ESSAYS IN COMPETITION AND INVESTMENT IN ELECTRICITY MARKET

A Dissertation

by

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ABSTRACT

Many jurisdiction has opened retail electricity markets to competition. In Texas, retailers offer hundreds of electricity plans with different prices. The first paper uses search cost and product differentiation to explain the price dispersion using only data on price. If search costs are present, the search burden can lead to market inefficiency. If product differentiation is the main cause of price dispersion, the market competition can increases consumer welfare. The model improves the current sequential search model by taking product differentiation into consideration. The results show that both product differentiation and search cost result in price dispersion. Product differentiation explains about 55% of the price dispersion. The magnitude of search costs is large and the counter-factual experiment shows that reduced search cost could reduce both market average price and price dispersion.

The second paper uses a dynamic investment model to tackle three critical issues in renewable energy in the electricity industry. First, current renewable energy policies do not differentiate the carbon intensity of nonrenewable resources, which makes them less cost effective in reducing the carbon emission. Second, when making investment decisions, power plants take uncertainties into consideration. Lastly, the electricity generation market is unique that the players in the market not only compete in the hourly spot market but also compete with long-term investment strategies. A dynamic investment model considers all three issues simultaneously by simulating both short term and long term firm behavior under different market design parameter settings.

DEDICATION

Along this tough but rewarding journey, there are a lot of persons I am thankful for. The most special feeling of gratitude goes to my loving parents, Yucheng Tang and Limin Ye. Without their generous giving and sacrifice all through years, I could not be in the U.S. to start the process. Without their continuous encouragement, I could not finish what I have accomplished. Their words always ring in my ears.

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I dedicate this work and give special thanks to my husband who is also my best friend Yiyi Wang for being there for me throughout my entire doctoral program. I dedicate my dissertation to my wonderful children Max and Mya. All of you are my best cheerleaders.

Words cannot express how much I love you all.

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CHAPTER I

INTRODUCTION

Restructuring of the Texas retail electricity market began in 2002. Prior to the deregulation, the Public Utility Commission of Texas (PUCT or Commission) certified three groups to serve customers in the service area exclusively. The three groups were investor-owned electric utilities, electric cooperatives $co-ops$, or municipally owned utilities $MOUs$, with most of the residential customers receiving their service from investor-owned electric utilities. According to PUCT's report on "Scope of Competition in Electric Markets in Texas" (2003), these utilities' responsibilities included "built and operated generation plants and transmission and distribution facilities, and performed retail functions such as customer service, billing, and collection". After deregulation, PUCT required those integrated investor-owned utilities to separate their business functions. Specifically, the businesses are separated into three distinct companies[1]: "a power generation company (PGC), a transmission and distribution utility (TDU), and a retail electric provider (REP)".

The first essay in this dissertation studies the electricity retail sector. Before deregulation, PUCT set electricity rates for those integrated investor-owned utilities. After deregulation, REPs' prices are not under Commission's regulation. Customers are free to choose all the available options from competitors in the marketplace, and market forces set the electricity rates.

To facilitate the introduction of competition in the electricity retail market, a website: powertochoose.com was established for consumers to compare and choose offers provided by all REPs.

[1]Source: 2003 Scope of Competition in Electric Markets in Texas.

One might expect the law of one price to hold in this commodity market, but there is large price dispersion on powertochoose website. For example, Figure 1.1 shows the histograms of Texas electricity prices for 2010. The wide spread of the prices implies that consumers have the incentive to search around since the saving could be over $100 every month.

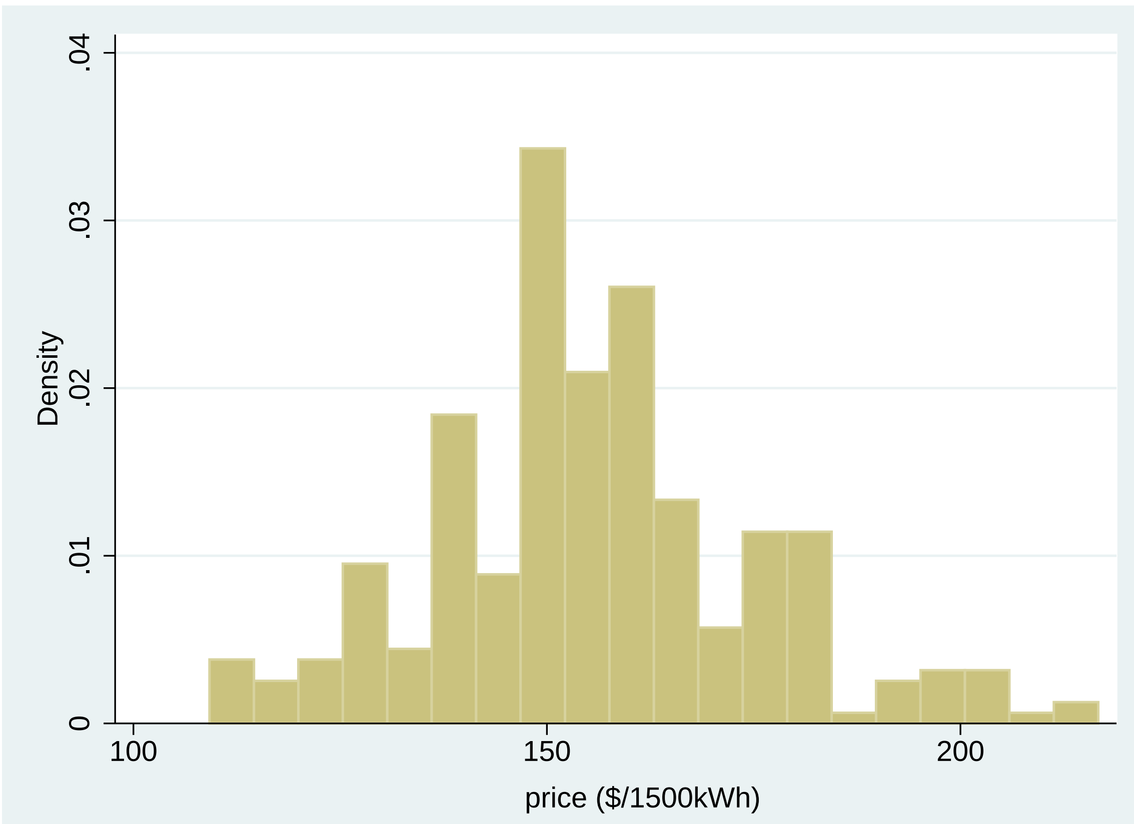

Figure 1.1: Histograms of Electricity Prices for 2010

From the literature, two explanations for price dispersion surface: search cost and product differentiation. Consumers will incur search cost when they search for a product or service. Intuitively, consumers will stop searching when the marginal benefit of searching equals to the marginal cost of searching.

Vertical product differentiation could be another cause of price dispersion. For example, the incumbent retailers in Texas may have long reputations among consumers. Also, firms create many offers ranged from fixed-12-month-20%-renewable-energy-offer to variable-3-month-80%-renewable-energy-offer. These different product characteristics may cause price dispersion.

Therefore, this essay will try to analyze the price dispersion by building up a search model considering product differentiation.

The second essay studies investment in renewable sources of electricity generation. Renewable Portfolio Standard (RPS) is one of the policies that promotes electricity generation from renewable energy, such as wind, solar, biomass and geothermal. It requires that a specified fraction of electricity must be generated from renewable energies sources. To comply with RPS, distribution utilities are obliged to purchase an appropriate number of renewable energy credits (REC), which represent corresponding MWh of renewable energy, from eligible renewable generators. The political appeal of RPS covers a wide range from energy security to environmental preservation, green jobs, and green technology.

Despite this appeal, we argue that one problem with RPS is that it does not differentiate between the carbon intensity of nonrenewable resources, like coal and gas. RPS only asks for the replacement of non-renewable energy by renewable energy. However, it does not consider the recent innovations in the ability to extract shale gas, which has created large opportunities to reduce the carbon footprint of the electricity generation sector; therefore, this policy will not provide meaningful incentives to shift production from coal to gas fired generation. This makes RPS a less cost effective policy in reducing the carbon emission, although it aims to "protect and enhance the quality of the environment through increased use of renewable resources"[2].

In addition, the current policy does not consider the intermittency problem of renewable energy as wind generation is only partially forecastable. Although wind generation has the lowest variable cost, it cannot be the base load because of its intermittency. A more efficient policy would be such that rewards the REC based on when the "green electricity" is generated. The electricity generated from wind during the day would be rewarded more while less during the night. This could give better incentive for renewable generators to choose their investment location and operation.

In the essay, I use an investment model to simulate the optimal electricity generation mix in a fashion that differentiates the carbon intensity and takes the intermittency problem into consideration.

[2]From the subsection (g) of P.U.C. Subst. R. 25.173, goal for renewable energy.

CHAPTER II

ESTIMATION OF SEARCH FRICTION IN TEXAS ELECTRICITY MARKET

2.1 Introduction

Prior to the deregulation in Texas electricity retail market in 2002, consumers were required to buy electricity from one utility company, where the electricity price was determined by the Public Utility Commission of Texas (PUCT). After the deregulation, many electricity providers are allowed to enter into the market, create offers, and set offer prices by themselves. Consumers could choose the optimal offer from multiple providers. To facilitate consumers' choosing process, PUCT launched a website called "powertochoose.org". Consumers can compare offers and switch providers using this website. In addition to using powertochoose website, consumers could still choose their provider in traditional ways such as making phone calls.

The deregulation makes this market competitive as compared to the old monopolistic electricity retail market, . In the perfect competition theory, when the market has a lot of firms and consumers, we should have a single equilibrium price for electricity. However, we observe a huge price dispersion in the market on powertochoose website. For example, Figure 2.1 shows the histogram of all the offer prices (for 1000 kWh usage) in the Texas Centerpoint service area (the service area map is in Figure 2.2, which is from Public Utility Commission of Texas [2014]) on September 7th, 2013. The lowest monthly cost for 1000 kWh electricity is $70, while the highest is above $160. Consumers who are with the highest offer can save around $100 by switching to the provider with the lowest offer. The widely spread prices imply that consumers have the incentive to search around for a potential saving.

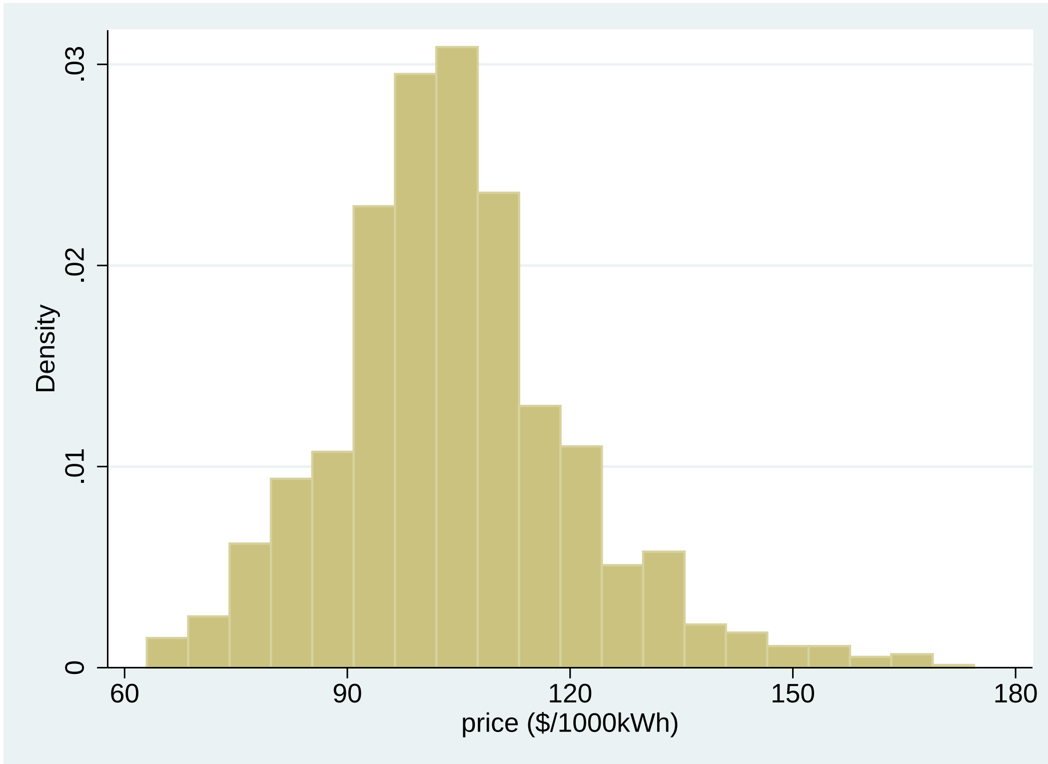

Figure 2.1: Histogram of Texas Electricity Price

This essay will explain the price dispersion from two perspectives: search cost and product differentiation by developing a search model taking both the product differentiation and search cost into consideration.

Search cost theory originates from the seminal paper by Stigler (1961). Consumers incur search cost when they search for a product or service. They keep searching until the marginal benefit of searching equals to the marginal cost of searching. For consumers with higher search cost, firms could choose to set a higher price to earn more rent from those consumers who are not willing to search. For consumers with lower search cost, firms can set lower prices to attract them. The heterogeneous consumers' search cost in the market lead to price dispersion. Furthermore, the higher the average search cost is, the higher the price dispersion should be. The emergence

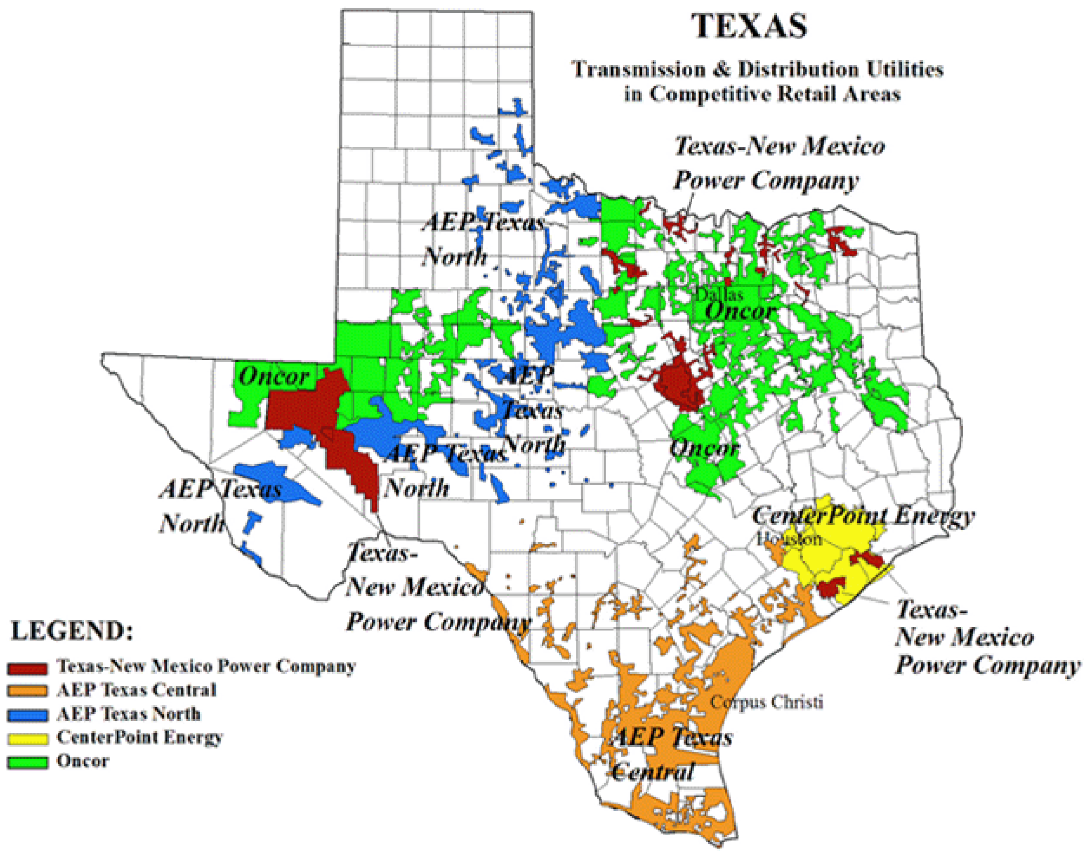

Figure 2.2: Texas Electricity Service Area Map

Source: Public Utility Commission of Texas [2014] of the Internet, especially the price comparison website, is expected to make consumers' search easier, which tends to decrease the search cost, hence decreasing the price dispersion.

From Figure 2.1, we can see the price ranges from $70 to $160 with most of them clustered in the middle range (around $100-$110). Assuming these offers are homogeneous products, this price dispersion indicates that there is some searching behavior in this market. However, this searching behavior is not too much, otherwise firms would all offer low prices which will lead the price to cluster in the lower range in Figure 2.1. Neither the searching behavior is too little, which could result in concentrated high price. Therefore, this market does have search behavior and people could save by searching and switching.

If the price dispersion is explained mostly by search cost, it means that the market has stickiness, that is, consumers tend to stick to their old providers because their search cost prevent them from searching for the best offer. Therefore, firms have the incentive to set up high price to earn higher rent. In that case, I suggest reducing the search cost to increase the competitiveness in the retail marketplace.

The second explanation of price dispersion is product differentiation, which could be caused by brand effect and different product characteristics. For example, the "Big Four" retailers in Texas (TXU, Reliant Energy, CPL retail energy and First Choice Energy) were in the market before deregulation. They have long reputations among consumers. Consumers tended to stick to them after deregulation. This may cause "Big Four" to have the power to price higher than other new retailers [Hortaçsu et al., 2010]. Also, firms create many offers ranging from fixed-12-month-20%-renewable-energy-offer to variable-3-month-80%-renewable-energy-offer. These different product characteristics may also explain the price dispersion.

If the price dispersion is due to the product differentiation, this market liberation increases consumers' welfare, because now consumers can choose the offers based on their preferences.

This paper is organized as follows; Section 2 introduces the Texas electricity market. Section 3 is the literature review regarding this topic. Section 4 presents the search model. Section 5 discusses the estimation. Section 6 contains a detailed data description. The results are shown in Section 7. Some counter-factual experiments are conducted in Section 8. Finally, Section 9 concludes this chapter.

2.2 Texas Electricity Retail Market

Texas electricity market deregulation started in 2002. Prior to the deregulation, the Public Utility Commission of Texas (PUCT or Commission) certified three groups to exclusively serve customers in each service area. The three groups were investor-owned electric utilities, electric cooperatives $co-ops$, or municipally owned utilities $MOUs$, with most of the residential customers receiving their service from investor-owned electric utilities. According to PUCT's report on "Scope of Competition in Electric Markets in Texas" 2003, these utilities' responsibilities included "built and operated generation plants and transmission and distribution facilities, and performed retail functions such as customer service, billing, and collection". The electricity rates were set by PUCT for those utilities. There are 5 service areas (Oncor, CenterPoint, Texas-New Mexico, AEP Texas Central and AEP Texas North, see Figure 2.2) in the Electric Reliability Council of Texas (ERCOT), and each area has its own utility.

