Essays in energy economics and industrial organization

Xueting Wang

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Abstract

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In chapter 1, I study long term contracts in retail electricity markets. Deregulation of retail electricity markets gives consumer choices over contracts of different lengths. Long term contracts allow consumers to hedge against future price increase, but they can be more expensive than spot contracts. There is little empirical evidence on how consumers value long term contracts. Using a dataset from an incumbent retailer containing 10-year panel of consumer contract choice data, this paper analyzes consumers' valuations of long term contracts. I first document that a significant percentage of consumers actively choose long term contracts when they are more expensive than shorter contracts. To quantify the value of long term contracts and welfare implication of product innovation after retail deregulation, I build and estimate a dynamic model that incorporates risk preference, price expectations and consumer inertia. Counterfactual calculation shows that on average consumers gain about 6% per month from long term contracts. In chapter 2, I quantify the effect of introducing large-scale renewable energy on the wholesale electricity market. Renewable energy capacity has increased in many markets as renewable is crucial to reduce emission in the energy sector. More than 8GWh of wind capacity has been added in Texas between 2014 and 2017. Using hourly data from Texas, I find increasing daily wind energy production results in statistically significant reduction of wholesale electricity price for all hours of the day except 10pm, and the effect is larger during peak hours. Increasing wind production reduces output from both coal and natural gas power plants. Using hours when no

transmission limit is binding and load is above 50th percentile in the load distribution, I find increasing hourly wind production reduces offer prices submitted by owners of fossil fuel power plants.

In chapter 3, I study the effect of transmission limit on market outcomes. Wholesale electricity markets are often subject to transmission constraints that prevent efficient dispatch of power. Increasing renewable capacity demands transmission infrastructure investment. In 2011 to 2013, Electricity Reliability Council of Texas (ERCOT) constructed several high voltage transmission lines from the wind-rich west Texas to demand centers. Using data on electricity production, demand, price and information on grid congestion, this paper shows that an increase of 100MW in the transmission limit from the West to the North reduces the hourly output of fossil fuel generators in the North by 71.1MWh and decreases the price in the North by 0.17$/MWh when the transmission constraint from the West to the North is binding. Meanwhile, the increase of the transmission limit reduces dispatch of coal and combined cycle gas power plants in the North, but increases production of simple cycle and steam gas power plants in the North.

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Chapter 1: Long term contracts in retail electricity

1.1 Introduction

Deregulation of retail electricity gives consumers the opportunity to select from a menu of contracts offered by retail electricity providers to meet their electricity consumption needs. While there is hope that deregulation of retail electricity could spur production innovations like what happened in telecommunication, electricity, as a physically homogeneous good, has much narrower range of products and services that could be offered. Most product innovation in retail electricity market occurs in financial arrangements including design of price and payment plans and bundling of purchases with complementary products[1] (Borenstein & Bushnell, 2015).

While deregulation gives large industrial consumers opportunities to participate directly in the wholesale market and get contracts catered for their specific needs, the major product differentiation residential and small business consumers see is contracts of different lengths. Wholesale electricity prices can be volatile, and long term contracting allows risk sharing between the electricity retailer and end consumer. When longer term contracts are more expensive than shorter contracts, consumers face a trade-off between paying less in the current month and potentially higher price and volatility in the future.

The goal of this paper is to understand how consumers trade-off price and risk exposure and to quantify the value of long term contracts and retail choice. Increasing penetration of intermittent renewable energy into the grid can potentially raise wholesale price volatility, which increases the volatility of consumers' electricity bill and retailers' cost. How this risk should be shared optimally depends on consumer's risk preference. Therefore, it is important to understand how consumers trade off price and risk exposure. Additionally, there have been policy debates on whether retail

[1] Bundling of renewable electricity with a electricity purchasing contract is very common in retail electricity market.

choice should be extended to small consumers. Since contract length is a major product differentiation for small consumers in deregulated retail electricity markets, studying consumers' valuations of long term contracts provide evidence on whether and how much small consumers have gained from deregulation in retail electricity market and how regulations that potentially restrict long term contracts affect consumer welfare.

To study consumers' risk preference and valuation of long term contracts, this paper develops and estimates a dynamic discrete choice model of electricity contract choice. Building on previous models of retail electricity contract choice, the model adds consumers' risk preference and their dynamic decision choosing between contracts of different lengths. The model can be applied to choice over electricity contracts in other markets and choice situations when contract length is an important characteristics.

The data used in this paper is a 10-year panel of residential consumer's plan choice data of a dominant retailer in a deregulated electricity market. It offers several advantages. First, a unique feature of the setting is the company is both the incumbent provider that offers the regulated rate and several unregulated contracts with different lengths. All consumers were defaulted to the regulated rate by the incumbent at the start of deregulation. Having the same retailer offering both the regulated rate and unregulated contracts allows me to separate preference for contracts from brand preferences. Second, in this market, more than 60% of households have selected an alternative contract other than the regulated rate, as opposed to many other markets in which the majority of consumers do not switch. Observing the majority of consumers moving away from the regulated rate helps to identify their preference over contracts. Additionally, having a long panel of consumer choice data allows me to observe more choices from the same consumer over time. More than 20% of households have actively selected at least two unregulated contracts from the incumbent retailers during the 10 year period.

I start by providing evidence that some consumers value price guarantee provided by long term contracts. First, I show that a significant percentage of consumers sign up for a longer term contract when its current price is higher than short term contracts. Second, some consumers renew their long term contracts prior to the expiration date under the same price. By doing so, consumers increase the length of price guarantee under the same rate. Moreover, the number of consumers doing this is positively correlated with the monthly spot contract price. This shows that consumers are forward looking and value longer price protection.

Overall, the reduced form evidence suggests that consumers value price protection offered by long term contracts. Motivated by this evidence, I develop and estimate a dynamic model of electricity contract choice. The model enables estimation of consumer's risk aversion and preference for contracts using the variations of contract prices and available products in the data. Additionally, the model allows me to study the effects of counterfactual design of regulations that remove retail choice and long term contracts for small consumers.

In the model, it is important to take into account consumer inertia. In the data, there is clear presence of consumer inertia because there is an unregulated plan that is cheaper and has the same contract length as the regulated rate but many consumers were still on the regulated rate for a long time. Without incorporating consumer inertia into the model, consumers are assumed to choose a contract every month, and would appear to like the more expensive contract due to inertia.

I model the consumer's decision in two stages. In the first stage, there is a fixed probability that a consumer is going to become active in choosing an electricity contract. Conditional on being active, each consumer chooses an electricity plan each month maximizing the sum of discounted expected utility. Each electricity plan is characterized by its price, contract length and whether it is the regulated plan. The value of longer term contract comes from consumers having access to the contract rate as long as the contract is not expired. When a contract expires, consumers are exposed to prices available at that time. By assuming a CRRA utility function, I allow the consumers to be risk averse.

The model is estimated using consumer-level plan choice data of about 400,000 consumers between 2009 and 2019. The data contains information on an account ID that tracks a consumer over time, the contracts signed, start date, end date, price, length and name of the plan. Large variation in the monthly spot contract price, change in volatility and introduction of new products of different contract lengths over time help to identify consumer's risk preference and valuation of different contract lengths. Also, the presence of an unregulated plan that has the same length as the regulated plan with a fixed discount help to separately identify consumer inertia.

I find that consumers are risk averse, and have low probability of re-optimizing their electricity contract choice each month. I use the estimated model of consumer's contract choice to perform counterfactual analyses that investigate how much alternative regulatory policies change consumer choice and welfare. The first counterfactual analyzes the impact of introducing consumer choice for small consumers in the retail electricity market. I calculate the change in consumer surplus comparing the current situation with retail choice and the case when only the regulated rate is available. Deregulation gives consumer access to new products and potential savings from unregulated contracts compared to the regulated rate but consumers have inertia that can diminish the gains. Holding the regulated rate unchanged, on average consumers gain about 10% of a typical consumer's monthly electricity bill with retail choice.

In the second counterfactual, I calculate how consumer surplus changes if long term fixed rate contracts are removed from consumer's choice set. Consumers now only have two choices: the regulated rate and the unregulated monthly contract. The change in consumer welfare provides a measure of the value of long term contracts and it relates to a policy that requires guaranteed savings of unregulated contracts compared to the regulated rate. If guaranteed saving is required, retailers may decide not to offer long term fixed rate contracts since these contracts may have premium compared to the regulated rate. If both the regulated rate and the unregulated one-month contract price do not change in the counterfactual scenario, on average consumer's welfare gain is about 6% of a typical consumer's monthly electricity bill.

This paper contributes to two different strands of the literature. First, it contributes to the literature that studies the effects of deregulation in retail electricity market. Recent literature has generally found ambiguous or positive effects of deregulation on retail price (Dormady et al., 2018; MacKay & Mercadal, 2019; Su, 2015) except Hartley et al. (2019). The literature also documented the presence of large consumer inertia of consumer contract choice (Dressler & Weiergraeber, 2018; Hortacsu et al., 2017; Vesterberg, 2018). Concerning the effect of product innovation after deregulation, Dressler and Weiergraeber (2018) found very low average willingness to pay for green electricity contracts but there is large variance. Using a dynamic random-effect probit model and a panel of Swedish household, Vesterberg (2018) found very strong state dependence of contract choice, and the prices of fixed and variable contracts have a small but significant effect on the probability of choosing a fixed rate contract. Goett et al. (2000) used stated choice experiment from 1205 commercial and industrial consumers, and found on average consumers dislike being locked into long term contracts. Ndebele et al. (2019) conducted a stated choice experiment of electricity contract choice for a sample of 224 residential consumers including length of fixed rate as a product attribute, and found consumers can be classified into different classes with different preferences over fixed rate contracts. This paper adds to the literature by developing a dynamic discrete choice model that links consumers' preference over different contract lengths to the degree of risk aversion and price expectations in a structural way, which enables the calculation of consumer surplus changes with changing product availability due to deregulation.

Second, this paper also relates to the literature on long term contracting. The literature has pointed out the existence of transaction cost (Gray, 1978; Masten, 2009) and risk sharing (Danziger, 1988; Holmstrom, 1983; Hubbard & Weiner, 1992; Polinsky, 1987) as motivations of signing long term contracts. In retail electricity market, consumers have inertia, so the retailer and consumer enters into long term contracts to specify future electricity prices. Polinsky (1987) derived theoretically that from the buyer's perspective fixed price contract is preferred with respect to supply-side uncertainty as it insures the buyer against this source of risk. Hubbard and Weiner (1992) showed theoretically that buyers are willing to accept fixed price contracts that are more expensive than spot price when all shocks are cost side shocks, and in market equilibrium fixed price contracting takes place if only the buyers are risk averse and uncertainty stems form the cost side. This paper shows empirically that long term contracts with different lengths of price guarantees can coexist, and when buyers are risk averse and uncertainties are from the electricity production cost, buyers and sellers can enter into long term fixed price contracts.

1.2 Institutional Background

When retail electricity is regulated, all consumers in a distribution area are served by one utility, and the rate consumers pay is regulated by the government. A distribution area is a geographical area where the transmission and distribution grid is managed by one company. One state or province can have several distribution areas. When the retail electricity market is deregulated, retail choice is introduced. Retailers can purchase electricity from the wholesale market or generate electricity from their own generators. Electricity retailers can offer multiple plans that differ in price, length of contract and source of electricity (e.g. green energy).

In the market under study, the company is the incumbent retailer in one of the distributional areas in the province. It offers both the regulated plan in that distribution area and unregulated plans to all consumers in the province. In its own distribution area, the company captures 85% to 90% of all residential and small commercial consumers from 2009 to 2019 including both consumers on the regulated rate and unregulated contracts (Figure 1.2). The price of the regulated rate is regulated by the government based on procurement cost and regulated profit margin. The retailer's procurement plan of electricity for the regulated rate must be approved in advance by the government and the price of the regulated rate is published on the first day of every month. Deregulation of retail electricity market started in 2002, and all consumers were assigned to the regulated rate at the start of deregulation. Consumers can leave the regulated rate and choose an unregulated contract free of charge. Companies can freely choose prices for unregulated plans, and can change price, add and remove products any time they want. In other distribution areas, the company's market share varies widely between 5-40%. Besides contract price, the primary product differentiation is contracts with different lengths of price guarantee[2]. The incumbent regulated plan is a monthly contract, so price the next month can be different from the current month. The incumbent retailer also offers several plans with longer term fixed rate contracts (Figure 1.1)[3]. One notable feature is customers can leave the contract any time without monetary penalty. For example, consumers sign

[2]The incumbent provider also offers the option to buy "Green Add-ons" in addition to regular contracts, but less than 1% of consumers have chosen the option.

[3]Other retailers also offer contracts of different lengths

- Regulated rate: everyone was defaulted to this plan at the start of deregulation; price varies month by month and is regulated by the government
- Unregulated contracts
  - One month contract: Price can change month by month. Matched the regulated rate before June 2012 and after 2015. The price was based on a monthly weighted average of wholesale electricity price between June 2012 and 2015.
  - Contract length of 1,3 and 5 years with fixed rate; no early termination fee[a]
  - $100 reward each year if sign up for any unregulated electricity contract and any unregulated natural gas plan together before July 2014[b].

[a]About 1% consumers have signed a 2 year contract at some point, which is not offered on the company's website, so I exclude the consumers who have ever signed a 2 year contract from the estimation.

[b]The regulated gas plan is a regulated monthly variable rate plan. The company offers both unregulated variable and fixed rate plans for natural gas. The unregulated variable gas rate is comparable to the regulated gas rate.

Figure 1.1: Description of plans offered by the incumbent retailer

up for a 6 cents/kwh 1-year plan can choose to change to other contracts before the contract end date without paying extra fees, but once they leave, they cannot go back to the original price of 6 cents/kwh if the price of 1-year contract has changed.

When consumers sign up for a new retailer, they enter a financial contract with the retailer. The transmission and distribution sector remains regulated, so customers in the same distribution area have the same price schedule for delivery fees, and the wires are maintained and upgraded by the distribution company that is separate from retailers. Therefore, the reliability of electricity itself is not related to the consumer's retailer. The electricity received by all customers is the same regardless of the retailer they choose.

In terms of the tariff structure, most contracts have a fixed administration fee each month and consumers pay a fixed per unit price for each unit of electricity consumed without block pricing. The similarity of tariff structures across contracts allows me to compare the prices of different contracts without worrying about different consumption levels across consumers.

The process of signing up for a new retailer or moving from regulated to an unregulated plan of the incumbent retailer usually involves filling in a short form online, via phone or mail with the

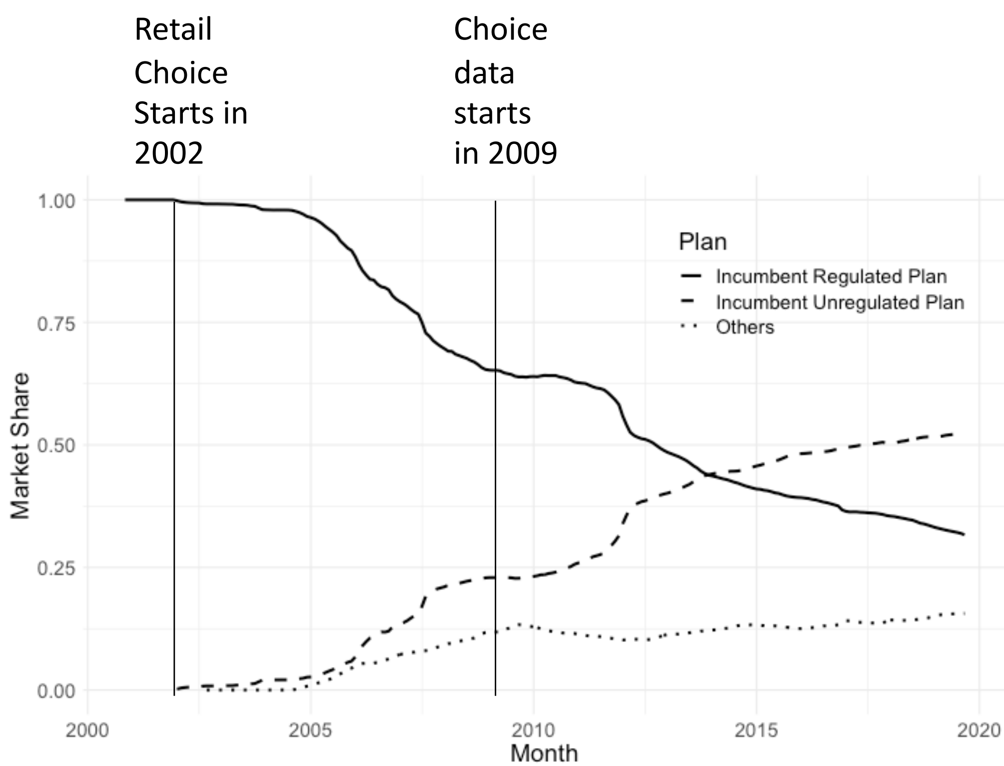

Figure 1.2: Market shares of regulated and unregulated products from 2000-2019

Notes: This figure plots the evolution of market shares of the regulated rate and the unregulated contracts from the same company and plans offered by other retailers. Market share of "Others" is the sum of market shares of all other retailers in the market.

consumer's address, electricity meter ID number and payment information. The processing time is usually 1-3 days. Once the consumer sign up for a retailer, the consumer can switch plans easily by logging in their account online and make a selection, and the change will take effect immediately.

Once signed up for a retailer, when the plan expires, if the consumer has taken no action, the customer's contract is usually renewed to a plan that is specified in the terms and conditions of the original contract. In the next section, I will describe the data in detail.

1.3 Data

Consumer choice at contract level The main dataset I use for demand estimation is a proprietary dataset of retail electricity plan choice from the incumbent retailer in a deregulated electricity market. The dataset contains all residential and small commercial customers of the company who have ever chosen an unregulated plan from 2009 to 2019, which includes about 700,000 residential consumers and 70,000 small commercial customers. There are about 400,000 residential consumers and 25,000 small commercial consumers in the company's own distribution area.[4].

I observe each customer's electricity plan choice including the name of the plan, contract length, the price they pay, the contract start day, contract end date, and the next plan the consumer enrolls in if the consumer chooses another plan within the same company[5] I am able to track the same customer's choice over time using a unique account ID. If a consumer moves to another place within the company's service area, the account number remains the same. In the subsequent descriptive and structural estimation, I assume an account is equivalent to a consumer. It is possible that a consumer has multiple accounts if they own multiple homes, so they can sign separate contracts for each home. In estimation, I remove accounts that have ever had more than one contract on the same date. Additionally, if a consumer leaves the company and come back to sign an unregulated contract later, a new account number may be created. I cannot distinguish this

[4]In the demand estimation, I only use residential consumers in the company's own distribution area as in other distribution areas, a different company offers the regulated rate and other companies' unregulated contracts have larger market shares.

[5]The regulated rate is considered as different from all unregulated contracts, so if the consumer chooses to go back to the regulated rate, the consumer's next plan is not recorded.

case from a different consumer signs up for a new contract, so I treat them as separate consumers[6].

From 2009 to 2019, the company offers the regulated rate and unregulated contracts including contracts of one month, 1 year, 3 year and 5 year (Figure 1.1). Consumers' electricity bill in a given month depends on the per unit rate specified in their contracts and their electricity consumption in the month. Table 1.1 shows that the regulated rate has large range, and can be very volatile[7]. The company provides $100 reward each year for consumers who sign up for any unregulated electricity plan together with any unregulated natural gas plan before July 2014. Survey data showed around 80% of consumers chooses the combination of electricity and natural gas from the same provider[8]. Since I don't observe people's natural gas provider choice, in the estimation, I assume people who signed up for unregulated plans before July 2014 received $100 reward each year. To reduce computational burden, I also assume the unregulated one month contract price always matches the regulated rate [9].

Limitations of the data One caveat of the data is when a consumer terminates a contract and does not choose any other unregulated contracts from the company, I do not observe the subsequent plan choice of the consumer. The consumer may have returned to the regulated rate or switch to another unregulated retailer. In the estimation, I use consumer choice data from the company's own distribution area where only 10-15% of consumers are with other retailers over the data period and the total market share of the other providers is fairly stable after 2009 (Figure 1.2), so I assume that when a consumer leaves an unregulated contract without signing up for a new unregulated contract from the incumbent, the consumer returns to the regulated rate.

Another related issue is the dataset does not contain every consumer in the company's own distribution area because some consumers never signed up for any unregulated contracts offered by the incumbent and some consumers sign up for a contract before 2009.

[6]From 2009 to 2014, only 5% of consumers have ever both leave an incumbent's unregulated contract and re-sign a new unregulated contract offered by the incumbent at a later date.

[7]I use standard deviation of past three-month regulated rate as an indicator of volatility.

[8]Some consumers live in co-op or the landlord may pay for natural gas, so they cannot choose both electricity and natural gas together.

[9]For the majority of the months in the data, the unregulated one month contract has the same rate as the regulated rate without considering the $100 reward. In some months, the unregulated one-month contract rate is calculated based on wholesale price, it followed similar trajectory as the regulated rate, but it was more volatile.

Table 1.1: Summary statistics on prices

	Min	25%	50%	Mean	75%	Max
Regulated rate (cent/kwh)	2.98	5.63	6.40	7.13	8.45	15.28
Fixed rate (cent/kwh)	5.5	5.9	6.6	6.8	8	8.9
S.D. of regulated rate	0	0.16	0.54	0.72	1.03	3.71

Notes: This table presents the distribution of prices for the regulated rate and long term fixed rate contracts. Long term contracts include 1 year, 3 year and 5 year contracts. The standard deviation of the regulated rate each month is the past 3-month rolling standard deviation.

Consumer inertia Consumers do not switch often though they have opportunity to do so every month. Among consumers on incumbent's unregulated plans, about 60% consumers never switch contracts, and about 20% do it once. A switch can be signing up for a new unregulated plan offered by the incumbent or renewing their existing plans. There is clear presence of consumer inertia in the market because the company offered an unregulated one-month plan that matched the regulated rate with $100 reward each year, but consumers only gradually moves away from the regulated rate. Hortacsu et al. (2017) found that in Texas retail electricity market, the incumbent provider has large brand premium and only about 2-3% of consumers search for alternative contracts each month. So when modeling electricity contract choice, inertia must be taken into account. If not, it will appear that consumers prefer more expensive contracts due to inertia, and the estimated consumer preferences will be biased.

Next, I present descriptive evidence on how contract length affects consumer's decision to choose an electricity contract.

1.4 Descriptive Analysis

In the descriptive analysis, I first provide evidence that consumers are forward looking and value the price guarantee offered by long term fixed rate contracts. Then I show that when longer term contracts have higher price, there is still a significant percentage of consumers actively choosing more expensive long term contracts.

1.4.1 Evidence of forward looking behavior

If consumers are myopic, they will choose a contract only based on current month prices, and the length of price guarantee does not matter. So a direct test for whether consumers value long term price protection is whether they value additional length of price guarantee. For example, if a consumer signs up for a 5 year contract in January 2010 at 8 cents/kwh, the contract will expire in January 2015. If in January 2013 the five year contract price is still 8 cents/kwh for new consumers, this consumer can "increase" the length of price guarantee by renewing existing 5 year contract, and now the 8 cents/kwh fixed rate will expire in January 2018.

Figure 1.3 shows that price of long term contracts do not change for an extended period of time. If consumers do not value longer price protection, they will not renew their contract early under the same price. On the other hand, if consumers value extra months of price guarantee, they may choose to renew early, though the contract price is the same, the price is guaranteed for longer time. The incentive to do so should increase if they see prices are likely to go up in the future.

Some contracts do get renewed early under the same price (Figure 1.3) [10]. Figure 1.4 plots the relationship between the one-month contract price and the number of long term contracts that get renewed early under the same price. High one-month contract price can suggest potentially higher future prices, so it is positively correlated with the number of long term contracts renewed early under the same price.

1.4.2 Consumers choose long term contracts when it is more expensive

Figure 1.5 shows the number of consumers that sign up for each unregulated plan each month[11] and also among the consumers that sign up for an unregulated plan each month, the percentage of consumers that sign up for each available unregulated plan given the prices of different unregulated contracts. Signing up for an unregulated plan includes consumers that switched from the regulated rate and other unregulated plans to a new plan as well as consumers renewing their existing plan.

[10] I exclude contracts that were renewed within a month of its expiration date and contracts that were renewed within one month of the first sign-up, which may be due to administrative reasons.

[11] In the following discussions, I use the number of accounts and number of consumers interchangeably.

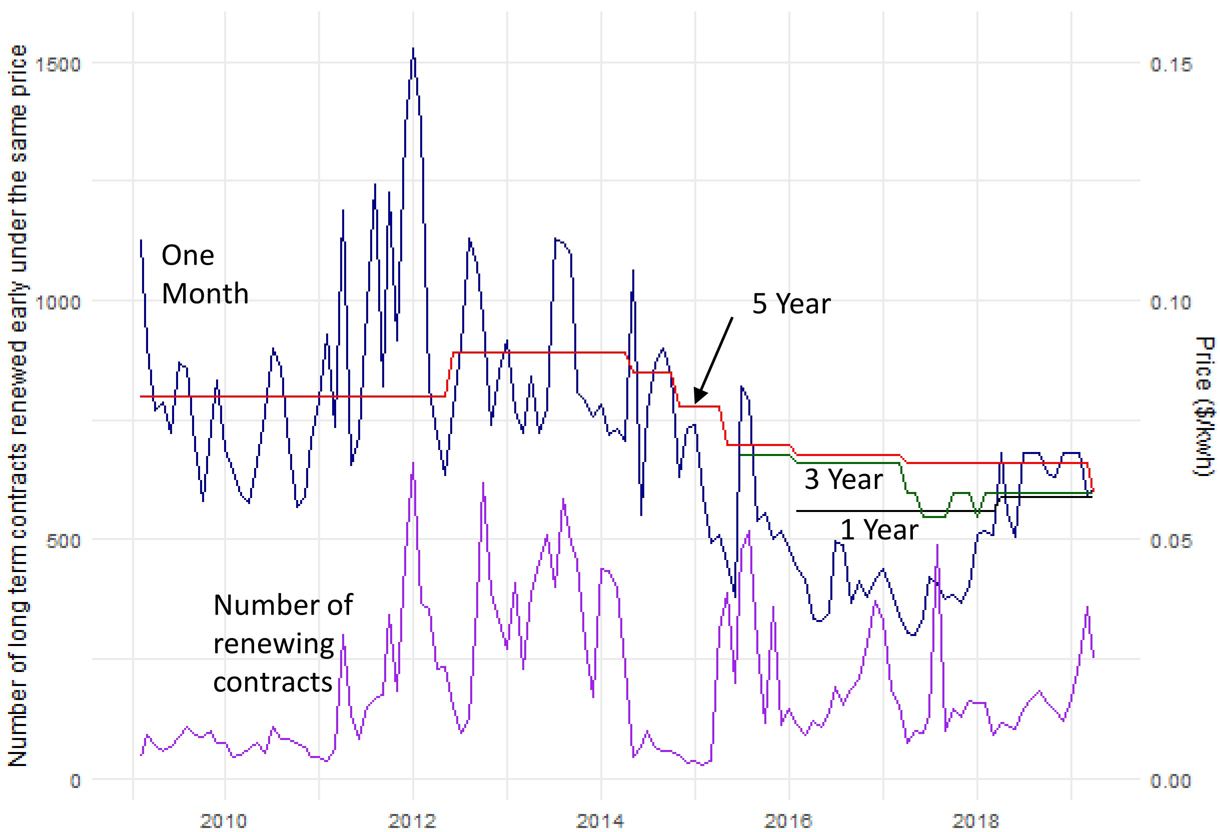

Figure 1.3: Number of contracts getting renewed early versus contract prices

Notes: This figure presents the number of long term fixed rate contracts that get renewed before its expiration date each month and the contract prices. The y-axis on the left represents the number of long term contracts, and the y-axis on the right represents the prices.

