Essays in Energy Markets

by

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

In this thesis, I empirically examine how strategic decisions of firms change under events such as input cost shocks and policy changes, in electricity markets. In the first chapter, I show that when the industry-wide cost shock impacts the cost of firms differently, the cost shock could change the strategic incentives of firms, which has important implications on the pass-through of the shock to prices. In the context of the New England electricity market, I show with a structural estimation that the extent of cost increase due to gas price shocks varies across firms and that this led to different levels of firm-level markup adjustments. The pass-through rates of cost shocks, which reflect different incentives for markup adjustments found in my analysis, are estimated to be heterogeneous as well, but close to one, on average. Because data does not fully capture heterogeneity in markup incentives or cost increases, I find that the reduced form pass-through estimate that relies only on data is underestimated compared to the rate implied by the structural estimation. In the second chapter, I examine how upcoming coal plant retirements in the New England electricity market affect the competition and market outcomes, especially when cost shocks occur. I reconstruct market conditions by letting coal plants to retire and replacing them with gas plants, which makes an increased proportion of the electricity generation in this market to be vulnerable to cost shocks caused by gas price shocks. I then simulate counterfactual outcomes with and without giving cost shocks to firms. I find that retirement causes electricity price to increase by 20 %, on average, and prices increase even further after retirement when a larger cost shock affects the market.

CHAPTER 1

Heterogeneous Impacts of Cost Shocks, Strategic Bidding, and Pass-Through: Evidence from the New England Electricity Market

1.1 Introduction

In the winters of 2013 and 2014, severe gas pipeline congestion in New England caused a series of natural gas price shocks. This led to a spike in electricity prices because gas price shock is an input cost shock to electricity generating firms. An important feature of the natural gas price shock to the New England electricity market is that the impact of this shock on generation cost is *heterogeneous* across firms. For instance, a firm that does not operate gas-fired generators will be unaffected by the gas price shock. Furthermore, even for the firms that operate gas generators, the extent of gas cost increases due to the shock may vary across firms because of different firm-specific characteristics. For example, the cost increase of firms that operate dual gas generators, which can switch to oil fuel when the gas price shock is severe, will be smaller than that of firms that do not operate any dual gas generators.

In this paper, I study how this gas price shock, which affected input cost of firms heterogeneously, was transmitted to the electricity price, namely the cost pass-through. I do this by examining how this cost shock affected the competition between firms in the electricity generation market. Heterogeneity of the impact is important in this context because when the costs of firms increase to a different extent due to the impact of the shock, it induces firms' strategic markup adjustments, the size and the direction of which vary significantly across firms. Since markup adjustment channels are important determinants of how much of the cost shock is passed on to the market price, I first use a structural model to examine how firms' costs and markups are adjusted. I then examine how these changes in costs and markups are reflected in the pass-through rates of this gas cost shock.

Any change in the competition that a firm faces, which depends on how its costs and those of competitors are affected by the shock, causes that firm to adjust its markup; the extent to which these shocks are passed on to the market price depends on firms' incentives to adjust markups. When a cost shock affects all firms homogeneously by increasing their costs by the same amount, those firms lack incentive to adjust their markups further. This was the case in the emissions cost shock described by Fabra and Reguant (2014), who found a lack of markup adjustments following the shock and a complete pass-through of cost shock as a result. On the other hand, when the cost impact is heterogeneous across firms, the costs of firms that are hit hard by the shock will increase by more than that of firms that are hit less hard by the shock. Such changes in costs relative to those of others induce markup adjustments; lower cost firms are capable of adding markups while higher cost firms may have to decrease their markups in order to compete with lower cost firms.

Another factor that affects competition in the setting that is considered in this paper is the overall size of the gas price shock. While gas units usually compete against nearby gas units as a result of moderated-sized shocks, they now have to compete with both gas and oil units when the shock is so big that it pushes the generation cost of gas units closer to that of oil units. Therefore, firms with a high proportion of gas generation units would face more intense competition than with a small shock as the size of the shock becomes larger; they would manage this by lowering markups.

In order to understand pass-through incentives in this rich heterogeneous setting, I develop and estimate a structural model of firm competition in the New England electricity market. Since electricity generating firms compete for sales in daily auctions, I develop a multi-unit uniform auction model and use high-frequency auction data to first estimate unit-specific marginal costs of electricity generation. The auction framework enables an estimation of unit-specific marginal costs that rationalize the bids of the firms in the auction, which reflect revealed-preference information on firm costs. The non-standard element of the cost-estimation is that I back out the gas price that rationalizes the firm's bid, which I term the *implied* gas price, from the estimated marginal costs; I do this by exploiting the simple marginal cost structure of electricity generation and the differences in gas price stability across two different samples. That is, I first estimate the heat rate – a physical efficiency – of a unit from days where there was no gas shock and I then separately back out the unit specific implied gas prices on days where there was a shock using the heat rate estimated from the no gas shock days.

The major advantage of using the implied gas prices in preference to marginal cost estimates is that it allows me to directly identify the heterogeneity of the shock's impacts on costs. Any differences in the implied gas prices across firms can be attributed to the heterogeneity of the impact that results from gas price shock alone; this is as a result of the partialling out of the unit-specific heat rates (efficiency) from the marginal costs in order to obtain implied gas prices. I also utilize the implied gas prices of dual gas units in order to identify whether dual units switched fuels, exploiting the fact that if a dual gas unit switches to oil on a given day, the estimated implied gas price will correspond to the price of oil, rather than the price of gas. Finally, implied gas prices offer more rich information on heterogeneity than gas price index data – a weighted-average value – and are better measures than over-the-counter gas prices because implied gas prices are the gas prices that rationalize the marginal opportunity costs that enter firms' bids.

To examine how this shock affects market competition, which can be shown with an analysis of how strategic markups were adjusted during the shock event, I measure markups at firm level with hourly frequency. In addition to measuring bid markup, I simulate endogenous markup adjustments to small-size cost shocks by implementing a semi-counterfactual simulation that is based on a first-order approach. The simulated markups reveal firm-level *changes* in markups that result from the shock alone. In order to avoid recomputing the equilibrium, which is challenging in such a multi-unit auction framework, I restrict the counterfactual cost shock to a small size (approximately a unit) so that the post-perturbation equilibrium does not depart significantly from the local equilibrium.

Results of markup analysis show that the heterogeneity of the shock induces firms' markup adjustments. The markup analysis also shows that these adjustments are heterogeneous, depending on the extent of the shock's impact on cost of a firm relative to that of others. I find that the patterns in markup adjustments over time and at different levels of shock vary across firms. That is, markup adjustments that were made by "hard-hit" firms were more negatively skewed than adjustments that were made by firms that were hit less by the shock, which were centered more at 0 or were positively skewed. The differences in the markup adjustment patterns between these two groups of firms increased with the size of the shock, especially under large shocks that make the post-shock gas prices to exceed the level of oil price.

The simulated markup adjustments to a unit cost shock are especially relevant to pass-through rates, because pass-through is, by definition, the price response to unit cost shock. The pass-through rate can be measured by a price bid change of the ex-post marginal unit in response to a system-wide unit cost shock. In this way, I simulate high-frequency pass-through rates at auction level by extending the first order approach markup simulation. I find that heterogeneity in markup adjustments, which I discovered from our main empirical analysis, is also reflected in the auction level simulated pass-through rates. That is, the rates were also heterogeneous, varying with the type of firm on the margin. I find that the rates were, on average, lower on occasions when a unit of a "hard-hit" firm set the price, compared to when firms hit less by the shock set the price. Despite the dispersed pass-through rates, the mean of pass-through rates was close to unity, implying that the gas cost shocks in this market were fully passed on to the market price, on average.

The simulation of pass-through rates, which exploits the structural model that fully accounts for both the heterogeneity in the impacts and the firm-level markup responses to that shock, is not easy to implement in general. The most commonly used method, especially by industry regulators, is a reduced form of regression that explores the relationship between costs and electricity prices, using data on prices and costs of gas-fired units that are measured with gas price index data. This type of regression does not yield precise pass-through rate estimate because the gas cost measured with the gas price index data, which is a weighted-average, does not properly capture existing heterogeneity in unit-specific gas costs. Indeed, such näive estimation yield a estimate of mean pass-through rate that is less than 0.5, which is significantly lower than a rate close to unity that simulated rates suggest. This bias is not present if I account for heterogeneity in the regression by using the gas cost variable constructed with the heat rates and the implied gas prices extracted from the structural model; in this case the average rate estimate is now close to the mean of simulated rates. This again suggests that heterogeneity is an important feature of the pass-through rates and the underlying strategic behaviors.

Quantifying the pass-through rate, which is the incidence of the cost shock, is important for understanding the (welfare) consequences of the shocks on market. My study provides precise estimates of pass-through which can be used to assess whether producers or consumers bear the larger burden of cost shocks, which is an important outcome from a regulatory perspective. For example, the pipeline congestion problem, which was the main cause of the natural gas price shocks in the winters, is an important issue in New England where people still debate on whether an expansion of pipeline is necessary for the region. The results of my study could assist decision making involved in this issue, by showing whether consumers or producers were adversely affected, which makes this paper important from a policy context.

This paper contributes to the literature on determinants of market power in the electricity market. In addition to forward contract (Bushnell et.al, 2008), transmission constraints (Borenstein et.al, 2000; Ryan, 2014), and dynamic cost (Reguant, 2014), this paper introduces heterogeneous transmission of input cost shocks across firms as a factor that affects competition among firms in the electricity market. By studying how such changes in competition are linked to final market pass-through, this paper also contributes to the empirical pass-through literature. Although strategic markup adjustments made by firms are emphasized as an important determinant of the cost pass-through in many studies, including De Loecker et.al (2016), Fabra and Reguant (2014), Goldberg and Hellerstein (2013), and Nakamura and Zerom (2010), few studies focus on the heterogeneity of the impacts of the cost shocks and their consequences on the pass-through of these cost shocks. This paper fills this gap and offers an in-depth analysis of the cost pass-through when heterogeneity is present, building on the structural model of firm competition.

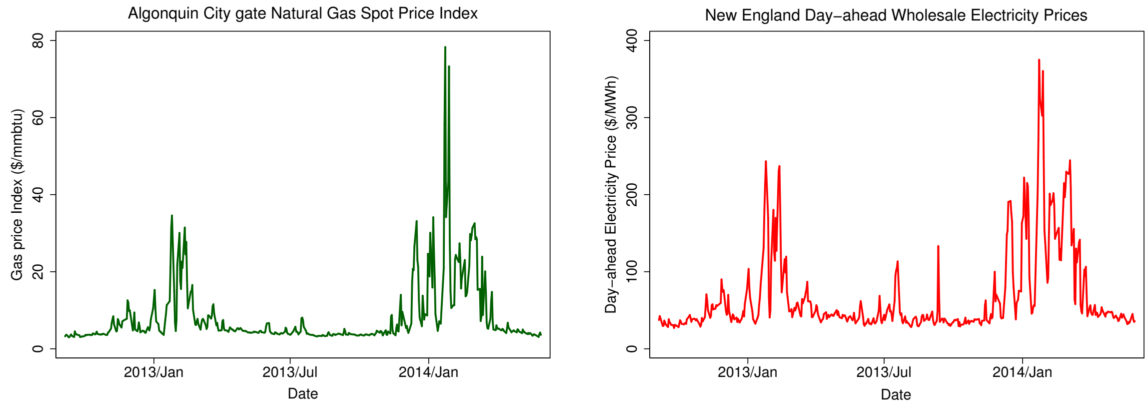
1.2 Gas Price Shocks in New England and the Heterogeneity of the Impact

1.2.1 Natural Gas Price Shocks in New England

In the winters of 2013 and 2014, there was a series of severe natural gas price shocks in New England, leading to wholesale electricity price spikes. Figure 1.1 shows an increase in gas spot prices at one of the major city gate in New England, and the corresponding increase in wholesale electricity prices in the New England electricity market. The surge in wholesale electricity prices as a result of natural gas price shocks is not surprising because gas is one of the key inputs for electricity generation in the New England grid. In the past decade, reliance of wholesale electricity generation on Natural Gas has increased substantially. The percentage of electricity coming from natural gas generation in the New England grid was only 15 % of the total generation in the year 2000, but it increased to 44-49% in the year 2014.[1] The natural gas price shocks in New England are weather related shocks, making these shocks exogenous. The New England winters of 2013 and 2014 experienced particularly record-low cold weather, which worsened the congestion of pipelines that deliver gas to the region because of the increased use of gas for residential heating.[2] While the gas spot prices (index) stay at around $4/MMBtu when there was no serious congestion in the gas pipelines (e.g. Spring - Summer), the gas spot prices increased significantly in winter days when congestions occurred; the index level reached $30/MMBtu in Februrary

[1]The grid's reliance on gas is expected to increase even further as more coal and nuclear generations plan to retire and are replaced with gas generation (EIA-report, 2015).

[2]Two major gas pipelines that deliver most of the natural gas into the region are Algonquin Gas transmission pipeline (AGT) and Tennessee Gas Pipeline (TGP). Total capacity of these two pipelines combined is 3.5 bcf/day (EIA report, 2014). Other than these major pipelines, Massachusetts's Everett liquefied natural gas (LNG) terminal also supplies natural gas to the region and is connected with the AGT and TGP pipelines. Also, Canaport LNG import terminal sends gas into the region through Maritimes & Northeast pipeline. Besides increased residential gas use, reduction in LNG imports through M & N and Everette pipelines also contributed to the pipeline congestions in the winter of 2013 and 2014, as it increased the demand of gas in Algonquin and Tennessee pipelines. The reason for the LNG supply reduction is because the gas prices in U.S. is too low compared to other countries, which is due to the shale gas boom in the U.S.



(a) Gas Spot Price Index

(b) Wholesale Electricity Prices

Note: Gas spot price index (source: NGI) and daily Locational Marginal Price (LMP) averaged across nodes and hours (source: ISO-NE SMD Daily) are shown in the graph

Figure 1.1: Daily Natural Gas Spot Price Index and Day-Ahead Electricity Prices (LMP)

of 2013 and even went up to $70/MMBtu in January of 2014. Other regions that do not have pipeline congestion problem did not experience such gas price shocks, which makes this event unique to the New England electricity market.[3]

As a result of these gas price shocks, wholesale electricity prices in the New England electricity market increased substantially. Electricity prices usually stay around $50 - $80/MWh when gas price shock is not present. However, over this time period of gas price shocks, electricity prices exceeded $100/MWh and even increased above $300/MWh on some days. As shown in Panel (b) of Figure 1.1, the (day-ahead) wholesale electricity prices in New England move together with the gas spot price indices, indicating that the gas price shock, an input cost shock on the supply side, is the major driver of the fluctuations observed in wholesale electricity prices. Electricity demand side shocks were not present over this time period, thus not the main cause of the increase in the electricity prices.[4]

When observing the event where input cost shocks lead to output price increases, it is natural to ask whether the output price increase is proportional to the input cost increase, or if the price increase is a result of some other factor such as market power. Pass-through rates of input cost shock which shows to what extent the cost shock was passed on to out-

[3]The highest gas spot price at Henry Hub, which offers a starting point of all regional gas spot prices at various trading locations, was $8/MMbtu in the winters of 2013-2014. Hence, this implies that the congested pipelines that deliver gas from Henry Hub to New England are the main cause of the gas price shocks observed in New England. New York grid has a similar pipeline congestion problem but not as severe as in New England.

[4]For example, while electricity demands were higher on days in December of year 2013 and early January of year 2014, the electricity prices were not as high compared to prices in mid January of 2014. Also, no significant demand shocks occurred in the winters of 2013-2014 as shown in the historical trends of the electricity demand provided in the graphs of electricity demands in the Appendix.

put price, would be a relevant statistics to look at in this case. Also, pass-through rate is an incidence measure that shows which side of the market – suppliers or consumers – bore more of the shock, which could be useful for assessing the aftermath from the shock. Given that pipeline congestion and the resulting gas spot price shocks are serious issues in New England, it is important to understand how market responded and what were the outcomes of these gas price shocks. However, heterogeneous feature of the gas price shock makes our market and pass-through analysis interesting. In the next section, I elaborate more on heterogeneity in impacts of the gas price shocks in New England, and discuss the sources of such heterogeneity that are specific in this electricity market.

1.2.2 Why Are the Impacts of Cost Shocks Heterogeneous Across Firms?

I now discuss why the impact of the gas price shock on generation costs may be heterogeneous across firms in the New England electricity market. While all firms operating in New England were subjected to the gas price shock, the impact of the shock on generating costs was heterogeneous across firms due to certain preexisting differences in generation mix, share of gas units and dual unit availability. I also discuss additional potential sources of heterogeneity that cannot be observed directly from the data.

1.2.2.1 Generation Mix Differences

Electricity generating firms in New England have different generation portfolio compositions. Table 1.1 shows the generation capacities of major firms in the New England electricity market, according to fuel type. Although all firms have some gas generation capacity, the percentage of gas generation, as part of the total generation capacity, differs significantly across firms; some firms have a balanced generation portfolio with sufficient oil/coal capacity, whereas others just have gas-only units in their portfolio. For example, EquiPower's 1880 MW generation capacity consists entirely of gas-only units, whereas NRG has a high percentage of oil generation, which more than doubles percentage share of gas generation.

The difference in the percentage of gas generation leads to different gas price shock exposure between firms because the gas price shock is an input cost shock to gas-fired units only; while gas price shock increases the costs of gas units, the costs of coal or oil-fired units remain unaffected. Therefore, costs of firms with a higher share of gas generation are affected more by the gas price shock than the costs of firms with a greater share of oil/coal units in their generation portfolio.

It should be noted that firms have significantly different percentages of dual-fuel gas

Table 1.1: Generation Mix Differences: Major Firms

	Generation Capacity (MW)						
Firm	Total	Gas	Oil	Gas/Oil	Coal	Hydro	Nuclear
Exelon	4,747	3,300	267	1,179	0	0	0
GDF Suez	2,649	1210	22	0	124	1,293	0
Dominion	2,607	0	0	510	0	0	2,097
NRG	1,985	0	1,383	603	0	0	0
EquiPower	1,880	1,880	0	0	0	0	0
TransCanada	1,210	635	0	0	0	575	0
PSNE	1080	0	199	400	535	0	0
PSEG	860	0	22	453	385	0	0
Dynegy	538	538	0	0	0	0	0

Notes: Capacities of 9 firms with significantly large generation capacities as of year 2014 are summarized in the table. *Gas* and *Oil* include capacities of non-dual generation units only, and Dual unit (that can fuel either gas or oil) capacities are summarized under *Gas/Oil* category. (*Source*: ISO-NE Seasonal Claimed Capacity data)

units. For example, Table 1.1 shows that Exelon has a well-balanced gas generation, with approximately a quarter of its gas generation coming from dual gas units. Furthermore, two firms, Dominion and Dynegy, operate similar sized gas capacities but have different proportions of dual-fuel gas units ; none of Dynegy's generation capacity is from dual-fuel generators, whereas Dominion's entire gas generation capacity is from dual units. Since the impact of the gas price shock on a dual unit's cost is smaller than the impact on a non-dual gas unit, which I will explain in detail in the following subsection, we expect the impact of the shock on firm-level costs to be smaller for Dominion than for Dynegy.

1.2.2.2 Dual Gas Units

A dual gas unit is an electricity generating unit that can use either natural gas or oil(petroleum liquid product) as a fuel; such units can switch quickly between fuels. The costs of dual units are less affected by a gas price shock once they switch, and the differences in the impacts between dual and non-dual gas units increase with the size of the gas price shock. Dual units can be used to avoid the impact of large sized gas price shocks by switching to oil, and the post-shock gas cost impact that is received by these switched dual gas units is bound by the cost of the oil fuel.

For example, if the gas spot price of the day increases to $25/MMBtu, dual units will switch to oil because it is cheaper than the current spot gas price (e.g. No.2 oil price is \$21/MMBtu), whereas non-dual gas units will have to continue to purchase gas at \$25/MMBtu in order to continue operating. Hence, the generation cost increases of dual gas units are substantially less than those of non-dual gas units on days when the gas price shock is large enough that it becomes economic for dual-fuel units to switch. Indeed, after experiencing consecutive years of winter gas shocks, ISO-NE (Independent System Operator of New England Grid) encouraged dual units to store on-site oil in order to prepare for the fuel switch as a means of reducing firms' exposure to gas cost shocks.

Fuel switch decisions made by dual-fuel units seem to be driven by cost minimizing behavior, along with the availability of on-site oil fuel stock. That is, dual units use gas to generate electricity when the gas price is lower than oil price, but they switch to oil when the gas price exceeds the oil price. However, not every dual unit switches to oil according to this cost minimizing behavior; there must also be enough on-site oil to make the switch.

More than 28 percent of natural gas generators in New England were dual units in 2014, and each firm had a different share of dual gas units, as shown in Table 1.1.[5] Differences in the share of dual gas units across firms creates heterogeneity in cost impacts from the gas price shock. We expect the generation cost of firms with a greater share of dual units to increase by less than the generation cost increase of firms operating no or few dual units, especially with large-sized gas price shocks.

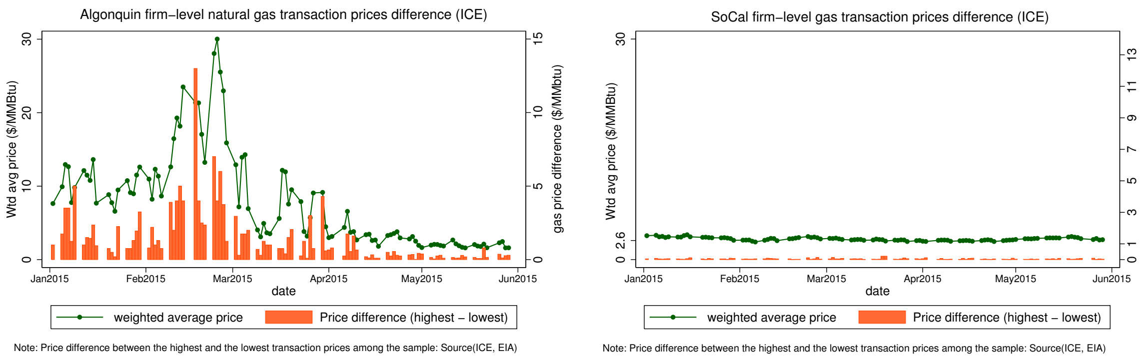
1.2.2.3 Other Sources: Long-Term Contract and The Increased Volatility of Spot Gas Price

There are other possible causes of heterogeneity in the impact arising from the gas price shocks; these causes cannot be observed directly from the data because firm-level information on costs is not publicly available.

The existence of long-term gas procurement contracts may cause heterogeneity in impacts among gas-fired units. There are two different ways that an electricity generating firm can procure natural gas: (i) by buying from the spot market or (ii) through a long-term contract with a gas supplier. Firms that enter into long-term contracts with gas suppliers are able to secure low priced gas, especially when the gas market is under stress, because the contracted price is not affected much by day-to-day spot price gas market conditions.[6]

[5] To install dual technology in a generator, one needs to change the nozzles, install equipment to handle fuel supply and modify the control system. Dual installed turbines can convert for use with one fuel to another quickly without much interruption. Although the installation of the technology is not difficult, not all gas units equipped the technology due to environmental regulations and lack of incentives during the low gas price period. Most of the existing dual units date back to either 1980s or early 2000s when the natural gas was relatively more expensive than other fuels(Power Engineering, 2004)

[6] A firm purchases gas with a long-term contract if it receives gas under a purchase order or contract with a term of one year or longer. Any contracts or purchase with a duration less than a year is considered Spot



(a) Algonquin citygate

(b) SoCal citygate

Figure 1.2: Over-The-Counter Gas Spot Prices: Year 2015

Notes: Data source is over-the-counter (OTC) individual transaction-level gas spot prices at two city gate points, provided by Intercontinental Exchange (ICE). Line in the figure shows the weighted average values of transaction-level gas prices, and bars show the difference between the highest and the lowest among transaction-level gas spot prices. Only the subset of transactions is available as data.

Therefore, the size of the gas cost increase is significantly lower for firms who have entered into long-term contracts with gas suppliers than for firms that purchase gas on the daily spot price gas market, even on days with substantially high spot gas prices. Details of specific firm-level contracts are confidential and difficult to obtain in general. Nonetheless, we know that the existence of such long-term contracts, and the variations in how firms procure gas, are sources of heterogeneity in gas costs.[7]

Increased volatility of spot gas price is another potential source of heterogeneity. Spot gas prices fluctuate over time, even within a single day if pipeline congestion occurs such that spot gas prices vary throughout the day. As the timing of gas procurement differs across firms, the gas price at which each firm purchases gas is also different. Figure 1.2 shows the existence of such heterogeneity of firm level spot gas prices, where minimum and maximum among firm level Over-the-Counter transaction prices at two city gates, Algonquin and SoCal, are plotted against time.[8] Algonquin is a city gate in New England where severe gas price shocks occurred in the winter (Jan. - Mar.) due to pipeline congestion, whereas SoCal is a city gate in California without any pipeline congestion. Large dispersion in Over-the-counter gas prices in New England compared to an absence of dispersion

purchase.(EIA-923)

[7] EIA-923 form reports some basic information about whether a firm purchases gas in the spot market or through a long-term contract. However, firms do not disclose the exact procurement prices or contract rates unless they are regulated. Long-term contract decisions are made at the longer time frame, meaning that a firm usually cannot go under a contract immediately as a response to a high spot gas prices. This makes the procurement channel variations across firms to be fairly exogenous.

[8] Over-the-counter data is hard to obtain in general. This data is provided by ICE to EIA starting from year 2015.

in California, indicating that gas prices were different across different firms in New England, even within a same day, is possibly due to gas price volatility caused by the pipeline congestion.

As a result of this heterogeneity, gas costs that are experienced by the gas units of all firms are impacted unequally by the shock, even on the same day. Depending on some unobserved sources, gas costs of certain firms, i.e. low impact firms, would increase by significantly less than those of highly impacted firms. Although I cannot clearly identify the sources of these impact variations, *implied* costs, which I estimate using a structural model in a later section, reveal such variations. The fact that we can still capture this heterogeneity without knowing the exact source is one of the advantages of estimating costs from the model and data in a revealed preference way.[9]

1.2.3 Data vs. Estimates: Why is the Gas Price Index Data Inaccurate?

I now demonstrate that using the gas spot price index to measure the marginal costs of gas-fired units is problematic if the post-shock gas prices are considerably different between units, which results from having different impacts from the shock. This is primarily because the gas spot price index is the quantity-weighted average of individual firm-level gas transaction prices; average values do not capture the dispersion of individual level gas prices.

If there is little or no dispersion among firm-specific gas prices, the weighted average value of gas spot prices of firms is a good measure of firm-level gas prices because each firm's gas price remains close to the average value. In this case, using an index data to measure the gas unit's cost is unproblematic. For this reason, many important studies of electricity markets use available gas spot price index data to measure the marginal costs of gas-fired units, since such an analysis does not involve heterogeneity in gas prices across firms or any input cost shocks.[10]

With substantial dispersion in individual firm-level gas prices, gas price index does not, however, represent the gas price of each firm because in this case the difference between average value and firm-level gas prices is substantial. Furthermore, the measurement error from using the gas price index becomes large if the firm purchases gas through a long-term

[9] Other than these, misalignment of operation times of gas market and (day-ahead) electricity market, additional cost associated with dispatch order uncertainty could be possible sources that cause actual gas cost to be heterogeneous across firms. More explanations of these can be found in Appendix.

[10] This is possible because the technology used in electricity generation is simple, where the primary input used is the fuel. Expression for marginal generation cost is introduced in the Model section of this paper.

contract because the contract price is not even included when generating the weighted-average gas price index. Hence, the marginal cost of each unit, if constructed based on a single gas price index, fails to capture such heterogeneity in the post-shock gas prices across firms. One possible solution to this scenario is to obtain data on firm-level over-the-counter gas transaction prices or long-term contract prices. Such high-frequency data are, however, not generally available.[11] Even if such high-frequency transaction prices are available, the gas costs constructed based on these prices may not reflect the true opportunity cost of generation. For example, the actual opportunity cost of dual gas units that switch fuel to oil is not the gas spot price.

Instead of measuring costs using the gas price index data, I exploit the structural bidding model and estimate the marginal generation cost that rationalizes firm bids. This estimate is the cost that is internalized by the firm in its bids, which we extract in a revealed-preference manner. In addition to estimating costs, I take a step further and extract firm-unit specific gas prices that rationalize firm bids and costs, which I term the *implied* gas prices. A major advantage of using such gas price estimates is that I can extract private information regarding a firm, in this case the fuel price, without having to obtain data on gas transaction prices or types of special contracts that the firm has entered into. The only assumption I need is that firms bid optimally in auctions.

