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

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Abstract

Recently, a series of natural gas price shocks in New England, which affected electricity generation costs of firms heterogeneously, led to a spike in electricity prices. I study the pass-through implications of the change in the competition between firms resulting from this gas price shock, focusing on the heterogeneous impacts of the shock. I use New England electricity auction bidding data and utilize the multi-unit uniform auction model to estimate gas prices implied by firms bids, which allows me to identify the impacts of the shock on the costs of each firm. To understand how differences in impacts affected the competition, I obtain firm-specific markups and relate them to costs. I find that firms less affected by the shock increase markups more than "hard-hit" firms, and this difference in adjustment increases in the size of the gas price shock. To explore how such heterogeneous incentives for markup adjustment are reflected in price, I then simulate the pass-through rates at the auction level. Although I find that firms completely passed on the cost shocks to prices on average, considerable variation exists in the rates depending on which type of firm sets the price in the auction. Therefore, any estimation of the pass-through rate that fails to incorporate heterogeneity of the underlying rates could yield estimates that are significantly biased downward. I illustrate this by comparing the simulated rates to the estimated ones from the reduced form.

Keywords: Electricity markets, Auction, Pass-through
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1 Introduction

In the winters of 2013 and 2014, severe gas pipeline congestion in New England caused a series of exogenous natural gas price shocks. These shocks led to significant increases in electricity prices in this region because the gas price shock is an input cost shock to electricity generating firms. One important feature of the gas price shocks to the New England electricity market is the heterogeneous impact of the shock across firms on the cost of electricity generation, caused by the differences in firm-specific characteristics. For instance, if a firm does not operate gas-fired generators, or has the option to switch its production to other generators that use cheaper fuels, its cost will be unaffected, or affected less, by the shock compared to other firms. Thus, firms may experience varying degrees of cost increases from the shock depending on their characteristics, which are considerably different across firms in the New England electricity market.

Two questions arise upon observing this incident: How much of the cost increase caused by the gas price shock was passed on to electricity prices, i.e., pass-through; and how does the heterogeneous feature of the cost shock affect my analysis of pass-through? This paper therefore studies the pass-through of the gas price shock to electricity prices in the New England electricity market, focusing particularly on the heterogeneous impacts of the shock to the costs of firms. The heterogeneity of the impact is important in this context because of the markup adjustment channel. That is, by increasing the costs of firms to different levels, the shock induces the firms' strategic markup adjustment, which is an important determinant of pass-through. Therefore, I study pass-through by first examining how the heterogeneity of the cost impacts affects competition between firms in this market, using a detailed analysis of the changes in costs and markups in a structural model set up. I then examine how these changes in costs and markups are reflected in the pass-through rate, and show that the pass-through rate is inaccurate – and in this case, underestimated – if the existing heterogeneity in the impacts and the resulting markup channels are not carefully accounted for in my estimation.

Simple economic intuition explains the link between cost shock, markups, and pass-through. The extent of cost pass-through is determined by how much and in which direction firms adjust markups in addition to the cost shock. Of considerable importance to a firm when making a strategic decision in response to a cost shock is whether its costs increase by more or less than its competitors'. With homogeneous impacts, which was the case of the emissions cost shocks in Fabra and Reguant (2014), firms did not have incentives to adjust markups, which explains the complete pass-through they find. However, with heterogeneous impacts, I expect to see changes in the strategic incentives of firms. Firms that experience an increase in costs smaller than others have the incentive to raise markups, while highly-impacted firms that experience a large increase in costs may decrease markups in order to compete with the less-impacted firms. Examining the resulting pass-through rates in this case is not simple, and must be based on a correct assessment of the changes in costs and markups.

I first start by empirically identifying the heterogeneity of the shock's impact on costs. The empirical challenge is such that to show how the opportunity costs of firms increase in different

ways due to a shock, detailed information on the firm- and generator-level costs is required, which is difficult to get from the data. For example, a specific type of generator, a dual unit, can switch its fuel from gas to oil when gas prices surge so that its generation cost does not significantly increase. However, a dual unit's fuel switch decision at the time of production is typically unobserved, which makes it difficult to measure its opportunity cost from the data. To overcome this challenge, I estimate costs from bids submitted by firms in wholesale electricity auctions, utilizing the methodologies developed in the empirical auction literature. Since electricity generating firms participate in daily auctions to sell electricity, high-frequency bid data is available in this market. I develop a multi-unit uniform auction model similar to Reguant (2014), in order to estimate a generator-level marginal cost that is revealed in firms' bids.

