions, the empirical models incorporate bidders' beliefs regarding uncertainties during the auctions. Using rich firm-level bidding data and plant-level costs from the Texas electricity market, I test whether bidders fully internalize the effect of FTRs on profits in their bidding or use FTRs merely as hedging instruments against volatile transportation costs. The empirical models give several testable hypothesis on firms' bidding strategies regarding FTRs. I find bidding behaviors converge towards theoretical equilibrium predictions over time with respect to firms' physical inframarginal capacity. With respect to FTRs, bidding strategies are converging towards optimal bidding during the course of the first year, but deviated from optimal bidding starting from the last period of the sample.

In terms of efficiency effects, in theory, when firms are net buyers in an import-constrained market, FTRs will improve market efficiency by eroding firms' local monopsony market power. When firms are net sellers in an import-constrained market, FTRs will distort market efficiency by enhancing firms' local monopoly market power. In the counterfactual study, I construct optimal bids that fully internalize FTRs in firms' bidding decisions to test the "worst/best case scenario" in the market. Counterfactual market outcomes reveal that even if firms fully internalize FTRs in their bidding, the marginal production efficiency is not affected much and that the effects of FTRs are mostly reflected in price level changes. I also conduct counterfactual studies to determine the optimal allocations of FTRs to major firms. Considering demand uncertainty, I find that in most months, the actual allocations of

FTRs are statistically equivalent to optimal allocations of FTRs in the improvement of wholesale market price signal efficiency.

The second part of the dissertation serves to empirically answer the question as to what the prices of FTRs are composed of, how we interpret market participants' purchasing behavior and what the magnitude of different components that constitute the price of FTRs are, for example, will market power effect be significant in the price of FTRs? In this part, the choice of the number of FTRs is endogenously decided during the bidding for FTRs, and I study the auctions for FTRs by integrating the FTR auction with the consequent wholesale market competition together. By integrating the two games together, I am able to test how FTR prices are affected by bidders' market power on the second-stage competition. Also the model I have facilitates testing the existence of bid shading[5] in the bid schedule they submit – another form of market power in the auctions when the bidders are buyers.

The types of bidders in the FTR auctions are different from those on the wholesale electricity market. In the wholesale electricity market real-time auctions, the bidders are power generation firms[6]. In the FTR auction, however, the bidders include not only power generation firms, but also traders and customer serving entities. For traders, they do not have any power generating facilities and do not serve customers, but they make profit in the electricity market by arbitraging price differences, for example trading electricity among different locations due to price differences. Traders also need FTRs to hedge against price volatility in their electricity transactions on the

[5]Bid shading refers to the gap that is between the bidder's true valuation and the bidder's bid price corresponding to each quantity level.

[6]In some market in the U.S., for example, the New York market, traders are allowed in the bidding to sell electricity on the wholesale electricity market. Such bidding is called "virtue bidding", meaning that even if the participant does not own any generation, it still can bid into the wholesale market. But virtue bidding was not introduced in the Texas market in the sample period I have for this dissertation.

wholesale market if they have trading positions on the wholesale market. The major reason for generators to buy FTRs is to protect themselves against price volatilities on the wholesale electricity market which I will explain in the next chapter. As was explained in the earlier part, FTRs can have some strategic impacts on the wholesale market competition, such impacts, in theory, should be transmitted to the price of FTRs as well. I derive empirical models that test the bidding strategies individually for traders and generators. Theory implies: Aside from hedging reasons, since generators have market power that's affected by the ownership of FTRs, the generators should include in their valuation the market power effect – additional benefit by using FTRs in the wholesale market competition. My empirical models test whether the market power effects are significant.

The FTR auctions are also in the format of multiple unit, uniform price, sealed-bid auctions. The empirical model for the FTR auction tests whether the bid schedules are consistent with equilibrium bidding strategies implied by theory. However, due to the limitations of the data, I am not able to use a fully structural model to back out bidders' true valuation, but rather, I use a reduced form model to test the essences of theory implications. I construct different measures of the expected future unit FTR credit and find that traders are forecasting future unit FTR credit very accurately; Large bidders who are generators forecast future unit FTR credit systematically higher than actual unit FTR credit while small generators' prediction on future unit FTR credit is very noisy. For the market power effect: Large bidders significantly included FTRs' impacts on market power into their bidding decisions while small bidders bidding strategy does not reflect such an concern. Different assumptions of value structures would lead to different empirical predictions and the empirical reduced form model used in this part of the dissertation represents a general model which allows value affiliation among the bidders. The empirical findings strongly supports the existence of a common value component in the value structure and the bid shading patterns for traders and large generators are consistent with multi-unit uniform-price theory implications.

CHAPTER II

THE TEXAS ELECTRICITY MARKET

The grid operator in Texas is called the Electric Reliability Council of Texas (ERCOT). The restructuring of the electricity market in Texas took place in August 2001. By the end of year 2001, the Texas market had 70,000 megawatts (MW) of installed generation, 37,000 miles of transmission and 57,600 megawatt hours (MWh) of peak demand.

A. How Electricity Is Traded in ERCOT

Unlike many the deregulated markets elsewhere in the United States where there are centralized power exchanges, or power is dispatched purely through auctions, 95% of power in the Texas electricity market is based on bilateral trading between buyers and sellers, i.e., the power transactions are settled by contracts between buyers and sellers. The remaining 5% is traded in the real-time market, also called Balancing Energy Service market where power is balanced between suppliers and consumers in the real time. In the real-time market, consumers do not respond to price, making demand perfectly inelastic. Congestion and congestion cost[1] are determined through this real-time market.

To supply electricity, firms operating in Texas must first give ERCOT information about their generation schedule one day ahead. No auction mechanism is involved in the one day ahead report. Then at the real time, firms can choose to bid into the spot market to provide balancing energy service so that in the real time, actual

[1]ERCOT uses a linear programming software to solve for the unit congestion cost called “shadow prices”(similar to a Lagrangian Multiplier) on each congested transmission line. Detailed calculation shadow price can be referred in Appendix A.

demand meets actual supply. The real-time market can be regarded as a residual market conditional on the scheduled supply one day ahead. In the real-time market (or the balancing market or the spot market: the names for this market will be used exchangeably but refer to the same market), a uniform-price, multi-unit, sealed-bid auction is conducted. It is hoped that through the market mechanism in the real-time, efficiency can be achieved if firms are perfectly competitive. This analysis focuses on the real-time market to test whether the spot market's price signal is further distorted by the ownership of FTRs if firms are already exercising local monopoly power.

Firms submit their bids to ERCOT no later than one hour ahead of the real time. Then the real-time market clears 20 minutes ahead for every following 15-minute interval. Although the time periods are divided into 15-minute intervals, the bid stack is fixed for each hour. Firms submit an hourly bid schedule for each regional market. Balancing bids are capped at $999/MWh.

B. Transmission Management and FTRs in ERCOT

When transmission lines are not congested[2], the ERCOT market can be regarded as integrated because the transportation cost is zero, or the marginal value of an additional transmission capacity is zero[3]. When the transmission lines are congested, the entire ERCOT market is separated into sub-markets with different prices known as zones. The price differences among the markets constitute the transportation cost (or congestion cost) for using the transmission line between two markets (Or you can

[2] Although the cause of congestion is complicated in engineering terminology, we can simply regard congestion as the case when the power flow along the transmission line reaches its upper-limit capacity of the transmission line.

[3] We can envision this "congestion cost" as a shadow price (a Lagrangian multiplier) attached to a binding constraint (the transmission capacity) when we solve a constrained optimization problem. When the constraint is not binding, the shadow price (the Lagrangian multiplier) is zero.

think of them as arbitrage costs). If we think of the transmission line as a "bridge", then without the rights, the merchant who wants to ship power across the "bridge" needs to pay "tolls". However, with transmission rights, he does not need to pay the "toll". The "toll" is the transportation cost, or congestion cost. Without FTRs, a firm cannot secure a stable profit stream since the congestion costs, which are determined by the real-time markets, are volatile. Owning FTRs allows the firm to use the transmission line for "free" so that the profit is more stable.

Transmission constraints are most likely to bind between zones and we call such congestion "zonal congestions". Within each zone, there are infrequent and random congestions called "local congestions". In the year 2001, there were three zones – South, North and West, and two major transmission constrains (South → North, and West → North). In 2002, a fourth zone was added - the Houston zone and there were four major transmission constraints: South → North, West → North, South → Houston and North → West. In 2003, the North → West constraint was dropped. Table I is a list of congestion frequency among most significantly constrained transmission interfaces from 2002 to 2003.

FTR program began in Texas on February 15, 2002[4]. There is no centralized

Table I. Frequency of Congestion on Major Transmission Constraints

(Jan. 2002 - May 2003, all hours)

	S → N	W → N	S → H	N → W
2002	26.6%	25.9%	26.7%	3.3%
2003	7.3%	7.3%	7.3%	–

[4]This date coincides with the direct assignment of congestion cost.

secondary market for FTRs[5], but FTRs can be traded bilaterally between market participants[6]. ERCOT auctions both monthly and annual FTRs. The annual auction distributes 60% of total FTRs with the remaining 40% distributed among each month. The FTRs awarded in the annual auction can be used for the entire year, while the monthly auctioned FTRs can only be used for the month specified. Once the bidders are awarded FTRs in the annual auction, the FTRs can be applied to any hours within the year. If the FTRs are awarded through monthly auctions, then the FTRs can only be applied to hours within the month specified. In view of possible market power effect, the rule stipulates that the individual can only holds no more than 25% of the entire stock of FTRs.

The FTR auction format in 2002 is uniform-price sealed-bid multi-unit auction. The bidders need to bid for each type of FTRs separately. In year 2003, the format for the FTR auction changed to multi-unit combinatorial auctions, i.e., the bidders buy different types of FTRs together as a bundle. Since both theory and empirical study for combinatorial auction, especially for multi-unit combinatorial auction are almost non-existent to my best knowledge, this study focuses on the FTR auctions in 2002. The auction for $N \to W$ FTR did not have many market participants in year 2002 and consequently this directional FTR is eliminated in the year 2003. In this research, I ignore the auction for this type of FTRs. In year 2002, on average there around 15 bidders in each auction (except $N \to W$ direction, which has less than 10 bidders in each round) with the annual auction has the largest number of participation.

[5]ERCOT does not monitor the secondary transactions.

[6]The bilateral trading is not registered with ERCOT and I do not have the information. Conversations with ERCOT staff members and industry practitioners reveal that the secondary trading is not liquid.

Once the bidder is awarded the FTRs, she needs to pay to the grid operator an amount that equals the FTR price times the FTR amount times the total time period in which the FTRs can be used. For example, if the bidder is awarded 10 units of $S \rightarrow N$ FTRs in the March FTR auction and the auction clearing price is \$5, she needs to pay a total amount of $\$5 \times 10 \times 31 days \times 24 hours = \$37200$. On the second-stage wholesale electricity market, she can then collect FTR credits whenever congestion happens in the direction of $S \rightarrow N$ in March. In year 2002, the FTR revenue from the FTR auction totaled \$91 million, exceeded ex-post FTR credit by \$62.4 million; in year 2003, the FTR revenue totalled \$27 million, while the ex-post FTR credit was \$30.5 million; in year 2004, total FTR revenue was \$34.5 million, and the realized FTR credit was \$43.9 million. Summer months always have the highest FTR prices and the FTR prices decrease from year 2002 to year 2003. This may be partially due to the changing of auction format which is beyond the discussion of this dissertation, and also reflect to some degree the learning of the bidders.

For this research, I look only at the first interval in the hour 18 (i.e. 18:00 - 18:15). Aggregate demand for electricity rises to peak demand around 1pm and stays stable till 8pm on an average day. In hour 18, firms usually have ample time to increase or decrease a unit's output so that there are only minimal inter-temporal adjustment costs in this hour.

CHAPTER III

THE IMPACT OF FTRS ON STRATEGIC BIDDINGS ON THE WHOLESALE ELECTRICITY MARKET

A. Theories

Wilson (1979)'s seminal paper on multi-unit auction offers a direction in performing empirical structural analysis on multi-unit auctions. Wilson collapses all the uncertainties that bidders have into the uncertainty of market clearing prices. Klemperer & Meyer (1989) explore the supply function equilibrium where the choice variable is upward sloping supply functions with multiple price and quantity pairs. Green & Newbery (1992) first applied the supply function concept in the study of the UK electricity market. Wolfram (1998) empirically studied multi-unit auctions with unit-specific bids in the England and Wales electricity market. Hortaçsu & Puller (2004) developed a structural method to analyze multi-unit uniform price auctions with portfolio bids in ERCOT. My paper extends their analysis to situations where the market is congested.

In most deregulated electricity markets, firms sign contracts with their customers at a fixed price PC_{it} and a fixed quantity. A firm can over/under-schedule in one day ahead from its actual total contract quantity, with the over/under-scheduled amount QC_{it} sold/bought in the real-time market. Total actual contracted quantity is then the sum of day-ahead scheduled quantity q_{it}^{DA} and QC_{it}. A positive QC_{it} means that the supplier is net short on its total contract volume in the real time and needs to buy back from the real-time market to supply its customer; a negative QC_{it} means that the supplier is net long on its contract in the real-time market and needs to sell to the real-time market. Usually the residual contract quantity (QC_{it}) in the real-time market is covered by a financial contract fixing the customers' price at the contract price (PC_{it}) if the customer gets QC_{it} from the real-time market[1]. According to the financial contract, if the real-time market price is higher than the contract price, then the supplier needs to pay its customer the difference for the contract quantity delivered in the real time and vice versa. Then the revenue from residual contract position (QC_{it}) in the real-time market is then $(PC_{it} - p_t^c)QC_{it}$ if p_t^c is the spot market price.

In the real-time market, a firm faces its own residual demand which is constructed by taking the aggregate real-time demand and subtracting the firm's competitors' supply. Below equation shows a firm's profit under the static setting without any uncertainty, i.e., a firm knows exactly the realization of its residual demand during a congestion period:

$$\pi_{it} = (S_{it}(p_t^c) - QC_{it})p_t^c + SP(p_t^c, \tilde{p}_t)FTR_{it} + PC_{it}(q_{it}^{DA} + QC_{it}) - C_{it}(S_{it} + q_{it}^{DA}) \quad (3.1)$$

where $S_{it}(p_t^c)$ is the supply function (the bid function) in the real-time and p_t^c is the real-time market clearing price. C_{it} is firm i's cost, $\tilde{p}_t$ represents prices in the other regional markets at time t, FTR_{it} represents the number of FTRs owned by firm i on a directional congested line at time t and $SP(p_t^c, \tilde{p}_t)$ is the corresponding unit congestion cost as a function of prices in each separated market.

The first term in the profit function is the revenue in the real-time market; the second term is the revenue from FTR payments; the third term is the revenue from selling the contract quantity and C_{it} is the cost of production. I ignore the sunk cost of purchasing FTRs in the profit function without any harm to the following analysis.

Unit congestion cost ($SP(p_t^c, \tilde{p}_t)$) is the marginal value for an additional unit

[1] These kinds of contracts are called Contract for Differences (CfD).

of transmission capacity, and is also the unit FTR credit payment. It is calculated as a linear function of regional prices with the coefficients decided by the line "shift factors". The shift factors indicate the impacts of power flow through one transmission line on the other transmission lines. When a generator send power through one transmission line, there will be part of the electricity "shifted" to other transmission lines. (The detailed calculation of the unit shadow price can be found in the Appendix A.) In its simplest form, the shadow price for a certain congested transmission line can be written as:

$$SP(P) = \alpha_1 P_N + \alpha_2 P_S + \alpha_3 P_W + \alpha_4 P_H \tag{3.2}$$

P_N P_S, P_W, and P_H are prices in the North, South, West and Houston region respectively. When the transmission lines are congested, prices in each market differ. α_is are constants from combinations of monthly average shift factors.

In all auction analysis, we need to model players' beliefs regarding the distribution of market outcome. In a multi-unit auction, Wilson (1979) uses $H(p, S_{it}(p))$ as players' beliefs of the distribution of market clearing price given their own submitted supply functions. More specifically, we can write:

$$H(p, S_{it}(p)) = Pr(p_t^c \leq p | S_{it}(p)) = Pr(S_{it}(p) + \sum_{j \neq i}^{N} S_{jt}(p) \geq \tilde{D}(p) | S_{it}(p)) \tag{3.3}$$

where $\tilde{D}(p)$ is the demand with a random noise. $H(p, S_{it}(p))$ is the probability that the market clearing price is lower than the bid price or the probability that there are excess supply on the market. Based on uncertainty about the market clearing price, the optimization is on the expected profit:

$$\max_{S_{it}(p_t)} \Pi = \int_0^{\bar{p}} \pi_{it} dH(p, S_{it}(p_t)) \tag{3.4}$$

where π is defined in equation (3.1).

By first order condition, we have[2]:

$$p_t - C'_{it}(S_{it} + q_{it}^{DA}) = (S_{it}(p_t) - QC_{it} + SP'(p_t, \tilde{p_t})FTR_{it})\frac{H_S}{H_p} \tag{3.5}$$

The left hand side (LHS) of equation (3.5) is the market clearing price-cost markup. Inside the parenthesis of the right hand side (RHS) of equation (3.5) are the quantities composed of real-time market clearing quantity $S_{it}(p_t)$, the net contract position in the real-time market QC_{it} and FTR quantity adjusted by shift factors. $S_{it}(p_t) - QC_{it}$ is the net real-time market sales. For example, if a firm sells 100 MW into the balancing market, but it still has contract obligation of 50 MW not scheduled day ahead, then it needs to buy back 50 MW from the real-time market, resulting in net selling 50 MW (100 MW - 50 MW) in the real-time market. There can also be cases where a firm is a net buyer ($S_{it}(p_t) - QC_{it} < 0$) in the real-time market.