Thus, the estimated fuel prices reflect any existing heterogeneity in the impact of the shock across firms. While the gas spot index, which is the only available data of spot gas prices, may be a good indicator of overall levels of post-shock gas prices, it does not accurately reflect the differences in the gas prices of individual firms, especially when gas prices are volatile as a result of a shock. This is also in line with Fabra and Reguant (2014)'s argument that a shock observed in the data cannot always be the actual shock internalized in auction bids.

[11] The ICE over-the-counter gas price data which I used to generate graphs in Table 1.2 is disclosed based on an agreement between EIA and ICE. However, data only discloses the sample statistics(average, minimum, and maximum) of the entire transaction prices, and the statistics start from the year 2015, which does not include the time period I study in this paper.

1.3 Strategic Responses to Cost Shocks: Markup Adjustments

1.3.1 Strategic Markup Adjustments in Auctions

According to strategic bidding literature, firms' incentives to increase or decrease markups in the presence of cost shock are affected by the (1) shape of the demand curve (2) marginal cost shocks (3) other firms' cost shocks, and (4) nature of competition among firms.[12]

Of these listed factors, demand side channel (factor (1)), can be ruled out in wholesale electricity market studies because wholesale electricity demand is inelastic; demand side auction participants (load-serving entities) submit bids that are insensitive to the price in order to secure the supply of electricity.[13] The ability of a firm to adjust markups is restricted by the demand especially when the demand is elastic because raising the price through an additional markup adjustment leads to a reduction in the quantity demanded. Because market demand for electricity is almost perfectly inelastic, any adjustments in markups that follow cost shocks is a result of strategic considerations made by firms which are closely related to the firm's actual impact from the shock on its cost and how the costs of others are affected by the shock. Therefore, I focus entirely on the factors (2),(3), and (4) throughout this analysis.

1.3.2 Heterogeneous Impacts at the Margin

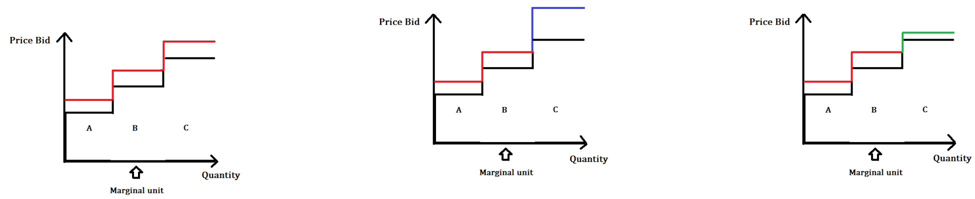
Here, I use a simple example to explain the intuition behind how firms with heterogeneous (rather than homogeneous) impacts on their costs, are incentivized to adjust their markups. I consider firms and units that are close to marginal (set the price of the auction) to illustrate firm incentives because strategic manipulation of price bids occurs only when a firm has an *ex-ante* positive chance of setting an auction price.

Figure 1.3 provides a graphical illustration of the situations where different types of shocks are imposed on the price bids of three units, A, B, and C owned by firms 1 and 2. Units A and B belong to firm 1 and unit C is to firm 2. Suppose that unit B is the marginal unit which sets the price of in this auction. I assume, for now, that firm price bid adjustments following a cost shock can be decomposed into a shift according to the size of cost shock and a subsequent shift according to the size of markup adjustments.

Panel (a) of Figure 1.3 illustrates a situation where three electricity generating units are

[12] This categorization is taken from Fabra and Reguant (2014).

[13] Fabra and Reguant (2014) also addressed the inelastic demand in their study of emissions cost pass-through and found the demand side indeed is not a critical determinant of the pass-through.



(a) Homogeneous

(b) Heterogeneous: low vs. high

(c) Heterogeneous: high vs. low

Figure 1.3: Graphical Illustration of Different Types of Cost Shocks

affected homogeneously by a shock; the price bid made by each unit increases by equal size cost shock. In this case, firms lack further incentives to adjust their markups because the slopes of bid curves (supply-offer curves) before and after the shifts are the same.

Panel (b) illustrates a different situation where the price bids are affected heterogeneously by the cost shock; the cost increase of Firm 2's unit is larger than cost increase of Firm 1's unit. In this case, Firm 1 now has the ability to raise the price bid of its marginal Unit B further by adding a markup. Because the competing Unit C increased its price bid by a size that is relatively larger than that of Unit B, Unit B will not lose its position as a price setter, even if it increases the price bid further. On the other hand, Firm 1 has different incentives for markup adjustment in the situation illustrated in Panel (c), where Unit B's cost increases more than that of Unit C. Unit B faces a trade-off because if it increases the bid too much, the dispatch order of Units B and C may be reversed, giving Firm 1 an incentive to add zero or negative markups in order to secure the dispatch of its marginal Unit B. Hence, based on strategic considerations, Firm 1 will add a positive markup on Unit B's price bid in the case of situation (b) and will add either no markup or a negative markup in the case of situation (c).

We can extend this logic by using residual demand to the case of competing multiple firms. In general, a firm's markup adjustment incentives to a cost shock - either raising or lowering- depends on the changes in the slopes of residual demand curves both before and after a shock. A homogeneous cost shock does not change the slope of the residual demand curve, implying that it creates no incentive to adjust markup. Heterogeneous cost impact results in a change in the slopes, giving firms have an incentive to adjust markups. The steeper (more inelastic) that a curve becomes, the greater the ability of a firm to raise markup. To what extent markups are adjusted is an empirical matter.

1.3.3 Size of the Shocks: Different Impacts Across Fuel Types

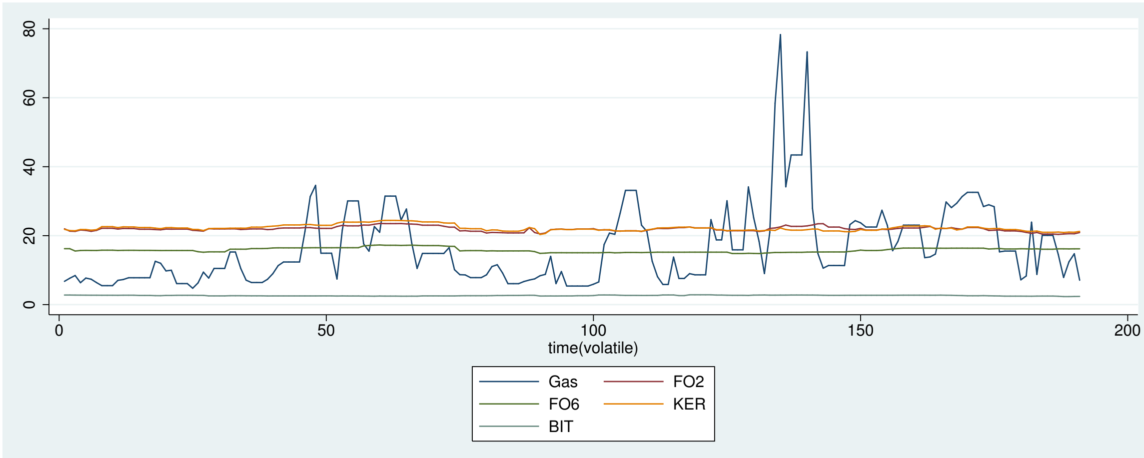
The sizes of gas price shocks differ across days in the sample depending on the extent of pipeline congestion of each day. Figure 1.4 shows such differences in the post-shock gas spot prices over the sample period, with price indices of gas, coal, and various oil products are plotted. While gas prices fluctuate due to different sized shocks, spot prices of coal and oil are stable.

The overall size of a gas price shock is an important factor that changes the intensity of the competition between gas and oil units because the shock only affects the marginal costs of gas units.[14] Gas units usually compete with each other when a small-size gas price shock hits the market, because the marginal cost of gas units, adjusted for the shock, is still substantially lower than the marginal cost of an oil unit. However, the marginal cost of a gas unit approaches that of an oil unit as the size of the gas price shock increases, making gas units compete with a large pool of competitors that includes both gas and oil units. In this case, a gas marginal unit is likely to face situation shown in Panel (c) of Figure 1.3, where the gas unit (Unit B) is incentivized to add smaller markups; this is because the marginal cost of a nearby oil unit (Unit C) does not increase with the shock, while Unit Bs marginal cost is increased. Thus, the location of gas unit bids on the supply-offer curve relative to the bids of oil units changes with the size of the shock, and the competition that a gas unit faces is expected to intensify as the size of the gas price shock increases.

This situation is depicted in Figure 1.4. According to the graph, oil prices range from \$16-\$22/MMBtu depending on the specific fuel content of the oil. This implies that the marginal cost of gas units will be similar than the marginal costs of oil units when the post-shock gas price lies within this price range; thus, gas and oil units are equally competitive within this range. Furthermore, if the price of gas exceeds \$22/MMBtu, then gas units become the most expensive units.

The competition that an oil unit and a dual unit faces changes with the overall size of the shock. Oil units are able to set the price in the auction more often when the shock size is large, because an increase in the marginal cost of gas units results in higher market clearing prices. In the absence of a large shock, the market is usually cleared by gas units that bid below the marginal costs of oil-fired units, thus most oil-fired units e do not have a chance to set the price in the auction. With larger size shocks, oil units set auction prices more often than with smaller size shocks, thereby having greater ability to manipulate the price through bid adjustments. Dual gas units are more likely to switch to oil as a result of experiencing gas price shocks that raise the post-shock gas price above the price of oil.

[14]Note that, the size of the shock is not an important factor of competition between gas and coal units as gas price always lies above coal price.



Notes: The graph above shows the spot prices of each fossil fuel over the period of days when gas price shocks were present. For gas price, I used daily day-ahead Gas Spot price *index* at Algonquin city gate (source: NGI, SNL), and prices of petroleum liquid (FO2, FO6, KER) and coal (BIT) are the daily spot price index taken from EIA and SNL. Price indices are converted to \$/MMBtu.

Figure 1.4: Spot Fuel Prices of Days When Gas Shocks Were Present

Once the fuel switch is made, the marginal costs of dual units are lower than the marginal costs of non-dual gas or oil units. This situation is similar to that illustrated in Panel (b), where a dual unit at the margin has greater incentives to add large markups on its bid.

1.4 Institutions and Data

1.4.1 Institutional Background on the New England Electricity Market

New England Electricity market supplies electricity to the region's 6.5 million households and businesses, serving 14 million people (ISO - NE *Market overview*, 2014). The market is operated by ISO-New England, a non-profit company that clears the electricity supply and demand for each hour every day. Electricity is supplied by firms that own generating assets, and demanded mostly by the local utility and distribution companies (LDCs) that offer retail electricity services to residential customers.[15] In this paper, I focus entirely on the generation side of the market, i.e. electricity supply.

Total 86 firms, including 32 small fringe suppliers that operate a single generating unit, appear in my sample. These firms together operate total 305 generating units (generators) that offer total 31,000 MW of generating capacity into the grid (ISO-NE, 2016). Substantial

[15] Some generating firms are affiliated to a company that offers retail services to residential customers. However, only a couple of firms operate retail services in New England market.

variations exist in the number of units and the fuel types of units owned by each firm in this market.

1.4.2 Auctions and Bidding

Electricity market supply and demand are cleared via a multi-unit uniform auction mechanism. There are two major auctions held in electricity markets, which are day-ahead auctions and real-time auctions. In this paper, I study strategic bidding and market outcomes of the day-ahead auction because of the following reasons. First, more than 95 % of the electricity supplied during the next day are scheduled in advance in the day-ahead auction. Secondly, the day-ahead auction offers a better set-up for studying strategic decisions made by firms than the real-time auction. This is because the goal of the real-time auction is to schedule any deviations in the real-time load from the commitments made in the day-ahead market, and such deviations are usually caused by unexpected real-time market conditions (e.g. transmission line congestions).[16] Also, it is common in the electricity market studies to use the day-ahead market when analyzing the strategic behaviors of firms (Borenstein et.al, 2002; Wolak, 2003; Reguant, 2014; Ryan, 2015).

In the day-ahead auction, electricity generating firms submit unit-specific supply bids for each of the generating units they operate, e.g. supply offer curves, and the demand side submits demand bids at firm-level. For supply bids, each unit is allowed to submit up to 10 steps of price and quantity bid pairs, i.e. $< p_{jk}, q_{jk} >$ where j =unit and k = step. More than half of units in this market submit single step supply bid, and about 90 % of units submit bids less than 5 steps. The number of steps each unit submits is summarized in Table A.1 of Appendix. While firms adjust price bids frequently, most of the firms do not adjust their quantity bids much, indicating that any adjustments in their bids following the change in the market conditions occur through the adjustment of their price bids.

Demand side participants are allowed to submit two types of bids; price sensitive and price insensitive (fixed) bids. Since most of the demand bids are price insensitive bids, electricity market demand is considered almost perfectly inelastic. Besides the supply and demand bids, I also incorporated the import/export bids and the financial bids into the estimation. More details on these additional bids are provided in the Appendix.

[16] In the New England grid, roughly 95 % of the load is committed in the day-ahead market (ISO-NE EMM Report, 2015) and no significant bid changes are made by firms in the real-time market. Day-ahead bids contain virtual bids which are financial bids without any physical obligations. In New England market, virtual bids accounted for only roughly 1.5 % of the actual load in the market, which is notably lower than in other grids like NYISO or MISO where financial bids take up more than 5 % of their total generation (ISO-NE EMM Report, 2015). In my main empirical analysis, I took out these financial bids from the analysis, but as a robustness check, I compared the outcomes with and without these bids. The difference was negligible.

Participants of the day-ahead auction simultaneously submit their bids for the 24 hours of the next day. Once the bids are submitted, ISO-NE clears the market for each hourly auctions by finding the price at which aggregate supply and demand curves intersect, accounting for the transmission constraints and other dynamic cost parameters.[17] Since the market uses multi-unit uniform auction, the generating units that submitted price bids that are lower than the market clearing price are accepted to be dispatched, and one single market clearing price is applied to all participants.[18] The accepted units have obligation to supply the committed amount of electricity on the day of generation at a cleared price unless they sell off or buy quantities in the real-time market.

1.4.3 Data

I use day-ahead wholesale electricity auction data published by ISO-NE, and supplement these with additional data on fuel prices and firm characteristics which I obtained from various sources. First, I use day-ahead energy offer data (supply offer bids) and day-ahead demand bids data available from ISO-NE website. These data sets contain hourly price bids and quantity bids submitted by electricity generating firms for each of their generating units.[19] The bidding data includes the must-take capacity, e.g. the minimum capacity a unit must dispatch in the auction, which I used to identify unavailable units. I used hourly net interchange data which contains the difference in hourly import and export of electricity to account for the imported and exported amount of electricity.

I use bidding data from September of 2012 to May of 2014, excluding samples from summer period (June - August). I excluded summer samples because firm-level forward contract parameters are likely to be different between winter and summer seasons.[20] Among total 305 units that show up in the bidding data, some firms and units retired, merged, or exited the market throughout the sample.

Additional data sets are coupled with the bidding data. I obtained market clearing prices

[17]Suppliers can submit the parameters that affect their dynamic supply decisions; must take capacity, economic minimum level of capacity, cold-start cost, etc.

[18]One single price that clears the entire system is termed as energy component(EC) price, and the final prices after adjusting for congestion costs etc. will be the locational marginal price (LMP). As LMP depends on hourly grid conditions of price nodes, it is hard to use LMP in electricity studies without detailed information and knowledge of ISO's clearing algorithm. Therefore, in this study, I use Energy Component marginal price.

[19] The identity of firms and units are masked, but I was able to identify some of them by matching the information from bids data to other data sets (Seasonal Capacity Auction data, ISO-NE). For those firms that I was not able to exactly identify the name, I was able to identify the types of fuels used by each unit, using my implied fuel price estimates.

[20] However, if I specify forward contracts at a shorter time period, monthly for example, I could use summer observations as well.

data (Energy Component Marginal Price), hourly market demand (load) forecast data and daily peak temperature data from the ISO-NE website. Market clearing prices will be used in the pass-through analysis, and the latter two data sets will be used as instruments in the main parameter estimation. I obtained data on firm characteristics, e.g. the type of fuel the generating unit uses and generation capacities of each unit, from ISO-NE's Seasonal Capacity Auction data which is updated every year.[21]

The fuel prices data and emissions permit prices data are also necessary for the analysis. I obtained Natural gas spot index data from *Natural Gas Intelligence* and *SNL Energy*. The spot prices of fossil fuels other than gas, such as Bituminous coal (BIT) and Oil (petroleum liquid products), are obtained from *EIA* and *SNL energy*. Emissions permit prices are obtained from *EPA RGGI* auctions data. More details on fuel price data and emission regulation status in New England are provided in the Appendix.

1.5 Model and Empirical Strategy

1.5.1 Multi-Unit Uniform Auction Model

The basic model considers the bidding decisions of the firm in a multi-unit uniform auction. The set up of this model follows the work of Reguant (2014) and Wolak (2007). Suppose there are $i = \{1, \dots, N\}$ firms that own J_i number of units that can generate electricity using multiple energy sources, i.e. gas, oil, coal, hydro, nuclear, etc. Denote these units by $j = \{1, \dots, J_i\}$. A firm submits hourly price and quantity bids for each unit it operates in the day-ahead electricity market. Since firms are allowed to submit bids up to 10 segments for each unit, I denote the segment with k where $k = \{1, \dots, 10\}$. Therefore, bids submitted for firm i's unit j of segment k at hour h is $< b_{ijhk}, q_{ijhk} >$.[22]

Hourly auctions are cleared at the intersection of aggregate supply and demand curves, and the price bid of the unit that clears the market, e.g. marginal unit, is the final market clearing price that applies to all units that are accepted in the auction.[23] Given this market

[21] This data, however, cannot be directly merged into the bidding data because the identity of firms and units are masked in bidding data, while in Seasonal Capacity data the actual name of the firm and its plants are reported.

[22] Once we aggregate bids of firm i's over all generating units, supply offer bid will be a step function and in this case k will denote the kth step bid of firm i, and denote this as b_{ihk}.

[23] New England grid adopted locational marginal price system, where the final market prices differ across nodes after adjusting for (transmission) congestion costs, etc. I do not consider this regional variation in prices in this analysis. In fact, locational marginal prices (LMP) do not differ much across p-nodes in my sample, which indicates that local market power coming from transmission constraint was not significant in the study period.

clearing price, firm i's (ex-post) profit function is shown below:

$$\pi_i(b_i, \mathbf{b}_{-i}) = \Big(\sum_{h=1}^{24} \{ \ P_h(b_{ih}, \mathbf{b}_{-ih}) \ (Q_{ih}(P_h(b_{ih}, \mathbf{b}_{-ih})) - \nu_{ih} \ ) \ \} \Big) - \sum_{j=1}^{J_i} C_{ij}(\ q_{ij}(P_h(b_i, \mathbf{b}_{-i})) \ ) \tag{1.1}$$

where P_h is the market clearing price of the hour h auction, Q_{ih} is the hourly generation quantity of firm i's entire units dispatched at hour h auction, and q_{ij} is unit j's generation quantity aggregated over hours. Also, b_{ih} is the bid vector (of all participating units) of firm i at hour h and $\mathbf{b}_{-ih}$ is bid vectors of other firms in this market.

The market clearing price is a function of the bid distribution, i.e. $P_h(b_{ih}, \mathbf{b}_{-ih})$, because the market clearing price of an auction depends on the supply bids of firms. A total quantity supplied by firm i at hour h, which is $Q_{ih}(P_h(b_{ih}, \mathbf{b}_{-ih}) \ )$, along with the quantity supplied by unit j of firm i, which is $q_{ij}(P_h(b_{ih}, \mathbf{b}_{-ih}))$, are also functions of the bid distribution because how many units (and their quantities) of firm i are dispatched depends on the market price, P_h.

Firms sell a certain amount of electricity at a pre-committed price in advance of the auction. Such forward contracted amount, ν_{ih}, must be subtracted from the total quantity supplied by the firm, Q_{ih}. I estimate the forward contract following Reguant (2014) because the forward contracts data are hard to obtain.

Optimization One of the important feature of the auction framework is that firms have uncertainty over the bids of their competitors. That is, the distribution of competitors' bids $\mathbf{b}_{-i}$ is uncertain to firm i in ex-ante, so the firm has to form a belief about the bid distribution of others. Therefore, given beliefs about $\mathbf{b}_{-i}$, firm i maximizes its *ex-ante expected* profit by optimally choosing the bidding strategy (price bid b_i). Equation(1.2) shows the maximization of the expected profit. Notice that the expectation is taken over the belief of the bids of other firms, $\widetilde{\mathbf{b}}_{-i}$:

$$\underset{\mathbf{b}_i}{max} \ \ \mathbb{E}_{-i}[\ \pi_i(b_i, \widetilde{\mathbf{b}}_{-i}) \ ] \tag{1.2}$$

Although only one unit sets the price of the auction in ex-post, the identity of the marginal unit is uncertain in ex-ante because the market price, which depends on $\widetilde{\mathbf{b}}_{-ih}$, is uncertain. When empirically implementing the multi-unit uniform auction model, we assume that firms optimally choose bids, b_i, for their units that have ex-ante positive probability of becoming marginal units. In other words, a firm would bid optimally for its units, according to its profit maximizing incentives, that are expected to set prices of the auctions. This is because the firm can manipulate the market price and increase its profit only if the unit is marginal. This implies that the optimality condition holds for any ex-ante marginal unit of a firm that has positive ex-ante probability of becoming marginals. Wolak(2003) provided an analytical expression for this probability, $\frac{\partial P_h}{\partial b_{ijkh}}$, which I provided in the Appendix.

Necessary first-order condition is derived by differentiating the expected profit with the (marginal unit's) bid price at step k, i.e. b_{ijkh}. This implies that a bid is optimal if there is no profitable local deviations (Wolak, 2003; Reguant, 2014; Ryan, 2015). Note that the necessary condition holds only when b_{ijkh} is ex-ante expected to be the marginal bid. Equation (1.3) is the final first-order condition that will be used for the estimation.

$$\mathbb{E}_{-i}[\frac{\partial\ \pi_i(b_i, b_{-i})}{\partial\ b_{ijhk}}]\,]\Big|_{P_h=b_{ijhk}} \ = \ \mathbb{E}_{-i}\Big[\frac{\partial\ P_h}{\partial\ b_{ijkh}}\ \frac{\partial\ \pi_i(P_h(b_i, b_{-i}))}{\partial\ P_h}\ \Big]\Big|_{P_h=b_{ijhk}} \ = \ 0$$

$$\Leftrightarrow \quad \mathbb{E}_{-i}\ \Big[\frac{\partial P_h}{\partial b_{ijkh}}\ [\ (Q_{ih}(P_h) - \nu_{ih})\ +\ \big(P_h -\ C_{ij}^{'}(Q_{ih}\ (P_h)\ )\ \big)\ \frac{\partial Q_{ih}(P_h)}{\partial P_h}\ ]\ \Big] = 0 \quad (1.3)$$

The market clearing equilibrium condition is that quantity supplied by firm i is equal to the residual demand of it. That is, net physical quantity supplied in this market by firm i at hour h, which is Q_{ih}, needs to equate the residual demand of firm i at hour h, denoted as RD_{ih}. Therefore, we can replace Q_{ih} in the above first-order condition with RD_{ih}. Also, P_h term is interchangeable with b_{ijkh} because the first-order condition holds for the marginal unit, the price bid of which is the market clearing price, i.e. $P_h = b_{ijhk}$.

Empirical Specifications The specification of the cost and forward contract are similar to Reguant (2014). First, I assume that the electricity generation cost $C_{ij}(q_{ij}(\mathbf{b}_i, \mathbf{b}_{-i}))$ is linear in quantity, $C_{ij}(q_{ij}(\mathbf{b}_i, \mathbf{b}_{-i})) = mc_{ij}\ q_{ij}$. Therefore, marginal cost is constant, the specification of which is shown below:

$$C_{ij}^{'}(q_{ij}(\mathbf{b}_i, \mathbf{b}_{-i})) \ = \ mc_{ij} \ + \ \epsilon_{ijkht}$$

Wolak (2003) and Reguant(2014) discuss the importance of dynamic cost components such as start-up costs or ramping costs. However, because my study focuses on the bidding differences across two different time periods, any change in profit maximization that comes from the dynamic component will be consistent across these samples, and will not critically affect my analysis. Also, using a constant marginal cost specification is justified when the steps of a unit accepted in the auction are small, which is the case of the New England electricity market where most of the generating units dispatch two to maximum four steps in the auction.[24] Despite this, I tried estimating with different cost specifications as a robustness check, by specifying quadratic and ramping cost terms.[25]

I assume forward contract size to be the percentage of their expected hourly output, following Reguant (2014).[26] Therefore, even though the actual hourly forward contracted amount ν_{iht} could vary across the sample because Q_{iht} changes every day and hour, the percentage rate parameter γ_{ih} is assumed to be constant within the sample. Thus, there will be total 24 hourly parameters per sample. The expression for the forward contracted electricity is shown below:

$$\nu_{iht} = \gamma_{ih} Q_{iht} + \varepsilon_{iht}$$

The main parameters of Reguant(2014)'s model are the marginal costs (mc_{ij}) and forward contract (γ_{ih}) parameters. Besides these, I estimate additional parameters which are unit-specific *heat rates* and *implied fuel prices*, which I introduce in the following section. The estimation of marginal cost and forward contract parameters follows the procedure common in the literature (Wolak, 2003; Reguant, 2014). However, I must make additional assumptions on the parameters and exploit the differences in gas price stability in order to estimate heat rates and implied fuel prices. I explain the empirical strategy of estimating heat rate and implied fuel prices in the next section.

1.5.2 Empirical Strategy: Estimating Implied Fuel Prices

In this section, I explain the samples, the decomposition of a marginal cost, and the assumptions that enable estimation of implied fuel price and heat rate parameters– which are the additional parameters derived from the decomposition of the marginal cost term. The key parameter is the implied fuel price which is the generating unit's fuel price component that composes the marginal cost of generation. Since the gas price shock will be entering the marginal cost through the fuel price part, I can identify the exact impact of the shock on firm's cost by separately backing out the implied fuel price parameters from marginal cost estimates. In order to separate out the implied fuel price from marginal cost, I need to first estimate the unit-specific heat rates, which is the physical efficiency of the unit, and partial

[24] Ryan(2015) justifies his use of constant marginal cost specification with the fact that most of the units cleared up from 2 to maximum 4 steps in Indian electricity market.

[25] Quadratic and Ramping Cost parameter estimates were not significant for most of the generating units, especially for the gas-fired units. As was discussed in Reguant (2014), dynamic cost or ramping cost terms are important for understanding the bidding decisions of base load generations such as coal-fired units. Since the focus of my study is in the cost changes of gas-fired generators, I disregard quadratic, ramping, or dynamic costs throughout the analysis.

[26] Reguant (2014) argues that it is quite common in the industry to set the amount of forward contracts as a per cent of the firm's expected production.

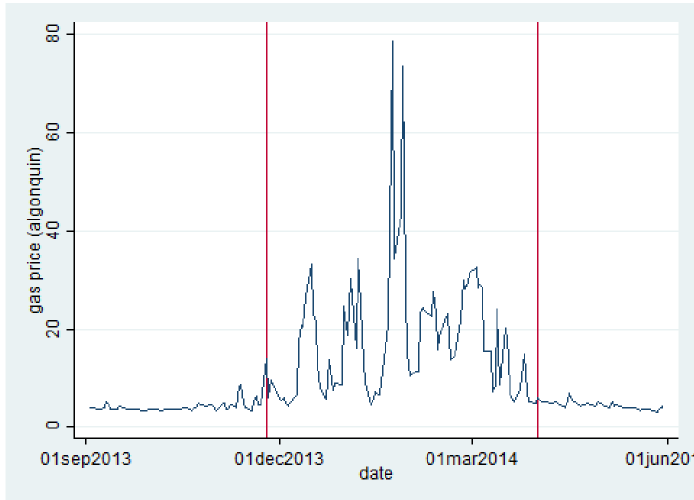


Figure 1.5: Illustration of Sample 0 (stable) and Sample 1 (volatile)

Notes: Days in between red lines are part of Sample 1 which is a collection of days when gas price shock was present. Days outside of red lines are part of Sample 0 where gas price shock was not present.

out the heat rate from the marginal cost estimates to obtain estimates of fuel prices.