Since 2002, in order to introduce competition and improve efficiency in the electricity market, PUCT required those integrated investor-owned utilities to separate their business functions. Specifically, the businesses are separated into three distinct companies [1]: "a power generation company (PGC), a transmission and distribution utility (TDU), and a retail electric provider (REP)". Meanwhile, PUCT granted the authority to the electric cooperatives (co-ops) and municipally owned utilities (MOUs) to decide if and when to open the service areas to retail competition. This paper focuses on the retail sector for the deregulated formerly integrated investor-owned utilities.

Since the deregulation, REPs serve two main functions: electricity retail providers and energy services. They have direct contact with retail consumers in the deregulated market. On January 1st, 2002, the five existing retail electric providers (affiliated REPs), which will hereafter be referred to as incumbent, were required to offer rates discounted from the existing rates. The discounts were partly regulated and were set at 6%. The discounted rates were referred to as "the price to beat" [2], and are allowed to be changed by the incumbent REPs up to twice a year, based on the changes in the natural gas prices. On the other hand, entrant firms (non-affiliated REPs) can set their prices by themselves which are not subject to Commission regulation or oversight. This set up created a marketplace with options that vary between all the competitors, among which the Texas customers can choose freely. Specifically, consumers can either choose to stay with their affiliated REPs and are placed on the price to beat rates, or choose to switch their providers to the non-affiliated REPs.

The requirement that the price to beat be offered to all customers continued till January 1, 2007 when all the customers began to be served at rates set by market forces. To better understand the competitive effect of the deregulation, my research period is after price to beat expires, that is, between 2007 and 2012.

To facilitate the introduction of competition in the electricity retail market, a

[1] Source: 2003 Scope of Competition in Electric Markets in Texas.

[2] Source: 2007 Scope of Competition in Electric Markets in Texas

website: powertochoose.com was set up for consumers to compare and choose offers provided by all the REPs. The process for switching a provider by using powertochoose website is as follows: after entering the zip code, consumers can see a list of offers, including information about the company name, plan details (fixed price or variable price, length of the contract, renewable energy content), price ($/kWh) for different levels of electricity usages, pricing details (minimum usage fees, cancellation fees, fact sheets, terms of service, etc.), ordering information, etc.. Consumers can click on fact sheet or terms of service to learn more about an offer. After comparing offers, consumers can sign up for the selected plan. The website will direct consumers to the provider's website. After completing some registration and forms, consumers can change over to the new supplier.

Figure 2.3 provides a very recent screen shot of powertochoose website. For example, the lowest unit price for 1000 kWh electricity usage in the market at that time is 7ℂ. This price is provided by the Reach Energy, and this offer is a 6-month, fixed-price, with no renewable energy content offer. The early cancellation fee is $ 60. The second lowest offer is provided by 4 Change Energy, which has 0.2ℂ higher with 10% more renewable energy content. The cancellation fee is $20 per remaining month. Consumers could also read the fact sheet or term of service through clicking on the tabs.

From this website we can see that there are a lot of product differentiations, such as different cancellation fees, different types of plans (fixed, variable, etc), the length of the plan, etc. It is very pricey for consumers searching through hundreds of offers.

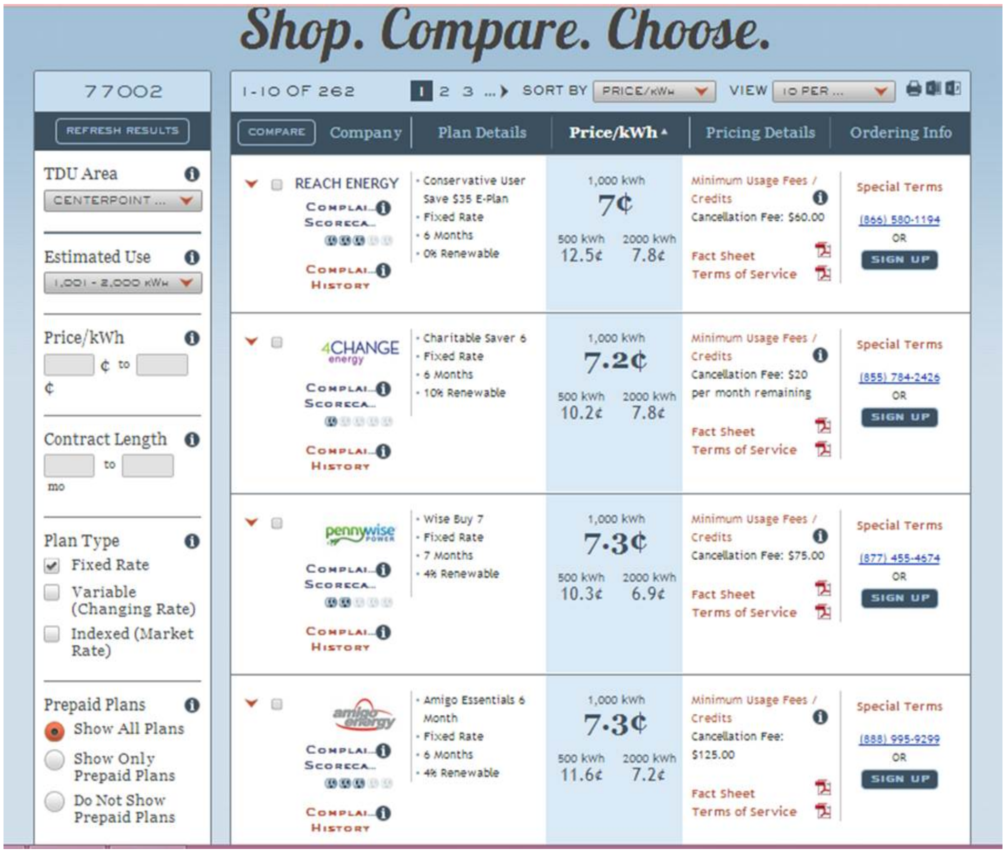

Figure 2.3: A Snapshot of Powertochoose Website

The liberation changes both the demand and supply in the Texas electricity retail market. From the demand side, in the first year after liberation (year 2002), 7% of the residential consumers switched to the non-affiliated REPs[3]. The switching rate stayed the same until 2009 and then started to decrease to 4% per year. As of 2013, around 40% consumers were still served by affiliated REPs while 60% had switched to non-affiliated REPs.

From the supply side, the number of REPs increased almost five times in each area. Take the Oncor service area for example, there were ten providers with eleven

[3]PUCT biannual report on the scope of competition in electric markets in Texas

plans in 2002, among which two plans had renewable energy content. Today, the figure has increased to 45 providers, 258 plans, with 62 plans related to renewable energy. On average, one provider has 5-6 plans to offer, giving consumers a wide range of choices. The incumbent for the Oncor service area is TXU Energy, its market share dropped from 100% in 2002 to 44% in 2012.

2.3 Literature

A lot of literature is available on estimating search cost. One type of search models uses both price data and product market share data. Hortaçsu and Syverson [2004] use this type of model to estimate search cost and product differentiation in the mutual fund industry. They first use a sequential model by utilizing price and market share data to estimate the search cost, then use the calculated utility level to see how product differentiation affects consumers' demand. They conclude that both product differentiation and search cost contribute to the mutual fund's price dispersion.

Another group of search models only use price data. The first paper in this group is Hong and Shum [2006]. They propose both sequential and non-sequential models to estimate the search cost and explain the price dispersion by only employing the price data.

Moraga-González and Wildenbeest [2008] improve the estimation of the non-sequential model by using Maximum Likelihood Estimation. Their model outperforms Hong and Shum [2006]'s in terms of both the numerical value and the goodness-of-fit test. They use online prices of different computer memory chips to estimate the search cost and conclude that consumers are split into two groups with either low search cost or high search cost. Wildenbeest [2011] applies this method to explain the price dispersion for grocery items by incorporating vertical product differentiation.

He found that most of price dispersion could be explained by store heterogeneity rather than search cost.

In addition, there are literatures of search models that emphasize electricity price empirical analysis. British electricity market opened to competition since 1999. Multiple scholars have written papers about the British electricity price from different perspectives. Giulietti et al. [2010] talk about the effect of New Electricity Trading Arrangements on electricity price from a descriptive angle. Wilson and Price [2010] measure the capacity of consumers to efficiently select between alternative suppliers. They find that search cost is high in the market and there is mis-selling from the suppliers. All of these papers use detailed survey data.

Hortaçsu et al. [2010] analyze the determinant of consumer choice in the Texas electricity market from 2002 to 2006. The main three determinants are non-price product differentiation, search cost and switch cost. Their conclusion is that the incumbents have a big brand effect. Different from their study horizon, I focus on the period after 2006 when the incumbent can offer competitive prices instead of "price to beat" to study the recent changes in the Texas electricity market. Also, Hortaçsu et al. [2010] use a discrete model to simulate consumer choice behavior without the explicit estimation for search and switching cost by using detailed consumer level data, while I use price data to estimate the search cost and measure the product differentiation effect on price dispersion.

The most relevant paper is Giulietti et al. [forthcoming]. They use the British electricity price data to estimate consumer search cost after the British electricity liberation, which is very similar to Texas electricity market, by utilizing sequential search model. Their model makes a difference between the incumbent firms and entrant firms which matches the post 2007 market that is open to competition. Also, their model divides consumers into searchers who would incur cost when they try to search and switch their providers and non-searchers who do not switch or switch with reasons other than price. These innovations make the model most suitable for the real world. Their estimation results show that the search cost "must be relatively high to rationalize observed pricing patterns". But they do not consider how product differentiation affects price which means they make a strong assumption that the products are homogeneous. However, as indicated in the previous section, firms offer heterogeneous goods in the real world, so it would make more sense to separate the effect between search cost and product differentiation.

This paper follows the Giulietti et al. [forthcoming]'s setup, but improves the model by taking the product differentiation into consideration. That is accomplished by first homogenizing the product price by removing the effects of all different product characteristics from the price, then using the adjusted homogeneous product price to estimate the search cost. This method fits the real world better as consumers may first use a filter to pick out products with certain features, such as, 6-month plan, 100% renewable content, etc. This method can also be applied to other industry with price comparison site on the Internet where the final products consumers receive are the same while firms create many add-on features to differentiate their products. For example, the price dispersion for consumer goods (books, DVDs, etc.). Different firms have different shipping cost, shipping method, service, etc. which differentiates the products. Consumers can compare prices and search for information about add-on features to make choices.

Furthermore, the Texas electricity market has been open to competition for over 10 years. This paper provides an insight on the recent changes in the market and provides policy implication on increasing the market competitiveness.

2.4 Sequential Search Model

Sequential search is that consumers decide whether to continue on to the next search after each search by comparing the expected benefit of one more search to the cost of the search. The expected benefit is the difference between the expected price and the already observed price (i.e. the offer price from the firm the consumer is already with). As long as the expected benefit is higher than the cost (or the observed price is higher than consumer's reservation price, which is the current provider's price + search cost), the consumer will continue searching. If the consumer finds a firm with a price lower than their reservation price, they will stop searching and choose this firm.

This fits my setting because whether consumers choose their providers through the Internet or traditional ways, they have to spend some time reading/calling to understand an offer. After understanding an offer, they decide whether to go after the next one.

I followed the sequential search model by Giulietti et al. [forthcoming] to estimate the search cost by nonlinear least square. A brief review of the model is as follows.

Consumers search sequentially with η share of non-searchers, who switch without search or switch for reasons other than price. The rest $1-\eta$ consumers will search around and incur search cost c. Each search is random and independent.

For searchers, the expected benefit from searching one more firm is the difference between the expected future searching price and consumer's current price $\hat{p}$. That is (Giulietti et al. [forthcoming]),

$$H(\hat{p}) = \int_{\underline{p}}^{\hat{p}} (p-\hat{p})f(p)dp = \int_{\underline{p}}^{\hat{p}} F(p)dp$$

where $F(p)$ is the price distribution.

The search cost is c and the search cost distribution is $G(c)$. We can set consumers' reservation price $\rho(c;F)$ to be the price that satisfies the following function (Giulietti et al. [forthcoming]),

$$H(\rho) = c$$

which means that the reservation price is the price at which the expected benefit from one more search $H(\rho)$ is equal to the search cost c. When the offer price is higher than the reservation price, the consumer will continue searching; while when the offer price is lower than the reservation price, the consumer will stop and switch.

From the firms' side, assume there is one incumbent firm with market share λ and N entrants share the remaining market share $1-\lambda$ equally. They all produce homogeneous goods. The incumbent firm has price v while entrants will set their price to attract consumers and maximize their profits. They all have the common marginal cost r for producing one unit of product. When $\lambda = 0$, there is no incumbent firm in the market. So this model is flexible enough for markets with incumbent and without incumbent firms.

At the beginning of the game, each entrant has $\frac{1-\lambda}{N}$ market share. They will face two kinds of consumers:

The first kind of consumer is the non-searcher. For an entrant firm, this group of consumer has share $\frac{\eta(1-\lambda)}{N}$.

The second type of consumer is searcher. These consumers can either choose to stay at their current providers or switch to other firms depending on their reservation price (or search cost) and the offer prices. Because the model takes the incumbent firm as given, an assumption made here which makes the model simplified is that the searchers will only switch from incumbent or other entrants to entrant firms, but will not switch from one entrant firm back to an incumbent firm. The behavior of the searchers can be divided into four cases: for one particular entrant firm, their current consumers who choose to stay, other entrants' consumers who switch to this firm, other incumbent firm's consumers who switch to this firm, and consumers with very low reservation price who choose this firm because this firm has the lowest price. More detailed description about these four cases is as follows,

The first case is the firm's existing consumers who choose to stay with their current provider because these consumers' search cost are higher than the expected benefit from searching. The probability is

$$\begin{aligned} & Pr(\text{stay}) \\ = \; & Pr(\text{search cost } c > \text{expected benefit } H(p)) \\ = \; & 1 - Pr(c \leq H(p)) \\ = \; & 1 - G(H(p)) \end{aligned}$$

This also means that current firm's offer price is lower than or equal to the consumer's reservation price. The share of these local consumers for the entrant firm is $\frac{1-\lambda}{N}(1 - G(H(p)))(1-\eta)$.

The second case is the consumers who switch from other entrant firms to this entrant firm. They search because the expected benefit of searching $H(p_{\text{old}})$ is greater than the search cost c. They stop searching and switch to this firm because when the consumer finds this firm's offer price p is lower than their reservation price ρ, their expected benefit from search more $H(p)$ is lower than the search cost c. In other words, the price of this firm is lower than the consumer's reservation price and the consumer's existing provider's price is higher than the consumer's reservation price). Consumers may find this firm at their first visit, second visit, or $\cdots$, (N-1)th visit.

The probability of the consumer visiting this firm at the kth visit is

$$
\begin{aligned}
& Pr(\text{choose this firm at the } k\text{th visit}) \\
= \;& Pr(\text{all the previous searches's price } p > \text{consumer's reservation price } \rho(c, F)) \\
= \;& (1 - Pr(p \leq \rho(c, F)))^k \\
= \;& (1 - F(\rho(c, F)))^k
\end{aligned}
$$

So the total probability for consumers visiting this firms at their first, $\cdots$, (N-1)th visit is $\sum_{k=1}^{N-1} (1 - F(\rho(c, F)))^k$. For all the consumers whose search cost c is higher than the expected benefit of searching when they find this firm $H(p)$ and lower than the expected benefit of searching from the firms who offer the highest price $H(\bar{p})$, they take the share for this entrant firm $\frac{1-\lambda}{N}(1-\eta) \int_{H(p)}^{H(\bar{p})} \sum_{k=1}^{N-1} (1 - F(\rho(c, F)))^k g(c) dc$.

The next case is similar to the second case in that these consumers were with incumbent firms and chose to switch to this entrant firm because this firm's price p is lower than the consumer's reservation price ρ and the incumbent firm's price v is higher than the consumer's reservation price ρ. In other words, the expected benefit of searching when consumers were with incumbent firms is $H(v) = v - E(p)$ which is greater than the consumers' search cost c. The total probability of finding this firm at the first visit, second visit, $\cdots$, Nth visit is $\sum_{k=1}^{N} (1 - F(\rho(c, F)))^k$. The share of this group of consumer is $\frac{\lambda}{N}(1-\eta) \int_{H(p)}^{v-E[p]} \sum_{k=1}^{N} (1 - F(\rho(c, F)))^k g(c) dc$.

The last case is that these consumers' reservation price is quite low so they search for all products and choose the lowest one, that is, every firm's offer price is higher than the consumer's reservation price and this firm has the lowest price in the market.

The probability for this firm having the lowest price is

$$\begin{aligned}
& Pr(\text{this firm has the lowest price}) \\
= \; & Pr(\text{every other firm's price } p^* > \text{this firm's price } p) \\
= \; & (1 - Pr(p^* \leq p))^{N-1} \\
= \; & (1 - F(p))^{N-1}
\end{aligned}$$

In this case, consumers take the share $G(H(p))(1 - F(p))^{N-1}(1 - \eta)$.

Adding these different sources of demand together would give us the total demand for this entrant firm. The profit for this entrant firm (Giulietti et al. [forthcoming]) is:

$$\pi_E(p) = (p - r)\Bigg[(1-\eta)\Bigg(\underbrace{\frac{1-\lambda}{N}(1 - G(H(p)))}_{\text{locals accepting current price}} + + \underbrace{G(H(p))(1 - F(p))^{N-1}}_{\text{consumers with lower } \rho \text{ if lowest price}}$$
$$\underbrace{\frac{1-\lambda}{N}\int_{H(p)}^{H(\bar{p})}\sum_{k=1}^{N-1}(1 - F(\rho(c, F)))^k g(c)dc}_{\text{switchers from other entrants}} + \underbrace{\frac{\lambda}{N}\int_{H(p)}^{v-E[p]}\sum_{k=1}^{N}(1 - F(\rho(c, F)))^k g(c)dc}_{\text{switchers from incumbent}}\Bigg)$$
$$+ \frac{\eta(1-\lambda)}{N}\Bigg]$$

In the mixed strategy equilibrium, firms will be indifferent setting any price within the price range, or, for simplification, firms will be indifferent between any price and the maximum price in the price range, that is,

$$\pi_E(p^m) = \pi_E(p)$$

where p^m is the maximum price. This equilibrium condition can be simplified to equation 2.1 (Giulietti et al. [forthcoming]).

$$
\begin{aligned}
(p-r)\left[\frac{1-\eta}{N}\left(\int_{H(p)}^{\infty}\sum_{k=1}^{N}(1-F(\rho(c)))^{k-1}g(c)dc-\lambda\left[1-G(H(v))\right]\right.\right.\\
\left.\left.+NG(H(\bar{p}))(1-F(p))^{N-1}\right)+\frac{\eta(1-\lambda)}{N}\right] \\
=(\bar{p}-r)\left[\frac{1-\eta}{N}\left(\left[1-G(H(\bar{p}))\right]-\lambda\left[1-G(H(v))\right]\right)+\frac{\eta(1-\lambda)}{N}\right]
\end{aligned}
\tag{2.1}
$$

The estimation is based on this equation and will be presented in the next section.