In the import-constrained market, the shift factor adjustment ($SP'(p_t, \tilde{p_t})$) is positive. Then based on equation (3.5), FTRs give the firm a "pseudo" additional capacity as if the firm were able to ship power from a lower priced market without any cost and sell it at a higher local price, receiving the arbitrage revenue. However the firm does not need to physically ship power across transmission lines because FTRs are financial instruments. This is intuitively the reason why FTRs create additional incentives to exercise market power: the firm has more "pseudo imported capacity" to enhance its market power in its own location. Same logic applies to firms holding FTRs in the export market where the shift factor adjustment is negative. Then FTRs act as if the firm ships power to other higher-priced markets so that it has less capacity in its own market. In this case FTRs serve as "pseudo exported capacity" to reduce

[2]The derivation can be found in Appendix B.

the firm's local market power. But since this capacity is "pseudo", an interesting empirical question is whether the firm realizes its "pseudo capacity" in the market.

$\frac{H_S}{H_p}$ is the ratio of densities. Let us imagine that the horizonal axis represents quantity and the vertical axis represents price, then H_S is the changing in the $H(p, S_{it}(p))$ distribution due to a leftward/rightward shift of bid curve (holding bid prices being constant). The higher the amount that the bidder supplies at a given price, the higher the probability that there is excess supply, H_S is therefore positive. H_p is the changing in $H(p, S_{it}(p))$ distribution due to an upward/downward shift of bid curve (holding bid quantities being constant). As bid quantities are fixed, the higher the price that the bidder requests to be paid, the higher the probability that the price is greater than the market clearing price, and this term is therefore also positive. Then the whole term $\frac{H_S}{H_p}$ is positive, an element that affects the markup amount through uncertainty.

To explore the uncertainties in detail, I group the uncertainties into two categories: 1), firm's private information, and 2), randomness in the aggregate demand. In equation (3.5), there are two pieces of firm's private information that adds to uncertainties in the market: The first is the net contract positions (QC_{it}) in the real-time market and the second is the FTR ownership. I assume that bidders' private information (the net contract position on the balancing market and FTRs) are additively separable to its bid slope in their bid schedule. More specifically, we can write the bidder's supply schedule as $S_i(p, QC_i, FTR_i) = \alpha_i(p) + \beta_i(QC_{it}, FTR_i)$ [3]. $\alpha_i(\cdot)$ and $\beta_i(\cdot)$ are flexible functional forms. Intuitively, This assumption serves to ensure

[3]Notice that in the function of $\beta_i(.)$, we do not know how FTR_i affects QC_{it} (because FTRs are determined before the decision of QC_{it}). But if FTRs affect QC_{it}, that effect is on the one day ahead and not on the balancing market. By conditioning on QC_{it}, we are able to detect the FTR's effect on the real-time market participants' behavior.

that bidder's private information only add noises to the bid function horizontally but won't change the shape of the bids. This assumption is similar to the assumption in Klemperer & Meyer (1989)'s derivation of supply function equilibrium where they assume that in a short time period, noises only translate demand horizontally but do not pivot demand. From a firm's perspective, locally it faces its own residual demand which is the perfect inelastic aggregate demand minus its rival's supply. Since the private information are all additive noises, the residual demand will also be translated horizontally without being pivoted by the private information.

Second, the aggregate demand ($\tilde{D}(p_t)$) itself contains some randomness. I assume that there are idiosyncratic additive errors to the expected demand ($\bar{D}(p_t)$), i.e., $\tilde{D}(p_t) = \bar{D}(p_t) + \epsilon_t$, where ϵ_t is random noises independent of private information and $\bar{D}(p_t)$ is the expectation of future demand. Under the above assumptions, the first-order condition in equation (3.5) can be reduced to[4]:

$$p_t^c - C_{it}'(S_{it} + q_{it}^{DA}) = \frac{(S_{it}(p_t^c) - QC_{it} + SP'(p_t^c)FTR_{it})}{-RD_{it}'(p_t^c)} \tag{3.6}$$

From equation (3.6), all the uncertainties can be captured by residual demand slope $RD_{it}'(p_t^c)$ at every price level. Rather than simulating the $H(p, S_{it}(p))$ distribution each time period, which requires tremendous computational burden, I can now only focus on the estimation of residual demand slope at each price level to measure the uncertainty component in the auction. The above analysis also carries through with the same results when the bidder is risk averse. The proof for a risk averse bidder can be found in Appendix D. My structural estimation is based on equation (3.6).

[4]detailed derivation can be found in the Appendix C

B. Empirical Model

1. Structural Estimation Equation

Based on equation (3.6), I can test whether or not the term $SP'(p_t)FTR_{it}$ is significant in equation (3.6). If the parameter before $SP'(p_t^c)FTR_{it}$ is statistically equivalent to one, then firms fully internalized FTRs into their bidding strategies: treating FTRs the same as their net physical balancing market sales. If the parameter is statistically insignificant, then FTRs are merely hedging instruments. The parameters will also reveal the magnitude of deviation from optimal behavior. The empirical structural model can be written as the following:

$$p_t^c - C'_{it}(S_{it} + q_{it}^{DA}) = \beta_1 \frac{S_{it}(p_t^c) - QC_{it} + \beta_2 SP'(p_t^c)FTR_{it}}{-RD'_{it}(p_t^c)} + \epsilon_{it} \tag{3.7}$$

where the LHS is the price cost markup at the market clearing point. On the RHS, $S_{it}(p_t^c) - QC_{it}$ is the net power supplied in the real-time market; $SP'(p_t^c)FTR_{it}$ is the FTR quantity adjusted by shift factors and $RD'_{it}(p_t^c)$ is the slope of the residual demand at the market clearing point. β_1 reflects a firm's bidding strategy with regard to its inframarginal capacities. β_2 reflects the effect of FTRs – the "pseudo capacity" – on the firm's bidding strategy and can be treated as the weight a firm puts on FTRs relative to its net balancing market physical sales in the bidding.

Denoting $\beta_1 \times \beta_2$ as γ_1, we can rewrite our previous equation (3.7) as:

$$p_t^c - C'_{it}(S_{it} + q_{it}^{DA}) = \beta_1 \frac{S_{it}(p_t^c) - QC_{it}}{-RD'_{it}(p_t^c)} + \gamma_1 \frac{SP'(p_t^c)FTR_{it}}{-RD'_{it}(p_t^c)} + \epsilon_{it} \tag{3.8}$$

Based on equation (3.8), β_2 can be recovered by $\beta_2 = \frac{\gamma_1}{\beta_1}$ and we can test the following sequence of hypothesis:

H_0: $\beta_2 = \beta_1 = 0$ perfect competitive case – the bidder is perfectly competitive not only with regard to net physical balancing market sales but also to FTRs, the pseudo quantity.

H_1**:** $\beta_2 = \beta_1 = 1$ optimal strategic equilibrium bidding – the bidder is optimally exercising market power unilaterally not only with regard to its net physical balancing market sales, but also to FTRs' pseudo quantity.

Relaxing the above joint hypothesis, I can further test:

H_2**:** $\gamma_2 = \beta_1$ relaxing the constraint that $\beta_1 = 1$, the bidder internalize FTRs identically as its own net physical balancing market sales.

H_3**:** $\beta_1 = 1$ Optimal strategic bidding only with regard to net balancing market physical sales.

2. Data

Based on equation (3.8), I need information on bid, cost, demand and FTRs. My data set includes the real-time market bid stack, hourly generation data, unit cost information, real-time balancing market demand data and FTR auction results. All the data are confined to weekdays.

- Balancing bid data: each bidder's hourly bids into each zone.
- Hourly generation data: whether a unit is available and operating during each hour, the location, the day-ahead scheduled amount of generation per unit and the real time actual amount of generation per unit. This data set also consists of a unit's engineering characteristics such as the minimum and maximum generation capacity available in each time period. These information are used to construct the marginal cost curves.
- Unit cost data: the marginal fuel cost of each unit is estimated using the direct fuel (gas or coal) costs and the unit's generation efficiency (heat rate). The

marginal cost of each unit is also composed of environmental cost (SO_2 and NO_x permit price) and variable operation and maintenance (O & M) costs. Each unit has a constant marginal cost reflecting the above elements until it reaches its capacity. The marginal cost for each unit is assumed to be infinite after a unit's generation capacity is reached. I measure each unit's marginal cost with methods that are standard in the electricity economics literature. I use the same data as Hortaçsu and Puller (2004) and the detail of the cost measurement can be found in the appendix of Hortaçsu and Puller (2004).

- Demand data: the 15-minute real-time market clearing price and the zonal amount of electricity demanded in the real-time.

I confine my study to "local monopolies" since the theory applies to firms with local monopoly power. I focus on TXU in the North zone and Reliant in the Houston zone. Reliant owns around 55% of total generation in the Houston zone and TXU owns around 60% of total generation in the North zone. If we compare Reliant and TXU with other firms in the balancing market from August 2001 - July 2002, Reliant and TXU combined realized almost 65% of total sales in the real-time market. TXU and Reliant are also important because they were active purchasers of FTRs throughout my sample period.

3. Measurement of Each Variable

Variables needed for the estimation of equation (3.8) are measured as the followings:

Residual Demand Slopes ($RD'_{it}(p^c_t)$) In the auctions, bid functions take the form of step functions. Since the residual demand is derived by subtracting the rival's supply function (bids) from the aggregate demand (which is perfectly inelastic in the real-time), the residual demand is also a step function. For a step function, the slope for each point is either 0 or ∞. A firm should have some prior on the shape of a relatively smooth residual demand to choose its bid schedule. To get a smoother residual demand, I use non-parametric kernel estimation to smooth out the residual demand without assuming any functional forms. I estimate the residual demand function using the following kernel regression:

$$p_t^c(RD) = \frac{\sum_{n=1}^{N} p_n K(\frac{RD-RD_n}{h})}{\sum_{n=1}^{N} K(\frac{RD-RD_n}{h})} \tag{3.9}$$

where n is the bid steps, N is the total bid steps for a single bid function, h is the smoothing parameter, and $K(\cdot)$ is the kernel function. In this estimation I use a normal kernel, with

$$K(\frac{RD - RD_n}{h}) = \frac{1}{(2\pi)^{1/2}} exp^{-\frac{(\frac{RD-RD_n}{h})^2}{2}} \tag{3.10}$$

The residual demand slope can be measured by taking derivatives of equation (3.9). h is selected according to the ad-hoc rule, where:

$$h = std(RD_n)n^{-\frac{1}{5}} \tag{3.11}$$

$std(RD_n)$ is the standard deviation within the sample at each time period, and n is the sample size. Due to large dimensionality of the data set, the ad-hoc method quickens the computing speed without losing much accuracy.

Market Clearing Price and Quantity The market clearing price (p_t^c) and quantity ($S(p_t^c)$)is at the intersection of firm i's bid schedule and the realization of its residual demand RD_{it}. $S_{it}(p_t^c) - QC_{it}$ is then the net physical balancing market sales for firm i at the market clearing price.

Residual Cost To construct a marginal cost curve, I first need to get each unit's flexible capacity on the balancing market. Most units cannot decrease their output down to zero. There are two measures in the data that give a hint of the minimum amount of output that needs to be sustained for each unit: 20% of the unit's maximum capacity (which is used in Hortaçsu and Puller (2004))and the reported minimum unit capacity. I define the maximum of the above two measures as the minimum required capacity to be running for each unit. The flexible capacity for each unit is then the difference between its maximum generation capacity and the minimum required capacity for operating derived as above. To construct the marginal cost curve, I stack the units with their flexible capacities according to an ascending cost rule. Since I am studying the balancing market (or the residual market), I re-center the origin to the day-ahead scheduled amount of generation because any increase or decrease of production in the real-time originates from this day-ahead scheduled production. To avoid the start-up cost adjustment problem, I only focus on units that are already operating during previous hours.

Markup Once the market clearing price and quantity is found, I calculate $C'_{it}(S_{it}(p_t^c))$ – the marginal cost of supplying the market clearing quantity. The markup is measured as $p_t^c - C'_{it}(S_{it})$.

4. Recover Private Information: Net Contract Position (QC_{it})

I have in data one piece of private information – the FTR ownership, but I do not have data on firm's net contract position QC_{it} in the real-time market. To measure contract quantities (QC_{it}) that have gone into the balancing market, Hortaçsu & Puller (2004) recover QC_{it} by finding the intersection point between the bid function and the marginal cost function, such as point A in Figure 1 where P(Q) is the bid function and MC is the marginal cost function. The intuition is that a firm will bid

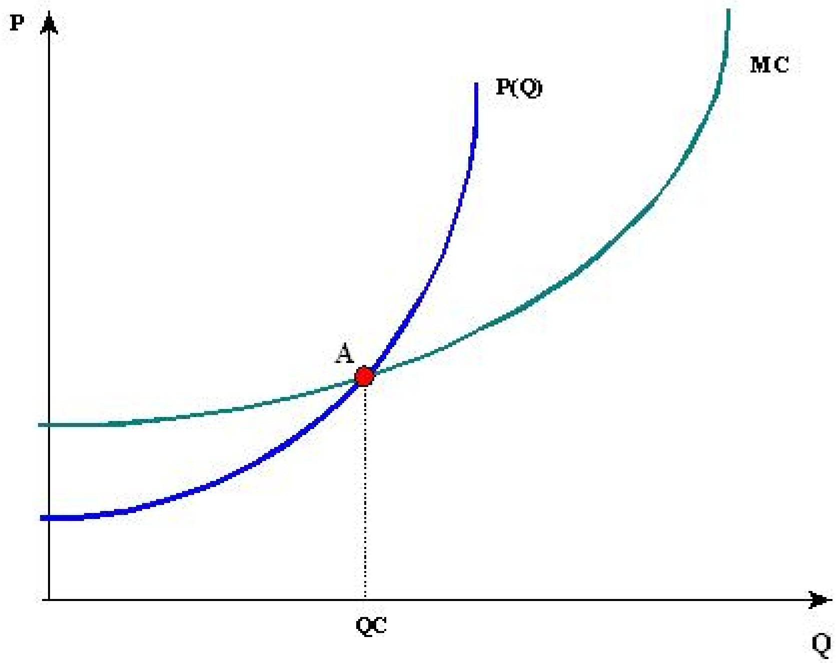

Fig. 1. QC When No Congestion

higher than marginal cost when it is a net seller on the balancing market, and bid lower than marginal cost when it is a net buyer on the balancing market to save its own production cost. In my case, however, the observed intersection point $QC_{it,obs}$ is composed of the true QC_{it} ($QC_{it,true}$) and FTRs. To understand this, we can rewrite our equation (3.7) as

$$p_t^c - C_{it}'(S_{it} + q_{it}^{DA}) = \beta_1 \frac{(S_{it}(p_t^c) - (QC_{it,true} - \beta_2 SP'(p_t^c) FTR_{it}))}{-RD_{it}'(p_t^c)} + \epsilon_{it}, \qquad (3.12)$$

and let

$$QC_{it,obs} = QC_{it,true} - \beta_2 SP'(p_t^c) FTR_{it} \qquad (3.13)$$

Intuitively, if $QC_{it,true} > 0$, the firm must buy the residual contract quantity ($QC_{it,true}$) from the real-time market but the FTRs allow it to import the FTR quantity for "free". Such a pseudo import quantity reduce the residual contract quantity to

$QC_{it,obs}$ in the real-time market so that the firm has more flexible capacities and market power is increased.

According to equation (3.13), I can still use the intersection point to identify $QC_{it,obs}$(the quantity combined of $QC_{it,true}$ and FTRs), but I cannot separately identify $QC_{it,true}$ from FTRs without further assumptions to recover the $QC_{it,true}$. Furthermore, the congestion status I observe is the ex-post realization, I need to have a metric that indicates the probability that the ex-post realized congestion is ex-ante forecasted. Only when a firm forecasts future congestion, it will bid to include FTRs. Notice that during non-congestion intervals (or a firm forecasts a future non-congestion), firms' profit functions do not include FTR credit revenue since congestion cost is zero, and hence the intersection of bids with cost curves reflects $QC_{it,true}$[5]. In order to measure the true contract quantity on the balancing market when a firm perceives future congestion and bids accordingly, we need to know the indicators of future congestion and the stable factor in the contracts[6] through time so that non-congestion and congestion periods can be related.

Sample Selection To determine how probable congestion will be, I construct a variable called "frequency of congestion (*freqoc*)" as the rough probability of

[5]There might be questions as to whether a firm has the ability to affect the congestion outcome. Since the balancing service market is only a residual market, the bids on the balancing market mostly affect the price on the market, but not the congestion outcome. If a firms' schedule one day ahead is the major source of congestion, then it can show willingness or unwillingness to relieve congestion through its bids. But usually balancing bids alone cannot cause congestion. Bids on the balancing market are finalized one hour ahead, so firms know the current market condition such as weather, market aggregate demand, etc., which is quite stable around hour 18:00 and congestion is well expected. This paper assumes that because congestion is exogenous on the balancing market and firms expect future market congestion outcome with some confidence since the "future" is not far away, they can update their information and change their bids accordingly. For example, from August 2002 - December 2002, Reliant and TXU on average change their bids three times before the finalizing stage.

[6]The elements that are related with contracts are: real total contract quantity, day-ahead scheduled quantity and real-time residual contract obligations.

congestion for time period 18:00 - 18:15. This index is measured by dividing the total number of congestions intervals during 13:00 - 17:00 by the total number of intervals during that time period[7]. From January 2002 - May 2003, 72% of total congestion occurred when the frequency of congestion in the afternoon was greater than 50% and 87% of total non-congestion occurred when the frequency of congestion in the afternoon was less than 50%. These numbers indicate that *freqoc* is an accurate predictor of congestion. For this study, I focus on time intervals 18:00 - 18:15 when *freqoc* was greater than 50%. This means that my selected sample include some congested intervals, but also some non-congestion intervals with perceived congestion.

Stable Factor I regard the total contract quantity as the most stable element related with contracts over time (at least within one week). We can observe a firm's day-ahead scheduled quantity, but we do not know whether it under- or over-scheduled in the day ahead. As was mentioned before, during time periods when a firm perceives a future non-congestion and bid accordingly, the intersection of bid curve with cost curve gives the net true contract position on the real-time market. Combined with day-ahead scheduled quantity, I can back out a firm's actual total contract quantity (Q_{it}^{CT}) during that time interval by $Q_{it}^{CT} = q_{it}^{DA} + QC_{it}$. I restrict to samples with very low *freqoc* ($freqoc < 20\%$) and back out the true total contract quantity (Q_{it}^{CT}) using the above methods. The variation within a week for the backed-out contract quantity is mostly less than 10% and sometimes even less than 1%. I calculate the average of the contract quantity ($\bar{Q}^{CT}$) for each week and assume that this is the actual contract quantity that

[7]Bids need to be finalized an hour ahead (i.e., 17:00 for the bidding for hour 18:00 - 19:00).

the firm needs to deliver to its customer each day during the week at this time interval.