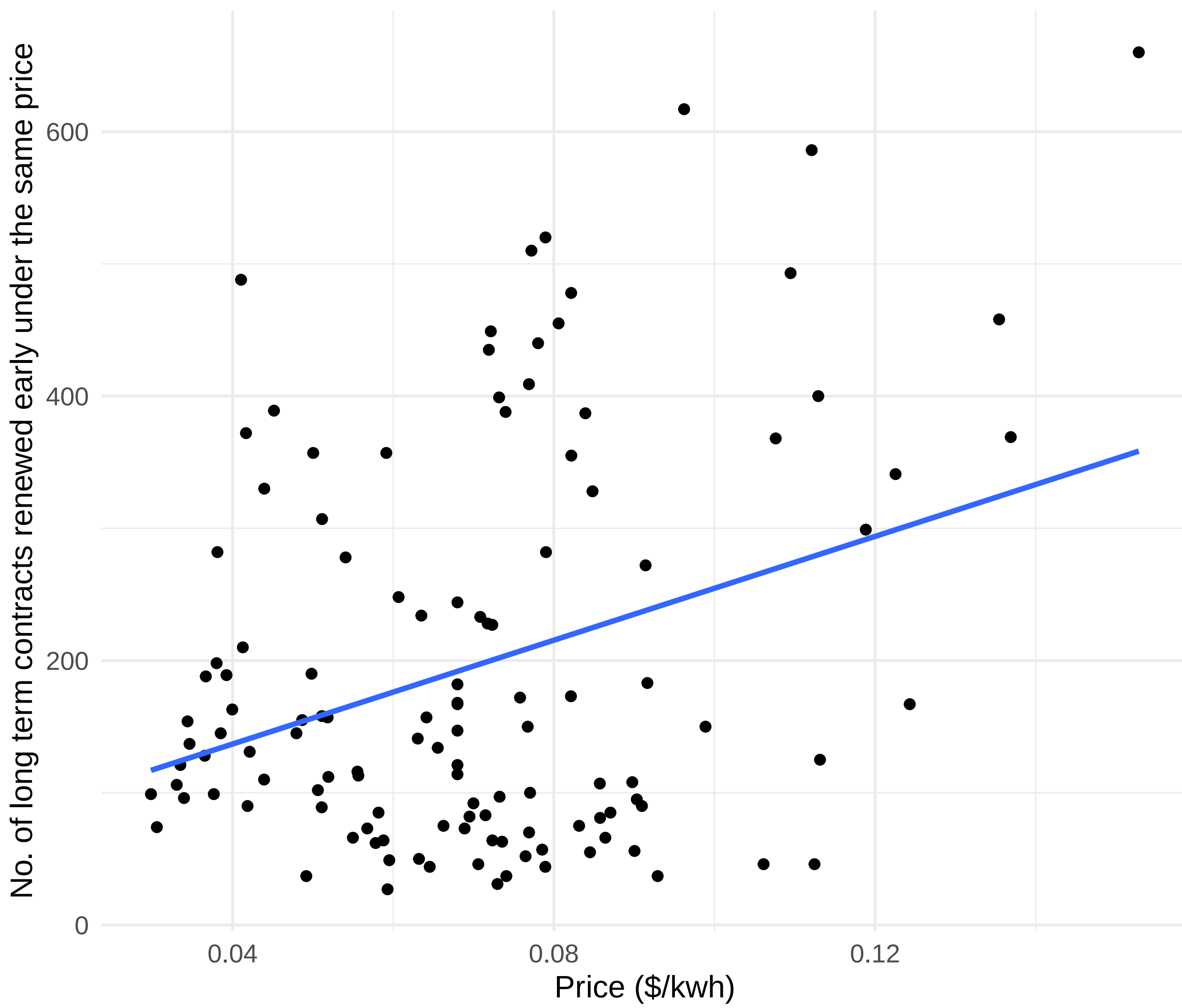

Figure 1.4: Number of contracts getting renewed early versus contract prices

Notes: This figure plots the relationship between the price of one-month contract and the number of long term contracts renewed early under the same price. The line is the fitted linear regression line.

Consumers respond to current prices when selecting a contract. When the price difference between contracts are very large, most consumers sign up for the cheaper contract. However, there is a significant percentage of consumers actively choosing a more expensive longer term contract. For example, between 2009 to 2015, when one-month contract price drops below 5 year contract price, though the number of consumers choosing 5 year contracts decreases, there is still large number of consumers choosing 5 year fixed rate. When 3 year and 1 year contracts are introduced, fewer consumers sign up for 5 year contracts. 1 year and 3 year contracts have shorter term of price guarantee, but are cheaper than 5 year contracts. So consumers are trading off between the length of price guarantee and the contract price.

The above descriptive evidence shows that consumers respond to price when they switch and they also value contracts of different lengths differently. However, as seen in Figure 1.5, at most about 8000 consumers switch each month. When the regulated rate and the unregulated one-month contract rate are over 15 cents/kwh in 2012, there were still over 50% of consumers on the regulated rate (Figure 1.2). If consumers have no inertia, everyone should switch to the 5 year contract, but among those consumers who are on the regulated rate or the unregulated one-month contract, only about 5% of those consumers made a switch.

Hence, to understand the value of the long term contracts and to compute counterfactual scenarios of not having long term contracts and not having retail choice, I develop a dynamic model incorporating consumer inertia and option value of long term contracts.

1.5 Model

This section provides an overview of the consumer choice model used in this paper. I develop a model that captures the essentials of consumer switching behavior, which is described below:

Contracts of different length: When selecting a contract, even when the price of the two contracts in the current month is the same, they can have different values because of different lengths of price guarantees. While it is possible to include contract length as a characteristics in the flow utility, the model will not be able to capture how the value of different contract lengths depends on consumer's

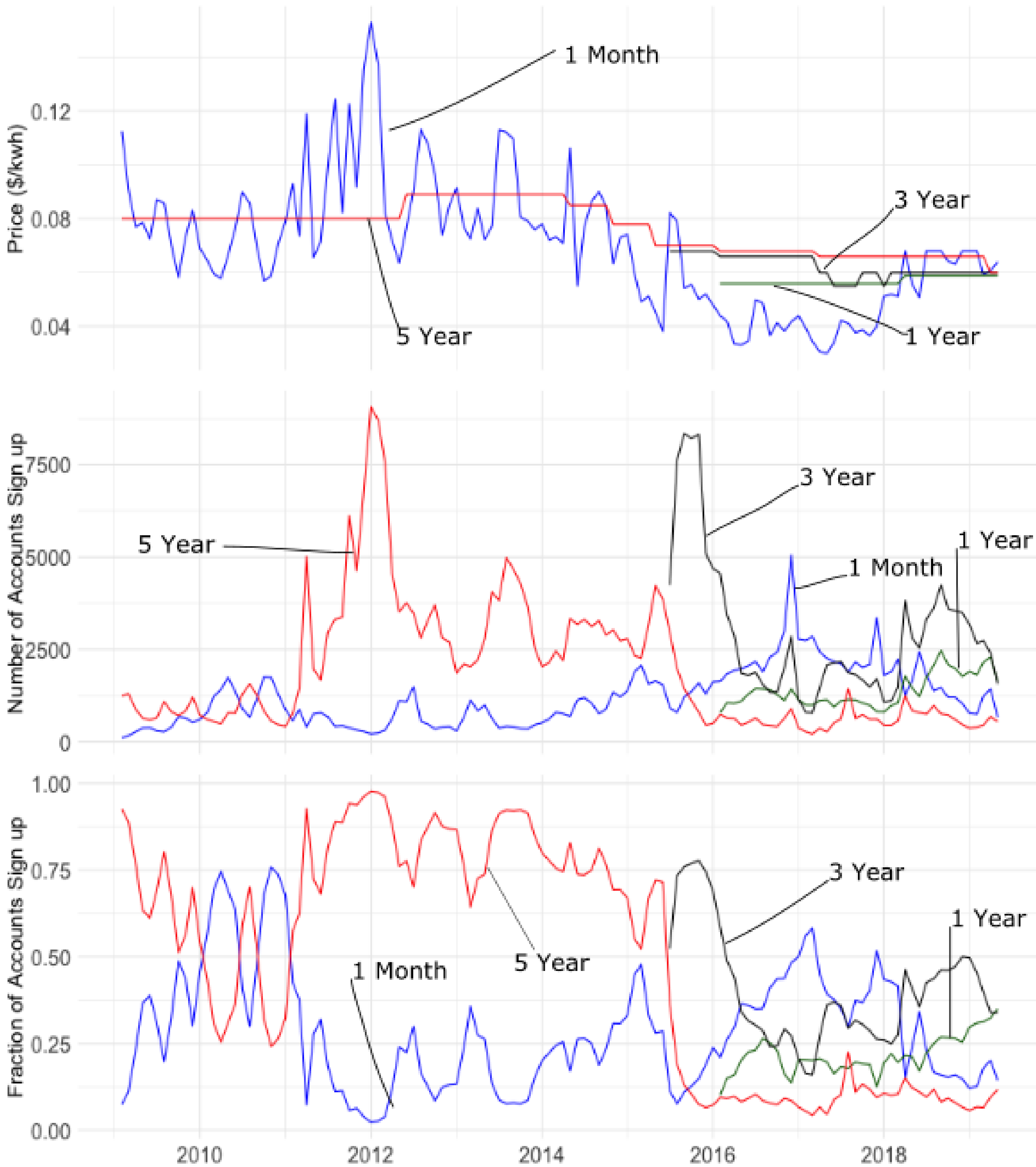

Figure 1.5: Number of consumers sign up for each plan each month versus plan prices

Notes: The top plot displays the contract prices from 2009-2019, the middle plot shows the number of consumers that sign up for each contract which include first time consumers signing up for a contract as well as renewing consumers, and the bottom plot shows that among all consumers that sign up for an unregulated plan including renewing existing unregulated plan in a given month, the fraction of consumers that sign up for each plan.

expectations of future prices and risk preference, and the counterfactual predictions will be biased. So I use remaining contract length as a state variable, and model consumer's expectations of future prices by assuming they have rational expectations of future prices.

Consumer Inertia: There are different ways to model consumer inertia. In this paper, I model consumer inertia as inattention similar to what Hortacsu et al. (2017) did in Texas retail electricity market. Consumer inertia also introduces dynamics into the model. Consumers know that they are not going to actively choose a contract every month, so when they are making a choice they are thinking about the possibility that they will be on this contract in the future too.

Choice heterogeneity: As shown in figure 1.5, when facing with the same contract offers, there are heterogeneity in consumers' choice. I capture this heterogeneity by heterogeneity in household income.

I begin by specifying the consumer's per period utility, then I describe the consumer's dynamic decision problem to choose among contracts of different lengths, and the section ends with description of the state variables and their transition processes.

1.5.1 Utility specification

The consumers' utility is comprised of consumption of the composite good and choosing an electricity contract. Consumers have CRRA utility in the consumption of composite good, and the consumption depends on the consumer's income and their electricity bill. Let γ be the coefficient of relative risk aversion, β be the preference for regulated rate, y_i be the monthly income and c be the monthly electricity consumption, the conditional indirect utility consumer i gets from choosing contract j in month t is

$$u_{ijt} = \frac{(y_i - p_j c)^{1-\gamma} - 1}{1-\gamma} + \beta reg + \xi_t + \epsilon_{ijt} \tag{1.1}$$

ξ_t is year fixed effect that captures unobserved year specific demand shocks over time. ϵ_{jt} is iid and follows iid Type-I extreme value distribution. In the per-period utility specification, besides the effect of consumption of the composite good, contracts only differ on whether it is the regulated rate or not. Although the regulated rate and the unregulated contracts are from the same retailer, people may value the regulated rate differently compared to the unregulated contracts because of the label 'regulated', and some consumers may not want to deal with unregulated contracts.

Household income y_i is not directly observed. I use the average income from three income groups corresponding to low median and high income defined as percentiles 0.2, 0.6, 0.8 of the income distribution from the census. Heterogeneity of contract choice comes from this income difference. Monthly electricity consumption c is also not observed. In the baseline specification, I use $600kwh$ per month which is about the average monthly consumption of residential consumers in this market.

One potential concern is the presence of price endogeneity. Price endogeneity can come from unobserved product quality, promotion or other demand shocks that may be correlated with the pricing decision. In this setting, since electricity itself is a homogeneous good and the contracts are from the same company, unobserved quality is not a big concern. To account for the possibility that unobserved demand shocks are correlated with price, I include year fixed effect ξ_t in the estimation. Since only differences of utilities matter, I normalize ξ_t for the regulated rate to be zero[12].

To simplify the estimation and due to data limitations, I make two assumptions. First, as discussed in section 1.3, I assume consumers only choose from plans offered by this company. Second, I assume consumers' electricity consumption choice is separate from the contract choice. This is similar to formulating consumer choice problem in three stages. In the first stage, consumers choose a electricity retailer, in the second stage they select a contract from the chosen retailer, and in the third stage consumers choose the amount of electricity to consume given the contract chosen in the second stage. The two assumptions I made means in the model I focus only on the second stage[13].

[12] I am also working on using whole electricity prices as instrument to address price endogeneity.

[13] I am working on incorporating consumption decision into the model.

1.5.2 Model of consumer's dynamic choice

The consumer's problem is to choose a sequence of electricity plans to meet electricity consumption needs every month. All consumers start with the regulated rate, which varies month by month. They can choose to leave the regulated rate and sign up for a unregulated plan. Each consumer can only choose one contract each month and the contract cannot be resold. So the consumer's problem can be formulated as a dynamic discrete choice problem. The problem is dynamic because the choice set available next period depends on the current choice and consumers have inertia, so future utility depends on the current choice.

Consumers are assumed to maximize the sum of expected discounted utility from their actions, and they face uncertain future prices of electricity plans. This uncertainty means consumers may still choose a longer term fixed rate contract even if its current rate is higher because next month prices may be much higher than current month. Available plans to consumer i at month t depend on choice in month $t-1$. Consumer i at each month t chooses one of the J plans in their choice set C to maximize the sum of expected discounted value of utilities conditional on her information at month t. It is natural to set the time interval as monthly since the regulated rate only changes monthly and consumers are only allowed to switch between contracts within this company once each month.

I assume consumers have infinite horizon and they discount the future with a common discount factor ρ. In the data, I observe a panel of consumers making choices of electricity contract. Let $\mathbf{x}$ be the observed state variables, $\boldsymbol{\epsilon}$ are the unobserved state variables and d be the actual choice.

At a given month t, consumers choose among $j \in C$ contracts to maximize the sum of discounted expected utility. Formally then,

$$max_{j\in C}\sum_{k=t}^{\infty}\rho^{k-t}u(\mathbf{x_t},\boldsymbol{\epsilon}_t) \tag{1.2}$$

where $\mathbf{x_t}$ and $\boldsymbol{\epsilon}_t$ are the state variables at time t, and only $\mathbf{x_t}$ is observed by the researcher. ρ is the discount factor. Consumer's decision problem is an infinite horizon dynamic programming problem. The Bellman equation is

$$V = max_{j \in C} u_j(\mathbf{x}, \boldsymbol{\epsilon}) + \rho E[V(\mathbf{x}', \boldsymbol{\epsilon}'|\mathbf{x}, \boldsymbol{\epsilon}, d = j)] \tag{1.3}$$

$\mathbf{x}'$ and $\boldsymbol{\epsilon}'$ are next month state variables.

One source of dynamics in the choice problem comes from the option value of long term contracts. C denotes the available choice set. C depends on the current state variables, which in turn depends on the consumer's previous choice. If the consumer is on a long term contract of price a with more than one month remaining at month t, at month $t+1$ this long term contract with price a will still be available, while if the consumer's contract is expiring in month t, their choice set at $t + 1$ will only be contracts offered by the company at month $t + 1$.

Another source of dynamics in the choice problem comes from consumer inertia. In each month, there is probability q that the consumer is going to pay attention to the retail electricity contract choice problem. With probability $1 - q$, the consumer does not pay attention to the electricity contract choice problem and is defaulted to the previous choice. Though there is no monetary cost to leave a contract, due to inattention, consumers are not re-optimizing their contract choice every month, and consumers' current choice will affect their future utility.

The expectation of the value function in the Bellman equation is taken over the distribution of unobserved state variables $\boldsymbol{\epsilon_t}$, the transition probability of observed state variables $\mathbf{x_t}$ and the probability q that the consumer is going to pay attention. The observed state variables include current contract prices, and I assume prices are set according to a first-order Markov process, which will be described in section 1.5.4.

The sequence of the event in the model is as followed. At the start of each month t, the prices of new electricity contracts are realized. "New" contracts are all contracts that are currently sold to all consumers, while the long term contract that the consumer had in the previous month is called the "old" contract. After both $\mathbf{x_t}$ and $\boldsymbol{\epsilon_t}$ are revealed to the consumer, the consumer can choose a "new contract" or keep the "old" contract as long as it is not expired. Once a consumer leaves an old long term contract, she cannot go back to it in future periods. If the consumer decides to keep the old contract, the price the consumer pays will be the same as the previous month. Consumers make a choice to maximize the sum of flow utility and continuation value of each contract. The continuation value of long term contracts depends on its guaranteed price, length remaining and expectations of future prices. I assume consumers have rational expectations of future prices. Future prices are drawn conditional on current prices and price volatility of the regulated rate.

Next, I describe the observed state variables in the decision problem, and then specify the state transition processes.

1.5.3 The state space

The observed state variables in this dynamic choice problem include the current listed product prices P_j, old contract rate if available P_{old}, remaining length in months of long term contract rl and volatility of the regulated rate σ.

$\mathbf{x} \equiv (P_j, P_{old}, rl, \sigma)$.

The price of a product is usually a continuous variable, but in this case, price is usually quoted as $X.XX$ or $X.X$ cents per kwh, and companies never go beyond three decimal places in cents. Practically speaking, differences in the second and third decimal places may not be important. Residential household consumes about 300-1000 kwh electricity per month, so 0.2 cents difference in per kwh price only translates into 0.6 to 2 dollar difference in monthly bill. Typical electricity prices are between 5 and 12 cents in this market. I discretize the price in estimation.

P_{old} is the old contract rate. This can be different from the current listed contract prices, and is only available for consumers who were on a long term contract in the previous month and whose contract has not expired.

rl does not enter the consumer's flow utility directly, but it is relevant for the dynamic problem because it affects the prices available next month. rl will be irrelevant in a myopic model. For contracts that have no long term price guarantee, $rl = 1$. The maximum contract length is 60 months in this market. The range of rl is from 1 to 60. The transition of rl is a simple deterministic relationship. If a consumer just signed up for a new five year contract last month, $rl = 60 - 1 = 59$ in the current month.

σ is the volatility of the regulated rate, which is calculated from the data using the past 3-month rolling standard deviation. Volatility of the regulated rate can change due to change of government regulations of the retailer for regulated rate on procurement strategy in the wholesale market over time. σ also does not enter the flow utility directly, but it affects the transition probability of prices. If volatility is higher, we are more likely to see extremely high and low prices.

A key computational challenge for solving dynamic problem is the curse of dimensionality due to large state space. To make the problem tractable, I exploit the fact that rl and P_{old} are only applicable when the contract has long term price guarantee, so in estimation, when calculating choice specific value functions for choosing the regulated rate and the unregulated one-month contract, the state space is significantly reduced. Another simplification I make is I assume the unregulated one-month contract and regulated rate always have a deterministic relationship. As described in section 1.3, the unregulated one-month contract follows the regulated rate for the majority of months in the data.

1.5.4 The state transition process

The transition of remaining contract length rl is given by $rl_{t+1} = rl_t - 1$. if $rl_t = 1$, at $t + 1$ the old rate is no longer available. When the consumer signs up for a new long term contract at month t with price a, at $t + 1$ $P_{old} = a$. If the consumer continues with this contract, $P_{old} = a$ until $rl = 1$. Next, I describe the price transition process.

I assume consumers have rational expectation of future prices. The prices of new long term fixed rate contracts do not change frequently. It is usually constant for several months followed by a discrete jump. This pricing pattern bears some similarity to the pricing of consumer packaged goods. Therefore, I model the price process similar to Erdem et al. (2003). There is probability π_{jt} that price of long term fixed rate contract j does not change in month t compared to price in t-1.

π_{jt} is described by a logistic function

$$\pi_{jt} = \frac{exp(\delta_{0j} + \delta_{1j} p_{jt-1} + \delta_{2j} p_{rt-1})}{1 + exp(\delta_{0j} + \delta_{1j} p_{jt-1} + \delta_{2j} p_{rt-1})} \tag{1.4}$$

where p_{rt-1} is the regulated rate in month $t-1$ and p_{jt-1} is the price of long term contract j in month $t-1$. High regulated rate in the previous month can cause the price of long term contracts to rise. The probability of rate change is also related to the price of the long term contract itself in the previous month.

So there is probability $1-\pi_{jt}$ that the price of long term contract j will change in month t. The new price is given by the following equation:

$$\begin{aligned} &ln[p_{jt}] = b_{0j} + b_{1j} ln[p_{jt-1}] + b_{2j} ln[p_{rt-1}] + \epsilon_{jt} \\ &\epsilon_{jt} \sim \mathcal{N}(0, \sigma_f) \end{aligned} \tag{1.5}$$

The parameters to be estimated are $b_{0j}, b_{1j}, b_{2j}, \sigma_f, \delta_{0j}, \delta_{1j}, \delta_{2j}$, and they are estimated by maximum likelihood using the price data.

The regulated rate and unregulated one-month contract price vary month by month. Since the unregulated one-month contract follows the regulated rate in the majority of months, I assume the unregulated one-month contract price and the regulated rate have a deterministic relationship to reduce the state space. The transition process of the regulated rate p_{rt} is modeled by a process similar to oil price transition in Kellogg (2014).

$$\begin{aligned} &ln[p_{rt}] = ln[p_{rt-1}] + b_{0r} + b_{1r} p_{rt-1} + b_{2r} \sigma_{t-1}^2 - \frac{\sigma_{t-1}^2}{2} + \sigma_{t-1} \epsilon_{rt} \\ &\epsilon_{jt} \sim \mathcal{N}(0, 1) \end{aligned} \tag{1.6}$$

σ_{t-1} is the past three month rolling standard deviation of the regulated rate. The parameters to be estimated are b_{0r}, b_{1r}, b_{2r}, and they are estimated by OLS regression.

Finally, I specify the transition process for σ_t. I assume volatility can take two values : high or low and the process is first-order Markov. The transition probabilities are estimated from the frequency each transition occurs in the data.

For the long term contracts, if the price changes, I assume it follows an autoregressive process. For the monthly price, I model the price process similar to a random walk with drift to incorporate the effect of price volatility as there are changes of price volatility over time of the monthly price. In the appendix, I also present the estimation result when the monthly price is assumed to follow an AR(1) process, and the estimated parameters are similar to the result from the main specification.

1.6 Identification and Estimation

I have developed a model of consumer choice of retail electricity contracts characterized by its price, contract length and whether it is the regulated rate. Consumers need to decide which plan to choose to meet their electricity consumption needs every month. I next discuss how the parameters of the consumer utility model are identified using the variation in the data, and then I detail the estimation process for the dynamic demand model using individual level consumer choice data.

1.6.1 Identification

I discuss the identification of model parameters to help understand what variations in the data permit the estimation of each of the parameters. First, consider the coefficient of relative risk aversion γ. γ is a key parameter to explain consumer's valuation of long term contracts. A higher value γ means consumers dislike risk exposure more, and are more likely to choose long term contracts, holding other factors constant. Variation of contract prices of different lengths over time and the change in consumer choice can help identify γ.

Additionally, new 3 year and 1 year contracts are introduced over time, and some consumers switch to the new contracts. For example, when a new 3 year contract is introduced, some consumers switched away from their existing 5 year or one-month contract to this new contract, and 3 year contract is cheaper than the 5 year contract, so consumer switching behavior helps to identify consumer's risk preference.

Next, consider the attention probability q. Consumers only slowly move away from the regulated rate though better options are available. The unregulated one-month contract followed the regulated rate and has a fixed discount to the regulated rate for many months, everyone who eventually switched to the discounted one-month rate would have done so in the first month if $q = 1$. This gradual change in market share of the regulated product helps to identify the attention probability q.

The premium on the regulated rate is identified by changing price differences between the regulated rate and unregulated contracts. In the estimation, I set the monthly discount factor ρ equal to 0.95.

1.6.2 Estimation

Let d_t be consumer's choice in month t. Since the flow utility has a Type-I extreme value random term ϵ_{ijt}, the choice probability of consumer i choosing contract j at month t is given by the well-known multinomial logit formula. $\boldsymbol{\theta}$ are the parameters to be estimated.

$$P(d_t = j|x, \boldsymbol{\theta}) = \frac{exp(u(x, d, \boldsymbol{\theta}) + \beta EV(x, d, \boldsymbol{\theta}))}{\sum_{j \in C} exp(u(x, j, \boldsymbol{\theta}) + \beta EV(x, j, \boldsymbol{\theta}))} \tag{1.7}$$

C is the consumer's choice set, which differs across consumers as some consumers may be on long term fixed rate contracts in the previous month that give them access to the old contract price.

Compared to the standard dynamic discrete choice models, I need to account for consumer inertia. In each month, there is probability q that the consumer is going to consider the electricity plan choice problem. So with probability q, the consumer will choose a plan by maximizing the expected discounted utility. With probability $1-q$, the consumer does not pay attention to the electricity plan choice problem, and will continue on the current plan. The expected continuation value EV is given by the solution to the functional equation 1.8. Let $\mathbf{y}$ be the possible realizations of next month's observed state variables and $\mathbf{m}$ be the possible realizations of next month's unobserved state variables. The expectation is taken over the joint distribution $p(\mathbf{dy}, \mathbf{dm}|\mathbf{x}, \boldsymbol{\epsilon}, d, \boldsymbol{\theta})$ in the next month conditional on the current choice d, the observed state variables $\mathbf{x}$ and the unobserved state variables $\boldsymbol{\epsilon}$. $\boldsymbol{\epsilon}$ contains J values, and J equals to the number of plans available.

$$\begin{aligned} EV(\mathbf{x}, d, \boldsymbol{\theta}) = & \int_{\mathbf{y}} \int_{\boldsymbol{m}} q(max_{j \in C} u(\mathbf{y}, j, \boldsymbol{\theta}) + \rho EV(\mathbf{y}, j, \boldsymbol{\theta})) \\ & + (1-q)(u(\mathbf{y}, d, \boldsymbol{\theta}) + \rho EV(\mathbf{y}, d, \boldsymbol{\theta})) dp(\mathbf{dy}, \mathbf{dm} | \mathbf{x}, \boldsymbol{\epsilon}, d, \boldsymbol{\theta}) \end{aligned} \tag{1.8}$$

Given that the random utility term ϵ_{ijt} is independent and identically distributed over consumers, contracts and time, conditional on the current choice and observed and unobserved state variables, I can assume the transition probabilities of the observed state variable $\mathbf{x}$ is independent of the transition of unobserved state variable $\boldsymbol{\epsilon}$, so that I can rewrite the joint probability $p(\mathbf{dy}, \mathbf{dm}|\mathbf{x}, \boldsymbol{\epsilon}, d, \boldsymbol{\theta})$ as $p(\mathbf{dm}|\boldsymbol{\epsilon}, d, \boldsymbol{\theta})p(\mathbf{dy}|\mathbf{x}, d, \boldsymbol{\theta})$. This is the conditional independence assumption that is standard in the dynamic discrete choice literature. $\boldsymbol{\epsilon}$ has J values, so in principle a J-dimensional integral needs to be computed over the density $p(d\mathbf{m}|\boldsymbol{\epsilon}, d, \boldsymbol{\theta})$. However, as $\boldsymbol{\epsilon}$ in the flow utility is Type-I extreme value, so the integral over the unobserved state variables has a closed form expression, so the expression in 1.8 is simplified to 1.9.

$$\begin{aligned} EV(x, d, \theta) = & \int_{\mathbf{y}} q log \sum_{j} exp[u(\mathbf{y}, j, \boldsymbol{\theta}) + \rho EV(\mathbf{y}, j, \boldsymbol{\theta})] \\ & + (1-q)(u(\mathbf{y}, d, \boldsymbol{\theta}) + \rho EV(\mathbf{y}, d, \boldsymbol{\theta})) p(\mathbf{dy}|\mathbf{x}, d, \boldsymbol{\theta}) \end{aligned} \tag{1.9}$$

The parameters are estimated in two steps. The transition probability matrix is estimated first before the dynamic consumer choice model. Conditional on the estimated parameters in the first step, the model is estimated by the Nested Fixed Point algorithm developed by Rust (1987). In the outer loop, the algorithm searches for parameters $\boldsymbol{\theta} \equiv (\gamma, q, \beta)$, and in the inner loop for a given set of parameters $\boldsymbol{\theta}$, the value function is solved by iterating over EV via successive approximation. The parameters are found by maximizing the likelihood of observing consumers' actual choice $d_1, ...d_T$ given the observed state variables $\mathbf{x_1}, ..., \mathbf{x_T}$. The likelihood function is given by

$$\begin{aligned} & \mathcal{L}(\mathbf{x_1}, ..., \mathbf{x_T}, d_1, ...d_T | \mathbf{x_0}, d_0, \boldsymbol{\theta}) = \\ & \Pi_{t=1}^{T} P(d_t|x_t, \boldsymbol{\theta}) p(\mathbf{x}_t|\mathbf{x}_{t-1}, d_{t-1}, \boldsymbol{\theta}) \end{aligned} \tag{1.10}$$

$p(\mathbf{x}_t|\mathbf{x}_{t-1}, d_{t-1}, \boldsymbol{\theta})$ is the transition probability matrix that has been estimated in the first step. $P(d_t|\mathbf{x}_t, \boldsymbol{\theta})$ is the choice probability given by equation 1.7.

1.7 Results

1.7.1 Structural Estimates

Table 1.2 shows the estimated model parameters of the dynamic model using all consumers in the company's own distribution area. The model estimates show that consumers are risk averse. The attention probability is 0.031. So consumers do not search for electricity contract frequently. The attention probability is very similar to what Hortacsu et al. (2017) find in Texas retail electricity market. Previous studies have also found the incumbent enjoys brand premium, and it is unclear whether the premium comes from better customer service, distrust of new retailers or false beliefs that the electricity is more reliable from the incumbent retailer. I find that even if the contracts are from the same retailer, there is some premium for the "regulated rate", so this premium is not just from potential quality differences of different companies. Previous literature has produced a wide range of estimates for coefficient of relative risk aversion, but the result from this study is lower than what many other papers suggest using different settings[14]. In lab experiments, the potential gain and loss in each scenario are made clear to the participants, but in this setting, some consumers may not be fully aware of the different price scenarios, so this may lead to the lower estimated risk aversion. If the risk aversion were higher, consumers incur higher loss of utility from uncertainty of future prices, so when they trade off the current month price and future price guarantee, they will put more weight on the later, and long term contracts become more valuable for consumers.

[14] Other papers have estimated the coefficient of relative risk aversion to be between 1 and 2, for example, see Carson et al. (2020) and Szpiro (1986).

Table 1.2: Parameter estimates of dynamic demand model

Parameters		
Relative Risk Aversion	0.60	0.56
	(0.02)	(0.01)
Attention Probability	0.031	0.033
	(0.0002)	(0.0002)
Regulated Rate	0.16	0.33
	(0.0009)	(0.0031)
Year fixed effect	No	Yes
Sample Size	387381 consumers x 122 months	

Note: This table presents the parameter estimates of the dynamic discrete choice model. The second column includes the year fixed effect.