1.5.2.1 Samples and Parameters

I exploit two different samples that enable estimation of different set of parameters; sample days with and without the gas price shock which I denote as *Sample 0* and *Sample 1*, respectively. Figure 1.5 shows the spot gas price indices over these samples. Days in between the two red lines form part of Sample 1, which exhibits volatile gas prices, and days outside these lines form part of Sample 0, in which the gas prices are stable and at low levels.

The key difference between these samples is the presence of the gas price shock. In the absence of severe gas pipeline congestion, the gas price usually stays around \$4/MMbtu without any significant fluctuations. However, the gas price rises above \$4/MMbtu when the pipeline is severely congested, and the exact levels of the daily post-shock gas prices depend on the degree of congestion of the day, which makes gas spot prices to fluctuate substantially within sample 1 as shown in Figure 1.5. Therefore, I grouped normal days, for which gas price indices stay around \$4/MMbtu, into Sample 0, and I grouped days for which gas price indices rose above \$4/MMbtu into volatile days, Sample 1.

Using the model, methodology and samples described so far, I estimate the following parameters: heat rates, forward contract, marginal costs, and implied fuel prices. From Sample 0, I estimate unit-specific heat rate parameter and firm-specific forward contract parameters. From Sample 1, I estimate marginal generation cost parameters and then back out the implied fuel prices from the marginal cost estimates using the heat rates estimated from sample 0. Implied fuel price is the fuel price component that rationalizes the firm's bid.

1.5.2.2 Marginal Cost Decomposition: Heat Rate and Implied Fuel Price Parameters

The additional parameters, heat rate (hr_{ij}) and implied fuel prices (FP_{ijt}), appear in the decomposed marginal cost expression. The marginal cost of generation mc_{ij}, which is assumed to be constant, can be decomposed further into two parts: fuel costs and emissions costs. Since each of these costs contains heat rate, which measures of how efficiently a generating unit converts fuels into electricity, the final expression of marginal generation cost becomes heat rate multiplied by the sum of fuel price and emissions price. Separating out the components of the marginal cost is not an easy task in other industries where various inputs and technologies are used for producing goods. Electricity generation, on the other hand, has a simple production technology and has fuel as its only major variable input. Such simplicity enables the decomposition of marginal cost of electricity generation.[27] Equation (1.4) shows the decomposition of day t's marginal cost of unit j of firm i:

$$mc_{ijt} \ = hr_{ij} \ (\ FP_{ijt} \ + \ \tau_t \ e_{j,fuel} \ ) \tag{1.4}$$

FP_{ijt} is the price of a fuel used by unit j at time t, which I term fuel price. hr_{ij} is the heat rate of unit j, which is specified not to vary across time because the physical efficiency of a generating unit does not vary across time. The variables that compose the emissions cost part are τ_t and $e_{j,fuel}$ which are emission permit price and emissions factor of the fuel used, respectively. Although the same marginal cost expression shown in equation(1.4) enters the first-order conditions of both sample 0 and sample 1, different parameters are estimated from different samples.

Heat Rate Parameters From stable Sample 0, I estimate heat rate parameters, hr_{ij}, which enters the marginal cost expression shown in equation(1.4). Heat rate represents the physical efficiency of a generating unit in converting fuel to electricity; heat rate is in-

[27]This way of marginal cost decomposition is commonly used in electricity industry studies (Wolfram,1999; Borenstein et.al, 2002 and among others). These papers exploit this decomposition to calculate marginal cost from available data on fuel price, emissions cost and heat rates (Wolfram,1999; Borenstein et.al,2002 and among others).

variant to any shocks or changes in market conditions.[28] Exploiting the invariant feature, I later use heat rates estimated from Sample 0 for estimation of implied fuel prices in Sample 1.

The fact that gas prices are stable across Sample 0 enables estimation of the heat rate. Days in Sample 0 have almost identical gas prices, at around $4/MMbtu, and the gas prices do not fluctuate significantly across days or even across hours within a day. This implies that the actual gas spot prices did not differ much across firms, across units, or over time in the stable Sample 0. Thus, firm-unit-specific gas spot prices that enter firms' bids will not depart much from the gas price indices, which are a weighted average of individually reported firm-level gas prices. Therefore, in stable Sample 0, I assume that the gas price index is an accurate measure of the gas prices of individual gas-fired units; this allows me to use gas price index data FP_{index} in place of fuel price, part FP_{ijt} of equation (1.4).[29] In sum, here I am implicitly assuming that;

$$FP_{ijt} \approx FP_{lkt} \approx FP_{index} \qquad i \neq l, \;\; j \neq k$$

Since I can use gas price index data in place of FP_{ijt}, I can separately estimate the heat rates of each unit from the stable period sample. After inserting gas price index data for FP_{ijt} and the emissions cost measured from the data for τ_t and $e_{j,fuel}$, the only remaining parameter is the unit-specific heat rate hr_{ij}. Since the stability argument holds for fuel spot prices of fossil fuels other than gas, e.g. coal and oil products, I can estimate the heat rates of all units that use fossil fuels to generate electricity. Equation (1.5) below shows the marginal cost expression that enters the first-order condition of Sample 0, where I highlighted the heat rate parameter with boldface type:

$$mc_{ijt} = \mathbf{hr}_{ij} \left(FP_{index} + \tau_t \, e_{j,fuel} \right) \qquad t \in \text{Sample 0} \qquad (1.5)$$

Note that I cannot use the gas price index data in place of FP_{ijt} in Sample 1 because the index data cannot represent unit-level gas prices in the presence of heterogeneity; the gas prices that apply to each firm and unit are heterogeneous. Thus, estimating heat rate is

[28] Heat rate of a dual unit does not change with the fuel switch. Heat rate is a characteristics of a turbine, thus does not vary much with the fuel's heat content. Heat rate may increase when the generator is ramping up quickly, which I do not consider in my model.

[29] Also, the stable nature of gas prices ensure that a firm's expected gas price to be close to the gas price index. For example, some firms that have not procured the gas for their generation use at the time of the bidding may have to construct their price bids based on the gas price expected at the time of future procurement. With stable gas price, as gas prices do not vary over time, the expected gas price has no difference in level with the current gas prices. How expectation over cost term enters the optimal bidding model is explained in Appendix.

only possible for Sample 0.

Implied Fuel Price Parameter The main parameter of interest in the estimation from Sample 1 is the implied fuel price parameter, FP_{ijt}, which is the generating unit's fuel price component that composes the marginal cost of generation shown in equation (1.4).

There are several advantages of using the implied fuel price over using the marginal cost term, particularly for gas-fired units. Firstly, implied gas price estimates allow me to identify the actual impact of the gas price shock on the unit's marginal cost, as measured by the gas prices reflected in firms' bids, net of unit-specific heat rates. Differences in the estimated marginal costs cannot be attributed to differences in the implied fuel prices because of the heterogeneity in the heat rates. Secondly, I can utilize the implied fuel prices of dual gas-fired units to identify whether they switched fuels. If a dual gas unit switches to oil on a given day, the estimated implied fuel price will correspond to the price of oil, rather than the price of gas. I will provide more details of the identification of fuel switching in the Estimation Results section. Finally, estimated implied gas prices reflect each gas unit's gas price that is used in their bids; this offers more rich information than gas price index data so that we can overcome the limitation of not having data regarding over-the-counter level gas prices. Furthermore, these estimates are better measures than over-the-counter gas prices because they are the gas prices that rationalize the marginal *opportunity* costs of generation embedded in firms' bids.

In order to obtain FP_{ijt} of Sample 1, I first need to estimate unit-specific marginal costs of each day in the Sample 1. That is, I estimate mc_{ijt} of unit j of firm i shown in equation(1.6) for each $t \in$ Sample 1. Because gas price levels vary substantially across days in Sample 1, marginal costs of gas-fired units are also different across days, implying that one unit-specific marginal cost parameter must be estimated per day. Although the marginal cost of coal or oil units do not fluctuate much across Sample 1, I estimate marginal cost of these units also at a daily level to make the analysis consistent.

Then I go a step further and back out the implied fuel price FP_{ijt} from the unit's marginal cost estimates, $\widehat{mc_{ijt}}$. Separately backing out the implied fuel prices from the marginal cost estimate is possible because I have estimates of unit-specific heat rates, $\widehat{hr_{ij}}$, and the emission cost term, $\tau_t e_{j,fuel}$, measured from the data (emissions permit prices and emission factor data). Heat rates estimated from Sample 0 can be used on the estimation of Sample 1 because heat rate represents a unit's physical efficiency, which is invariant to any shocks or changes in market conditions.[30] Therefore, the invariance of heat rate across

[30] Heat rate of a dual unit does not change with the fuel switch. Heat rate is a characteristics of a turbine, thus does not vary much with the fuel's heat content. Heat rate may increase when the generator is ramping

Sample 0 and Sample 1 is the key feature that enables extraction of implied fuel price. The equation(1.6) below shows the marginal cost expression for Sample 1, where the implied fuel price parameter is shown in boldface type:

$$\widehat{mc_{ijt}} = \widehat{hr_{ij}} \left(\mathbf{FP}_{ijt} + \tau_t \, e_{j,fuel} \right) \qquad t \in \text{Sample 1} \tag{1.6}$$

1.5.2.3 Forward Contract Parameter

I estimate forward contract parameter, γ_{ih}, from Sample 0 only and use these estimates in the marginal cost estimation in Sample 1. As will be discussed in identification section, identifying forward contract parameters together with the heat rate parameter (or marginal cost parameter) relies on the assumption that heat rate and forward contract parameters are constant within the sample; one heat rate parameter per unit, and one set of forward contract parameters per firm in the sample. Because marginal costs of each unit vary across days in Sample 1, I cannot estimate both $mc_{ijt,1}$ and γ_{ih} parameters in Sample 1.

1.5.3 Estimation

1.5.3.1 Resampling: Treatment of the Expectation Term

For the estimation, I need to derive an empirical analogue of the first-order condition shown in equation (1.3), which involves a treatment of the expectation over the bids of other firms, $\mathbf{b}_{-i}$, that are uncertain to firm i in ex-ante. I approximate the expectation terms following the method developed by Hortaçsu (2002), which has been applied to the electricity market auction settings in Reguant (2014). The basic idea of the methodology is to approximate the expected term using the resampling procedure. Each resampled set of bids represent one possible realization of the ex-ante expected bids, thus a collection of resampled bids will approximate the ex-ante expected bid distribution of a firm.

It was pointed out in Hortaçsu and Kastl (2012) and Reguant (2014) that resampling method can be extended to allow for the ex-ante observable asymmetries between days by performing the resampling within the ex-ante symmetric group of days, i.e *Similar days*. I adopt this and selected similar days for each day t in the sample based on the following criteria: forecasted demand, peak temperature, weekday, and the gas market conditions. Selected similar days of day t have levels of each criteria similar to those of day t. Bidding patterns of firms are also similar across these selected days. In the main estimation, I used 6 similar days when resampling.

up quickly, which I do not consider in my model.

	Resampling $\mathbf{b}_{-i}$ of firm i on auction day t:
Step 1:	Fix the bids of firm i to its actual ex-post observed bids of day t
Step 2:	Randomly sample the bids of each firm $j \neq i$ from the pool of days that are similar to day t. That is, if the similar days of day t are $T_t = \{t1, t2, t3\}$, randomly sample one day from the set T_t for each firm j.
Step 3:	Clear the market using the supply offer curve constructed using the resampled bids from steps 1-2, and the ex-post demand bid curve of day t. Market clearing yields one market price, $P_{h,s}$
Step 4:	Step 1-3 is for one resampled draw, i.e. s = 1. Thus, repeat the steps 1-3 for S = 100 times, and get $P_{h,i} = \{P_{h,1}, \ldots, P_{h,S}\}$
Step 4:	Going through Steps 1-4 gives a set of resampled prices for firm i, i.e.$P_{h,i}$. Now repeat steps 1-4 for each firm in the sample, $i \in F$ and get $P_{h,i}$ for $i \in F$

Table 1.2: Resampling Procedure

I need to first resample firm i's beliefs about its competitors' bids, $\mathbf{b}_{-i}$, on day t by randomly drawing a set of bids from the ex-post realized bids of similar days of t. I resampled $S = 100$ sets of bids for each firm i. For each resampled set of bids, I obtain a market clearing price where the supply bid curve constructed with the resampled bids intersects with the ex-post realized demand bid curve of day t. Doing the clearing process for the entire resampled draws gives a distribution of market prices that is expected by each firm in ex-ante, and I use the distribution to construct the ex-ante expected first-order condition. More details of the procedure, which is similar to that of Hortaçsu (2002) and Reguant (2014), are provided in Table 1.2.

1.5.3.2 Smoothing Supply Bid and Residual Demand Curves

Besides the expectation term, the derivatives of the supply offer curves and the residual demand curves enter the empirical analogue of the first-order condition. However, these curves are not smooth because firms submit supply offer and demand curves in the form of steps functions. To obtain derivatives, I smooth the supply offer curve and the residual demand curve using normal kernel smoothing approach following Wolak (2007). I used bandwidth of $3/MWh for the Sample 0 estimations, and $6/MWh for the Sample 1 estimations.[31] Functional forms of the smoothed residual demand and supply offer curves are provided in the Appendix.

[31] As a robustness check, I tried different bandwidths to see how sensitive the derivatives are to the bandwidth selection. Results are quite robust across bandwidths except for some days when electricity prices are extremely high.

1.5.3.3 GMM Moment Condition

I estimate parameters of the model via GMM, which exploits the empirical analogue of the first-order condition which is shown below:

$$m^{T}_{ijkht}(\theta_{\mathbf{T}}\,; bw, S) = \frac{1}{S}\sum_{s=1}^{S} \frac{\partial \widehat{P^s_{ht}}}{\partial b_{ijkht}}\Big(\; (Q^s_{ikht} - \nu_{iht}(\gamma_{ih})\;) \; + \; (b_{ijkht} - mc_{ijt}\;) \; \frac{\partial \widehat{RD^s_{iht}}}{\partial P_{ht}}\Big) \tag{1.7}$$

where T denotes the Sample, i.e. Sample 0 ($T = 0$) or Sample 1 ($T = 1$), and the wide hat denotes kernel smoothed values.

The slope of a residual demand could be potentially endogenous if unobserved cost shock is present. Firm specific unobserved cost shock could shift the firm's bid up, resulting in a larger residual demand slope. Failing to account for such cost shock will misleadingly conclude that a firm behaves less competitively by adding higher markup, when actually the higher bid is a reflection of unobserved cost shock. Therefore, following Reguant(2014) and Ryan(2015), in Sample 0 estimation, I instrument residual demand slope with hourly forecasted demand and daily forecasted temperature variables that exogenously shift the endogenous slope variable, but not correlated with the unobserved supply shock. In Sample 1 estimation, I use forecasted demand error (i.e. actual demand - forecasted demand) to eliminate moments' dependency across hours.

The empirical moment conditions of Sample 0 and Sample 1 are shown below in equations (1.8) and (1.9):

$$\sum_{t=1}^{T}\sum_{k=1}^{K} Z'_{0,ht} m^{0}_{ijkht}(hr_{ij}, \gamma_{ih}) = 0, \quad \forall j, h \tag{1.8}$$

$$\sum_{h=1}^{H}\sum_{k=1}^{K} Z'_{1,ht} m^{1}_{ijkht}(mc_{ijt}; \hat{hr}_{ij}, \hat{\gamma}_{ih}) = 0, \quad \forall j \tag{1.9}$$

1.5.4 Identification and Inference

1.5.4.1 Identification

Identification of both heat rate and forward contract parameters in Sample 0 estimation is possible by imposing reasonable restrictions on these parameters, which I follow Reguant (2014). The first identifying assumption made on both parameters is that hr_{ij} and γ_{ih} parameters are constant within Sample 0; parameters do not vary across $t \in$ Sample 0. Additional restrictions are imposed on heat rates and forward contract parameters. First, heat rate parameter is defined at a generating unit level and does not vary across hours. This is a reasonable assumption as heat rate is a measure of a generator's physical efficiency. On the other hand, forward contract parameter is defined at a firm level and differs across hours. Thus, each firm has 24 forward contract parameters, one per hour.[32]

To understand from which variations the parameters are identified, I provide a simplified version of the first-order condition below.[33]

$$b_{ijkth} = hr_{ij}(FP_{ij} + \tau e) + \frac{Q_{ijkth}}{RD'_{ith}} - \frac{\gamma_{ih} Q_{ith}}{RD'_{ith}} \tag{1.10}$$

In order to identify forward contract parameter γ_{ih}, we need an exogenous variation that shifts $\frac{Q_{ith}}{RD'_{ith}}$, given the heat rate hr_{ij} fixed. Thus, unit-specific variations at the same hour across steps and across days identify γ_{ih}. Once the γ_{ih} parameters are identified, the identification of unit-specific heat rate hr_{ij} is straightforward.[34]

1.5.4.2 Inference

Standard errors of the heat rates and forward contract parameters estimated from Sample 0 are constructed using a bootstrap method. In Reguant (2014), block-bootstrap method is used to address the temporal nature of the data. Although I do not incorporate generating units' dynamic decisions (dynamic parameters) in my model, I implement block bootstrap for generating standard errors addressing the possibility of the temporal dependence in the underlying data process. Standard errors of the Sample 1 marginal cost parameters are generated using a standard GMM standard error formula. Because this Sample 1 GMM estimation is indeed a linear IV estimation, I used IV standard errors.

1.6 Estimation Results

1.6.1 Heat Rates and Forward Contract Estimates

In Table 1.3, I report the average values of the heat rate estimates by the fuel types of generating units. Average heat rates of gas-fired units is 9.09, oil-fired units is 12.39, and gas/oil

[32] Recall that an additional structure imposed on the forward parameter is that it is a fraction of the expected hourly output; thus, the actual amount of forward contract could vary even if we assume forward contract parameters to be constant across days in the sample.

[33] This equation is taken from the working paper version of Reguant (2013).

[34] The variations that can be used are slightly different depending on the specification of the marginal cost. If we assume a constant marginal cost, $mc_{ij} = \alpha_0$, variation across steps(k) and days(t) can be used. However, if quadratic cost are specified, $mc_{ij} = \alpha_0 + \alpha_1 Q_j$, only the variation across days(t) can be used because across steps variation is no longer an excluded variable of marginal costs.

Fuel	Average heat rate (MMbtu/MWh)
Natural Gas	9.09
Oil	12.39
Dual Units	11.01

Table 1.3: Heatrate Estimates

dual units is 11.01.[35] Note that heat rates estimated from the model does not necessarily have to equal the physical heat rates that engineers use; it is more like a measure of generator efficiency that reflects how effectively fuel is converted into energy. Despite this, my estimates are close to EIA's report on heat rates: average heat rate of gas units lies between 7.6 - 11.3, and that of oil units lies between 9.9- 13.5, depending on the types of turbines a generating unit installed.[36]

The estimates of firm-specific hourly forward contract rates parameter, which are estimated from the stable Sample 0, varies substantially across firms and hours. The average taken across hours and across firms is around 47 %. More information about the firm-level forward contract estimates will be provided in the Data Appendix.

1.6.2 Heterogeneous Impacts on Costs: Marginal Cost and Implied Fuel Price Estimates From the Volatile Sample

In this section, I characterize the heterogeneity of the impacts of the gas price shock on firm costs, with estimates of marginal costs and implied fuel prices obtained from the model. I first report unit-specific marginal costs and show how these estimates differ across units' fuel types and different sizes of the shock. I then report unit-specific implied fuel prices, which I backed out from the marginal cost estimates using the heat rate estimates, for each day in the volatile gas price sample 1. Additionally, I discuss how implied fuel prices can be used to identify dual unit's switch decision. The estimates suggest that the impact of the gas price shock on firms' costs was indeed heterogeneous across units and firms.

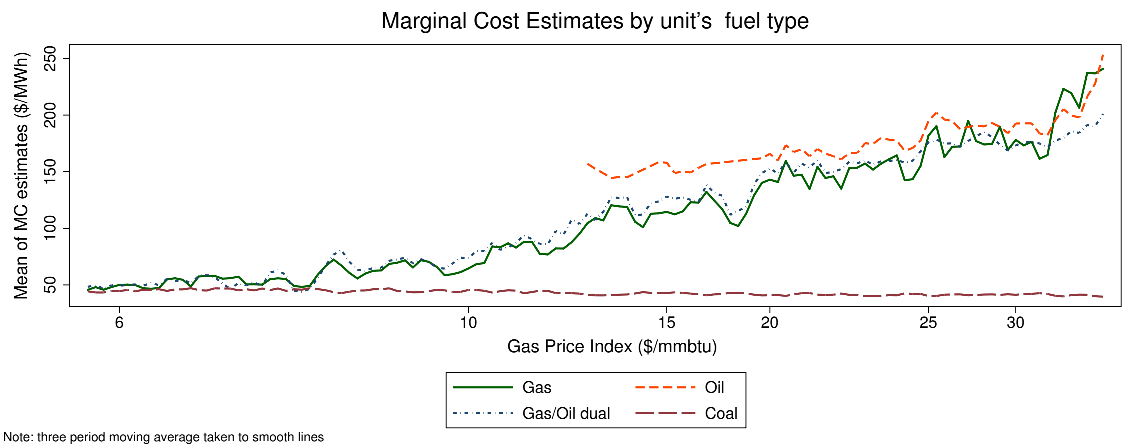
1.6.2.1 Marginal Cost Estimates Across Fuel Types

From the volatile gas price sample days, i.e. Sample 1, I estimate unit-specific marginal costs of generation ($\widehat{mc_{ijt}}$) for each day in the sample. A unit's marginal cost can be esti-

[35] Dual gas units have heat rates higher than those of non-dual gas units because dual technology was actively installed during the period of early 2000s when the natural gas prices were significantly higher than the oil prices. As the prevailing turbine technology at then was inefficient steam turbine, dual units in my sample tend to be old and thus inefficient than other gas generators.

[36] Unfortunately, I cannot identify the type of turbine technology of each generator in my sample.

Figure 1.6: Estimated Marginal Generation Costs By Fuel Type: Averaged Across Firms



Notes: Unit-specific marginal cost estimates of days in Sample 1 are averaged within each fuel type categories: Gas, Oil, Dual, and Coal. Set of units included in the calculation of the average value changes over time. Averaged estimates are plotted against the gas price indice values of the days in the sample.

mated if it has some positive ex-ante probability of setting the market price across several hours of the day. Therefore, marginal costs of units too far away from being marginal unit (having zero probability weight of $\frac{\partial p}{\partial b}$) cannot be estimated.

Figure 1.6 gives the paths of marginal generation cost estimates of days in Sample 1 averaged within each fuel category. That is, I took a daily average of the marginal cost estimates of coal, gas, dual and oil units separately within each category. Since gas price index levels, a proxy for an overall gas price shock on a given day, vary across days in the sample, I plotted these daily averages of marginal cost estimates against the gas price indices for each day. Thus, the horizontal axis values are increasing in the overall size of the gas price shocks.

While marginal cost estimates of coal and oil units do not change much in the sample, the marginal cost estimates of gas-fired units, on average, increase continuously with the levels of gas price shock, approaching those of oil-fired units.[37] The cost estimates of gas, dual and oil units are similar around the gas spot index price of $20/MMBtu which is an approximate threshold gas price that equates marginal costs of gas and oil units.[38] Also,

[37]Note that because marginal cost estimation exploits the necessary first order condition that holds for units having a positive probability of becoming a marginal unit, the average marginal cost value shown in the graph includes units close to equilibrium price only. Thus, small variations in oil units' marginal costs are due to sample selection problem. Higher gas price shock leads to higher market clearing prices, and more oil units with higher heat rates will become potential marginal units. And since higher heat rate units will have higher marginal cost, the average marginal cost value might slightly increase with the gas prices.

[38] Gas price in between $16 - 22/MMbtu is the gas price at which a firm would be indifferent between generating electricity using gas and oil. Because of the heterogeneity in the implied gas prices across firms, the exact threshold prices for each firm that equates gas and oil costs may be different from the suggested

within the range of gas price index values above \$25/MMBtu, the marginal cost of gas units is sometimes greater than that of oil units. This result confirms the previous discussion that the relative cost advantage of gas-fired units over other fuel type units changes with the overall size of the gas price shock. As shown by the estimates in Figure 1.6, with larger size shocks, the cost estimates of gas units approach, and even exceed, those of oil units, indicating that they now compete against nearby oil-fired units.

1.6.2.2 Implied Fuel Price Estimates

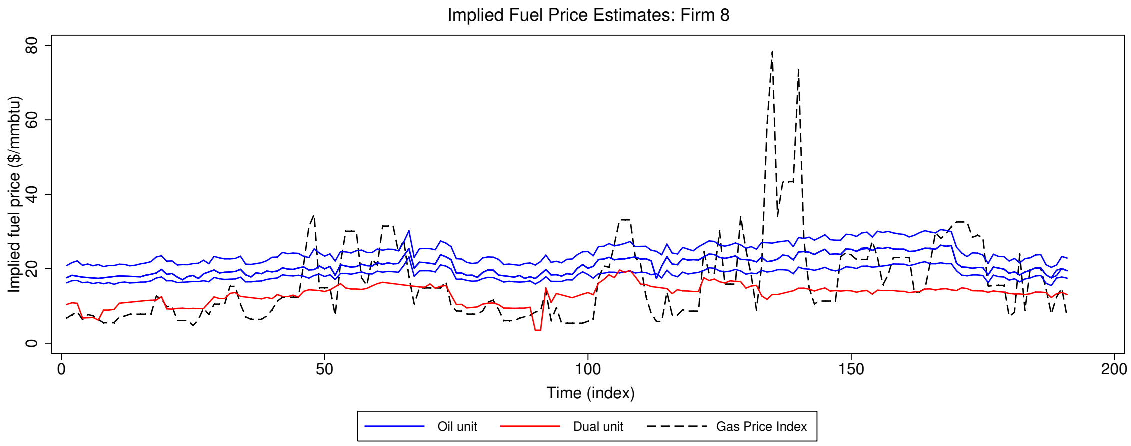
Because I can estimate implied fuel price of a unit as long as heat rate estimates and marginal cost estimates exist, I could obtain implied fuel price estimates for coal, oil, and even dual units regardless of their switch decisions. In order to illustrate this heterogeneity and to discuss dual unit switch identification, I plot daily unit-specific implied fuel price estimates of three firms that have different generation fuel mixes; Firms 8, 9 and 33. Firm 8 has oil and dual gas units, firm 9 has non-dual gas units, and firm 33 has both dual and non-dual gas units. Implied fuel price estimates of each of their generating units are shown in panels (a),(b), and (c) of Figure 1.7. I distinguished units' fuel types by different colors. In the same graph, I additionally plot the gas price index data together with these implied fuel price estimates in order to create a point of reference against which the implied fuel price estimates can be compared.

Dual unit switch identified from implied fuel price estimates Although there is no clear and consistent rule for when a firm decides to switch fuel, implied fuel prices can be used to identify the type of fuel that is used by a dual gas unit; this enables identification of the dual unit's fuel switch decision. Identification of switch decisions exploits the fact that fuel price fluctuations occur only for gas, so that price fluctuations will be reflected in the implied fuel price only if the unit used gas to generate electricity on that day. Thus, a relatively stable path of estimated implied fuel prices compared to the reference gas price indices indicates that the fuel used by the unit is not gas. Panel (c) of Figure 1.7 illustrates this method. In the time period of time index 75 to 125, dual unit fuel price estimates (red line) are stable, at a level around \$20/MMbtu, while gas price indices (dashed line) and gas unit estimates (green line) fluctuate, indicating that the dual unit did not use gas for generation within this time period.