Measure $QC_{it,true}$ After finding the actual total contract quantity ($\bar{Q}^{CT}$), I can recover $QC_{it,true}$ by relating the total contract quantity ($\bar{Q}^{CT}$) to its day-ahead schedule (q_{it}^{DA}) during my selected sample periods: $QC_{it,true}$ is then recovered by subtracting the day-ahead schedule from the total contract quantity ($QC_{it,true} = \bar{Q}_{it}^{CT} - q^{DA}$). Table II shows the summary statistics of the QCs as measured above in both "mostly likely" congestion and non-congestion periods for Reliant and TXU. QC_{obs} (the actual intersection point of bid and cost curves without adjusting for FTRs) during most likely congestion periods are also listed in the third row for each firm. For comparison purpose, the absolute magnitude of the market clearing quantity $S_{it}(p_t^c)$ are given in the fourth row for each firm.

On average, residual contract positions (QC_{true}) during congestion periods are larger than the numbers during non-congestion periods. If a firm strategically deploys its contract quantities into day-ahead (q^{DA})and real-time (QC), then QCs should reflect such behavioral difference but is beyond the scope of the analysis in this dissertation.

5. Apply to the Notion of Supply Functions

Klemperer & Meyer (1989)'s supply function is derived by assuming additive noises to the residual demand. They argue that firms submit multi-unit bids because of uncertainty in the location of residual demand. If a firm knows for sure where the residual demand lies, it can do as well by just bid only one point to equalize marginal revenue with marginal cost and maximize its profit. The authors argue that when

Table II. Comparison of QCs in Different Scenarios

Feb. 2002 - May 2003; 18:00 - 18:15; $freqoc > 0.5$

		mean	s.e.	min	max
Reliant	congestion (QC_{true})	761.68	1137.31	-1691.75	3254
	non-congestion (QC_{true})	210.88	351.07	-400	1601
	congestion (QC_{obs})	492.27	575.47	-1000	2619
	$S_{it}(p_t^c)$ (congestion)	350.42	364.46	0	1400
TXU	congestion (QC_{true})	624.79	1242.12	-3092	3407
	non-congestion (QC_{true})	444.91	533.22	-1750	2320
	congestion (QC_{obs})	400	493.95	-250	2380
	$S_{it}(p_t^c)$ (congestion)	332.19	465.22	0	2017

Note: "congestion" refers to intervals with *freqoc*>0.5;"non-congestion" refers to intervals with *freqoc* < 0.5.

demand is translated horizontally by uncertainty, firms have a positively sloped supply function, rather than a vertical Cournot supply function or a horizontal Bertrand supply function[8]. My assumption of private information serving to affect the residual demand position but not the slope is in compliance with the conditions for an upward sloping supply function.

In this structural estimation, I add noises to the ex-post realized residual demand curve to simulate demand uncertainty. Theory indicates that if a firm is optimizing, it should do so along each bid point. I shift residual demand horizontally by adding noises randomly drawn from a normal distribution with a standard deviation of 300 MW[9]. If the clearing point is the same as the previous shifting (either the clearing price or the quantity), I drop that observation since it is redundant. Hence the resulting clearing points from the shifting of residual demand should be reflective of the bid points "supposedly" be cleared on a single bid curve each day. In this way, my estimation results show the optimality of the entire bid schedule.

C. Estimation

Table III gives summary statistics of the variables in equation (3.8). All numbers are in absolute values[10]. Both Reliant and TXU are in the import zone with variable importing FTRs through time. Both Reliant and TXU on average price differently from marginal costs, but their markups vary substantially over time.

To detect the evolution of strategies over time, I divide the sample into three

[8] By vertical, I mean that the horizontal axis is quantity while the vertical axis is price.

[9] The standard deviation of daily demand is around 250MW and the stand deviation of weekly demand during the hour 18 is around 400MW.

[10] When firms are decreasing their supply in the real time, the markup and the market sales are negative.

Table III. Summary Statistics for Reliant (Houston) and TXU (North)

Feb 2002 - May 2003; 18:00 - 18:15; $freqoc > 0.5$

Reliant (Houston)	mean	s.d.	obs
Markup	28.90	115.74	78
Net Market Sale (S - QC_{true})	533.03	629.25	78
FTR ($S \rightarrow H$)	140.56	54.40	78
TXU (North)	mean	s.d.	obs
Markup	26.82	92.33	78
Net Market Sale (S - QC_{true})	1035.74	793.97	78
FTR ($S \rightarrow N$)	117.63	39.79	78
FTR ($W \rightarrow N$)	100.01	57.54	78

periods: Period 1: February-June 2002; Period 2: July-December 2002; Period 3: January-May 2003. Historically, period 2 shows more congestion since summer peak demands are within the sample. Period 1 and Period 3 are off-peak and shoulder months, but for the month of March, April, October and November, generation and transmission outages are often in ERCOT.

1. Metrics of Optimality

This section provides several qualitative metrics in the testing of optimality with FTRs in the bids.

a. Distance From Actual Bids to Optimal Bids

First I check how far apart the actual bids are from the "optimal" ones. FTRs are acting as "pseudo quantities" that shifts the bid curve: "QC_{true}" is shifted leftward

Table IV. Closeness to "Optimal" Bids: $\hat{S}(p_t) - S^*(p_t)$

(Feb 2002-May 2003, 18:00 - 18:15, $freqoc > 0.5$)

Period	mean (mw)	s.d.	obs.
Reliant			
1	695.22	892.66	30
2	-155.23	937.87	31
3	229.514	483.98	17
TXU			
1	719.29	1166.32	30
2	66.67	639.69	31
3	-64.22	529.69	17

Note: $\hat{S}(p_t)$: actual bids; $S^*(p_t)$: optimal bids.

(reduced) by FTRs to "QC_{obs}" according to equation (3.13). To get the bids that fully internalize FTRs, I keep the original bid shape so that β_1 is not affected, and shift the bid in a way that it crosses the marginal cost curve at the "optimal" point where $\beta_2 = 1$ in equation (3.13) ($QC_{it,obs} = QC_{it,true} - SP'FTR_{it}$). I measure the quantity deviation between actual and optimal bids at the same price level to assess the optimality with FTRs in the actual bids. Table IV gives the summary statistics of the distance deviations.

If $\beta_2 = 0$, or the firm does not internalize FTRs into its bidding decision, the bid curve should lie to the right (the bid curve is not shifted) of the "optimal" bid curve, i.e., corresponding to each price level the actual quantity bids should have a larger quantity than the optimal quantity bids. Note that in Period 2, the mean for Reliant is negative, meaning that Reliant shifted the bid curve so much that it is to the left of the “optimal” bids. The absolute magnitude of the closeness of actual bid curve to the “optimal” bid is smaller for Reliant during Periods 2 and 3 than Period 1, with period 3’s variance being the smallest. These statistics indicate qualitatively that Reliant is bidding better through time. For TXU, the absolute magnitude is also drastically smaller during Period 2 and 3 than Period 1, showing a degree of behavioral improvement.

b. Measurement of β_2s

β_2 can be measured day-by-day from equation (3.13) and in theory, β_2 should equal 1. The measurement of β_2 uses the intersection of the bid curve with the cost curve ($QC_{it,obs}$). The drawbacks of looking at this intersection point alone is that we ignore the entire bid schedule. Each bid point informs us about the bidding strategy under other possible realizations of residual demand. By looking only at the information conveyed by the intersection point, we might ignore the optimality at other bid points. Nevertheless this is an important piece of information. Table V gives the measurement results. The consistency with Table 4 is that Reliant in the second period and TXU in the last period shifted their bid curves too much that β_2 is greater than one. Again, starting from Period 2, both players are showing significant improvement in the bidding strategy with regard to FTRs. The following histograms in Figure 2 and Figure 3 give a clearer picture of the distribution of β_2 over time. The histograms reflect the overall precision of the β_2 during each sample period.

The numbers and the histograms show that for both Reliant and TXU during Period 2, the means of β_2s are closer to 1 and the distributions have thinner tails.

Table V. Test of Optimal Shifting – β_2

(Feb 2002-May 2003, 18:00 - 18:15, $freqoc > 0.5$)

Period	β_2	s.d.	min	max	obs.
Reliant					
1	-.69	1.75	-3.31	2.50	23
2	1.25	1.71	-3.25	4.41	30
3	-.03	1.76	-3.46	3.31	17
TXU					
1	-.57	2.47	-5.32	3.73	24
2	.75	1.16	-1.89	3.24	29
3	1.41	2.37	-2.46	6.93	17

Note: β_2 is measured by $QC_{it,obs} = QC_{it,true} - \beta_2 SP'(p_t^c)FTR_{it}$

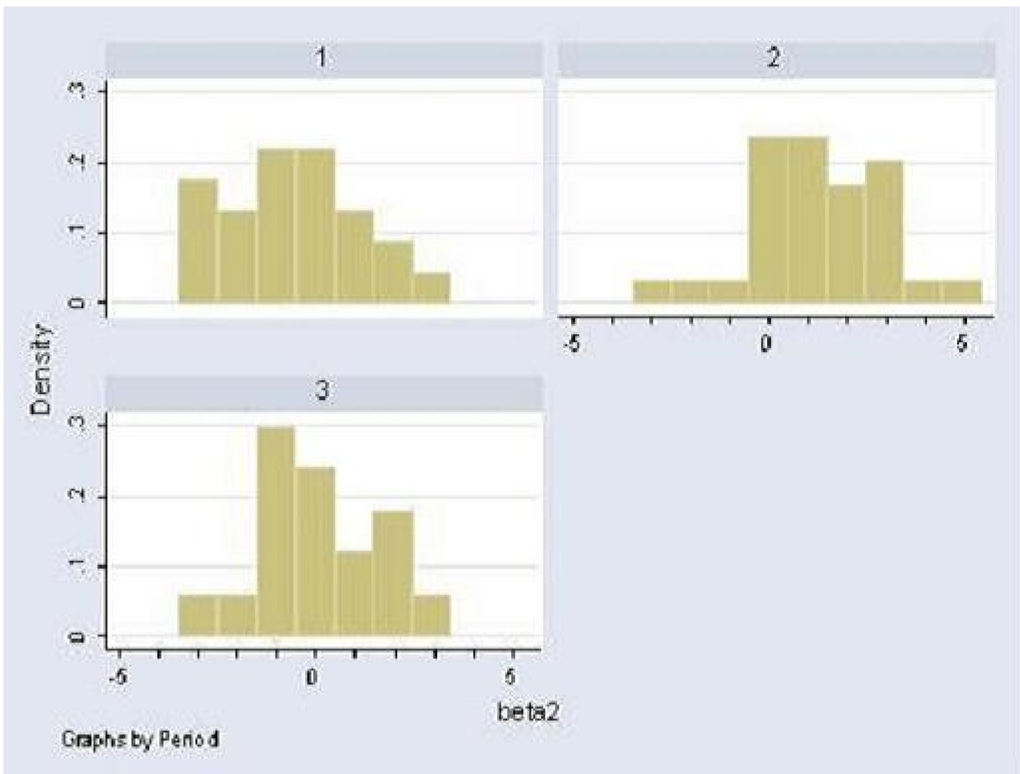

Fig. 2. Reliant β_2 Histogram

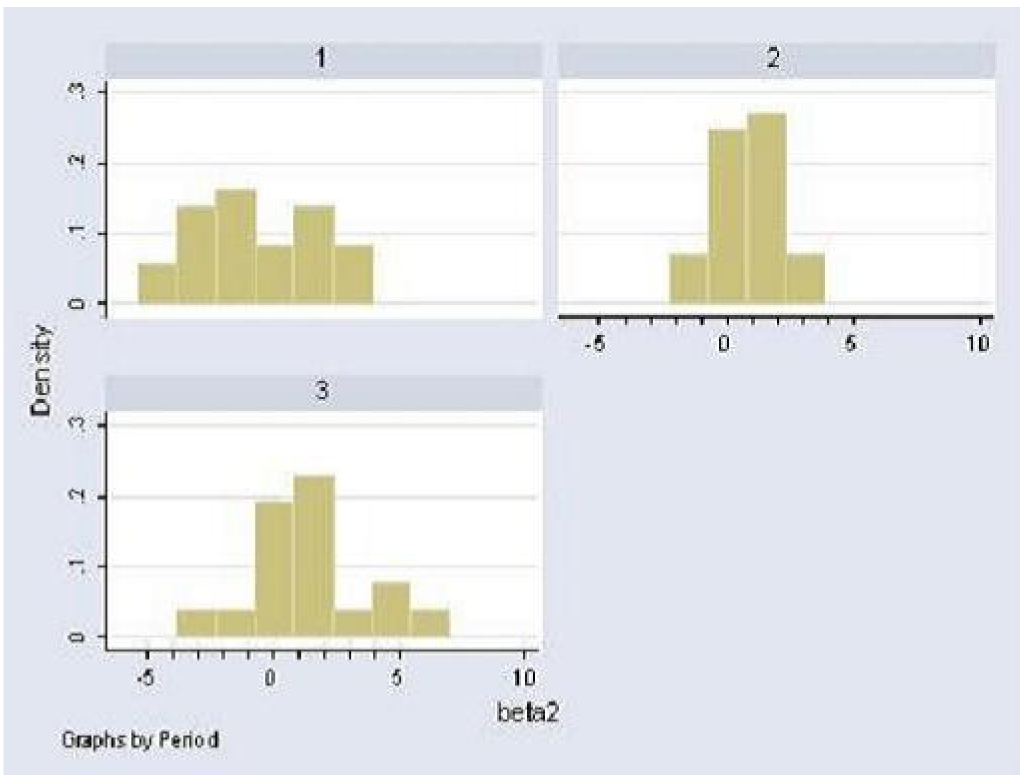

Fig. 3. TXU β_2 Histogram

Table VI. Estimation Results

(Feb. 2002-May 2003, LHS variable: $p_t^c - C'(S(p_t^c))$)

Period	β_1	s.e.	β_2	s.e.	γ_1	s.e.	H_0	H_1	H_2	H_3	obs.
Reliant											
1	.17	.13	.31	.28	.05	.08	R	R	R	R	264
2	.10	.06	2.29*	.51	.23	.18	R	R	A	R	350
3	.82*	.15	.34*	.14	.28*	.13	R	R	R	A	80
TXU											
1	.10*	.03	-.46	.69	-.05	.06	R	R	R	R	303
2	.14*	.05	.57	.44	.08	.08	R	R	A	R	343
3	1.01*	.44	1.96*	.32	1.99*	.86	R	R	R	A	86

Note: R stands for reject, A stands for accept; * indicates significant differently from zero at 5% significance level; Hypothesis tests use 90% confidence interval; Standard errors are robust.

2. Estimation Results

Previous sections give qualitative measures of bidding optimality regarding FTRs. This section quantitatively estimates FTRs' impacts on bidding decisions. Rather than looking at one point on the bid curve (such as the intersection point Q_{obs}), estimation equation (3.8) checks bid points on the entire bid schedule by allowing residual demand to shift by random noises. Table VI reports the estimation results[11].

For both firms, the perfect competitive and optimal strategic bidding test was rejected. However, the equivalent treatment of net physical balancing market sales and FTR "pseudo" capacity is not rejected in some periods and we see some learning

[11] In the estimations, due to possible stronger correlation within each bid curve, the errors are robust to the extend that the intra-day correlations are corrected.

pattern for the bidders.

Strategic Bidding on Inframarginal Capacity (β_1) Neither firm shows optimality with regard to physical inframarginal capacity except in the last period – Period 3. All the estimates for β_1 are very significant for TXU. However for Reliant, the β_1 estimates are very noisy until Period 3. A learning pattern is shown by the fact that β_1 converges towards 1 for both firms through time.

Strategic Weights on FTRs (β_2) Reliant significantly increased the weight on FTRs during Period 2, but seems to revert to the bidding behavior with regard to FTRs in period 1 during Period 3. The difference between Period 1 and Period 3 for Reliant is that in Period 3, the bidding strategies with regard to FTRs becomes more consistent in Period 3 (the standard error is much smaller in Period 3). TXU increased the weight on FTRs during Period 2, and continues to internalize FTRs effects during Period 3. But obviously for TXU, the weight being put on FTRs is greater than the optimal weight ($\beta_2 = 1$) during Period 3. These estimates also explains our first qualitative measure of the distance deviation from actual bid curve to the optimal bid curve: Since Reliant over-weighted FTRs in its bidding during Period 2, it shifted the bid curve to the left of the optimal bid curve, resulting in the distance being negative. Also due to the over-weighting of FTRs during Period 3, TXU's actual bids lie to the left of optimal bids. These observations agree with each other: both Reliant and TXU added weights to FTRs significantly more starting Period 2, but deviated from optimal in Period 3. Based on our estimates from different perspectives, the estimation results are fairly robust.

3. Explanation of Results

The estimation results show that both firms began to strategically internalize FTRs into their bidding decisions in Period 2. But some deviations from optimal behavior require us to explore the data in more detail. I group the possible explanations into two broad categories: 1), firms' learning from the market, and 2), unit specific characteristics that constraint or affect the optimization behavior.

a. Learning

The sample I study is the first one and a half years that FTRs are distributed to the market participants. This time period also correspond to the beginning of the second half of the first year that the Texas wholesale electricity market was opened. The estimations show a significant trend of firms' learning from the market: β_1 is significant and converging towards optimal bidding through time and β_2 becomes significant for both Periods 2 and 3. During the third sample period (Period 3), both Reliant and TXU reached the optimal β_1 as theory predicts. Statistical tests for β_2 show that FTRs are fully internalized into Reliant's bidding strategies during Period 2 ($\beta_1 = \gamma_1$). Although both Reliant and TXU showed deviation from optimal internalization of FTRs during Period 3, FTRs' effects are statistically significant in their markup decision.