1.7.2 Contract Length

Figure 1.6 illustrates the value of long term contracts. The value of 5 year contract generally declines with fewer months remaining as expected[15]. Compared to the value function of a cheaper one month contract, a more expensive 5 year contract with large number of months remaining is more valuable because it offers long term price protection, so even if there is a cheaper one month contract available, consumers may still choose the 5 year contract. When the volatility of the one-month contract is high, long term contracts are slightly more valuable compared to in the low volatility state because consumers are more likely to see price spikes.

1.7.3 Model Fit

Before calculating the counterfactuals, figure 1.7 presents the the actual and simulated switching to 5 year contract over time. For the actual switching I take a random sample of 100,000 of the consumers. In the simulation, I take the actual choice of the sampled consumers in month 0 as given, and simulate a sequence of choices made by each consumer if they face the same prices as the actual consumer by comparing the value functions and drawing the random utility term ϵ for each option using the model without the year fixed effect.

[15]The value function is non-monotonic when it is close to expiration because when the long term contract expires, it is auto-renewed to the one-month contract. Given that the current one-month contract is cheaper than 5-year contract, the one-month contract is likely to be cheaper when the 5-year contract expires, so short-term price guarantee is not very valuable in this situation.

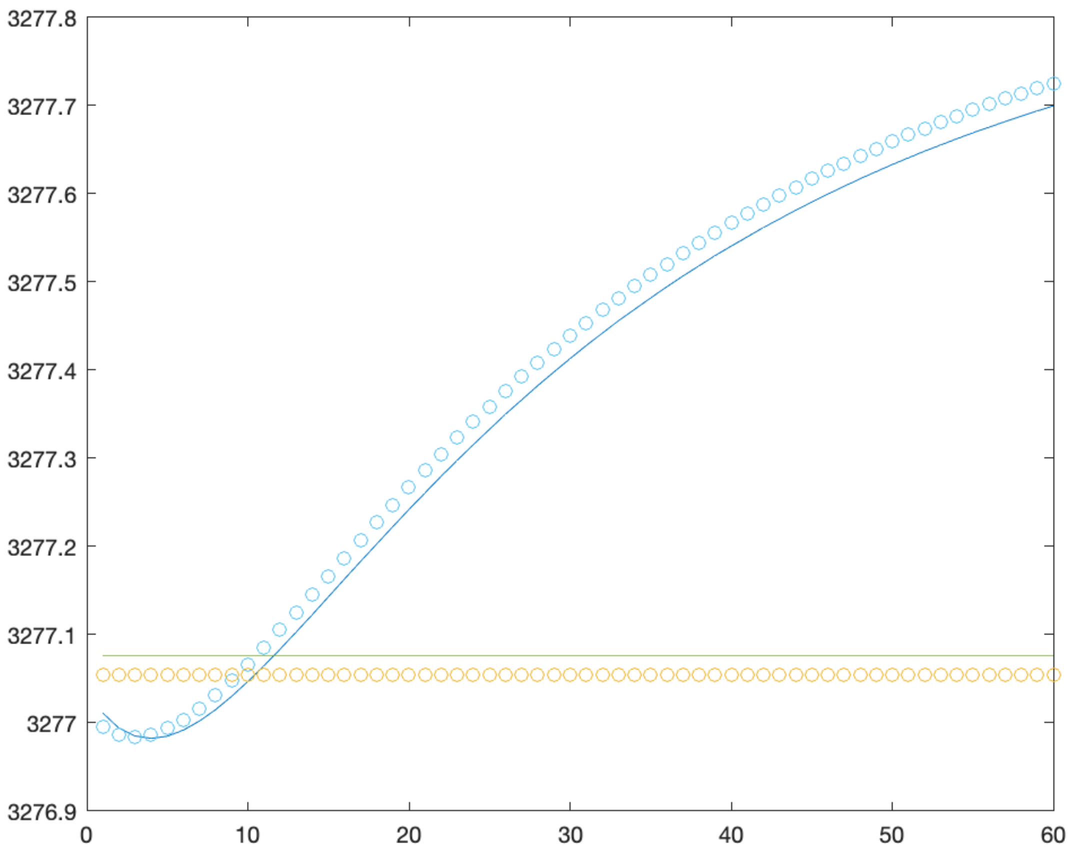

Figure 1.6: Value function of 5 year contract versus one month contract

Notes: "o" curve is the value function for 5 year contract at high volatility state and the solid curve is the value function for 5 year contract at low volatility state. Similarly, "o" horizontal line is the value of one-month contract at high volatility state and the solid line in the value of one-month contract at low volatility state.

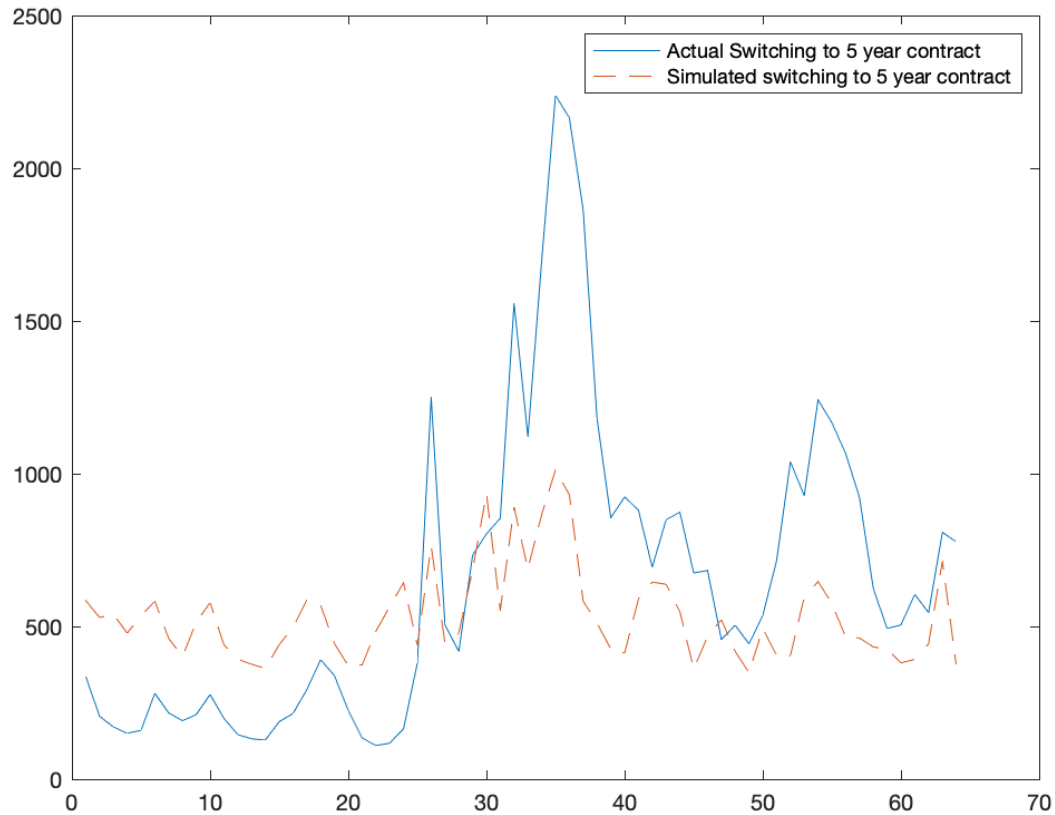

Figure 1.7: Simulated versus actual switching to 5 year contract

Notes: The figure presents the number of actual versus simulated consumers' switching to the 5 year contract each month using the estimated model without year fixed effect.

As shown in the figure, the simulated switching to 5 year contract captures the general switching pattern of the actual switching, but it does not predict the level of very high and very low switching well without year fixed effect. In the next section, I will use the model and the estimated parameters to evaluate the impacts of alternative regulations in the retail electricity market.

1.8 Counterfactuals

Next, I use the estimated model of consumers' contract choice with year fixed effects to perform counterfactual analyses that investigate how alternative regulatory policies impact consumer choice and welfare. I first describe the counterfactuals and then explain the procedure to calculate the counterfactuals.

The first counterfactual analyzes how consumer surplus changes if contracts longer than a month are removed from consumers' choice set. Consumers now only have two choices: the regulated monthly contract and the unregulated monthly contract. The change in consumer welfare provides a measure of the value of long term contracts and it relates to a policy that requires guaranteed savings of unregulated contracts compared to the regulated rate. This policy has been proposed in New York and was motivated by the fact that consumers on unregulated contracts paid more ex-post compared to consumers on the regulated rate, so the regulator is requiring contracts to be offered to have guaranteed savings compared to the regulated rate[16]. Long term fixed rate contracts are only allowed to have 5% premium compared to the 12-month average of the regulated rate, so companies many stop offering long term contracts if it is not profitable.

In order to calculate the change in consumer surplus, I simulate a sequence of choice of 100 consumers[17] based on the observed prices by computing the choice specific value function and the i.i.d draw of random utility term ϵ. I first compute the value a consumer obtains from the current choice situation and then calculate the amount of income change cv that will equate the value pre and post the policy change following the procedures summarized in Herriges and Kling (1999).

[16]If the electricity contract is bundled with renewable energy, the requirement can be waived.

[17]I simulate 20 consumers from the high income group, 60 consumers from the median income group and 20 consumers from the low income group according to the income distribution used in the model.

Table 1.3: Counterfactual change in consumer surplus

Counterfactuals	Average Change in CS
Regulated rate only	-$11.0
Regulated rate + unregulated 1 month	-$6.2

Notes: This table presents the average change in consumer surplus after the policy change compared to the current choice set using the sequence of choices of 100 consumers.

$$\max_{j \in J^0} U(y - p_j^0, \epsilon_j) = \max_{j \in J^1} U(y - p_j^1 - cv, \epsilon_j)$$

J^1 denotes choice set after change, and J^0 is the choice set of the current situation.

In the counterfactual calculation, I assume the regulated rate and unregulated one-month rate are unchanged. As the regulated rate is regulated by the government, I assume it cannot respond to the removal of long term contracts. The unregulated one-month rate can potentially change if no long term contracts are allowed[18]. I also assume the quality of electricity and services consumers receive is the same whether the plan is regulated or not, so in the counterfactual calculation, the premium on regulated rate and time fixed effects only affect choice but not actual utility[19].

Under these assumptions, on average consumer welfare decreased $6.2 dollar per month by removing long term contracts. An average consumer's total electricity bill each month in this market is around $110 dollars, and about half is energy charge, so the change in consumer surplus is about 6% of the total electricity bill, or 12% of energy-only cost. Though there can be large gains by having long term contracts in some months, consumers only slowly move to unregulated contracts from the regulated rate. In the second counterfactual, I calculate welfare change comparing the current situation with retail choice and the case when only the regulated rate is available. The method is similar to the calculation of the first counterfactual, and in the counterfactual scenario there is no choice involved since everyone will be on the regulated rate. This counterfactual is related to the policy debate about whether deregulation of retail electricity markets has provided benefits to consumers. Deregulation gives consumer access to new products and potential savings

[18] I am working on calculating the the amount of guaranteed savings the regulated one-month contract must provide to equate the value pre and post the policy change.

[19] I am also working on alternative ways to measure consumer surplus changes.

but consumers have inertia that can diminish the gains. Holding the regulated rate unchanged, on average, consumer welfare decreases \$11.0 per person per month if retail choice is removed, which is about 10% of a consumer's total electricity bill, or 20% of energy-only cost. While if retail choice is completely eliminated, it is possible that the regulated rate may be different. However, this paper's main focus is on small consumers whose total electricity consumption is about 30% of the total demand. If retail choice is still open for large industrial and commercial consumers, it may be reasonable to assume regulated rate is still the same.

1.9 Conclusion

In this paper, I develop and estimate a dynamic discrete choice model of electricity contract choice to study the effect of long term contracts in a deregulated retail electricity market. The use of a detailed proprietary dataset of individual-level retail electricity contract choice from an incumbent provider that offers contracts of different lengths allows me to model consumer's decision over contract length. The model help understand consumer's risk preferences and enables the calculation of counterfactuals to evaluate the impact on alternative regulations of retail electricity markets.

In the model, there is a fixed probability that a consumer will pay attention to the electricity contract choice problem. When making a choice, consumers choose a contract that maximizes the sum of discounted utility based on expected future prices, risk preference and future attention probability. The results shows that consumers are risk averse and search for electricity contract infrequently. In addition, the regulated rate has premium even though it comes from the same brand as other unregulated contracts.

The estimated model allows me to conduct counterfactual simulations. The first counterfactual studies the effect of removing long term contracts from consumers' choice set, and the second counterfactual computes the change in consumer surplus without retail choice. These simulation results indicate that removing long term contracts reduces consumer surplus by \$6.2 per month per consumer and removing retail choice reduces consumer surplus by \$11.0 per month per consumer.

In short, this paper provides the first evidence of quantifying the value of long term contracts in retail electricity market, contributing to the literature on retail electricity deregulation and understanding of consumer's risk preference over electricity prices, which is important given the fact that large penetration of renewable generation can increase price volatility.

Chapter 2: The price effect of large-scale wind energy

2.1 Introduction

In recent years, renewable energy has been growing in many markets. In the US, several states set ambitious targets for solar and wind power development to reduce emission in the electricity sector. Solar and wind energy differ from fossil fuel power plants because they have close to zero marginal cost and their production quantity can vary a lot within a short period of time due to changes in weather conditions. Therefore, the massive entry of wind and solar power can have large consequences for the wholesale electricity market.

Renewable energy can affect wholesale electricity price through several channels with both positive and negative effects. As solar and wind have close to zero marginal cost, when solar and wind production increases, it can depress the wholesale electricity price due to the cost ranking of the generation fuel mix. The system operator in the wholesale electricity market usually dispatches power based on the energy offer curve submitted by each generator. Wind and solar usually offer their capacity at much lower price compared to conventional power plants, so when the capacities of other generations are unchanged, increasing renewable production will displace higher cost power plants. Also, increasing renewable production reduces the net demand faced by fossil fuel power plants, which may reduce their ability to exercise market power (Karaduman, 2020b). On the other hand, power companies have both conventional and renewable power plants may withhold production from their conventional power plants when their renewable power plants produce more electricity (Acemoglu et al., 2017; Butner, 2019). In addition, the intermittent nature of solar and wind may impose more dynamic startup and ramping cost for conventional generators and raise price when renewable production falls (Bushnell & Novan, 2018; Jha & Leslie, 2020).

In the longer run, with more renewable energy in the grid, more fast-ramping generators may enter the market. Grid scale battery storage may play an important role in markets with a lot of intermittent renewable production to arbitrage the market (Karaduman, 2020a; Lamp & Samano, 2021). Also, coal power and other types of power plants that were traditionally considered base load power plants may exit the market due to the low average wholesale price.

This paper uses an econometric model to quantify the effect of wind production on the wholesale electricity market. The setting of wholesale electricity market in Texas offer several advantages to answer this question. First, wind capacity has increased rapidly in Texas in recent years. Texas has the highest amount of wind production in the US, and wind power supplies more than 15% of demand from 2016 to 2020. Second, I observe not only the equilibrium price, but all energy offer curves submitted by each generator. Third, the electricity grid in Texas has very limited connection with other parts of the US, so import and export is of minor concern.

To study the effect of increasing renewable capacity on the wholesale electricity market, I use the data from the Electricity Reliability Council of Texas (ERCOT) from 2014 to 2017 when wind capacity increased rapidly. I regress real time hourly wholesale electricity price on daily wind production controlling for demand, solar production, natural gas price, daily temperature and month of the year fixed effect. To explore the potential heterogeneous effect on price, I run separate regressions for each hour of the day. The identifying assumption is the controls have accounted for the factors that correlate with renewable production and wholesale price. I find increase of daily wind production reduces wholesale electricity price for all hours of the day except 10pm, and the reduction is larger in the late afternoon when electricity demand is higher. An 1GWh increase of daily wind production reduces the real time price by 0.13$/MWh in 4pm. The average daily production of wind has increased over 70GWh from 2014 to 2017, so the magnitude of price reduction is about 9$/MWh.

To investigate the effect of wind production on the output of other types of generation, I regress the hourly output of other types of generation on daily wind production. An 1GWh increase of daily wind production reduces both coal and natural gas production for all hours of the day. Less efficient natural gas power plants reduces more production during the peak hours because they are usually dispatched to meet electricity demand during those hours, and increasing wind production reduces dispatch of power plants higher on the static cost curve.

To estimate the effect of wind production on fossil fuel power plants' ability to exercise market power, I use the energy offer curve submitted by each generator in the real time market during hours when no transmission constraint is binding. I develop a dataset to match the generation resource code used in the energy offer curve to power plant and owner name. I regress the offer price submitted by each owner at different percentages of its generating capacity on hourly wind production with owner, hour and month of year fixed effects. Increasing wind production does not have statistically significant effect on the energy offer prices when using all non-congested hours. Using the hours when load is greater than the 50th percentile in the load distribution, an 1GWh increase of hourly wind production decreases offer price at 50% of the average HSL by 8.5$/MWh, and it decreases offer price at 75% of the average HSL by 9.3$/MWh. For owners that have both conventional generation and wind farms, the effect of wind production of their own wind farms on energy offer price is not statistically significant.

This paper contributes to the literature on the effect of renewable energy on wholesale electricity price. There is a large literature using econometric model and simulation methods to study the price effect of renewable production (Clo et al., 2015; Cludius et al., 2014; Forrest & MacGill, 2013; Gelabert et al., 2011; McConnell et al., 2013; Mills et al., 2021; Sirin & Yilmaz, 2020; Woo et al., 2016; Woo et al., 2015). This paper is closely related to Bushnell and Novan (2018) from a methodological standpoint. Bushnell and Novan (2018) measures the effect of solar and wind production on wholesale market price in California where solar capacity has increased over time and wind capacity is relatively stable. This paper uses Texas as the setting to study the effect of increasing wind capacity on whole electricity price during periods when wind power was generating more than 10% of electricity and was increasing rapidly. Woo et al. (2011) and Tsai and Tsai (2018) find increasing wind production reduces wholesale electricity price in ERCOT using econometric models controlling for lagged price or time trends. Cullen (2013) quantified the environmental value of wind production in ERCOT. Fell et al. (2021), Kaffine et al. (2013), and Novan (2015) explored the heterogeneity of emission avoided across hours. This paper is also related to Karaduman (2020b), which runs a counterfactual analysis of the impact of large scale wind investment by estimating a structural model of the south Australia electricity market. This paper contributes to the literature by estimating the effect of large wind capacity investment using the actual data and analyzing the heterogeneous effects on the production of fossil fuel power plants for each hour of the day.

This study also contributes to the literature on market power in the wholesale electricity market (Borenstein et al., 2002; Bushnell et al., 2008; Ciarreta et al., 2017; Green & Newbery, 1992; Hortacsu & Puller, 2008; Ito & Reguant, 2016; Jha & Leslie, 2020; Mercadal, 2021; Puller, 2007; Twomey & Neuhoff, 2010; Woerman, 2019; Wolfram, 1998, 1999). Acemoglu et al. (2017) developed a theoretical model using Cournot competition, and showed firms producing both renewable and conventional energy exercise more market power by withholding their conventional energy output when renewable production is higher. Butner (2019) discusses the same issue using a supply function equilibrium framework, and empirically tests it using data from Midcontinent Independent System Operator. He finds firms owning both wind and conventional power plants withhold output from their conventional power plants with increasing production from their own wind farms. Karaduman (2020b) stimulates counterfactuals with increasing wind capacity using a supply function equilibrium framework, where wind farms are owned by firms that do not have conventional power plants. He finds gas and diesel power plants reduce less output when strategic responses are incorporated because these power plants bid more aggressively when they face smaller net demand. This paper contributes to the literature by empirically estimating the effect on power plants' energy offer curves when there is rapid increase of wind capacity.

The rest of the chapter proceeds as follows, section 2.2 discusses how renewable energy affects wholesale electricity price, section 3.2 discusses the ERCOT electricity market, section 3.4 explains the data and section 3.5 discusses the empirical strategy used in this paper. Section 3.6 presents the results, and section 2.7 concludes the chapter.

2.2 Conceptual Framework

This section discusses the channels through which wind production may affect wholesale electricity price. I use the model notations of Butner (2019). Let W be the amount of wind energy produced at time t, and let $S_o(p)$ be the energy offer curve of each owner of conventional generation resource. $S_o(p)$ specifies how much the firm is willing to produce at a given price. $d(p)$ is the deterministic part of electricity demand that is forecastable. ϵ is a random variable representing demand fluctuation. ϵ is i.i.d. with an expectation of zero. $C_o(q)$ is the cost function. The market clearing condition is given by equation 2.1.

$$d(p) + \epsilon = \sum_o S_o(p) + W \tag{2.1}$$

By implicitly differentiating equation 2.1, Butner (2019) shows the effect of wind production on price is given by the following equation:

$$\frac{dp}{dW} = -\frac{1 + \sum_o \frac{\partial S_o(p)}{\partial W}}{\sum_o \frac{dS_o(p)}{dp} + \frac{dW}{dp} - d'(p)} \tag{2.2}$$

Real time electricity demand is almost perfectly inelastic, so $d'(p) = 0$. If we assume wind production does not respond to price, $\frac{dW}{dp} = 0$[1]. The denominator is left with the derivative of the energy supply function with respect to price. This term is positive.

Static Cost Effect $\sum_o \frac{\partial S_o(p)}{\partial W}$ represents the strategic response of conventional generation. Under perfect competition, firms bid their marginal cost, so $\sum_o \frac{\partial S_o(p)}{\partial W} = 0$. $\frac{dp}{dW}$ is negative. Figure 2.1 illustrates the effect of increasing wind production on price under perfect competition. If all power plants submit energy offer curves based on their static marginal costs, increasing wind production shifts the supply curve to the right because wind energy has close to zero marginal cost. The price under new equilibrium at point B decreases compared to the original equilibrium at point A. I call

[1]When renewable penetration is very high, strategic behavior of renewable generation may become important, for example, see Fabra (2021) and Fabra and Llobet (2021). In the ERCOT data from 2014 to 2017, wind farms almost always offer their capacity at zero or negative price.

this effect "static cost effect".

Dynamic Cost Effect Dynamic constraints of fossil fuel generators may also affect wholesale electricity price. Due to the intermittent nature of wind, when wind output falls, other generators need to make up for the loss quickly to ensure demand is met in the real time. The fast-ramping generators may have higher static marginal cost, so wholesale electricity price may increase when wind production falls sharply. Meanwhile, base load generation sometimes may continue to produce when the current wind production is high because they want to avoid startup cost, which further depresses the wholesale price.

Market Power Effect When power plants have market power, they may not offer their capacity at the marginal cost. If they exercise more market power, the equilibrium price will be higher than at point B. If they exercise less market power, the equilibrium price will be lower than at point B. Wind production can affect market power in two ways. First, as discussed by Acemoglu et al. (2017) and Butner (2019), firms that own both wind and conventional generation have incentive to withhold output from their conventional generators when the wind farms they own produce more electricity. In ERCOT, over 90% of wind power is owned by independent wind producers that do not have conventional power plants, so this effect may be small.

Another effect of increasing wind production is the reduction of residual demand faced by all fossil fuel power plants. Klemperer and Meyer (1989) developed supply function equilibria in oligopoly setting with uncertainty, and it has been used extensively to model competition in the wholesale electricity market. Examples include Butner (2019), Green and Newbery (1992), and Hortacsu and Puller (2008). In the basic supply function equilibrium framework, the supply function each firm submits depends on the slope of the residual demand curve,. but it does not depend on the level of residual demand. For example, Butner (2019) shows the markup is given by equation 2.3. RD_p is the slope of the residual demand curve firm o faced. θ_o is the fraction of wind produced by firm o. In this formulation, only the amount of wind produced by the firm's own wind farms affects the supply function submitted as the total wind production only changes the level of residual demand. Genc and Reynolds (2011) shows from simulation that if capacity

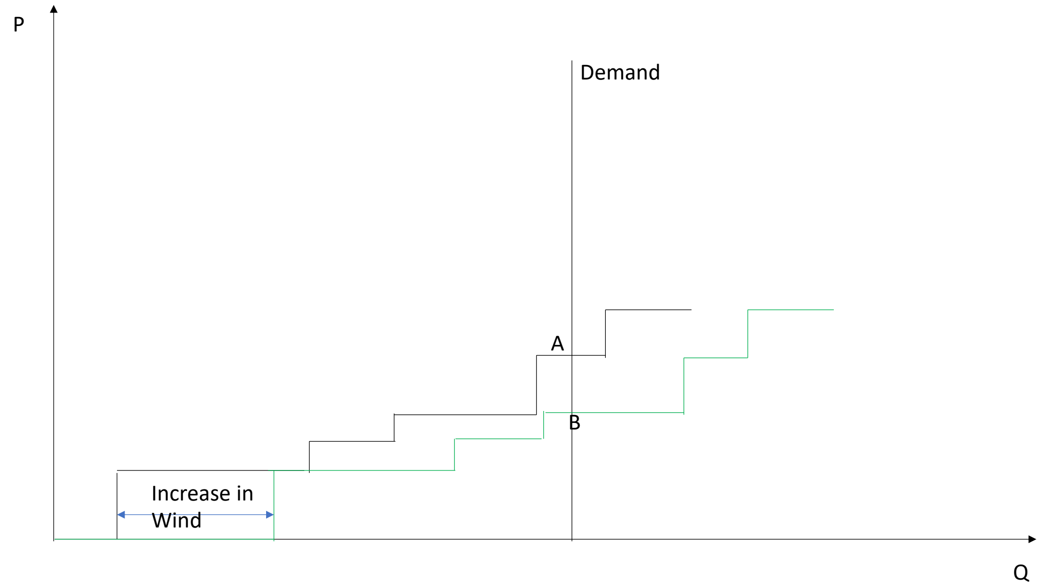

Figure 2.1: Illustration of the static cost effect of wind production

Note: This figure illustrates how wholesale electricity price changes when wind production increases under perfect competition and no dynamic consideration.

constraint is introduced and a firm have some chance to be the pivotal supplier to meet demand, when demand distribution is more concentrated close to the maximum value, markup increases in the supply function equilibria. Increasing wind power will reduce the chance that demand is close to the maximum value, so more competitive supply function equilibria are supported.

Overall, the "static cost effect" reduces wholesale electricity price. The "dynamic cost effect" and "market power effect" have ambiguous effect on price. In addition, in the longer run, entry and exit happens, and it will also change the wholesale electricity price. In the next section, I introduce the ERCOT wholesale electricity market.

$$p - C'(S_o(q)) = -\frac{S_o(p) + \theta_o W}{RD_p} \tag{2.3}$$

2.3 The ERCOT electricity market

The Electricity Reliability Council of Texas (ERCOT) manages 90% of Texas load. It is a relatively isolated grid with some DC Ties to other regions. ERCOT is responsible for matching generation with demand and operating the transmission systems within the established limits. ERCOT is an energy-only market. It does not have a capacity market, which means power plants recover fixed costs from revenue of energy production and operating reserves. Between June 2015 and March 2021, generators can submit an offer price as high as 9000$/MWh. From June 1st 2014, ERCOT implements a real time reserve price adder to reflect the economics value of reserves that are available for dispatch in the real time. Under tight reserve margin, the loss of load probability is positive, so real time reserve price adder is positive. The price adder is zero for a lot of hours because the reserve capacity is large.

2.3.1 Locational Marginal Pricing

Electricity can be sold through bilateral trade[2], and ERCOT facilitated centralized day ahead and real time market. The wholesale electricity price in the day ahead and real time market is determined through Locational Marginal Pricing (LMP), which reflects the cost of serving the next increment of demand at a particular location in the electricity grid. Each generator submits an energy offer curve to indicate how much electricity it is willing to supply at a given price. The LMP has two components: Energy and Congestion[3]. If there is no congestion, LMP will be determined by the aggregate energy offer curve of all generators and the demand in ERCOT, and LMP will be the same everywhere. If there is congestion, LMP at a particular location will be determined by the local supply, demand and the transmission limits. In the real time market, LMP at each location is calculated about every 5 minutes. The real time settlement price is calculated every 15 minutes.

[2] Bilateral contracts refer to the transaction between electricity buyer and seller. The contracts can include physical delivery of power, or they can be pure financial transactions for risk management. Power plants can sell electricity to utilities and other consumers through long term power purchase agreements.

[3] In some markets, there also a component for losses, but it is not included in ERCOT.

The settlement price is the time weighted average of the LMP plus reserve price adder[4].

2.3.2 Energy Offer Curve

Generators can submit energy offer curves to indicate how much electricity they are willing to produce at a given price[5]. Each generator can submit an offer curve in maximum 10 price and quantity pairs, which must be monotonically increasing. The submitted price must be between -$250/MWh and $9000/MWh. By taking the offer curves submitted by each generator, ERCOT runs the Security Constrained Economic Dispatch (SCED) every 5 minutes to meet the real time electricity demand in the least cost way while respecting the transmission and other operating constraints. Further details about the SCED process is provided in the appendix.

2.3.3 Renewable Energy in Texas

Texas has the largest installed wind capacity in the US, and wind capacity has grown over years (Figue 2.2). On 7pm of March 23, 2017, wind generation supplies more than 50% of demand for the first time. Figure 2.3 shows the percentage of demand met by wind power has increased from less than 10% in 2011 to more than 20% in 2020. Other types of generation mainly include solar, hydro and biomass power plants. There is some increase in generation by other types of generation since 2017, and it mainly comes from the growth of utility-scale solar capacity in ERCOT. Compared to other electricity market in the US, ERCOT's renewable portfolio mainly contains wind and solar. Hydro and biomass only constitute a very small percentage of the generation portfolio. Given the presence of large percentage of intermittent renewable generation, grid scale battery storage is also growing in ERCOT particularly after 2017. Up to the end of 2020, battery storage capacity increased to 225MW from 69MW in 2017.

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[4] Since June 2015, ERCOT introduces another adder: the reliability deployment adder. Some generation resources may be dispatched in the real time for reliability purposes, and their production may depress wholesale electricity price. This reliability price adder reverses the price suppression.