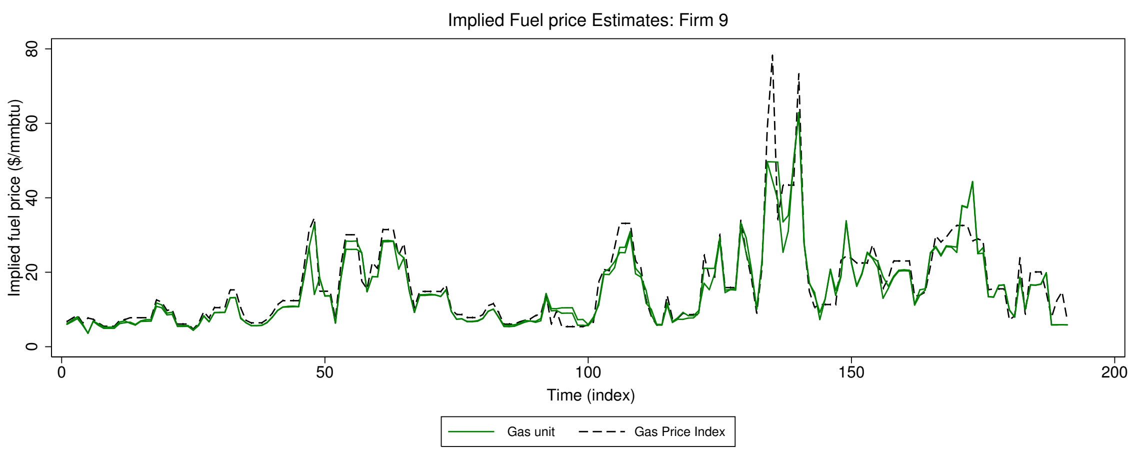
The overall pattern of implied fuel price estimates for dual units that switched fuel is as follows; implied fuel price estimates of dual units closely track the gas price indices when

threshold.

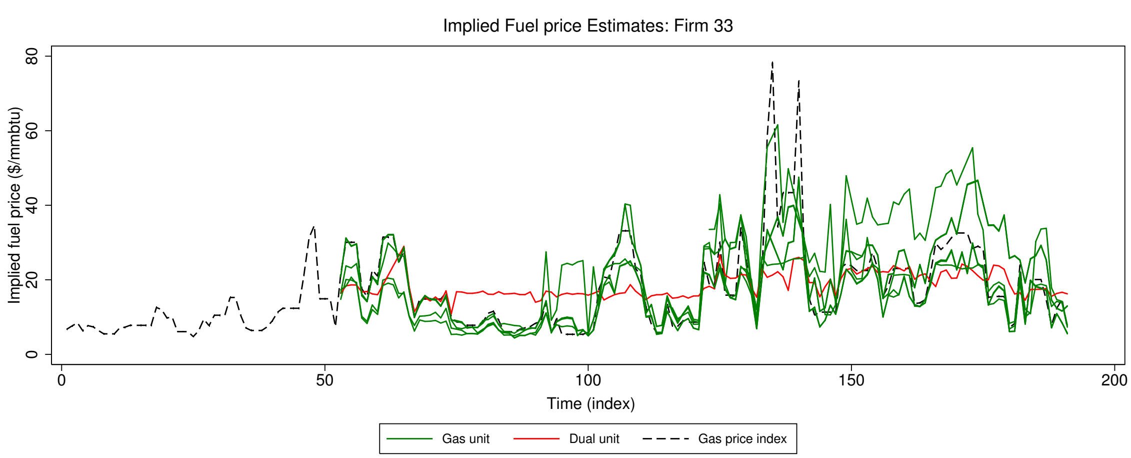
Figure 1.7: Implied Fuel Price Estimates



(a) Firm 8



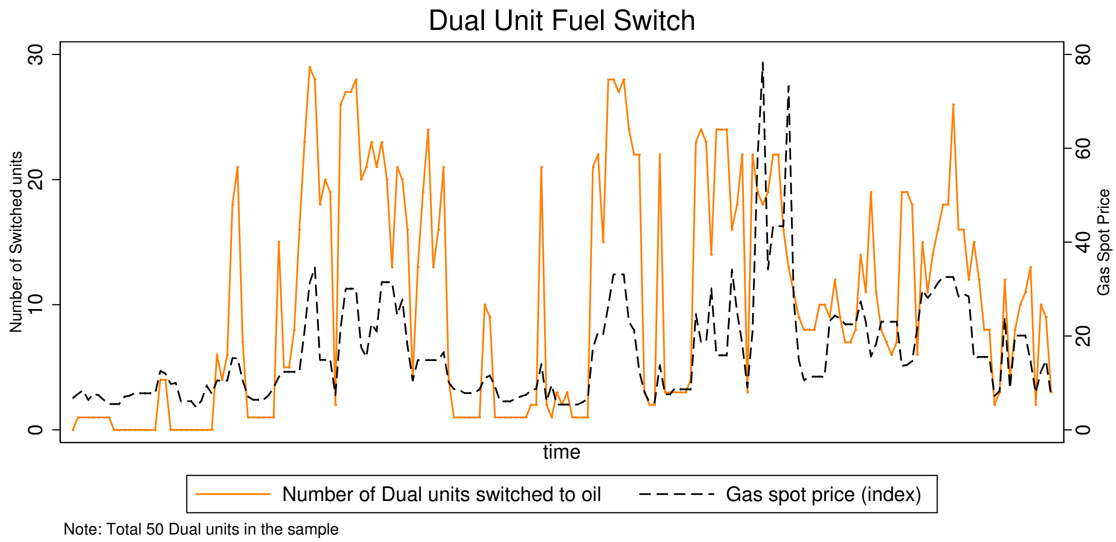
(b) Firm 9



(c) Firm 33

Notes: Implied fuel price estimates of non-dual gas units (green line), dual gas units (red line), and oil units (blue line) are plotted over time. The black dash line shows the gas price indices (data) of the corresponding days.

Figure 1.8: Dual Unit Fuel Switch Decision Identified



Notes: Solid (orange) line shows the number of dual gas units that switched to using oil for electricity generation, which is identified from the implied fuel price estimates. Black dash line shows the gas price index data. Both lines are plotted over days when gas price shock occurred.

the index values are small, but once the gas price indices exceed the level of oil spot prices, which ranges from 16 $ to $21/MMbtu, implied fuel prices stay at that level without any fluctuations. Using this method, I identified the fuel switch decisions of dual units for each day in the sample[39]. Figure 1.8 shows the total number of fuel switches, from gas to oil, that are made by dual units, plotted alongside daily gas spot price indices. The pattern of switches corresponds approximately to the cost minimizing behavior discussed earlier. The identified switch information will later be used in the markup simulations as well.

Implied gas price differences across firms Here, we limit our attention to gas-fired units and investigate the heterogeneity found in the implied gas price estimates. The actual impacts of the shock, as captured by the estimated implied gas prices, are heterogeneous across units and firms; firms have different levels of unit-specific implied gas price estimates, even within a single day. This is shown in panels (b) and (c) of Figure 1.7 where daily estimates of implied gas prices of each gas unit of firm 9 and 33(green lines) are plotted against the gas price indices. While the implied fuel price estimates of gas-fired units of Firm 9 track the gas price indices closely, implied fuel price estimates of Firm 33's gas units depart from the gas price index, indicating that the implied gas prices of units differ across the two firms. Furthermore, the implied gas price estimates even differ across gas

[39] Only for those units with heat rate estimates and volatile sample marginal cost estimates

units within the same firm, which is shown by a variation in the implied fuel price estimates of Firm 33's gas units, seen in Panel (c).

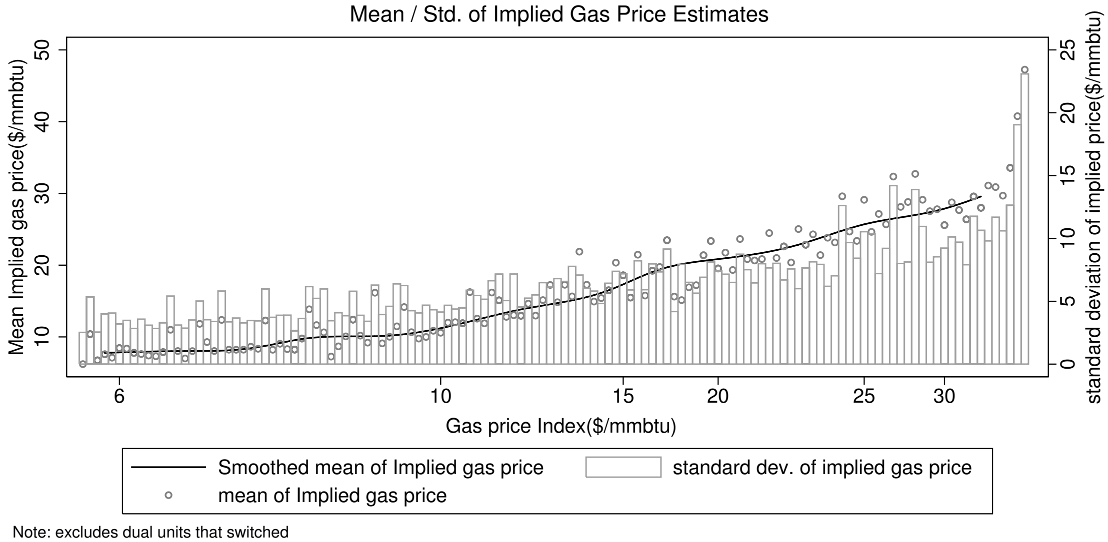
Another interesting observation is that the heterogeneity in the estimates of implied gas price increases with the overall size of the shock, as shown in Figure 1.9. Figure 1.9 summarizes the implied gas price estimates of all gas units in the sample; means and standard deviations of daily unit-specific implied gas price estimates are plotted against the daily gas indices. The graph shows that dispersion, as measured by the standard deviation, of the estimates increases with the size of the shock, indicating that the heterogeneity in the impacts of the shock on firms' gas costs increases with the size of the shock.

Why does such dispersion exist among estimated implied gas prices, and why does the dispersion increases with the overall size of the shock? As discussed earlier, firms that procure gas through long-term contracts with gas suppliers are able to purchase gas at a price that is substantially lower than the spot price, and the difference between the contracted price and the spot gas prices increases when post-shock spot prices increase substantially due to severe shock.[40] In addition, firm-level gas prices may well be different for firms that procure gas from the spot market at different times during the day, since spot gas prices fluctuate throughout the day. Since the intra-day fluctuations in spot gas prices become exacerbated as the shock becomes larger, dispersion across unit-level gas prices is likely to increase with larger shocks. Finally, for firms that operate multiple generating units, the gas procurement behavior may vary between units; gas may be procured at a unit level, and how gas is purchased may also differ by unit. For example, as shown in EIA-923 data, firms usually enter into long-term contracts for specific generators, so that it is possible for gas to be purchased differently at different units owned by the same firm.

By verifying the existing heterogeneity in post-shock gas prices, our estimates demonstrate why the gas price index cannot be an accurate measure of unit-level gas prices; the aggregate index cannot properly account for the differences in gas prices that are implied in firms bids. The importance of distinguishing between the cost shock that is observed from data and the actual cost shock that is internalized in the bids was addressed in Fabra and Reguant (2014). Fabra and Reguant (2014) tested whether the observed emission cost shock that is measured using the permit price data is the actual shock as reflected in firms equilibrium bids; they did this by regressing measured cost shock on bids. Instead of ver-

[40]Gas prices that are determined in long-term gas procurement contracts do not usually exceed \$10 - \$15/MMbtu. This is observed in my estimates, and can be verified by EIA-923 form where the fuel purchase prices of long-term contracted plants are documented. However, EIA-923 reports the fuel price of regulated firms and plants only, thus information available from this data set is limited. Some energy sector reports and brochures mention that long-term contracted firms' gas price during volatile period won't differ much from that in stable period.

Figure 1.9: Estimated Implied Gas Prices: Mean and Standard Deviation



Notes: The graph contains the mean and standard deviation of the estimated implied gas prices of all gas units in the sample.Statistics are plotted against daily gas spot price indices that are represented as a dash line.

ifying the validity of the observed shock, I estimated the actual gas price shock each unit internalizes from the bid data utilizing the structural model.

Grouping firms based on the estimated impacts: "hard-hit" vs. "not" The cost and implied price estimates show that firms in this electricity generating market are exposed differently to gas price shocks. For our subsequent markup analysis, instead of conducting a firm-level analysis, it is convenient to group firms according to their impacts from the shock. I generated two different groups of firms that were identified as having been hit hard by the gas price shock versus those hit less hard by the shock. I categorized firms as being "hard hit" according to two different criteria, which use quantitative indicators of the intensity of the impact from the shock: (i) share of gas generation out of total generation capacity, and (ii) firm-specific average impact on gas costs as measured by implied gas price estimates.

For the first criterion, I defined "hard-hit" firms as being those with a gas generation share greater than 80% of their total generation capacity; I term these hard-hit firms as *gas intensive* firms.[41] Gas intensive firms are hit relatively hard by gas price shocks since their generation capacity is comprised of fewer dual and oil units that are not/less affected by the shock; thus, gas intensive firms do not have the option of switching to dual-fuel or oil

[41] Dual gas units were omitted from gas generation capacity.

based generation when the shock is severe.[42]

The second criterion focuses on cross-firm variations in impacts on gas costs, as measured by estimated implied gas prices. That is, I constructed a distribution of daily implied gas price estimates of firms that operate at least one gas-fired unit, and I categorized firms that fall above the 50th percentile in the distribution as being "hard-hit" firms. I denote this group of firms as *high impact* firms. More details of this grouping are provided in Appendix.[43] Because firms fit the definition of both *gas intensive* and *high impact* for most of the days in my sample, the results from each categorization are also similar.[44] Therefore, I will mainly use the *gas intensive* grouping throughout the markup analysis section when reporting the results.

1.7 Markup Analysis

Theory predicts that firms with costs that are lower than the costs of other firms are capable of exercising market power by raising their markups. In other words, those firms that are impacted by the gas cost shock less than others have a greater ability to raise their markups. I now explore how markup changes in response to gas cost shocks differs across firms and by cost impact, and, finally, by the size of the overall gas price.

I measure two different types of markups that reveal similar information: bid markups and simulated markups. Both markup types are measured daily in the shocked sample, at firm level. While bid markups are obtained directly from cost estimates, I conducted a separate simulation semi-counterfactually in order to obtain the simulated markups. Although bid markup is common in the auction literature, it is not suitable for measuring the *change* in markups that results solely from a cost shock, net of other factors such as electricity demand. On the other hand, simulated markup measures endogenous changes in markups that are due to small cost shock perturbations that arise purely from the cost shock; such markups are, therefore, most relevant for pass-through analysis.

[42] I observe, from the estimates, that costs of gas intensive firms increase more when hit by a shock, compared to firms that operate well-balanced generation having large proportions of dual, oil, and other base load units (hydro and nuclear).

[43] While the first criterion, *gas intensive*, is related to generation mix differences, the second criterion can be linked to the post-shock gas price differences across firms that show up in the implied gas price estimates.

[44] Two criteria are similar except that while a set of firms grouped under *Gas intensive* is fixed over time and across auctions, those grouped under *High impact* criterion may change. Also, while the criterion used for the *Gas intensive*, which is the share of gas generation, is observed directly from the data, the implied gas prices used for the second criterion has to be estimated from the model, thus unobserved in general.

1.7.1 Bid Markups

Bid markups are closely related to the degree of competition that a firm faces in a market ex-ante. Ideally, if a market is operated as if it were perfectly competitive, firms would not add any bid markups to their marginal costs, i.e. they would bid at their marginal costs. On the other hand, a firm with some degree of market power would be able to submit higher bids by adding bid markups over its marginal costs, expecting, ex-ante, to manipulate the market price.

Bid Markup Expression and Measurement Bid markup expression can be derived from the first order necessary condition of the optimal bidding in multi-unit uniform auction. Suppose the marginal unit which sets the price in day t and at hour j is firm i's unit j's kth step bid. Then, after rearranging the (ex-ante) first order condition derived from the bidding model that applies to this marginal unit, the bid markup of this marginal unit is shown below in equation (1.11):

$$b_{ijkht} - mc_{ijt} \;=\; \frac{\mathbb{E}_{-i}[\; Q_{ijkht} - \nu_{iht} \;]}{\mathbb{E}_{-i}[\; \partial RD_{iht}/\partial p_{ht} \;]} \tag{1.11}$$

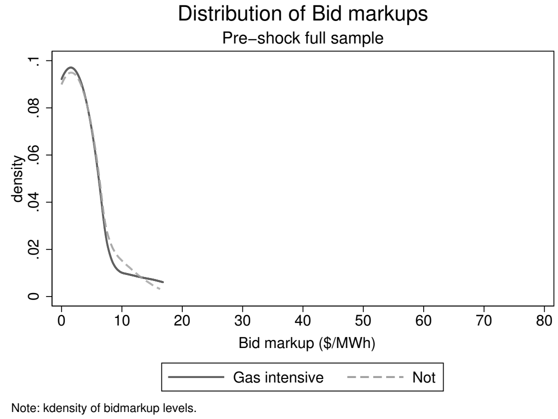
Since we have estimates of the marginal cost of generation, mc_{ijt}, the bid markups can be constructed by subtracting the marginal cost estimate $\widehat{mc_{ijt}}$ from the bids data, i.e. $b_{ijkht} - \widehat{mc_{ijt}}$.[45]

Note that the above condition holds for units that are ex-post marginal or at least having positive probability of setting the price in the auction ex-ante. Although the market price will be set by a single unit ex-post, the above optimality condition holds for firms that believe and behave in ex-ante as if their unit will be marginal in the auction. This is because the final market price is uncertain ex-ante, thus firms that have ex-ante belief about being marginal would behave according to optimal bidding. I restrict the sample bids to the ones with positive probability(weight) of setting the price, $\partial p_{ht}/\partial b_{ijkht} > 0$.[46] To measure bid markup, we need unit-level price bids. More details on how I selected price bids is explained in the Appendix.

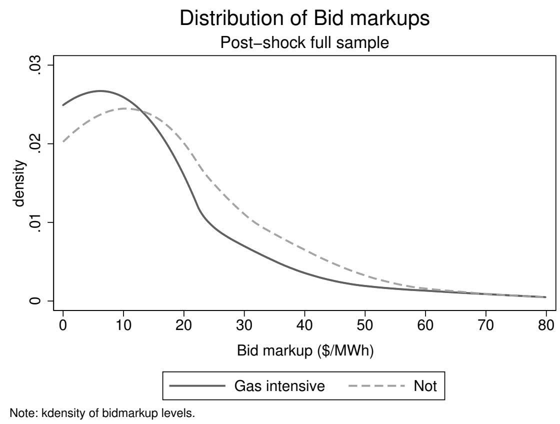
[45] While I have marginal cost estimates for days in Sample 1, I need to measure the marginal costs of days in Sample 0. I generated marginal cost of Sample 0 by multiplying the estimated heat rate $\widehat{hr_{ij}}$ with the spot price index of a fuel used by unit j on a given day, i.e. $mc_{ijt} = \widehat{hr_{ij}} * FP_{ijt}\ t \in$ Sample 0

[46] Therefore, bids submitted by base load units such as nuclear or coal generation that bid close to 0 price bids or that of reserve capacity that usually bid high price in the auction are not included for markup calculation.

Figure 1.10: Bid Markup Distributions: Gas Intensive vs. Non-Intensive Groups



(a) Pre-shock Bid Markup Distribution



(b) Post-shock Bid Markup Distribution

Note: Kernel densities of levels of bid markups (*unit*: $/MWh) of firms are plotted. Pre-shock sample is sample 0 where there was no gas price shock, and post-shock sample is sample 1 where gas price shock was present. Bold line is the density of *Gas Intensive* firm group, and dash line is the density of those not Gas-intensive.

Results Firm-specific bid markups are measured for each hour-day auctions of Sample 0 and Sample 1. In order to see whether firms, on average, added more bid markups during periods of gas price shock, I plotted pre-shock and post-shock distributions of bid markups; see Figure 1.10. A comparison between Panels (a) and (b) demonstrates that firms added, on average, more bid markups after the shock when compared to bid markups that were made before the shock; this is shown by a rightward shift in the mean of the distributions in Panel (b).

Figure 1.10 also shows how bid markup adjustments are different across two different groups of firms. Figure 1.10 shows distributions of bid markups of gas intensive and non-intensive groups, for pre-shock and post-shock samples. In the pre-shock sample, the distribution of gas intensive firms is located to the right of non-intensive group's distribution, implying that gas intensive firms added, on average, larger markups to their bids. We see the opposite in the post-shock period, where the distribution of the non-intensive group is located to the right of the gas-intensive group's distribution. This indicates that, on average, firms that were "hard-hit" by the shock increased bid markups less than those that were less affected by the shock.

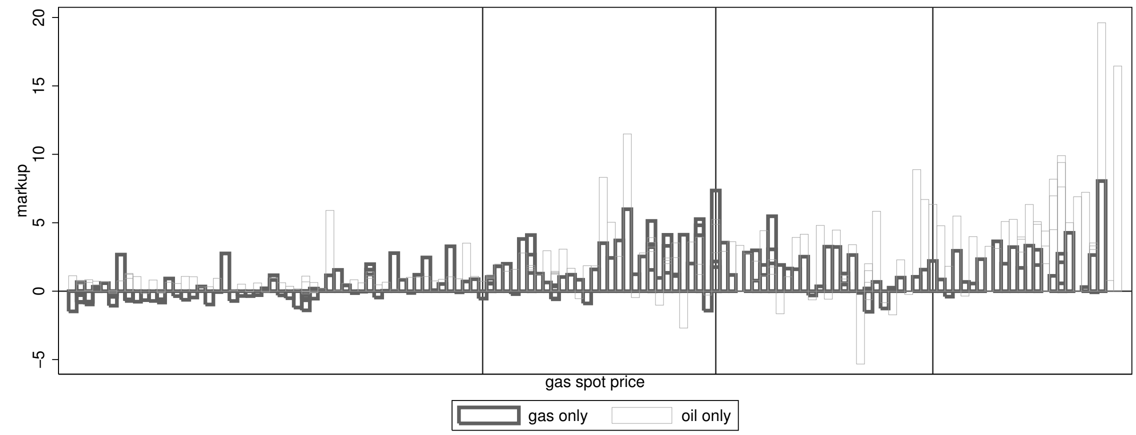
Another important observation from Figure 1.10 is that the post-shock bid markup distribution is more dispersed than the pre-shock bid markup distribution. Such dispersion implies that firm-level bid markups in the post-shock period were substantially heterogeneous. To explore how bid markups of firms are different within this post-shock sample, I plot in Figure 1.11 daily bid markups of two firms– firm 9 and 53 – against the gas price indices of each day. I find that both firms added higher bid markups, on average, as the size of the gas price shock increased; this is shown by the size of the bars in the graph increasing along the horizontal axis. However, bid markups made by *gas-only* firms start decreasing within the competitive range, daily gas indices of between \$15 and \$25/MMbtu, while bid markups made by *oil-only* firms increase constantly. Therefore, firms adjust bid markups according to different patterns depending on their impact from the gas price shock.

The increased dispersion in post-shock bid markup distribution may be coming from heterogeneity in bid markups across firms and across days which have different levels of gas price shocks. To further explore how bid markups of firms change with the size of the gas prices in a more general way, I run a set of regressions using bid markups including all strategic firms. Table A.2 in Appendix shows the results.

1.7.2 Markup Simulation: First-Order Approach

Bid markup estimate reveals the actual markup that was added to a firm's price bid; this reflects the degree of ex-ante competition that a firm faces at auction. One caveat is that this does not reflect the markup adjustments to a *change* in the cost. The only possible way to examine how a shock affects markups is to compare pre-shock bid markup data to post-shock bid markup data. However, since pre- and post-shock periods exhibit different levels of demand and other market conditions, these differences do not reveal effects that are due solely to the cost shock. Conditions other than cost must be the same in order to properly measure the adjustments in markup in response to a cost shock. For this reason, I implement a more marginal approach to understand firm incentives to adjust markups to cost shocks; I semi-counterfactually simulate firm-specific endogenous markup at each auction; this is a better means of analyzing changes in markups.

Figure 1.11: Bid Markups of Two Firms: Volatile Sample 1



Note: The graph shows daily bid markups of two specific firms, firm 9 and 53, plotted against the gas price indices of a given day. Thus, overall size of the gas price shock increases along the x-axis. Firm 9 is gas intensive, and firm 53 is not gas intensive. Three vertical lines show gas spot index prices of \$15, \$20, and \$25,respectively.

1.7.2.1 Overview of the simulation and first-order condition equation

First-order approach simulation, which is implemented in Fabra and Reguant (2014) and is originally derived by Jaffe and Weyl (2013), exploits the information around the current local equilibrium by imposing a *small* cost shock perturbation to the entire supply offer curve. The small perturbation ensures that the post-shock equilibrium does not depart much from the local equilibrium. This simulation is an alternative to a full counterfactual simulation where the new equilibrium must be computed, accounting for firms' participation decision and strategy changes, under the shock conditions. Studies found a full counterfactual simulation to be challenging in the multi-unit auction setting due to the problem of multiple equilibria (Klemperer and Meyer, 1989), as well as because the model relies on the necessary condition of optimal bidding in order to estimate parameters without modeling the bid formation decision structurally. Thus, a first-order semi-counterfactual simulation is especially useful in our auction setting.

Equation (1.12) below summarizes the basic concept of the simulation. First, $\Delta pbid_{ij}$ is the price bid change of an ex-ante marginal unit j of firm i, which represents how much a price bid of this unit increases. $mc_j(q_j)$ denote marginal cost of unit j, and $\frac{\partial p(q_i)}{\partial q_i}\tilde{q}_i$ is an expression for firm i's markup where $\tilde{q}_i$ is the infra-marginal quantity of firm i net of forward contracted amount. Dashed variables denote post-shock values, and non-dashed variables denote pre-shock values. Therefore, the first part of equation (1.12) represents the size of the direct cost shock, and the second part shows the change in markups.

The principles of equation (1.12) are now described. The price bid of a (marginal) unit is composed of marginal cost and the strategic component that arises from the competition between firms, namely the markups. When a cost shock hits a firm, the price bid of that firm will adjust by an amount that is equivalent to a combination of marginal cost increase and any markup adjustments associated with that cost change. Given that the post-shock equilibrium is still the local equilibrium, we can derive each firm's best response to the shock from their (ex-ante) first-order condition.

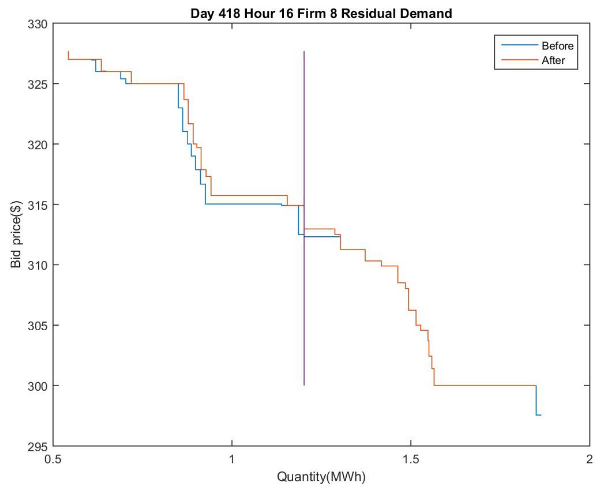
Because it is difficult to simulate this overall bid adjustment to the cost shock without a full structural model, we assume that each firm initially adjusts its price bid by the size of the gas cost shock in the simulation. In other words, I assume a counterfactual situation in which firms temporarily fully internalize the gas cost shock by increasing the price bids made by their gas units exactly by the size of the gas cost shock. This is shown as the *direct cost shock* part of the first line of equation (1.12). Again, this direct cost shock part, to which I perturb the bids, must be very small so that the counterfactual equilibrium after the shock does not depart much from the original equilibrium.

$$\Delta pbid_{ij} = \underbrace{mc_j^{'}(q_j) - mc_j(q_j)}_{\text{direct cost shock}} + \underbrace{|\frac{\partial p'(q_i')}{\partial q_i'}|\, \tilde{q'}_i - |\frac{\partial p(q_i)}{\partial q_i}|\, \tilde{q}_i}_{\text{Markup Change}} \tag{1.12}$$

After the perturbation, the infra-marginal quantity and slope of the residual demand of a firm will change, along with the equilibrium electricity price that clears the auction. These changes occur because the perturbation shifts the price bids of all firms participating in the auction, not only the price bids of its own. Figure 1.12 is an example of a firm's residual demand curve being shifted by the size of a gas cost shock. Since the markup of a firm is defined as being equivalent to infra-marginal quantity over the slope of the residual demand curve, changes in the variables (the slopes of residual demand, infra-marginal quantity, and the market clearing price at which the slope is evaluated) will result in an endogenous change in the firm's markup. Since I observe all of these variables before and after the perturbation, the endogenous markup change component, shown as *markup change* in equation (1.12), is measured directly from these values.