To give further evidence for firm's learning behavior, there are other metrics that reflect the increasing of sophistication of firms bidding strategies. In theory, a perfect competitive firm should not consider demand elasticity and just bid according to its generation units' marginal costs. A more sophisticated bidder should bid reflecting its beliefs of all possible realizations of residual demand in the market and the bid points on a single bid schedule need not be a one-to-one correspondence to its power

Table VII. Summary Statistics of Number of Bid Points on a Single Bid Schedule

(Feb 2002-May 2003,

18:00 - 18:15, all intervals)

Period	mean	s.d.	min	max
Reliant				
1	18.25	5.85	8	28
2	18.09	1.78	12	22
3	12.03	2.27	6	22
TXU				
1	12.81	4.69	8	24
2	12.88	1.81	7	20
3	14.29	2.86	8	30

plants. The more sophisticated the bidder is, the more bid points should be on a single bid schedule to maximize the likelihood of profit maximization given possible realizations of residual demand. I check how many bid points there are on a single bid curve through time [12]. Table VII gives the summary statistics of the number of bid points on a single bid schedule.

For TXU at the mean, there's an increasing trend for the number of bid points on a single bid schedule. In Period 3, not only the mean is larger than Period 1, but the distribution is tighter around the mean than Period 1. For Reliant at the mean, the increase of the bid points is not significant. But for Period 2, although the mean of bid points is less than that in Period 1, the distribution of the total number of bid

[12]ERCOT confine the maximum number of bid points to be 20 on the increasing and decreasing bids respectively.

points is much tighter around the mean during Period 2 than Period 1. However, in Period 3, Reliant's average bid points on a single bid schedule decreased significantly.

b. Unit Specifics

Unit specific characteristics will lead to constraints on the actual bids or marginal cost curve. This section assesses those impacts on the optimal behavior.

One important unit specific characteristic is the ramp rate. Ramp rate indicates the maximum speed at which a supplier can provide additional energy. For example, if the market needs 100 MW of additional supply during a certain 15-minute interval and a supplier informs ERCOT that it can provide 100 MW at a ramp rate of 10 MW per minute. Then the generator can provide 100 MW of its offer during the first 10-minute interval if the unit is called; but if the ramp rate is only 3 MW per minute, it can only produce 45 MW during the entire 15-minute interval so that it cannot meet the 100 MW need. The larger the ramp rate, the more flexible the unit is on the real-time market. Based on the unit-specific ramp rates, ERCOT will invalidate some bids due to the infeasibility caused by ramp rate constraints. After invalidating some bids, ERCOT has to move to the next available higher bids, resulting in actual market clearing prices being higher than my simulated prices. I do not observe those invalidated bids on the bid curve. One metric that can be used to assess the degree of bias in my estimation is the comparison between the simulated market clearing price and the actual clearing price. The comparison in Table VIII gives a possible error range as to how often the bids I observe are the actual bids used by ERCOT. The error is large for TXU, almost 10%. Reliant is around 5%. I also list the comparison during non-congestion intervals using the same market price simulation methods. It is obvious that during congestion periods when the transmission lines are constrained, the regional market is less flexible than the integrated ERCOT-wide market and hence

Table VIII. Comparison of Actual Market Clearing Price and Simulated Market Clearing Price

(Feb 2002-May 2003, 18:00 - 18:15)

	Actual price	Simulated price
Congestion intervals		
Reliant	42.60	40.84
TXU	39.79	35.86
Non-congestion intervals		
Reliant	26.45	26.48
TXU	26.45	26.43

Note: the congestion and non-congestion intervals are ex-post realizations.

the ramp rate constraints are more severe.

The above bias is between the observed bid stack and actual bid stack and the bias is caused by all the firms on the market. To check the impact of this constraint on Reliant and TXU's cost side, I check for each firm their marginal units that have lower than average ramp rate. Marginal units refer to those units that is most likely to be called on the balancing market to increase or decrease production. For Reliant, among the 5 marginal generation units in the Houston zone, 2 units have below average ramp rates. For TXU, among the 4 marginal generation units in the North zone, 1 unit has below average ramp rates. Overall, these units with low ramp rates do not compose the majority of marginal unit and the constraints' impact on the cost side is minimum. Combine the above two factors, it is likely that the LHS is biased downward with the possible bias range of 10% for TXU and 5% for Reliant. The estimation coefficient is correspondingly biased downward within that range.

c. Behavioral Stickiness

Hortaçsu & Puller (2004)'s study about bidders' strategic behavior in year 2002 shows that Reliant is bidding close to optimal and TXU is bidding higher than the optimal bidding strategy. Although Hortaçsu & Puller (2004) do not calculate explicitly the β_1s, the implication from their paper is that Reliant's β_1 is close to 1 in year 2002 while TXU's β_1 is significantly higher than 1 in year 2002. These are different results from this research, where both Reliant and TXU's β_1 are significantly lower than 1 in year 2002.

The sample in Hortaçsu & Puller (2004) is non-congestion hours while the sample in this paper is most likely congestion hours (mostly are ex-post congestion hours). The data shows significant bidders' behavioral stickiness that attributes to the behavioral differences between the two researches. In non-congestion hours, the residual demand is the system-wide residual demand that includes all four zones in the Texas market. In congestion hours, however, the residual demand is only composed of zonal residual demand because of the binding transmission constraints. Due to fewer players in the zonal market, the shape of the residual demand slope within each zone is different from the aggregate residual demand – the potential to exercise market power is greater in import-constrained zonal markets. However, the data show that although the residual demand changes from system-wide market to zonal market, bidders' bid slopes are sticky from the earlier time period, in that in congestion hours, the bid slopes do not rise in a manner that captures the potential to exercise market power in an import-constrained market. Table IX is the comparison of the curvature changes for residual demand and bids. The curvatures are slope estimates from simple least square regressions between the price and quantity. I examine the residual demand slope at different prices ranges serving to "magnify" the residual demand slope at

Table IX. Comparison of Residual Demand Slope and Bid Slope Changes

Period	RD250	RD100	RDall	RD500	bid slope
1					
Reliant	22.61	10.12	20.20	14.47	0.97
TXU	5.73	6.22	6.85	8.14	1.36
2					
Reliant	11.21	10.11	12.60	9.93	1.02
TXU	6.78	7.17	6.66	9.07	1.38

specific price ranges. The statistics listed in the table for residual demand are the ratios of zonal residual demand slope at time t to system-wide residual demand slope at *t-1*. For example, "RD250" indicates the ratio of zonal residual demand slope at time t to the aggregate residual demand slope at time *t-1* within the price range of \$-250 to \$+250. The statistics for the bid slopes are the ratio of zonal bid slope at time t to the system-wide bid slope at time *t-1*. Time t is the ex-post congestion hours at hour 18 while time *t-1* is the ex-post non-congestion hours one day earlier at hour 18.

The comparison shows that the zonal residual demand in an import-constrained zonal market is much steeper than the aggregate residual demand in the common market, but the bid slopes do not seem to change from the last time period, which is what I refer to as "behavioral stickiness". Based on those statistics, the reason for the discrepancy of the β_1 between this research and Hortaçsu & Puller (2004) is due to the behavioral stickiness: the bidders did not increase their bid slopes enough during the congested time periods to capture their increased market power reflected in their steeper zonal residual demand.

D. Counterfactual Studies

Based on structural estimation equation (3.6), I can construct counterfactual bid curves assuming that firms are optimizing with FTRs in their bidding decisions to study the "best/worst case" scenario. To study the effect of FTRs only, I keep the original bid shape assuming that firms still make the same bidding decisions with respect to their net physical balancing market sales, but I shift the bid curves so that the "weight" being put on FTRs is 1. The counterfactual optimal bid curves further allow me to calculate the optimal allocation of the FTRs. I can then compare the current allocation with the optimal ones to detect the efficiency effect of the current allocation of FTRs.

1. Price and Cost Effect

By intersecting the counterfactual bids with the realized residual demand, I am able to find the counterfactual market clearing points and the corresponding marginal production costs. Table X and Table XI show the comparison of price and cost under current allocation of FTRs and also the counterfactual scenario when there are no FTRs owned. Since Reliant and TXU are major players in their own regional market, the statistics are reflective of the overall market in the following two ways: first, the market clearing price constructed for Reliant and TXU should also be the zonal market clearing price, and second, since TXU and Reliant are major suppliers and also marginal on the balancing market, their marginal cost should roughly reflect the overall market's marginal production cost.

By fully internalizing FTRs, the market clearing prices are strictly higher than without the ownership of FTRs based on the ex-post realized residual demand. The comparison for market marginal production costs under counterfactual scenarios

Table X. Comparison Between Counterfactual Market Clearing Prices

	Reliant (Houston)		TXU (North)	
Month	p^*	p^*_{noFTR}	p^*	p^*_{noFTR}
2002 Feb	14.6	9.5	20.54	19.75
Mar	30.5	18	59.00	40
Apr	51.25	40.1	38.62	30.50
May	43.94	43.67	33	33
June	26.37	23.02	32.98	25.74
July	25.76	22.88	28.35	18.99
Aug	32.22	27.97	34.13	25.24
Sept	49.10	20.81	34.87	23.28
Oct	69.65	41	37.88	25.88
2003 Jan	67.50	35	20.75	10.5
Mar	107.14	32.67	39.95	30.50
Apr	53.01	34.94	26.08	19.04
May	166.00	151.5	195.68	132.62

Note: p^* is the market clearing price when current ownership of FTRs are fully internalized into firm's bidding; p^*_{noFTR} is the market clearing price when no FTRs are owned by the firms.

shows that the ownership of FTRs leads to lower marginal production costs, but such changes are not significant compared to price changes. Most of FTRs' impacts on the bidding is reflected by higher market clearing prices in the counterfactual scenarios.

For some months, the average market clearing prices are lower than the average marginal cost, meaning that the firm is mostly cleared on the market as a net buyer. For a net buyer, FTRs erodes its monopsony power and can lead to an improvement in the price signal efficiency. The next section explores the price signal improvement by the ownership of FTRs and hence an optimal allocation of FTRs.

2. Optimal Allocations of FTRs.

An important policy question is: how many FTRs should be assigned to the major firms with market power. If we regard FTRs as a form of contract, then their assignment can be used to optimize the contract quantity that enters the balancing market. Such an optimality can be achieved through forcing the intersection of bids and marginal cost curve (the combined effect of true net contract position and FTRs) as close to the market clearing point for the firm as possible. The market-clearing price could then be closely reflective of marginal production cost. If the firm is cleared as a net seller, then no FTRs would be optimal since any FTRs on the increasing supply side would cause "QC_{obs}" to be smaller and a firm's market power on the balancing market would be higher due to greater capacity flexibility. However, if the firm is cleared as a net buyer, then increasing the ownership of FTRs essentially decreases the firm's available decreasing capacity and hence erode its monopsony power. Figure 4 illustrates the price efficiency gain when a market participant is a net buyer in the balancing market. For this counterfactual study, I assume that firms fully

Table XI. Comparison Between Counterfactual Marginal Production Costs

	Reliant (Houston)		TXU (North)	
Month	c^*	c^*_{noFTR}	c^*	c^*_{noFTR}
2002 Feb	18.08	19.37	21.57	21.70
Mar	28.08	28.08	24.30	24.30
Apr	32.84	32.84	37.51	38.37
May	34.66	34.66	35.10	35.10
June	35.98	36.41	36.58	37.53
July	32.89	32.94	33.53	36.41
Aug	31.99	32.16	37.09	37.87
Sept	32.96	35.70	39.13	39.79
Oct	43.18	44.07	39.53	41.00
2003 Jan	16.59	17.12	52.13	52.34
Mar	44.39	60.84	27.12	27.32
Apr	49.12	50.90	25.90	32.52
May	56.05	56.44	62.79	63.54

Note: c^* is the marginal cost when current ownership of FTRs are fully internalized into firm's bidding; c^*_{noFTR} is the marginal cost when no FTRs are owned by the firms.

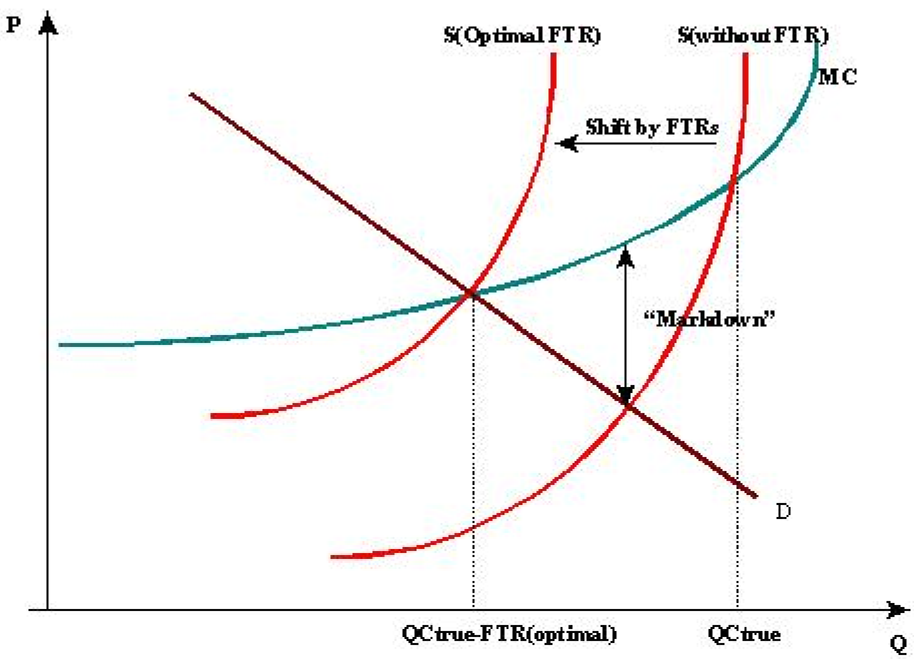

Fig. 4. Optimal FTRs – Erode Monopsony Power

internalize FTRs into their bidding by letting $\beta_2 = 1$[13]. I search on the entire range of FTRs with a grid of 20 FTRs[14]. For each level of FTRs, I calculate the markups using the ex-post realized residual demand. Then the daily markups are averaged to the monthly level. The optimal assignment of FTRs should result in the smallest monthly average markup to effectively curbing market power.

For Reliant in the Houston zone, only the South-to-Houston FTRs are involved. For TXU in the North zone, there are two types of FTRs involved: South-to-North FTRs and West-to-North FTRs. Since there are no good rules of weights to be put on each FTR, I only consider the optimal allocation of South-to-North FTRs [15]. Table XII lists the comparison of optimal assignment of FTRs and the actual assignment of FTRs. Due to confidentiality, these numbers are inflated but the orders are kept the same.

Based on ex-post realization of residual demand, the optimal allocation of FTRs in most months differ greatly from the actual allocations. Table XIII reports the average markups under optimal, actual and no allocations of FTRs.

Using ex-post realizations of residual demands, we see that the optimal allocation of FTRs lead to market price efficiency in terms of lowering firms mark down abilities. Also the comparisons show that under current allocations, however, there are months that the market price signal is less accurate than without the ownership of FTRs.

[13] From my estimation results, we notice that firms are doing better through time, or they are more aware of FTRs when congestion is more often. The only relevant parameter for β_2 in the counterfactual study is the optimal level since this is the only equilibrium point that's stable in a firm's best response.

[14] Since the total FTRs are on a magnitude of over 400 each month, I regard the grid of being 20 as fine enough.

[15] TXU also owns generation in the West zone so that the West-to-North FTRs are internal to TXU (TXU cannot control price in the South zone but it can in the West zone).

Table XII. Optimal Assignment of FTRs

month	Reliant		TXU	
	optimal	actual	optimal	actual
2002 Feb	460	488.5	190	242.5
Mar	340	361	370	538
Apr	**580**	**328**	**670**	**454**
May	**190**	**361**	**160**	**454**
June	430	361	460	454
July	**580**	**391**	**190**	**454**
Aug	**1180**	**328**	**580**	**454**
Sept	**670**	**328**	**700**	**529**
Oct	250	328	**190**	**454**
2004 Jan	**100**	**205**	460	398.27
Mar	**100**	**205**	**610**	**285.59**
Apr	130	205	370	285.59
May	**370**	**205**	**100**	**285.59**

Note: numbers in bold represent large differences between optimal allocations and actual allocations in the magnitude of greater than 100 FTRs.

Table XIII. Markups Under Optimal, Actual and No Assignment of FTRs

month	Reliant			TXU		
	optimal	actual	no FTRs	optimal	actual	no FTRs
2002 Feb	3.38	4.89	5.08	6.43	7.04	7.71
Mar	0	4.57	6.43	15.85	**34.70**	15.70
Apr	9.88	20.08	22.02	22.89	25.53	34.51
May	9.61	**10.12**	9.75	73.81	**75.15**	73.81
June	9.93	13.51	17.39	12.58	15.47	16.61
July	8.33	10.07	13.58	14.93	**23.63**	16.96
Aug	1.65	5.62	7.74	2.45	6.44	11.87
Sept	6.94	**36.7**	24.68	4.47	10.18	20.34
Oct	6.97	**28.12**	7.66	4.94	6.93	15.13
2004 Jan	20.90	**50.91**	17.88	16.54	**31.59**	20.34
Mar	69.58	**79.51**	69.58	14.99	**17.35**	17.2
Apr	22.57	**30.53**	28.2	4.83	7.13	18.58
May	121.61	132.53	147.48	84.26	**134.91**	84.26

Note: Numbers in bold indicate that under the current allocations of FTRs, the market price efficiency is adversely impacted by FTRs comparing to no ownership of FTRs; residual demand is the ex-post realization.

The tables report the results under the ex-post realization of FTRs. If demand is uncertain, then it is the average effect of FTRs under all possible demand realizations that matters. By considering demand uncertainty, I can also statistically compare the actual allocations of FTRs with the optimal ones. To assess demand uncertainty, I constructed two metrics: 1) daily demand variation and, 2) weekly demand variation. The first is constructed using standard deviations of demand levels in a single day from 1pm to 8pm. The second metric is constructed using standard deviations of demand levels for the interval 18:00-18:15 only within the same week. All the demand variations are then averaged to a monthly level. The demand uncertainty (standard deviation) is in the range of 250 MW daily and 400 MW weekly for both North and Houston zones. To allow demand uncertainty to be within a larger range, I use randomly generated numbers from a normal distribution with weekly demand variation[16]. I generate demand uncertainty 100 times for each time period. I report the mean, the 5% percentile, the median and the 95% percentile for the monthly distribution of markup differences ($|markup_{it,actual}| - |markup_{it,opt}|$) between the ownership of optimal level of FTRs and the actual level under possible realizations of residual demands, see Table XIV.