[5] The energy offer curve also includes startup offer and minimum energy offer, which describes the cost to start the unit and what is the minimum amount of energy it must produce for sustainable production.

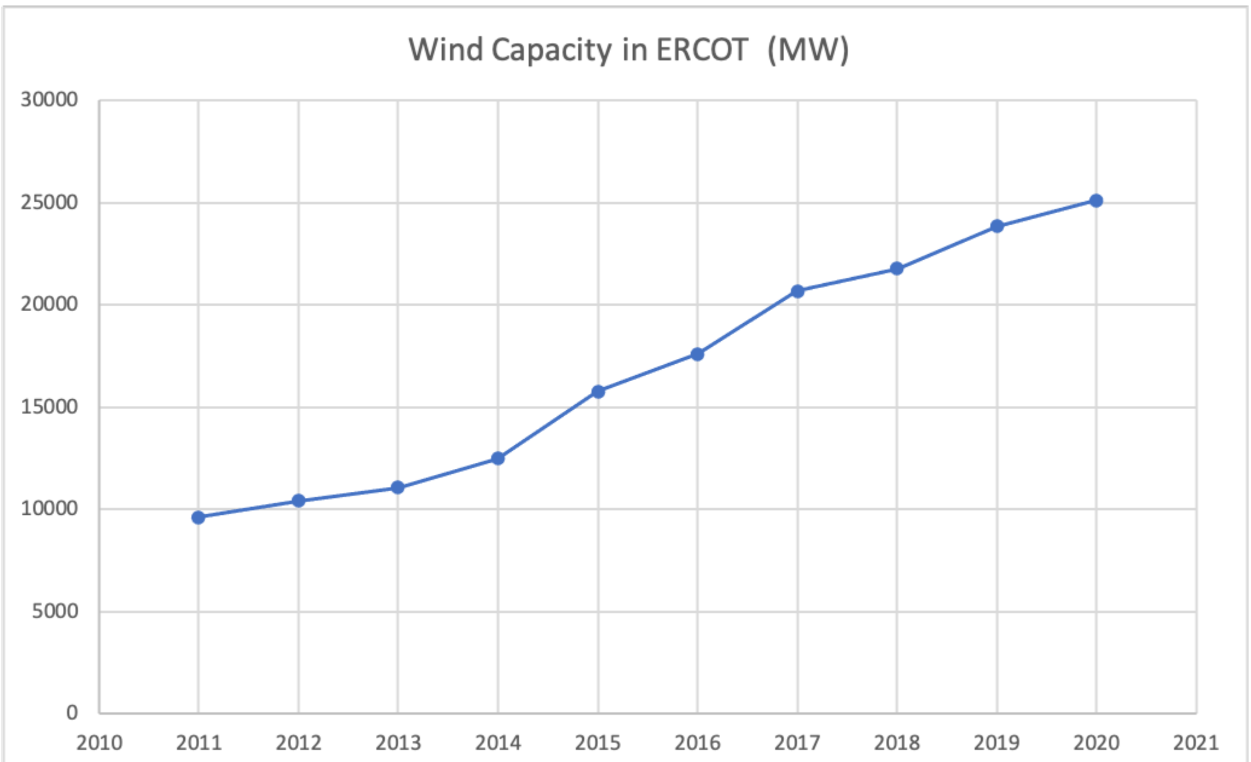

Figure 2.2: Growth of wind capacity in ERCOT

Source: ERCOT state of grid reports

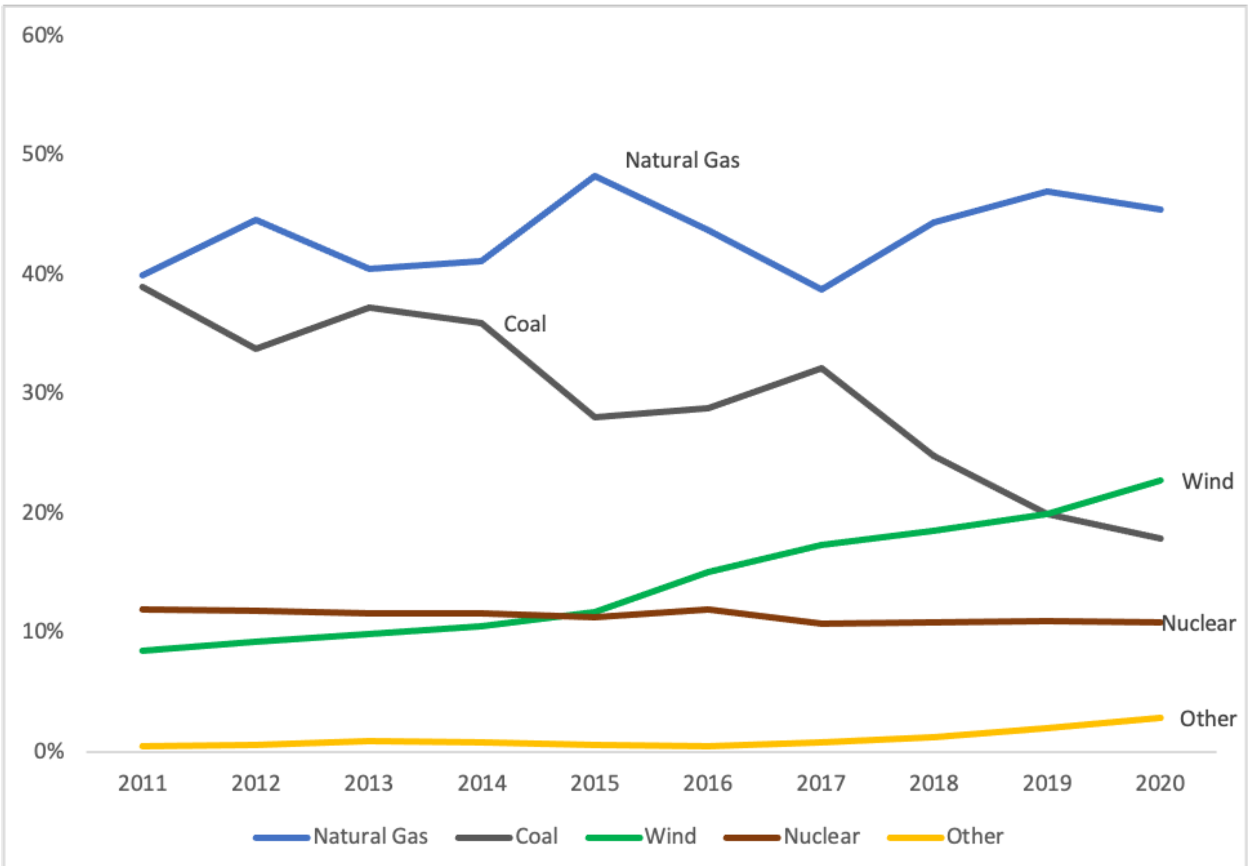

Figure 2.3: Energy Use by Fuel Type in ERCOT 2011-2010

Note: Other types of generation mainly include solar, hydro and biomass power plants.

Source: ERCOT annual fact sheets

2.4 Data

To estimate the effect of increasing wind capacity on wholesale electricity price, I choose 2014 to 2017 to perform the analysis because as shown in figure 2.2 wind capacity has increased over 8000MW between 2014 and 2017, which is a significant addition of supply capacity[6]. Also, by 2014, ERCOT has completed a large transmission project to bring wind power to the demand center.

ERCOT reports generation by fuel type every 15 minutes. Figure 2.4 shows the total daily wind production during 2014 to 2017. Though wind production has an increasing trend, wind has a lot of day-to-day production variation even within the same month due to changes in meteorological conditions. The within-day production pattern is similar across years (Figure 2.5). Wind tends to produce more at night and less during 10am to 3pm.

To investigate the changes of other types of generation, in addition to the aggregate data of generation by fuel type, I also use the real time generation data for each generator, and the data records generator type, for example, it distinguishes between simple cycle and steam gas plant. I aggregate the generation data by generator type.

Similarly, ERCOT reports the settlement price at each location every 15 minutes. In the main analysis, I use the settlement price in the North Load Zone, which contains the Dallas-Fort Worth metroplex. The Load Zone price is a weighted average price of all settlement points in the North. Wholesale price tends to be higher during the late afternoon and lower at night. The average price in 2014 is higher than the other years partly due to higher natural gas price.

In the regression analysis, I aggregate the production data to hourly level. I merge the production data with ERCOT's hourly load data and the daily spot price of nature gas at Henry Hub from the EIA[7]. I also include the daily maximum and minimum temperature at Fort Worth city and monthly precipitation in Texas. The temperature and precipitation data are obtained from NOAA online database.

[6]The average load in ERCOT is about 40000MW, and the capacity factor of wind power is about 25%-35%, so an increase of over 8000MW wind capacity can increase supply by more by 5% of the average load.

[7]The daily price is not available for weekend and holidays, so for those days, I use the latest available price.

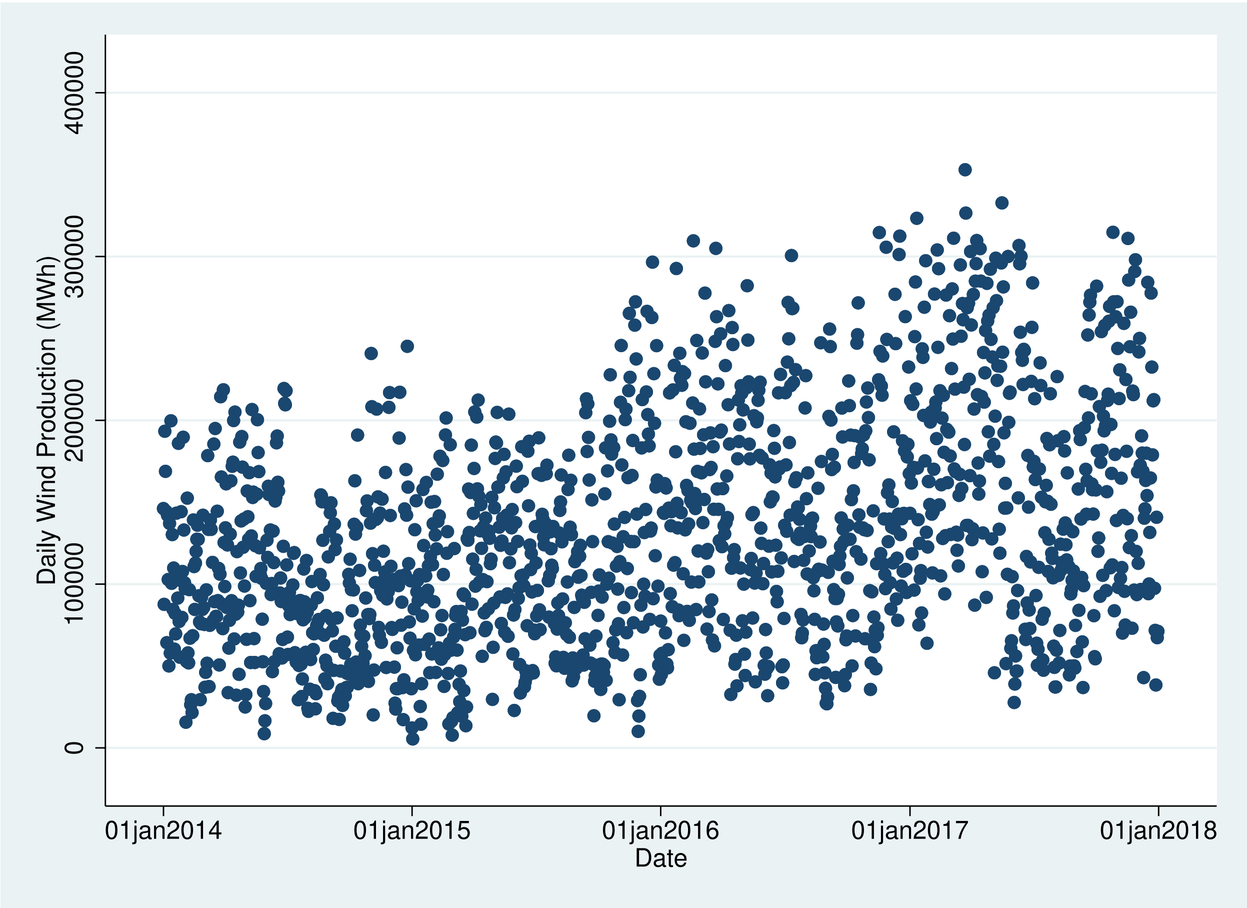

Figure 2.4: Daily wind production in ERCOT 2014-2017

Note: This figure shows the total daily production of wind from 2014 to 2017 in ERCOT.

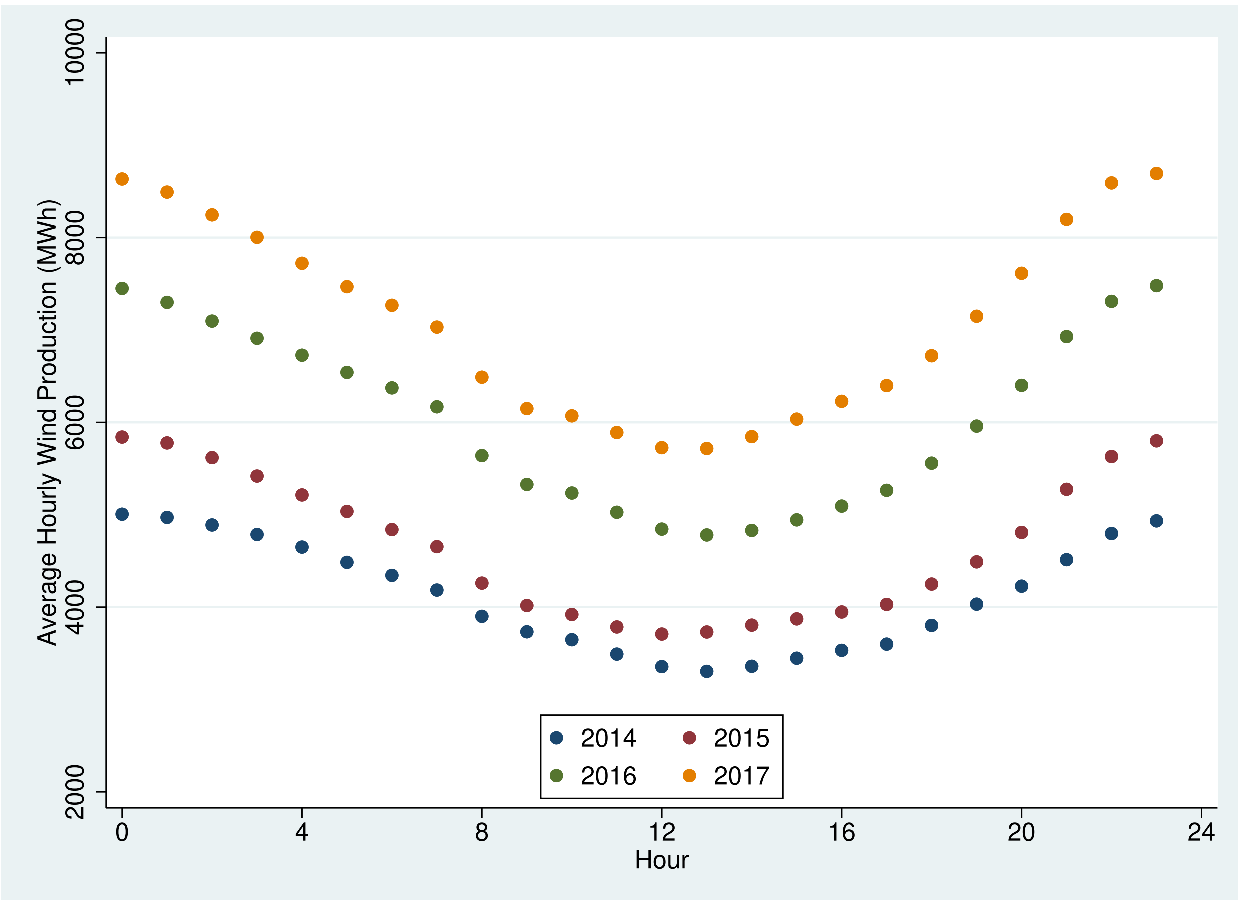

Figure 2.5: Average hourly wind production in ERCOT 2014-2017
Note: This figure shows the average hourly production of wind from 2014 to 2017 for each hour of the day in ERCOT.

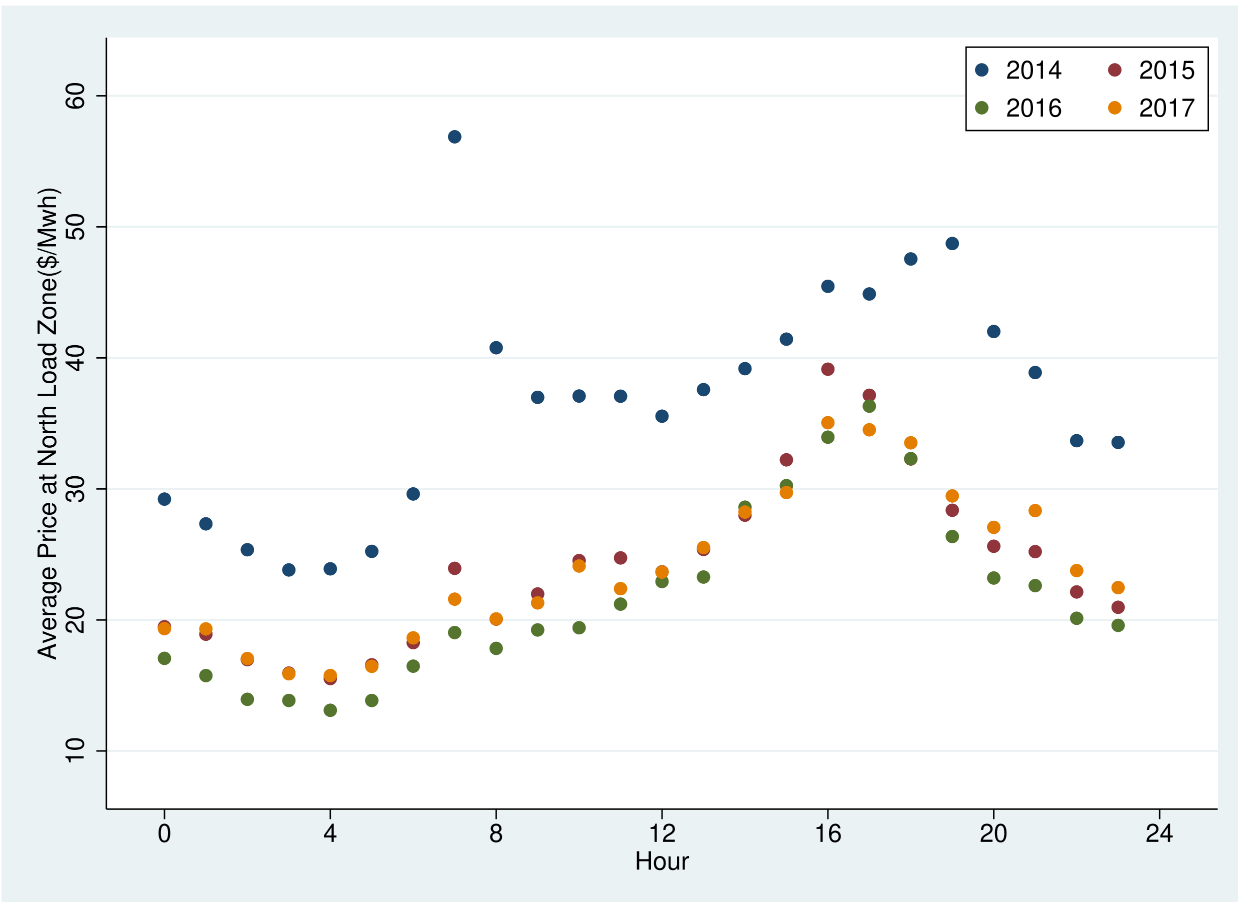

Figure 2.6: Average wholesale price at North Load Zone for each hour of the day 2014-2017
Note: This figure shows the average hourly whole electricity price at the North Load Zone in ERCOT for each hour of the day fro 2014 to 2017.

Table 2.1: Summary statistics of energy offer prices 2014-2017

	min	25%	50%	mean	75%	max
50% of owner's average HSL	-1374.98	-250	17.4	61.1	24.8	9000
75% of owner's average HSL	-1375	0.01	19.7	165.6	29.2	9000
90% of owner's average HSL	-1375	5.4	21.6	222.0	33.8	14000
100% of owner's average HSL	-1375	5.4	23.0	342.5	37.1	14228

Note: This table presents the summary statistics of energy offer prices from the real time energy offer curves submitted by resources available to produce electricity. The energy offer curve is aggregated at owner level.

To study the effect of renewable production on fossil fuel generator's market power, I use the energy offer curve of each generator in every 15 minutes interval in the first step of SCED. The energy offer curve in the first step of SCED is as submitted and extended (truncated) according to the generator's operating limits. ERCOT publishes all offer curves submitted by each generator 60 days after the settlement day. The generators included in this analysis are all natural gas and coal generators in ERCOT.

I develop a new dataset of generator and power plant ownership in ERCOT using ERCOT reports, company websites and other publicly available information[8]. I combine this dataset with the Highest Sustained Limit (HSL) of each generator, and compute the sum of all generators' HSL and the sum of all wind generators' HSL for each owner in each hour. HSL is the the amount of power the generator can consistently produce, which is usually lower than the nameplate capacity of the generator. The HSL can vary a lot for wind energy across hours, so I calculate the average of the sum of all generator's HSL and the average of the sum of wind generators' HSL for each owner between 2014 and 2017. I use these average HSLs as a measure of generation capacity owned by each firm. About 9% of wind capacity is owned by companies that also have fossil fuel power plants in ERCOT, and the rest is owned by other companies that only have renewable generation in ERCOT.

In the main analysis, I aggregate the energy offer curves by owner. I use the offer price at different percentages of the average HSL of each owner of conventional energy. Table 2.1 presents the summary statistics of offer prices at different percentages of the average HSL of each owner. ERCOT has an offer price cap that have been raised several times. The cap was raised to $5000/MWh

[8]There could be some changes in the ownership over time or co-ownership that are not included in the dataset.

in June 2013, \$7000/MWh in June 2014, and \$9000/MWh since June 2015. Generators may offer at the cap due to reasons like outage, tight supply condition and market power. The offer curve is bounded below at -\$250/MWh. Plants may offer at -\$250/MWh because they want to make sure being taken to supply power. Table 2.1 shows there are a few cases when the offer price is below the lower bound and above the upper bound. In the analysis, I replace those values with the corresponding offer floor or cap.

2.5 Empirical Strategy

2.5.1 The effect of wind production on price

The goal of the analysis is to study the effect of increasing wind production on wholesale electricity price. I follow the strategy of Bushnell and Novan (2018). In the main specification, I use total daily wind production to explore the non-contemporaneous effects of wind production on wholesale electricity price and quantity produced by different types of generators. The difference between using daily and hourly wind production is daily production allows non-contemporaneous effects and does not use the hourly variation of wind production across days. For example, given the same total daily wind production, wind production at 1am may be higher in one day than the other. Wind production has a daily pattern as shown in figure 2.5. The correlation between daily wind production and wind production at each hour of the day ranges from 0.73 to 0.93 in the data. The correlation between daily and hourly wind production is higher during daytime than at night. I present the results using hourly wind production in the appendix as a robustness check. In addition, I use the price at the North Load Zone in the main specification, and I control for the electricity demand in north Texas[9] because transmission constraints may prevent generation from other regions to be sent to the North so local demand also matters. I also control for daily

[9]The Load Zone used in price and electricity demand are different. The load data has 8 zones: East, Far West, West, North, North Central, South, South Central and Coast. I sum the load in the North and North Central.

maximum and minimum temperature. The general estimating equation is

$$p_{h,d} = \beta_1 wind_d + \beta_2 solar_d + \beta_3 load_{h,total} + \beta_4 load_{h,north} + \beta_5 \mathbf{X}_d + \eta_{mofy} + \epsilon_{h,d} \tag{2.4}$$

h represents the hour of the day, and d represents each day in the period from January 1st 2014 to December 31st 2017. $wind_d$ is the total daily wind production in GWh. $\mathbf{X}_d$ includes the daily gas spot price at Henry Hub, monthly precipitation in Texas[10] and daily maximum and minimum temperature.

I perform the analysis for each hour of the day separately to capture the heterogeneous response across hours. I regress the price at hour h, day d on daily total wind production controlling for the daily solar production, total electricity demand in ERCOT, hourly demand in the North, daily gas spot price at Henry Hub, monthly precipitation, daily maximum and minimum temperature and month of year fixed effect. This regression intends to measure the effect of increasing renewable capacity on the wholesale market price, and the estimation relies on the variation of wholesale price and daily wind production for the same month of year, for example, between September 2015 and September 2016. However, as pointed out by Bushnell and Novan (2018), it is possible that the time series of price and renewable production have spurious correlations due to trends of other omitted variables or there are problems of reverse causality. To uncover the causal effect of renewable capacity increase on price, the identifying assumption is the controls are sufficient to account for other factors that are correlated with the trend of renewable production and price. For example, one long run trend is the retirement of coal fired power plants in ERCOT as shown in Figure 2.3. The retirement of coal plants will also have effects on price. The decision to retire is affected by the increasing renewable capacity, but it is also affected by other factors like the age of the power plant and low natural gas price. In the regression, β_1 will also capture the effect of the retirement, and this is another reason why the period between 2014 and 2017 is used in the regression analysis. In early 2018, ERCOT lost around 4000MW coal capacity due to retirement. Reduction in coal capacity can cause increase in wholesale electricity price as coal is usually

[10] Bushnell and Novan (2018) uses monthly precipitation in California as an indicator of hydroelectric potential.

regarded as base load generation.

In the short run, it is unlikely that wholesale electricity price drives wind production. Production potential of wind is determined by wind speed and other weather conditions. Wind power usually offers their capacity at very low price so they are usually producing at its full potential if the system conditions allow. Wholesale price may affect the decision to invest in renewable capacity. However, from planning to actual connection to the grid, wind power project usually take 3 years or more to develop, so current price level does not affect current wind capacity. In Texas, the increase in wind capacity is also driven by the great wind resource in west Texas, the accessibility of land, the transmission expansion and the renewable portfolio standard.

To investigate how increasing wind capacity affect the production of other generators, I use a similar regression specification. The dependent variable is the quantity produced by each type of generation. h represents the hour of the day, and d represents each day in the period from January 1st 2014 to December 31st 2017.

$$q_{h,d} = \beta_1 wind_d + \beta_2 solar_d + \beta_3 load_{h,total} + \beta_4 \mathbf{X}_d + \eta_{mofy} + \epsilon_{h,d} \tag{2.5}$$

To understand the effect of wind production on market power, I use the offer price op of each owner i of conventional generation at 50%, 75%, 90% and 100% of the average HSL at each hour h. Woerman (2019) used offer price at different percentages of generating capacity to measure market power in ERCOT. I regress this offer price on hourly wind production. In addition to daily gas price and temperature, $\mathbf{X}_d$ also includes the hourly HSL, which controls for the generation resource availability. Besides month of year fixed effect, η also includes the owner and hour fixed effects. To explore whether firms respond to production of their own wind farms, I include an interaction term of $wind_{ih} * owind$. $owind$ is a dummy variable representing whether the owner of fossil fuel generators also has wind farms. $wind_{ih}$ is the hourly wind production of those wind farms. I only include generation resources that are available to be dispatched by SCED with an energy offer curve. As discussed in section 3.4, the offer price cap increases over time. Such increase can cause positive correlation between offer price and wind production because wind capacity also increases over time, so I change all offer prices that was at price cap at the time when the energy offer curve was submitted to the current price cap \$9000/MWh. Transmission congestion may also affect offer prices submitted by each owner (Woerman, 2019), so I use the hours that do not have any transmission congestion.

$$op_{ih} = \beta_1 wind_h + \beta_2 wind_{ih} * owind + \beta_3 solar_h + \beta_4 load_{h,total} + \beta_5 \mathbf{X}_d + \eta + \epsilon_{h,d} \tag{2.6}$$

2.6 Results

2.6.1 The effect of wind production on price

This section presents the regression results. Figure 2.7 shows the coefficient and 95% confidence interval for an 1GWh increase of daily wind production and an 1\$/MMBtu increase of gas price using equation 2.4. For all estimates, the newey west standard error with 7 lags is used to account for serial correlations in the data following Bushnell and Novan (2018). The effect of total daily wind production on wholesale price is negative and significant for all hours except 10pm. For example, one GWh increase of daily wind production reduces real time electricity price in the North Load Zone in ERCOT by 0.13\$/MWh at 4pm. The average total daily wind production is 145GWh in 2016 and 170GWh in 2017, so there is an increase of 25GWh. From the regression estimate, this will result in reduction of wholesale electricity price at 4pm by 3.2\$/MWh. The average wholesale electricity price is about \$30/MWh, so this is a significant reduction of wholesale electricity price. The reduction in price is higher in the late afternoon than other hours. The electricity demand usually peaks during late afternoon, and production of more expensive generators increase during this time (See Figure B.1 and Figure B.7) to meet increasing demand.

As in Bushnell and Novan (2018), I present the effect of changing natural gas price on the real time price for reference. When natural gas price increases by \$1/MMBtu, the change in average hourly price ranges from about 5\$/MWh to 15\$MWh. This implies the heat rate of natural gas power plant to be around 5 to 15 MMBtu/MWh, which is close to the range of actual heat rate of gas power plants.