Because this simulation exploits the first-order condition, which holds in ex-ante, a more accurate simulation would require a perturbation of an ex-ante supply offer curve on which a firm's first-order condition is based. This method is a slight extension of the first-order approach simulation used by Fabra and Reguant (2014) where they perturbed ex-post realized bids for the simulation. More details of the construction of an average offer curve and the simulation procedures are outlined in the Appendix.

Figure 1.12: Example of a Shift of a Residual Demand After the Perturbation



Simulated endogenous changes in markups measure firms' incentives to adjust their price bids further after raising their price bids by the size of the cost shock. Therefore, the final simulated price bid adjustment $\Delta pbid$ in equation (1.12) is the sum of the cost shock imposed in the simulation and the resulting markup adjustment. A positive markup adjustment indicates having incentives to further increase the bid by the size of the markup, whereas a negative markup adjustment is seen when a firm wishes to decrease its price bids in order to stay competitive.

1.7.2.2 Types of perturbations

Since the gas price shock affects the generation costs of gas units only, I perturbed only the price bids of gas-fired units in the simulation. When perturbing the bids, I accounted for the dual gas units' fuel switch decision which I identified from the implied fuel price estimates. That is, I did not perturb the price bids of the dual gas units that switched fuel from gas to oil.[47] Therefore, price bids of coal, oil, hydro, nuclear, and fuel-switched dual gas units are not perturbed in the simulation.

I simulated the changes in firms' best responses following a \$0.1/MMBtu increase in the gas price, which leads to approximately a \$1/MWh increase in their gas generation costs. Table 1.4 summarizes the sizes of gas cost perturbations at unit-level and firm-level. Because each unit has different heat rates and each firm has a different proportion of gas

[47] By doing so, I am implicitly assuming that firms can form an expectation of competitors' switch decision ex-ante, which is not a strong assumption as dual units' switch decision is mostly governed by the cost-minimizing behavior. Summary of the total number of dual units that switched fuels is provided in Figure 1.8.

Table 1.4: Summary of Changes in Marginal Cost When Gas Price Increases By $0.1/MMBtu

Δ MC	mean	min	max	p25	p50	p75	s.d
Generator level	0.47	0	1.896	0	0	0.941	0.55
Firm level	3.20	0	8.9	0.754	2.70	5.48	2.68

Notes: Unit of the change in marginal cost is $/MWh

generation, the perturbation sizes vary across units and firms. Note that the identical size of gas price shock, e.g. $0.1/MMBtu, is imposed across days in the sample.

While the perturbation described above is the base of the main simulation, I also implemented a slightly different version of perturbation as a robustness check, where I imposed gas price shocks that are proportional to the firm's actual shock as measured by the estimated implied gas price. I provide more details about this perturbation in the Appendix.

1.7.2.3 Result

For the analysis, I selected hours at which the firm actually produced non-zero amount of electricity (i.e. at least one unit of the firm dispatched), and take an average of each firm's hourly markup changes across hours. All simulated markup variables are at levels ($/MWh).[48]

Simulated markups are noisy in both size and direction, and they vary significantly across days and firms. This result is not surprising since both electricity and gas market conditions change every day; each day has different levels of electricity demand, the overall sizes of gas price shock and, thus, different levels of equilibrium electricity prices. The changes in these conditions give firms different incentives to adjust markups. In order to see the pattern of markup adjustments in a more structured way, I plotted graphs by different groups of firms, over different auction days that are categorized according to sizes of gas price shock on the auction day.

Strategic Firms vs. Fringe Suppliers I first compare the simulated endogenous changes in markups of small fringe suppliers and large-scale strategic suppliers. Studies in electricity market have found that small fringe suppliers behave competitively by bidding their marginal costs, which implies that they have little incentives to adjust markups upon cost shock. I find, corresponding to the results of previous studies, that the sizes of the simulated

[48] In Appendix, I additionally calculated the proportion of a firm's markup changes to its marginal cost changes together with the level of markup changes. For example, percent change of a markup of a firm with a cost perturbation of $ 1(/MWh) and the resulting endogenous markup change of $ 0.5 (/MWh) is calculated as a 50 % markup increase.

changes in markups of small fringe firms are below 1 $\%$ of their marginal cost perturbation. On the other hand, markup responses of strategic firms that operate multiple units and large generation capacities are significantly greater than that of fringes, though sizes and directions of their markup changes vary substantially across firms. I exclude small fringe firms from the subsequent markup analysis as the lack of markup adjustments by these suppliers suggests that they do not behave strategically under the presence of cost shock.

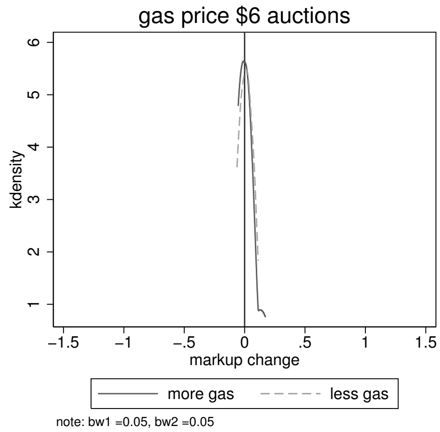
"Hard-hit" Firms vs."Not" In order to explore how strategic markup adjustments that are made by firms are related to their impacts from the cost shock, in Figure 1.13 I plotted the cross-sectional density of endogenous changes in markups separately for two different groups of firms: *gas intensive* and *non-intensive* groups. Gas intensive firms are hit relatively hard by the gas price shock compared to non-intensive firms. Graphs plotted with *high impact* criterion grouping give similar results to those of the gas-intensive grouping (results in the Appendix).

Since the size of the overall gas price shock of the auction day is another important determinant of markup adjustments, I plotted these densities separately for auction days with different levels of gas price indices, where I selected the following indices : \$6, \$10, \$18, \$24, \$28 and greater than \$38/MMBtu. Comparing the markup adjustments of two groups along the dimension of different levels of post-shock gas prices shows how the size of the (initial) shock affects the competition between firms.[49] In order to control for the factors that might affect markup adjustments other than gas price shock, I chose days within the set of *similar days*, which I used for resampling when estimating parameters. The gas price indices, electricity demand, daily peak-temperature and spot gas market conditions are similar within this *similar days* group.

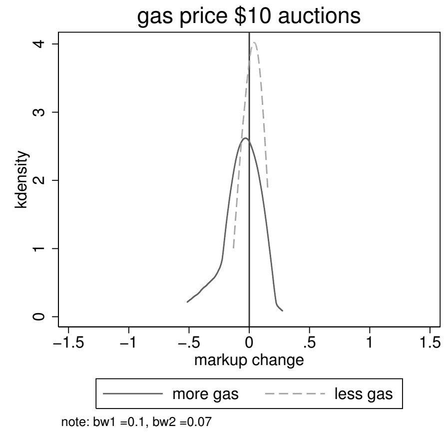
The first finding from Figure 1.13 is that markup adjustments depart constantly from zero as the overall size of gas price shock increases. With a small shock, markup adjustments are mostly zero for both groups of firm. For example, we observe close to zero markup adjustments by all firms in Panel (a) of Figure 1.13, where markup density is centered at zero. This result is convincing since a small gas price shock would not induce any significant markup adjustments due to the fact that the heterogeneity in cost impacts is insufficient to change competition in this market. However, the range of markup adjustments increases as the sizes of the shock becomes larger. In Panels (b) to (f), we observe that markup densities become more dispersed and depart from zero. For instance, the markup

[49] This size of the shock refers to the initial shock level of a given auction which is measured by the gas price index of the day. It is not the size of the additional cost shock perturbation imposed in the simulation. Note that size of the shock perturbation is the same across auctions, approximately \$1/MWh (that results from a 10 cents gas price shock)

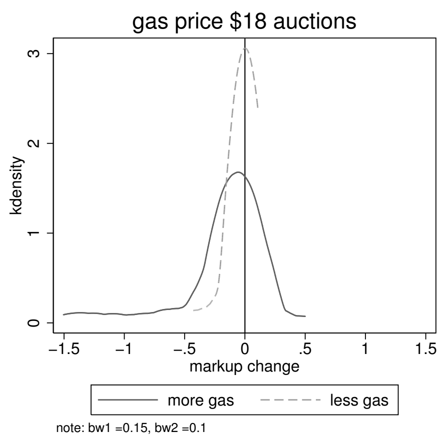
Figure 1.13: Simulated Markups: Gas Intensive vs. Non-Intensive Groups



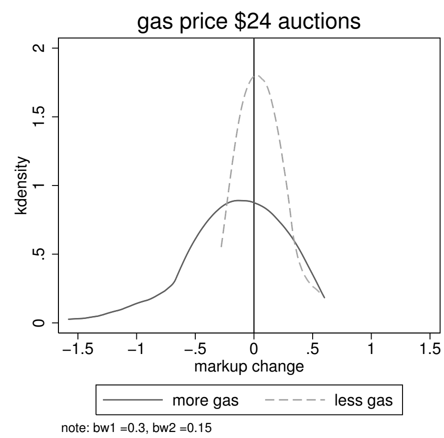
(a) Gas price index $6/MMbtu days



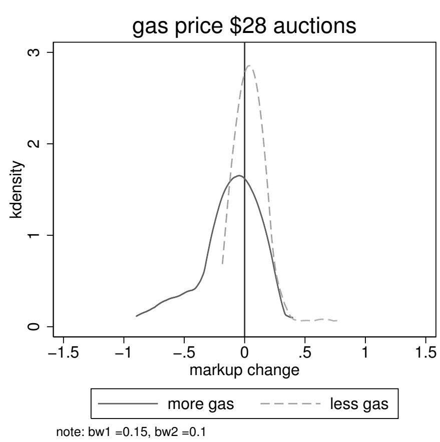
(b) Gas price index $10/MMbtu days



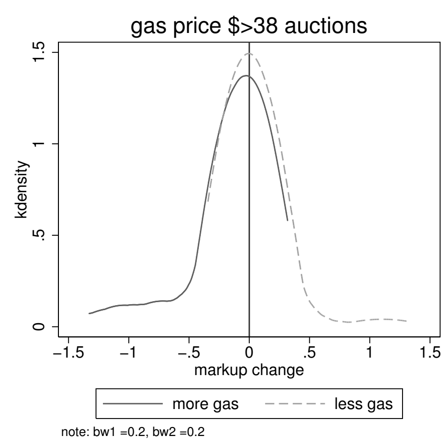
(c) Gas price index $18/MMbtu days



(d) Gas price index $24/MMbtu days



(e) Gas price index $28/MMbtu days



(f) Gas price index $>$ $38/MMbtu days

Notes: Levels of the changes in markups ($/MWh) to cost shocks of approximately $1/MWh are plotted across days with different levels of gas spot price indices.

density of above \$38/MMbtu gas index auctions ranges from -1.5 to 1.5, and is not so centered around zero. This finding confirms our prediction that heterogeneity in the impact of a cost shock induces markup adjustments.

The second finding from Figure 1.13 is that firms adjust their markups differently depending on their cost impacts from the shock; firms that are hit hard by the shock tend to decrease their markups compared to firms that are hit less by the shock. Furthermore, such differences in markup adjustments between the two groups increase as the overall size of the shock increases.

Figure 1.13 shows how simulated markup responses differ between the *gas intensive* group and the *non-intensive* group, and across different levels of gas price shocks. First of all, the shapes of markup distributions are different between the two groups for auctions with gas price indices greater than \$6. As the shock becomes larger, as measured by higher gas price indices, the density of the gas-intensive group shifts more to the left, while the density of the non-intensive group shifts more to the right. Since the cost impact differences between gas-intensive and non-intensive groups increase with the overall intensity of the gas price shock, we observe more different markup adjustment patterns between these groups as the size of the shock increases.

Panel (f) of Figure 1.13, which shows the markup density of auctions with gas indices above \$38/MMbtu, reveals a stark difference in the densities of the two groups; the density of the gas-intensive group is located more in a negative range, while density of the non-intensive group is located more in a positive range. This finding corresponds to that predicted by theory; it is more difficult for gas-intensive firms to add positive markups given a large shock due to increased competition. That is, with a severe gas price shock, gas units become more expensive to operate than oil units and, as a result, they are pushed off from being marginal. Moreover, competitors to gas intensive firms become increasingly less affected by the shock as the size of the shock gets bigger because more of the dual-fuel units that are owned by non-intensive firms switch to oil and more of their oil units are located close to marginal.

1.8 Cost Shocks and Market Price: Pass-through Analysis

Having estimated the heterogeneous responses in costs and markups to the gas cost shock, now I analyze how these changes affected electricity prices. Since input gas cost shock unavoidably leads to an increase in output electricity price, not just how much the electricity price increased but whether the price increased proportionally to the cost shock is a more policy-relevant question to ask. For this reason, I study how much of the cost shock is passed on to the output price, i.e. the cost *pass-through*. The pass-through rate reveals the incidence of a gas cost shock, which in our case provides information on whether electricity generators or retail service providers (LDC) bear more of the cost shock.

Pass-through is closely related to strategic markup adjustments; how much firms add markup over to the cost shock adjusted price determines the final change in the price and thus the extent of pass-through. That is, conditioned on cost shock being positive, adding a positive markup implies more than complete pass-through, a negative markup implies incomplete pass-through, and not adding any markup implies a complete pass-through.[50] Note that because electricity market uses a multi-unit uniform auction to clear the market, only one firm's unit will set the price of electricity ex-post. Thus, only the costs and markups incentives of a price setting marginal unit are relevant to the pass-through rates. Therefore, while obtaining a full distribution of responses of costs and markups to a shock is necessary for understanding the shock's effect on the market price, it is not sufficient.

As we have obtained endogenous markup responses from the first-order approach simulation and know the identities of the marginal units of each auction, we can measure high-frequency pass-through rates at auction level. The high-frequency rates simulated are useful for understanding the implications of such heterogeneous shock impacts and markup adjustments on the pass-through.

This type of simulation is not easy to conduct in general as it requires a structural model to implement. Most commonly, regulators may run a simple reduced-form type of regression using available data on prices and costs to estimate the pass-through, which is also a standard way of doing it in the general empirical pass-through studies. However, the reduced-form analysis faces challenges when heterogeneity is present in the impacts of the cost shock because it is hard to incorporate into the analysis the existing heterogeneity and the richness in firms' responses with available data only. By comparing the simulated rates to the reduced-form estimates, I show that a näive estimation that does not properly account for such heterogeneity in the regression could yield a biased and inaccurate rate estimate in our case. Furthermore, I show that using the cost information extracted from the structural model which contains heterogeneity information in it, could improve the precision of the reduced-form estimation at least on average.

Before proceeding to the analysis, I explain how I selected ex-post marginal units to use throughout the pass-through analysis. I identified the ex-post marginal unit that set the

[50] In exchange rate pass-through studies, they find exchange rate to be incompletely passed on to the commodity prices, with the rate significantly less than 1, due to markup adjustments(De Loecker et.al, 2016). And in electricity market context, Fabra and Reguant (2014) find that emission cost shocks are almost completely passed through the electricity price, with the estimated rate close to 1, because emission cost shock does not induce significant markup adjustments.

price in the day-ahead electricity auction using two data sources: hourly day-ahead electricity auction bids (supply offer bids) and the hourly equilibrium market clearing prices (energy component of locational marginal price), both of which are published in ISO-NE website.[51] From the auction data, I selected the unit with a price bid that equals the market clearing price of an auction, and identified it as a marginal unit of the auction.[52]

1.8.1 Simulated Pass-Through

The semi-counterfactual simulation, which based on a first-order approach, and which I conducted in the previous section (markup analysis), enables measurement of pass-through rates at each auction. That is, the marginal change in the equilibrium price is approximated by the simulated price bid change of a marginal unit because the size of the price bid perturbation is very small (approximately $1/Mwh). This simulated change in price divided by the cost shock imposed on the marginal unit is the pass-through rate of the auction. Note that simulated pass-through rates exist only for auctions in which gas units set the price (marginal unit). This is because only price bids from gas-fired units are perturbed within the simulation since the gas price shock applies to those only.

The price bid change of a marginal unit is simply the sum of its cost shock and the endogenous markup adjustment following the shock. As the sizes of the cost shocks used for the perturbation of each unit are not exactly unity and are not the same across units, I divided the price bid change of the marginal unit by the size of its cost shock in order to measure the price change per unit cost. In order to guarantee that the price bid change of a unit, which is ex-post marginal before the perturbation, is the equilibrium price change, we must assume that the identity of the marginal unit does not change with a small perturbation.

$$\Delta p_s = \Delta b_{s,margin} = \Delta \text{mc}_{s,margin} + \Delta\widehat{\text{markup}}_{s,f,margin} \tag{1.13}$$

$$\text{pass-through}_s = \rho_s = \frac{\Delta p_s}{\Delta \text{mc}_{s,margin}}$$

[51] Energy component price is a single price that clears aggregate demand and supply of the entire grid, and it is same across nodes. Additional congestion components are added to this energy component price differently across nodes.

[52] Note that ex-post marginal units I've identified may be different from actual marginal unit when financial bids set the price. In this case, I found the unit that is closest to the equilibrium price. Financial bids do not have physical load obligations, so these bids must be taken out from the market analysis. Furthermore, as financial bids take up only 1 % of the entire load in New England, neglecting financial bids does not change the result of my analysis substantially.

Table 1.5: Summary Statistics: Simulated Cost Pass-through Rates

Summary statistics	Simulated pass-through rates, ρ_s
Mean	0.974
Min	0.004
Max	2.198
S.d.	0.204
Obs	2,661

Note: Pass-through rates of each auction at which gas units are marginal units are used in the regression. Outliers above and below 98th and 2nd percentiles are dropped.

Results and Analysis Table 1.5 provides summary statistics of the simulated pass-through rates of total 2,661 hourly auctions. Mean of the pass-through rates is 0.974, which is close to 1, indicating a near complete pass-through of the cost shocks on average. However, the rates range from 0.004 to 2.198 with a standard deviation of 0.204, implying that considerable heterogeneity exists in the rates. Therefore, though on average firms pass on cost shocks completely, pass-through rates vary significantly across auctions.

Heterogeneous pass-through rates may have resulted from each auction having different marginal units, thereby having different levels of gas cost shocks and different incentives for markup adjustment at the margin. In order to verify the relationship between the pass-through rates and these determinants, I related the simulated pass-through rates to variables that are associated with a firm's impact from the shock and incentives to adjust markups in a regression framework. That is, I checked how simulated pass-through rates differ when "hard-hit" firms set the price by using the two different categories of hard-hit firms: *Gas intensive* and *High impact* firms. In addition to this, I specified a mean-differenced logarithmic spot gas price index (*ln(Dgas)*) in order to investigate how pass-through differences between these auctions change with the size of the gas price shock.

Table 1.6 presents the regression results. Column (1) regression compares the average pass-through rate differences between auctions that have *Gas intensive* firms as marginal and not. Column (2) regression compares the average pass-through rate differences between having *High impact* firms as marginal and not.

Estimates suggest that pass-through rates are, on average, lower in auctions where "hard-hit" firms are at the margin, compared to "less-hit" firms being at the margin. Pass-through rates are, on average, 0.046 lower in auctions where gas-intensive firms set the price in the auction, compared to the pass-through rates when non-intensive firms are at the margin, with pass-through rates averaging at 1.005. Similarly, when high-impact firms set the price, pass-through rates are, on average, 0.032 lower than rates of auctions where

Table 1.6: Simulated Pass-through Regressed on Cost Impacts and Gas Price Index Variables

	(1)		(2)
	ρ_s		ρ_s
Gas intensive	-0.046***	*High impact*	-0.032**
	(0.008)		(0.012)
*GI * ln(Dgas)*	-0.041**	*HI * ln(Dgas)*	-0.076***
	(0.006)		(0.021)
ln(Dgas)	0.002	*ln(Dgas)*	0.020
	(0.006)		(0.012)
Constant	1.005***	Constant	0.993***
	(0.0048)		(0.009)
Observations	2223	Observations	2229

Note: Pass-through rates of each auction at which gas units are marginal units are used in the regression. Both *gas intensive* and *high impact* are group dummies at firm level, and *ln(Dgas)* is a difference between gas price index of auction day and average gas price over the sample which is 21 $/MMbtu. Outliers above and below 98th and 2nd percentiles are dropped. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

low-impact firms are at the margin, when the average rate is 0.993. Note that average rate of "less-hit" group auctions, represented by the constant term, is the average at a mean gas price index of $20/MMBtu. The rate differences between the two groups increases as the overall size of the gas price shock exceeds the mean level of $20/MMBtu; a 1% increase in the shock size leads to an additional 0.041 rate drop for gas intensive firm set auctions, as shown in (1) of Table 1.6, and leads to a 0.076 rate drop for high impact firms set auctions as reported in (2) of Table 1.6.

These results are convincing since firms that are more affected by the shock tend to add lower markups than less-affected firms. Therefore, even if the cost shock imposed on marginal units of "hard-hit" and "less-hit" firms is the same, the difference in firm-level markup adjustments across these two types of firm leads to different levels of pass-through rates at the margin.

1.8.2 Reduced Form Pass-through Regression: Concerns and Limitations Under Heterogeneity

The advantage of a simple reduced form regression is that it is possible to estimate the rate with only equilibrium prices and cost shock data.[53] Regression identifies a single pass-through rate using variations in costs and prices across auctions; cost changes from one auction to the other are interpreted as cost shocks. This contrasts to the simulation method where I imposed small cost shocks of the same size on each auction.[54]

There are challenges in conducting a reduced form regression when the shock heterogeneity is present, which I now demonstrate by running three specifications of reduced form regression that differ in the measurement of gas cost shocks, and by comparing these reduced form results to the simulated pass-through rates. Whether or not the gas cost measure accounts for the existing heterogeneity in cost impacts across firms is the key difference between these specifications.

1.8.2.1 Regression specifications

Conventional approach to measuring cost pass-through run the following regression provided in equation (1.14) below:[55]

$$p_{th} \;= \rho\, hr_{th} G_{th} \;+\; \beta_0 \mathbf{X}^D_{th} \;+\; \beta_1 \mathbf{I}_{th} \;+\; \epsilon_{th} \tag{1.14}$$

ρ is the parameter of interest which captures the overall rate of gas cost pass-through. Having ρ estimate close to 1 indicates a complete pass-through of the cost shock, and indicates an incomplete pass-through if it is significantly below 1. Although not common in the literature, ρ being greater than 1 is when the outcome price increases by more than the cost increase, possibly due to positive markups added to the price.

The regression is intended to measure the effect of marginal increase in gas cost on electricity prices using cross-sectional variations in gas cost and prices. While in other industries price exists per firm because each firm sets its own price, one single price exists

[53] Although the cost data is hard to obtain in general, there are some industries or types of shocks where measuring the cost shock is relatively easier, such as exchange rate shocks or emissions cost shock. Electricity market is also one of the industry where cost is quite transparent and easy to measure, so some studies like Fabra and Reguant (2014) find reliable estimates of emissions cost pass-through rates from the IV regression.

[54] Our auction set-up is a special case. In general, pass-through estimation exploits variations in costs and prices over time.

[55] This specification follows the ones used in the extensive literature in pass-through, including Goldberg and Knetter (1997), Nakamura and Zerom (2008), Nakamura and Steinsson (2012), and Fabra and Reguant (2014). Among these, Fabra and Reguant (2014) is the only paper that studies electricity industry, thus the specification used in this paper is closest to the one used in this section.

per auction in electricity industry as the market is cleared via uniform auction mechanism. And since the goal of this regression is to show the rate of *gas* cost change being passed on to the electricity prices, I limit observations to auctions in which gas units set the price in the market.

Dependent variable p_{th} is the Day-ahead energy component price of an auction on day t and hour h, which is the actual ex-post market clearing prices published by ISO-NE.[56] The gas cost component $hr_{th}G_{th}$ is measured as a heat rate of the marginal unit(hr_{th}) multiplied by the gas price of a given day(G_{th}). Finally, $\mathbf{X}_{th}^{D}$, $\mathbf{I}_{th}$ are demand side control (peak-time temperature used) and fixed effects (month, day of the week, hour fixed effects), respectively. Gas cost component $hr_{th}G_{th}$ is subject to potential endogeneity; the heat rate hr_{th} of the marginal unit is determined from the market equilibrium that is affected by the unobserved demand and supply factors. Therefore, I instrumented the gas cost term with the spot gas price index, G_t, which is exogenous to electricity prices as it is determined in gas market. The selection of instrument follows Fabra and Reguant(2014).

I implemented three variants of pass-through regressions that differ in how the gas cost term, $hr_{th}G_{th}$, is constructed. Table 1.7 reports estimated rates of each specifications in columns (1), (2) and (3), respectively. First specification, the results of which are shown in (1), is a naive implementation of a pass-through regression where a researcher uses publicly available average heat rate data ($\bar{hr}$) and gas spot price index data, both of which do not reflect existing heterogeneity. Therefore, the first specification would yield pass-through estimates when the gas cost terms are constructed to be homogeneous across firms. For all gas units, I used average heat rate of gas-fired units taken from EIA's 2015 report, and gas spot price index data to generate their gas cost variable.[57]

In the next two specifications that are shown in columns (2) and (3) of Table 1.7, I used unit-specific heat rates $\widehat{hr_{ij}}$ estimated from the model, which reflect differences in efficiencies across generating units. Two specifications differ in that I use the gas price index data for G_{th} in (2), while in (3) I use the implied gas prices estimated from the model, $\widehat{FP_{ijt}}$ for G_{th}. Therefore, specification in (2) incorporates heterogeneity in heat rates only because I use estimates for h_{th} but index data for G_{th}, and specification in (3)

[56] Energy component price is the grid-wide price that clears aggregate demand and supply, and any additional adjustment cost such as congestion costs are added by nodes to construct the final nodal price.

[57] According to ISO-NE published gas unit turbine technology information (*Source: Seasonal Claimed Capacity Info.*), more than 80 % of non-dual gas units use Combined Cycle(CC) technology, and the rest are Gas turbine (GT) or Internal Combustion (IC). On the other hand, dual units in ISO-NE are mostly gas turbine (GT). Therefore, I used CC heat rate for all non-dual gas units and GT heat rate for all dual gas units. *EIA* reports annual average heat rates by fuel type and turbine technology. For sample period of 2012 -2014, CC technology heat rate is 7.6 on average, and GT heat rate is 11.5 on average. These heat rate values are used in Specification (1) when generating gas cost

Table 1.7: Reduced Form Pass-through Regression: Three Specifications

	ρ (cost pass-through rate)		
	(1)	(2)	(3)
	$\bar{hr}$ = Average hr	hr = Estimated hr	
Sample	G_t = Gas index	G_t = Gas index	G_t = Implied gas price
full sample	0.481	0.457	1.118
	(0.042)	(0.052)	(0.040)
duals dropped	0.585	0.531	1.085
	(0.063)	(0.086)	(0.046)
below \$15	0.833	0.882	0.979
	(0.085)	(0.068)	(0.020)
btw \$15 and \$25	0.606	0.520	1.007
	(0.119)	(0.096)	(0.052)
above \$25	0.306	0.302	1.498
	(0.069)	(0.070)	(0.216)
Observations(full)	3,129	3,129	3,110

Note: Month, hour, and daytime fixed effects are included in all specifications. Subsamples are constructed based on different levels of daily gas spot index prices, where auctions with spot gas prices (1) below \$10/MMbtu (2) between \$15-\$25/MMbtu and (3) above \$25/MMbtu are grouped separately. *full sample* includes dual gas units that switched to oil on a given auction day, while in *duals dropped* I droped those switched dual units from the sample. All standard errors are clustered at firm, hour level.

incorporates heterogeneity in both heat rates and gas prices because I use estimates for both h_{th} and G_{th}.

Furthermore, I ran these three specifications on different samples. The *full sample* sample contains all gas marginal units, including the dual units that switched to oil fuel on a given auction day. In *duals dropped* sample, I dropped dual units that switched fuel from gas to oil. Lastly, I ran specifications on subsamples that are constructed based on the overall size of the gas price shock of the auction day– represented by spot gas price index. This last specification is intended to verify whether the pass-through rate is indeed homogeneous across different parts of sample.

1.8.2.2 Results

The first row of Table 1.7 reports the result of *full sample* regressions. By comparing (1) to (2), we see how incorporating unit-level heat rate heterogeneity into the cost measure changes the resultant pass-through estimates. Although pass-through rate estimates are slightly different, being 0.481 in (1) and 0.457 in (2), the difference is not substantial. These estimates imply that heat rate is not the major source of heterogeneity and heat rate is, thus, not a critical factor that causes the differences in the estimates. Indeed, the estimated heat rates in my sample are similar across units. Finally, both specifications yield pass-through rates that are below 0.5; this indicates an incomplete pass-through of cost shock.