The improvements are determined looking at the mean and the median[17]. If both the mean and the median is strictly positive – meaning that the markup under actual allocation is greater than under the optimal allocation – then the optimal allocation improves price signal efficiency in the wholesale market. Considering demand uncertainty, the improvement by optimal allocations of FTRs is limited. For Reliant,

[16] I also used random draws from a normal distribution with daily demand variation. The results are quite similar.

[17] In case of extreme distributions, the median is a better statistics than the mean in explaining the average.

Table XIV. Statistics for Markup Difference:$|markup_{actual}| - |markup_{opt}|$

month	Reliant				TXU			
	mean	5%	median	95%	mean	5%	median	95%
2002 Feb	.24	-1.07	0	2.93	-.06	-8	0	8.24
Mar	-.17	-3.22	0	2	**43.75**	-12	**32.71**	54.08
Apr	19.02	-17.42	0	29	**6.14**	-19.09	**0.51**	33.93
May	1.22	-1.78	0	7.5	0	-16.62	0	2.47
Jun	.65	-7.68	0	10.75	2.02	-11.69	0	12.39
Jul	**1.14**	-22.54	**1**	13	2.5	-6.18	0	20
Aug	**1.67**	-22.57	**2.52**	23.44	-3.49	-18.68	1.75	12.12
Sept	-2.21	-254.82	2.11	252.73	**5.39**	-17.16	**1.71**	25.86
Oct	**13.66**	-5.33	**5**	50	-0.61	-11	0	4.11
Jan	**24.46**	-0.2	**5.01**	199	**20.6**	-12.01	**18.41**	38.59
Mar	14.48	-54.83	-1.18	199	2.08	-91.81	-1.02	16.79
Apr	-.55	-29.99	-4.03	104	0.06	-2.01	0	10
May	2.66	-99	0	31.3	98.31	-8.32	0	223.02

Note: Numbers in bold indicate improvement by optimal allocations of FTRs – both at the mean and at the median, the absolute magnitude of markup under actual ownership of FTRs is larger than under the optimal ownership of FTRs.

the improvements from actual allocations can only be made at July, August, October in 2002 and January in 2003. For TXU, the improvements from actual allocations can only be made at March, April, September in 2002 and January in 2003. In most months, the actual allocations of FTRs are statistically equivalent to optimal ones.

An immediate question is that whether we should assign FTRs to market participants when demand is uncertain. Table XV lists the markup differences under the optimal allocations of FTRs and no ownership of FTRs.

Only when both the mean and the median are strictly negative that I regard the optimal allocations of FTRs as having an improvement on the price efficiency. For both Reliant and TXU, 7 out of 13 months in the study has a significant improvement by the optimal allocations of FTRs under uncertain demand. This counterfactual study indicates that if FTRs are allocated optimally and players fully internalize FTRs into their bidding, the market has an efficiency improvement in the spot market price signal.

Since this counterfactual study only involves the optimal allocation of FTRs and not the designing of FTR auction, the numbers in Table XI indicate that if any firm wish to own FTRs and the FTRs are assigned by the grid operator, then the grid operator can optimize in the assignment FTRs. Another direction of research is to give a firm incentive to acquire not only the individually optimal amount of FTRs but also the socially optimal (or sub-optimal) amount of FTRs from the FTR auction. Similar literature can be found in the designing of contract where information is asymmetric. But this auction mechanism design is beyond the scope of this dissertation.

Table XV. Statistics for Markup Difference:$|markup_{opt}| - |markup_{noFTR}|$

month	Reliant				TXU			
	mean	5%	median	95%	mean	5%	median	95%
2002 Feb	**-1.62**	-10.42	**-1**	4	-.58	-10.5	0	9.01
Mar	**-3.12**	-10.03	**-4**	2.23	2.24	-32.7	-0.01	35.07
Apr	-29.34	-20	0	18.21	**-9.84**	-34.25	**-12.56**	11
May	2.69	-0.96	0	17.31	1.17	0	0	10
Jun	**-11.02**	-27.49	**-1.13**	14.31	**-3.21**	-23.5	**-3.16**	16
Jul	**-29.90**	-27.96	**-4.23**	22.3	1.88	-23.3	0	18.8
Aug	**-5.62**	-28.78	**-5.75**	21.44	**-1.12**	-14	**-6.06**	16.49
Sept	**-2.24**	-205	**-7.54**	249.3	**-8.69**	-33.72	**-11.03**	12.4
Oct	17.63	-14.38	3.76	95	**-6.13**	-12.63	**-9.04**	7.95
Jan	**-6.42**	-7.81	**-5.01**	1.05	**-55.81**	-618.72	**-30.27**	30.29
Mar	0	0	0	0	13.70	-22.56	0	83.99
Apr	-4.56	-22.11	0	25.81	**-3.13**	-28.57	**-2.8**	30.55
May	34.70	-51.88	-13.77	224	0	0	0	0

Note: Numbers in bold indicate improvement by optimal allocations of FTRs – both at the mean and at the median, the absolute magnitude of markup under optimal ownership of FTRs is smaller than under no ownership of FTRs.

CHAPTER IV

FTR AUCTIONS

A. Theories

This section derives value functions for different types of bidders in the FTR auction. Then equilibrium bidding strategies are presented. The equilibrium bidding strategies include not only the independent private value (IPV) case, but also the affiliated valuation (AV) case.

The time line for the entire games is: first participants purchase FTRs in the FTR auction, then use FTRs on the wholesale market. In this chapter, I call the wholesale market competition as the *second stage game* and the FTR auction itself as the *first stage game*. In the following subsections, I first study the wholesale market competition to derive the marginal valuation of FTRs for different types of bidders. Then given those valuations, I derive equilibrium bidding in the FTR auctions.

1. Generator's Valuation of FTRs

At the second stage, with the ownership of a certain amount of FTRs that's awarded from the FTR auctions, the generators bid into the energy market to supply electricity as was described in the previous chapter. In all the following analysis, I assume that the bidders are competing in a Cournot Nash-in-quantity game [1] on the wholesale electricity market, and that there are no dynamics of the game (that players are not

[1] In an ideal set up, the strategy should follow a supply function equilibrium game where the choice variable is not a single quantity point q, but rather a supply function *S(p)*. However, in most cases, it is not possible to derive an analytical closed form solution to the supply function equilibrium unless we impose some functional form restrictions on the supply function. For ease of illustration, I use the Cournot game in this theory section without loss of the essence of the important aspects of the results.

colluding). The first two sub-sections are valuation analysis for generators. The third sub-section discusses a trader's valuation.

a. Risk Neutral Bidders

First for simplicity, I assume that bidders are risk neutral, in that their utility functions are linear in their profit[2]. My following analysis focuses on the bidders in the import-constrained market. We only need to reverse the signs for the cases of export-constrained bidders without any complexity. For a bidder in an import-constrained market, her profit on the wholesale market is given by:

$$\pi_{it} = P_{M,t}q_{it} - C_{it}(q_{it}) + (P_{M,t} - P_{X,t})k_{it} \tag{4.1}$$

Where $P_{M,t}$ is the spot price in the import-constrained region at time t, $P_{X,t}$ is the spot price in the export-constrained region at time t. C_{it} is the generator's cost at time t when supplying q_{it} quantity of electricity. k_{it} is the number of FTRs the generator has at time t. In the above profit function, the only variables that are exogenous to the firms at this stage are $P_{X,t}$ and k_{it}[3] if the firm only has generation in the import-constrained region. The first term in the profit function is the revenue from sales on the spot market, the second term is the production cost and the last term is the FTR revenue[4]. By assumptions, in a Cournot game the generator chooses q_{it} to maximize profit. The following example shows how the number of FTRs plays a role in the profit maximization problem.

[2]The assumption of risk neutral is not convincing for generators who wish to purchase FTRs. The purpose of this section is to illustrate major components in the value structure from the easiest case and I will relax this assumption in the next subsection.

[3]The number of FTRs is pre-determined in the first stage game.

[4]For detailed discussion of FTR revenue, please refer to Chapter III theory section.

Suppose that there are n symmetric generators in the import-constrained region, the demand function is linear: $P_{M,t} = 1 - (Q_t + K_t)$. Q_t indicates the total energy supplied in that region and K_t is the total amount of imports, which at the time of congestion is the maximum transmission line capacity. Suppose that each generator's cost function is linear in output: $C_{it} = c_{it}q_{it}$, then using equation (4.1), we can get the equilibrium Cournot quantities and prices as being:

$$q_{it} = \tfrac{1}{n+1}(1 - K_t + \textstyle\sum_{j\neq i} c_{jt} + \sum_{j\neq i} k_{jt} - n(k_{it} + c_{it}))$$

$$P_{M,t} = \tfrac{1}{n+1}(1 - K_t + \textstyle\sum_{j\neq i} k_{jt} + k_{it} + \sum_i c_{it})$$

$$Q_t = \tfrac{1}{n+1}(n - nK_t - \textstyle\sum_{j\neq i} k_{jt} - k_{it} - \sum_i c_{it})$$

The above equilibrium solutions show that the output is partially decided by the number of FTRs that's given to the firm exogenously at the second stage. As I have shown in the previous chapter that by studying bidder's bid schedules on this second stage, I find that FTRs have strategic effects on bidders' bidding strategy on the wholesale electricity market. The above solutions are examples that FTRs will enter the decision of the choice variables in the second stage electricity supply.

More interestingly, if we put those equilibrium solutions back into the profit function of the individual player as a function of the FTRs, we will get a profit function that only consists of the number of FTRs and the total line capacity – which are exogenous to the firm on that stage. Taking derivative with respect to the number of FTRs, we get the "marginal valuation of FTR" as:

$$\frac{\partial \pi_{it}}{\partial k_{it}} = V_{k_{it}} = (P_{M.t} - P_{X,t}) + \frac{1}{n+1}(q_{it} + k_{it}) + (-\frac{n}{n+1})(P_{M,t} - c_{it}) \tag{4.2}$$

The first term is the per unit FTR credit[5]; the second term is the marginal profit

[5] Description about unit FTR credit can be found in Chapter III.

increase due to the importer's ability to increase price by the ownership of FTRs, the third term is the marginal profit decrease due to the withholding of supply. The economic intuition underlying the above equation is quite clear: the valuation of FTRs for the importer is not only decided by the unit FTR credit, but is also affected by the marginal profit change due to FTRs' impacts on market power.

The above solution is specific to our assumptions of cost function and market demand function. In the real world, the market demand function might not be strictly linear as it is in the example, and the cost functions vary among market participants. Further, when the market demand and cost functions become more complex for market participants, we will have difficulty deriving analytically the market equilibrium. However based on the above intuition, we can write the FTR value function for the individual player as:

$$V_{k_{it}} = (P_{M.t} - P_{X,t}) + \frac{\partial P_{M,t}}{\partial k_{it}}(q_{it} + k_{it}) + \frac{\partial q_{it}}{\partial k_{it}}(P_{M,t} - C'_{it}) \tag{4.3}$$

Since the valuations are decided ex-ante before the real-time competition, the valuations should be made with expectations. We can re-write our valuation in an ex-ante format as:

$$V_{k_{it}} = E(P_{M.t} - P_{X,t}) + E(\frac{\partial P_{M,t}}{\partial k_{it}}(q_{it} + k_{it})) + E(\frac{\partial q_{it}}{\partial k_{it}}(P_{M,t} - C'_{it})) \tag{4.4}$$

where $E(\cdot)$ represents expectations. The first term is FTRs' contribution to the marginal revenue of FTR credits – the unit FTR credit, the second and the third term are FTRs' contribution to additional profit change due to the affected market power on the wholesale market.

b. Risk Averse Bidders

Part of the reason for designing FTRs is to provide market participants with some hedging instruments against the volatile transmission cost. A more reasonable set up is to model bidders as being risk averse. Suppose that a risk averse firm has the following utility function[6]:

$$U(\tilde{\pi}_{it}) = -e^{-\gamma\tilde{\pi}_{it}} \tag{4.5}$$

With the profit $\tilde{\pi}_{it}$ defined the same way as was in equation (4.1) except that the profit is now uncertain which is denoted by a tilde. γ is the Arrow-Pratt coefficient of absolute risk aversion. The higher the γ, the more risk averse the bidder is. The bidder maximizes on her expected utility which is $E(U(\tilde{\pi}_{it}))$. When the noises are distributed normal, the expected utility can be re-written as:

$$E(-e^{-r\tilde{\pi}}) = -e^{-r(E(\tilde{\pi})-\frac{\gamma}{2}var(\tilde{\pi}))} \tag{4.6}$$

And the certainty equivalent $CE(\tilde{\pi})$ of the random $\tilde{\pi}$ is equal to $E(\tilde{\pi}) - \frac{\gamma}{2}var(\tilde{\pi})$. Since the utility function is an increasing function in the certainty equivalent, we can focus only on $CE(\tilde{\pi})$ alone without any loss of the analysis.

Following the same logic from the last sub-section, we need to find out the marginal valuation of FTRs when bidders are risk averse. As is shown in the earlier example, in equilibrium, the equilibrium prices and quantities are all functions of FTRs, i.e. $P_{M,t} = P_{M,t}(k_{it})$ and $q_{it} = q_{it}(k_{it})$, then the marginal valuation of FTRs are decided by:

$$\begin{aligned}\tfrac{\partial CE(\tilde{\pi})}{\partial k_{it}} &= V_{k_{it}} = E((P_{M,t} - P_{X,t})) \\ &+E(\frac{\partial P_{M,t}}{\partial k_{it}}(q_{it}+k_{it})) + E(\frac{\partial q_{it}}{\partial k_{it}}(P_{M,t}-C'_{it})) - \frac{\gamma}{2}\cdot\frac{\partial Var(\tilde{\pi})}{\partial k_{it}}\end{aligned} \tag{4.7}$$

[6]In this chapter I assume that the bidder's risk aversion is CARA (Constant Absolute Risk Aversion).

Different from previous risk neutral case, a risk averse bidder is willing to pay risk premiums if FTRs can decrease their profit volatility ($\frac{\partial Var(\tilde{\pi})}{\partial k_{it}} \leq 0$).

2. Trader's Valuation of FTRs

Traders are defined as those entities that neither represent generation side nor represent consumer service side. They enter this market to maximize their profits through various means of arbitrage behaviors. Since FTRs are purely financial in nature, traders can buy FTRs to obtain arbitrage revenue through the differences between FTR auction payments and ex-post FTR credits. Traders can also sell FTRs on the secondary market. We can write a trader's profit on the wholesale market as:

$$\pi_{it}^{trader} = \pi_{wholesale\_trading,it} + (P_{M,t} - P_{X,t})k_{it} \tag{4.8}$$

The first term is the profit the trader get from trading on the wholesale market and the second term is the FTR revenue. Notice that both the $P_{M,t}$ and the $P_{X,t}$ are not functions of k_{it}: The trader cannot participant in the real-time market so that it does not have any influence on the wholesale market price[7]. Given the profit function and if we regard traders as being risk neutral, by taking derivative of the profit function with respect to the amount of FTRs, their true valuations for FTRs are the future expected unit FTR credit. In its simplest form, the unit FTR credit is the price spread between two markets with different prices separated by a constrained transmission

[7]There can be arguments that the amount of FTRs a trader own would affect the leftover amount of FTRs that generators would own, so that traders can indirectly affect the wholesale market price. But the set up here on the second stage is for the FTRs that's already awarded. Given that a trader hold k_{it} amount of FTRs, it cannot affect the real-time market price but it can make forecasts of the difference between $P_{M,t}$ and $P_{X,t}$. The reason apply the same way in our later study of bidding equilibrium: given a certain amount of FTRs the trader would bid, the trader can make forecast of the future market price spread based on the leftover amount that the generators would own, but it cannot affect the future market price spread given the amount of FTRs already owned.

interface. Written in the ex-ante form, we have:

$$V_{it} = E(P_{M,t} - P_{X,t}) \tag{4.9}$$

However, if the traders' purpose of purchasing FTRs is also to hedge against the volatility of congestion cost incurred in the second stage game, a trader should also be risk averse. In the same logic as the analysis for the generators, the traders' marginal valuation of FTRs can also include the risk premium that a trader is willing to pay to reduce the volatility in the transaction, and can be written down as:

$$V_{it} = E(P_{M,t} - P_{X,t}) - \frac{\delta}{2} \cdot \frac{\partial Var(\tilde{\pi}_{it}^{trader})}{\partial k_{it}} \tag{4.10}$$

In the following analysis for traders, I will use equation (4.10).

3. Equilibrium Bidding

Our previous section derives different value functions. In the bidding for FTRs, auction theory implies that the bidders should shade their bids below their true value in the uniform-price auction. The below analysis gives equilibrium bidding strategies in the FTR auction given that the valuation of FTRs are privately known for each bidders. Their valuations are denoted as V_{it}, keeping in mind that different bidders have different V_{it}. The following analysis again adopt notations from Wilson (1979) where he collapses all the uncertainties in the multi-unit auction into the uncertainty of market clearing prices, and is denoted by the "$H(\cdot)$" function.

Generally, the bidder in the FTR auction tries to maximize the following expected utility conditional on her own private signal:

$$U_{it} = E(V_{k_{it}} - p(k_{it})|s_i) = \int_0^{\infty} \int_0^{k(p)} [E_{s_{-i}|p,s_i}(V_{k_{it}}) - k^{-1}(k_{it})] dk dH(p, k_{it}(p, s_i)) \tag{4.11}$$

where s_i denote the signals that bidder i has. $k^{-1}(k_{it})$ is the inverse function of the bids where $k_{it} = k(p_{it})$. $H(p, k(p, s_i))$ is the probability of the market clearing price being p:

$$H(p, k_{it}(p, s_{it})) = Prob(k_{it}(p, s_{it}) \leq K - \textstyle\sum_{j \neq i}^{N} k_{jt}(p, s_{jt})) = Prob(p^c \leq p | k_{it}(p, s_{it}))$$

The above model does not make any explicit restriction on whether the valuation is independent or affiliated, neither does it put on any restrictions as to whether the bidders are ex-ante symmetric or asymmetric. The above model is also general in terms of the auction format – can be applied to both discriminatory- and uniform-price auction. However, different assumptions would make our model predictions being different, which are shown in the following subsections.

a. An Independent Private Value (IPV) Uniform-Price Auction Model

Let us first consider an independent private value case. When the values are assumed to be independent, we are saying that the loser will not envy the winner, in that there is no common value component in the goods being auctioned. Put in the context of the FTR auction, an independent private value indicates that bidders value FTRs differently due to their differences in market power. As we have seen in the theory section, when the player has market power different from her rivals and can use the FTRs strategically to manipulate the wholesale market clearing price, the privately expected market power effect will be different for different players.