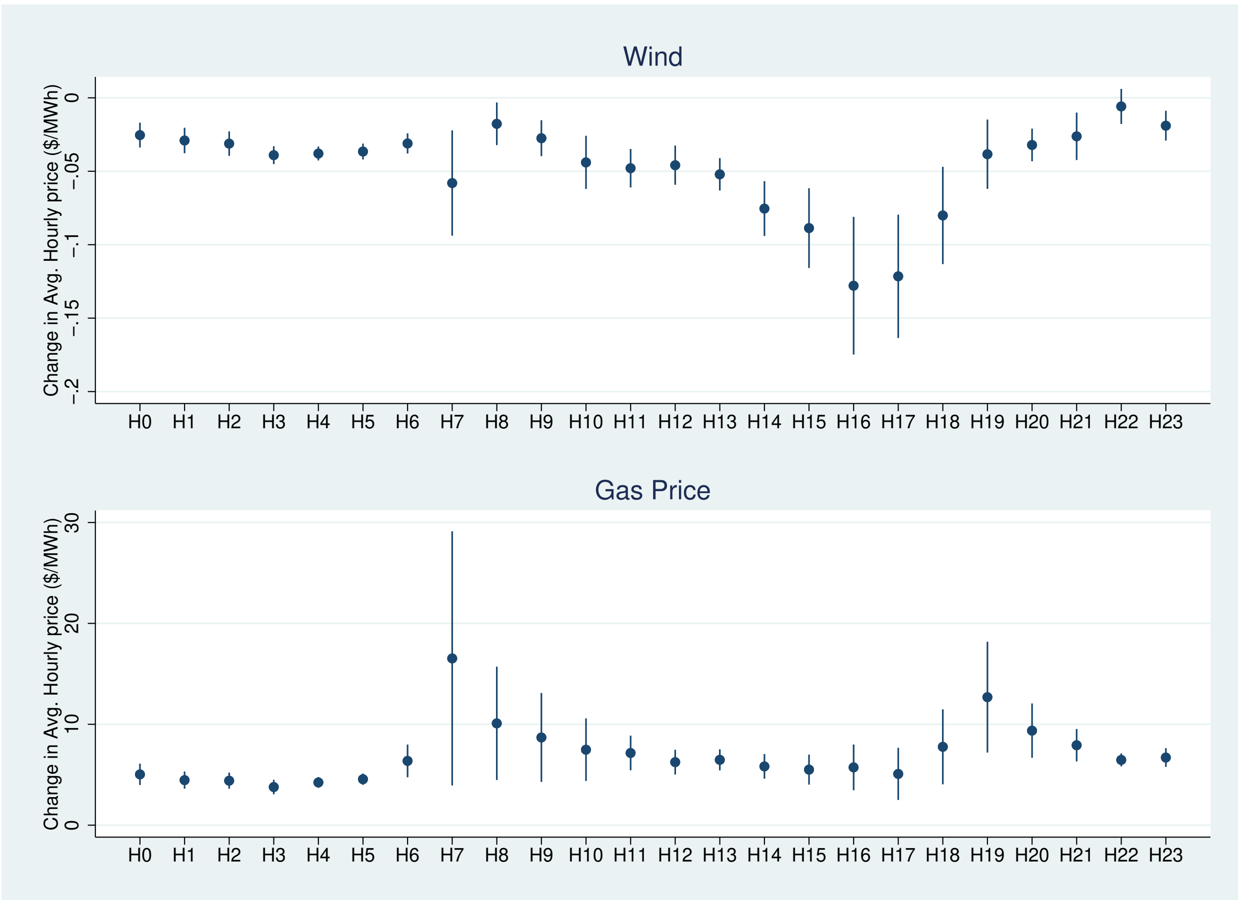

Figure 2.7: Regression coefficients of wind and gas price using equation 2.4 with 95% confidence interval

Note: This figure shows the effect of an 1GWh increase of daily wind production and 1$/MMBTU increase of natural gas price on hourly wholesale electricity price for each hour of the day using equation 2.4 with 95% confidence interval.

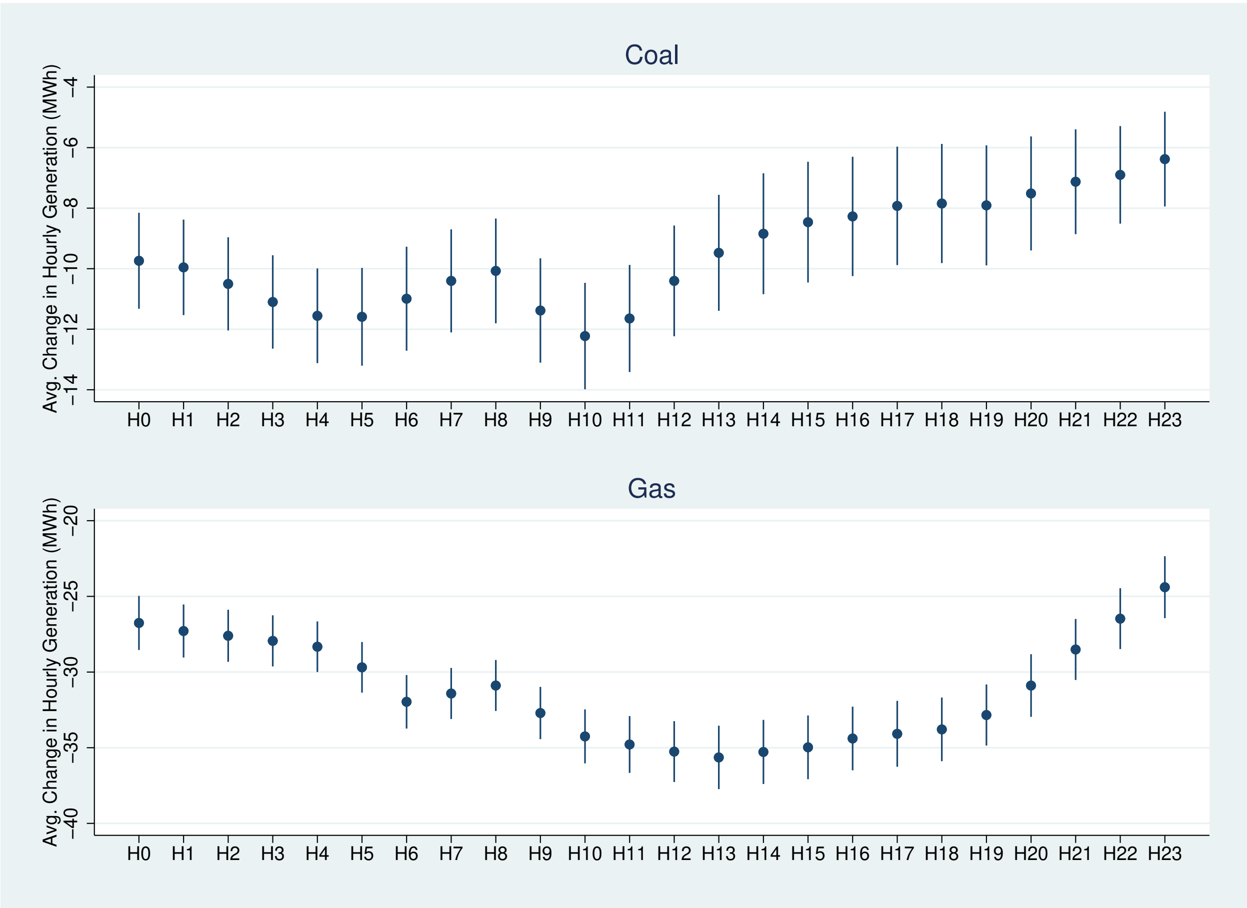

Figure 2.8: Regression results of the effect of wind on quantity produced by coal and gas with 95% confidence interval

Note: This figure shows the effect of an 1GWh increase of daily wind production on hourly output of coal and gas power plants for each hour of the day with 95% confidence interval.

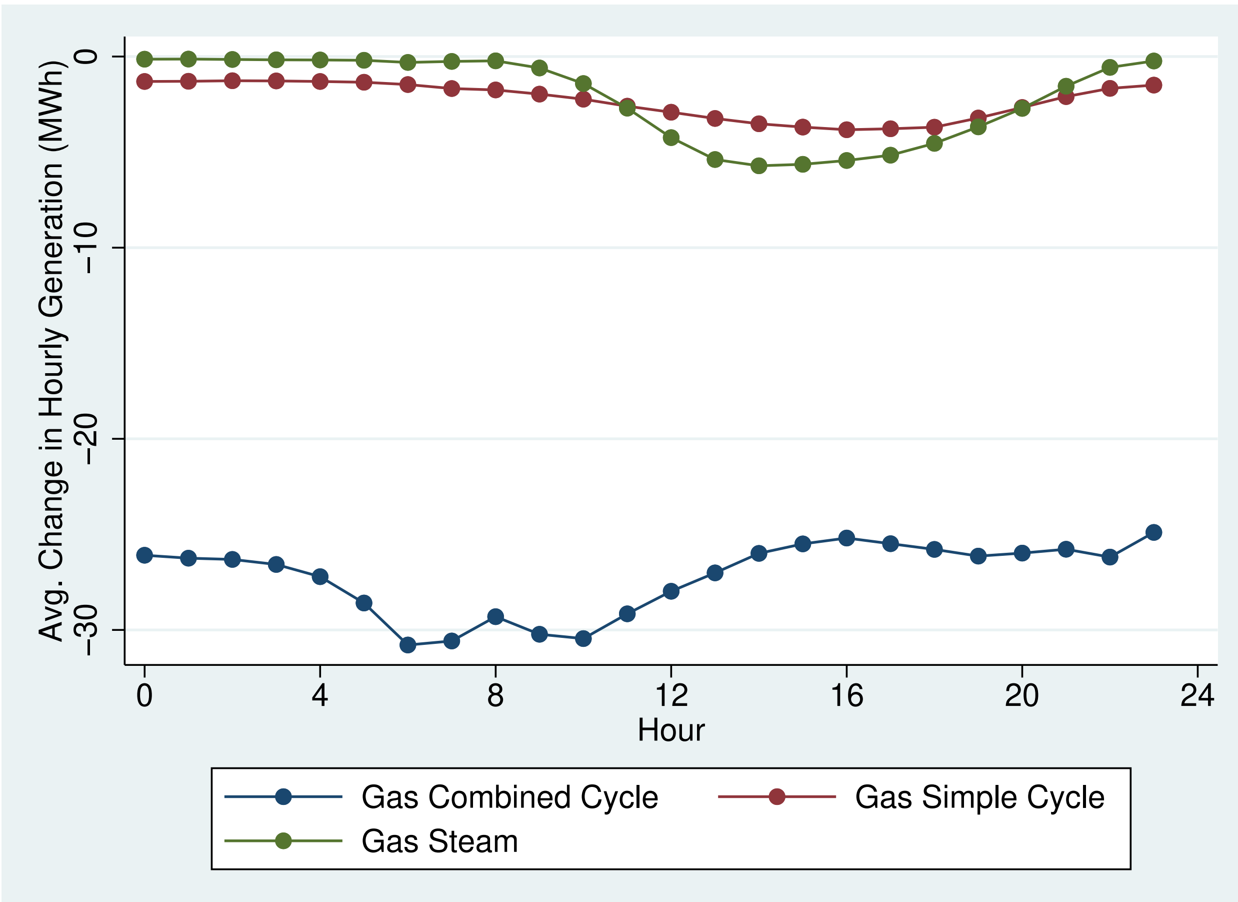

Figure 2.9: Regression results of the effect of wind on quantity produced by different types of gas generators

Note: This figure shows the effect of an 1GWh increase of daily wind production on hourly output of combined cycle, simple cycle and steam gas turbine for each hour of the day. Simple cycle gas plants use gas turbines that generate electricity by gas combustion. Natural gas steam turbines use natural gas to heat water that evaporates into steam to rotate the turbine. Combined cycle power plants use both gas turbine and steam turbine.

2.6.2 The effect of wind production on quantity produced

Figure 2.8 shows the effect of increasing wind production on the quantity produced by coal and natural gas power plants. Both coal and natural gas power plants produce less power across all hours when wind production increases. The magnitude of the reduction in output is much larger for natural gas than for coal because natural gas is usually higher in the merit order stack. Figure 2.9 shows the effect of wind power on different types of natural gas power plants. Simple cycle gas plants use gas turbines that generate electricity by gas combustion. Natural gas steam turbines use natural gas to heat water that evaporates into steam to rotate the turbine. Combined cycle power plants use both gas turbine and steam turbine. Simple cycle and steam gas plants are generally less efficient than combined cycle natural gas plants, and they generate more power between noon and 8pm. The electricity demand is higher in those hours, so the less efficient plants are called for production. The reduction in output increases substantially during the peak hours in the afternoon. When wind production is higher in those hours, it reduces output from these higher cost power plants, and this also explains why the reduction in price is higher in the late afternoon. There is not much reduction in output outside of peak hours as simple cycle and steam gas power plants generate much less power outside of peak hours.

The sum of coefficients of the effect of daily wind production on output for all types of power plants equals -0.98GWh. Increasing 1GWh of wind should displace 1GWh of other generation, and the estimated sum of coefficients is close to -1GWh. Wind power has small effects on production of other types of generators (Figure 2.10). Wind power does not have statistically significant effect on nuclear production as nuclear power plants are not flexible to change their outputs. ERCOT has very small capacity of hydro and biomass. The average hourly production of biomass power plants is 66MWh between 2014 and 2017. For biomass, there is a small and significant increase in production across all hours when using the sample period from 2014 to 2017. A new biomass power plant went online in October 2014. If I run the regression from 2015 to 2017, the coefficients for all hours are statistically non-significant.

The average hourly production of hydroelectric power plants is 94MWh between 2014 and

2017. Hydro capacity varies with hydroelectric potential and it is dispatchable, so the output also depends on market conditions. There is small and statistically significant increase in hydro production during the peak hours in the afternoon with increase in daily wind production. When hourly wind production is used, the effect of hourly wind production on hydro production is still positive during the peak hours but is statistically non-significant (figure B.6). Unlike solar, wind production does not fall to zero at a particular time of day. When the total daily solar production increases, more solar generation is lost at sunset, and other types of generation need to make up for the loss. When the total daily wind production increases, the average standard deviation of hourly wind production within each day increases from 1344MWh to 1987MWh. It is possible that hydro is dispatched to meet electricity demand when wind power production drops during the peak hours, so there is an increase of hydro production when daily wind production increases. On the other hand, monthly precipitation may not fully capture the variation in hydroelectric potential. If hydroelectric potential increases over time, more hydro power is available to be dispatched, and this may lead to positive correlation between wind production and hydro output.

One issue raised by Bushnell and Novan (2018) is curtailment of renewable energy may be affected by the wholesale electricity price. In ERCOT, after the completion of a large transmission project, curtailment of wind is small (Figure B.9). I also use daily wind potential as an instrument for wind production, and the results are very similar (Figure B.2).

2.6.3 The effect of wind production on market power

Table 2.2 presents the results of wind production on market power of conventional generation. I present the results for all non-congested hours and hours when total load is above the 50th percentile in the load distribution between 2014 and 2017. When load is higher, power plants may have more opportunity to exercise market power due to tighter supply. For firms that have both conventional generation and wind farms, the theoretical model predicts if a firm also have wind farms, it offers its fossil fuel generation resource at higher price when its own wind farms increases production. For owners that do not have wind farms, both $owind$ and $wind_i$ are zero.

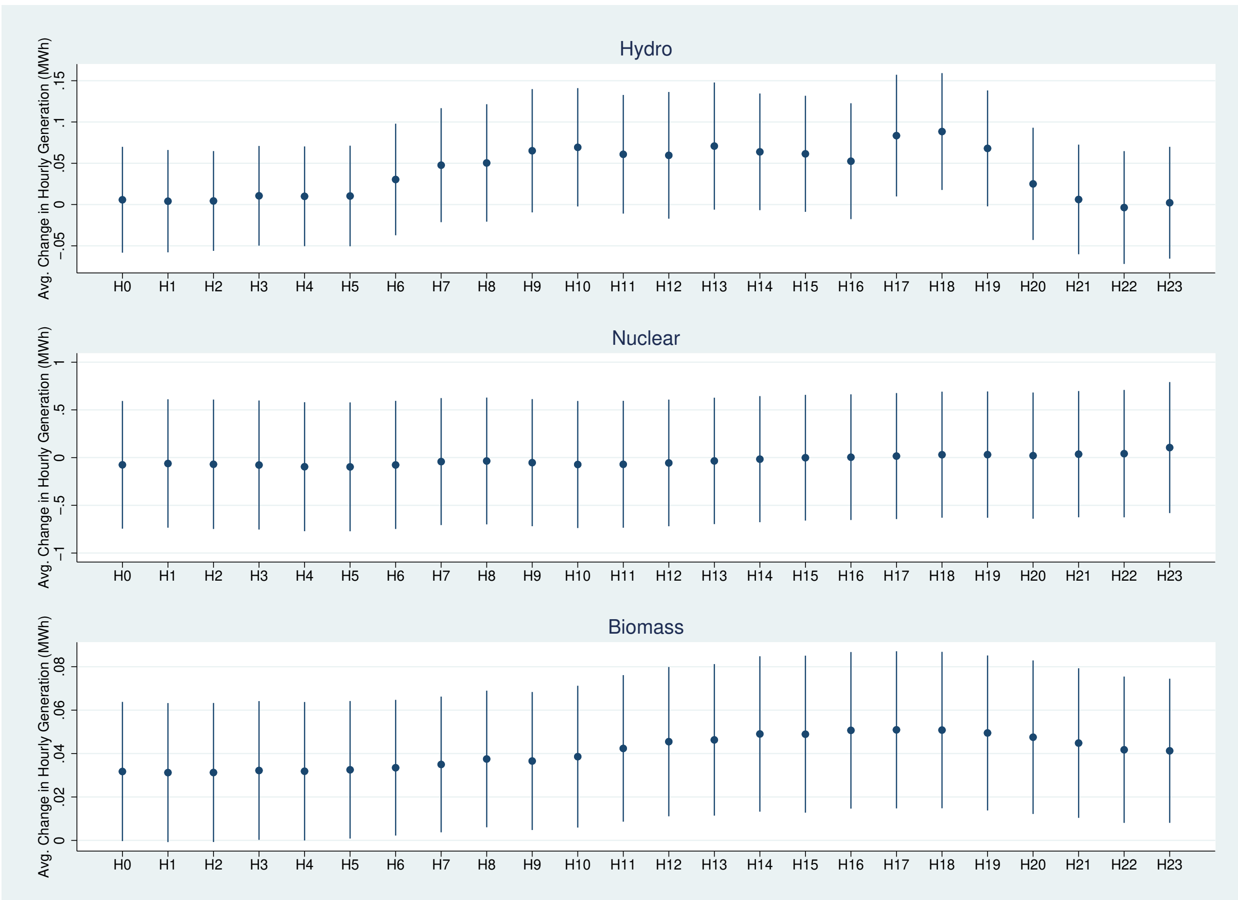

Figure 2.10: Regression results of the effect of wind on quantity produced by hydro, biomass and nuclear generation with 95% confidence interval

Note: This figure shows the effect of an 1GWh increase of daily wind production on output for hydro, biomass and nuclear power plants for each hour of the day with 95% confidence interval.

Table 2.2: Regression Results-effect of wind production (MW) on offer price

	All non-congested Hours	Load greater than 50th percentile
offer price at 50% of average HSL		
Total wind	-0.0037	-0.0085*
	(0.0041)	(0.0045)
$wind_i * owind$	0.94	1.03
	(1.12)	(1.03)
Number of Obs.	120314	40842
offer price at 75% of average HSL		
Total wind	-0.0091	-0.0093***
	(0.0075)	(0.0026)
$wind_i * owind$	0.44	0.92
	(0.48)	(0.64)
Number of Obs.	88027	30610
offer price at 90% of average HSL		
Total wind	0.000086	0.00049
	(0.0056)	(0.0067)
$wind_i * owind$	0.15	0.52
	(0.56)	(0.81)
Number of Obs.	78676	27514
offer price at 100% of average HSL		
Total wind	-0.00079	-0.00236
	(0.0045)	(0.0035)
$wind_i * owind$	-0.103	0.33
	(0.50)	(0.82)
Number of Obs.	71697	24604

Note: This table presents the detailed regression results using equation 2.6 on offer price of owners of conventional generation. $owind$ is a dummy variable representing whether the owner of fossil fuel generators also has wind farms. $wind_i$ is the hourly wind production of wind farms owned by owner i. * represents statistical significance at 10%, ** represents statistical significant at 5%, and *** represents statistical significance at 1% level. The standard errors are two-way clustered by sample day and owner, and are shown in the parenthesis. The regression is performed using STATA command reghdfe developed by Sergio Correia.

For owners that have both conventional generation and wind farms, $owind$ is one, and $wind_{ih}$ is the hourly wind production of their own wind farms. The sign of the coefficient on the interaction term $wind_i * owind$ is positive except for offer price at 100% of the average HSL using all non-congested hours, but the coefficients in all cases are not statistically significant. Most wind farms in ERCOT are owned by companies that only have renewable portfolios, and the companies that rank top 10 in terms of generation capacity only produce 144MWh of wind on average each hour, so the effect is not significant.

For total wind production, the theoretical prediction is ambiguous. The results show that total wind production has negative and significant effect on offer price at 50% and 75% of the average HSL using data when load is greater than 50th percentile. The estimates suggest an 1GWh increase of hourly wind production reduces offer price at 75% of the average HSL by 9.3$/MWh. The average hourly wind production increases by 2.7GWh from 2014 to 2017, and this leads to a reduction of offer price at 75th percentile by 25$/MWh. When all non-congested hours are used, total wind production does not have statistically significant effect on offer price.

This analysis has some limitations. First, I use only the generation resources that are available to produce power with an energy offer curve. It is possible that the decision to take the power plant off line is strategic. Second, this paper has not considered firms' forward contract position. With more renewable energy enters into the grid, price may become more volatile, and power generating companies may change their strategy of forward contracting. Such changes can also affect their incentives to exercise market power in the real time market.

2.7 Conclusion

Increasing the percentage of electricity generated from renewable energy is a crucial part of the energy transition. This paper showed increasing renewable generation has important consequences for the wholesale electricity market using data from ERCOT. ERCOT has the largest wind capacity in the US, and has seen rapid increase in wind capacity in recent years.

I quantified the effect of increasing wind capacity on price using hourly price and daily wind production in ERCOT controlling for electricity demand, solar production, gas price, daily temperature, and month of year fixed effect. I find increasing wind production decreases the real time price for all hours except 10pm, and the effect is particularly large in the late afternoon when demand reaches the peak. An 1GWh increase of daily wind production reduces the wholesale electricity price by 0.13$/MWh at 4pm. From 2014 to 2017, the daily production of wind has increased over 70GWh on average, so the magnitude of price reduction is about 9$/MWh.

Increasing wind production reduces output for coal and natural gas power plants for all hours of the day, and the effect is larger for natural gas power plants. With an 1GWh increase of daily wind production, gas plants reduce production by more than 24MWh for all hours. The majority of the reduction comes from the combined cycle natural gas plants, which has the largest capacity among all gas plants. The less efficient simple cycle and steam gas power plants on average produce much less power than combined cycle gas plants. Increasing wind production causes these plants to reduce output particularly when electricity demand is higher.

I investigated the effect of wind production on market power. I regressed the energy offer price at different percentages of generating capacity on hourly wind production using non-congested hours. The effect of wind production is not statistically significant when using all non-congested hours. When using data when load is greater than 50th percentile in the load distribution, an 1GWh increase of hourly wind production decreases offer price at 50% of the average HSL by 8.5$/MWh, and it decreases offer price at 75% of the average HSL by 9.3$/MWh.

In the longer run, with more renewable generation, the generation mix is likely to change. The capacity of battery storage facility is growing in ERCOT. Solar generation has a generation pattern that is complementary to wind, so solar is rapidly developing in ERCOT. Several coal power plants have retired in recently year across the US. The long run effect of increasing renewable capacity is an interesting area of future research.

Chapter 3: The effect of transmission limit on market outcome: evidence from ERCOT

3.1 Introduction

Geographic constraints often limit the ability of sellers in one region to sell products to another region. This prevents the potential trade that would have occurred without the constraints, and the two markets will clear with separate prices. The cost of supplying electricity in different regions may be different because different regions have diverse generation portfolios and transmission constraints in the electricity market limit the transmission of electricity between regions. With the growing capacity in renewable energy, the effect of transmission congestion becomes more salient. Renewable resource-rich areas may be sparsely populated, so transmission infrastructure is needed to integrate the renewable generation into the larger electricity market.

New transmission lines have been constructed or in the planning stage in many electricity markets, so it is important to understand how increase in transmission limits affect market price and electricity production. In this paper, I use the large transmission investment project in the Electricity Reliability Council of Texas (ERCOT) to study the effect of increasing transmission limit on market price and power plant output. ERCOT invested 7 billion dollars in the Competitive Renewable Energy Zone (CREZ) project for transmission capacity expansion to accommodate the growing wind generation in west Texas between 2010 and 2013. The large transmission investment and renewable generating capacity provide significant variation in transmission limits and wind energy production, which helps to identify the effect of transmission limit on market outcomes. The construction of new transmission lines provides exogenous variation in transmission limits. In addition, ERCOT is a relatively isolated grid with little import and export, so there are less confounding factors due to changes in the outside markets.

To analyze the effect on output of different generator types in different regions, I develop a dataset of generator locations. Using hourly ERCOT data on transmission limit from the West to the North, price and generator output from December 2010 to 2013, I find an increase of 100MW in the transmission limit increases the hourly output of generators in the West by 23.7MWh and increases price in the West by 1.12$/MWh during the congested hours. For the North Load Zone, generators reduce hourly output by 71.1MWh and price in the North Load Zone is reduced by 0.17$/MWh for an 100MW increase in the transmission limit during the congested hours. The increase in transmission capacity for the whole CREZ project is more than 2000MW. For 2000MW increase in the transmission limit, during the congested hours, price in the North increases by 3.4$/MWh on average, and price in the West increases by 22$/MWh on average.

To investigate different types of generators' response, I run separate regressions for each type of fossil fuel generators. In the West, all types of generators have increased production. In the North, the lower cost coal and combined cycle gas power plants decrease production due to increase of the transmission limit from the West to North, but the increase in transmission limit leads to higher production of the less efficient simple cycle and steam gas power plants. More wind power is imported to the North, and wind power is intermittent, so the more flexible and higher marginal cost gas power plants are dispatched when wind power production fluctuates. In the South, there is also increase of steam gas power plant production during the congested hours when the transmission limit increases. The increase of production of simple cycle and steam gas power plants is generally larger during off-peak hours.

This paper contributes to the literature on electricity trade and transmission network. Previous literature discussed the gains from trading electricity between different regions and countries (Abrell & Rausch, 2016; Antweiler, 2016; Cicala, 2017; von der Fehr & Sandsbråten, 1997), and used theoretical models to study transmission right allocation and investment (Joskow & Tirole, 2005; Joskow & Tirole, 2000; Zerrahn & Huppmann, 2017). Several papers calculated the counterfactual scenarios of transmission expansion using model calibrated from existing markets (Ryan, 2021; Wolak, 2015; Yang, 2020). This paper uses the actual data from a transmission expansion project. Other studies have explored the effect of transmission expansion in ERCOT (Doshi & Du, 2021; Du & Rubin, 2018; Fell et al., 2021; Jang, 2020; LaRiviere & Lyu, 2018). This paper differs from the existing literature in two regards. First, this paper uses the actual value of transmission limit in ERCOT instead of completion of CREZ or an indicator for congestion, so the analysis quantifies the effect of an 1MW increase of transmission capacity. Second, this paper also analyzes how additional transmission capacity affects production of fossil fuel generators in each region by constructing a dataset matching the location of each generator to the electricity production data. Furthermore, the analysis shows the responses of production for different types of fossil fuel generators are heterogeneous.

This paper also relates to the literature on the response of conventional generation to supply shocks. Davis and Hausman (2016) studied the effect of closure of a nuclear power plant on generator production and cost. Cullen (2013) analyzed what types of generations are replaced by wind in Texas using data between 2005 and 2007 when wind capacity was much lower. Bushnell and Novan (2018) showed when solar capacity increased, the more flexible and higher marginal cost gas power plants increased production after sunset. Fell and Kaffine (2018) discussed how the interaction of wind energy and gas price affected coal power plant retirement. This paper contributes to the literature by providing evidence on how relaxing transmission constraints in the renewable energy-rich area affects the production of different types of generations. More flexible and higher cost generators increase production in the importing area because wind power can have large short run variation in output.

The remainder of this chapter is organized as followed. Section 3.2 introduces the ERCOT electricity market and the CREZ transmission project. Section 3.3 develops a stylized model on the effect of transmission limit between two regions. Section 3.4 describes the data source and presents the summary statistics. Section 3.5 discusses the empirical strategy, and section 3.6 presents the results. Finally, Section 3.7 concludes the chapter.

3.2 Institutional Setting

3.2.1 ERCOT Wholesale Electricity Market

ERCOT is the Independent System Operator (ISO) of about 90% of Texas load. The electricity grid at ERCOT does not have much connection with outside markets, so there is little import or export. In ERCOT, generators can sell power through bilateral contracts[1], day-ahead market and real time market. The day-ahead and real time markets are centralized wholesale electricity markets managed by ERCOT. Generators can voluntarily participate in the day-ahead market, and the power sold in the day-ahead market become financial obligations for the generators. I focus on the real time market because generators must participate in the real time market if they want to sell physical power and all transmission constraints are considered in the real time dispatch. Real time demand must be met during the real time dispatch.

The real time price is determined by the demand and supply conditions. Generators submit energy supply curves to specify how much electricity they are willing to produce at a given price. Figure 3.1 shows an example of the energy supply curve aggregated over all generators. If there is no transmission constraints, the price is determined by the intersection of the supply and demand curve. Since December 2010, ERCOT implements a nodal market design in the wholesale electricity market. every grid interconnection is considered to be a node. Every generator resource and load is assigned to a node at its location. The price at each node is calculated using the locational based marginal price (LMP), i.e, the cost of supplying an additional MW of electricity at a specific location. The marginal cost of supply depends on the supply offer curves submitted by generators and transmission constraints. The price of two nodes will be the same if the transmission limit between them is not reached. If no transmission lines are constrained, the LMP will be the same for all nodes, and it is determined by the aggregate supply curves submitted by all the generators and the real time electricity demand. Figure 3.1 shows an example of the aggregate supply curve and the real time electricity demand.