The pass-through rate estimate from specification (3) of Table 1.7, which accounts for heterogeneity in both heat rates and gas prices, is significantly different from that of the other two specifications. Specifically, the estimated pass-through rate is 1.11, indicating a complete or slightly excessive pass-through of cost shocks ; this is a significantly different result from the incomplete pass-through rate that is obtained from the previous two specifications. Since the only difference between (2) and (3) is whether or not the gas price variable G_{th} reflects heterogeneity, heterogeneity in gas prices seems to be a more critical factor of pass-through than heterogeneity in efficiencies (heat rates).

duals dropped sample estimates reported in the second row of Table 1.7 are similar to *full sample* estimates. In specifications (1) and (2) of Table 1.7, although the pass-through rate estimates are larger than for the full sample estimates, they nonetheless indicate incomplete pass-through on average. The estimate of specification (3) is slightly lower than estimates of the full samples, having a value close to unity, indicating a complete pass-through on average.

The last three rows of Table 1.7 show pass-through rates estimated on different *subsamples*. I choose three subsamples with gas price indices (i) below \$15, (ii) between \$15 and \$25, and (iii) above \$25.[58] This categorization is related to the overall competition between firms and, thus, has implications on markup adjustments. I find that pass-through rate estimates vary across subsamples for all three specifications; this suggests that pass-through rate is non-linear and substantially heterogeneous.

1.8.2.3 Comparison with Simulated Pass-Through Rates

We compared reduced form pass-through estimates with simulated pass-through rates. The homogeneous pass-through parameter ρ is estimated from the reduced form regression measures of the *average* pass-through rates. Although our findings from the simulated pass-through rates suggest that rates are, indeed, heterogeneous across auctions, the average of these rates still conveys useful information of the overall incidence of a cost shock.

Therefore, I compare ρ estimates of Table 1.7 to the *mean* of simulated pass-through

[58] Note that the actual cutoff may be different when accounting for the fact that the gas index price is not representative of the actual cost impact of a firm

rates across auctions reported in Table 1.5 which is 0.974, a value close to 1. Note that ρ estimates from Specifications (1) and (2) of Table 1.7 do not correspond to the simulated pass-through results, since they yield ρ values of 0.481 and 0.457, respectively, both of which are far from unity. On the other hand, the estimation of Specification (3), which is close to unity, corresponds to the mean simulated pass-through.

Another point to note from the reduced form estimation is that ρ estimates vary across subsamples, reflecting heterogeneity of pass-through rates with respect to the size of the gas price shocks. This finding again corresponds to the previously mentioned feature of the simulated pass-through rates; that is, that the pass-through rate itself is not homogeneous over the sample and, instead, it depends on state variables that govern the price setter's incentive for markup adjustment at a given auction.

1.9 Conclusion

This paper studies the cost pass-through implications of changes in competition between firms that result from the natural gas price shocks in New England, with a particular focus on the heterogeneity in the impact of these shocks on the input costs of electricity generating firms. This paper looks into a series of natural gas price shocks that occurred in the winters of 2013-2014 in New England, which led to a spike in electricity prices in the region. I observe and document that the costs of firms in this market are affected heterogeneously by this gas price shock.

This heterogeneity of impacts has not been addressed much before and, based on my analysis, appears to be a crucial factor in determining market competition and pass-through outcomes. I find that the heterogeneity of the impacts give firms different incentives to adjust markups, and these incentives change with the sizes of the overall gas price shocks. I also find that these heterogeneous markup adjustments are reflected in the simulated pass-through rates; although I find that the cost shocks are, on average, completely passed on to the market prices, considerable heterogeneity exists in the rates depending on which type of firm sets the price in the auction. Based on these findings, I argue and show that any reduced form estimation that fails to incorporate the heterogeneity of the cost impacts, which is not often reflected in the available data on costs, could yield an estimate that is significantly biased downwards with respect to what the simulation suggests. I additionally show that such bias can be corrected by using the cost information obtained from the structural model when conducting reduced-form estimation.

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CHAPTER 2

The Effect of Coal Plant Retirement on the New England Electricity Market Prices under Natural Gas Price Shocks

2.1 Introduction

In the U.S., where about 40 % of carbon dioxide emissions originate from electricity generation (Goulder et.al, 2014), policies are being implemented to cut the use of highly-polluting fossil fuels such as coal and increase the use of less-polluting natural gas (or renewable) for generating electricity.[1]. Besides environmental concerns, a significant drop in the price of natural gas, mainly driven by the shale gas boom, is making the historically cheap coals to lose its cost competitiveness to natural gas, resulting in coal-fired plants to retire from the grid and be replaced with gas-fired plants.

However, a key problem with generating electricity with gas is that the supply of gas is often unstable and its prices are vulnerable to volatility. Gas must be delivered through pipelines at the time of use, which makes its spot prices sensitive to congestions in the pipeline. Indeed, gas spot prices in the Northeastern U.S. rose sharply over past winters due to severe pipeline congestion, making it expensive to generate electricity with gas. In contrast, the price of coal and nuclear fuels has always been low and stable. Therefore, such a remarkable transition of the wholesale electricity industry towards cleaner energy sources like gas is making the industry more vulnerable to input cost shock.

This paper examines how the market outcome will change when more coal plants retire from the grid and are replaced with gas plants so that an increased proportion of the market's generation capacity becomes vulnerable to cost shock. I conduct counterfactual analyses where I reconstruct market conditions by first applying the planned coal plant retirements, and then applying counterfactual cost shocks to firms. Because counterfactual

[1]EPA, *Clean Power Plan*

cost shocks result from shocks to gas spot prices, I increase marginal costs of gas-fired generators only in the counterfactual situation. Also, I treat gas price shock as exogenous to plant retirements assuming that an increase in gas usage due to an increase in gas-fired plants does not marginally affect pipeline congestion.

I simulate the market outcomes and firm-level production decisions under each of the reconstructed market conditions. Such counterfactual outcomes are obtained for two different forms of competition– perfect competition and Cournot competition. Because the counterfactual non-cooperative outcome, which is difficult to obtain due to multiple equilibria problem, is bound by competitive and Cournot outcomes (Klemperer and Meyer, 1989), the simulated competitive and Cournot outcomes allow me to construct the range of prices and quantities expected to occur in the actual counterfactual equilibrium.[2]

I study this in the context of the New England wholesale electricity market which relies heavily on gas-fired electricity generation and that often experiences severe gas spot price shocks. The proportion of gas generation in the New England grid has risen from 19 % to 50 % (2015) since the early 2000s, which is remarkable growth. This rate is expected to increase further because the grid is awaiting the retirements of several large coal and nuclear plants that are base loads, which will be replaced with gas plants planned for construction. However, the pipeline that transports gas to the New England area is limited and frequently congested compared to other regions. As a result, the market experienced huge increases in gas prices over the past few winters, which was a shock to the production cost of gas-fired generators. More importantly, with no plans to expand the capacity of the pipeline, the region still faces the threat of gas price shocks.

Although the wholesale electricity market seems competitive, the degree of competition in wholesale electricity market can vary depending on the market condition, which may lead to an increase in market prices. The New England electricity market has already learned how important it is to stabilize electricity prices through the experience of an enormous rise in electricity prices caused by cost shocks over the past few winters. Therefore, it is important to carefully examine how this ongoing transformation of the New England electricity market would affect electricity prices and market competition, which makes this paper timely and policy-relevant.

This paper, however, does not provide a comprehensive analysis of the change in market competition because I mainly focus on reporting the competitive outcomes and only provide limited results for Cournot outcomes. Since Cournot outcomes are essential for

[2] Because wholesale electricity market uses (multi-unit uniform) auctions to meet the supply and demand, the static, non-cooperative equilibrium in this market is best described by the supply function equilibrium (Klemperer and Meyer, 1989).

examining the change in strategic decisions of firms, it is difficult to show the change in competition with competitive outcomes only. Thus, I focus on examining the market impacts of coal plant retirement with an analysis of the change in electricity prices. The extended version of this paper will contain more detailed analysis of competition change resulting from retirements.

In the first set of counterfactual analyses, I let coal plants to retire but did not give gas price shocks to firms that result in shocks to their marginal costs. In the absence of cost shocks, I find a minimal impact of retirement on market prices if retired coal plants are replaced with new and efficient gas plants. This is because the cost of generating electricity with gas is comparable to that with coal when the gas prices are low. However, I get different results when gas prices are high due to shocks, even if the retired plants are replaced with efficient gas plants. This is shown in the second set of counterfactual analyses where I let gas prices to increase to a much larger value than when it is stable. With larger cost shocks, I find that electricity prices with the retirements are higher than prices without the retirements, on average. Especially during off-peak (low demand) hours, simulated electricity prices are up to 20 $\%$ higher with the retirements compared to those without. Also, differences in prices with and without retirements grow as the size of the gas price shock increases.

This paper contributes to the literature that studies the competition in the wholesale electricity market. The methodology used in this paper is close to that of Bushnell, Mansur, and Saravia (2008) where they examined the impact of vertical arrangements on competition in the wholesale electricity market. Regarding the topic similarity, this paper is related to Davis and Hausman (2016) in that it considers the market impact of closure or retirement of power plants. This paper is distinguished from theirs in that it addresses more counterfactual studies involving cost shock events, and that it focuses more on the competition side of the market.

2.2 Coal plant and Other Non Gas-Fired Plant Retirements in New England

Major significant coal plant retirements have been ongoing for several years. Since 2012, almost 19 GW of coal plants retired from the grid and coal makes up almost 80 $\%$ of retired generation in 2015 (Brattle group report, EIA 2016 report). Coal-fired capacity available for operation has dropped by approximately 47.2 GW between 2011 and 2016, which is equivalent to a 15 $\%$ reduction in the coal-fired generation over five years period (EIA,

Table 2.1: Major Plant Retirements in New England

Plant Name	Capacity (MW)	Fuel type	Date of shutdown
Norwalk Harbor Station	342	oil	June, 2013
Salem Harbor Station	749	coal/oil	June, 2014
Mount Tom Station	143	coal	Oct. 2014
Vermont Yankee	604	nuclear	Dec., 2014
Brayton Point Station	1,535	coal/oil	May, 2017
Pilgrim Nuclear Station	677	nuclear	2019

2017).

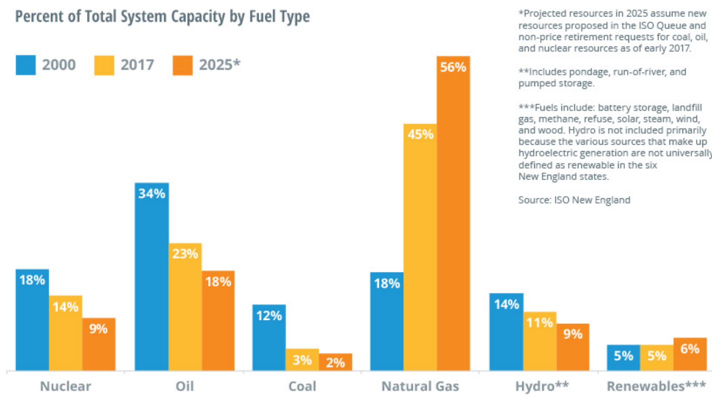
New England is not an exception. More than 4,200 MW of non-gas fired generation (equal to almost 15 % of the total generation capacity as of 2016) which mostly consists of coal and oil plants, along with nuclear generation plants have retired and soon to retire by 2020. Table 2.1 shows some major plant retirements already in effect or soon to take place in New England. The retired generation will be replaced primarily by natural gas fired plants. For example, Salem Harbor Station, a coal-fired plant that was closed in 2014, is under construction to convert the site into a natural gas-fired plant.

The New England electricity market has experienced a rapid change in the energy resource mix of electricity production for the past decade, as shown in Figure 2.1. In 2000, only 18 % of the grid's capacity was gas-fired generation, when oil, coal and nuclear fuels accounted for 34 %, 12 % and 18 % of total generation capacity (shown in Figure 2.1a). However, by 2017, the ratio has changed dramatically, and now the gas accounts for about 45% of generation capacity, which is expected increase up to 56% once the planned retirements are completed and replaced with new gas-fired generation (projected ratio by 2025, ISO-NE report in 2017). Including the plants at risk of retirement will further increase the grid's dependency on gas generation.

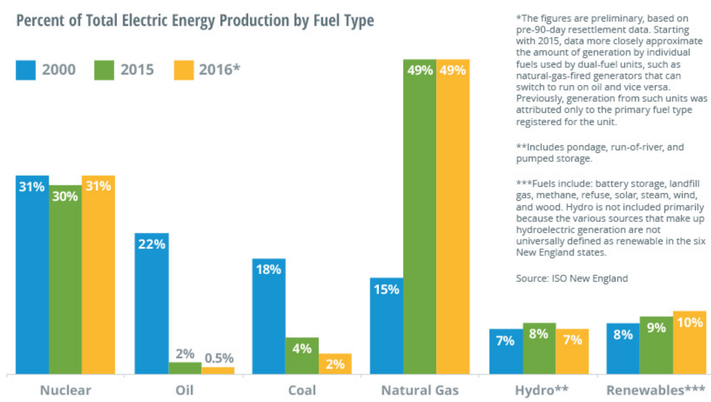
Several factors have caused coal fired plants to retire from the grid. First is the rising environmental costs that are incurred to meet stringent state, regional, and federal environmental regulation.[3] Environmental costs of coal plants are greater than gas plants because they emit more air pollutants than gas generators. More important factor, however, is the significant decline of gas price that is caused by the recent shale gas boom in the U.S. The drop in gas prices made it more expensive to generate electricity with coal than with gas and has also caused a decline in wholesale electricity prices set by low-cost gas generators. Low electricity prices reduced the revenues for these non-gas-fired resources, making it difficult for them to recover both the operating and fixed cost of generation (ISO-NE,

[3]EPA regulations such as Mercury and Air Toxics Standards (MATS) and Cross-state Air Pollution Rule (CSAPR) affect coal plants.

Figure 2.1: Change in Capacity and Productions Over Time: By Fuel Type



(a) Percentage of Total Capacity by Fuel Type



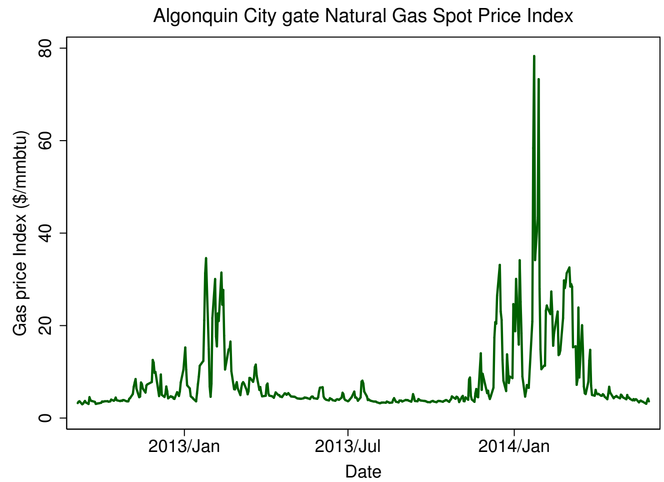
(b) Percentage of Total Capacity by Fuel Type

Source: *ISO-New England*

2016: power plant retirements, EIA- today in energy). Nuclear plants, another important base load generation, are driven out of the market for similar economic reasons (Davis and Hausman, 2016).

There are some notable things about the grid's transition. First, shares of fuel sources such as coal and nuclear, which have been primarily responsible for the production of base load electricity, have declined sharply over the past decade; coal and nuclear together now consist of only 11 % of the total capacity. The retirement of the base load could have some significant market impacts and incur efficiency loss, which was studied by Davis and Hausman (2016) in the context of a nuclear plant closure. Therefore, the loss of the conventional non-gas fired base load generation raises concern over the market operation and efficiency.

Figure 2.2: Gas Spot Price Shocks in New England: Winters of 2013 and 2014



Notes: Natural gas price index plotted against date. Source: *Natural Gas Intelligence*

Besides the fact that the grid loses a significant amount of conventional base load, what types of generation will prevail in the industry after these base loads retire is also important. That is, the transition is moving the industry toward using fuel that is cleaner but unstable in supply and is vulnerable to price volatility. Unlike coal and oil, which can be stored on site, natural gas needs to be supplied in the spot market every day, so the procurement price of it is affected by the market condition on that day. While in other regions the gas market conditions are fairly stable and the gas price volatility is low, the New England gas market experienced frequent spikes and increased volatility in the gas spot prices, especially in the winter when the pipelines are congested. Figure 2.2 shows the spot gas prices at the local gas trading hub of New England (Algonquin city gate), and the figure exhibits a series of shocks to the gas prices in the winters of 2013 and 2014.[4]

In the absence of a clear pipeline expansion plan, the congestion issue will not be addressed shortly, indicating that New England can not be completely free from gas price shocks in the future. Thus, after the grid eventually undergoes this process of transition to gas, more generators in the grid are in fact under the threat of cost shock resulting from shocks to gas spot prices. Although the gas price shock event may occur infrequently, it is policy relevant to study how the market outcomes would be in this situation given that regulators are sensitive to the rise in electricity prices.

[4] The shock is exogenous to the electricity market because the driving force of the congestion was the increased gas demand for residential heating which is not necessarily correlated with the residential electricity demand.

Table 2.2: Summary of Counterfactual Simulations

Group	Sample	Applied retirements	Retired capacity (MW)	Replace with gas?	Cost shock?
(a)	2013 (Sep.-Oct.)	Salem Harbor, Mt.Tom Station, Vermont Yankee (2014)	1,496	Yes/No	Yes/No
(b)	2013 (Sep.-Oct.)	Brayton Point (2017) in addition to retirements in (2)	1,535	Yes/No	Yes/No
(c)	2013 (Sep.-Oct.)	All planned retirements (including Pilgrim Nuclear Station (2019)	677<	Yes/No	Yes/No

Note: A sample day consists of peak hours and off-peak hours. Peak includes hours from 11 am to 8 pm and off-peak includes hours from 6 am to 10 am (excluded off-peak at night). Years listed inside the parenthesis is the year of retirement (or planned retirement).

2.3 Empirical Analysis

The main empirical analysis of this paper involves counterfactual analyses which require computation of new market equilibria under various counterfactual situations. In this section, I describe the details of counterfactual market conditions and introduce the equilibrium concept used in the analysis.

2.3.1 Counterfactuals

A summary of counterfactual situations simulated in this paper is provided in Table 2.2, and graphical illustration of two different types of counterfactual adjustments are shown in Figure 2.3. The days when gas price shocks did not occur – thus, firms not affected by the cost shocks – are selected as samples to be used for counterfactual analysis. I chose sample days from September, 15th, 2013 to October, 31st, 2013. Since the daily wholesale electricity market consists of 24 hourly markets, I conducted a counterfactual analysis for each hourly market, assuming each market to be independent across hours. I compute counterfactual equilibria based on these sample day-hour pairs by changing market conditions and parameters of the model. I do not adjust the demand variables in the counterfactuals.

2.3.1.1 Accounting for Plant Retirements

The first market condition that I change is the generation capacities of firms facing retirement of their coal (and other non-gas base loads) plants. Major retirement events accounted for in the counterfactual analysis are listed in Table 2.2. Because these events occurred sporadically over time, I grouped them into three based on the year of retirement.[5] The first group (a) has a total retired capacity of 1,496 MW, which includes both coal and nuclear generation capacities. Group (b) has total 1,535 MW of retired coal generation capacity in it. Finally, in the group (c), all planned retirements and capacities at risk of retirement are included.

I applied retirements in each retirement groups sequentially in counterfactuals to make the total capacities of retired plants to increase gradually. Generation capacities of power plants that retire were excluded from the model while everything else – aggregate demand, the total number of firms, and the marginal cost of electricity generation – was held to the level same as in the original equilibrium (the actual observations of day-hour sample used in the analysis).[6] The set of simulated market outcomes under each of these counterfactual situations that have different levels of retired capacities show how market outcomes vary with the increase in the capacity of coal plants that retired.

I consider two different types of counterfactual market conditions that differ in how the retired generation is replaced. In the first case, I reduce the capacity of the firm that operates a retired plant by the size of the retired plant without any replacement of the lost capacity with a new gas plant. The reduced base load generation is met by electricity production of other firms that previously were not dispatched due to the high cost of electricity generation.

In the second case, I replace the capacity of retired coal plants with new *gas-fired* plants that have the size equivalent to the ones retired so that the total capacity of firms that operated retired plants do not change after the retirement. In this counterfactual situation, the fuel sources of the firm's electricity generation become more gas-intensive, with its total capacity held fixed. Therefore, this counterfactual equilibrium is more informative of how having more gas-intensive firms in the market would affect the market outcome.

The variables directly affected by the capacity adjustment are the composition of the fuel sources of the generation capacity and the firm-level marginal cost curves of the firms affected by the retirement. Since we do not know what the marginal cost of hypothetical gas-fired plants that have not been constructed yet, I approximated the marginal costs of these generators using the average heat rate (efficiency) of the recently constructed gas

[5] Norwalk Harbor Station was excluded from the counterfactual analysis because it had already retired before the time of the sample used for analysis (retired on June 1st, 2013).

[6] This implies that demand bids submitted by the demand side won't be changing in our counterfactual. Fixed demand (price insensitive) will remain the same, but some price sensitive demand may change in the counterfactual equilibrium if the electricity price changes. However, price sensitive demand bid takes up very small amount of the aggregate demand.

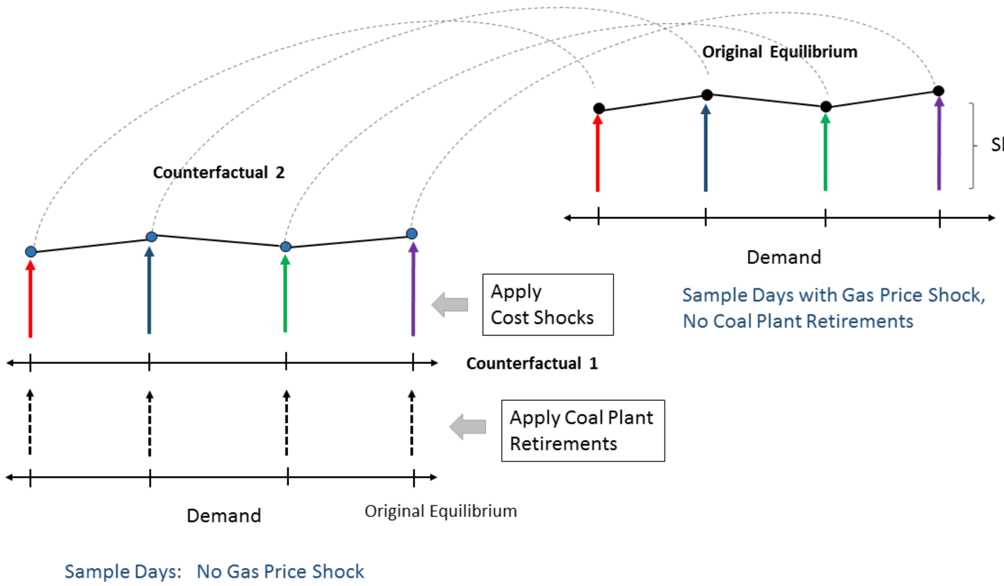


Figure 2.3: Description of Counterfactuals

power plants as well as the data on gas price index and emissions costs.[7]

Comparing the simulated counterfactual equilibrium to the original equilibrium shows how market outcomes and strategic behavior of firms – either having retired plants or not – changes in response to a significant loss in conventional base load generation. Counterfactual 1 of Figure 2.3 describes the counterfactual explained in this section.

2.3.1.2 Accounting for Gas Price Shocks: Input Cost Shocks to Gas-Fired Plants

In the following counterfactual, I gave shocks to the marginal cost of gas-fired generators in addition to coal plant retirements, in order to mimic the situation in which gas price shocks affect firms in the market. This is done by raising the marginal cost of gas-fired plants by the exact size of the impact it received from the gas price shock.

The easiest way to account for cost shocks in the counterfactual simulations is to take a day when the cost shock actually occurred and then apply the coal plant retirements to the day. In this paper, however, I take a slightly different approach where I take a day when cost shocks did not occur and then apply retirements and marginal cost shocks at the same time. Note that the starting point of counterfactuals is different between the former and the latter; former approach base the simulation on days with cost shock, while latter base it on days without cost shocks.

[7] The average heat rate of new gas power plants that started production in 2014 was taken from EIA's report. Marginal cost is represented as the heat rate multiplied by the sum of gas price and emission price.

The size of the actual impact of the gas price shock is measured as the marginal cost of the gas-fired generators on the day of the impact. For example, suppose that the marginal cost of the gas-fired unit is \$4/MWh on the day when there was no gas price shock, but the marginal cost increased to \$8/MWh on the day of the shock. Then, we can make the market conditions of our baseline day and the cost shock days similar by replacing the marginal cost of the baseline day with the marginal cost of the cost shock day, which is \$8/MWh in this example.

Because the demand of days from which we take marginal cost estimates and the demand of days we base our simulation on are different, it is important to control for the aggregate market demand when conducting counterfactuals with cost shocks. To address this issue, I picked a day from the set of days with cost shocks that has the demand closest to the demand of the day in our (no-shock) sample. Then, the only difference between the market condition of the chosen "cost shock" day and the conditions of the cost-shock applied counterfactuals is the capacity of retired plants and the proportion of gas-fired generation in the grid. This allows direct comparison of simulated prices under counterfactual situations to the actual equilibrium prices of the cost shock days to examine the effect of retirement on market prices when market is affected by cost shocks. The cost shock counterfactual is depicted in Counterfactual 2 of Figure 2.3.

It has been addressed in Kim (2017) that actual impacts of the gas price shock on generation costs of gas-fired plants could be heterogeneous because of the different gas procurement channels and technology used by power plants, all of which make the extents of gas cost increases to be different across firms.[8] I address this issue by using marginal costs estimated from Kim (2017) that estimates marginal costs from bids firms submit in electricity auctions. Because the estimated marginal costs reveal the underlying true cost of supplying electricity revealed in firms' bids, these capture the existing heterogeneity in impacts on their costs better than the marginal cost generated with data (which is incomplete).

One caveat is that the model used to estimate the marginal costs, the optimal bidding model, enables estimation of marginal costs of generators that bid close to the market clearing prices, thus having ex-ante market power. Therefore, I cannot estimate marginal costs of generators that are located far away from the final market clearing price. For these generators, I use price bids they bid in auctions in place of the marginal cost. Using price bids as a measure of marginal costs for generators that are not close to being marginal, thus having

[8]Example of technology that causes impact heterogeneity is the dual fuel technology. About 25 % of gas power plants in New England can fuel on either gas or oil. When the gas price surges above the level that exceeds the price of oil, these dual fuel plants tend to switch fuels to oil to mitigate their cost impacts from the shock. Precise number of switches is documented in Kim (2017).

no ability to manipulate market prices in ex-ante, is plausible because firms have incentives to bid marginal costs for these generators without adding any markups over costs.

Generating marginal cost variables of new gas-fired plants that replace the retired coal plants, but not yet exist in the data, is again an issue in this counterfactual analysis. I measured marginal costs of these generators in a similar way as before, using the average heat rate of recently constructed gas power plants reported by EIA, gas price index data, and emissions price data.

2.3.2 Equilibrium Model

To compute the equilibrium under counterfactual situations, we need a model that describes decision makings of firms. Since firms in the wholesale electricity market compete for production in the auction, the supply function equilibrium (SFE) model best describes the competition between electricity generating firms and the resulting market equilibrium.

However, computation of counterfactual supply function equilibrium is challenging due to a well-known multiple equilibria problem (Klemperer and Meyer, 1989). Also, the optimal bidding model in the multi-unit uniform auction, which relies on necessary condition of optimization, does not describe the structural bidding decisions of firms.[9]Therefore, in many cases, the counterfactual analysis in the wholesale electricity market has mostly relied on simulating the Cournot and competitive equilibria to obtain bounds that include counterfactual SFE. This paper adopts this methodology and obtains estimates for both competitive and Cournot equilibrium.

According to Klemperer and Meyer (1989), multiple supply function equilibria are bounded by the perfectly competitive equilibrium and the Cournot equilibrium. Therefore, the competitive and Cournot equilibria simulated under counterfactual situations become lower and upper bounds of the market outcomes we expect to see in the actual counterfactual supply function equilibrium. Figure 2.4 illustrates these findings where it shows the upper and lower bounds of multiple supply function equilibria.