After we made those assumptions, equation (4.11) can be reduced to:

$$U_{it} = \int_0^\infty ([\int_0^{k(p^c)} V(k_{it}(p), s_i) dk] - k(p)p) dH(p^c, k(p^c, s_i)) \qquad (4.12)$$

A major distinction from equation (4.11) is that the bidder's own signal does not depend on other player's signal, but only on its own.

Using the variation approach, we get the necessary condition for maximizing the above utility function[8]:

$$V(k_{it}(p), s_i) = p_{it} + k_{it}\frac{-H_k}{H_p} \tag{4.13}$$

This Euler equation shows that valuation is shaded by a factor $k_{it}\frac{-H_k}{H_p}$. H_k is the change in the probability of there being excess supply when the bidder submits another quantity, holding bid price being fixed. The intuition is that the higher quantity the bidder request the amount to be awarded at a given price, the lower the probability that the quantity is inframarginal, and hence the lower the probability of there being excess supply: so H_k is negative. H_p is the change in the probability of the bid price being higher than the market clearing price when the bidder bids another price, holding the bid quantity being fixed. Since the bid quantity is fixed, the higher the price that the bidder is willing to pay, the higher the probability that the price is higher than the market clearing price: so H_p is positive. Then the entire term $k\frac{-H_k}{H_p}$ is positive, which is the bid shading amount.

Intuitively, the bid shading in the multi-unit uniform price auction is similar to demand reduction for a monopsony buyer. The greater the quantity the buyer demands, the lower the price the monopsony would pay by exercising its monopsony market power. In the case of multiple unit demand auction, the buyers are able to shade their bids in a similar way to extract surplus from the auction. The greater the quantity they demand, the greater they can shade (or the lower they would bid) from their marginal valuation of the goods since the marginal price they pay applies to all inframarginal quantities awarded in a uniform price auction. In this sense, when we say that a bidder has market power, we are essentially saying that the bidder is able to shade her bids from her own marginal valuation of the good.

[8] Detailed derivation can be found in the appendix

b. An Affiliated Value (AV) Uniform-Price Auction Model

This subsection discusses the case where the valuations have a common value component, in other words, the bidder's valuation is affiliated with the other bidders' valuation. In this case, we cannot say that the loser will not envy the winner since there is a common component in their valuation. In the case of FTR auction, the common value might be the expected unit FTR credit.

Given the above intuitions, and suppose that the bidders' valuation are affiliated through the "shadow price" of FTRs that partially decides the FTR valuation, then we can reduce equation (4.11) to:

$$U_{it} = \int_0^\infty [\int_0^{k(p^c)} V(k_{it}(p), s_i, p)dk] - k(p)pdH(p^c, k(p^c, s_i) \tag{4.14}$$

The only difference in the above equation is that valuation is now affiliated through a common factor p, or the market clearing price, which is partially reflective of the possible ex-post unit FTR credit.

Using variation approach, we can get the necessary condition as:

$$V(k_{it}(p), s_i, p) = p_{it} + k_{it}\frac{-H_k}{H_p} + \frac{H_k}{H_p}\int_0^{k(p^c)} \frac{\partial V(k_{it}(p), s_i, p)}{\partial p}dk \tag{4.15}$$

In addition to the RHS of the necessary condition for IPV model, there's an extra term $\frac{H_k}{H_p}\int_0^{k(p^c)} \frac{\partial V(k_{it}(p), s_i, p)}{\partial p}dk$ which makes the bid shading decisions being different from the IPV model. If we assume that in the independent private value case, the individual valuation is purely dependent on the bidder's own signal s_{it}, we can write the value function as a function of s_{it} only[9]. According to equation (4.15), the last term should be zero because there's no common component p in it. If the valuation

[9] In our earlier sections, the s_{it} can be regarded as the individual market power, based on the individual market power, the bidder can make future price difference predictions and so forth.

is affiliated among each other, and the auction clearing price is an indication of the common value, then we can write down the value function as a function of both s_{it} and p_t and the last term for value affiliation will appear.

The additional value shading has two implications: First, due to the common value existence, "winner's curse" arises. Different from IPV, where a winner should not worry about whether her own valuation is too high upon winning, in an affiliated value auction, the winner is worried about valuating the object higher than the actual value and the additional value shading captures the avoidance of the "winner's curse" effect. In addition to the original shading in the IPV case, the bidder wishes to shade even lower to avoid the "winner's curse". Second, in the presence of a common value, the larger the variance in the supported uncertainty distribution, the more the bidder is willing to shade. For example, if a bidder knows for certain that a certain quantity is worth \$5, it might bid \$4 if the optimal shading is \$1 in an affiliated value auction; but if the value can go up or down around the mean of \$5 with 20%, then the bidder is not willing to bid \$4, rather she would bid some amount less than \$4 because of the "winner's curse" problem – she is more uncertain of the common value and will worry whether her draw from the uncertainty distribution is too high. In an IPV case, however, even if the uncertainty goes up, the bidder can still bid \$4 because her mean valuation is \$5, independent of how the other bidder would value the object.

Notice that the above analysis for IPV and AV bidding strategy carries through with a risk averse bidder, as is proved in Appendix D for multi-unit auctions.

B. Theory Implications

In this section I derive equilibrium bidding models in the FTR auction and give theory implications for empirical testing of bidding strategies in the auction for FTRs.

1. IPV Case

For generators, their full model of bidding is the following:

$$V(k_{it}(p), s_i) = p_{it}^g + k_{it}\tfrac{-H_k}{H_p}$$

$\Rightarrow$

$$E((P_{M.t} - P_{X,t})) + E(\frac{\partial P_{M,t}}{\partial k_{it}}(q_{it} + k_{it})) + E(\frac{\partial q_{it}}{\partial k_{it}}(P_{M,t} - C'_{it})) - \frac{\gamma}{2} \cdot \frac{\partial Var(\tilde{\pi})}{\partial k_{it}} = p_{it}^g + k_{it}\frac{-H_k}{H_p} \tag{4.16}$$

for traders, their full model of bidding is the following:

$$V(k_{it}(p), s_i) = p_{it}^t + k_{it}\tfrac{-H_k}{H_p}$$

$\Rightarrow$

$$E((P_{M.t} - P_{X,t})) - \frac{\delta}{2} \cdot \frac{\partial Var(\tilde{\pi})}{\partial k_{it}} = p_{it}^t + k_{it}\frac{-H_k}{H_p} \tag{4.17}$$

2. AV Case

For generators, their full model of bidding is the following:

$$V_{it} = p_{it}^g + k_{it}\tfrac{-H_k}{H_p} + \tfrac{H_k}{H_p}\int_0^{k(p^c)} \tfrac{\partial V(k_{it}(p), s_i, p)}{\partial p} dk$$

$\Rightarrow$

$$\begin{aligned} E((P_{M.t} - P_{X,t})) + E(\tfrac{\partial P_{M,t}}{\partial k_{it}}(q_{it} + k_{it})) + E(\tfrac{\partial q_{it}}{\partial k_{it}}(P_{M,t} - C'_{it})) - \tfrac{\gamma}{2} \cdot \tfrac{\partial Var(\tilde{\pi})}{\partial k_{it}} \\ = p_{it}^g + k_{it}\frac{-H_k}{H_p} + \frac{H_k}{H_p}\int_0^{k(p^c)} \frac{\partial V(k_{it}(p), s_i, p)}{\partial p} dk \end{aligned} \tag{4.18}$$

for traders, their full model of bidding is the following:

$$V(k_{it}(p), s_i) = p_{it}^t + k_{it}\tfrac{-H_k}{H_p} + \tfrac{H_k}{H_p}\int_0^{k(p^c)} \tfrac{\partial V(k_{it}(p), s_i, p)}{\partial p} dk$$

$\Rightarrow$

$$\begin{aligned} E((P_{M.t} - P_{X,t})) - \tfrac{\delta}{2} \cdot \tfrac{\partial Var(\tilde{\pi})}{\partial k_{it}} \\ = p_{it}^t + k_{it}\frac{-H_k}{H_p} + \frac{H_k}{H_p}\int_0^{k(p^c)} \frac{\partial V(k_{it}(p), s_i, p)}{\partial p} dk \end{aligned} \tag{4.19}$$

3. Empirical Predictions

The models yield testable predictions about bidding behaviors for generators and traders:

1. The bidders' bids are positively correlated with expected FTR shadow price. Ideally, the correlation should be one.

2. A generator with market power should take into account FTRs' effect on the exercising of market power. However, the effect can be both positive and negative depending on the market demand functions and firm's cost functions[10].

3. A bidder is willing to pay risk premiums if she is risk averse. However, in an affiliated value model, since the higher the variation in the value of the FTR credit, the more the bidder is willing to shade or pay less. Then the combined effect of the uncertainty is ambiguous. If we get a positive effect regarding the uncertainty payment, we cannot separate out the risk premium from the bid shading; if we get a negative effect regarding the uncertainty payment, we can conclude with confidence that valuations are affiliated and the bid shading dominates the risk premium payment.

[10] In equation (4.7), the market power effect is the combination of the second and third term. Although we can predict the sign for the second and third term, the combined effect is ambiguous.

C. Empirical Models

1. Model of Trader's Bidding

The empirical model of traders' bidding is the following[11]:

$$p_{jt} = \beta_1 E(SP)_{jt} + \beta_2 E(var)_{jt} + \beta_3 FTR_{jt} + \beta_4 + \beta_5 annual + \zeta_j + \epsilon_{jt} \qquad (4.20)$$

The LHS is the bid price for FTRs. The first term on the RHS is the expected unit FTR credit – the shadow price (SP) of the transmission line; the second term is the volatility of congestion cost approximated by the variance of the unit FTR credit; FTR is the amount of FTRs the bidder wishes to purchase corresponding to that price bid – this term is supposed to pick up the bid shading amount that's existent in both the IPV case and in the AV case. "annual" is a dummy controlling for the fact that the auction is annual auction. Since the annual auction auctions off 60% of the total FTRs, I put a dummy here to capture any unobserved effects that I did not measure for the annual auction. ζ_j is the different FTR specific type effect, ϵ_{jt} is assumed to be i.i.d. random errors. The coefficients convey the following implications:

- β_1: According to theory, equilibrium bidding implies $\beta_1 = 1$
- β_2: This term reflects the combination of the bidders' risk premium payment and the bid shading due to uncertainty. The sign of the coefficient is ambiguous depending on which term dominates.
- β_3: This term reflects the bid shading component corresponding to each FTR amount bid. This coefficient is predicted to be negative.

[11] Since there is only one trader in the FTR auction in Texas, there is no need for trader specific fixed effects.

2. Model of Generator's Bidding

Based on (4.18), we can test whether the ex-post market power effect is significant in the generators' bidding strategy. The simplest empirical model is:

$$p_{ijt} = \beta_1 E(SP)_{jt} + \beta_2 E(var)_{jt} + \beta_3 E(Market\_Power)_{ijt} + \beta_4 FTR_{ijt} + \beta_5 + \zeta_j + \epsilon_{jt} \tag{4.21}$$

Our earlier models are based on the assumption that the generators only own generation in one regional market. In my data, however, there are generators who own generation in multiple regions. We need to modify our model in the following ways:

- Generation locates in regions with the same direction of flow constraints.

  If a generator has generation in market A and market B all import-constrained, then we can write the profit function as[12]:

$$\pi_{it} = P_{MA,t}q_{A,it} + P_{MB,t}q_{B,it} - C_{A,it}(q_{A,it}) - C_{B,it}(q_{B,it})$$

$$+(P_{MA,t} - P_{X,t})k_{A,it} + (P_{MB,t} - P_{X,t})k_{B,it} \tag{4.22}$$

  Solving for optimal output choices $q_{A,it}$ and $q_{B,it}$, they are functions of their own regional FTRs, i.e. $q_{A,it} = q_{A,it}(k_{A,it})$ and $q_{B,it} = q_{B,it}(k_{B,it})$. The optimal bidding solution is the same as in earlier models.

- Generation locates in regions with different direction of flow constraints.

  Suppose these two regions A and B are adjacent and the power flow is from B to A, then the profit function can be re-written as:

$$\pi_{it} = P_{MA,t}q_{A,it} + P_{XB,t}q_{B,it} - C_{A,it}(q_{A,it}) - C_{B,it}(q_{B,it}) + (P_{MA,t} - P_{XB,t})k_{it} \tag{4.23}$$

[12] In the profit function, I assume that the cost is additively separable in different regions.

Now the optimal solution of $q_{A,it}$ and $q_{B,it}$ are both functions of k_{it}. Deriving the marginal valuation of FTRs, we have:

$$V_{it} = \frac{\partial \pi_{it}}{\partial k_{it}} = (P_{MA,t} - P_{XB,t}) + \frac{\partial P_{MA,t}}{\partial k_{it}}(q_{A,it} + k_{it}) + \frac{\partial P_{XB,t}}{\partial k_{it}}(q_{B,it} + k_{it})$$
$$+ \frac{\partial q_{A,it}}{\partial k_{it}}(P_{MA,t} - C'_{it}) + \frac{\partial q_{B,it}}{\partial k_{it}}(P_{XB,t} - C'_{it})$$

In this case, we have extra terms for the marginal value of FTRs if the owner of FTRs have generation on the two sides of the transmission line.

Based on the institutions, I modify the empirical model in the following way:

$$p_{ijt} = \beta_1 E(SP)_{jt} + \beta_2 E(var)_{jt} + \beta_3 E(Market\_Power)_{ijt,imp}$$

$$+\beta_4 E(Market\_Power)_{ijt,exp} + \beta_5 FTR_{ijt} + \beta_6 + \beta_7 annual + \mu_i + \zeta_j + \epsilon_{ijt} \quad (4.24)$$

Bid price is on the LHS. There are three additional terms in this estimation equation for generators: the term "Market_Power" is to test whether FTRs' strategic effect on profit is significant in the bid price. As is discussed in earlier section, such an effect can be both positive and negative. For generators only have generation in one regional market or in multiple regional markets with the same direction of power flow constraints, the $Market\_Power_{ijt,imp}$ is simply the own regional market power. For generators have generation in multiple zones with opposite direction of power flow constraints, this market power term is composed of two parts: $Market\_Power_{ijt,imp}$ is the market power in the import-constrained market and $Market\_Power_{ijt,exp}$ is the market power in the export-constrained market. The term μ_i is to control for individual firm specific effects that the econometrician cannot observe.

3. Data

This section describes the measurement of each RHS variable from the data set. Since the terms on RHS are in expectations, I take the average within the FTR defined time period as an approximation to the expectation. I focus in this paper on 5 generators and a trader. These generators are active in the FTR auction and participated in the the wholesale spot market, but their generation capacity as well as spot market sale varies a lot which can be observed from the summary statistics about the bidders after the descriptions of the measurements.

Expected Unit FTR Credit In measuring the expected unit FTR credit, we need to average the realized shadow price over all time periods, not only congested time periods. The reason is that when the bidder pays for the awarded amount of FTRs, she is paying for all the time periods within the FTR defined time length. So the expectation should also take into account the probability of future congestion. For example, if the average anticipated shadow price is $10, but congestion only occurs half of the entire period, the bidder should pay no more than $5. Also we need to know how would bidders form their expectation. In the following, I have two ways of measuring expected unit FTR credit, or the shadow price:

- Measure 1: The expected shadow price is measured by the ex-post realized shadow price of the corresponding transmission line averaged over all time periods. If we find that bidders are hedging against this number, then they perfectly forecast the future shadow price as well as the future probability of congestion.
- Measure 2: The first measure assumes that the bidders are perfectly rational in that they can perfectly predict the future outcome given their behavior on the first stage. A less-than-rational setting would be adapted expectation in that the bidders use ex-ante information to infer the ex-post realizations. The second measure use the ex-ante information on the

wholesale electricity market. The expected shadow price is measured by the ex-ante shadow price averaged over all periods in the earlier year or month. For the annual auction, I use shadow price averaged over all time periods in earlier year[13]. For the monthly auction, I use the realized shadow price averaged over all time periods in the previous month.

Shadow Price Volatility There are 2 measures of volatility in shadow price corresponding to the 2 measures of the expected shadow price. Namely, for the first measure, I use the variance of shadow price in all the ex-post periods; for the second measure, I use the variance of shadow price in all the ex-ante periods.

Market Power An ideal measurement of the market power based on equation (4.18) would be to estimate both the price-cost margin and the dispatched quantity on the wholesale real-time market. However, we should notice that since market price is a function of the dispatched quantity, we can just measure the amount of dispatched quantity on the balancing market as an approximate to the market power effect. Also notice that since we combine the two FTR effects together, the sign for the market power will be ambiguous. A perfect rational bidder should base her expectation on the future amount of dispatched quantity on the balancing market. If the bidder is less than rational, then a rough estimate of her market power should be positively correlated with the ex-post dispatched quantity on the balancing market. In my data, such a rough correlated measure can be measured as the total metered generation on the wholesale electricity

[13]For the South to Houston shadow price, since in year 2001 there is no Houston zone, I construct the annual South to Houston expected shadow price by using the realization in January 2002, and discount by 20%: because in 2002, January is the month with the most frequency of congestion and the summer months' frequency of congestion is only around 80% of the January one.

market. To summarize, I have the following measures for measuring market power:

- Balancing Market Sale (BMS): The measure here uses the ex-post measures. The balancing market sales include physical balancing power supply, fulfilment of contract obligation on the balancing market and FTR ownership. The physical balancing power supply q is measured by intersecting bidder's own bids on the wholesale balancing market with her residual demand. The combination of contract obligation and FTR ownership is measured by the intersection of bidder's own bids with her marginal cost curve. The intersection point is called QC_{obs}[14]. $q - QC_{obs}$ then can be used as the total flexible quantity on the spot market.
- Metered Generation (MG): I use the ex-post measure of the average metered generation across all time periods in hour 18 corresponding to the FTR defined time length as an approximation to the market power.