2.5 Estimation

As shown in the last section, the equilibrium condition is not tractable. To estimate the parameters in the model, several assumptions are needed to simplify equation 2.1.

First, assume that the search cost distribution is log-normal with parameters mean of μ and standard deviation of σ. Gamma distribution is also considered and generates similar fitting results.

Second, sort observed price increasing from p_1 to p_M, so the empirical price distribution for $F(p)$ is $\tilde{F}(p) = \frac{1}{M}\sum_{i=1}^{M}\mathbb{1}(p_i < p)$.

Third, as defined earlier, when a consumer finds a price equal to his reservation price, his expected benefit from searching one more time equals the search cost, that is, $c = H(\rho; F)$, for a consumer with reservation price ρ equal to the observed price p_j, $c_j = H(p_j)$. Since $H(p_j) = \int_{\underline{p}}^{p_j} F(p)dp$, we can approximate c_j to be $H(p_j) = \int_{\underline{p}}^{p_j} F(p)dp = \frac{1}{M}\sum_{k=1}^{j}(p_j - p_k)$.

The last assumption is that all the products would be purchased by consumers, so there is no "bait-and-switch"[Ellison and Ellison, 2009].

With all these assumptions and simplifications, Equation 2.1 can be rewritten as (Giulietti et al. [forthcoming]):

$$p_i = r + \frac{(\bar{p} - r)\left[(1 - G(c_M)) - \lambda(1 - G(\bar{c})) + \frac{\eta(1-\lambda)}{1-\eta}\right]}{\begin{array}{c}\displaystyle\sum_{j=i}^{M}\sum_{k=1}^{N}(1 - F(p_j))^{k-1}\Delta G(c_j) + NG(c_j)(1 - F(p_i))^{N-1} \\ +(1 - G(c_M)) - \lambda(1 - G(\bar{c})) + \frac{\eta(1-\lambda)}{1-\eta}\end{array}} \tag{2.2}$$

where $\bar{c} = \frac{1}{N}\sum_{k=1}^{M}(v - p_k)$. The left hand side is the observed price and the right hand side is the calculated price related to the observed price, search cost, price distribution, and search cost distribution. The objective is to find the search cost distribution parameters μ and σ to minimize the distance between the observed and calculated price by using nonlinear least square estimation.

The detailed estimation process is described as follows:

1. Set initial value of the search cost distribution parameters μ and σ.

2. Calculate search cost c_j and empirical price distribution $\tilde{F}(p_j)$ based on equations $c_j = \frac{1}{M}\sum_{k=1}^{j}(p_j - p_k)$, and $\tilde{F}(p) = \frac{1}{M}\sum_{i=1}^{M}\mathbb{1}(p_i < p)$ with observed price.

3. With calculated search cost c_j and search cost distribution parameters μ, σ, the search cost distribution $G(c_j)$ can be calculated.

4. By using price data p, empirical price distribution $\tilde{F}(p_j)$, search cost c, search cost distribution $G(c)$, the share of non-searchers η, incumbent market share λ, marginal cost r, calculate the price $\hat{p}_j$ by using the right hand side of Equation 2.2.

5. Utilize non-linear least square estimation method to minimize the distance

between observed price p_j and calculated price $\hat{p}_j$ to estimate the parameters $\hat{\mu}$ and $\hat{\sigma}$.

6. Because this is a static model, we need to do the whole estimation for each year/area to see the area differences and yearly differences.

2.6 Data

Public Utility Commission of Texas provides monthly retail electric service bill comparison data on their website. They compiled the data from publicly available information from the retail electric providers using representative usage levels. The data contains information about the retailer's name, selected offers provided by each retailer and corresponding total price for four levels of monthly usage (500kWh, 1000kWh, 1500kWh, and 2000kWh) in five service areas.

Figure 2.4 shows the average electricity price (dollars for 1500 kWh usage each month) for the five areas in Texas from 2007 to 2012 based on my data. The five regions share a similar price pattern during the six years. The AEP Texas Central area has the highest average price most of the time, while Oncor area has the lowest. The red solid line shows Texas monthly natural gas price (dollars per thousand cubic feet). During the summer of 2008, there is a spike in the natural gas price meaning all the electricity prices soared during that time and rose to their highest during the six years. After that, the natural gas price dropped down quickly, while the electricity price did not drop that fast. Since most of the electricity in Texas is generated from natural gas, this figure shows that overall, the price reflects the cost.

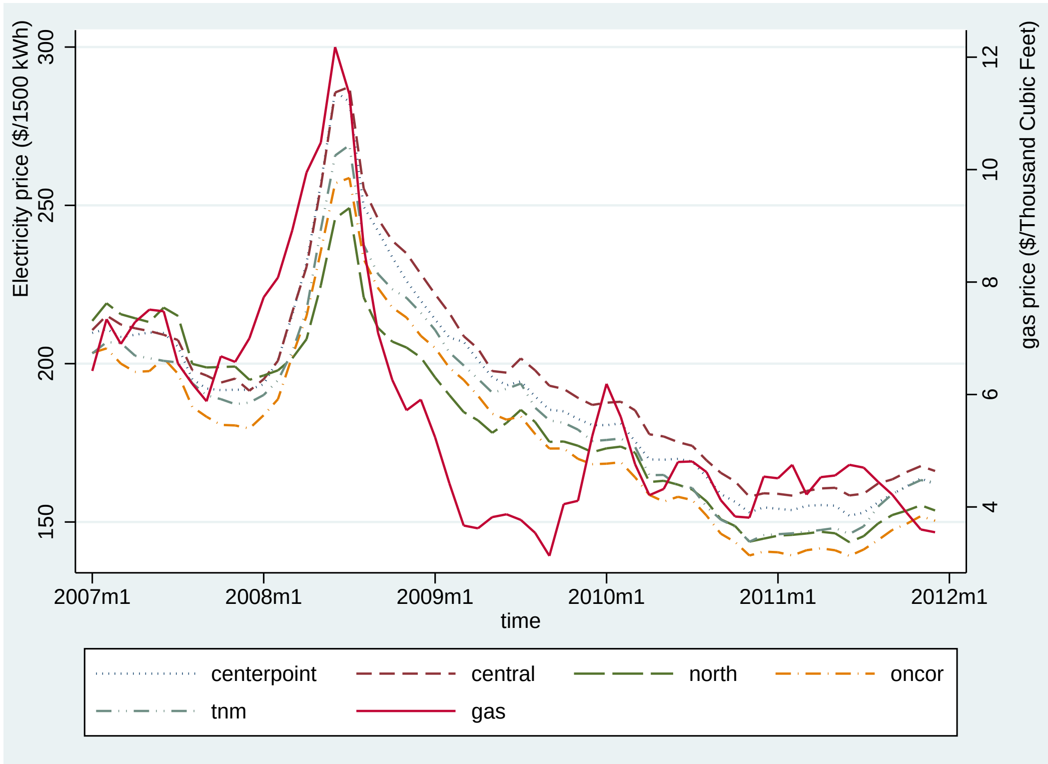

Figure 2.4: Average Electricity Price For Five Areas Over Time

Figure 2.5 shows the fluctuation of electricity prices of the offers that last more than two years in the AEP Texas Central area. Most of these offer prices fluctuate a lot, and do not share a similar price change pattern. Firms change price in different directions and in different magnitude. They may change their pricing rank unpredictably which makes it difficult for consumers to stick to one firm and they have to search and switch.

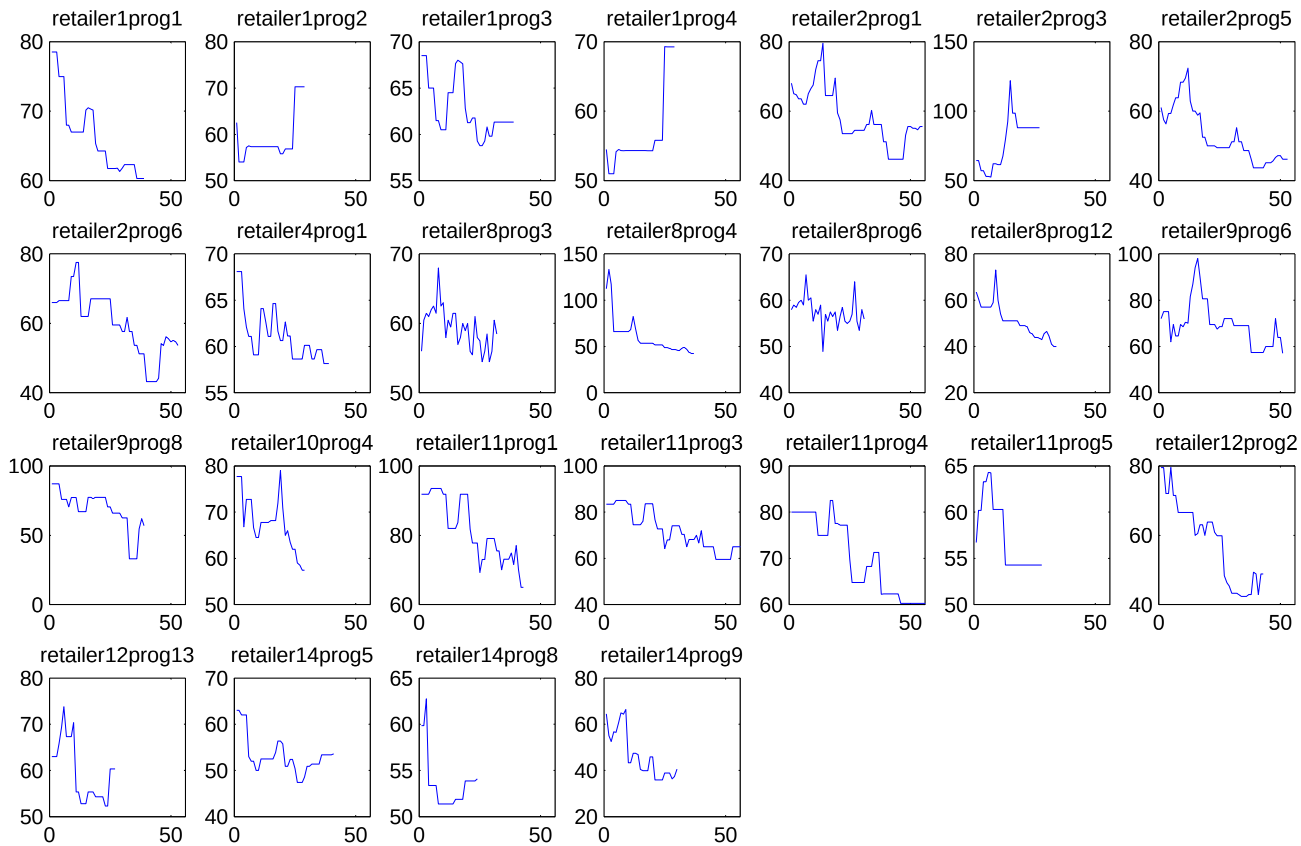

Figure 2.5: Electricity Price Trend Over Time For AEP Texas Central Area

Table 2.1 presents the summary statistics for the electricity price in the five areas, which does not show a very big area differentiation. In terms of the average area electricity price, Oncor has the lowest, \$173.59, while AEP Texas Central area has the highest price, \$190.01. The average electricity price per 1500 kWh electricity usage for the whole state of Texas during 2007-2012 is \$181.35. The price variation and range are big for each region, meaning price dispersion is present in the Texas reformed electricity market.

Area	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
TNM	1970	179.90	37.28	70.95	389.1
Centerpoint	2089	185.95	39.28	76.93	389.1
Central	2079	190.01	38.84	84.45	414.45
North	2057	177.20	37.04	73.95	389.1
Oncor	2090	173.59	38.28	64.95	389.1
Total	10285	181.35	38.62	64.95	414.45

Table 2.1: Price Dispersion For Five Areas and Whole Texas

In addition to the price data, we need retailers' annual marginal cost and incumbent market share data. For marginal cost, I use the annually weighted average electricity wholesale price in Texas. For incumbent market share, the data is obtained from PUCT "report cards on retail competition and summary of market share data" [4](The market share data are shown in Table 2.2). Incumbent market share drops from 65% in 2007 to 47% in 2012.

[4]PUCT website

Year	Incumbent Market Share
2007	0.6476
2008	0.6088
2009	0.5993
2010	0.5689
2011	0.5208
2012	0.471

Table 2.2: Incumbent Firms Market Share

2.7 Results

2.7.1 Search Model Without Product Differentiation

Assume all the products are homogeneous, we apply the sequential search model to estimate the search cost by using the price data introduced in section 6.

The search model is a static model, which does not take other periods into consideration. In order to allow differentiation for each region and year, we do the estimation for each area and year separately. By using annual electricity price data, marginal cost data, incumbent market share and allowing for time and area differentiation, Table 2.3 shows the estimated search cost distribution parameter μ, which is the mean of log(search cost). The estimated parameter is for all of the five areas and the whole state of Texas in six years. For a given year, this parameter does not differentiate greatly between the areas and the whole of Texas. Also, for a given area, the parameter varies little across years.

Table 2.4 shows the annual average search cost, average electricity price, and the search cost corresponding to the lower quartile of search cost distribution for the whole state of Texas. On average, electricity price for 1500 kWh usage is \$200 per

Year	Oncor	North	Central	Centerpoint	TNM	Texas
2007	6.06	5.86	5.80	6.09	6.29	5.99
2008	5.78	5.73	5.73	6.15	5.49	5.72
2009	5.76	5.86	5.91	5.98	5.97	5.81
2010	5.37	5.77	5.73	5.92	5.17	5.35
2011	4.62	5.54	5.68	5.57	5.13	5.17
2012	5.10	5.52	5.63	5.60	5.54	5.52

Table 2.3: Estimated Parameter μ

month, consumers have to pay \$10-\$13 to search for one more offer. The average search cost is calculated by using the price data, that is, the simplified equation from estimation section $c_j = \frac{1}{M}\sum_{k=1}^{j}(p_j - p_k)$. Since the search cost corresponding to the lower quartile of the search cost distribution is an extrapolation based on the estimated search cost distribution $G(c)$, not the real data, the extrapolated search cost is much higher than the average search cost calculated by using the price data. From this extrapolated search cost value, it appears relatively huge compared to the average electricity price.

With estimated search cost parameters, we can have Figure 2.6 which shows the search cost distribution for Texas from 2007-2012. The distribution curves move to the left from 2007 to 2012 with the exception of 2009 and 2012. This indicates that the average search cost is decreasing. This could suggest that with more and more consumers aware of and using the powertochoose website, the search cost decreases.

Year	Average search cost	Average price	Lower quartile $G(c)$
2007	13.52	196.92	68.13
2008	19.22	222	53.41
2009	15.7	183.32	67.57
2010	10.88	155.75	39.56
2011	10.85	148.18	28.08
2012	10.37	155.23	48.24

Table 2.4: Estimated Search Cost

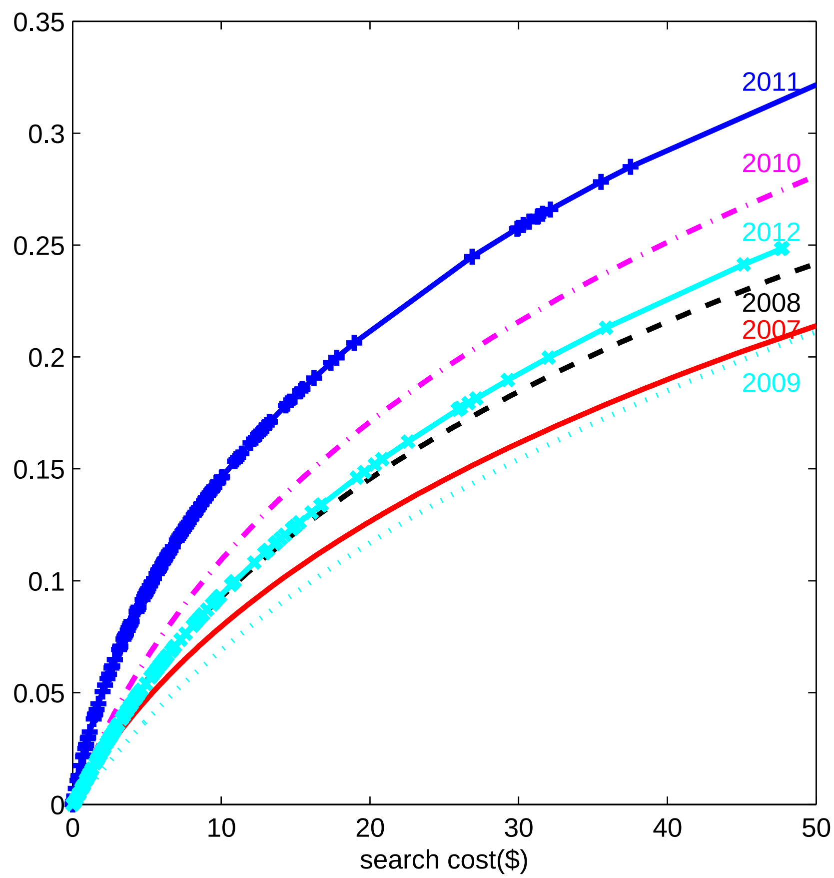

Figure 2.6: Search Cost Distribution For Texas from 2007-2012

Figure 2.7 shows the search cost distribution in the year 2010 for different service areas. The search cost distribution of the state of Texas is the green solid line which lies between the Texas New-Mexico area, which provides the lower bound, and the Centerpoint area, which is the upper bound.