If the transmission constraint from A to B is binding, if more electricity is demanded at node

[1]Bilateral contracts refer to the transaction between electricity buyer and seller. The contracts can include physical delivery of power, or they can be pure financial transactions for risk management. Power plants can sell electricity to utilities and other consumers through long term power purchase agreements.

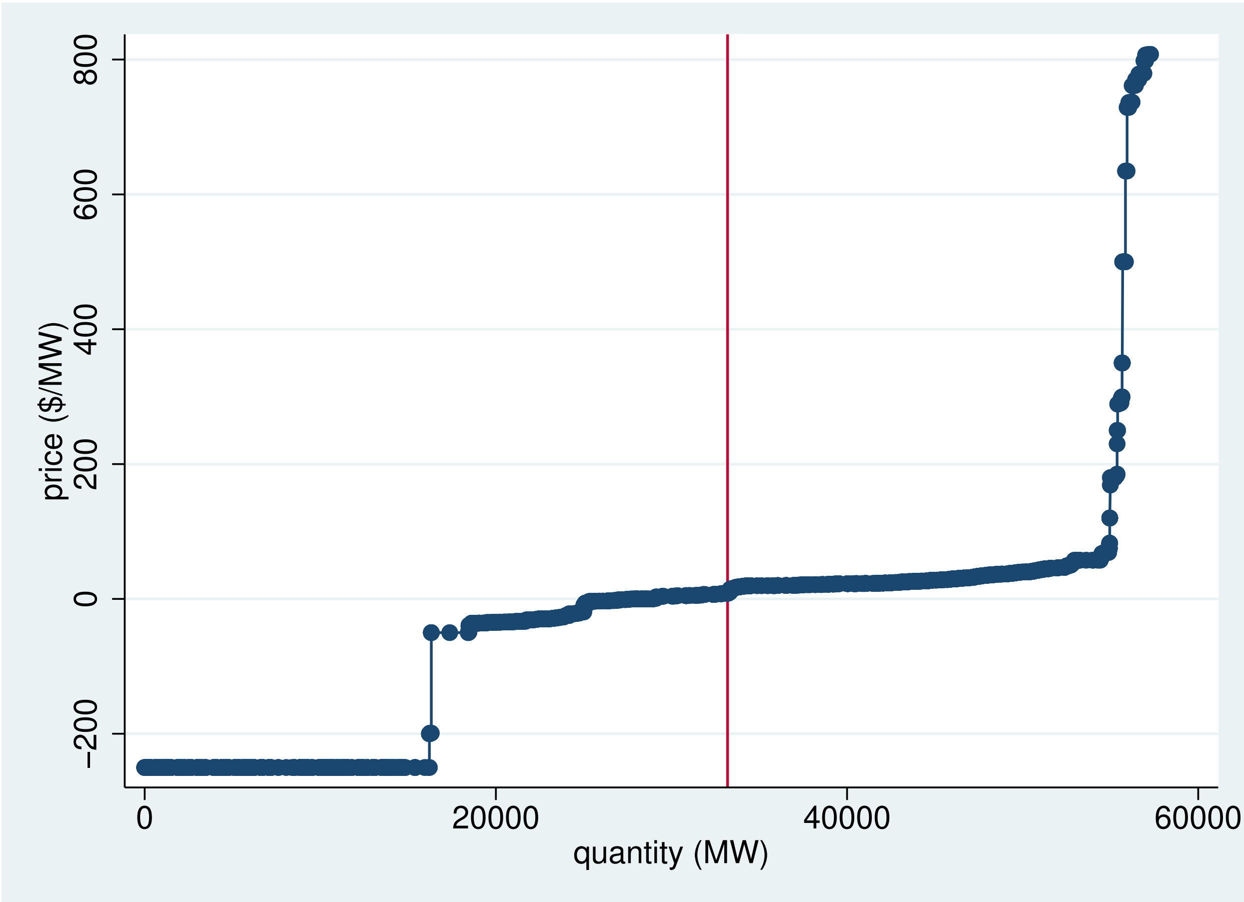

Figure 3.1: An example aggregate energy offer curve in ERCOT on 8pm, November 3rd 2013
Note: This is an aggregate energy supply curve aggregated from real energy offer data of all generators on 8pm, November 3rd 2013. The vertical line represents the total demand in that hour.

B, generators at node A cannot supply more electricity to node B. ERCOT runs the lowest cost dispatch respecting the transmission constraints, and the LMPs are determined at each node. The buyers of electricity pays the load-weighted average of all LMPs in a Load Zone, which is called Load Zone price. ERCOT has four Load Zone: West, North, South and Houston.

The number of wind farms has increased significantly in the West Load Zone in recent years, while demand is the West Load Zone is small. So in the Competitive Renewable Energy Zone (CREZ) project, ERCOT has invested 7 billion dollars to expand transmission capacity from the West to the demand centers (Figure 3.2).

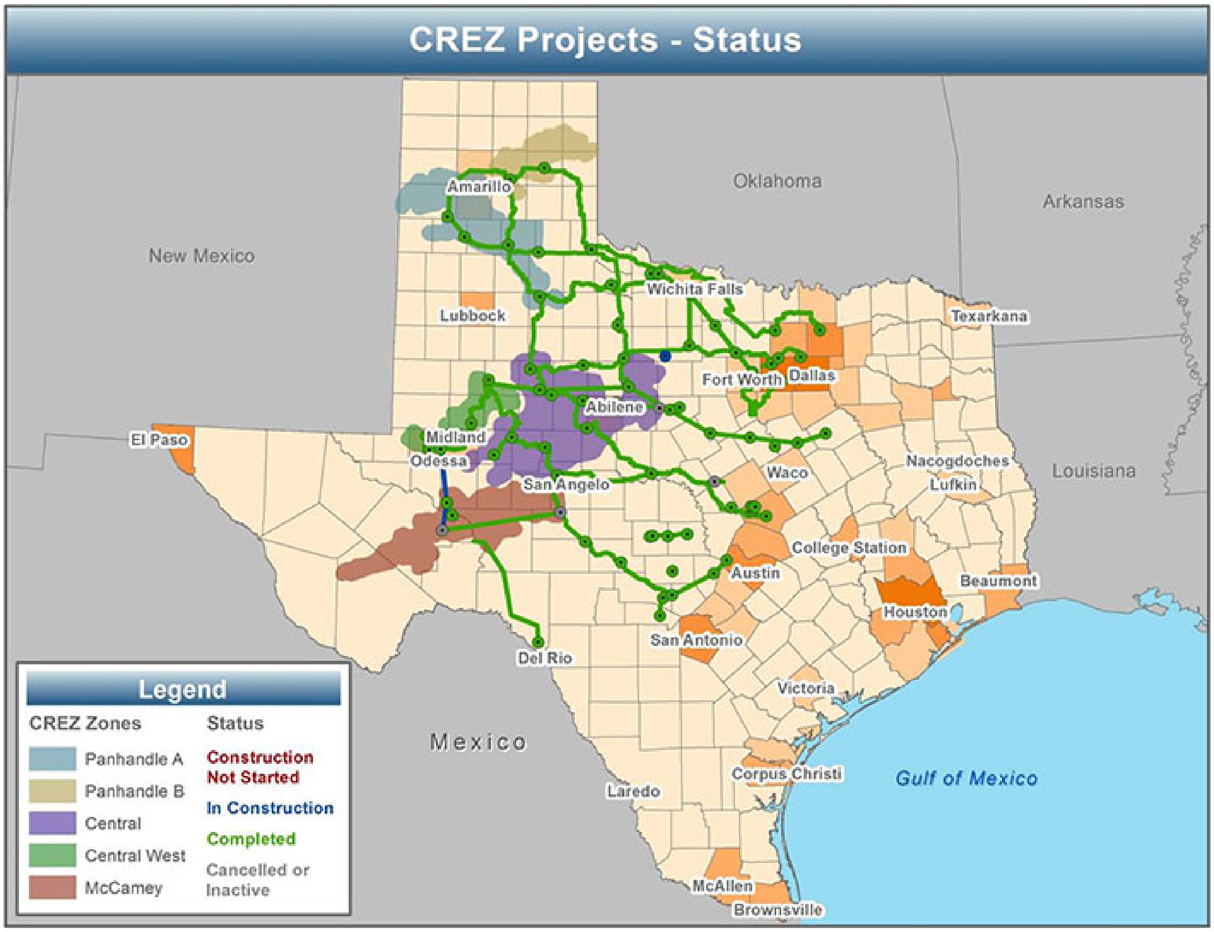

Figure 3.2: Transmission lines constructed in the CREZ project
Source: CREZ Map from the Public Utility Commission of Texas website http://www.puc.texas.gov/industry/maps/electricity.aspx

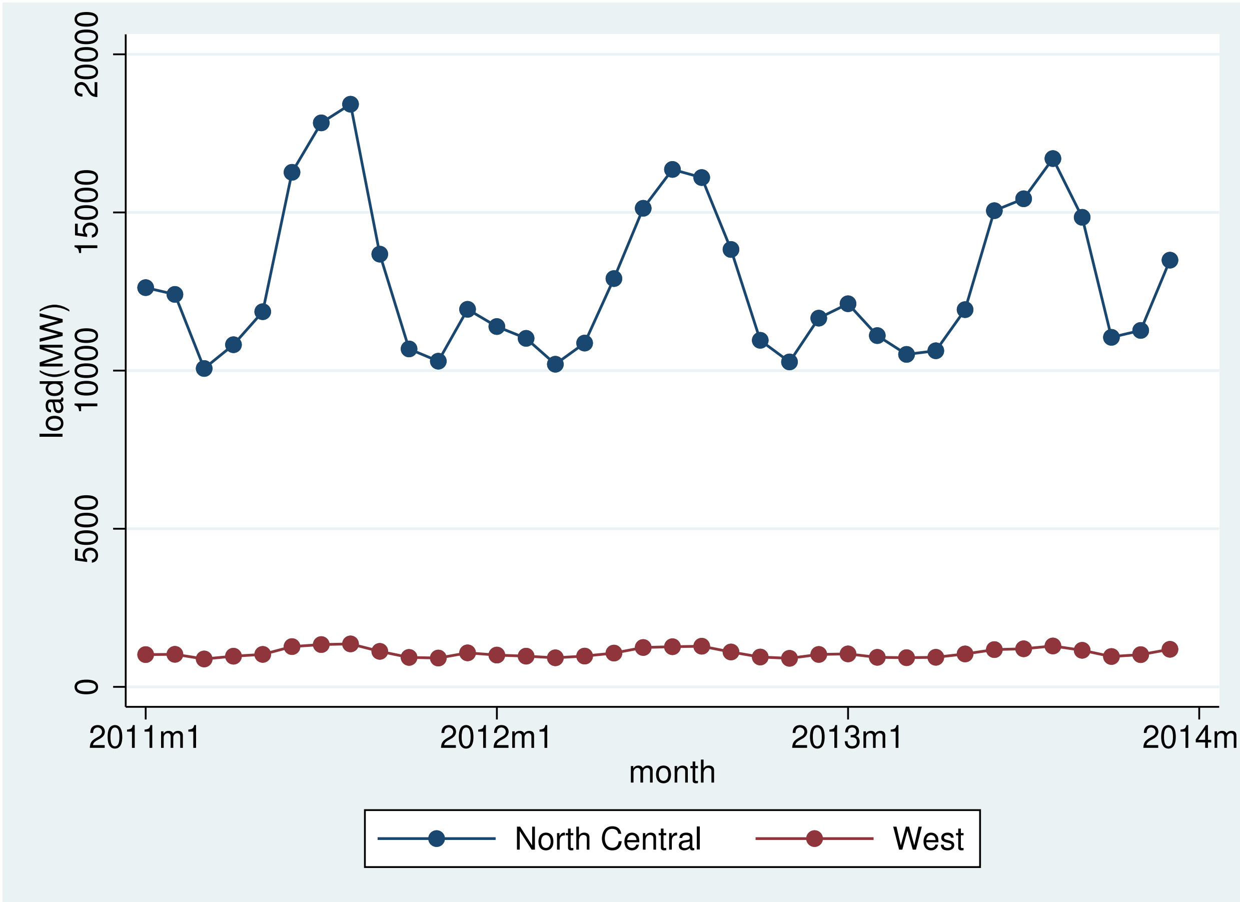

Figure 3.3: Average Hourly Load in the North and West

3.2.2 The CREZ project

Figure 3.3 shows the average hourly electricity demand per month in the West and North Central region of Texas. The motivation of the CREZ project comes from the mismatch in demand and supply in the west Texas and other areas. The demand in the north central Texas is much higher than the west Texas because Dallas-Fort Worth metroplex is located in the north central Texas, while population is much more sparse in the west Texas. On the other hand, west Texas is particularly suitable to develop wind power. Wind energy has close to zero marginal cost, but due to transmission congestion, this cheap supply of power sometimes cannot be supplied to where it is needed.

The construction of new lines and upgrade to existing infrastructure are based on engineering study and projected supply and demand growth. More than 3000 miles of transmission lines were completed at the end of 2013. 3.4 shows the frequency of transmission congestion occurrence from the West to the North. I define transmission congestion from the West to the North as when shadow price reported for this constraint is positive, which means it is more costly to supply electricity in the North than in the West. System constraints are recorded for approximately every 5 minutes. For example, in figure 3.4, if the frequency is 1500, it means for about 125 hours in the month, West to North limit is reached. This West to North export constraint is the most frequently occurred constraint in the whole system in 2011 to 2012, and it occurred more than twice than the second largest constraint. In 2012, it had the second highest frequency. However, in 2013 the frequency declines dramatically, and there is no single incidence when the West to North constraint is binding after April 2014 till 2016. This observed pattern agrees very well with the construction of CREZ projects.

3.3 A stylized model

In this section, I develop a stylized model to understand the effect of transmission limits on market outcomes. I only focus on the case when the transmission constraint from the West to the North is binding because when the transmission constraint is not binding, an increase of transmission limit has no effect on the market outcomes. While it is possible that the reverse limit from the North to the West is binding, I only consider the case when the West is the exporting region because the goal of the CREZ transmission project is to bring wind power to the demand centers. When the transmission constraint is binding, the West and the rest of ERCOT become separate markets. Let the demand in the West be A_w, and the demand in the rest of ERCOT be A_n. I denote the transmission limit as L. The model does not consider local transmission constraints within each region.

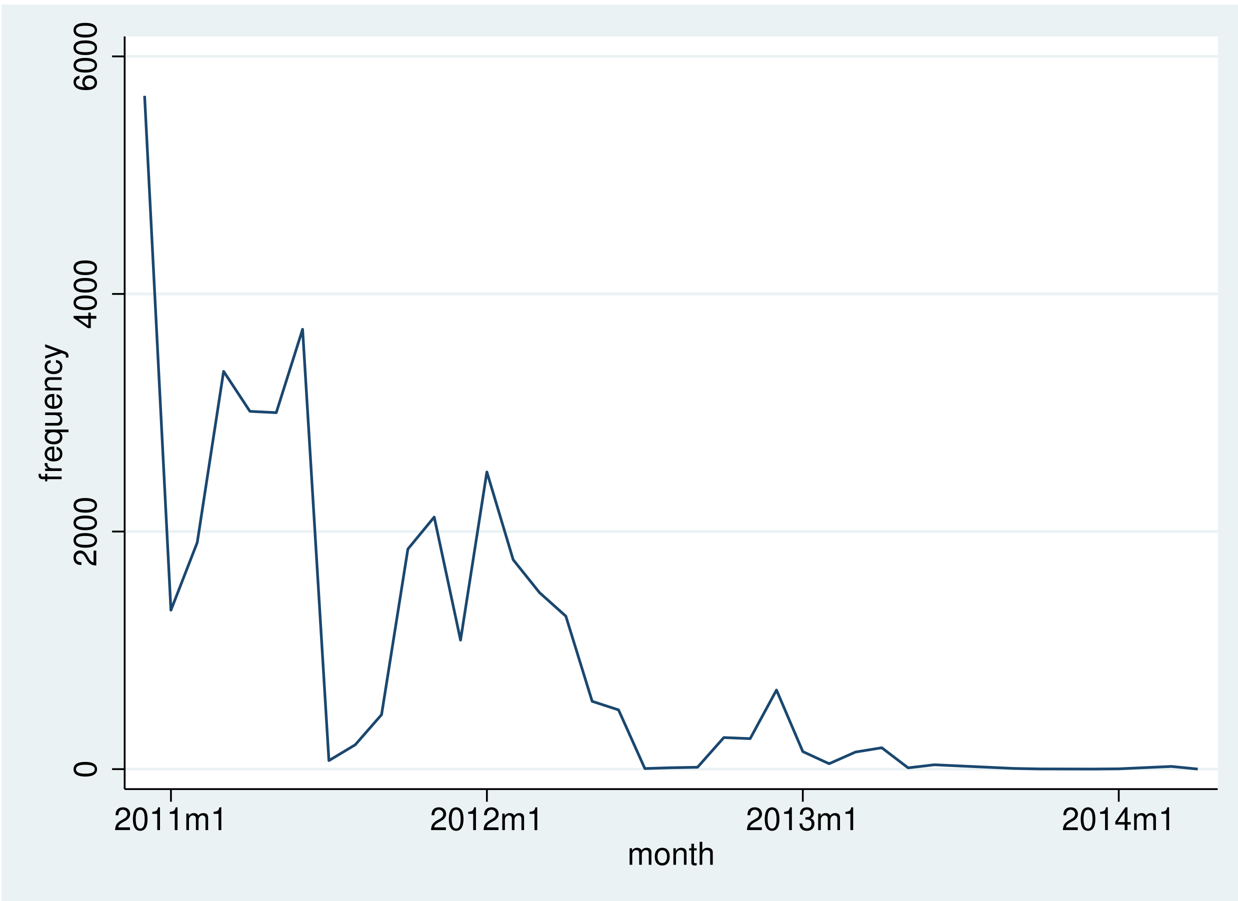

Figure 3.4: Number of times transmission congestion occurs from West to North

Note: The y axis represents the total number of times the "West to North" transmission constraint is binding in every 5 minutes.

3.3.1 Exporting Region-West

When the transmission constraint from the West to the rest of ERCOT is binding, in equilibrium, the local supply in the West must be equal to the local demand plus export. Each generator submits an energy supply curve that is weakly increasing in price. Let the aggregate local supply function be $S_w(p)$, we have

$$A_w + L = S_w(p). \tag{3.1}$$

In the wholesale electricity market, short run demand is very inelastic[2] because most consumers do not pay time-varying price so they do not have much incentive to adjust their electricity consumption according to the short run wholesale price. I assume the real time demand is perfectly inelastic.

Equation 3.1 implicitly defines p as a function of L. By applying the implicit function theorem, we get

$$\frac{\partial p}{\partial L} = \frac{1 - \frac{\partial S_w(p)}{\partial L}}{\frac{\partial S_w(p)}{\partial p}} \tag{3.2}$$

$\frac{\partial S_w(p)}{\partial L}$ represents changes in firms' bidding strategy in response to the change in transmission limit. Under perfect competition, $\frac{\partial S_w(p)}{\partial L} = 0$. Under perfect competition, if $S_w(p)$ in strictly increasing in price, the effect of increasing transmission limit on price is positive in the West.

In the West, wind energy represents a large percentage of generating capacity, and the rest is from fossil fuel power plants. I denote the wind power production in the West as Q_{ww}, and wind power potential as $\bar{Q}_{ww}$. Wind power plants cannot control their potential to produce as it is determined by the amount and direction of wind and other meteorological factors on site. But wind production can be lower than its potential, and I denote unused wind potential as U. Sometimes wind production must be curtailed due to transmission constraints, and I can rewrite equation 3.1 as:

$$Q_{wf} = NL_w + L + U \tag{3.3}$$

[2]It is possible to have some demand response in real time, but it is not widely used.

Q_{wf} refers to the output of fossil fuel power plants in the West and NL_w is the total demand A_w minus the wind potential $\bar{Q}_{ww}$. Wind power plants usually offer their capacity at very low price (often negative price) because they have close to zero marginal cost and they receive federal subsidy for every MWh generated. So in theory, the system operator should always dispatch wind to it full potential. However, due to transmission constraint from the West to the rest of ERCOT, wind production is often lower than its full potential[3]. By taking the derivative of equation 3.3 with respect to the transmission limit L, we get

$$\frac{\partial Q_{wf}}{\partial L} = \frac{\partial NL_w}{\partial L} + 1 + \frac{\partial U}{\partial L} \tag{3.4}$$

In the short run, if we assume new wind farms are not be built due to the expansion of transmission lines, $\frac{\partial NL_w}{\partial L}$ is zero as it does not depend on the transmission limit. $\frac{\partial U}{\partial L}$ is weakly negative because as the transmission limit increases, the unused wind potential should reduce if the full potential has not been reached. Also, $\frac{\partial U}{\partial L}$ cannot be larger than negative one because reduction in used wind cannot be more than the transmission capacity increase. Therefore, the output of fossil fuel power plants should increase, and the change should be between zero and one.

3.3.2 Importing Region-the rest of ERCOT

If we group the importing region as the rest of ERCOT, it contains Dallas, Houston and other metropolitan areas, so its demand is much higher than in the West. When the transmission constraint from the West is binding, import from the West is equal to L as shown in equation 3.5. The aggregate supply $S_n(p)$ in the rest of ERCOT plus the import from the West equals to the total demand in the rest of ERCOT.

$$S_n(p) + L = A_n \tag{3.5}$$

[3]There are also frequency requirements and local transmission constraints that cause wind power to be dispatched less than its potential.

If the demand A_n is perfectly inelastic, applying the implicit function theorem, we get

$$\frac{\partial p}{\partial L} = -\frac{\frac{\partial S_n(p)}{\partial L} + 1}{\frac{\partial S_n(p)}{\partial p}} \tag{3.6}$$

Similarly, $\frac{\partial S_n(p)}{\partial L}$ represents firms' strategic response to transmission limit change. Under perfect competition, if $S_n(p)$ is strictly increasing in price, the effect of increasing transmission limit on price is negative in the rest of ERCOT.

Let the total fossil fuel production be Q_{nf} and the production of other types of generation be Q_{no}. Q_{no} includes wind, hydro, nuclear and biomass power plants. Wind and nuclear in the rest of ERCOT usually do not respond to the transmission limit increase, and the generating capacity of hydro and biomass is veyr small in ERCOT. If Q_{no} does not respond to the change in import, total output reduction of fossil fuel power plants equals to 1.

$$\frac{\partial S_{nf}(p)}{\partial L} = \frac{\partial A_n}{\partial L} + \frac{\partial Q_{no}}{\partial L} - 1 = -1 \tag{3.7}$$

In this stylized model, I have not considered dynamic constraints of generators. As wind power is intermittent, startup and ramping costs may affect the supply curve, so different types of generators may respond differently to transmission limit increase.

3.4 Data

In this section, I describe the data source and present summary statistics of the key variables. The primary data source is reports published by ERCOT. I use the data period from December 2010[4] to the end of 2013.

Generator Production Data ERCOT reports the telemetered output of each generator every 15 minutes in the real time market. I aggregate the data to hourly production by taking the average. To compute production by power plants in the west Texas and other regions in ERCOT, I construct

[4]ERCOT starts the nodal wholesale market on December 1st, 2010, but the generator real time production data is only available starting from December 20th, 2020. So in the analysis, data period starts from December 20th, 2020.

a dataset on the location of each generator using ERCOT's reports of generation resources, and I merge the dataset with ERCOT's generator production data. For wind power, I use the Highest Sustainable Limit (HSL) reported for each wind generator as its potential in each hour. I obtain the wind production potential in each region by summing the HSL of each wind generator in the region in each hour.

Demand and Price ERCOT publishes hourly electricity demand in ERCOT as well as each sub-region and price at each Load Zone every 15 minutes in the real time market[5]. I aggregate the price data to hourly price by taking the average for each Load Zone. I also use the daily gas spot price at Henry Hub from the EIA to control for changes in the input price[6].

Transmission Constraints ERCOT report on transmission constraints is run about every 5 minutes in the real time market, and shows the transmission limit when a particular transmission constraint is reached or close to binding. I use the "West to North" transmission constraints to represent the transmission limits from the West to the rest of ERCOT. I aggregate the data to hourly level by taking the average of the transmission limit.

Daily Temperature I get daily temperature data from NOAA online database. I use the daily maximum and minimum temperature data in four cities in Texas. I use Lubbock for the West, Fort Worth for the North, San Antonio for the South and Houston for Houston Load Zone.

Figure 3.6 shows the "West to North" transmission limit averaged by day during the hours when the shadow price from the West to the North is positive[7]. The transmission limit generally increases over time from December 2010 to 2014 because more transmission lines are completed in the CREZ project, and the occurrence of transmission congestion is greatly reduced when CREZ is close to completion.

Figure 3.5 shows the trend of wind potential and production. More wind farms are built over

[5]The Load Zone used in price and electricity demand are different. The load data has 8 zones: East, Far West, West, North, North Central, South, South Central and Coast. I aggregate the 8 zones to the West, North, South and Houston Load Zones according to the maps provided by ERCOT, though there are still differences in the boundary areas.

[6]The daily price is not available for weekend and holidays, so for those days, I use the latest available price.

[7]Positive shadow price means the system would like to transmit more electricity from the West to the North if transmission limit increases.

Table 3.1: Summary statistics of load zone prices for all hours

Load Zone	min	25%	50%	mean	75%	max
West	-36.6	19.5	24.6	37.0	34.8	3001
North	-9.93	21.5	24.7	33.1	30.4	3001
South	-29.2	21.3	24.6	34.3	30.9	3001
Houston	-21.3	21.5	24.8	33.5	31.1	3001

Note: This table presents the summary statistics of Load Zone prices for all hours from December 20th, 2010 to the end of 2013.

Table 3.2: Summary statistics of load zone prices when west to north transmission is congested

Load Zone	min	25%	50%	mean	75%	max
West	-31.3	-1.20	2.2	6.57	15.4	190.8
North	-3.02	18.9	23.1	24.6	26.9	451.1
South	-3.10	17.8	21.8	24.6	26.1	805.1
Houston	-21.3	18.6	22.7	24.8	26.8	438.4

Note: This table presents the summary statistics of Load Zone prices from December 20th, 2010 to the end of 2013 when the "West to North" transmission constraint is binding.

time, and the gap between wind potential and wind production diminishes partly because wind power can be exported to the rest of ERCOT with transmission expansion. Table 3.1 presents the summary statistics of Load Zone price for all hours. Load Zone prices are the weighted average prices of all nodes in a Load Zone, which are also the prices buyers pay. It can be different from the price generators in a region receives which differed by resource node due to local transmission constraints and such difference is not the focus of this study. The North, South and Houston Load Zone have very similar distributions of price. The West Load Zone has more occurrence of low price compared to the rest of ERCOT because when there is a lot of wind power and it cannot be exported to other areas, price will be very low as wind power usually offer to produce at low prices. When the "West to North" transmission lines are congested, the West experiences much lower price on average because wind energy must be used to meet local demand (Table 3.2). For the other Load Zones, the distribution of prices are similar. The median price is lower than the average price.

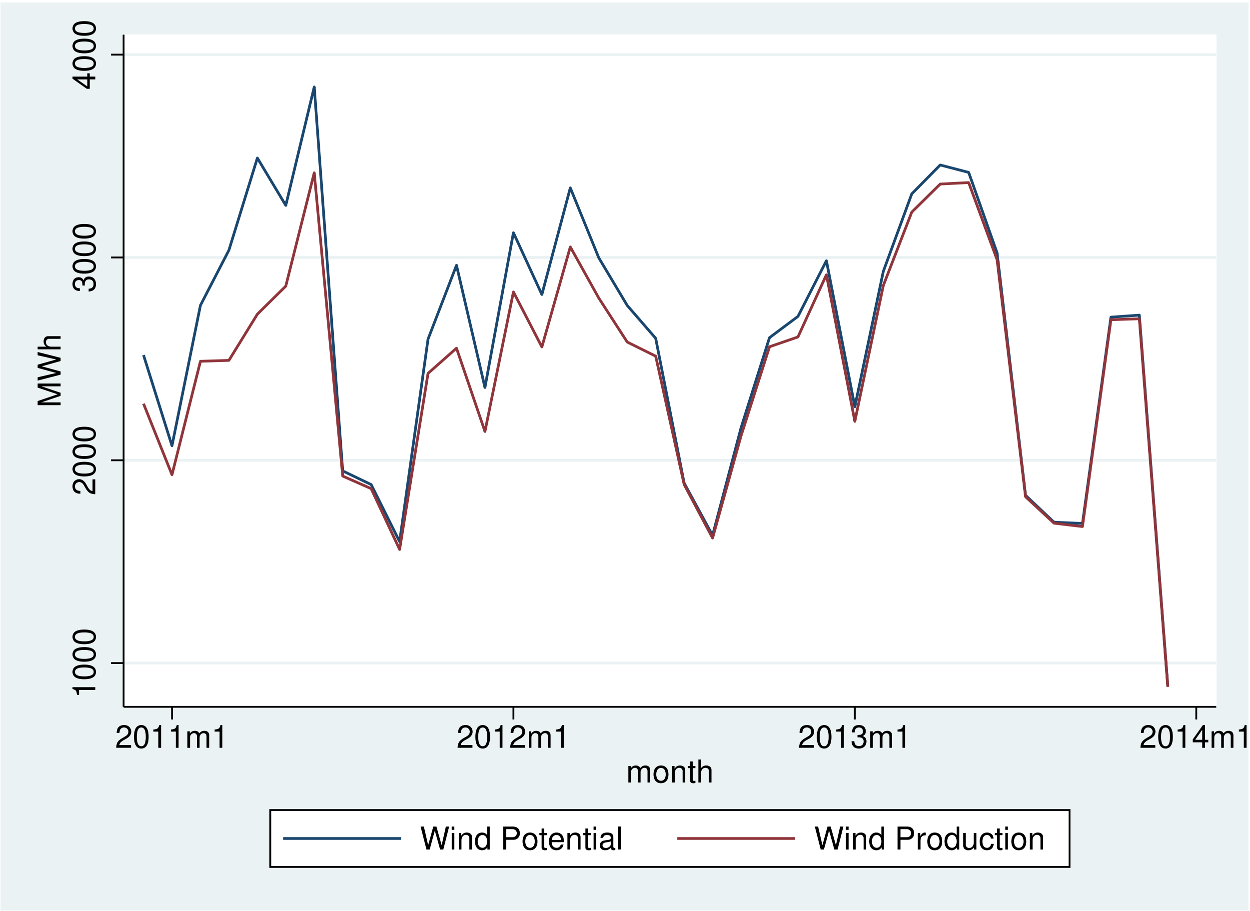

Figure 3.5: Average Hourly Wind production versus wind potential in west Texas
Note: This figure presents the average hourly wind potential and production each month in west Texas. As more transmission lines are constructed from 2011 to 2014, the gas between wind production and wind potential narrows.