The non-standard element of cost estimation that is useful in the electricity market setting is that I back out the gas price component of the marginal cost, which I define as the implied gas price. The marginal cost of generating electricity using gas is comprised of (i) the price of gas which is affected by the shock, and (ii) the physical efficiency (heat rate) of a generator that is invariant to the shock. Exploiting this feature, I first estimate heat rates from sample days without the shock and use these to separately back out the implied gas price from the marginal cost estimated from sample days when there was a shock. The variation in implied gas prices across firms and units, therefore, shows a clearer picture of the heterogeneity of the impact resulting from a gas price shock alone. I also use the implied gas prices of dual units to identify their fuel switch decision, which is an important source of heterogeneous impacts. From the estimates, I document substantial heterogeneity in the impact of the shock on firms' costs, and find that heterogeneity in the impact increases as the market is hit by a more intense, that is, a larger, gas price shock.

I then obtain firm-level markups and auction-level pass-through rates, accounting for the identified heterogeneous impacts on costs. I conduct a simulation that builds on the first-order approach (Jaffe and Weyl, 2013) so as to obtain firms' markup adjustments in response to a counterfactual unit-size cost shock. The advantage of using simulation is that I can control for every other factor except for the shock, in order to simulate the adjustments in markup that result from the shock alone. Using this method, I can also simulate by how much the price of each auction increases after a unit-size cost shock is imposed, which I interpret as the auction-level pass-through rate. This model-implied, simulated pass-through rate accurately reflects the firm-level differences in the responses of costs and markups to the shock.

From the analysis of simulated markups, I find that markup adjustments constantly depart from zero as the heterogeneity in the impact of the shock increases, implying that the heterogeneous feature of the shock changes the strategic incentives of firms. However, the pattern of adjustment differs across firms: the "hard-hit" firms, the costs of which are affected more by the shock, added markups that are smaller and more negative than those of "not-hard-hit" firms. Interestingly, adjustment patterns across hard-hit and not hard-hit firms become more distinct as the overall size of the shock increases. While gas units compete with nearby gas units when the shock is small, they now compete with both gas and oil units when the shock is sufficiently large that it pushes the cost

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of gas units closer to that of oil units. In this case, the hard-hit firms that are more gas-intensive in their generation face more intense competition than with a small shock, which they manage by further lowering markups.

Since a uniform auction is used in this market, the markup adjustment of a single price-setting firm, the identity of which varies across auctions, is relevant for pass-through. Reflecting different firm-level incentives to adjust markups, the simulated auction-level pass-through rates are also heterogeneous. I find that pass-through rates are lower in auctions where a hard-hit firm which is not capable of adding large markups to raise the price, is a price setter, than in auctions where less-impacted firms set the price. Despite the cross-auction dispersion, the mean of pass-through rates is 97 percent, implying a near complete pass-through of cost shock to electricity prices, on average.

To show the importance of incorporating heterogeneous impacts and the underlying strategic incentives of firms into this pass-through estimation, as a comparison, I conduct a reduced form regression that does not properly account for these impacts and incentives. I regress electricity prices on the cost variable measured with aggregate data, the gas price index, which does not correctly represent the cost of each firm, and is thus not precise enough to reflect cost differences across firms. I find that the pass-through rate is underestimated – close to 50 percent, on average – compared to the almost complete (97 percent) pass-through rate obtained from the simulation. Underestimation results because the costs of low-impacted firms, which take up a large proportion of price setting firms in this sample, are measured to be higher than the actual value. As a result, while the substantial portion of price increased by these low-impacted firms results from markup adjustments, the näive regression that uses imprecise cost measures misleadingly attributes the price increase more to the increase in costs, thereby underestimating the pass-through rate. However, I also show that when using the implied gas prices instead, which capture the heterogeneity, the reduced-form pass-through estimate is again close to complete.