2.4 Description of Model and Data

It is straightforward to compute the perfectly competitive market equilibrium; firms produce electricity as long as the marginal cost of production is less than or equal to the market price, and the market clearing price is determined at the intersection of aggregate supply

[9] However, multiple equilibria problem does not pose any challenge to *estimation* of model parameters that use necessary condition of optimization at the observed equilibrium.

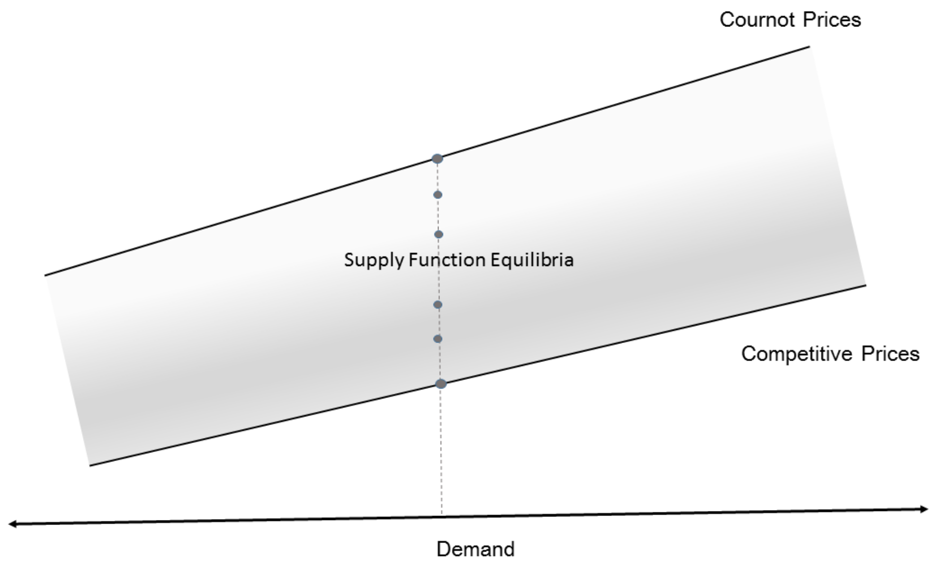


Figure 2.4: Graphical Illustration of Bounds of Supply Function Equilibrium

and demand for electricity. To compute Cournot equilibrium outcomes, general formulation of how strategic firms compete according to the Cournot assumption is necessary. I adopt the Cournot model used in Bushnell, Mansur and Saravia (2008) to compute counterfactual Cournot outcomes. In the subsequent sections, I describe the model and several assumptions imposed when applying the data to the model.

2.4.1 Model Description

2.4.1.1 Residual Demand Curve

We need a (smooth) demand function to clear the market within the model.[10] I adopt a simple linear demand specification used in Bushnell, Mansur, and Saravia (2008). Specifically, the demand curve used in BMS (2008) is a linearly specified *residual* demand of N_{st} strategic firms.

Residual demand is the demand faced by strategic firms together. I define strategic firms as those operate more than one generator or a single generator with a large capacity (e.g. greater than 100 MW). Therefore, residual demand, $Q_{s,t}$, must equal the aggregate electricity demand ($\bar{D}_t$) less the electricity generated by non-strategic fringe suppliers together

[10] Although we have complete data on demand side bids which can be used to construct demand curve, it is better to have a more general demand function that applies to the entire sample. Also, because I model firms to compete in quantity, rather than with the bid that contains both price and quantity bids, it is difficult to obtain market clearing price without a general form of market demand function.

($Q_{ns,t}$), which is shown below. Subscripts s and ns denote strategic and non-strategic, respectively.

$$Q_{s,t} = \bar{D}_t \ - Q_{ns,t}(p_t)$$

Because the demand side of the wholesale electricity market – local distribution companies – has obligations to supply electricity to residential customers, they tend to submit price insensitive bids which make the aggregate demand ($\bar{D}_t$) to be almost perfectly inelastic. However, the residual demand faced by strategic firms is not completely inelastic because the electricity supplied by non-strategic firms, which includes quantity supplied by small fringe firms less net imported amount of electricity from adjacent markets, is responsive to the market price.[11]

Functional form of a residual demand curve is specified as follows:

$$Q_{s,t} = \alpha - \beta \ ln(p_t) \quad \Leftrightarrow \quad p_t = \exp((\alpha - Q_{s,t})/\beta) \tag{2.1}$$

Parameter α and β must be determined before we run counterfactuals. Following BMS (2008), I estimate β, the price elasticity of non-strategic supply ($Q_{ns,t}$), using observed variations in quantities of fringe supply and net imported electricity over time. I provide more details of the 2SLS regression used for estimating β in the Appendix. The β estimated from my 2012-2014 sample is $\beta =$ 1,896.5. This is not much different from the $\beta = 1391$ that BMS (2008) estimated from the sample of 1999, given that the size of the New England electricity market has grown considerably since 1999.[12] The intercept of the residual demand,α, is calculated using the price and the firm-level quantities of the observed equilibrium. That is, exploiting the fact that ($Q_{s,t}$, P_t) of the equilibrium day is a point on the residual demand curve, I plug in $Q_{s,t} = \sum_{i=1}^{N_{st}} q_{it}$ and the actual market clearing price P_t to obtain value of the intercept α.

2.4.1.2 Firm's problem

For each strategic firm $i \in \{1, \ldots, N_{st}\}$ and for time $t \in \{1, \ldots, T\}$, firm i choose to produce electricity q_{it} that maximizes profits:

$$\max_{q_{it}} \ \pi_{i,t}(q_{it} \ , q_{-it}) \ = \ p_t \ (q_{it} \ , q_{-it}) \ [q_{it} - q_{it}^f] \ + p_{it}^f \ (q_{it}^f, q_{-it}^f) \ q_{it}^f \ - \ C(q_{it}) \qquad \text{for } \forall \ i \tag{2.2}$$

[11]The New England electricity market usually imports or exports wholesale electricity from the Canadian electricity market and the New York electricity market (ISO-NY). It mainly imports from Canada, while imports and exports to the New York market depending on the daily market and transmission conditions.

[12]Also, the set of firms classified as non-strategic firms in 2012-2014 has changed from the set in 1999.

$$s.t. \quad q_{it} \geq 0 \quad \text{and} \quad q_{it} \leq q_{i,max}$$

Electricity producing firms tend to forward contract a certain amount of their generation with the demand side, shown as q^f_{it}, at a pre determined price, shown as p^f_{it}. They mutually agree to buy and sell the contracted amount at a forward price, before the actual production takes place. For this reason, the forwarded quantity and forward price are assumed to be exogenous at the time of the firm's production decision, thus do not affect strategic decisions of firms regarding the quantity produced, q_{it}.[13]

2.4.1.3 Cost Functions

We need a firm-specific cost function because firms in the model optimally decide on single q_{it}. If a firm operates total J number of generating units, we can construct a cost curve $C(q_{it})$ of firm i by arranging the marginal cost values of these units in order from the smallest value. Then, the marginal cost is represented as below:

$$C'(q_{it}) = mc_j \qquad \text{if} \qquad q_{it} \in (\sum_{k=1}^{j-1} q_{ik}, \sum_{k=1}^{j} q_{ik}) \tag{2.3}$$

I assume the cost curve to be linear so that the marginal cost of each generator is constant over quantity, i.e. scalar value. Linear cost assumption is common in the literature (Bushnell, Mansur, and Saravia, 2008; Ryan, 2017) and many others have made this assumption in their analysis. As mentioned in Reguant (2014), generators can have a non-linear component in their cost curve, in which case the marginal cost would increase with quantity. Omitting the non-linear component would be problematic for coal plants, but not a critical problem as many of the coal plants in our study are being excluded in counterfactual simulations. Later, I will add a non-linear component to the cost to further complement the analysis.

2.4.1.4 Cournot Equilibrium Outcomes

Cournot equilibrium is represented as a set of quantities, $\mathbf{q}^*_t = [q^*_{1t}, \ldots, q^*_N]$, that simultaneously satisfy the system of first order conditions. The first order conditions of strategic firms are shown below:

$$\mathcal{L} \equiv \pi_{it} + \lambda_{it}(q_{i,max} - q_{it}) \quad \forall i \in \mathcal{F}_s \tag{2.4}$$

[13] p_f disappears from the first order condition in the process of differentiating profit with respect to q_{it}.

$$\frac{\partial \mathcal{L}}{\partial q_{it}} = \frac{\partial \pi_{it}}{\partial q_{it}} - \lambda_{it} \leq 0, \qquad q_{it} \geq 0, \qquad \frac{\partial \mathcal{L}}{\partial q_{it}}\ q_{it} = 0 \tag{2.5}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_{it}} = q_{i,max} - q_{it} \geq 0, \qquad \lambda_{it} \geq 0, \qquad \frac{\partial \mathcal{L}}{\partial \lambda_{it}}\ \lambda_{it} = 0 \tag{2.6}$$

We can rewrite equations (2.5) and (2.6) by plugging in the actual specifications, which are shown below in equations (2.5a) and (2.6a):

$$\frac{\partial p_t}{\partial q_{it}}\ [q_{it} - q_{it}^f] + p_t - C'(q_{it}) - \lambda_{it} \leq 0, \;\; q_{it} \geq 0, \;\; \frac{\partial p_t}{\partial q_{it}}\ [q_{it} - q_{it}^f] + p_t - C'(q_{it}) - \lambda_{it}\ q_{it} = 0 \tag{2.5a}$$

$$q_{i,max} - q_{it} \geq 0, \quad \lambda_{it} \geq 0 \quad q_{i,max} - q_{it}\ \lambda_{it} \tag{2.6a}$$

Nonstrategic, fringe suppliers are assumed to be price takers. First order conditions of non-strategic fringe suppliers are shown below:

$$p_t\ - C'(q_{it}) - \lambda_{it} \leq 0, \quad q_{it} \geq 0, \quad p_t\ - C'(q_{it}) - \lambda_{it}\ q_{it} = 0 \tag{2.7}$$

$$q_{i,max} - q_{it} \geq 0, \quad \lambda_{it} \geq 0 \quad q_{i,max} - q_{it}\ \lambda_{it} \tag{2.8}$$

Derived conditions become a standard (non-linear) mixed complementarity problem (MCP). Now we can summarize the above conditions using complementarity symbols:

$$\begin{aligned} \frac{\partial p_t}{\partial q_{it}}\ [q_{it} - q_{it}^f]\ +\ p_t\ -\ C'(q_{it})\ -\ \lambda_{it} \leq 0 \ \ \perp \ \ q_{it} \geq 0 \qquad & \forall i \in \mathcal{F}_s \\ p_t\ -\ C'(q_{it})\ -\ \lambda_{it} \leq 0 \ \ \perp \ \ q_{it} \geq 0 \qquad & \forall i \in \mathcal{F}_{ns} \\ q_{i,max}\ -\ q_{it} \geq 0 \ \ \perp \ \ \lambda_{it} \geq 0 \qquad & \forall i \end{aligned} \tag{2.9}$$

These complementarity conditions are similar to the ones derived in Bushnell, Mansur, and Saravia (2008). We can also convert the system to a new form by removing multiplier λ_{it}

from the equations,

$$\text{For } \forall i \in \mathcal{F}$$
$$\begin{aligned} 0 < q_{it} < q_{i,max} &\Rightarrow \frac{\partial \pi_{it}}{\partial q_{it}} = 0 \\ q_{it} = 0 &\Rightarrow \frac{\partial \pi_{it}}{\partial q_{it}} \leq 0 \\ q_{it} = q_{i,max} &\Rightarrow \frac{\partial \pi_{it}}{\partial q_{it}} \geq 0 \end{aligned} \tag{2.10}$$

where the derivative of profit, $\frac{\partial \pi_{it}}{\partial q_{it}}$, of strategic and nonstrategic firms take different forms.

The Cournot equilibrium quantities of production, $\mathbf{q}_t^* = [q_{1t}^*, \ldots, q_{Nt}^*]$, is the $\mathbf{q_t}$ that simultaneously solve the above system of complementarity conditions. To obtain the solution of this problem, I use PATH algorithm which is effective in solving mixed complementarity problem (Kolstad and Mathiesen, 1991; Dirkse and Ferris, 1998).

2.4.2 Data

Data on firm-level quantity and maximum capacity comes from bidding data available from ISO-NE website. Electricity generating firms in wholesale electricity market must sell electricity in a daily auction which consists of total 24 hourly auctions. A typical bid submitted by a firm consists of price and quantity pairs, $< p_{ijht}, q_{ijht} >$, which exist for each generating unit operated by the firm. Firm-level quantity of hour h of day t, which is q_{iht}, can be measured by adding up the unit-level quantity bids, q_{ijht}. Because the demand side of the wholesale electricity market – local distribution companies – bids in the auction as well, bidding data offers a nice dataset of market demand. Also, the net imported amount of electricity is taken from ISO-NE's report on the final net interchange (net import).

Actual market (auction) clearing prices also come from ISO-NE website. I use energy component price, which is a single price that clears the entire system that does not reflect congestion costs that vary across locations within the grid. Because I cannot account for the complicated process of determining transmission congestion costs when clearing the market in my model, I use energy component price as a reference price level throughout my analysis.

As mentioned in the previous section, I use *estimates* of marginal costs instead of measuring them. In the wholesale electricity market studies, there are broadly two ways of obtaining marginal costs of (thermal) electricity generators. Most commonly used approach is to measure the marginal costs using data on fuel price and heat rate (efficiency) of generators in the market. Another approach is to estimate the marginal costs that rationalize the bids that firms submit in the electricity auctions. Although the latter approach involves additional modeling of optimal bidding decision of firms and requires additional computation, it suits better to capture the real opportunity costs of firms especially when the market experiences input cost shocks. Because an important element of my study is to understand how market outcomes and firm behavior changes under cost shocks, I rely on the second approach and use the *estimated* marginal costs. Details of the bidding model and the estimation procedure are elaborated in Kim (2017).

However, marginal cost estimates cannot be obtained for some small fringe generators, hydroelectric plants and base load generators that usually bid zero price bids – such as nuclear plants – because the optimal bidding model can get estimates for units that are close to being marginal. These units are far away from the market clearing price, thus have no chance of becoming the marginal unit. I use price bid of these units as a measure of marginal costs because firms will simply submit a bid that equals the marginal cost of its unit if the unit has no ability to set the market price i.e. not ex-ante marginal. For this reason, price bid is a good measure of marginal costs for these units.

Finally, we need information on the forward contracted amount of electricity, represented as q_{it}^f in our model. Unfortunately, data does not exist for the contract position because it is determined through confidential bilateral negotiations between electricity generating firms and the demand side. The optimal bidding model used to estimate the marginal cost enables estimation of the forward contract parameters as well. I use the forward contract rate parameter (represented as a $\%$ of the firm's daily electricity generation) estimated in Kim (2017) and multiply the rate with the actual quantity produced by the firm to generate the forward contracted amount of quantity, q_{it}^f.

2.5 Results

2.5.1 Perfectly Competitive Outcomes

2.5.1.1 No replacement of retired capacity and no cost shock

I first simulated competitive market prices when coal and nuclear plants scheduled to retire are excluded from the grid. This counterfactual analysis is more relevant to assessing the short-term impact of a coal plant's retirement on market outcomes, because it is a situation where a base load coal plant suddenly stops operation. Although a firm announces retirement of its plant several years in advance of the actual date of shut-down, it is hard for these firms to finish construction of the replacing plants and connect it to the grid by the time of the retirement. Therefore, in most of these cases, the lost base load electricity

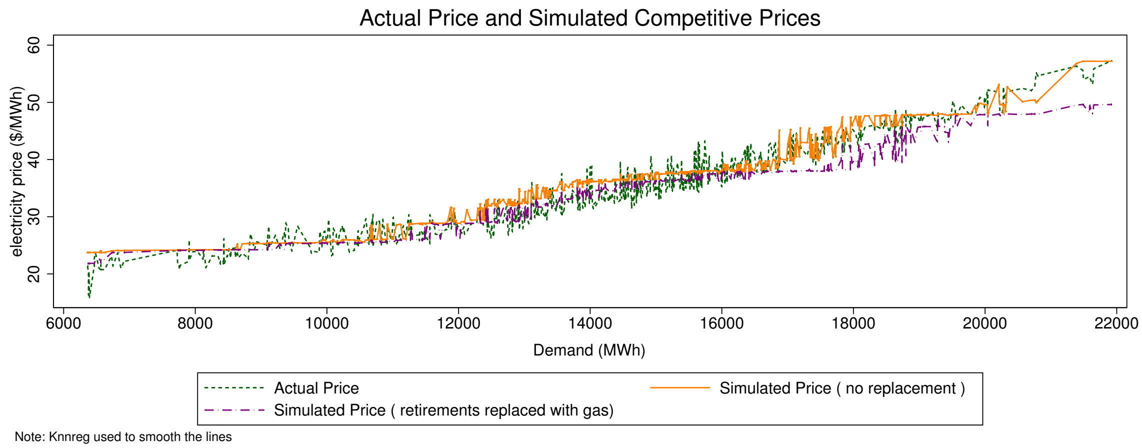
Table 2.3: Estimates of Competitive Prices: Retired plants not replaced with gas, no cost shocks

Demand	Statistics	Electricity Prices ($/MWh) (1) original equilibrium	(2) retirement (a)	(3) retirement (a)+(b)
All Hours				
p25	Mean	25.5	26.4	26.5
	S.d.	3.09	2.30	2.46
p50	Mean	32.2	34.7	35.2
	S.d.	2.70	1.81	1.71
p75	Mean	37.3	37.9	38.4
	S.d.	2.46	0.66	1.38
p100	Mean	45.5	45.8	55.4
	S.d.	3.37	4.37	25.1

generation is met by increased generation from preexisting plants in the grid that may have marginal cost higher than that of the retired plants. For this reason, we expect to see a rise in electricity market prices if the grid is not yet ready to replace the retired generation with new gas generation.

Table 2.3 show the original equilibrium prices, which come from data, and the simulated prices under reconstructed market conditions. Original equilibrium prices in column (1) refer to prices of days we observe in data where none of the coal plants retired. Note that prices in column (1) are prices that emerge in supply function equilibrium (SFE) because it is the equilibrium concept that applies to the wholesale electricity market. Other two columns show the simulated prices when I apply the scheduled plant retirements in the group (a), shown in column (2), and additionally apply retirements in the group (b), shown in column (3), in the counterfactual simulations. These prices are competitive prices, assuming that firms compete in a perfectly competitive setting. Also, I report the mean of prices within each demand bins constructed based on the percentiles of the demand distribution.

Indeed, as shown in Table 2.3, the simulated competitive market prices – reported in columns (2) and (3)– are higher than the actual (SFE) equilibrium prices –shown in column (1)– as more coal plants retire from the grid. The difference may not seem significant when comparing prices in column (1) to those in column (2), but considering that prices reported in column (2) is competitive prices – lower bound of the actual SFE prices –, the market price clearly increases after the retirement. As the size of the retired capacity increases, the rise of the market prices becomes more apparent. Especially when the market demand is high (e.g. Demand p100), the average of market competitive price rises from $45.8/MWh to $55.4/MWh.



Note: Prices are smoothed using Kth-nearest neighbor regression (knnreg, with K = 20)

Figure 2.5: Comparison of Prices: Retired Plants Replaced with Gas vs. Not Replaced

2.5.1.2 Retired Capacity Replaced with Gas Generation, No Cost Shock

Now I report the results of the counterfactual analysis where the capacity of retired coal (and other base load) generation is replaced with the new gas generation having the same capacity as retired ones.

Table 2.4 show the original equilibrium prices, which come from data, and the simulated prices under reconstructed market conditions. Original equilibrium prices in column (1) refer to prices of days we observe in data where none of the coal plants retired. Note that prices in column (1) are prices that emerge in supply function equilibrium (SFE) because it is the equilibrium concept that applies to the wholesale electricity market. Other two columns show the simulated prices when I apply the scheduled plant retirements in the group (a), shown in column (2), and additionally apply retirements in the group (b), shown in column (3), in the counterfactual simulations. In both cases, retired capacities are replaced with new hypothetical gas-fired plants. The simulated prices are competitive prices; prices that emerge when firms compete in a perfectly competitive setting. Also, I report the mean of prices within each demand bins constructed based on the percentiles of the demand distribution. Because the levels of capacity retired increases from column (2) to column (3), the comparison across columns shows the effect of having greater proportion of gas-fired generation on market prices.

Note that there was no change in the gas spot prices in the sample of original equilibrium and the counterfactual simulations. Thus, the marginal cost of generating electricity using gas was stable and low, and the cost was comparable to that of coal. The marginal costs of some of the new gas plants that replaced retired ones were even lower than that of the retired coal plants because of the way that I approximated the marginal costs of these new plants. That is, I used the average heat rates of the recently constructed gas plants (which is based on EIA's report in 2014) which are far more efficient, thus having a lower marginal cost of electricity generation, than those built in the past.

According to the results, it appears that replacing the coal generation with the gas gen-

Demand	statistics	Electricity Prices ($/MWh) (1) original equilibrium	(2) retirement (a)	(3) retirement (a)+(b)
		Off-Peak Hours (4-8 am, 10- 12 pm)		
p25	Mean	23.1	23.8	23.9
	S.d.	2.31	0.92	0.92
p50	Mean	26.9	26.2	26.2
	S.d.	2.00	1.19	1.19
p75	Mean	30.5	30.8	31.1
	S.d.	2.07	1.71	1.87
p100	Mean	36.8	36.1	35.7
	S.d.	3.37	1.24	1.11
		Peak Hours (11am - 8pm)		
p25	Mean	32.7	33.1	33.1
	S.d.	2.89	2.31	2.10
p50	Mean	36.8	36.7	36.2
	S.d.	2.15	0.60	0.51
p75	Mean	41.1	38.0	37.6
	S.d.	2.35	0.78	0.50
p100	Mean	48.3	45.1	42.8
	S.d.	3.31	3.03	3.84
		All hours		
p25	Mean	25.5	25.4	25.4
	S.d.	3.09	1.95	1.96
p50	Mean	32.2	32.7	32.9
	S.d.	2.70	2.14	1.91
p75	Mean	37.3	36.8	36.3
	S.d.	2.46	0.73	0.74
p100	Mean	45.5	42.0	40.6
	S.d.	4.31	4.16	3.80

Notes: Demand distributions are obtained separately for *Off-peak Hours*, *Peak Hours*, and *All hours*.

Table 2.4: Estimates of Competitive Prices: Retired Plants Replaced, No Cost Shocks

eration that has marginal cost similar to or sometimes lower than that of the coal plants does not have a significant impact on market prices. During off-peak hours when demand is low, we do not find a significant increase in prices after the retirement, as shown in the *Off-peak Hours* panel of Table 2.4. During peak hours, simulated competitive prices are even lower than the prices in the original equilibrium. For example, during peak-hours where levels of demand falls between 50th and 75th percentiles (shown as p75 of *Peak Hours* panel of Table

2.4), prices drop from \$41.1/MWh to \$38.0/MWh after the retirement of plants in the group (a), and further drop to \$37.6/MWh when additional plants in the group (b) retire. During peak hours when the demand levels are high, the market is usually cleared by gas-fired plants. Thus the observed price drop after the retirement is probably due to having more efficient, new gas-fired plants in the system.

Also, the simulated prices with plant replacement were lower than the simulated prices when the retired plants are not replaced with new gas plants. Table 2.5 shows the smoothed lines of original equilibrium prices and simulated prices under two different replacement scenarios. Prices without replacement are higher than the prices with replacement, especially on days with high electricity demands.

2.5.1.3 Retired Capacity Replaced, Cost Shocks Given

Now, in addition to coal plant retirements, I gave counterfactual cost shocks to firms by increasing the marginal costs of their gas-fired generators. Table 2.5 reports the original equilibrium prices along with the simulated prices. While I base the analysis on sample days when there was no cost shock in the market, marginal cost estimates used in the simulation are taken from the days on which cost shocks occurred. I term these days as original equilibrium days.

In panel A and panel B, I report original equilibrium prices and the simulated prices when the gas price shock with a size between \$10 to \$15/mmbtu and between \$20 to \$25/mmbtu are applied to the market, respectively. Therefore, a panel-to-panel comparison shows how the market impact of retirement differs by the intensity of the gas price shock (cost shock). Considering that the gas prices during the period without the shock stay around \$4/mmbtu, the marginal costs of gas-fired generators in panel A and B are about three times and five times greater than marginal costs of days without a shock.

Column (1) of Table 2.5 shows the prices of original equilibrium days and columns (2) and (3) show the simulated prices under counterfactual situations where I let coal plants to retire. Because no coal plants retired in the original equilibrium, the capacity of retired plants, as well as the proportion of gas-fired generation in the market, gradually increases from columns (1) to (3). Thus, comparison across columns show the effect of the retirement on prices, having fixed the size of the cost shock.

I first find that, during off-peak hours, the simulated competitive prices are much higher compared to prices of original equilibrium, which suggests that a retirement has significant impact on market prices when firms are affected by cost shocks. Furthermore, I find that the impact is much greater as the size of the cost shock increases.

For example, in p50 of *Off-peak Hours* panel A, the mean of wholesale electricity price

Table 2.5: Estimates of Competitive Prices: Retired Plants Replaced, Cost Shocks Given

		A. Gas price range $10-15/MMbtu			B. Gas price range $20-25/MMbtu		
		Electricity Prices ($/MWh)					
		(1)	(2)	(3)	(1)	(2)	(3)
Demand	Statistics	original eqm	retirement (a)	retirement (a)+(b)	original eqm	retirement (a)	retirement (a)+(b)
Off-Peak Hours (4-8 am, 10- 12 pm)							
p25	Mean	53.1	57.2	59.0	67.0	88.4	94.9
	S.d.	20.5	26.6	27.4	37.8	48.2	50.4
p50	Mean	71.5	83.7	83.8	109.7	136.3	136.9
	S.d.	23.3	24.4	24.0	43.7	31.0	30.3
p75	Mean	94.9	103.5	102.7	129.5	138.5	137.8
	S.d.	35.4	21.0	19.6	57.8	44.4	44.0
p100	Mean	118.8	120.0	118.4	166.5	173.2	171.2
	S.d.	35.4	21.0	19.6	49.2	40.8	40.0
Peak Hours (11am - 8pm)							
p25	Mean	108.9	104.2	103.4	155.5	149.9	148.1
	S.d.	33.9	23.4	23.1	42.3	30.4	30.5
p50	Mean	116.2	123.1	121.6	173.9	177.6	174.7
	S.d.	38.7	28.3	28.2	47.6	50.3	50.8
p75	Mean	130.9	140.7	138.8	179.6	191.3	189.0
	S.d.	45.8	37.3	37.1	57.8	51.9	51.9
p100	Mean	148.0	189.5	188.2	194.7	227.5	224.4
	S.d.	54.7	72.1	72.7	47.0	46.5	47.9

Notes: Percentiles of demand are calculated within each hours category. Original equilibrium price is the actual market clearing price of the day when the market was affected by gas price shocks (cost shocks). Column (2) and (3) show the simulated prices of counterfactual situations where coal plants in retirement groups (a) and (b) retire and the same size gas price shock as in the original equilibrium is given to firms.

estimates shown in columns (2) and (3) are $83.7/MWh and $83.8/MWh, both of which are about %17 higher than the mean of original equilibrium prices, $71.5/MWh. In p50 of panel B, I find a more significant increase in prices; the simulated competitive prices in columns (2) and (3) are almost 20 % higher than the original equilibrium prices. These results are convincing because the marginal cost of gas generators which are now responsible for electricity generation during off-peak hours increases when the spot gas prices go up.

Peak-hour prices increase after the retirement as well, but overall, the size of the increase is not as big as in low-demand off-peak hours, except for days when the demand is at the highest tier (between 75th and 100th percentiles, shown as p100 in Table 2.5). That is, the mean of simulated competitive prices (columns (2) and (3)) in p100 of *Peak Hours* is about 22 % and 17 % higher than the mean of original prices (column (1)).

As mentioned earlier, the simulated competitive prices are the lower bounds of what we would observe in the counterfactual (supply function) equilibrium. Therefore, having lower bounds that are greater than the original (supply function) equilibrium implies that the post-retirement prices in actual counterfactual equilibria may be significantly higher than the original equilibrium prices.

The original equilibrium days used in our counterfactuals are selected from the sample that includes the winters of 2013 and 2014 when the huge increase in wholesale electricity prices, as a result of the gas price shock, was a big issue at the time. Our simulation results suggest that the market would have faced even more severe shocks to electricity prices if the wholesale electricity industry at that time had transformed into a more gas-concentrated industry than it used to be.