Table XVI and Table XVII give summary statistics of some of the RHS variables of equation (4.24).

Table XVII also reflects the fact that the two measures of market power are positively correlated with each other.

In all the estimations, I study only the clearing bid point. The clearing bid is constructed by intersecting the bidder's own bid with her residual supply curve. The residual supply curve is constructed by taking the aggregate supply (which is a perfectly inelastic supply of the total available amount of FTRs), and subtract the bidder's rivals' aggregate demand bid curve. The rationale to check the clearing bid

[14] Detailed measurement of $q - QC_{obs}$ can be found in Chapter III.

Table XVI. Summary Statistics of Monthly Unit FTR Credit Volatility

	Shadow Price		Volatility	
	mean	s.d.	mean	s.d.
South → Houston	3.79	3.33	1479.73	2682.02
South → North	4.00	5.64	2927.91	4710.33
West → North	2.02	4.23	1021.06	1419.88

Table XVII. Summary Statistics of Market Power Measures

	North		South		West		Houston	
	BMS	MG	BMS	M.G.	BMS	MG	BMS	MG
	s.d.	s.d.	s.d.	s.d.	s.d.	s.d.	s.d.	s.d.
Bidder 1	51	1489	–	–	–	–	759	5101
	41	75	–	–	–	–	242	1777
Bidder 2	362	6860	64	303	239	816	–	–
	124	1398	113	40	96	251	–	–
Bidder 3	157	742	–	–	–	–	–	–
	42	119	–	–	–	–	–	–
Bidder 4	120	96	–	–	–	–	–	–
	22	1	–	–	–	–	–	–
Bidder 5	–	–	45	176	–	–	–	–
	–	–	27	61	–	–	–	–

is that on the RHS, the ex-post measures are corresponding to the awarded FTRs, so the clearing bid point is the relevant bid point to check.

D. Estimation Results

In all the tables that report my estimation results, I use I, II to represent the two measurements of the expected unit FTR credit (the shadow price) and corresponding variance in the shadow price.

1. Trader's Bidding Strategy

As a summary statistics, the trader in average holds 13% of the total available FTRs. The trader wins over 70% of the entire time in the South-Houston and West-North FTR auctions and wins over 50% of the time in the South-North FTR auctions. The trader also participates in over 50% of the auctions. In view of these statistics, the trader is very active in the FTR auctions. Table XVIII reports the estimates of trader's bidding strategy.

Expectation on Future Shadow Price By using different measures of expectations on future shadow price, it is clear that the trader very accurately forecasts the future shadow price by using the first measure. The expectation is not adapted from the earlier period. The coefficient for this measure is very significant and statistically equal to one. This result reflects the fact that the trader is rational in making expectations on future shadow price of the transmission line. For the second measure, not only the coefficient is very noisy, but the mean of the coefficient is not even close to one, indicating that this measure is irrelevant to the trader.

Future Shadow Price Uncertainty As was discussed in the theory sections, the

Table XVIII. Traders Bidding Strategy

LHS variable: clearing bid

number of observations: 20

	I		II	
	coef.	s.e.	coef.	s.e.
unit FTR credit	1.169*	0.328	0.301	0.279
Var(SP)	-0.001*	0.000	0.000	0.000
FTR	-0.025*	0.008	-0.021*	0.009

* indicates significance at 5% significance level.

future shadow price uncertainty will have two different impacts on the bidding strategy. The first impact is in the value function – a risk averse player is willing to pay risk premium if the uncertainty is high. On the other hand, the precision of the uncertainty distribution will have impact on the bid shading strategy if the valuation is affiliated: the higher the uncertainty, the more the bidder is willing to shade her bids to avoid "winner's curse" problem. In view of this, if the coefficients are shown to be negative, we can say with confidence that the valuations are affiliated among the bidders and the bid shading effects dominate the risk premium amount. From our estimation results, we see that using the first measure, the coefficient for uncertainty is significantly negative, indicating that the bid shading due to value affiliation dominates risk premium. Again the second measure is irrelevant to the trader's bidding strategy.

Bid Shading The normal bid shading effect (in both IPV and AV models) is reflected in the coefficient with "FTR". The estimation result for the first measure reveals that the bid shading component is significant. This is consistent with theory predictions that a large buyer with market power can shade her bids and affect the market clearing price in the uniform price auction.

From the estimation results, we see that the trader is perfectly forecasting the future shadow price of the transmission constraints and exercises market power. Through the estimation results, we see that the valuations are affiliated among the bidders so that the trader is shading more when it is more uncertain of the exact value of the future shadow price of the transmission constraints. In all the auctions, the trader is willing to pay more in the annual auctions holding everything else constant.

2. Generator's Bidding Strategy

a. Pooling Large and Small Bidders

Table XIX and Table XX report the estimation results for generators' bidding strategy.

The estimation pools large and small bidders altogether. My following discussion will be focusing on the fixed effect estimation results if the estimates from fixed effect estimations are different from OLS estimations.

Expectation on Future Shadow Price The OLS as well as the fixed effects regression reflect that the first measure of the future shadow price fits better with theory predictions. The coefficient for the first measure is very significant and statistically equal to one. This coefficient indicates that at the mean, the bidders are forecasting quite well of the future shadow price. Similar to the trader's estimation results, the second measure is not significant at 5% significance level.

Future Shadow Price Uncertainty Using the first measure, both the OLS and fixed effects regressions reveal that the bid shading effect statistically dominates

Table XIX. Generator's Bidding Strategy (Market power uses $q - QC$)

LHS: clear bid, 62 obs.

	I		II	
	OLS	F.E.	OLS	F.E.
	coef.	coef.	coef.	coef.
	s.e	s.e	s.e	s.e
unit FTR credit	1.311*	1.254*	0.218	-0.016
	0.547	0.480	0.195	0.228
Var(SP)	-0.001*	-0.001*	0.000	0.000
	0.000	0.000	0.000	0.000
$Market\_Power_{imp}$	0.004*	0.003	0.006*	0.001
	0.002	0.003	0.002	0.003
$Market\_Power_{exp}$	-0.011*	-0.002	-0.012	0.007
	0.005	0.010	0.008	0.010
FTR	-0.001	-0.020	0.004	-0.020
	0.014	0.013	0.012	0.013

* indicates significance at 5% significance level, ** indicates significance at 10% significance level.

Table XX. Generator's Bidding Strategy (Market power uses $metergen$)

LHS: clearing bid, 71 obs.

	I		II	
	OLS	F.E.	OLS	F.E.
	coef.	coef.	coef.	coef.
	s.e	s.e	s.e	s.e
unit FTR credit	1.341*	1.435*	0.274**	0.082
	0.481	0.405	0.162	0.194
Var(SP)	-0.001*	-0.001*	0.000	0.000
	0.000	0.000	0.000	0.000
$Market\_Power_{imp}$	0.001*	0.000	0.001*	0.001**
	0.000	0.000	0.000	0.000
$Market\_Power_{exp}$	-0.006*	-0.001	-0.009*	-0.003
	0.002	0.003	0.003	0.003
FTR	0.001	-0.018	0.005	-0.011
	0.014	0.013	0.011	0.012

* indicates significance at 5% significance level, ** indicates significance at 10% significance level.

the risk premium payment. This again confirms that the valuations are affiliated among the bidders.

Market Power In all the fixed effect estimations, the market power effect is not significant in all the measures. In the following subsection, I will test the robustness of this result including the examination of the endogeneity problem for the estimations.

Bid Shading By pooling all the bidders, the bid shading effect is not significant in the fixed effect estimates – indicating that bidders are not exercising market power. However, since we are pooling large and small bidders together, there might be the case that the insignificant shading effect is dominated by small bidders who do not have much market power in the FTR auction. I will check the robustness of this result again in the following subsection.

In all the estimates, the bidders are willing to pay more in the annual auction.

b. Robustness

For a robustness check, I re-group the bidders so that their bidding behaviors can be observed more closely. Table XXI collects several statistics that reveal the heterogeneity among the bidders.

From Table XXI, we see that there are a lot of heterogeneity among the bidders: some bidders hold large percentage of the entire amount of FTRs (almost reach the percentage limit which is 25%) while some bidders hold on average no more than 1% of the total amount of FTRs. In terms of participation, some bidders participate almost in every round of auctions while some bidders participate no more than one third of the entire auctions. In view of this, I re-group the bidders so that the bidding strategies can be similar within each group. I categorize the bidders into large bidders

Table XXI. Bidders Participation Statistics

LHS: clearing bid, 71 obs.

	I	II	III	IV
Bidder1 S-N	0.023	0.167	0	0.462
Bidder1 W-N	0.141	0.667	1	0.462
Bidder1 S-H	0.235	0.778	1	0.692
Bidder2 S-N	0.234	0.500	1	0.769
Bidder2 W-N	0.233	0.500	1	0.615
Bidder2 S-H	0.233	0.857	1	0.538
Bidder3 S-N	0.013	0.333	0	0.692
Bidder3 W-N	0.068	0.444	1	0.692
Bidder4 S-N	0.014	0.600	0	0.385
Bidder4 W-N	0.002	0.333	0	0.231
Bidder5 S-N	0.004	0.400	0	0.385

I: amount of FTR owned as a percentage of total available FTRs = $\frac{FTR_{it}}{total_F TR_i}$
II: percentage of time that is awarded the FTRs = (number of times awarded FTR)/(total number of times participated)
III: 1 indicates the ownership of annual FTR, 0 otherwise
IV: percentage of time that the bidder participated in the auctions = (total number of times participated)/(total number of times FTRs are auctioned)

with the following criteria: 1) ownership of FTRs is over 20% of the total FTRs; 2) the percentage of time that the bidder wins the auction is over 50% of the time that she participates; 3) owns annual FTRs, and 4) participation in the FTR auction is over 50% of the total rounds of auctions conducted by the grid operator. "Bidder1 S-H", "Bidder2 S-N", "Bidder2 W-N" and "Bidder2 S-H" are grouped into this "large bidder" group. The others are grouped into the "small bidder" group. Table XXII and Table XXIII report the estimation results about large bidders.

Comparing the large bidders' bidding strategy with our earlier estimation results, we see that the majority of the findings are very consistent:

- the bidders are forecasting future expected shadow price using the first measure;
- the bidders are shading significantly not only in the regular terms (which is reflected in the coefficient with FTR), but they also shade more due to more uncertainty of the future shadow price.
- The significant coefficient associated with FTR reveals that large bidders are able to exercise market power in the FTR auctions by shading from their valuation.
- Again using both measures, the market power term is not significant,

A major significant change from our earlier results (Table XIX and Table XX) is that large bidders "over-pay" on the expected future shadow price using the first measure, in that the coefficient now is far above the theory implication of one. This means that the bidders are expecting too high on future shadow price. The result is also consistent with the fact that in the first year, the bidders are paying above the ex-post realized shadow price for the FTRs. Conditioning on other factors, large bidders are expecting too high on future unit FTR credit.

Table XXII. Large Bidders' Bidding Strategy (Market power uses $q - QC$)

LHS: clearing bid, 29 obs.

	I		II	
	OLS	F.E.	OLS	F.E.
	coef.	coef.	coef.	coef.
	s.e	s.e	s.e	s.e
unit FTR credit	1.532*	2.115*	0.228	0.121
	0.635	0.495	0.343	0.323
Var(SP)	-0.001*	-0.002*	0.000	0.000
	0.000	0.000	0.000	0.000
$Market\_Power_{imp}$	0.004	0.000	0.004	-0.002
	0.003	0.004	0.003	0.006
$Market\_Power_{exp}$	-0.010**	-0.008	-0.017**	0.014
	0.006	0.011	0.009	0.013
FTR	-0.015	-0.045*	-0.007	-0.033
	0.017	0.016	0.016	0.021

* indicates significance at 5% significance level, ** indicates significance at 10% significance level.

Table XXIII. Large Bidders' Bidding Strategy (Market power uses *metergen*)

LHS: clearing bid, 32 obs.

	I		II	
	OLS	F.E.	OLS	F.E.
	coef.	coef.	coef.	coef.
	s.e	s.e	s.e	s.e
unit FTR credit	1.692*	2.458*	0.443	0.324
	0.554	0.450	0.287	0.282
Var(SP)	-0.001*	-0.002*	0.000	0.000
	0.000	0.000	0.000	0.000
$Market\_Power_{imp}$	0.001**	-0.001	0.001**	0.001
	0.000	0.001	0.000	0.001
$Market\_Power_{exp}$	-0.005**	0.004	-0.008*	-0.08
	0.002	0.005	0.003	0.006
FTR	-0.010	-0.051*	-0.001	-0.022
	0.017	0.015	0.015	0.020

* indicates significance at 5% significance level, ** indicates significance at 10% significance level.

Table XXIV. Small Bidders' Bidding Strategy (Market power uses $q - QC$)

LHS: clearing bid, 33 obs.

	I		II	
	OLS	F.E.	OLS	F.E.
	coef.	coef.	coef.	coef.
	s.e	s.e	s.e	s.e
unit FTR credit	1.076	-0.547	0.126	0.029
	0.893	0.942	0.256	0.252
Var(SP)	-0.001	0.000	0.000	0.000
	0.001	0.001	0.000	0.000
$Market\_Power$	0.018	0.020	0.014	0.017
	0.010	0.018	0.009	0.014
FTR	0.036	-0.008	0.025	-0.005
	0.019	0.032	0.016	0.025

* indicates significance at 5% significance level, ** indicates significance at 10% significance level.

Table XXIV and Table XXV report the estimation results about small bidders.

The estimation for small bidders are very noisy, indicating that the small bidders are not able to either forecast future price systematically or exercise market power. This also reveals that the smaller magnitude of the first coefficient estimate in Table XIX and Table XX than the estimate in Table XXII and XXIII for large bidders is because the dilution by the noisy strategies from the small bidders. Also the insignificance results of bid shading in Table XIX and Table XX are due to the inability of small bidders to exercise market power.

Table XXV. Small Bidder's Bidding Strategy (Market power uses *metergen*)

LHS: clearing bid, 39 obs.

	I		II	
	OLS	F.E.	OLS	F.E.
	coef.	coef.	coef.	coef.
	s.e	s.e	s.e	s.e
unit FTR credit	0.936	0.132	0.116	-0.007
	0.828	0.766	0.222	0.195
Var(SP)	-0.001	0.000	0.000*	0.000*
	0.001	0.001	0.000	0.000
$Market\_Power$	0.001	0.008	0.001	0.008
	0.001	0.006	0.001	0.005
FTR	0.013	0.008	0.001	-0.001
	0.020	0.028	0.018	0.022

* indicates significance at 5% significance level, ** indicates significance at 10% significance level.

Another concern about the robustness of the estimation result is that if the bidders are able to exercising market power on the subsequent power market, then the choice of FTRs and the consequent supply and market price will all be endogenous to the firm rather than exogenously given. The endogenous variables can be the ex-post shadow price measure, the ex-post quantity on the balancing market and the amount of FTR chosen. To test for the endogeneity issue, I selected the following variables as exogenous instruments to the system:

- Shadow price $t-1$. This is under the assumption that the shadow price realized in the earlier period is not controlled by the firm at current time t, or the current market condition does not cause earlier market outcome. This is essentially the second measure of the shadow price.

- Number of total FTRs to be auctioned. This is public information that every bidder knows before she goes to the auction and is exogenous to the auction strategies.

- Frequency of outage. In ERCOT's study, in the months of March, April, October and November, there are more frequent transmission and generation outages. I use a dummy equal to one indicating those months. I also dummy the month of July and August as one because they are summer peak months.

- Number of bidders in the auction. Total number of bidders are not known to the auction participants before the auction. However, I use this statistic as an exogenous variable to approximate the intensity of the auction. The bidders should have some beliefs as to whether the auction will receive more attention or not and such exogenous factor will affect the bidders' bidding behavior.

By using the above instruments, the Durbin-Wu-Hausman statistics report that actually for the trader and small bidders, there are no endogeneity problems for earlier estimations[15]. For large bidders, statistics strongly support that endogeneity exists. This is not a surprise because for trader and small bidders, they do not have much influence on the wholesale market outcome, so that their expectation of market outcome should be exogenous to them, in that they are not able to “choose” a particular outcome. For large bidders, due to their market power, they can expect particular market outcome that they can “choose”, or in other words, endogenous to them. Table XXVI reports the IV estimation results using the above instruments for large bidders. Since their market powers are mostly reflected in the balancing market bidding, I include here only the variable measuring “market power” using the ex-post balancing market outcome instrumented by the above instruments. The price measure is using the ex-post shadow price again instrumented by the above instruments. Also the FTR amount is assumed to be endogenous and instrumented by the above instruments. The estimation uses panel level fixed effect and corrects for panel-wise heteroscedasticity.

A striking result is that after controlling for the endogeneity, FTRs' impact on market power becomes significant in the bidding strategy. Another distinction is that the expectation on future unit FTR credit is biased upward greater than our previous estimates for large bidders. Again the valuation structure is revealed to be affiliated because the bid shading effect from uncertainty dominates risk premium payment. Large bidders are able to exercise market power in the FTR auction which is reflected by the significant shading factor attached to the FTR amount in their bids.

[15]The Durbin-Wu-Hausman statistic for the trader's estimation is 1.17, which confirms the null hypothesis that OLS is consistent with a Chi-square distribution with 2 degrees of freedom. For the small bidders, the statistic is 4.32. Under a Chi-square distribution with 3 degrees of freedom, the null hypothesis is again confirmed.

Table XXVI. Large Bidders' Bidding Strategy (IV estimates) (Market power uses $q - QC$)

LHS: clearing bid, 32 obs.

	coef.	s.e
unit FTR credit	7.709*	2.310
Var(SP)	-.006*	.002
$Market\_Power_{imp}$	.026*	.013
$Market\_Power_{exp}$	-.185	.121
FTR	-.105*	.036

* indicates significance at 5% significance level, ** indicates significance at 10% significance level.