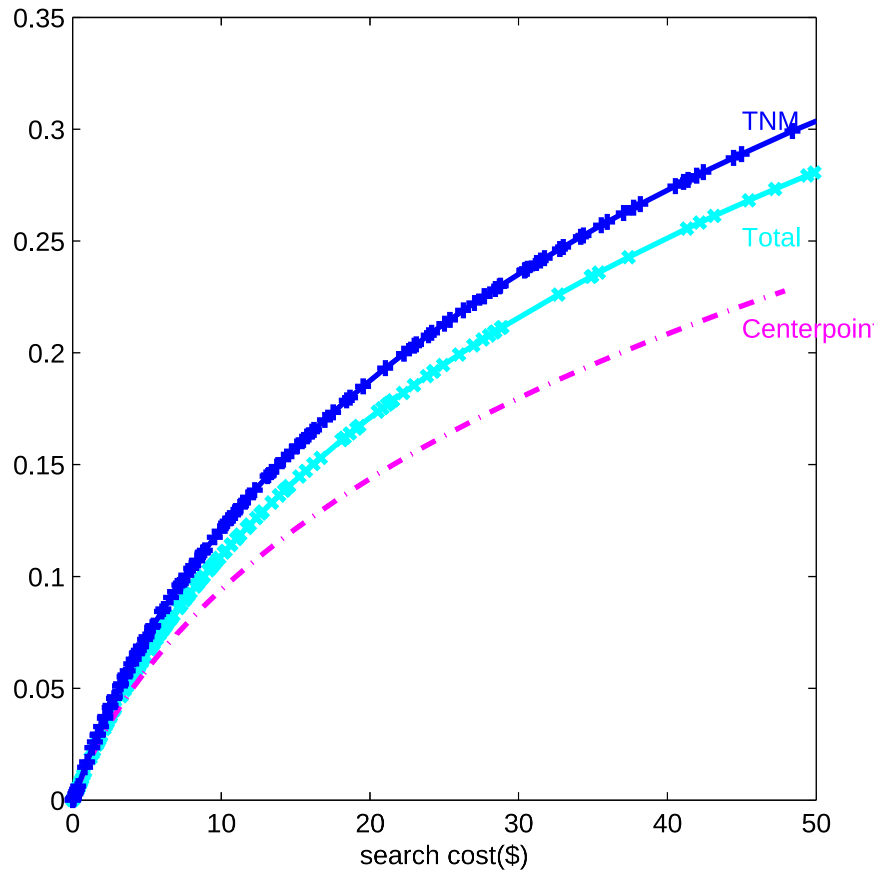

Figure 2.7: Search Cost Distribution For Year 2010

With the estimated search cost distribution, I can not only simulate the firms' behavior, but also simulate the consumers' search behavior. Consumers' search cost can be drawn from the estimated search cost distribution. Given a random price distribution, consumers' expected benefit from one more search could be calculated. If we compared the expected benefit to the search cost, we could get an estimate of the number of searches a consumer does. By simulating 10000 consumers' search behavior, the market average number of searches is estimated. Given the high extrapolated search cost, we expect the number of searches to be low. In 2007, on average, there are only 0.35 searches in the market. The year 2011 has the lowest search cost, the average number of searches increases by monre than three times from 2007, that is, 1.40. So when the search cost is low, the number of searches increases.

2.7.2 Search Model With Product Differentiation

The result shown in the previous part is based on the assumption that all the products are homogeneous. Although the electricity everyone uses are the same, the characteristics added into each offer are different. The data provided by the PUCT includes information on firm names which allows us to measure the firm effect. However, the data does not contain detailed product level information which prevents one from measuring the product level characteristics effect on price. This problem is solved by downloading detailed offer data from powertochoose.org website[5].

This data contains details about offer area, firm name, product (offer name), unit price for a certain level of usage (e.g. unit price for 1000 kWh electricity usage), fees related to this offer, rate type (fixed, variable, or indexed), renewable energy content, term value, special terms and promotion information. With this information, we can measure how product differentiation affects the price by doing a regression of price on product characteristics and firm dummy variables. The predicted error term from

[5]The data was downloaded on September 7th, 2013. It only represents the offer price and offer information at that time.

the regression can be treated as the homogenized price. With homogeneous goods, we can estimate the search cost distribution by using the sequential search model.

The detailed product information includes the following aspects: fees related to the offer, which are the fees charged for using less or more than a certain amount of electricity (usually a fixed fee charged for using less than 1000 kWh for one month).

According to powertochoose website, "A fixed-rate plan has a set rate that doesn't change throughout the contract period. Variable rate plans have no monthly contract or cancellation fee, but the rate consumers pay per kWh can vary from month to month. Consumers' rates can go up or down based on the market and the discretion of consumers' electric companies. An indexed rate plan (also called the market rate plan) is similar to a variable plan in that the price per kWh can go up or down each month. The difference is that the rates for these plans are directly tied to a pricing formula connected to a publicly available index. If the index rises, consumers' monthly rates will also, but if the index falls, consumers' rates will be lower."

Renewable energy content is the percentage of renewable energy included in the plan. It ranges from 0 to 100%. Term value is the length of the contract period. Normally, fixed rate plan ranges from 3 months to 60 months. Variable rate plans always last less than one month, and the indexed rate plan is for either 0 months or 12 months.

The special term refers to some special requirement for the offer. For example, new customer only offer, online contract and payment offer, etc. Promotion information usually means that the price for the first month is lower.

The detailed summary statistics are in Table 2.5. On average, the price for 1000 kWh electricity usage is $100, renewable content is 30%, length of contract is one year. Among the offers, 85% have special terms, 96% charge fee for lower usage, and 2.4% are under promotion.

Variable	Mean	Std. Dev.	Min.	Max.
Price	104.329	16.088	63	174.4
Renewable	28.947	40.146	0	100
Term value	11.186	9.247	0	60
Special terms	0.858	0.349	0	1
Promotion	0.024	0.153	0	1
Fees	0.959	0.198	0	1
$N = 1465$				

Table 2.5: Summary Statistics For Detailed Offer Data

There are 54 firms in the market. 17 firms have market share higher than 0.5% in the whole Texas area which is shown in Table 2.6. Incumbent firms (the firms in red) still have most of the market share, especially TXU and Reliant. But a lot of entrants firms hold some market shares in the market. This means that deregulation makes a lot of entrant firms entering into the market and some of these firms do well in the market.

Firm Name	Market Share	Number of Offers	Percentage
TXU Energy Retail	34.36	44	3
Reliant	25	54	3.69
Stream	7.45	25	1.71
Ambit Energy	4.26	30	2.05
Direct Energy	4.15	24	1.64
CPL Retail Energy	3.64	9	0.61
First Choice Power	3.04	14	0.96
Green Mountain Energy	2.63	15	1.02
StarTex Power	2.34	32	2.18
Cirro Group	1.67	38	2.59
Just Energy	1.57	24	1.64
Champion Energy	1.35	30	2.05
GEXA	1.32	25	1.71
Amigo Energy	0.93	40	2.73
Spark Energy	0.78	14	0.96
Bounce Energy	0.73	115	7.85
WTU Energy	0.72	7	0.48

Table 2.6: Firms with Highest Market Share

Table 2.7 shows the distribution of contract length and term value. Most of the variable price plans last less than one month. Fixed rate plans are all longer than 3 months. While the indexed price plans are either with no contract or one year. Most of the contracts are fixed rate for one year, half a year, or two years.

Term	**Variable**	**Fixed**	**Indexed**	**Total**
0	136	0	14	150
1	75	0	0	75
3	0	100	0	100
6	1	245	0	246
7	0	5	0	5
8	1	39	0	40
9	0	77	0	77
10	0	10	0	10
12	0	443	15	458
18	0	58	0	58
20	0	15	0	15
21	0	5	0	5
24	1	150	0	151
36	0	70	0	70
60	0	5	0	5
Total	214	1,222	29	1,465

Table 2.7: Distribution of Contract Length and Rate Type

After introducing the data, we can measure what impact these characteristics have on price by using a regression of price on all of the variables.

$$p = \beta_0 + \gamma * \text{product characteristics} + \theta * \text{firm dummies} + u$$

The result is in Table 2.8.

Variable	**Coefficient**	**(Std. Err.)**
Fees	-5.960	(2.091)
Renewable	0.083	(0.008)
Term	0.158	(0.040)
Special	-5.035	(1.523)
Promotion	5.358	(2.156)
Fiexed	-20.481	(2.455)
Variable	-2.792	(2.587)
Intercept	112.360	(3.762)
With firm fixed effect		
$R^2 = 0.55$		

Table 2.8: Regression Result

The result shows that the higher fees an offer charges, the lower offer price is. Consumers who do not look at these terms carefully and with low electricity usage would incur this kind of fee even though their electricity price is lower.

The more renewable energy an offer contains, the higher the electricity price is. An offer with 100 percent renewable energy content on average is $8.3 higher than an offer with no renewable energy.

The length of the contract also has a positive influence on electricity price. For an offer lasting 12 months, its price is around $8 lower than a five-year plan[6].

Offers which are under promotion (usually first month low price) have higher prices. Although consumers pay less for the first month, they would actually pay more for the remaining contract period.

Offers with special terms have lower prices which are $5 lower than the offers without special terms. Fixed price offers have the lowest price as compared to variable price offers. And the indexed price offers' price is the highest, that is about $20 higher than the fixed price offer.

These product characteristics and firm fixed effect explain 55% of the price dispersion.

Taking these product level information into consideration, I use the predicted error term from the regression to be the homogenized price. We can use the sequential search model framework introduced in section four to estimate the search cost distribution.

The result is in Table 2.9. It includes the estimation results for two cases: only search cost estimation and search cost estimation with quality control. After taking product differentiation into consideration, average search cost drop from around $9 to $6 for one more search. The average number of searches increases from 0.38 to 1.25.

[6] I used the dummy variables for each type of contract lengths, the result is noisy and not monotonic.

	μ	**Mean Search Cost**	**Number of Search**
W/o product diff	2.58	8.91	0.38
W product diff	1.76	5.93	1.25

Table 2.9: Estimation Result

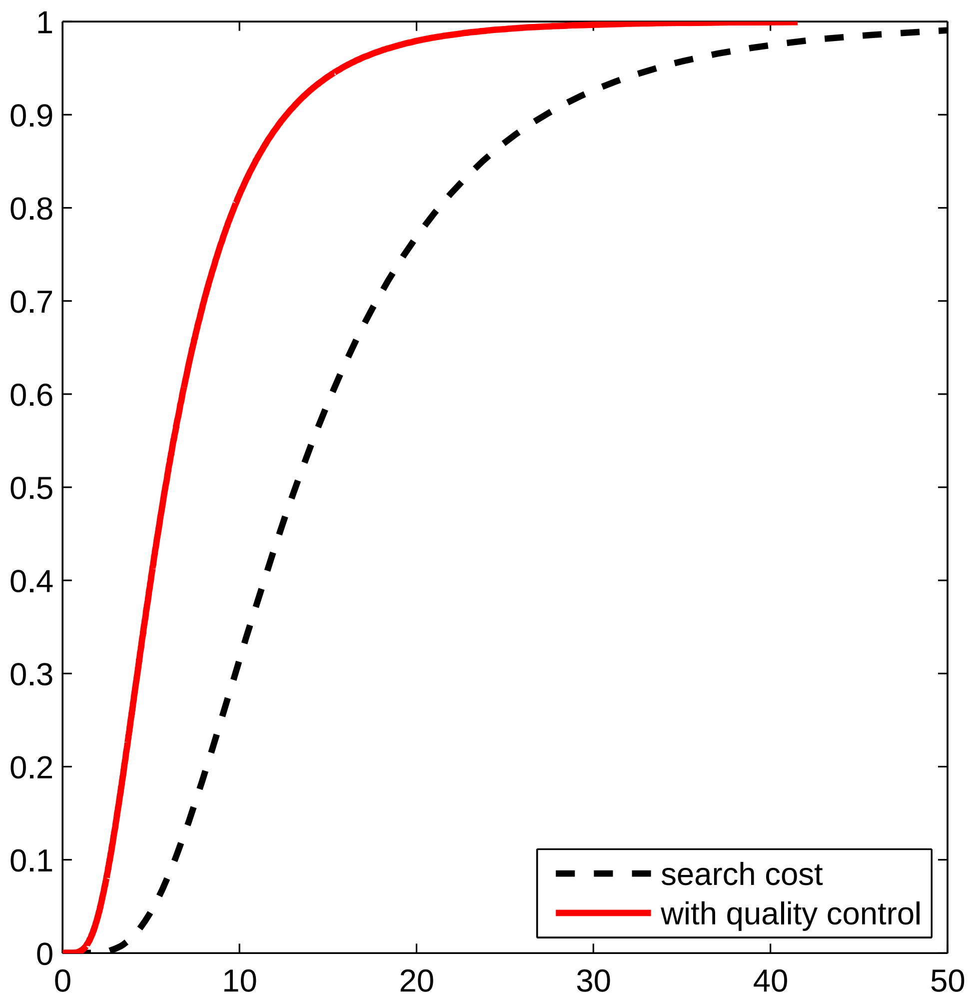

Figure 2.8: Search Cost Distribution Comparison Between With Product Differentiation And Without Product Differentiation

The search cost distribution graph is showed in Figure 2.8. With homogenized price, the search cost distribution moves to the left, which indicates that the average search cost decreases after taking product differentiation into consideration.

Therefore, the product differentiation does explain a big part of the price dispersion. Without considering the product level information, the estimated search cost distribution would be biased.

2.8 Counter-factual Experiments

In the literature, the share of non-searcher is $\frac{1}{3}$ (Giulietti et al. [forthcoming]). In the first experiment, I tried using a number that is more realistic in the Texas market.

Public Utility Commission of Texas did a bi-annual report about the scope of competition in electric markets in Texas. In their report, they keep records on unique visitor counts for powertochoose website. On average, 10% of consumers click on this website every year. This could serve as the maximum amount of consumers who use the website to search around. I treat these consumers as searchers. The remaining 90% consumers are non-searchers. They either switch without search or switch for reasons other than price.

When the share of non-searchers increases, we would expect that the price will become higher because fewer people seek better prices. Those searchers have to be more price sensitive, or more willing to search, to make up for the increased share of non-searchers, so that the market price would not change. Becoming more price sensitive or searching more means searchers' search cost has to decrease. So as the share of non-searchers increases, the search cost should decrease.

I use 0.9 as the new share of non-searchers. The new estimation results (Figure 2.9) show that the mean of the search cost distribution increases, that is, the new search cost cumulative distribution curve moves to the left.

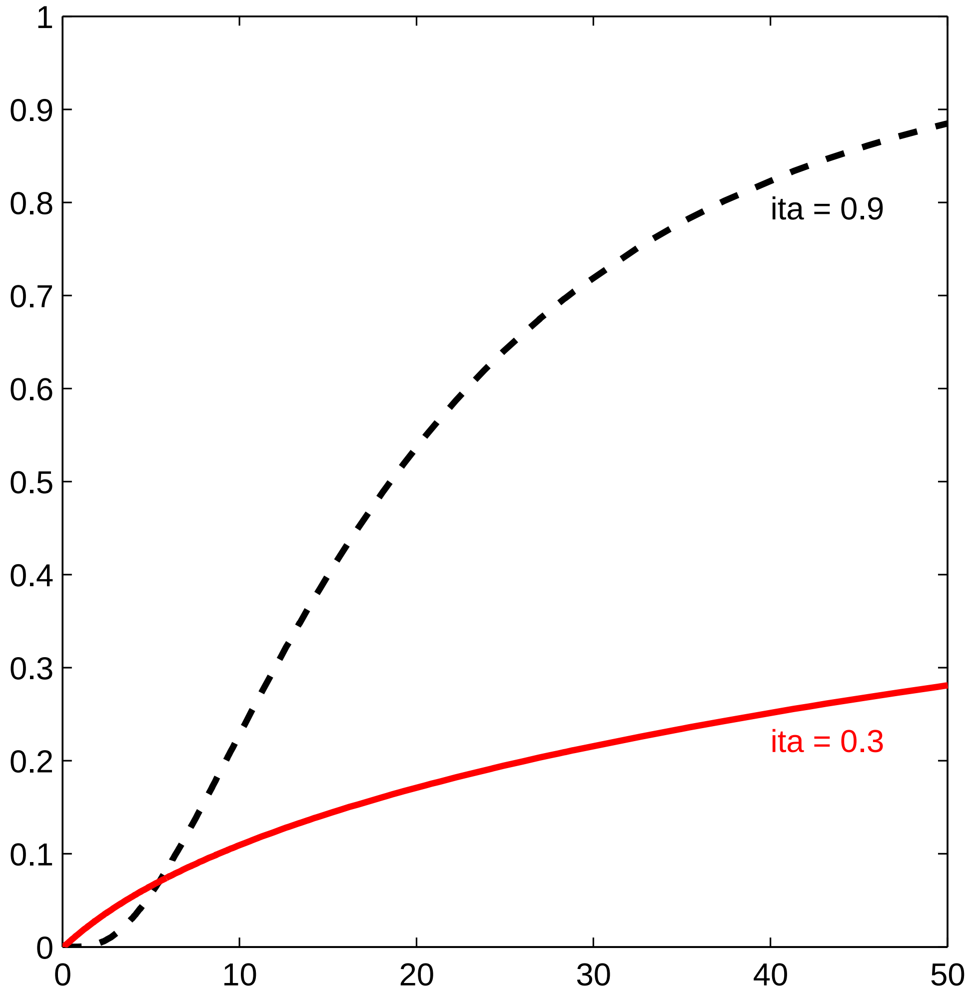

Figure 2.9: Search Cost Distribution When Share of Non-Searcher Increases (Year 2010)

From the first experiment, we can see that very few people use the website to search for offers. What would be the new price equilibrium if we could make more people search? To make more people search the website, we have to have a better web design and easier access to the powertochoose website. For example, instead of all kinds of offers, the PUCT may require all the firms to have at least one standard product to make the comparison easier. Decreasing the number of documents for consumers to read is another possible suggestion. In this case, there is no hidden information which makes consumers confused. PUCT could make Smartphone app for powertochoose website, so search and switch could take just a few touches. By doing this, we could reduce consumers' search cost. Intuitively, as searching becomes easier, consumers would search more which could make the market more competitive. Both price and price dispersion should be lower.

So in the second experiment, I cut the log-normal distribution mean and standard deviation parameters to half which means both the average and the variation of search cost are decreased. The red solid line is the original price distribution. The black dotted line is the new price distribution with decreased mean and standard deviation. Figure 2.10 shows that the new prices are clustered around the lower range of current offer prices.