2.5.2 Cournot Equilibrium Outcomes

2.5.2.1 Retired Capacity Replaced, Cost Shocks Given

In this section, I report Cournot outcomes simulated for 6 days in the sample, where I applied both coal plant retirements and cost shocks in the counterfactuals. I gave cost shocks that firms would face when the gas price shock that ranges between $10-15/mmbtu prevails in the market. Table 2.6 shows the original equilibrium prices, competitive prices and Cournot prices for different levels of retired capacities. Column (1) is the original equilibrium prices of days when the gas price shock occurred, which is observed in data. Column (2) and (3) show the prices simulated under counterfactual where the retirements in the group (a) was applied in the simulation, while columns (4) and (5) show simulated prices when retirements in Group (b) are applied in addition to those in Group (a). Columns (2) and (4) are competitive prices, which are lower bounds of the SFE counterfactual equilibria, and columns (3) and (5) are Cournot prices which are upper bounds of the SFE equilibria.

As expected, Cournot prices lie above competitive prices. The supply function equilibrium under counterfactual market conditions would fall between competitive and Cournot prices. When compared to the original equilibrium prices, Cournot prices are higher than the original equilibrium prices, on average. Also, Cournot prices further increase when more coal plants retire from the grid, which can be shown by comparing column (3) to column (5). However, the results must be interpreted with caution because the sample size used in this analysis is small and not representative of the entire sample.

Table 2.6: Estimates of Cournot and Competitive Prices: Cost Shocks Given

Demand	Statistics	Electricity Prices ($/MWh) A. Gas price range $10-15 /MMbtu				
		(1)	(2)	(3)	(4)	(5)
		Original eq'm	Retirement (a)		Retirement (a)+(b)	
			Competitive	Cournot	Competitive	Cournot
Less than 14,000 MWh	Mean	61.8	65.4	69.7	67.8	73.4
	Median	57.5	65.4	70.2	65.9	70.5
	S.d.	18.8	20.6	22.8	21.2	25.9
Greater than 14,000 MWh	Mean	120.0	145.4	155.8	155.8	170.8
	Median	123.7	145.5	149.7	157.2	184.4
	S.d.	34.6	47.3	52.9	53.9	59.6

Notes: Original equilibrium prices, Competitive prices and Cournot prices of 6 days in the sample are reported in this table. Minimum and maximum of demands of total 6 days are 6,565 MWh and 19,566 MWh, respectively. Column (1) is the original equilibrium prices of days when gas price shocks occurred but no coal plants had retired yet. Columns (2) and (3) show the simulated market prices when retirements in Group (a) are applied, and columns (4) and (5) show the simulated prices when Group (b) retirements are applied in addition to Group (a). Columns (2) and (4) are prices simulated under perfect competition assumption, and columns (3) and (5) are prices simulated under Cournot competition assumption.

2.5.2.2 Firm-level Analysis

To understand how the change in firm-level strategic production decisions have contributed to the higher Cournot prices after the retirement, we must conduct a comprehensive analysis of how firm-level quantity or markups change as more coal plants retire from the grid and when firms are affected by cost shocks.

In this paper, I provide a preliminary evidence of the change in firm-level strategies by examining how Cournot quantities of firms change when the levels of retired capacities increase. In other words, I examine whether firm-level Cournot quantities under market conditions considered in columns (3) and (5) are different from each other. If we find that firms decrease quantities as more coal plants retire, this suggests that firms exercise market power as the market transforms into a more gas concentrated industry due to additional retirements of coal plants.

Figure 2.6 shows whether firms, indexed by numbers reported in the horizontal axis, increased or decreased their quantities when the total set of retired plants increase from Group (a) to Group (a) and (b) together. Positive indicator implies an increase and negative indicator implies a decrease in quantities. As shown in the figure, most of the firms decrease

Notes: Day 127, Hour 4

Notes: Quantity changes of strategic firms plotted in this figure. Horizontal axis shows the index of strategic firms and vertical axis variable is the indicator that shows whether firm-level quantity increased or decreased when additional retirements in Group (b) are applied in the counterfactual simulation.

Figure 2.6: Change in Firm-Level Quantity As More Coal Plants Retire

their quantities as more retirements are applied in counterfactuals, and this finding serves as a preliminary evidence of firm-level strategy changes due to increased plant retirements.

2.6 Conclusion

Coal-fired generation is the oldest form of electricity generation, but it is now retiring from the grid due to environmental and economic reasons. Electricity markets are now shifting towards generating electricity with gas that is cleaner and has a comparably low cost of generation. However, the cost of generating electricity with gas, which is proportional to the spot prices of gas, can fluctuate and increase substantially depending on the conditions of the daily spot gas markets. Therefore, more coal plants retiring implies that the market will be more concentrated with generation assets that are vulnerable to volatility and cost shocks.

This paper focuses on this aspect of the ongoing transition of the grid and examines how the market outcomes would change after the retirement of coal plants, especially when the firms in this electricity market are affected by the cost shock that is caused by increases in gas prices. I study this in the context of the New England wholesale electricity market, the market in which the increased reliance on gas generation combined with frequent spikes in gas spot prices are raising concerns.

I implement sets of counterfactual analyses where I vary the number of coal plant retirements that will also change the proportion of gas-fired generation, and vary the levels of gas prices to increase the electricity generation costs of gas-fired plants. I estimate market outcomes under two different modeling assumptions: perfectly competitive and Cournot. These estimates construct a bound of actual supply function equilibria outcomes that will prevail in the market. In this paper, I limit my analysis to competitive outcomes, and will later extend the analysis to Cournot outcomes.

First, in the absence of cost shocks, I find that electricity prices rise after the retirement in the short-term because the loss of baseload generation shifts the supply curve inward, making high-cost generators to fill in the lost load. On the other hand, prices do not increase much when new and efficient gas plants immediately replace the retired ones, which mimics a situation likely to occur in the long-term. This is because the cost of generating with gas is comparable to that of generating with coal when gas prices are low. However, when the gas prices increase due to shocks in spot gas markets, I find that electricity prices are up to 20 $\%$ higher after the retirement compared to prices of actual days in the sample when retirement did not happen. The prices of these sample days were the highest values in the New England electricity market history. The fact that post-retirement prices are estimated to be even higher than these record high-level prices indicates that if there will be a similar degree of cost shock impact on a more gas-centered grid, the market will be hit harder than before.

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APPENDIX A

Chapter 1 Appendix

A.1 Additional Graphs

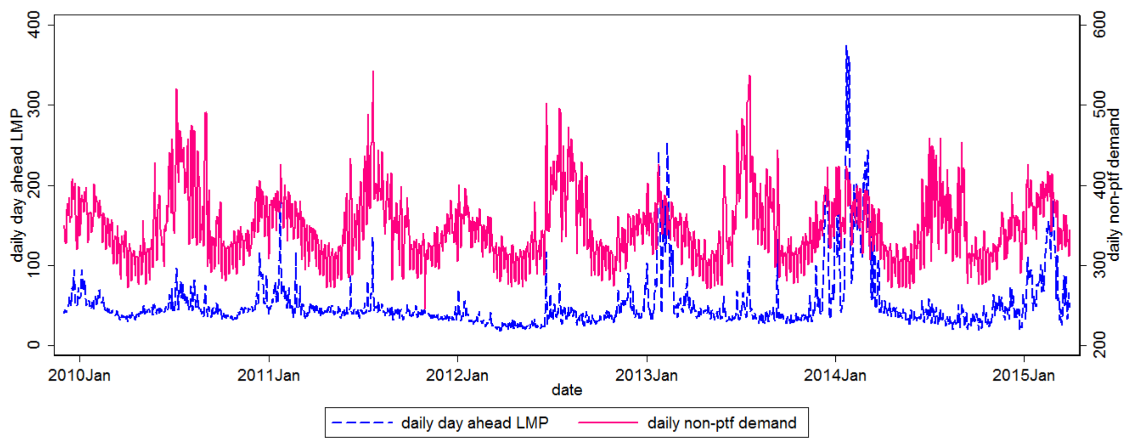

Figure A.1: Daily Day-Ahead Electricity Demand: year 2010 - 2015

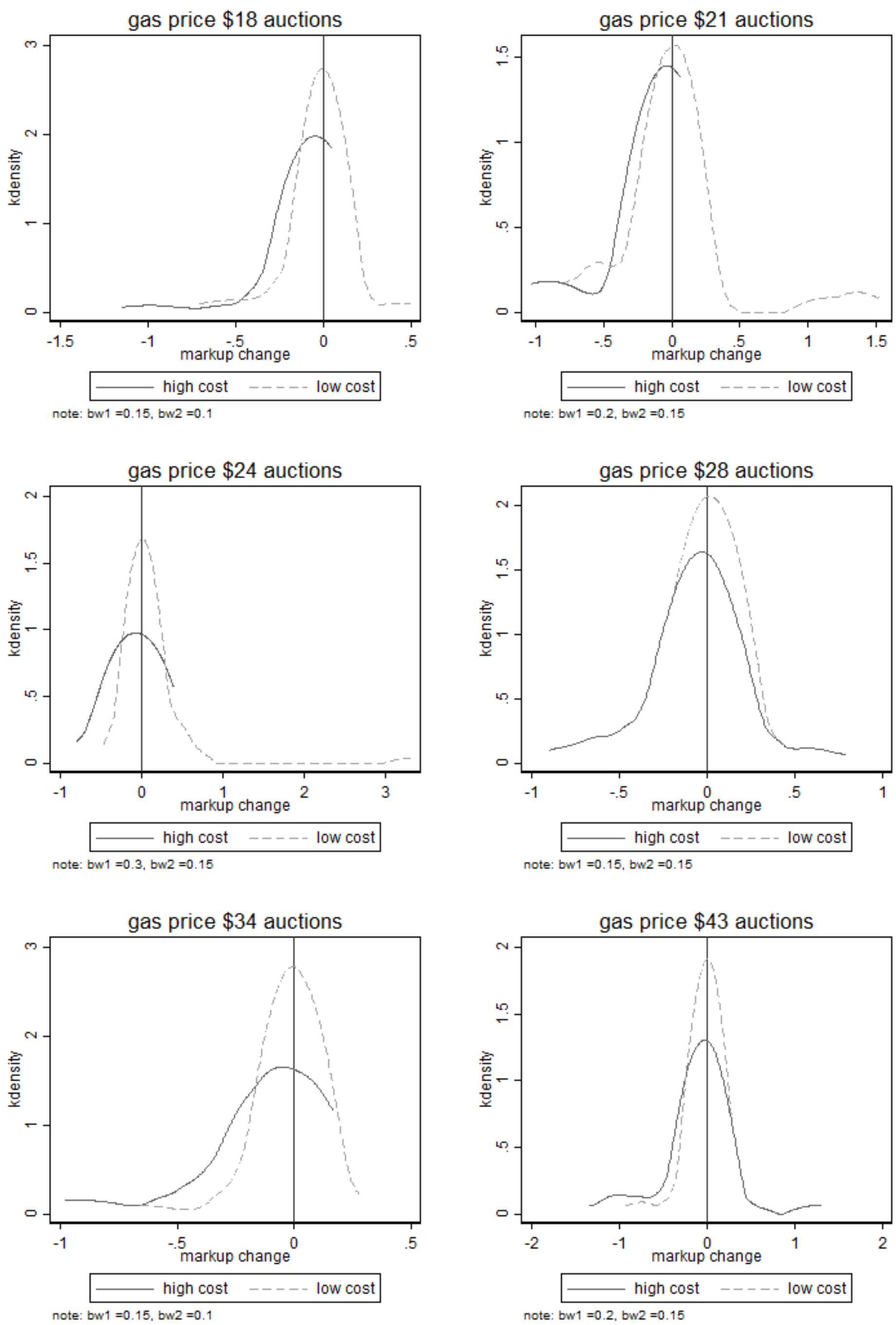

Figure A.2: High vs. Low Implied Gas Cost, By Gas Levels

A.2 Additional Tables

Number of Segments	Generator Count	Percentage (%)
1	166	54.43
2	21	6.89
3	39	12.79
4	23	7.54
5	28	9.18
6	2	0.66
7	3	0.98
8	5	1.64
9	4	1.31
10	14	4.59
Total	305	100

Notes: Number of segments is the total number of bid steps submitted by each generators in the sample. For example, total 166 generators, which account for 54.43 % of the entire generators in this market, submit bids that has only one step.

Table A.1: Summary of Steps of Bids Submitted in Day-ahead Auction

	ln(bidmarkup)		
	(1)	(2)	(3)
$ln(P_{gas})$	1.242***	1.290***	1.402***
$ln(P_{gas})$*ln(gas/oil)	-0.137***		-0.057
(\$15< P_{gas} < \$25)		3.514***	3.442***
(\$15< P_{gas} < \$25)*$ln(P_{gas})$		-1.382***	-0.929*
(\$15< P_{gas} < \$25)*$ln(P_{gas})$*ln(gas/oil)			-0.094*
(P_{gas} > \$25)		1.148	-1.920
(P_{gas} > \$25)*$ln(P_{gas})$		-0.613***	-0.611
(P_{gas} > \$25)*$ln(P_{gas})$*ln(gas/oil)			-0.053
constant	-0.458***	-2.210***	-1.851***
firm FE	o	o	x

Notes: Hourly bid markup estimates are averaged over hours to generate bid markup measures at a daily level. P_{gas} is the spot gas price index and *gas/oil* is the relative share of the gas capacity, i.e. $Q_{gas}/(Q_{gas}+Q_{oil})$ where Q_{gas} includes the capacity of dual gas units. Different levels of gas spot prices can be interpreted as difference sizes of daily gas price shocks.

Table A.2: Regression of Bid Markup on Log of Gas Spot Prices

A.3 Emissions Cost and Fuel Cost of Electricity Generation

A.3.1 Overview of Emissions Regulations in New England

Electricity generating firms in the Northeast region (e.g. New England) are regulated under the following programs: RGGI (Regional Greenhouse Gas Initiative), Acid Rain Program (under regulation of EPA NE), and CAIR (applied only to MA and CT).

Acid Rain Program implements emissions trading that primarily targets coal-burning power plants, allowing them to sell and buy emissions permits of SO2 and NOx. This program was replaced by Cross-state Air Pollution Rule (CSAPR) starting from year 2011, and the Northeast region (all states in New England) is exempted from this new regulation.

CAIR (Clean Air Interstate Rule) is a program that aims to reduce the Ozone level by suppressing SO2 and NOx emissions in 28 eastern states. This program was replaced by Cross-state Air Pollution Rule (CSAPR) starting from January, 2015. All states affected by this regulation choose to meet their emission reduction requirements by controlling power plant emissions through three separate interstate cap and trade programs: CAIR SO2 annual trading program, NOx annual trading program, and NOx Ozone season trading program. This program was temporarily reinstated until EPA could issue its new CSAPR rule. Ever since CSAPR was announced in 2010, permit price has dropped to zero and the allowances issued under this program will become invalid effective January 1st, 2012 (ICAPEnergy, Schmalensee and Stavins, 2013). Therefore, the only effective emissions regulation during the study period is the RGGI.

A.3.2 EPA's Regional Greenhouse Gas Initiative (RGGI)

RGGI is the first market-based regulatory program in the U.S. that aims to reduce greenhouse gas emissions.[1] All states in the New England region, along with NY and MD participate in this program. RGGI caps the CO2 emissions and the capped amount of emissions decrease every year. It requires fossil fuel-fired electric power generators with a capacity of 25MWh or greater to hold allowances equal to their CO2 emissions over a three-year control period. And then, the state allocate CO2 allowances via quarterly, regional CO2 allowance auctions. There were total 29 auctions so far (as of September, 23rd, 2015). Market participants can obtain CO2 allowances at the quarterly allowance auctions or in the secondary market, such as the ICE and NYMEX Green Exchange, or via over-the-

[1] More information available at RGGI.org

counter transactions.

A.3.3 Calculating the Emissions Cost

We can calculate the amount of CO2 produced per KWh for specific fuels and types of generators by multiplying CO2 emissions factor with the heat rate. Information of CO2 emissions factor (lb of CO2/MMbtu) is available from a Energy Information Administration (EIA).[2]

A.3.4 Calculating the Marginal Fuel Cost

The unit of the heat rate is MMBtu/MWh (millions of British thermal unit per Mega-Watt-Hour) and the unit of gas price is $/MMBtu. Hence, the marginal cost of gas-fired units is simply the heat rate multiplied by the gas price. The calculation of the costs of oil-fired units is a little complicated because spot oil prices are reported in $/gallon or $/barrel. In order to convert this price into a price per MMbtu, I divided spot oil prices by the heat conversion rate which is reported in EIA website (2013). According to the report, 1 gallon of oil is equivalent to 138,690 Btu for diesel fuel and heating oil, and 1 barrel of crude oil is equivalent to 5,800,000 Btu.

A.4 Dispatch Uncertainty and Gas Procurement Behavior of Firms

Although the bulk of natural gas trading occurs in the morning of the day-ahead market, natural gas can trade at different points of time both on the day before and during the operating day. The problem is that electricity bidding must be completed before the noon of day before the generation. The uncertainty in whether each unit will be dispatched in the market gives firms more incentive to hold on their gas procurement for some of their gas units with uncertain dispatch probability. Generators often acquire some additional gas after the day-ahead schedules are published, as well as during the day, or may wait until the final dispatch order to be released to purchase the gas. In this case, the bids they submit may have to be based on their estimate of gas prices at the time of the expected procurement, and the gas costs will vary across gas units depending on their usual dispatch orders.

[2] I used 2013 report of the emissions factor. Emissions factor is in other words, the emissions rate.

A.5 Treatment of Import/Export and Financial Bids

About 10 $\%$ of the New England's electricity demand is met by imports from Canada. Because the imported and exported amounts of electricity depend on the transmission constraint which I do not have data on, it is difficult to incorporate import/export bids into the model. Instead, I use the hourly net-interchange data, which is the final net flow into the grid measured by the difference in import and export. I subtract this from the total demand to generate the net demand that has to be met by the internal market supply.

On the other hand, financial bids accounts for a small portion of the day-ahead electricity transactions (about 1 to 5 $\%$), and these bids are not associated with physical assets. I compared the outcomes of having and not having financial bids in the model, and found no significant differences in the result. Despite this, I included financial bids in my main estimation, treating them as bids submitted by non-strategic, price takers.

A.6 Smoothing Supply Bid Curves, Residual Demand Curves and Weights

I follow the smoothing technique used in Wolak (2007) and Reguant (2013). Let firm i's unit j's step k bid to be $< b_{ijkh}, q_{ijkh} >$. Suppose the market clearing price at hour h is p_h. Then, the smoothed supply bid curve of firm i with the bandwidth bw is represented as below:

$$\widehat{Q}_{ih}\ (p_h, \mathbf{b}_{ih}) = \sum_{j \in J_i} \sum_{k} q_{ijkh}\ \mathcal{K}\big(\frac{p_h - b_{ijkh}}{bw}\big)$$

The smoothed residual demand curve of firm i with bandwidth bw is shown below:

$$\widehat{RD}_{ih}\ (p_h, \mathbf{b}_{-ih}) = D_h\ -\ \sum_{m \neq i} \sum_{j \in J_m} \sum_{k} q_{mjkh}\ \mathcal{K}\big(\frac{p_h - b_{mjkh}}{bw}\big)$$

Then the derivative of the residual demand curve is:

$$\frac{\partial \widehat{RD}_{ih}}{\partial p_h}\ (p_h, \mathbf{b}_{-ih}) = -\frac{1}{bw}\ \sum_{m \neq i} \sum_{j \in J_m} \sum_{k} q_{mjkh}\ \kappa\big(\frac{p_h - b_{mjkh}}{bw}\big)$$

Finally, the expression of the weights (ex-ante probability of setting the market price) that appear in the first-order condition is shown below (Wolak, 2007):

$$\frac{\partial p_h}{\partial b_{ijkh}} = \frac{\partial \widehat{Q}_{ih}(p_h)}{\partial b_{ijkh}} \Big/ \Big(\frac{\partial \widehat{RD}_{ih}(p_h)}{\partial p_h} - \frac{\partial \widehat{Q}_{ih}(p_h)}{\partial p_h}\Big)$$

A.7 More on *High Impact* Categorization

Daily implied gas price distribution changes across days in the sample, hence the location of a firm on the distribution changes across days as well. When constructing the daily distribution of firm-specific implied gas prices, I used weighted-average implied gas price for those firms that operate multiple gas units because the levels of implied gas prices differ even across gas units operated by the same firm. I generated a firm-specific average implied gas price that is weighted by the quantity bids (capacity) of each of their gas units. Thus, the average implied gas price measures the on average exposure to the gas price shock. For example, a firm that operates mostly dual gas units would have firm-specific average implied price measure smaller than that of others, indicating that the firm's impact from the gas price shock is smaller than others.

A.8 Selection of Unit-Specific Price Bids to Use in the Bid Markup Analysis

If most of the generating units submit single step ($k = 1$) bids, the price bid of the first step can be used to measure firm-level bid markup. However, if a unit submits multiple steps of supply bids, which step to use to measure the bid markup is not straightforward. To tackle this problem, I used the quantity-weighted price bids that are often reported and used in markup calculations in multi-unit auction literature (Wolfram(1999); Cassola et.al (2013); Ryan(2015)). This measure basically takes an average value of price bids of multiple price bid steps submitted by each generating unit, where each price bid values are weighted by the quantity bid values of each step. Expression of this weighted price bid is shown below:

$$b_{ij} = \frac{q_{ij1} * b_{ij1} + q_{ij2} * b_{ij2} + \ldots + q_{ijK} * b_{ijK}}{\sum_{k=1}^{K} q_{ijk}}$$

Because I included all steps below (and equal to) the step l with the highest weight when generating b_{ij}, i.e. $k \leq l$, the total number of step K is equal to l.

As a robustness check, I also generated bid markups using (1) the price bid of the step that has the highest (probability) weight and (2) the price bid of the unit that has the highest marginal cost among others. All three specifications give qualitatively similar results.

A.9 Different Perturbations Used in Markup Simulations

Instead of giving the same size cost perturbations, e.g. 10 cents, to all the impacted gas units, I tried different sizes of perturbations by weighting the 10 cents gas price increase with the actual impacts gas-fired units received. For example, if the gas price index of the day is $20/MMbtu and a unit's implied gas price is $ 18/MMbtu, I gave gas price shock of size $(18/20) * 0.1 = 0.09$ (9 cents) which is equivalent to a cost increase of $hr * 0.09$. This types of perturbation incorporates the heterogeneity in implied gas prices across firms and units.

A.10 Ex-ante First-Order Conditions

Bids of competitors that are realized in the auction in ex-post is not the information that a firm had used when optimizing in ex-ante: firm chooses its optimal bid based on its expectations of competitors' bids. To tackle this, I exploited the similar resampling technique used in the parameter estimation and constructed an average supply offer curve from the set of resampled supply offer curves. This average curve mimics the supply offer curve the firm expected in ex-ante. The following steps – perturbation of average curve and measurement of endogenous markups– are implemented separately for each firm, because each firm has different ex-ante expected supply offer curve as they have different set of beliefs of others' bids. This method is a slight extension of Fabra and Reguant (2014)'s first order approach simulation where they perturbed ex-post realized bids for the simulation.

I used random day-firm bids resampled from the pools of 6 similar days and 3 similar days. The results reported in this paper are based on 3 similar day random draws. Because it is practically hard to take an average of multiple curves, I instead took a weighted average of the implied markups obtained from the perturbation of the each resampled supply curve. The weight used is the probability of setting the price, $\frac{\partial p_h}{\partial b_{ijkh}}$

For example, firm i's markup response was simulated in a following way. I used S number of random draws of other firms' bids from 3 similar days pool, while fixing firm i's bid to the ex-post realized bid. I then perturbed the S supply curves and obtained endogenous markup changes for each perturbation, i.e. Δmarkup_s for $S = 1 \ldots S$. I The weighted average endogenous markup term is generated with Δmarkup_b, weighted by $\frac{\partial p_h}{\partial b_{ijkh}}$.

A.11 Markups Plotted by Fuel Types of Marginal Units

In the empirical section of this paper, I plotted distributions of markups separately by "gas-intensive" and "non-intensive" groups. The grouping was based on the percentage of gas generation out of the total generation capacity of each firms.

A firm's incentive to adjust markups is affected by how much the cost of its marginal unit increases relative to units of competing firms. To verify this, I plotted the simulated markups by fuel types of marginal units of firms. That is, I grouped firms into those having (1) gas-fired unit (2) gas dual unit and (3) oil-fired units as marginal units, and plotted markups separately for each group. Under gas price shocks, gas-fired units that are not dual generators, grouped into (1), experience the highest increase in their generation costs, followed by gas dual units and oil-fired units.

Figure A.3: Markups by Fuel Types of Marginal Units

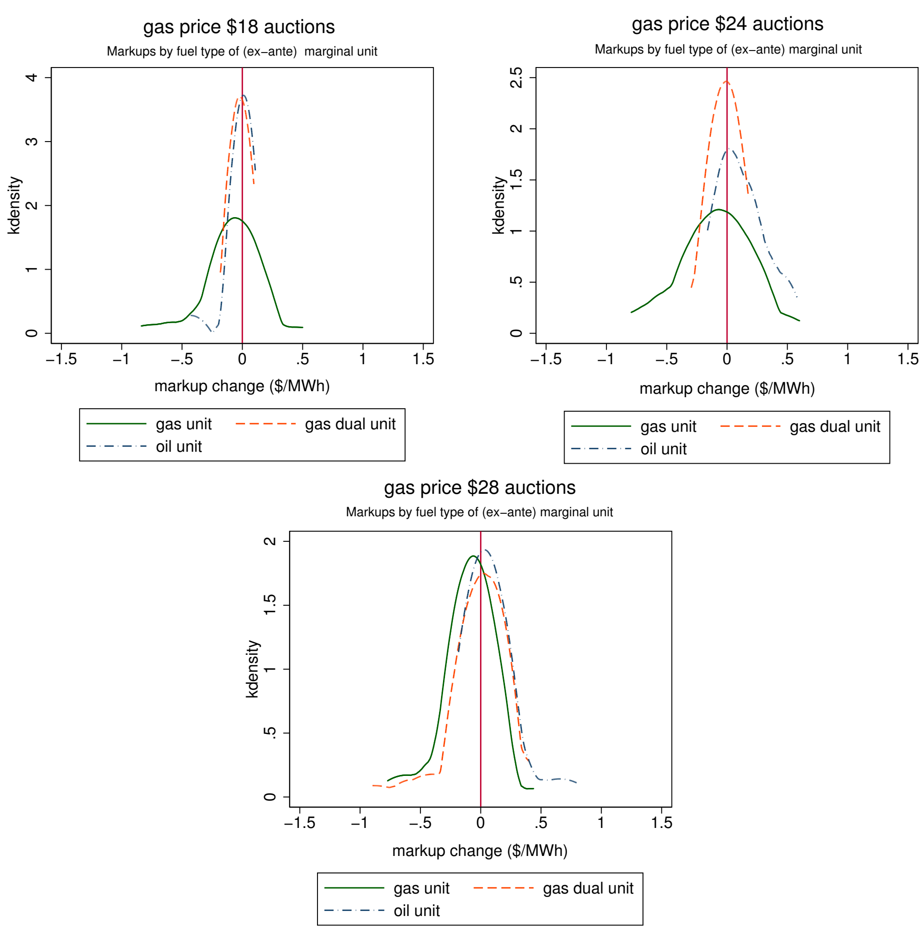

Figure A.3 shows the distributions of markups for days when gas prices were $18, $24, and \$28, respectively. Overall, the shape of the distribution is similar to those with gas-intensive firms grouping. This is because if a firm is categorized into a more gas-intensive firm group, the firm is more likely to have a highly impacted gas-fired unit as a marginal unit. Also, the relative locations of distributions of each fuel type groups correspond to the conjecture; having a unit that is highly impacted by the cost shocks as a marginal unit leads to adding markups that are lower than markups of other firms that have less impacted units as marginal units. For example, distributions of gas dual units and oil unit groups in the gas \$24 auctions panel of Figure A.3 are located to the right of gas unit group's distribution, on average. This pattern is consistent across all panels as well. In sum, regardless of the grouping of firms we use to plot the simulated markups, distributions of markups confirm our conjecture about the relationship between impacts on costs and markup adjustments.