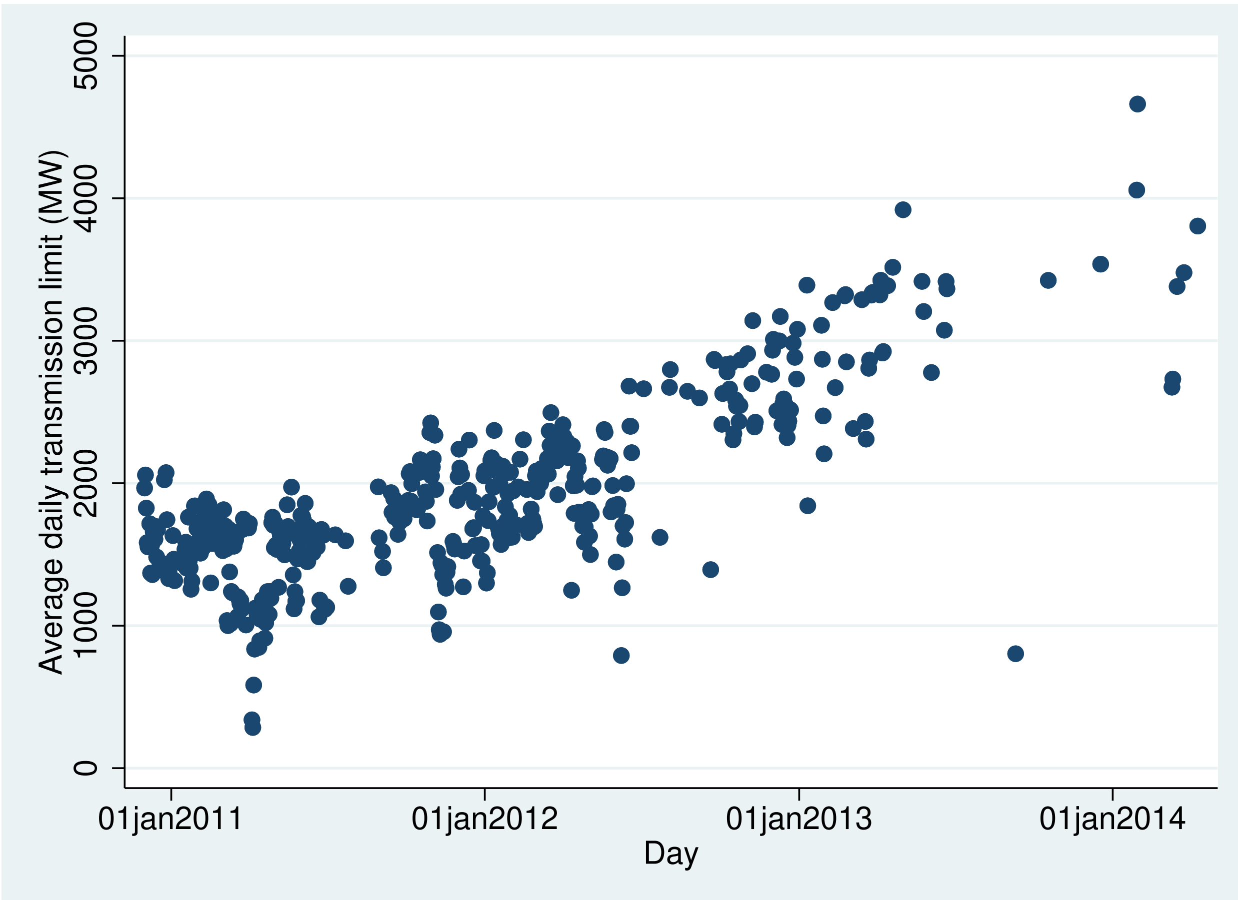

Figure 3.6: Average daily transmission limit from West to North

Note: This figure reports the average daily transmission limit from the West to North when the transmission constraint is binding. ERCOT publishes the shadow price and binding transmission constraints about every 5 minutes in the real time dispatch. The average daily transmission limit is calculated as the average of the published transmission limit data in a given day when the transmission constraint from the West to the North is binding. In these cases, the actual flow of power from the West to the North is the same as what the system can allow.

3.5 Empirical Strategy

The goal of the analysis is to estimate the effect of increasing transmission limit on price and production quantity in the constrained areas. I estimate the following model:

$$Y_{rt} = \beta_1 limit_t + \beta_2 westwind + \beta_3 otherwind + \beta_4 westload + \beta_5 load_r + \beta_6 totalload + \gamma \boldsymbol{X_t} + \epsilon_t \quad (3.8)$$

Y_{rt} are price and production by fossil fuel power plants in each of the four Load Zone r in each hour t from December 20th 2010 to the end of 2013. $limit$ is the reported transmission limit in 100MW when the "West to North" transmission constraint is binding. The coefficient of interest is β_1, which represents the average effect of increasing transmission limit by 100MW when the transmission constraint is binding. I also include wind potential and electricity load as controls. The West has much higher wind production than the rest of ERCOT, and I control for both wind production potential in the West and the rest of ERCOT. I control for the load in the West, the load in the specific Load Zone of the outcome variable and the total ERCOT load. For example, if the dependent variable is price in the North Load Zone, I include the load in the West, North and total load in ERCOT. $\boldsymbol{X_t}$ are additional controls including daily gas spot price at Henry Hub, daily maximum and minimum temperature in the specific Load Zone of the outcome variable, hour of the day and month of year fixed effects. Gas prices affect the input cost of power plants, and hence affects wholesale electricity price.

To claim causal effect, the identifying assumption is after controlling for the wind potential, demand, gas price, daily temperature, hour of the day and month of the year fixed effects, the transmission limit does not correlate with other factors that may affect price and fossil fuel power plant's output. The transmission limit is determined by the physical transmission lines, meteorological and other technical specifications. In this case, the construction of CREZ transmission lines increases the transmission limit over time. There are also shorter term variations in the limit as shown in figure 3.6. These variations can be due to outage in transmission lines or changes in meteorological conditions. However, large changes in generations in the importing and exporting region may also cause short term changes in transmission capacity, so this is a potential caveat for this analysis. I control for the hour of day and the month of year fixed effects to capture part of power plant's daily operating decisions and seasonal variation, so the estimate relies on the variation of transmission limit and outcome variables for the same hour in a day in the same month of the year.

3.6 Results and Discussions

Table 3.3 presents the the effect of transmission limit on output by fossil fuel power plants and price in each lone zone using equation 3.8. The standard errors are clustered by sample day. The detailed regression results are presented in the appendix. Column 1 of table 3.3 shows the effect on output by fossil fuel power plants when the transmission constraint is binding. Increasing transmission limit by 100MW increases the hourly output of fossil fuel power plants in the West by 23.7MWh. The effect on fossil fuel power plant production in Houston is very small and non-significant. In the North and South Load Zone, increasing the transmission limit reduces production of fossil fuel power plants, and the sum of the coefficients is close to 100. These results are consistent with the prediction from the stylized model in section 3.3.

The transmission limit increase has the largest effect on price in the West. Increasing the transmission limit by 100MW will on average increase the price in the West by 1.12$/MWh when the transmission constraint is binding. The transmission limit has increased by more than 2000MW when the CREZ project is completed, so the increase in price is in the West is more than 22$/MWh during congested hours. For the rest of ERCOT, an 100MW increase in the "West to North" transmission has decreased the price in the North by 0.17$/MWh. The effect is not statistically significant for the South, and it is marginally significant for Houston Load Zone. As I am using the transmission limit from "West to North", it is likely that the North benefit the most from the increase of transmission limit though it may also have effects in other areas through the transmission network connecting them. As seen in the effect on output quantity, the reduction in output is larger in magnitude in the North than in the South and Houston. In other settings, there could

Table 3.3: The effect of transmission limit (unit: 100MW) on price and output

	Output Quantity	Price
West	23.7***	1.12***
	(4.27)	(0.097)
North	-71.1***	-0.17***
	(9.96)	(0.049)
South	-28.1***	0.029
	(6.19)	(0.095)
Houston	-0.62	-0.10*
	(5.36)	(0.052)
Number of Obs.	3283	3283

Note: This table presents the regression results using equation 3.8. * represents statistical significance at 10%, ** represents statistical significant at 5%, and *** represents statistical significance at 1% level. The standard errors are clustered by sample day, and are shown in the parenthesis.

Table 3.4: The effect of transmission limit (unit:100MW) on different types of generators

	Coal	Gas-Combined Cycle	Gas-Simple Cycle	Gas-Steam
West	11.8***	11.0***	0.61**	0.31**
	(1.35)	(3.60)	(0.29)	(0.15)
North	-63.5***	-19.5***	8.46***	3.37***
	(7.63)	(7.64)	(1.96)	(3.38)
South	-24.2***	-8.13*	0.50	3.66***
	(5.45)	(4.80)	(1.30)	(1.18)
Houston	9.96**	-16.13***	1.04**	4.51**
	(4.05)	(3.84)	(0.49)	(2.03)
Number of Obs.	3238	3238	3238	3238

Note: This table presents the regression results using equation 3.8 on different types of generators. * represents statistical significance at 10%, ** represents statistical significant at 5%, and *** represents statistical significance at 1% level. The standard errors are clustered by sample day, and shown in the parenthesis.

be concerns that new infrastructure investment is endogenous, which leads to spurious correlation between the construction of new infrastructure project and the outcome variable. In this setting, the CREZ project was built based on ERCOT's study in 2006 on wind potential in the West and what are the potential transmission constraints that will limit the delivery of wind power, so the goal of the project is to bring electricity from the region with high wind potential to the population centers. It is very unlikely that the increase of price in the exporting or the decrease of price in the importing areas has a spurious correlation with the construction of transmission lines.

The effect on price depends on the shape of the supply curve in the region, which is determined by marginal cost, dynamic constraints and market power. The expansion of transmission lines also changed the power plants' expectation of future prices and volatility, and hence change their operating decisions. To further analyze the impact of transmission limit on output, I run the same regression on different types of generations. Table 3.4 presents the results. There are only a few fossil fuel generators in the West, and there is increase of dispatch for all types of fossil fuel generators. On the other hand, when the transmission limit increases, coal and combined cycle gas power plants reduces production in the North, but there is increase of production of simple cycle and steam gas power plants[8]. As more wind is imported into the region, it displaces the higher cost generators, but there can be large short run fluctuations in electricity generation. Du and Rubin (2018) showed the daily price volatility increased in ERCOT for all regions after transmission expansion. In order to meet the electricity demand all the time, more flexible generators must be dispatched when wind production is lower. Simple cycle and steam gas plants are generally less efficient than combined cycle gas plants, but they are easier to ramp up and down quickly. So with increasing transmission limit, simple cycle and steam gas plants may increase production though it has higher marginal cost than coal and combined cycle plants. Similarly, when the transmission limit increases, coal and combined cycle natural gas power plants reduce production, and there is small increase in production for steam gas power plants in the South. In Houston, combined cycle power plants reduce production when transmission limit increases, but the reduction is offset by increase in simple cycle and steam gas power plants as well as coal power plants.

To explore the potential heterogeneous effect of transmission limit across hours, I use ERCOT's definition of on-peak and off-peak hours. ERCOT defines 7am-10pm Monday to Friday as on-peak hours excluding holidays[9], and the rest of hours are off-peak hours. In the regression, I allow the effect of transmission limit to vary by whether the hour is on-peak or off-peak by including an interaction term of the transmission limit and a dummy variable of whether the hour is on-peak or off-peak.

For price and total fossil fuel output, I do not find statistically significant difference between

[8]Simple cycle gas plants use gas turbines that generate electricity by gas combustion. Natural gas steam turbines use natural gas to heat water that evaporates into steam to rotate the turbine. Combined cycle power plants are more efficient than simple cycle and steam turbines alone because they recover the waste heat from the gas turbine to drive a steam turbine.

[9]I use ERCOT holidays provided by energygps.com.

Table 3.5: The effect of transmission limit (unit:100MW) on different types of generators- peak and off-peak hours

	West	North	South	Houston
Coal: limit	11.5***	-64.1***	-25.0***	10.6**
	(1.38)	(7.68)	(5.64)	(4.18)
Coal: limit×on-peak	1.05	1.74	2.32	-2.10
	(0.80)	(5.32)	(3.92)	(3.18)
Gas-Combined Cycle: limit	10.9***	-21.3***	-8.02	-16.1***
	(3.67)	(7.89)	(4.91)	(3.79)
Gas-Combined Cycle: limit×on-peak	0.17	5.14	-0.31	-0.18
	(1.17)	(5.29)	(3.07)	(3.01)
Gas-Simple Cycle: limit	0.75**	10.3***	1.32	0.98*
	(0.30)	(2.02)	(1.29)	(0.18)
Gas-Simple Cycle: limit×on-peak	-0.43**	-5.22***	-2.43**	0.18
	(0.21)	(1.25)	(0.97)	(0.36)
Gas-Steam: limit	0.33**	3.66***	4.65***	4.73**
	(0.15)	(1.17)	(1.25)	(2.00)
Gas-Steam: limit×on-peak	-0.08	-0.83	-2.89***	-0.69
	(0.11)	(0.91)	(0.88)	(1.25)
Number of Obs.	3238	3238	3238	3238

Note: This table presents the regression results for output of different types of generators adding an interaction term of a dummy variable for on-peak hours and the transmission limit in equation 3.8. * represents statistical significance at 10%, ** represents statistical significant at 5%, and *** represents statistical significance at 1% level. The standard errors are clustered by sample day, and shown in the parenthesis.

the effect on off-peak and on-peak hours. For fossil fuel production by type, I find the increase of simple cycle and steam gas power plant production tends to be larger during off-peak than on-peak hours (table 3.5).

3.7 Conclusion

Transmission infrastructure in the electricity grid helps to integrate the electricity market and allow power generated to meet electricity demand at a different location. In recent years, many electricity markets invested in expansion of transmission infrastructure to integrate renewable energy into the grid as the areas renewable energy are located may not be demand centers. Bringing cheap renewable generation to the demand centers may reduce cost of meeting electricity demand.

ERCOT invested 7 billion dollars in the CREZ project between 2010 to 2013 to connect the wind-rich west Texas to the demand centers. This paper analyzed the effect of transmission expansion on market outcomes. I construct a dataset matching generator location with its production and price data, and I combine this dataset with ERCOT reported real time transmission limit and shadow price data. Using the congested hours from December 2010 to 2013, I find on average, increasing the "West to North" transmission limit by 100MW increases hourly production of fossil fuel power plants in the West by 23.7MWh and the Load Zone price in the West increases by 1.12$/MWh when the transmission limit is binding. On the other hand, in the North Load Zone, during the congested hours, 100MW increase of the transmission limit reduces hourly fossil fuel production by 71.1MWh, and price in the North Load Zone is reduced by 0.17$/MWh. The effect on price is not statistically significant for the South and marginally significant in Houston. The estimation results are for hours when the transmission constraint is binding. When the transmission constraint is not binding, an increase of transmission limit does not change the dispatch of power plants and the wholesale electricity price.

Though increasing transmission limit reduces total output by fossil fuel power plants in the North, the reduction is from coal and combine cycle power plants. The higher cost and more flexible simple cycle and steam gas power plants see some increase in output. As the increase in transmission limit brings in more wind power in the importing areas, more flexible types of generation are needed because of the intermittent nature of wind power. The increase of production of simple cycle and steam gas power plants tends to be larger during off-peak hours.

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Appendix A: Long term contracts in retail electricity

Table A.1: Parameter estimates of dynamic demand model using AR(1) process

Parameters	
Relative Risk Aversion	0.65
	(0.00015)
Attention Probability	0.031
	(0.000038)
Regulated Rate	0.13
	(0.00013)
Year fixed effect	No
Sample Size	387381 consumers x 122 months

Note: This table presents the parameter estimates of the dynamic discrete choice model when the monthly price is assumed to follow an AR(1) process.

Appendix B: The price effect of large-scale wind energy

The SCED process in ERCOT

In the real time market, ERCOT uses the SCED process to dispatch generators to meet electricity demand. SCED processes the energy offer curves submitted by each generator in two steps. In the first step, SCED establishes the reference LMP for each location in the grid by using the energy offer curves as submitted for each generator and only considers competitive constraints on the transmission system[1]. In this second step, SCED caps the energy offer curves using the greater of the applicable reference LMP established in step 1 or the mitigated offer cap[2], and uses the mitigated energy offer curves along with all constraints to determine the LMP at each location and quantity produced by each generation resource.

[1]Transmission constraints are classified to competitive and non competitive constraints. Competitiveness of a constraint is determined by the market concentration in the importing and exporting region and whether there is a pivotal player to serve the load.

[2]Mitigated Offer cap is based on the resource's verifiable heat rate and operation & management cost.

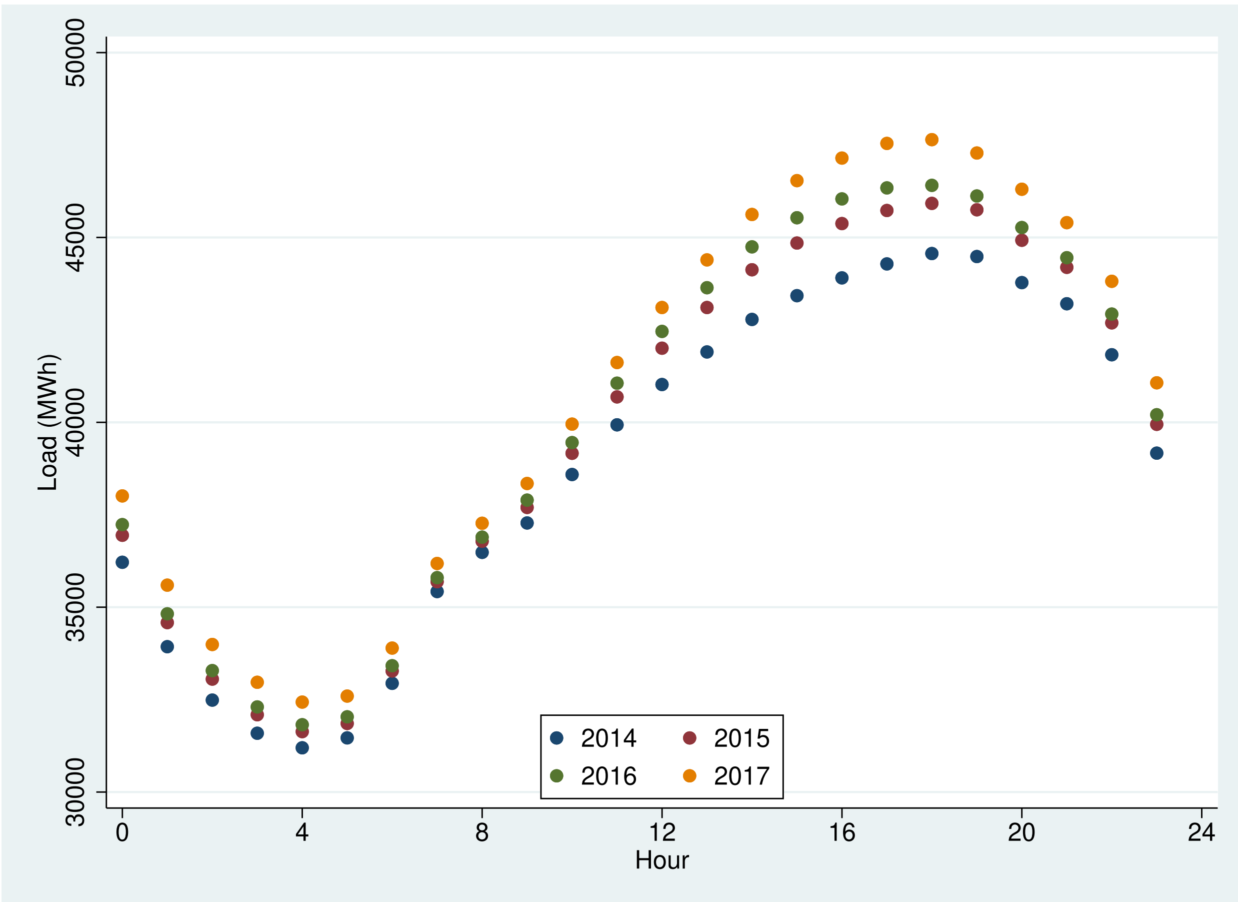

Figure B.1: Hourly Load Pattern 2014-2017

Note: This figure plots the average hourly load per year from 2014 to 2017.

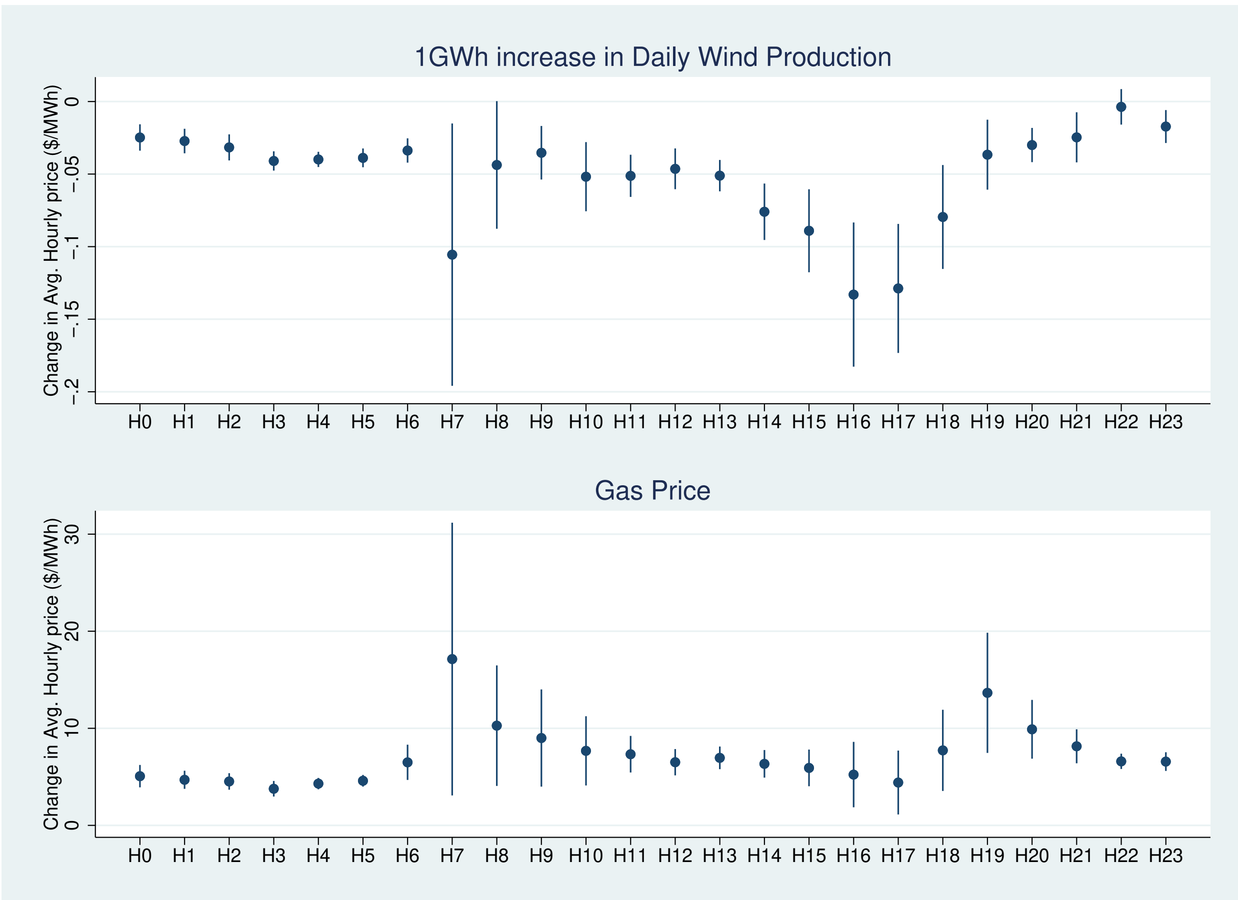

Figure B.2: Effect of daily Wind production on real time price using wind potential as an instrument

Note: This figure presents the the point estimates and 95% confidence interval of daily wind production on real time price using the daily wind potential as an instrument.

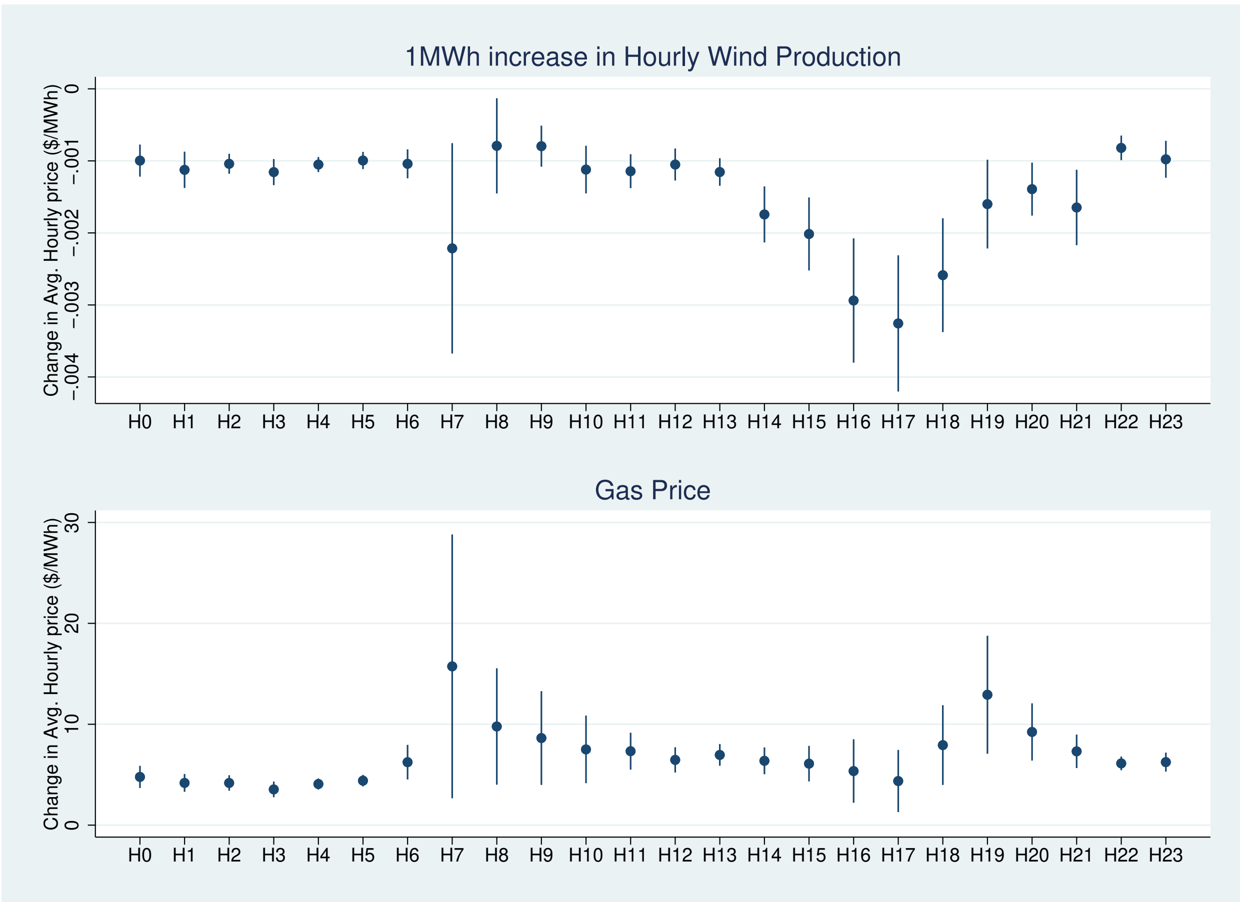

Figure B.3: Effect of Hourly Wind production on real time price

Note: This figure presents the the point estimates and 95% confidence interval of hourly wind production on real time price.