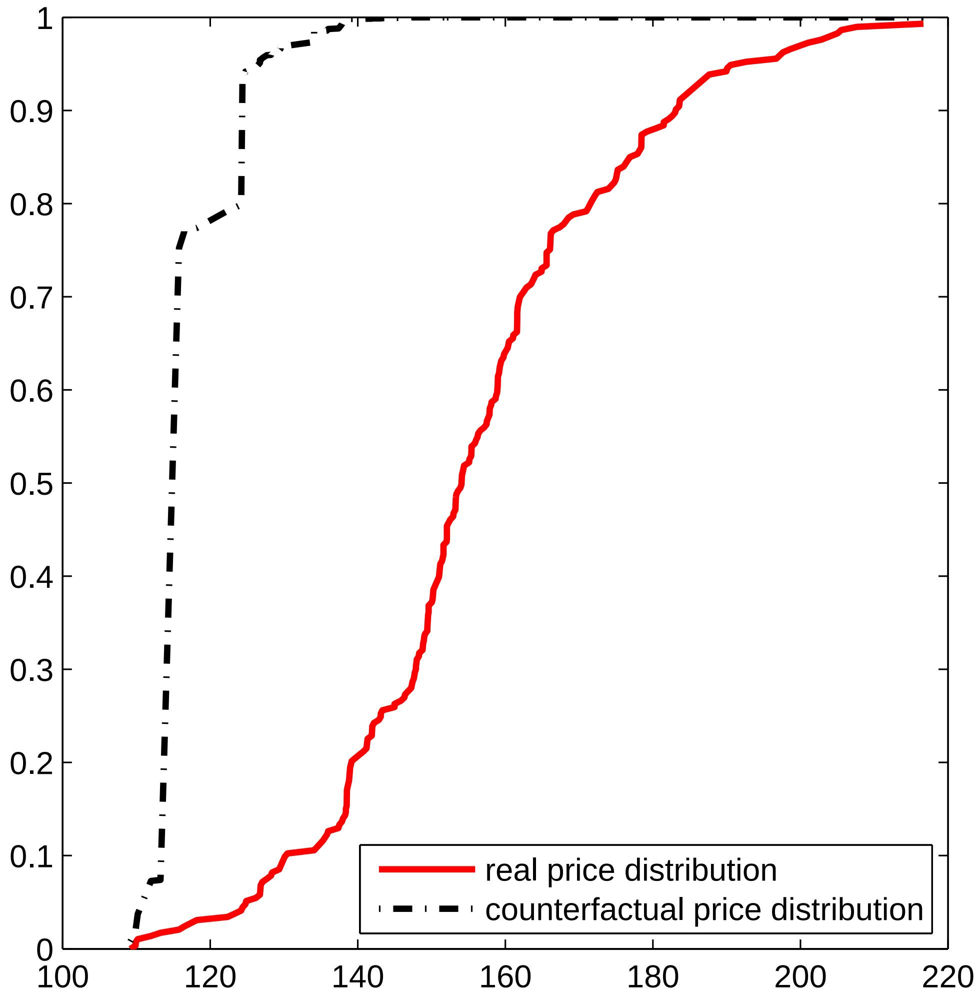

Figure 2.10: New Price Distribution When Search Cost Is Decreased

2.9 Conclusion

In this paper, I follow Giulietti et al. [forthcoming]'s sequential search model. I improved the model by taking product level differentiation into consideration to estimate the search cost. Both product differentiation and search cost explain the price dispersion. Results show that about half of the price dispersion could be explained by product differentiation. The magnitude of search cost is big, on average, consumers search only one time. The counter-factual experiment shows that reduced search cost could make the market more competitive by reducing both market average price and price dispersion.

Currently, I assume that consumers and firms play the repeated game every period. There is no connection between periods. It would be interesting to further the experiment and see the dynamic effect of searching because in the real world, both consumers and firms take previous condition into consideration.

CHAPTER III

OPTIMAL RENEWABLE ENERGY POLICY AND THE IMPACT ON TEXAS ELECTRICITY MARKET

3.1 Introduction

As controlling climate change becomes increasingly important, the electricity sector, the major source of greenhouse gas, has received a lot of environmental regulations. One of the policies most U.S. states adopted is the Renewable Portfolio Standard (RPS). This policy requires that a specified fraction of electricity be generated from renewable energy sources, such as wind, solar, biomass and geothermal. RPS has been adopted in 30 of 50 U.S. states, and the District of Columbia. To comply with RPS, distribution utilities are obligated to purchase a certain number of Renewable Energy Credit (REC), which represents corresponding MWh of renewable energy, from eligible renewable generators. This policy varies from state to state.

Another policy, which aims to promote the generation of electricity from renewable energy and reduce carbon emission, is federal Production Tax Credit (PTC). All of the renewable generators in the U.S. receive these credits. It gives renewable generators an inflation-adjusted tax credit of ₵2.2/kWh for the first ten years of production from the facility. "Originally enacted in 1992, the PTC has been renewed and expanded numerous times, most recently by H.R. 1424 (Div. B, Sec. 101 & 102) on October 2008 and again by H.R. 1 (Div. B, Section 1101 & 1102) in February 2009[1]."

The political appeal of these renewable energy policies ranges from energy security to environmental preservation green jobs and green technology. Despite these

[1]From Database of State Incentives for Renewables & Efficiency website

appeals, the problem with renewable energy is that it suffers from intermittency because weather varies a lot in a day and is only partially forecastable. Although wind generation has the lowest variable cost, compared to traditional dispatchable generating technologies which can be called on reliably to supply electricity during all hours even when the electricity market prices are high, it may not be cheap because the output is available mainly during night when electricity price is very low (Joskow(2010)). These policies do not consider the intermittency problems of renewable energy. Beside, these policies only ask for the replacement of non-renewable energy by renewable energy, but they neither differentiate the carbon intensity of nonrenewable resources, such as coal and gas, nor the replacement cost of the non-renewable energy. For example, both natural gas and wind are cleaner than coal, but compared to wind, natural gas requires a lower capital investment cost. The recent innovations in the ability to extract shale gas created great opportunities to reduce the carbon footprint of the electricity generation sector in a less costly way. RPS and PTC do not provide meaningful incentives to shift production from coal to gas fired generation. In this sense, these policies are less cost effective in reducing carbon emissions, although they aim to "protect and enhance the quality of the environment through increased use of renewable resources"[2].

Besides RPS and PTC, there are several other renewable energy policies. For example, outside the U.S., the Feed-in Tariff (FIT) policy has been much more popular. In general, FIT policy requires that electricity generated from renewable energy be purchased at a fixed, premium price. Fischer and Preonas [2010], Palmer and Burtraw [2005] and Fischer and Newell [2008] "compare the cost-effectiveness of individual renewable energy policies for achieving environmental and renewable energy goals" by setting up theoretical models. It is concluded that the cost effectiveness of

[2]From the subsection (g) of P.U.C. Subst. R. 25.173, goal for renewable energy.

different policies varies depending on the primary goal. When the goal is to reduce emission, renewable energy policies, including price-based or quantity-based policy, are always more expensive than a cap-and-trade or carbon pricing policy; while if the goal is to expand renewable energy in general, the renewable quotas, including Renewable Energy Certificates or RPS, are relatively less expensive than price-based based policies, such as technology-specific FITs.

When firms make long run investment decisions, several uncertainties need to be considered.

The first one is regulatory uncertainty. PTC launched in 1992 and was not rescinded completely in 1999 as scheduled, but instead, continued through a series of extensions of one-to-two years in length. The policy did however, expire three times for a short period (at the end of 1999, 2001 and 2003) before its renewal and was renewed retroactively after a 3-to-10 month lapse (AWEA 2008). Since a retroactive extension is always included in the renewals, technically the PTC has never experienced a gap in its coverage. However, investors still took the risk of no renewal or a non-retroactive renewal. This concern from investors strongly delayed the investment decision of renewable energy. Subsequently, new wind farm installations dropped precipitously in 2000, 2002, and 2004, which coincides with the expiration of the PTC in each preceding year. The annual new installations of wind farms in the U.S. are plotted in Figure 3.1 which is from Cullen [2013]. The vertical axis shows the total installed wind capacity. In year 2000, 2002, and 2004, the years the policy expired, the installation shows distinct reduction.

The second uncertainty comes from the fuel price, especially the natural gas price. Figure 3.2 shows the fluctuations of natural gas price since 1997 from the U.S. Energy Information Administration [2012]. Expected future low gas price may give entrants incentive to make new investments while the expected high price may deter the

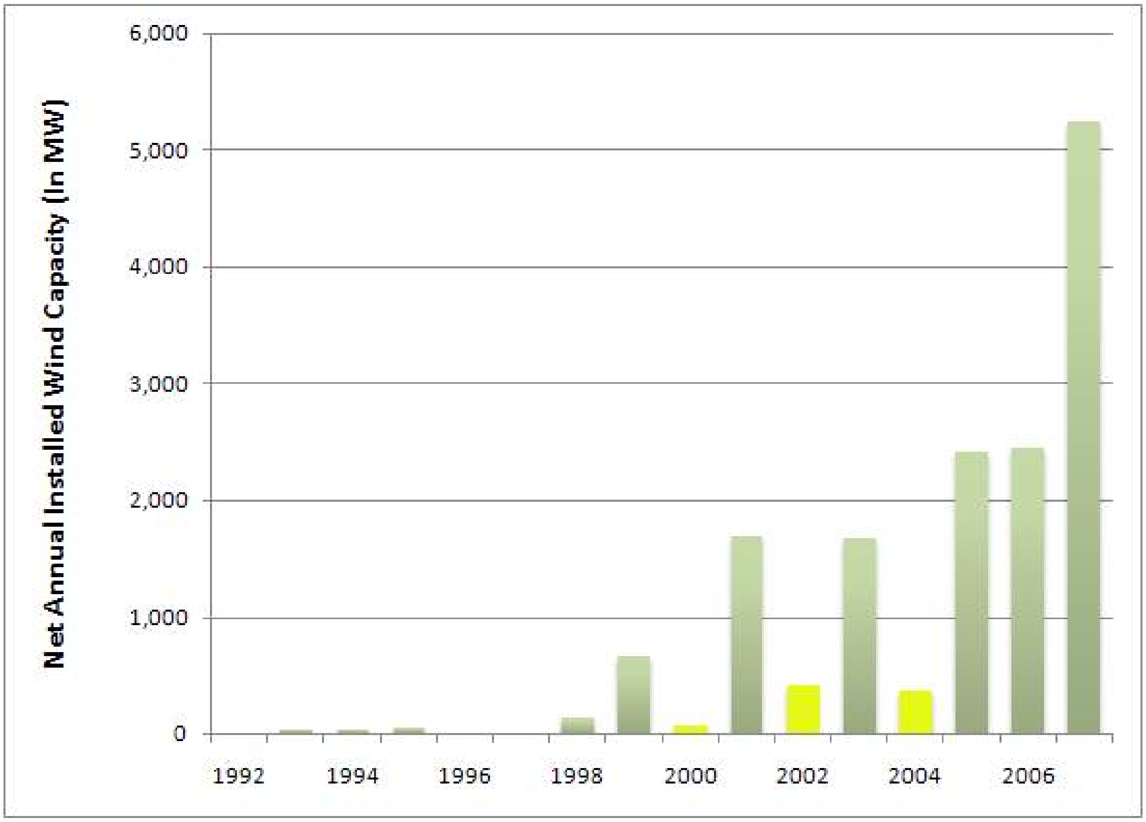

Figure 3.1: Annual Installations of Wind Capacity in the U.S.

Source: Cullen [2013]

entry. Furthermore, the recent low gas price makes natural gas a competitive energy resource compared to wind. I do not include the coal price change for three reasons. First, Texas electricity market relies heavily on natural gas while coal plants do not take much share. Second, for the calculation simplicity, I only allow one uncertainty at one time. Third, compared to the natural gas price change, coal price does not change too much during recent years.

Besides the policy and fuel price uncertainty, the third uncertainty comes from demand. Although Electric Reliability Council of Texas (ERCOT) can make forecasts about future demand, there is still unforecastable demand. Figure 3.3 is a long

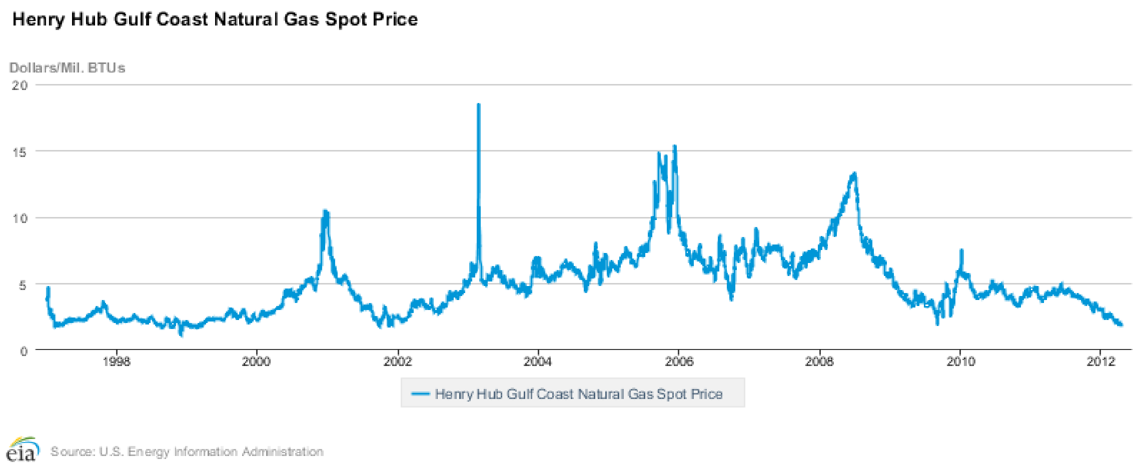

Figure 3.2: Future Natural Gas Price Change

Source: U.S. Energy Information Administration [2012]

term demand forecast for the ERCOT area from ERCOT Planning 2012 Long-Term Demand and Energy Forecast report (ERCOT [2011]). Different levels of future demand could have impacts on the firm's investment decision. For example, expected high level of future demand would incentivize firm's future investment.

Therefore, a dynamic investment model that takes all three uncertainties into consideration is desired.

In another papers about renewable energy, Cullen [2013] identified the substitution pattern between non-renewable generators and wind generators, that is, when the wind blows, which non-renewable generator would produce less. Then he calculated the emissions offset by wind generators and attached a monetary value to the offset. By setting up this model, he compared two policies: a carbon-trade program and a production tax credit and concluded that the cost effectiveness depends on the credit and social cost of carbon. In another paper, Cullen and Shcherbakov [2010] set up a structural model to estimate the cost of the dynamic process of generators

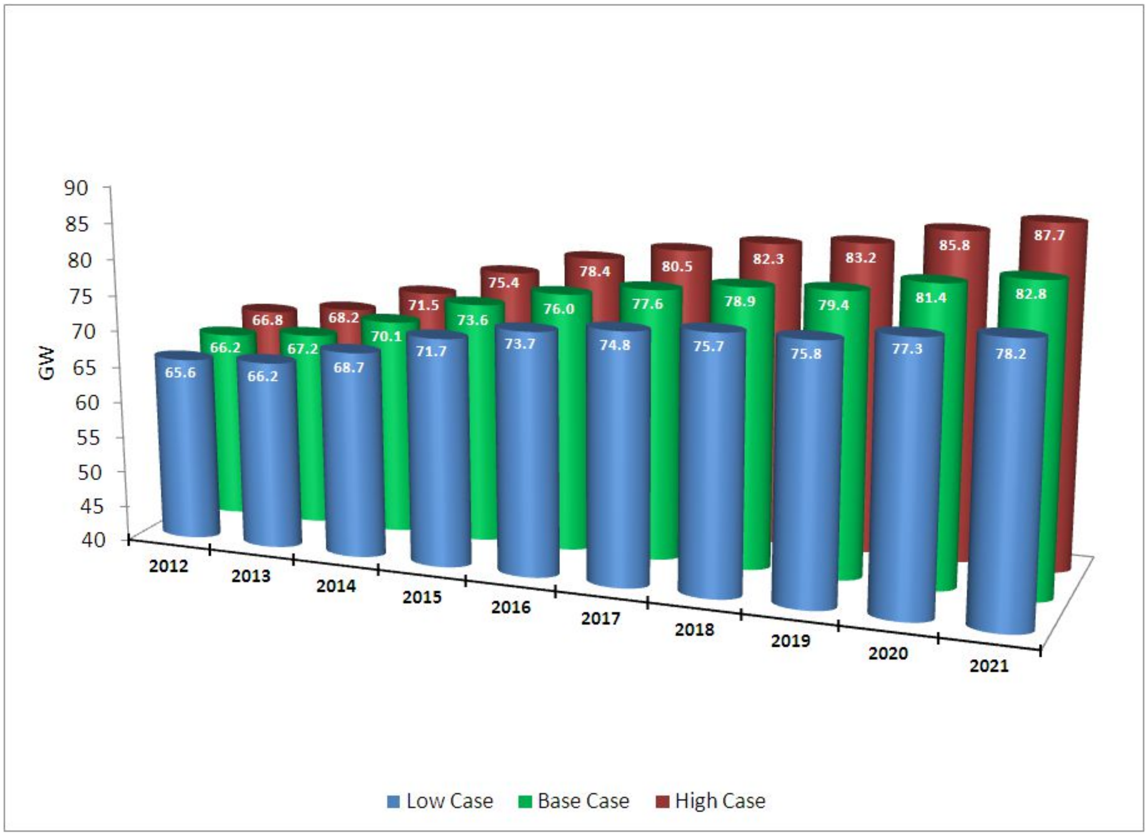

Figure 3.3: Electricity Demand Forecast

Source: ERCOT [2011]

starting and shutting off the turbines. He did the counterfactual analysis for different level of carbon tax (low, middle, high) under an inelastic and an elastic demand curve. Gowrisankaran et al. [2011] estimated the value of solar by modeling an electricity system operator who optimizes the amount of generation capacity. However, neither of these papers considered the three uncertainties discussed earlier in this section.

In this paper, I study how better designed policies could reduce carbon emissions from the electricity sector in a lower cost manner and how those policies impact the demand for different types of generations. In particular, I follow Bushnell and

Ishii [2007]'s investment model by utilizing the electricity generation in Texas to simulate the long run optimal investment path. By simulating firms' investment behaviors dynamically, I can see how future uncertainties such as fuel price and demand fluctuation have different impacts on firms' behaviors and calculate the carbon reduction cost under different policies.

The model consists two parts. The first part is static spot market competition. I assume that power plants compete perfectly in the spot market. They submit their bids every hour of the price they are willing to produce based on their capacity and marginal cost. The dispatch process is that the lower cost firms produce first, then the higher cost firms produce. The hourly price is the highest bid price which makes total supply equal total demand. Based on the hourly price, I calculate profits for each firm. The second part is the dynamic investment model. Firms form their expectations over future industry environment such as fuel price, demand and policy. Incumbent firms make their investment decisions by comparing the value of the investment to the cost, while entrants make theirs by comparing the value of entry with different technologies (e.g. wind, natural gas, coal, etc.) to staying outside the market. With this dynamic investment model, I simulate the electricity market and firms' investment behavior under different scenarios and different policy designs.

This paper shares a similar model as Bushnell and Ishii [2007]'s model. But this paper makes three main improvements: first, their spot market model is based on oligopoly competition, while mine is for perfect competition which is more appropriate for the Texas market. Second, my model takes current electricity capacity as given market capacity condition and simulate new firms' entry, while their simulation just includes two incumbent firms and one entrant. Last but not the least, I take policy, demand and fuel price uncertainties into consideration.

The remainder of the paper proceeds as follows. First, in Section 2, I introduce the Texas electricity market, especially the renewable energy development. This is followed by Section 3, which describes the model. Section 4 summarizes the data that will be used in the simulation. The simulation method and two model simplifications are discussed in Section 5. In Section 6, I present the results and Section 7 discusses conclusions and future work.