CHAPTER V

CONCLUSIONS

This research empirically addresses the question on the electricity market as to what the FTR price tells us. To answer this question, I empirically study FTRs' impacts on bidders' strategic behaviors as well as such strategic behaviors' impact on FTR prices. This research also contributes to the recently developed literature of empirical study of multi-unit auctions and uniform-price auctions in particular. By using rich data on the electricity market, I am able to test some of the major empirical implications from multi-unit auction theories.

The first part of this dissertation empirically examines the impact of FTRs on firm's bidding strategies on the wholesale electricity market in Texas. I focus on the two largest players in the Texas electricity market – Reliant in the Houston zone and TXU in the North zone. I find bidding behaviors converge towards theoretical equilibrium predictions over time with respect to firms' physical inframarginal capacity. With respect to FTRs, bidding strategies are converging towards optimal bidding during the course of the first year, but deviated from optimal bidding starting from the last period of the sample. Quantitatively, during my sample periods when FTRs are statistically significant (β_2 is significant) in players' bidding strategy, Reliant's markup is marginally affected by FTRs around 23 cents and 28 cents in Period 2 and Period 3 respectively, while TXU around \$1.99 in Period 3. Counterfactual studies show that the FTR effects are mostly reflected through market price level changes rather than production efficiency. Considering demand uncertainty, the current allocation of FTRs is not statistically different from optimal FTR allocation in most months. If the market is mostly cleared at the decreasing production side, then the allocation of FTRs would improve market price signal efficiency. Compared with counterfactual scenarios where no FTRs are allocated, optimal allocations of FTRs statistically increase spot market price signal efficiency for most of the months on the wholesale electricity market.

The second part of the dissertation studies bidding strategies in the FTR auctions and serves to detect whether FTRs' strategic impacts on the wholesale market would be reflected in the FTR prices. I prescribe a methodology that tests bidders' bidding behavior and price components in FTRs by studying the year 2002 FTR auctions. Theory implies that the difference in bidding between traders and generators can be explained by generator's market power. By integrating bidders ex-post wholesale market auction behavior with the FTR auction together, I develop empirical models that allows the testings of theory predictions.

My empirical results for the bidding strategy in the FTR auctions show that the trader can very accurately forecast future shadow price and is able to exercising market power by shading its bids from its marginal valuation of FTRs. The estimation of generators' bidding strategies concludes that generators also bid on the expected future shadow price and such expectations are not adapted from earlier periods. For large bidders, their forecasts of future unit FTR credit biased upward, but the correlation with realized shadow price is still positive and very significant. For small bidders, they are not able to accurately forecast future shadow price consistently and the estimates for bids' correlation with realized shadow price is very noisy. In terms of market power in FTR auctions, large bidders are able to exercise market power by shading their bids from their marginal value of FTRs. Small bidders are not able to exercise market power and the coefficient estimates are again very noisy.

The valuation structure are revealed to be affiliated among the bidders in the FTR auctions. In all the estimation results for traders and large bidders, the bid shading effect resulted from value affiliation dominates the risk premium payment.

The more uncertain the future shadow price is, the more the bidders wish to shade down from their valuation.

After correcting endogeneity issues in the bidding strategy, the FTRs' market power effect is significant in the bids for large bidders but not for small bidders. In Chapter III, I find that firms significantly included FTRs into their bidding strategy starting the second half of the year. Such an effect is significantly reflected through the bidding strategy in the FTR auction for those large bidders and hence the FTR prices are affected by the market power on the wholesale market.

REFERENCES

Ausubel, L., Cramton, P., 2002. Demand Reduction and Inefficiency in Multi-Unit Auctions. Mimeo, University of Maryland.

Back, K., Zender, J.F., 1993. Auctions of Divisible Goods: On the Rationale for the Treasury Experiment. The Review of Financial Studies 6(4), 733-764.

Brunekreeft, G., 2003. Market Based Investment in Electricity Transmission Networks: Controllable Flow. CMI working paper No.19.

Bushnell, J.B., Stoft, S. 1996. Electric Grid Investment Under a Contract Network Regime. Journal of Regulatory Economics 10, 61-79.

Bushnell, J.B., Stoft. S. 1997. Improving Private Incentives for Electric Grid Investment. Resource and Energy Economics 19, 85-108.

Bushnell, J. B., 1999. Transmission Rights and Market Power. Electric Journal 12(8),77-85.

Gilbert,R.J., Neuhoff, K and Newbery, forthcoming. D.M. Allocating Transmission to Mitigate Market Power in Electricity Networks. RAND Journal of Economics.

Hogan, W.W., 1992. Contract Networks for Electric Power Transmission.

Journal of Regulatory Economics 4, 211-242.

Hogan, W.W., 2002. Financial Transmission Rights Formulations. Mimeo, Harvard University.

Hortaçsu, A., forthcoming. Mechanism Choice and Strategic Bidding in Divisible Good Auctions: An Empirical Analysis of the Turkish Treasury Auction Market. Econometrica.

Hortaçsu, A., Puller, S.L., 2004. Testing Strategic Models of Firm Behavior in Restructured Electricity Markets: A Case Study of ERCOT. Mimeo, CSEM working paper No.125.

Joskow, P., forthcoming 2005. Transmission Policy in the United States. Utilities Policy.

Joskow, P., Tirole, J, 2000. Transmission Rights and Market Power on Electric Power Networks. RAND Journal of Economics 31(3), 450-487.

Joskow, P. & Tirole, J, 2003., forthcoming 2005. Merchant Transmission Investment. Journal of Industrial Economics.

Klemperer, P.D. & Meyer, M.A., 1989. Supply Function Equilibria in Oligopoly under Uncertainty. Econometrica 57, 1243-1277.

Stoft. S, 1999. Financial Transmission Rights Meet Cournot: How TCCs

Curb Market Power. The Energy Journal 20, 1-23.

Wilson, R., 1979. Auctions of Shares. Quarterly Journal of Economics 93, 675-689.

Wolfram, C. D., 1998. Strategic Bidding in a Multiunit Auction: An Empirical Analysis of Bids to Supply Electricity in England and Wales. RAND Journal of Economics 29(4), 703-725.

APPENDIX A

ERCOT SHADOW PRICE CALCULATION

$$\begin{pmatrix} MCPE_{system} \\ SP_{SN} \\ SP_{SH} \\ SP_{WN} \end{pmatrix} = \begin{pmatrix} 1 & -SF_{N,SN} & -SF_{N,SH} & -SF_{N,WN} \\ 1 & -SF_{S,SN} & -SF_{S,SH} & -SF_{S,WN} \\ 1 & -SF_{W,SN} & -SF_{W,SH} & -SF_{W,WN} \\ 1 & -SF_{H,SN} & -SF_{H,SH} & -SF_{H,WN} \end{pmatrix}^{-1} \times \begin{pmatrix} MCPE_{N} \\ MCPE_{S} \\ MCPE_{W} \\ MCPE_{H} \end{pmatrix} \tag{A.1}$$

Note: SP stands for Shadow Price, SF stands for Shift Factor, subscripts represent zones. MCPE represents Market Clearing Price for Electricity. For example: SP_{SN} represents shadow price for transmission line from south to north; $SF_{N,SN}$ represents shift factor in the north zone on the directional transmission line from south to north.

APPENDIX B

DERIVATION OF FOC FROM EQUATION (3.4)

Integration by parts, we have

$$\int_0^{\bar{p}} \pi_{it} dH(p, S_{it}(p_t)) = \pi_{it} H(p, S_{it}(p, S_{it})|_0^{\bar{p}} - \int_0^{\bar{p}} H(p, y_{it}(p, s_{it})) \frac{d\pi_{it}}{dp} dp \tag{B.1}$$

Notice that

$$\frac{d\pi_{it}}{dp} = pS'_{it} + S_{it} - C'_{it}S'_{it} \tag{B.2}$$

Equation (B.1) can be re-written as

$$\int_0^{\bar{p}} \pi_{it} dH(p, S_{it}(p_t)) = \pi_{it} H(p, S_{it}(p, S_{it})|_0^{\bar{p}} - \int_0^{\bar{p}} H(p, y_{it}(p, s_{it}))(pS'_{it} + S_{it} - C'_{it}S'_{it}) dp \tag{B.3}$$

The first part in equation (B.3) is a constant so that we ignore that part in the derivation of first order condition. Define

$$F = H(p, y_{it}(p, s_{it}))(pS'_{it} + S_{it} - C'_{it}S'_{it}), \tag{B.4}$$

the integrand, the Euler equation is given by

$$F_S = \frac{dF_{S'}}{dp} \tag{B.5}$$

using equation (B.4), $F_S = H_S(pS'_{it} + S_{it} - C'_{it}S'_{it}) + H$, $F_{S'} = H(p - C'_{it}) \Rightarrow \frac{dF_{S'}}{dp} = H_p(p - C'_{it}) + H_{S\prime}S(p - C'_{it}) + H$. Then our first order condition of equation (3.5) is derived by applying the Euler equation (B.5).

APPENDIX C

SIMPLIFICATION OF $\frac{H_S}{H_P}$

Proof:

$$H(p, s(p)) = Pr(p^c < p|S(p)) \tag{C.1}$$

$\Rightarrow$

$$H(p, s(p)) = Pr(S(p) > \tilde{D}(p)|S_i(p)) \tag{C.2}$$

$\Rightarrow$

$$H(p, s(p)) = Pr(S_i + S_{-i} > \tilde{D}(p)|S_i(p)) \tag{C.3}$$

If we assume that $S_i(p, QC_i, FTR_i) = \alpha_i(p) + \beta_i(QC_i, FTR_i)\ \forall i$, then

$$H(p, s(p)) = Pr(\alpha_i(p) + \beta_i(QC_i, FTR_i) + \alpha_{-i}(p) + \beta_{-i}(QC_{-i}, FTR_{-i})$$

$$> \bar{D}(p) + \epsilon|S_i(p)) \tag{C.4}$$

$\Rightarrow$

$$H(p, s(p)) = Pr(\beta_{-i}(QC_{-i}, FTR_{-i}) - \epsilon > \bar{D}(p) - S_i - \alpha_{-i}(p)) \tag{C.5}$$

Based on the above H function, we can deriv H_s and H_p. Let $F(\bar{D}(p) - S_i - \alpha_{-i}(p))$ be the cumulative distribution, then $H(p, s(p)) = 1 - F(\bar{D}(p) - S_i - \alpha_{-i}(p))$; let $f(\cdot)$ be the corresponding density function.

$$H_s(\cdot) = \tfrac{\partial H}{\partial S} = \tfrac{\partial(1-F(\bar{D}(p)-S_i-\alpha_{-i}(p)))}{\partial S}$$

$$= -f(\bar{D}(p)S_i - \alpha_{-i}(p))\frac{\partial(\bar{D}(p) - S_i - \alpha_{-i}(p))}{\partial S_i} \tag{C.6}$$

$$H_p(\cdot) = \tfrac{\partial H}{\partial p} = \tfrac{\partial(1-F(\bar{D}(p)-S_i-\alpha_{-i}(p))}{\partial p}$$

$$= -f(\bar{D}(p) - S_i - \alpha_{-i}(p))\frac{\partial(\bar{D}(p) - S_i - \alpha_{-i}(p))}{\partial p} \tag{C.7}$$

Notice that $\frac{\partial(\bar{D}(p)-S_i-\alpha_{-i}(p))}{\partial S_i}=-1$ and $\frac{\partial(\bar{D}(p)-S_i-\alpha_{-i}(p))}{\partial p}=\bar{D}'(p)-\alpha'_{-i}(p)=RD'(p)$. Combine the above equations (C.6) and (C.7) together, we get

$$\frac{H_S}{H_p}=-\frac{1}{RD'(p)} \tag{C.8}$$

Q.E.D.

APPENDIX D

RISK AVERSE

Assume that the utility function of a risk averse bidder is[1]

$$u(\pi_{it}) = -e^{-\gamma\pi_{it}} \tag{D.1}$$

The expected utility maximization problem becomes:

$$\max_{S_{it}(p_t^c)} U_{\pi_{it}} = \int_0^{\bar{p}} u(\pi_{it})dH(p, S_{it}(p_t)) = \int_0^{\bar{p}} -e^{-\gamma\pi_{it}}dH(p, S_{it}(p_t)) \tag{D.2}$$

Integration by parts, we get

$$\int_0^{\bar{p}} u(\pi_{it})dH(p, S_{it}(p_t)) = u(\pi_{it})H(p, S_{it}(p, S_{it})|_0^{\bar{p}} - \int_0^{\bar{p}} H(p, y_{it}(p, s_{it})\frac{du(\pi_{it})}{dp}dp \tag{D.3}$$

Again the first term is a constant, and the second term can be re-written as

$$\begin{aligned} &- \textstyle\int_0^{\bar{p}} H(p, y_{it}(p, s_{it})) - re^{-\gamma\pi_{it}}\frac{d\pi}{dp}dp \\ &= \int_0^{\bar{p}} H(p, y_{it}(p, s_{it}))re^{-\gamma\pi_{it}}(pS'_{it} + S_{it} - C'_{it}S'_{it})dp \end{aligned} \tag{D.4}$$

Let

$$F = H(p, y_{it}(p, s_{it}))re^{-\gamma\pi_{it}}(p\prime S_{it} + S_{it} - C'_{it}S'_{it}), \tag{D.5}$$

then

$$F_S = H_S re^{-\gamma\pi_{it}}(pS'_{it} + S_{it} - C'_{it}S'_{it}) - Hr^2e^{-\gamma\pi_{it}}(pS'_{it} + S_{it} - C'_{it}S'_{it})(p - C') + Hre^{-\gamma\pi_{it}}, \tag{D.6}$$

$$F_{S'} = Hre^{-\gamma\pi_{it}}(p - C') \tag{D.7}$$

$\Rightarrow$

[1]The utility function used is just for illustration purpose in this exercise. The result applies to any risk averse utility functional forms.

$$\frac{dF_{S'}}{dp} = H_p r e^{-\gamma\pi_{it}}(p - C') + H_S S' r e^{-\gamma\pi_{it}}(p - C')$$

$$-Hr^2 e^{-\gamma\pi_{it}}(pS'_{it} + S_{it} - C'_{it}S'_{it})(p - C') + Hre^{-\gamma\pi_{it}} \tag{D.8}$$

By applying Euler equation $F_S = \frac{dF_{S'}}{dp}$ for first order condition, we get exactly the same first order condition as is in equation (3.5)

APPENDIX E

DERIVATION OF EQUATION (4.11) FOR IPV MODEL

Our equation (4.5) can be written as: $U_{it} = \int_0^\infty \pi_{it} dH(p, k_{it}(p, s_{it})$, with the profit π being:

$$\pi = \int_0^{k(p)} V(k_{it}(p), s_i)dk - k(p)p$$

Integral by parts, we get:

$$\int_0^\infty \pi_{it} dH(p, k_{it}(p, s_{it}) = \pi_{it} H(p, k_{it}(p, s_{it})|_0^\infty - \int_0^{k(p)} H(p, k_{it}(p, s_{it}) \frac{d\pi_{it}}{dp} dp \tag{E.1}$$

Notice that

$$\frac{\partial \pi}{\partial p} = \int_0^{k(p)} (dV(k_{it}(p), s_i)/dp)dk + V(k_{it}(p), s_i)k'(p) - k(p) - k'(p)p$$

$$= V(k_{it}(p), s_i)k'(p) - k(p) - k'(p)p = (V(k(p), s_i) - p)k'(p) - k(p) \tag{E.2}$$

Equation (E.1) can be re-written as:

$$\int_0^\infty \pi_{it} dH(p, k_{it}(p, s_{it}) = -\int_0^\infty H(p, k_{it}(p, s_{it})[(V(k(p), s_i)) - p)k'(p) - k(p)]dp \tag{E.3}$$

Let $F = H(p, k_{it}(p, s_{it})[(V(k(p), s_i) - p)k'(p) - k(p)]$, the integrand, then the Euler equation is given by

$$F_k = \frac{dF_{k'(p)}}{dp} \tag{E.4}$$

By using equation (E.4), we get our necessary condition for optimality which is

$$V(k(p), s_i) = p + k\frac{-H_k}{H_p} \tag{E.5}$$

Q.E.D

APPENDIX F

DERIVATION OF EQUATION (4.13) FOR AV MODE

In AV model,

$$U_{it} = \int_0^\infty [\int_0^{k(p^c)} V(k_{it}(p), s_i, p)dk] - k(p)pdH(p^c, k(p^c, s_i) \tag{F.1}$$

Similar as we have in the previous proof, the static profit can be written as $\pi_{it} = [\int_0^{k(p^c)} V(k_{it}(p), s_i, p)dk] - k(p)p$, Integral by parts, we get:

$$\int_0^\infty \pi_{it} dH(p, k_{it}(p, s_{it}) = \pi_{it} H(p, k_{it}(p, s_{it})|_0^\infty - \int_0^{k(p)} H(p, k_{it}(p, s_{it}) \frac{d\pi_{it}}{dp} dp \tag{F.2}$$

Notice that this time,

$$\frac{\partial \pi}{\partial p} = \int_0^{k(p)} (dV(k_{it}(p), s_i)/dp)dk + V(k_{it}(p), s_i)k'(p) - k(p) - k'(p)p$$

$$= V(k_{it}(p), s_i)k'(p) - k(p) - k'(p)p$$

$$= \int_0^{k(p)} (dV(k_{it}(p), s_i)/dp)dk + (V(k(p), s_i) - p)k'(p) - k(p) \tag{F.3}$$

So that our utility function U_{it} can be reduced to :

$$-\int_0^{k(p)} H(p, k_{it}(p, s_{it})[\int_0^{k(p)} (dV(k_{it}(p), s_i)/dp)dk + (V(k(p), s_i) - p)k'(p) - k(p)]dp \tag{F.4}$$

Again let $F = H(p, k_{it}(p, s_{it})[\int_0^{k(p)} (dV(k_{it}(p), s_i)/dp)dk + (V(k(p), s_i) - p)k'(p) - k(p)]$, use the Euler equation, we can get the necessary condition as:

$$V(k_{it}(p), s_i, p) = p + k\frac{-H_k}{H_p} + \frac{H_k}{H_p} \int_0^{k(p^c)} \frac{\partial V(k_{it}(p), s_i, p)}{\partial p} dk \tag{F.5}$$

Q.E.D

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