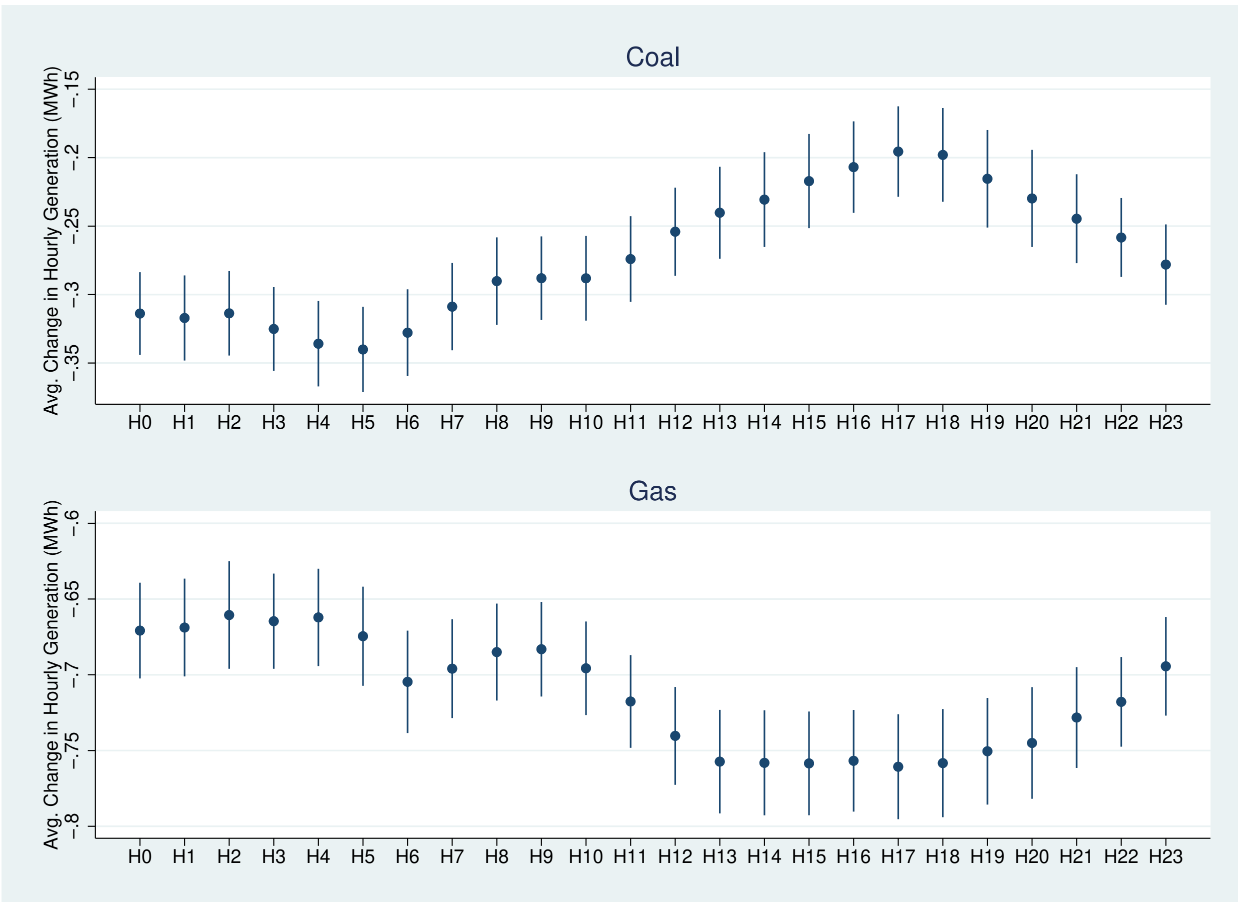

Figure B.4: Regression results of the effect of hourly wind production (Unit:MWh) on quantity produced by coal and gas power plants

Note: This figure presents the the point estimates and 95% confidence interval of hourly wind production on coal and gas production.

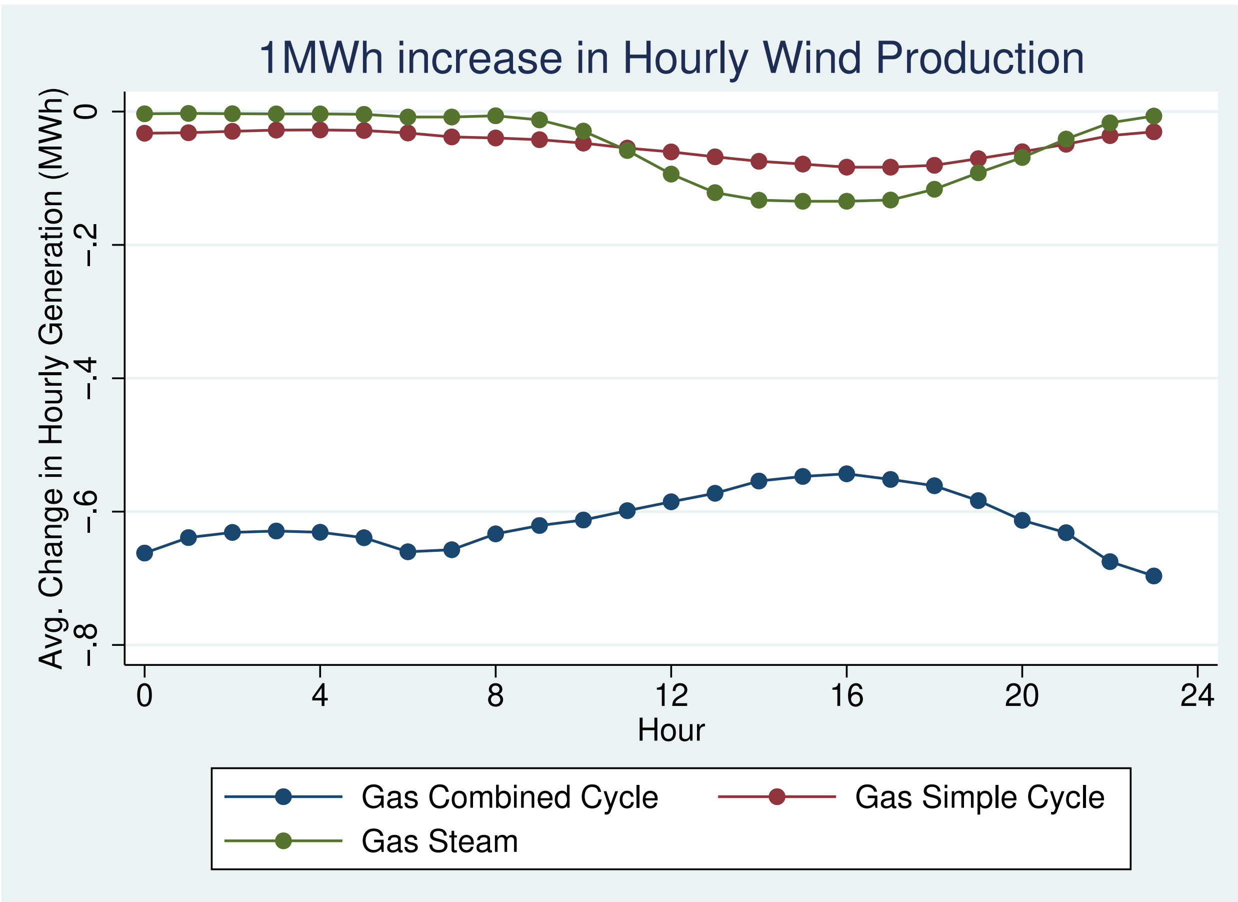

Figure B.5: Regression results of the effect of hourly wind production (Unit:MWh) on hourly output by different types of gas generators

Note: This figure shows the effect of an 1MWh increase of hourly wind on hourly output of combined cycle, simple cycle and steam gas turbine for each hour of the day. Simple cycle gas plants use gas turbines that generate electricity by gas combustion. Natural gas steam turbines use natural gas to heat water that evaporates into steam to rotate the turbine. Combined cycle power plants use both gas turbine and steam turbine.

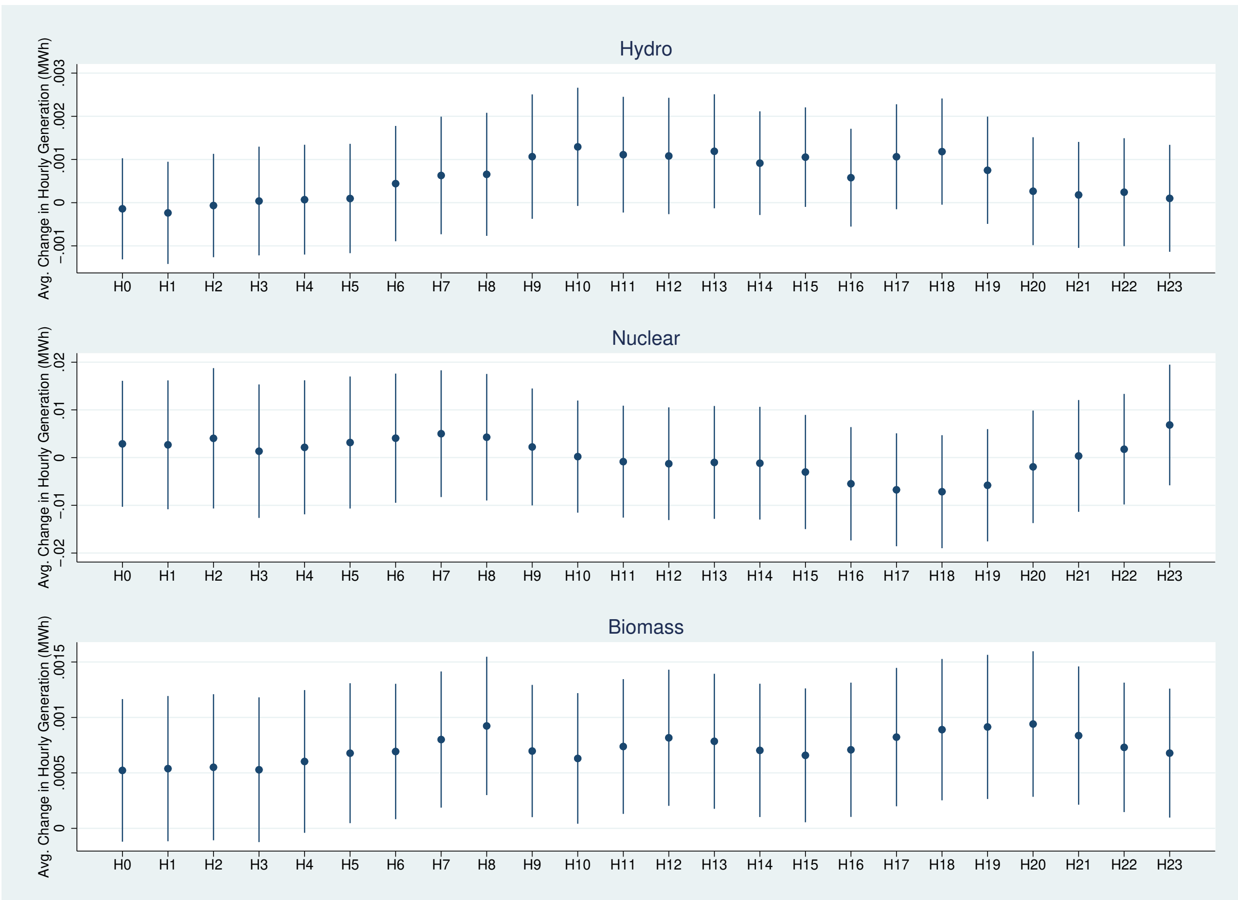

Figure B.6: Regression results of the effect of hourly wind production (Unit:MWh) on hourly output by hydro, biomass and nuclear generation with 95% confidence interval

Note: This figure shows the effect of an 1MWh increase of hourly wind production on hourly output of hydro, biomass and nuclear power plants for each hour of the day with 95% confidence interval.

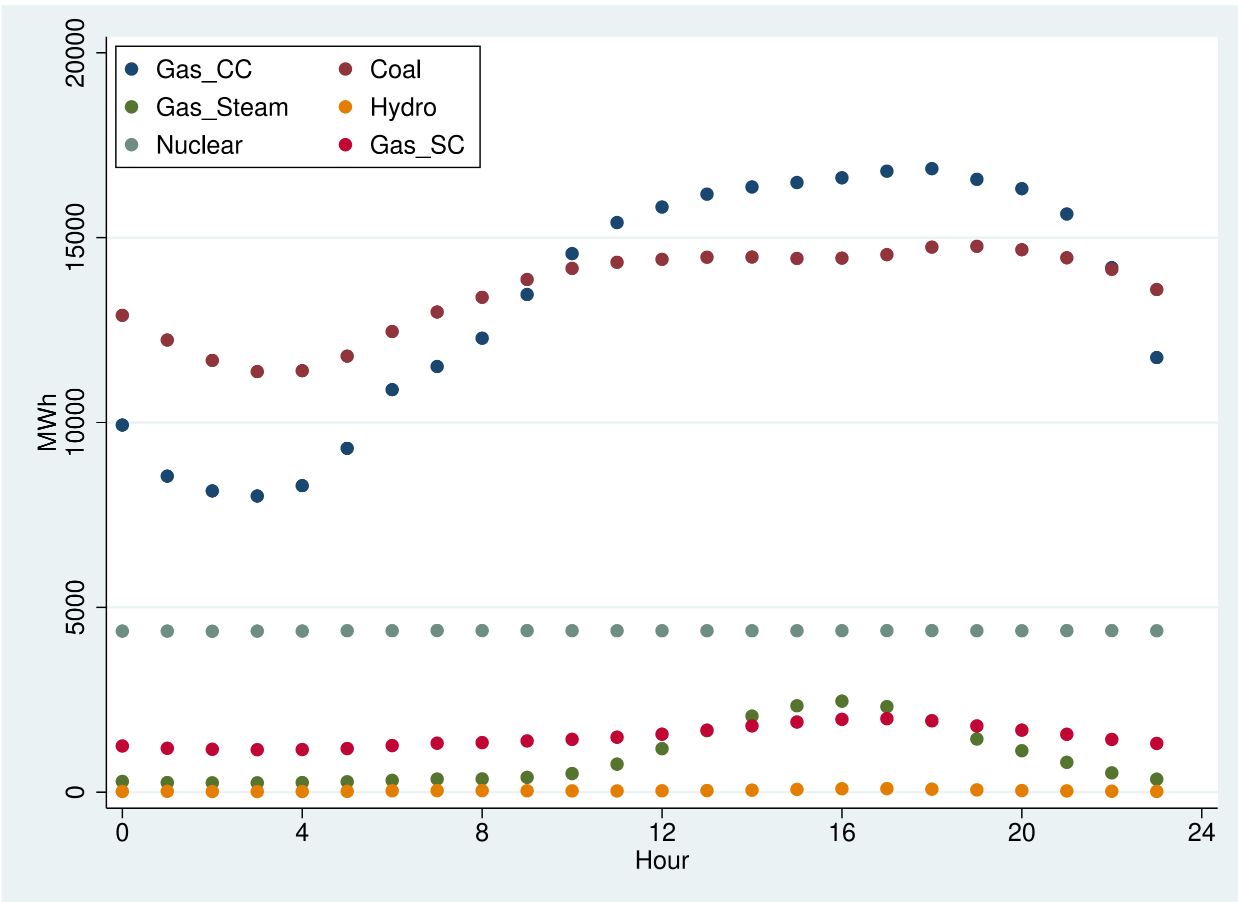

Figure B.7: Average Hourly Production by Fuel Type December 2010-2013

Note: This figure plots the average hourly electricity generation by fuel type between December 2010 and 2013.

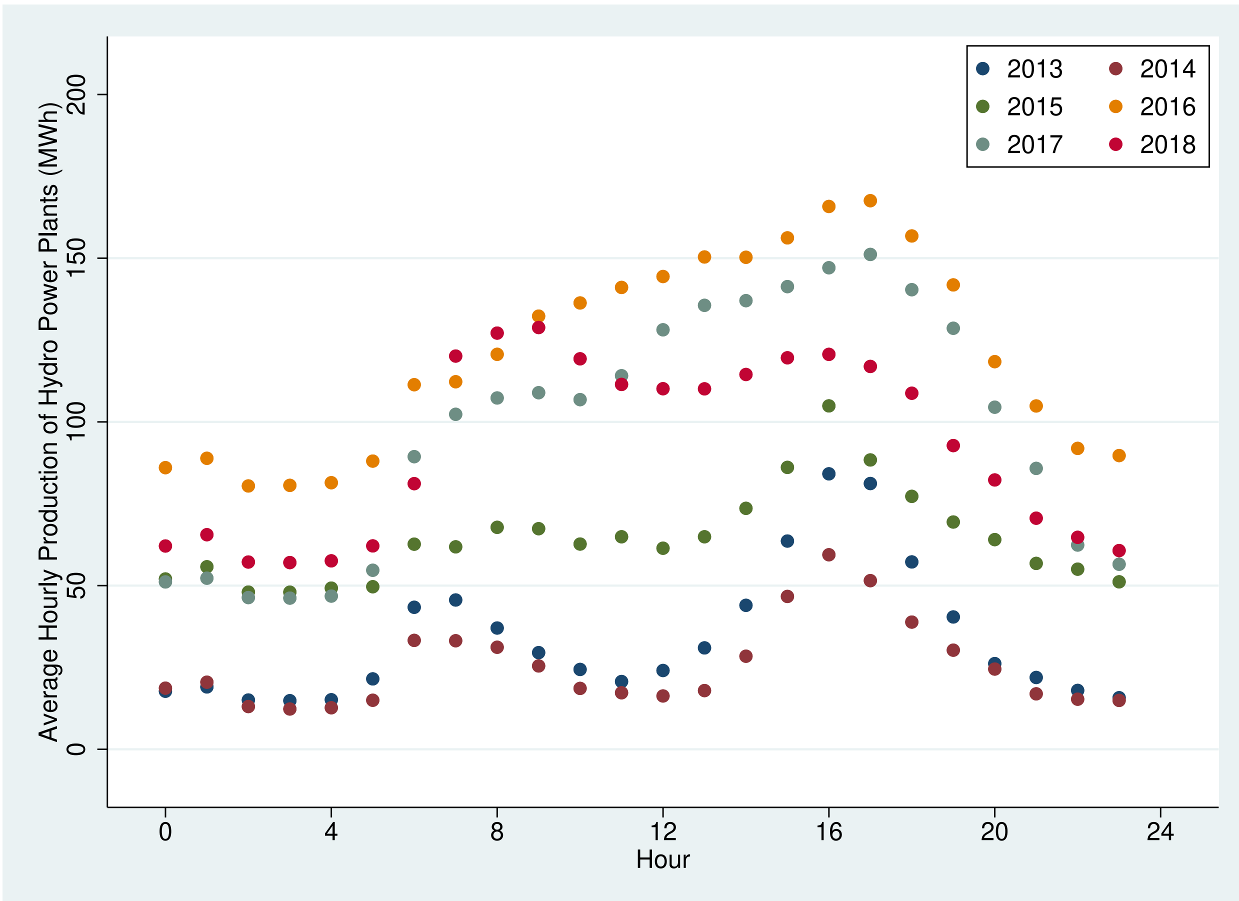

Figure B.8: Average Hourly Production of hydro power plants 2013-2018

Note: This figure plots the average hourly electricity generation by year for hydro power plants between 2013 and 2018.

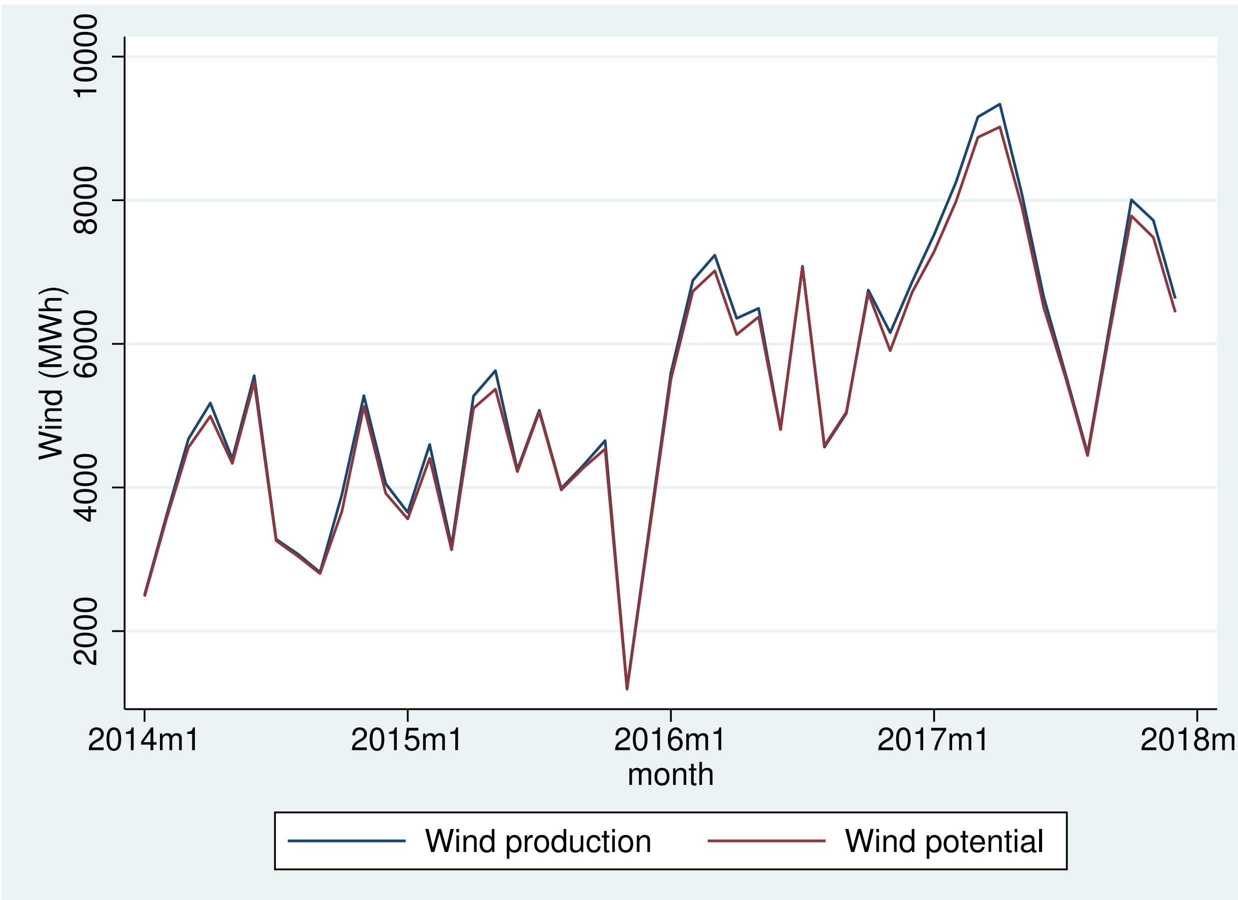

Figure B.9: Average hourly wind production and wind potential 2014-2017

Note: This figure shows the average hourly wind potential and wind production per month from 2014 to 2017.

Appendix C: The effect of transmission limit on market outcome: evidence from ERCOT

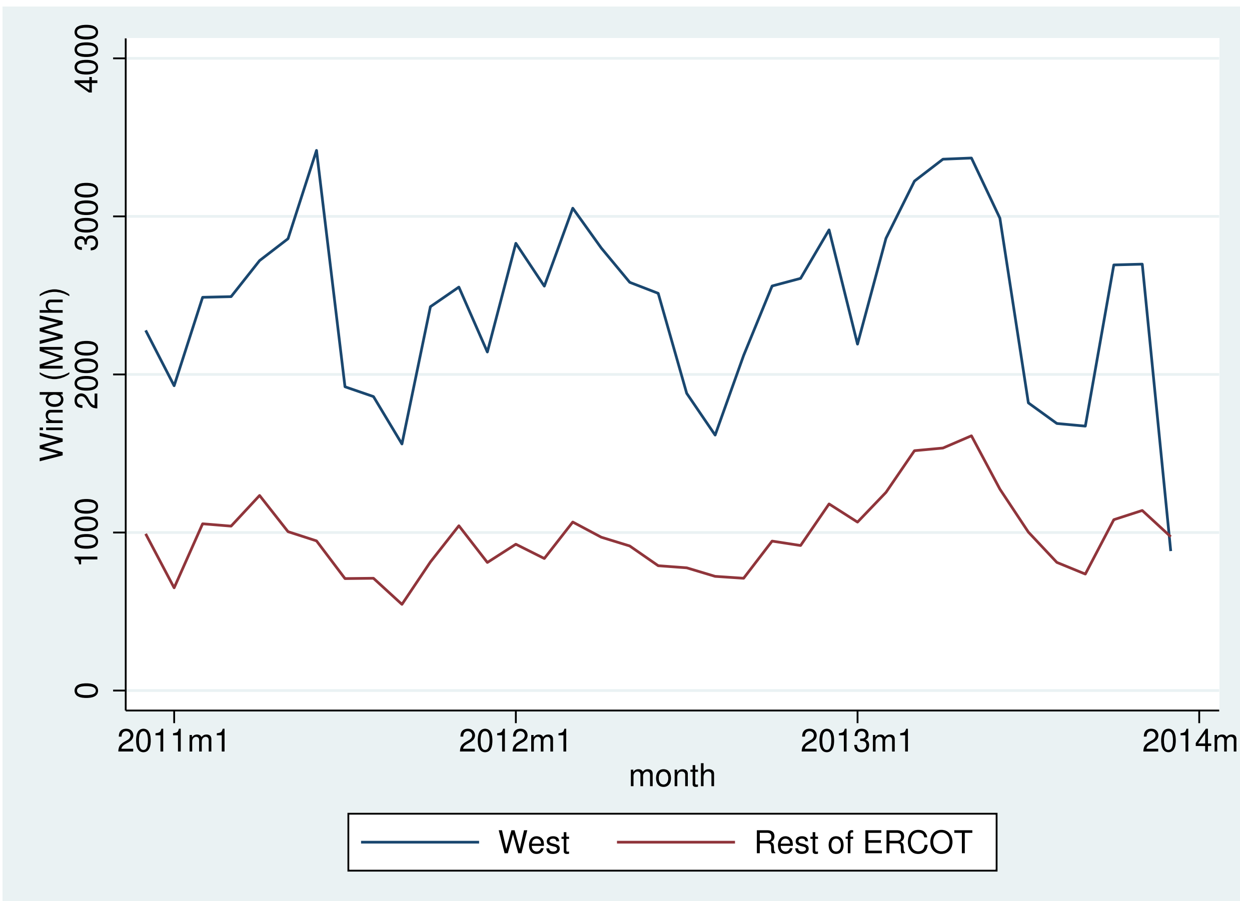

Figure C.1: Average Hourly Wind production in the west and the rest of ERCOT

Note: This figure shows the average hourly wind production each month in west Texas and the rest of ERCOT.

Table C.1: Detailed Regression Results-transmission limit (unit:100MW) on price

	West	North	South	Houston
limit	1.12***	-0.17***	0.0296	-0.10*
	(0.097)	(0.049)	(0.095)	(0.052)
West wind	-0.0095***	0.00059	-0.00022	0.00054
	(0.00046)	(0.00036)	(0.00067)	(0.0004)
other wind	-0.0012	-0.0010	-0.0027**	-0.0021***
	(0.00097)	(0.00077)	(0.0013)	(0.00077)
gas price	0.89	4.28***	4.08***	4.48***
	(0.53)	(0.57)	(0.75)	(0.64)
total load	0.00021***	0.00042***	0.0015**	0.0011***
	(0.00024)	(0.00040)	(0.00074)	(0.00029)
Load West	0.016***	-0.00085	-0.022	-0.0037
	(0.0040)	(0.0033)	(0.015)	(0.0039)
Load North	-	0.0015**	-	-
	-	(0.00078)	-	-
Load South	-	-	0.0038	-
	-	-	(0.0031)	-
Load Houston	-	-	-	0.00068
	-	-	-	(0.0010)
tmax	0.018	0.042	-0.79	0.15**
	(0.039)	(0.051)	(0.63)	(0.075)
tmin	0.11**	0.062	0.30	-0.00019
	(0.053)	(0.068)	(0.22)	(0.051)
Hour of Day	Yes	Yes	Yes	Yes
Month of Year	Yes	Yes	Yes	Yes
Number of Obs.	3283	3283	3283	3283

Note: This table presents the detailed regression results using equation 3.8 on price in each Load Zone. * represents statistical significance at 10%, ** represents statistical significant at 5%, and *** represents statistical significance at 1% level. The standard errors are clustered by sample day, and are shown in the parenthesis.

Table C.2: Detailed Regression Results-transmission limit (unit:100MW) on output by fossil fuel plants

	West	North	South	Houston
limit	23.7***	-71.2***	-28.1***	-0.63
	(4.27)	(9.96)	(6.20)	(5.37)
West wind	-0.18***	0.086**	-0.020	0.016
	(0.014)	(0.029)	(0.051)	(0.025)
other wind	-0.68***	-0.42***	-0.31***	-0.41***
	(0.022)	(0.00052)	(0.10)	(0.057)
gas price	19.75	158.5**	68.9	-229.51***
	(13.4)	(27.47)	(70.40)	(34.0)
total load	0.026***	0.24***	0.14***	0.21***
	(0.0064)	(0.037)	(0.011)	(0.026)
Load West	0.14	-0.046	0.16	-1.25***
	(0.11)	(0.42)	(0.28)	(0.27)
Load North	-	0.34***	-	-
	-	(0.077)	-	-
Load South	-	-	0.37***	-
	-	-	(0.073)	-
Load Houston	-	-	-	0.28***
	-	-	-	(0.075)
tmax	1.37	-0.37	13.5**	-17.5**
	(1.27)	(9.25)	(6.22)	(8.33)
tmin	-3.88**	-3.25	5.33	1.47
	(1.87)	(8.46)	(4.30)	(5.53)
Hour of Day	Yes	Yes	Yes	Yes
Month of Year	Yes	Yes	Yes	Yes
Number of Obs.	3283	3283	3283	3283

Note: This table presents the detailed regression results using equation 3.8 on output of fossil fuel power plants in each Load Zone. * represents statistical significance at 10%, ** represents statistical significant at 5%, and *** represents statistical significance at 1% level. The standard errors are clustered by sample day, and are shown in the parenthesis.