3.2 Texas Electricity Market

The Texas electricity market started the deregulation in 2002. Due to the increased natural gas usage right after the deregulation, new-era energy tools such as wind power and smart-grid technology were introduced. Texas' "Renewable Portfolio Standard (RPS)" was signed into law in 1999, as part of the same legislation that deregulated the electricity market. The deregulation separates the integrated investor-owned utilities into three distinct companies: power generation companies, transmission and distribution utilities, and retail electric providers.

RPS is a regulation that requires an increased production of energy from renewable energy sources, such as wind, solar, biomass, and geothermal. This policy differs from state to state. Unlike other states that set RPS as generation requirements, for example, California's RPS requires that by 2010, 20 percentage of electricity generation should be from renewable energy, Texas sets requirements for capacity. Table 3.1 shows Texas' renewable energy capacity targets (in MW) for each year[3]. In 2014, the total renewable capacity target is 5880 MW.

Compliance markets are created following RPS. A green energy provider (such as a wind farm) is credited with one Renewable Energy Credit (REC) for every 1,000 kWh or 1 MWh of electricity it produces. The electricity produced from the

[3] ERCOT protocols Section 14: State of Texas renewable energy credit trading program

Annual Capacity Target (MW)	**Existing Renewable Capacity (MW)**	**Total Renewable Capacity Target (MW)**	**Compliance Period (Years)**
400	880	1280	2002, 2003
850	880	1730	2004, 2005
1400	880	2280	2006, 2007
2392	880	3272	2008, 2009
3384	880	4264	2010, 2011
4376	880	5256	2012, 2013
5000	880	5880	2014, and each year after 2014

Table 3.1: Texas RPS Target

green energy provider is fed into the electrical grid, and the accompanying REC is sold in the compliance market. The electricity companies are required to supply a certain percentage of their electricity from renewable energy source each year. They demonstrate their compliance by purchasing the corresponding amount of RECs.

When Texas adopted the RPS program with binding obligations beginning in 2002, there was an extraordinary growth in wind power, which can be seen in Figure 3.4. The electricity generated from wind increased from only less than 1% of the total generation in 2002 to more than 5% in 2010. Also, the fast development of wind makes RPS unbinding after 2006 which means that the supply of RECs is much more than the demand of RECs. The price of REC varied between \$4 and \$18 before 2006. After 2006, especially in recent years, REC price dropped to around \$1. Compared to the almost flat trend of coal generation and gas generation as seen in Figure 3.5 after deregulation, wind generation increased at a very fast pace. Also, the number of wind farms grew rapidly compared to coal plants and natural gas plants (Figure 3.6).

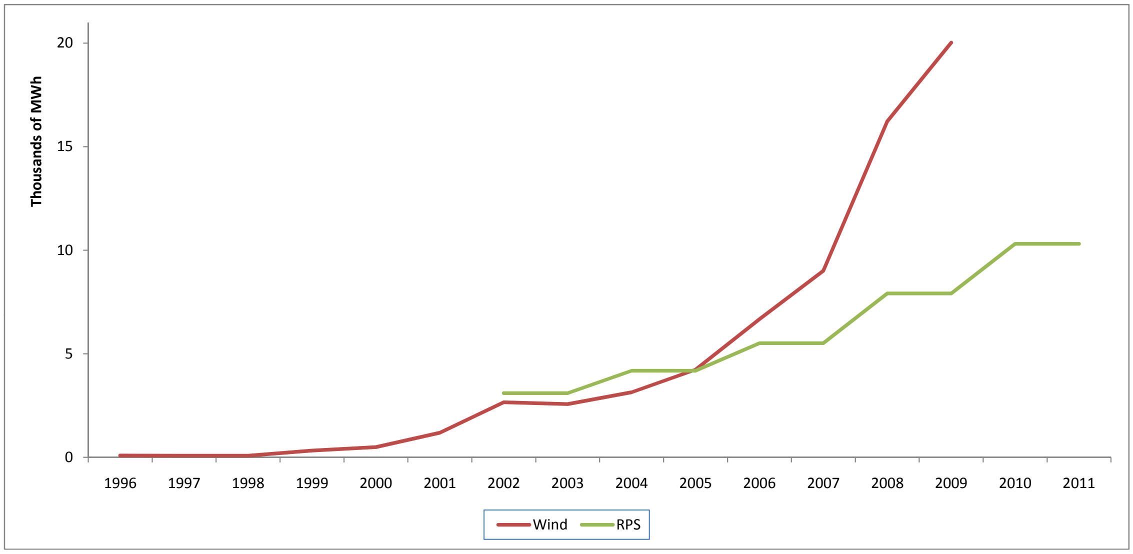

Figure 3.4: Electricity Generation From Wind in Texas And RPS Requirement

Several energy types can represent renewable energy. In this paper, I use wind as the representing renewable energy for several reasons. Although most states in the U.S. have RPS, no two are the same. For example, the green certificate system in the State of Arizona only includes solar energy, whereas in the State of Connecticut natural gas fuel cells are counted as renewable energy sources (Schaeffer et al. [1999]). Because of this, RECs cannot be traded between states. Besides, as the local resource endowments are different across states, each state has different development pace for different types of renewable energy. In Texas, the system was technology-neutral, so that the most economical resource – wind in this case – is used most intensively. Compared to wind, other renewable energy types take fewer shares in Texas. In 2009, wind capacity is 9915 MW, while landfill gas is 80MW, hydro capacity is 33MW, and biomass is 40MW and solar is 1MW. So in this paper, wind represents all the renewable energy capacity and generation in Texas.

Another reason that the wind generation increased rapidly is the federal renewable

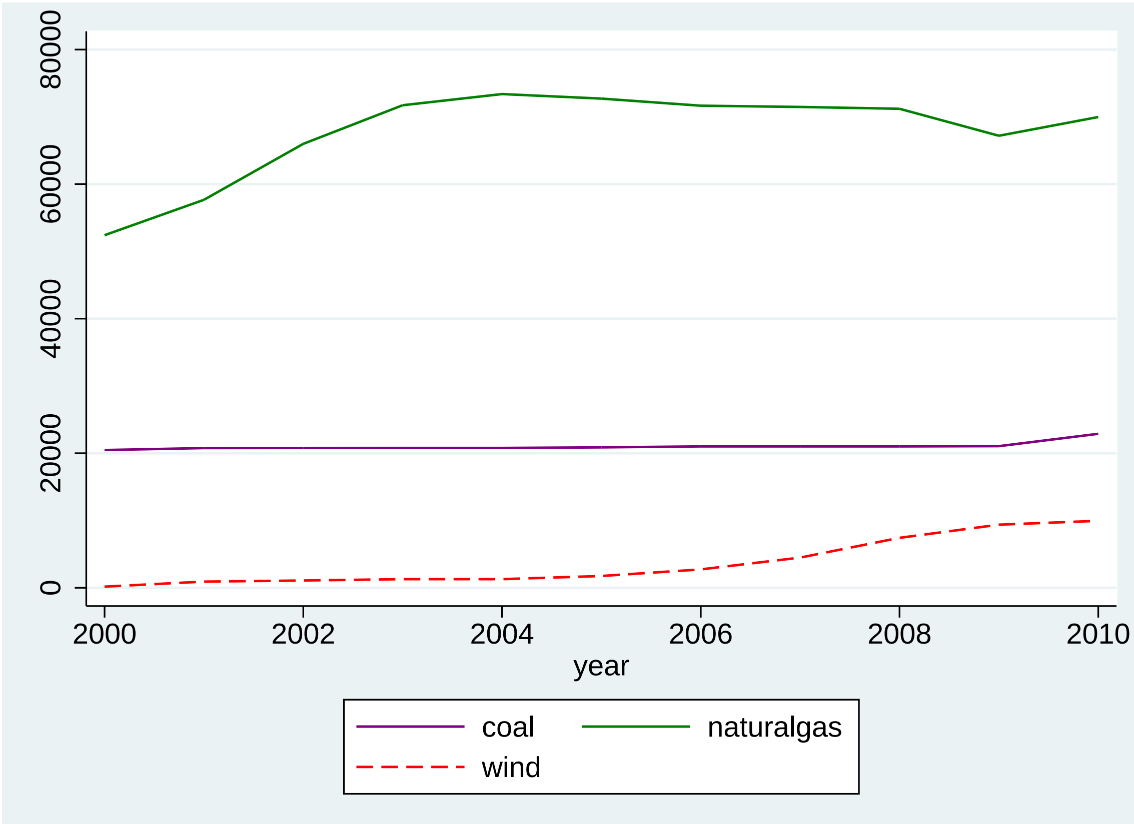

Figure 3.5: The Electricity Generation From Coal, Natural Gas And Wind

energy Production Tax Credit (PTC). By definition from Database of State Incentives for Renewables & Efficiency website, PTC is a per-kilowatt-hour tax credit for electricity generated by qualified energy resources and sold by the taxpayer to an unrelated person during the taxable year. Originally enacted in 1992, the PTC has been renewed and extended numerous times, most recently by H.R. 1424 (Div. B, Sec. 101 & 102) on October 2008 and again by H.R. 1 (Div. B, Section 1101 & 1102) in February 2009[4].

There are three reasons that makes the Texas grid a good choice for analysis. First, ERCOT's grid is relatively isolated from other grids in the U.S.. All of the

[4]From Database of State Incentives for Renewables & Efficiency website

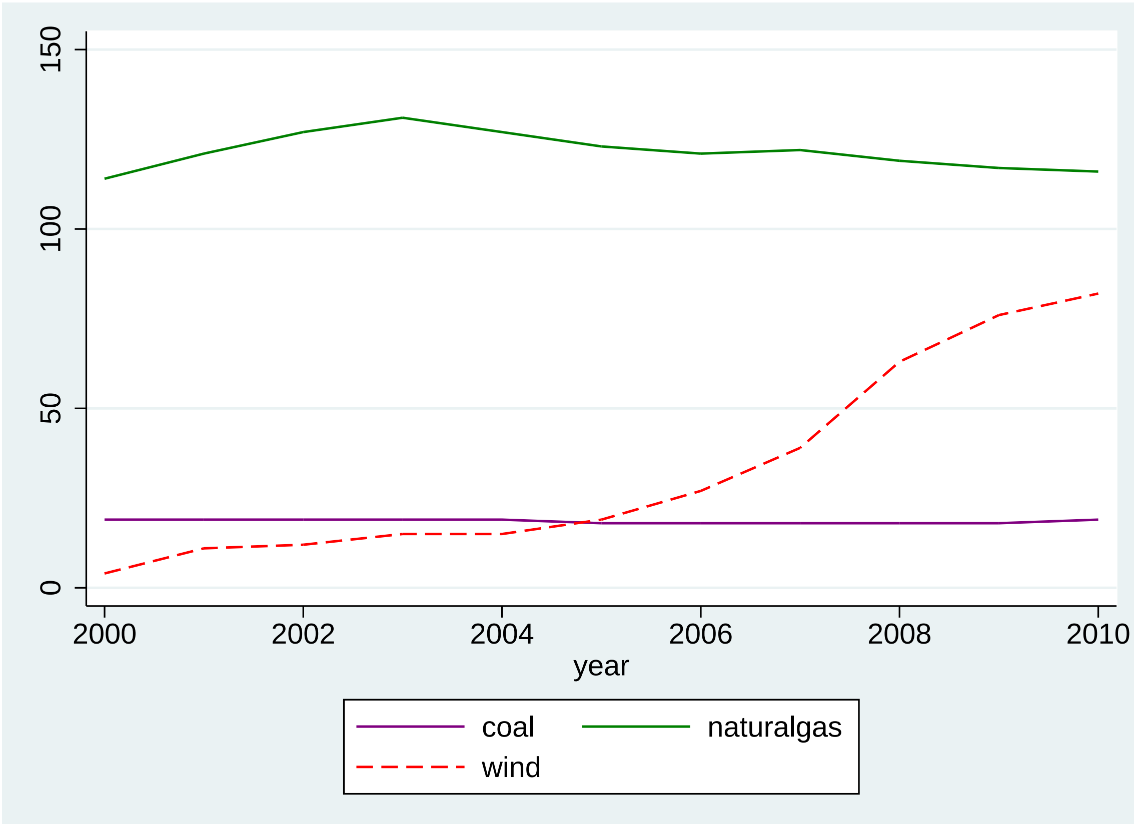

Figure 3.6: The Number of Plants For Coal, Natural Gas And Wind

electricity is generated and consumed within Texas, which removes the complication of electricity import and export. Second, compared to other states in the U.S., Texas wind generation, or renewable generation, takes a nontrivial share of total electricity generation. Moreover, the Texas electricity market provides us with many useful datasets about wind development and generation.

3.3 Model

When a power generation company makes an investment decision, the firm usually considers its current profit and investment cost, other competitors' capacity, and market conditions (such as future demand, fuel price, policy, etc.). In order to simulate firms' future investment decisions and take firms' forward-looking behavior into consideration, a dynamic investment model is necessary.

Unlike Pakes and McGuire [1994]'s framework, that is, firms' behaviors have no impact on market price and price is constant through periods for each firm, power plants' investment behaviors have an impact on market price and the market price would change from hour to hour based on the market demand. So I follow Bushnell and Ishii [2007]'s framework by separating spot market competition from long run investment behavior.

In the spot market, firms compete perfectly in hourly price and earn profit through their generation. Although power plants usually earn 95% of the profit through long-term contract with retailers and 5% of the profit through spot market competition, due to the unavailability of the long-term contract data, it is assumed that all the profits come from the spot market competition. For each firm, hourly profit from the spot market are aggregated to generate the total profit for one period. The period can represent a year or several years by user's definition. In the following model, one year is treated as a period.

In the long run, firms make investment decisions based on current period profit, which is calculated from the spot market competition and their expectations for the future market. They compare the expected benefit of investment to that of no investment and then make the decision. The detailed model is followed.

3.3.1 Spot Market Competition

In the spot market, I assume that power plants compete perfectly each hour by bidding a price they are willing to produce. Because of the perfect competition assumption, the bidding price is firm's marginal cost. The spot market equilibrium price is set in the following way: the lower marginal cost energy plant provides generation first (Borenstein [2005]), then higher marginal cost firms produce. Given one demand level, the equilibrium price is the highest bidding price from the firm who is willing to provide electricity. Figure 3.7 shows an example how the market equilibrium price is determined. The horizontal axis is supply/demand and the vertical axis is the price/marginal cost. The dashed curve is the market supply curve. At the beginning, the market is supplied by the lowest marginal cost firms, in this case, wind. Then some higher marginal cost firms serve the market at their capacity. The solid vertical line is the market demand at a certain hour, which varies by hour. The intersection is the market equilibrium price for this hour. The equilibrium price is the same for all three technologies considered in this paper: coal, natural gas and wind.

In one period (one year hereafter), for non-renewable energy firm $i \in \{1, 2, ..., N-m\}$, the profit π^n at hour $h \in \{1, 2, ..., 8760\}$ in year t (notation for year is dismissed here) is

$$\pi^n(q^n_{ih}, \Omega) = \mathbb{1}(p_h > MC^n_i) * (p_h - MC^n_i) * q^n_{ih},$$

where q^n_{ih} is the MWh of electricity generated by firm i at hour h, Ω is the market condition (including the fuel price which has impact on marginal cost MC, demand growth for this year, and policy), p_h is the market equilibrium price, and MC^n_i is the firm's marginal cost. The equation means that at hour h, as long as the market price p_h is higher than the firm i's marginal cost MC^n_i, the firm will produce at its full capacity. The market condition Ω is assumed to be constant in one period. I assume that generators' turbines can be turned on and off immediately. For example, firm f is the marginal firm which means that its marginal cost is high and this firm will turn on its turbines only when the demand is high enough so that the market price is higher than its marginal cost. My assumption is that at hour h when the demand

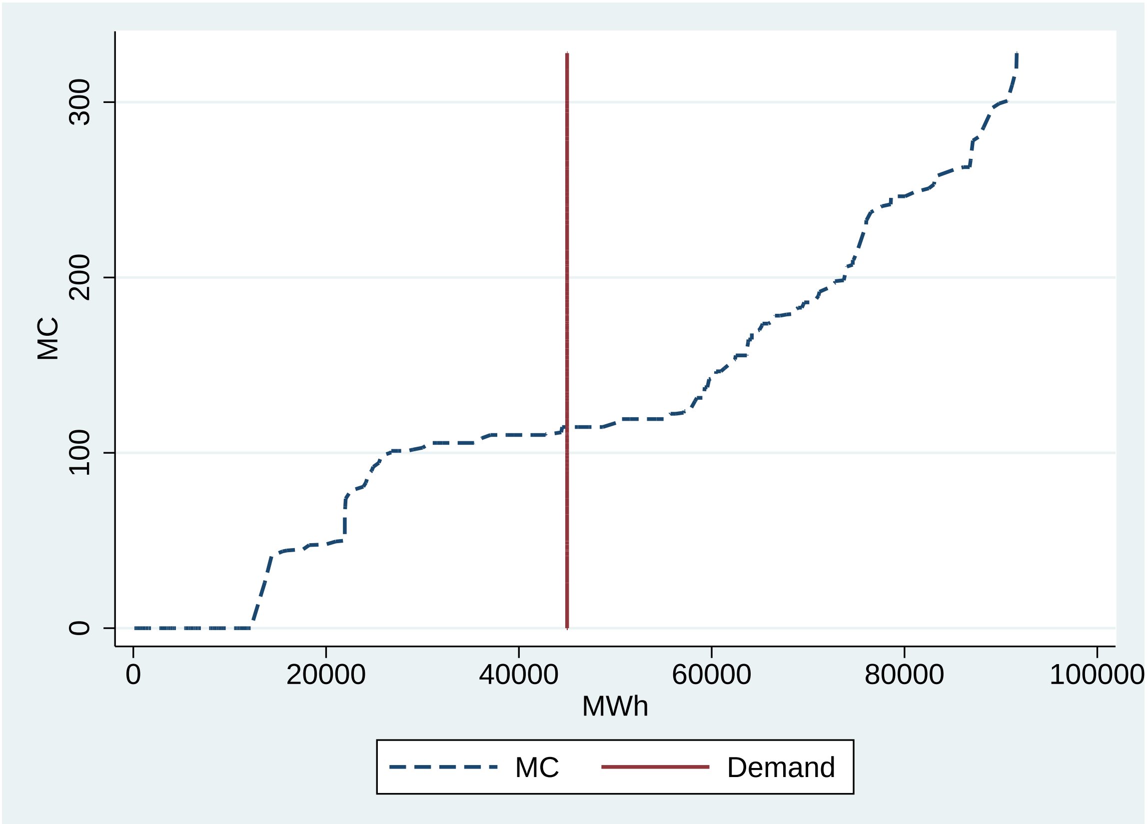

Figure 3.7: Spot Market Equilibrium Price Determination

is high, firm f starts to generate electricity; while at the next hour $h+1$, demand dropped so does the market price, firm f would shut down its turbine immediately without considering any related cost.

For wind firms $i \in \{N-m+1, ..., N\}$, the profit π^w is different as renewable energy receive subsidies (Production Tax Credit and Renewable Energy Credit) for every unit of electricity they generate. Therefore, their production decision depends on whether the price and subsidy are higher than their marginal cost. Because renewable energy has very low marginal cost, this means that as long as the wind blows, wind firms would produce and earn profit π^w:

$$\pi^w(q^w_{ih}, \Omega) = (p_h + subsidy) * q^w_{ih}.$$

Three assumptions are made here: first, it is hard to get hourly wind speed data or hourly generation data for each wind farm. Moreover, it is impossible for a power plant to produce at full nameplate capacity in a year. Therefore, I use an average capacity factor, which is an engineer-estimated ratio of the total amount of energy the plant produces during a period and the amount of energy the plant would have produced at full capacity, for each type of energy sources. Normally, wind firm's capacity factor is very low while coal plant's is high. The hourly electricity generation from wind firms q^w_{ih}, is calculated as

$$q^w_{ih} = \text{capacity}_i * \text{capacity factor}_{ih}.$$

Wind usually blows more during the winter and at night when the electricity demand is low; while it blows less during the day, especially during summer, when the demand is the highest. To reflect the variability of wind speed, wind capacity factor is different across hours. For example, at peak hours, the capacity factor is 0.15, while at off peak hours, the capacity factor is 0.35. The hourly electricity generation from non-wind firms q^n_{ih} is calculated as

$$q^n_{ih} = \text{capacity}_i * \text{capacity factor}_i,$$

where the capacity factor stays the same through simulation periods.

Second, generators can be turned on and off immediately with no startup cost. Although based on the estimation from the literature, the startup cost ranges from

\$300-\$80,000 for gas turbines and \$15,000-\$500,000 for steam gas and coal plants (Cullen and Shcherbakov [2010]), it is not considered due to the difficulty of modeling and calculation.

Third, each firm's production marginal cost is calculated as

$$MC_{it} = \text{heat rate}_i * \text{fuel price}_{it}.$$

Heat rate is a measure of the turbine efficiency. It is determined by the total energy input supplied to the turbine divided by the electrical energy output. In general, within the same technology, the older the firm is, the higher the heat rate is. So it varies across firms. However, I assume the heat rate to be constant during simulation periods for a given firm. In addition, I assume that fuel price can change from period to period, but stays the same within one period.

3.3.2 Long-Run Investment Model

Investment in a new power plant affects the spot market by changing the firm's capacity and lowering its marginal cost by using newer technology. With higher capacity and lower marginal cost, firms can supply more in spot market and make more profit in the long run. So when the benefit from expanded capacity is higher than the investment cost, the power plant would invest in the new plant.

In the investment model, one period t is assumed to be a year. The profit that firm i makes depends on two state variables: market capacity (C_t), which includes the firm's own capacity ($C_{i,t}$) and other firms' total capacity ($C_{-i,t}$); and market condition (Ω_t), which includes three variables. The first is a technology-specific variable, fuel price θ_{it}, which has an impact on the marginal cost. The second market state variable is regulatory uncertainty λ_t, which indicates whether the renewable energy policy is in effect or expired. The last state variable is market demand growth M_t, which describes the demand growth in year t. These market condition variables evolve exogenously each period. Investment decisions are made based on firms' expectation to future market conditions.

The model outlined above can be characterized by the following Bellman's equations for firm i:

$$V_{i,t}(C_t, \Omega_t) = \max_{I_{i,t}} - \phi(I_{i,t}) + \Pi_{i,t}(C_t, \Omega_t) + \beta E_t[V_{i,t+1}(C_{t+1}, \Omega_{t+1})],$$

where $V_{i,t}$ is firm i's value at period t, C_t is market capacity, Ω_t is market condition, $I_{i,t}$ is a dummy variable that indicates firm i's investment decision at period t, $\phi(I_{i,t})$ is the investment fixed cost, $\Pi_{i,t}(C_t, \Omega_t) = \sum_{h=1}^{8760} \pi_{iht}$ is firm i's current profit, and β is the discount factor. The equation means that firm i makes its investment decision $I_{i,t}$ at period t to maximize its current value $V_{i,t}$, that is, current period profit $\Pi_{i,t}$ minus the investment fixed cost $\phi(I_{i,t})$ if making investment plus the discounted future value $V_{i,t+1}$ which depends on future market capacity C_{t+1} and future market condition Ω_{t+1}, where Ω_t represents the market environment in period t which includes fuel price, policy and demand growth.

Market future capacity C_{t+1} depends on the current market capacity C_t and firms' investment decisions $I_{i,t}$, which can be represented as,

$$(C_t, \{I_{1,t}, ...I_{N,t}\}) \rightarrow C_{t+1}.$$

The future market condition is evolved following a exogenously given distribution that is independent of the firm's investment decision. Firms only know its distribution $f(\cdot|\Omega_t)$. So the expected value of future value is evolved as,

$$E_t[V_{i,t+1}(C_{t+1}, \Omega_{t+1})] = \sum V_{i,t+1}(C_{t+1}, \Omega')f(\Omega'|\Omega),$$

where $f(\Omega'|\Omega)$ is the probability of future market condition.

Following Bushnell and Ishii [2007], I use the Markov Perfect Equilibrium (MPE) framework to incorporate firms' strategic behavior and intertemporal decision-making. For each firm, the investment decision that maximize its profit is the solution to a dynamic programming (DP) problem.

Firms' strategic behavior includes both the conjecture about other competitors' investment decision-making and the market condition (such as the demand growth, fuel price, policy, etc.), so in the MPE framework, I use Nash equilibrium to rationalize each firm's decision. They will maximize their values based on their conjectures about others' behavior. In the equilibrium, no one will deviate from their decision.

3.4 Data

My simulation started from the year 2012. There were 261 power plants: 9 coal plants, 152 natural gas plants and 102 wind farms. The total capacity is 9751.7 MW, 69753.7 MW, and 12185 MW for each technology. This is shown in Table 3.2.

	Coal	**Natural Gas**	**Wind**
Number of Plants	9	152	102
Total Capacity (MW)	9751.7	69753.7	12185

Table 3.2: Incumbent Firms In the Simulation

Based on the data, coal firms and wind firms do not make investment after the plant is built. So for the incumbent firms, only natural gas firms could make new investment decisions. After observing the data, I notice that most of the natural gas firms make new investment in neighboring years, that is, if one firm built a new firm in 1993, there is a higher probability that this firm would build a new plant in 1994 or 1995 then in 2000. So I pick up 2 incumbents who built their natural gas plants in 2010 or 2011 as they have a high probability of building new plants in the near future.

For the entrants, I also allow 2 firms to make investment decisions. They can choose which technology (wind, natural gas, coal) to invest. But the capacity and all the other characteristics about the invested technology are exogenously given. Table 3.3 shows the characteristics for each newly invested technology. The capacity is chosen to be the average capacity growth for each technology every year. For example, in Texas, on average, total installed wind capacity increases 1000MW per year. So I choose the newly invested wind farm capacity to be 1,000 MW and the simulation results can tell us how many more wind turbines would increase each year. The heat rate and investment fixed cost data are obtained from the EIA website.

Technology	**Capacity (MW)**	**Heat Rate (BTU/kWh)**	**Fixed Cost ($)**
Coal	1,000	10,373	333,000,000
Natural Gas	2,000	8,551	32,000,000
Wind	1,000	0	30,000,000

Table 3.3: Entrants New Investment Characteristics

I assume the planning horizon is 4 years and the discount rate β is 0.9.

Besides the firm data, we need market environment relevant data. As introduced earlier, there are three market variables.

The first one is demand growth. Figure 3.8 shows the load duration curve, which shows the amount of time the grid is above a given electrical demand level based on the real demand data in the year 2012. The electricity demand, or electric load, is plotted on the vertical axis, and the number of occurrences, throughout the year, is plotted on the horizontal axis. For example, based on Table 3.4 for the first 100 hours, the demand is at 55,821 MW while for the next 1260 hours the demand is at 44,453 MW.

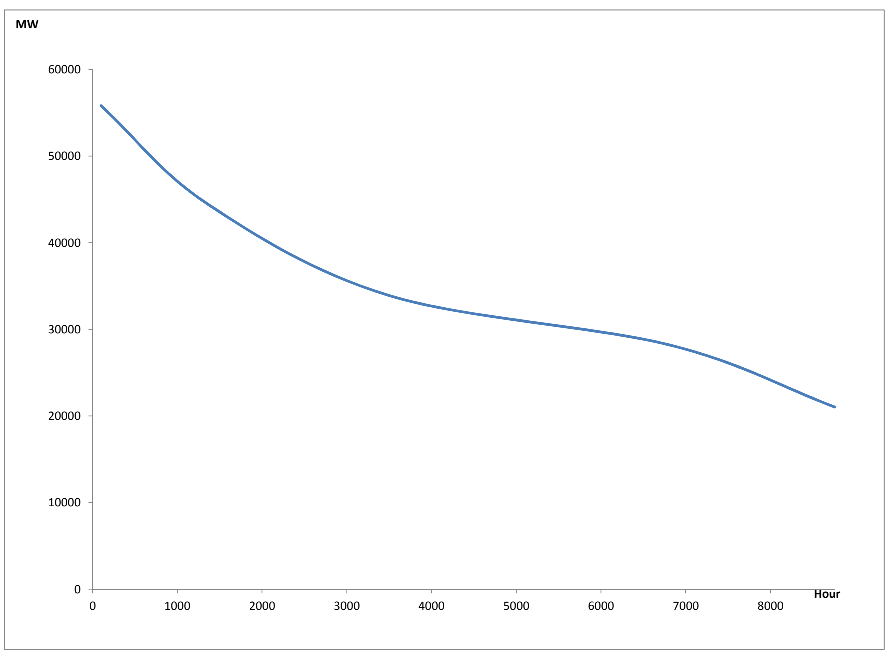

Figure 3.8: Load Duration Curve

To reduce the computational burden, demand is divided into 5 levels. Table 3.4 summarizes the five levels faced by all of the firms. The second column lists the number of hours in a year that demand is at a certain level. In a year, there is a small number of hours when demand is at its peak and most of the demands are in the middle to low demand levels.

Demand	**No of Hours**	**Demand Quantity (MW)**
Level 1	100	55,821
Level 2	1260	44,453
Level 3	2040	33,903
Level 4	3300	28,221
Level 5	2060	21,036
Total	8760	

Table 3.4: Market Demand

During the simulation, the demand growth is random with an expected positive trend τ. In one simulation year t, the growth of demand at hour h is assume to be represented by the following formula,

$$D_{t+1,h} = D_{t,h} + \tau + \Delta_{t+1},$$

where τ is the trend and Δ_{t+1} is the deviation from the trend. This could take different values with an assumption of equal probability, which is represented by the following formula,

$$\Delta_{t+1} = \begin{cases} \text{high growth} & \text{with } Pr_1 \\ \text{median growth} & \text{with } Pr_2 \\ \text{low growth} & \text{with } Pr_3 \end{cases} .$$

By using hourly demand data from 2004 to 2011 from the ERCOT website, τ is estimated to be 300 and

$$\Delta_{t+1} = \begin{cases} -300 & \text{with } Pr = \frac{1}{3} \\ 0 & \text{with } Pr = \frac{1}{3} \\ 300 & \text{with } Pr = \frac{1}{3} \end{cases} .$$

Thus $\tau + \Delta_{t+1}$ is,

$$\tau + \Delta_{t+1} = \begin{cases} 0 & \text{with } Pr = \frac{1}{3} \\ 300 & \text{with } Pr = \frac{1}{3} \\ 600 & \text{with } Pr = \frac{1}{3} \end{cases} .$$

This means that on average, demand growth could be low, medium, and high with equal probability. So in the simulation, in the first year, demand growth could be (0,300,600), while in the second year, it could be (0,300,600,900,1200). In the fourth year, demand growth could be (0,300,600,900,1200,1500,1800,2100,2400). Each year, the demand growth is independent, that is, in period one, demand growth could be (0,300,600) with equal probability, while in period two, demand could change from 300 to (300,600,900) with equal probability as well.

The second market variable is the fuel price. The data is from the EIA website. The coal price is 0.0014\$/Btu while the natural gas price is 0.0075\$/Btu. In the simulation of fuel price uncertainty, natural gas price could change to low, median, high level with an average of 0.0075$/Btu.

The last market variable is policy. There are two sources of subsidy for renewable energy: PTC and REC. Under current policy, Federal Production Tax Credit is $22/MWh for wind. The other one, Renewable Energy Credit is tradable. Its market price varied from $1/MWh to $20/MWh. But in recent years, the fast development of wind farms makes the Renewable Portfolio Standard unbinding which means that the supply of the REC is much more than the demand. This also makes the REC price drop to around $1/MWh in recent years. To make the calculation simple, I would not include the market for trading REC and just assume there is just one subsidy for renewable energy, which is at a fixed price $30/MWh.

3.5 Estimation

To reduce the computational burden, I use several simplifications as in Bushnell and Ishii [2007].

3.5.1 Simplification I: Finite Planning Horizon

In Bushnell and Ishii's framework, "finite planning horizon" is introduced to solve the infinite decision-making computational problem. "Finite planning horizon" means that firms often make finite years planning. It is realistic as firms make near-future forecast on market condition and competitors' behaviors more precisely than they do for far future.

Thus firms' expected discounted profit stream is decomposed into the profit stream in the near future and far future. The latter of which is called the "salvage" value. The decomposition can be represented as,

$$E_t\left[\sum_{s=0}^{\infty}\beta^s\Pi_{i,t+s}\right] = \underbrace{(E_t\left[\sum_{s=0}^{H-1}\beta^s\Pi_{i,t+s}\right])}_{\text{near-future value}} + \underbrace{(E_t\left[\sum_{s=H}^{\infty}\beta^s\Pi_{i,t+s}\right])}_{\text{salvage value}},$$

where the second part is the total profit from the planning horizon and the third part is the salvage value.

The salvage value can be simplified by using the condition from the period after the planning horizon, which can be assumed as firm's best conjecture about the future. The simplification is shown as,

$$E_t\left[\sum_{s=H}^{\infty}\beta^s\Pi_{i,t+s}\right] = \beta^H E_t\left[S_i(C_{t+H},\Omega_{t+H})\right].$$

So the salvage value depends on the market condition and other firms' condition in period $t+H$. In this paper, S_i is approximated as the profit earned from the last period,

$$S_i(C_{t+H},\Omega_{t+H}) = \sum_{s=0}^{\infty}\beta^s\Pi_{i,t+H}(C_{t+H},\Omega_{t+H}) = \frac{1}{1-\beta}\Pi_{i,t+H}(C_{t+H},\Omega_{t+H}).$$

3.5.2 Simplification II: Static-Dynamic Separation

The electricity market includes two types of competition: price bid in the spot market and investment behavior in the long run, both of which can have influences on each other. For example, firm's investment decision in this period could have an impact on firm's bidding behavior in the next period. So when a firm makes a strategic decision, the firm has to jointly consider these two parts. But this would create a huge computational burden for estimation.

I limit the interaction between bidding and investment behavior by only allowing the relationship between current investment and future bidding, but not current bidding and future investment. That is, current investment behavior could have an impact on future bidding behavior and future bidding could also have influences on current investment decision.

The simplification allows us to simulate the firm's behavior in the spot market in order to depend on market generation portfolio in the current period but not future. Also, this allows the static bidding game and dynamic investment game to be solved sequentially. The estimation method will be discussed in the following section.

3.5.3 Estimation

We can solve the equilibrium and find out the firms' optimal investment path using the above two simplifications and the Bellman equation. From the Bellman equation we know that firm i would choose what to invest to maximize its value function which is a sum of current profit and discounted future value. Given the other firms' investment decision, firm i can make its decision based on the conjecture on the market condition, that is,

$$V_{i,t}(C_t, \Omega_t) = \max_{I_{i,t}} - \phi(I_{i,t}) + \Pi_{i,t}(C_t, \Omega_t) + \beta E_t[V_{i,t+1}(C_{t+1}, \Omega_{t+1})].$$

Suppose we know at period t, firm i's investment is $\bar{I}_{i,t}$,

its competing firms $(-i)$ make their investment decisions $J_{-i,t}$ to maximize their value function such that

$$J_{-i,t}(C_t, \Omega_t, \bar{I}_{i,t}) = \max - \phi(I_{-i,t}) + \Pi_{-i,t}(C_t, \Omega_t) + \beta E_t[V_{-i,t+1}(C_{t+1}, \Omega_{t+1})],$$

where

$$C_{t+1} = (C_t, \bar{I}_{i,t}, J_{-i,t}),$$

that is, the market capacity in the next period is the market capacity in the current period and investment decisions made in this period.

The firm i's Bellman equation can be rewritten as

$$\begin{aligned} V_{i,t}(C_t, \Omega_t) &= \max_{I_{i,t}} - \phi(I_{i,t}) + \Pi_{i,t}(C_t, \Omega_t) \\ &\quad + \beta E_t[V_{i,t+1}(\underbrace{(C_t, I_{i,t}, J_{-i,t}(C_t, \Omega_t, I_{i,t}))}_{C_{t+1}}, \Omega_{t+1})]. \end{aligned}$$

And the competitors' Bellman equation can also be rewritten as

$$\begin{aligned} V_{-i,t}(C_t, \Omega_t) &= \max_{J_{-i,t}} - \phi(I_{-i,t}) + \Pi_{-i,t}(C_t, \Omega_t) \\ &\quad + \beta E_t[V_{-i,t+1}(\underbrace{(C_t, I_{-i,t}, J_{i,t}(C_t, \Omega_t, I_{-i,t}))}_{C_{t+1}}, \Omega_{t+1})]. \end{aligned}$$

It can be seen that the value functions are related by $(J_{i,t}, J_{-i,t})$. And firms' reaction functions are

$$\begin{aligned} I^*_{i,t} &= J_{i,t}(C_t, \Omega_t, I^*_{-i,t}), \\ J_{-i,t}(C_t, \Omega_t, I^*_{i,t}) &= I^*_{-i,t}. \end{aligned}$$

The intersection of these two reaction functions would give firms the optimal investment choices $(I^*_{i,t}, I^*_{-i,t})$.

From the above derivation we can see that to solve for $(J_{i,t}, J_{-i,t})$, we first have to solve $(V_{i,t+1}, V_{-i,t+1})$; to solve for $(V_{i,t+1}, V_{-i,t+1})$, we have to solve $(J_{i,t+1}, J_{-i,t+1})$ first; and so forth. As discussed earlier of using discounted profit earned from the last planning period to be the salvage value $S_i(C_{t+H}, \Omega_{t+H})$ as the ending point, we can solve the model backward from the period before the last period $t + H - 1$, such that,

$$V_{i,t+H-1}(C_{t+H-1},\Omega_{t+H-1}) = \max_{I_{i,t+H-1}} \; -\phi(I_{i,t+H-1}) + \Pi_{i,t+H-1}(C_{t+H-1},\Omega_{t+H-1}) + \beta E_{t+H-1}[S_i(C_{t+H},\Omega_{t+H})],$$

then solve the previous period such that,

$$V_{i,t+H-2}(C_{t+H-2},\Omega_{t+H-2}) = \max_{I_{i,t+H-2}} \; -\phi(I_{i,t+H-2}) + \Pi_{i,t+H-2}(C_{t+H-2},\Omega_{t+H-2}) + \beta E_{t+H-2}[V_{i,t+H-1}(C_{t+H-1},\Omega_{t+H-1})],$$

until the first period t such that,

$$V_{i,t}(C_t,\Omega_t) = \max_{I_{i,t}} - \phi(I_{i,t}) + \Pi_{i,t}(C_t,\Omega_t) + \beta E_t[V_{i,t+1}(C_{t+1},\Omega_{t+1})].$$

The detailed estimation steps are described below,

1. List all the possible market conditions and market capacity conditions for each period.

   For example, as described in the simulation section, in the last period, each incumbent can have five capacity conditions: no investment, 20% investment, finish the first investment, add 20% investment, finish two investments. Each entrant has 13 conditions because they can choose the technology in which to invest. But in the second period, incumbents can have three possible capacity conditions: no investment, 20% investment, finish the first investment, while entrants have seven choices. Market conditions include different demand growth pattern, possible fuel price, etc.

   A sample table containing possible states (market condition only includes demand) looks like Table 3.5. The first three lines have the same market capacity: the first incumbent spends 20% of its capital investment in natural gas while the second incumbent does not make any investment; the first entrant builds 20% of the first investment on wind while the second entrant builds 20% of the first investment on natural gas. The difference in the first three lines is the demand growth condition: median, low, and high demand growth in each state respectively. In the fourth state, first incumbent makes two new natural gas investments and the first entrant makes one new investment in coal. The last example has the second incumbent makes one complete investment and 20% for the second investment in natural gas, the first entrant also makes one investment in wind and 20% for the second. For the last two states, demand growths are all median growth. Demand growth can be replaced by fuel price, policy, etc.

State	**Demand**	**Incumbent 1**	**Incumbent 2**	**Entrant 1**	**Entrant 2**
1	median	0.2	0	0.2(w)	0.2(ng)
2	low	0.2	0	0.2(w)	0.2(ng)
3	high	0.2	0	0.2(w)	0.2(ng)
4	median	2	0	1(c)	0
5	median	0	1.2	1.2(w)	0

Table 3.5: Possible Spot Market Simulation States

2. Calculate all of the possible annual spot market profits for each firm under different market conditions and market capacity conditions.

3. Calculate firms' salvage value by using all the possible last period $(t+H)$ profits $\Pi_{i,t+H}(C_{t+H}, \Omega_{t+H})$.

4. Calculate values for all of the possible market conditions and market capacity conditions for each firm in period $t + H - 1$ by using the following equation,

$$
\begin{aligned}
V_{i,t+H-1}(C_{t+H-1}, \Omega_{t+H-1}) = \quad & \max_{I_{i,t+H-1}} - \phi(I_{i,t+H-1}) \\
& + \Pi_{i,t+H-1}(C_{t+H-1}, \Omega_{t+H-1}) \\
& + \beta \sum_{C_{t+H}, \Omega_{t+H}} S_i(C_{t+H}, \Omega_{t+H}) \times Pr(\Omega_{t+H}),
\end{aligned}
$$

where $Pr(\Omega_{t+H})$ is the probability distribution for market condition.

5. Calculate backwards until the values in the first period $V_{i,t}$ are solved.

6. Simulate the firms' optimal investment behavior from the first period to the last period by randomly drawing market conditions.

3.6 Simulations and Results

Based on the process described in the estimation section, the first step is to calculate spot market equilibrium and spot market profit for each firm under every market condition.

The time lag for a new plant is 2 years. That is, in the first year, firms make the initial 20% investment. During the second year, firms could choose to finish their investment. During the third year, if the plant is finished, they can start earning profit and decide whether to make another new investment. So in the simulation period, a firm can build up to 2 new plants.

I assume there are 4 players in the market, two firms are incumbents and two firms are entrants. For the 2 incumbent firms, they can only choose to invest in more natural gas generators or not. So in 4 years, their choice set is (spend 20% of first investment, invest 1 natural gas, spend another 20% of second investment, invest 2 natural gas, no investment). As each incumbent has 5 choices, there could be $5^2 = 25$ scenarios for incumbents making investment decisions. For 2 entrants, they can choose from three technologies: coal, natural gas, wind or not enter. In the simulation period, their choice set is (invest 0.2 coal, invest 1 coal, invest 1.2 coal, invest 2 coal, invest 0.2 natural gas, invest 1 natural gas, invest 1.2 natural gas, invest 2 natural gas, invest 0.2 wind, invest 1 wind, invest 1.2 wind, invest 2 wind, no investment). These 13 cases give entrant firms $13^2 = 169$ supply scenarios. Therefore, there are a total of $25 * 169 = 4225$ market capacity scenarios.

From the demand side, three possible demand changes per year could occur and nine demand growth patterns in 4 years. For 5 demand level, this gives $5 * 9 = 45$ possible demand conditions.

Simulating these market capacity scenarios over 45 demand conditions would bring $4225 * 45 = 190125$ simulated spot market equilibria. Under each market equilibrium, I calculate market equilibrium price and profit for each of the four firms.

With the profits for all the possible states, I calculate firms' salvage values and back up firms' investment decisions as introduced earlier.

In the simulation, I have several scenarios to calculate and compare, which are listed in Table 3.6:

The first scenario is the base case. The subsidy for renewable energy is $30/MWh. The only uncertainty that firms face is the demand growth, that is, it could be a low growth, median growth, or high growth next period with equal probability. Both incumbent firms and entrants make new investment decisions. Entrants also pick the technology in wihch they invest. Based on this setup, the simulation result is

Scenarios	Detail
Base Case	Only with demand uncertainty
Fuel Price Uncertainty	Fuel price uncertainty and demand uncertainty
Regulatory Uncertainty	Regulatory uncertainty and demand uncertainty
Demand Uncertainty	Increase demand uncertainty
New Policy	A policy that differentiates the carbon intensity

Table 3.6: List of Simulation Scenarios

in Table 3.7. Suppose the demand increases at a medium speed each period, for two incumbent natural gas firms, the first firm would make two new investments during the simulation period, while the second incumbent firm would make one new investment in the third period. While the 2 entrant firms would pick up wind as the invested technology and build up 2 new plants, that is, make the initial 20% of the investment in the period 1 (which is shown as 0.2 in Table 3.7) and finish the first investment in the period 2; make another 20% of the investment in the period 3 and finish it in the last period. Therefore, the result implies that the optimal future investment choice would include building up more natural gas firms and wind farms.

Year	Demand	Incumbent 1 Natural Gas	Incumbent 2 Natural Gas	Entrant 1 Wind	Entrant 2 Wind
Year 1	median	0.2	0	0.2	0.2
Year 2	median	1	0	1	1
Year 3	median	1.2	0.2	1.2	1.2
Year 4	median	2	1	2	2

Table 3.7: Base Case Result

The second scenario simulates the firms' behavior with the uncertainty of the future natural gas price. Instead of fixed natural gas price in all 4 years, I allow natural gas price to be at three levels: high, middle, and low with value: 0.014, 0.0075, and 0.001 ($/Btu) with respectively equal probability each year. Every year is independent, for example, in the first year, the price could be high, and in the second year, it has 1/3 probability changing to other levels. All the other factors, such as subsidy, demand, are the same as the base case.

The simulation result is in Table 3.8. With the median natural gas price realization in each year, which is the same fuel price as in the base case, the simulation results are different from the base case. With the uncertainty in the fuel price, while the two entrant firms still pick up wind as the new invested technology and built up two wind farms in 4 periods, only the first incumbent natural gas firm would make two new investments in the 4 periods and the second incumbent firm would make no new investment. The uncertainty from fuel price stops the incumbent firm's investment behavior.

Year	**Demand**	**Fuel**	**Incumbent 1**	**Incumbent 2**	**Entrant 1**	**Entrant 2**
			Natural Gas	**Natural Gas**	**Wind**	**Wind**
Year 1	median	median	0.2	0	0.2	0.2
Year 2	median	median	1	0	1	1
Year 3	median	median	1.2	0	1.2	1.2
Year 4	median	median	2	0	2	2

Table 3.8: Fuel Price Uncertainty

Next simulation will add in regulatory uncertainty which mimics the current uncertainty of PTC expiration and renewal. Aside from the demand uncertainty in the base case, wind farms can now receive either a total subsidy of the original \$30/MWh or just \$1/MWh with equal probability in the next period. Table 3.9 shows that this regulatory uncertainty does delay the second wind farms' investment, that is, after the initial 20% investment in the first period, the investment is delayed until the last period.

Year	**Demand**	**Incumbent 1 Natural Gas**	**Incumbent 2 Natural Gas**	**Entrant 1 Wind**	**Entrant 2 Wind**
Year 1	median	0.2	0	0.2	0.2
Year 2	median	1	0	1	0.2
Year 3	median	1.2	0.2	1.2	0.2
Year 4	median	2	1	2	1

Table 3.9: Regulatory Uncertainty

The fourth scenario is to change the demand uncertainty. Instead of equal probability of low, medium, high demand growth, I change the probability to (0.475, 0.05, 0.475) to increase uncertainty. With higher uncertainty, the value of delaying investments until some of the uncertainty has been resolved should increase (Dixit & Pindyck 1994). The result is in Table 3.10. Only the first incumbent firm would make one new investment while entrant firms' optimal choices are still investing two new wind farms.

The last scenario is a new policy that differentiates carbon intensity. In this case,

Year	Demand	Incumbent 1 Natural Gas	Incumbent 2 Natural Gas	Entrant 1 Wind	Entrant 2 Wind
Year 1	median	0.2	0	0.2	0.2
Year 2	median	1	0	1	1
Year 3	median	0	0	1.2	1.2
Year 4	median	0	0	2	2

Table 3.10: Demand Uncertainty

both natural gas and wind firms would receive subsidy every year. Natural gas firms receive \$10/MWh, wind farm subsidy is \$20/MWh. Compared to the base case, incumbent natural gas firms would make two new investments under the new policy which is shown in Table 3.11.

Year	Incumbent 1 Natural Gas	Incumbent 2 Natural Gas	Entrant 1 Wind	Entrant 2 Wind
Year 1	0.2	0.2	0.2	0.2
Year 2	1	1	1	1
Year 3	1.2	1.2	1.2	1.2
Year 4	2	2	2	2

Table 3.11: New Policy

Table 3.12 shows the policy comparison result for reducing carbon emission. Based on the information provided by the EPA, the average carbon emission rate in the United States from natural gas-fired generation is 1135 lbs./MWh of carbon dioxide, while the average carbon emission rate in the United States from coal-fired generation is 2249 lbs./MWh of carbon dioxide.

Under these two policies, the carbon emission is 44939 tons under original policy, which just subsidizes wind $30/MWh, and 44726 ton under the new policy, which subsidizes both wind and natural gas; the subsidy provides $616648.5 and $595603.5 respectively. Compared to the market with no policy, the cost of reducing carbon is $132/ton for original RPS and $122/lb for the new policy. Proving the new policy, which differentiates the carbon intensity, is more cost efficient in terms of reducing carbon.

Policy	**Carbon Emission(ton)**	**Subsidy ($)**	**Cost ($/ton)**
No Subsidy	49585		
Original policy	44939	616648.5	132
Modified policy	44726	595603.5	122

Table 3.12: Policies Comparison

It is noted that the subsidy reduction is not much under the new policy. This is because under my setting, the marginal cost of natural gas plants is much higher than coal. Even with the $10/MWh subsidy, most natural gas plants' marginal cost cannot be lowered to be below coal plants' marginal cost. This means that under the new policy, the production reduction from coal is very small while the production increase from natural gas is also not big. Therefore, the subsidy is reduced to in a small amount. On the other hand, this number is scalable under some circumstances. The simulated policy is just for Texas. If it were a national policy, this subsidy reduction could be much larger; if the policy requires higher renewable energy capacity percentage than the current RPS policy; this reduction could also be even greater still. Besides, Texas electricity market heavily relies on natural gas while many other states mostly rely on coal. Figure 3.9 shows the electricity market supply and demand in Pennsylvania-New Jersey-Maryland(PJM) (Griffin and Puller [2005]). In this market, almost half of the natural gas plants have lower marginal cost than coal plants if they receive the $10/MWh subsidy. Under this case, the subsidy reduction could be more.

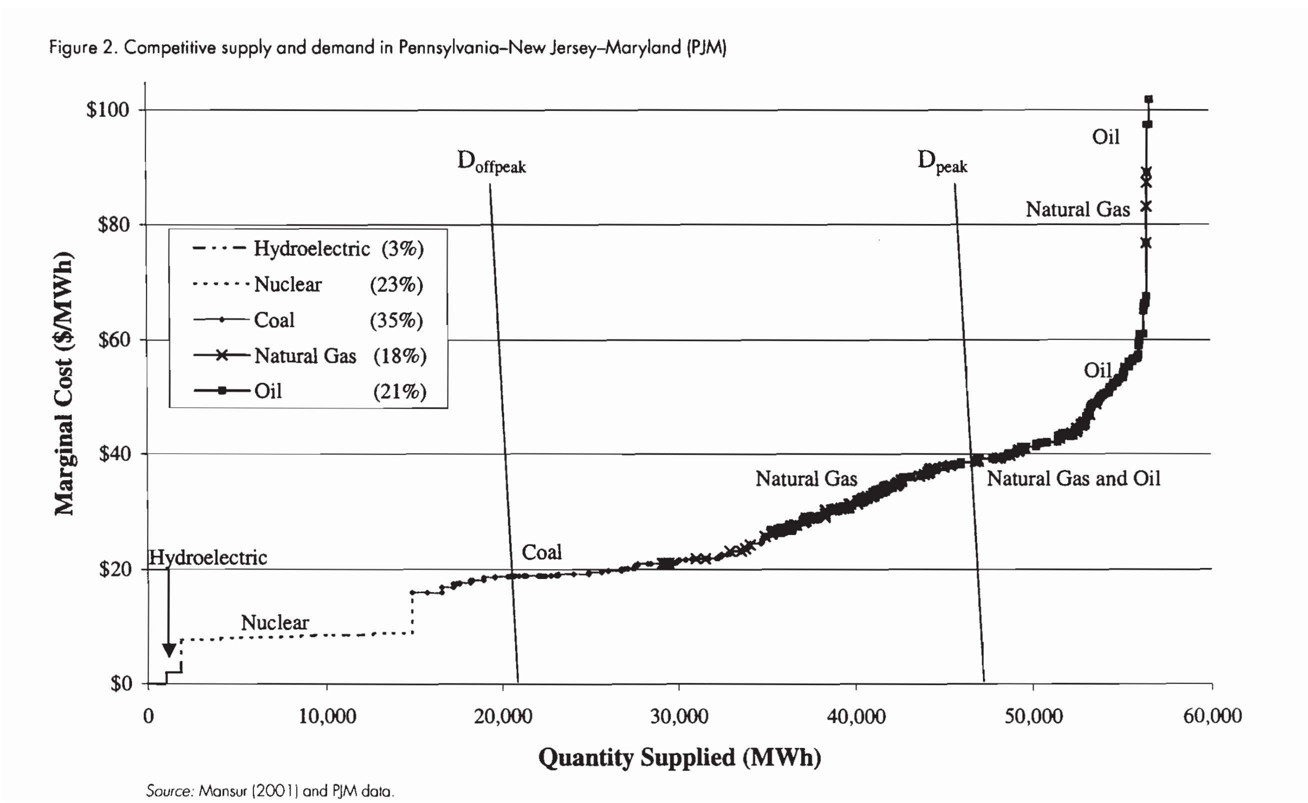

Figure 3.9: Electricity Market Demand and Supply In Other States

Source: Griffin and Puller [2005]

3.7 Conclusions and Further Development

In this paper, I follow Bushnell and Ishii [2007]'s dynamic investment model to simulate the electricity generation firms' investment behaviors by incorporating several important uncertainties firms would face: fuel price, policy, and demand. By allowing two incumbent firms and two entrant firms to make investment decisions, the results show that uncertainties play important roles in firms' decision-making process.

Besides, the model allows me to simulate a better designed renewable energy policy that differentiates energy's carbon intensity. The simulation results show that compared to the current policy, this policy could not only reduce carbon levels, but also cost less. The cost of reducing carbon is lowered by about 10%.

The limitations of my papers are as follows: first, I assume there is no transmission constraint. Second, because of the computational burden, the maximum number of new firms is limited to two. Third, during the simulation period, the firms' marginal cost remains the same. Fourth, market demand and wind speed keep the similar pattern each year in my simulation, which would likely not occur in actuality.

A more realistic investment model would include a more detailed dispatch process about generators' shutdown and startup. In this case, firms' profit maximization problem would include the startup cost. By adding in the dispatch process, it would give the possibility to calculate how the wind intermittency problem would have an impact on other types of technologies and how wind farms' choices of location could reduce the intermittency problem.

Also, a fuller model would include the trading market for REC. Although recent REC price is very low, adding in the REC trading market into the model would give a constraint to the level of renewable energy capacity and endogenize the subsidy.

CHAPTER IV

CONCLUSIONS

In the first chapter, I follow Giulietti et al. [forthcoming]'s sequential search model. I improved the model by taking product level differentiation into consideration to estimate the search cost. The model first homogenizes the electricity retail price and then estimate the search cost by using the sequential search model. Both product differentiation and search cost explain the price dispersion. Results show that about half of the price dispersion could be explained by product differentiation. The magnitude of search cost is big, on average, consumers search only one time. The counter-factual experiment shows that reduced search cost could make the market more competitive by reducing both market average price and price dispersion.

In the second chapter, I follow Bushnell and Ishii [2007]'s dynamic investment model to simulate electricity generation firms' investment behaviors by incorporating several important uncertainties firms would face: fuel price, policy, and demand. When allowing two incumbent firms and two entrant firms to make investment decisions, the results show that uncertainties play important roles in firms' decision-making process.

This model allows me to simulate a better designed renewable energy policy that differentiates energy's carbon intensity. The simulation result shows that compared to the current policy, this policy could not only reduce more carbon, but also cost less. In total, the proposed policy could lower the cost of reducing carbon emissions by approximately 10%.

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