The findings of this paper have important implications for the studies of market power and cost pass-through, both of which are related. First, this paper provides an interesting view of cost shocks as a source of market power in the electricity market. Using a structural analysis of markups, I show that certain shocks, if transmitted heterogeneously across firms' costs, can change the way firms compete, making some firms capable of exercising market power. Because of these complicated changes in strategic incentives caused by a shock, a reduced form relationship of prices and costs observed from the data may not reveal the true picture of market competition unless carefully executed, which I show with a näive pass-through estimation. Therefore, trying to infer market structure from a pass-through estimate may be misleading, especially when heterogeneous impacts of the cost shock are suspected. Finally, significantly underestimating the pass-through rate that I obtain when not properly accounting for the heterogeneity has some implications on the empirical pass-through literature. My findings suggest that non-careful implementation of the estimation, especially regarding the measurement of cost shock, could lead to finding incomplete pass-through that currently prevails in the literature. Strikingly, such underestimation disappears

once I use the cost information extracted from the structural model in my regression. This finding highlights the importance of understanding the features of the shock, as well as the firms and the industry to which the shock will be transmitted, when conducting pass-through estimation.

Related Literature   This paper is in line with papers that study market power in electricity markets that consider forward contracting (Bushnell et al., 2008), transmission constraints (Borenstein et al., 2000; Ryan, 2014) and dynamic cost (Reguant, 2014) as factors that affect competition among firms in the electricity market. Regarding methodology and the industry being studied, my paper is closest to Fabra and Reguant (2014) which studies the pass-through of emission cost shocks in the Spanish electricity market. Pass-through is also actively studied in the exchange rate pass-through literature (Nakamura and Zerom, 2010; Goldberg and Hellerstein, 2013; Amiti, Itskhoki, and Konings, 2014). The concept of heterogeneous impacts introduced here is similar to the non-traded cost that is found to be the primary source of incomplete pass-through, in Goldberg and Hellerstein (2013). My paper differs from theirs in that I focus more on how the presence of the part of the cost that is irresponsive to the shock induces strategic incentives of firms, and its relation to the pass-through.

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

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 shows an increase in gas spot prices at one of the major citygate 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

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[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, Massachusettss 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
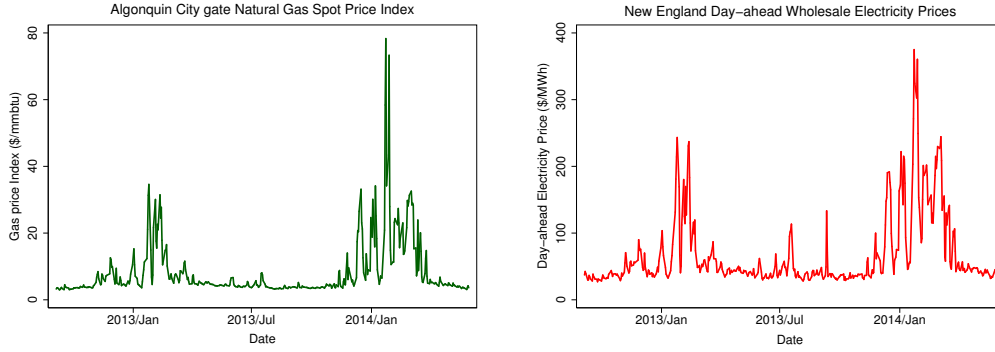
(a) Gas Spot Price Index　　　　(b) Wholesale Electricity Prices

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: Daily Natural Gas Spot Price Index and Day-ahead LMP

$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 occured; the index level reached $30/MMBtu in Februrary 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, 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

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 Tenessee 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.

[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 Janurary of 2014. Also, no significant demand shocks occured 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.

| | Generation Capacity (MWh) | | | | | | |
Firm	Total	Gas	Oil	Gas/Oil	Coal	Hydro	Nuclear
Exelon	4747	3300	267	1179	0	0	0
GDF Suez	2649	1210	22	0	124	1293	0
Dominion	2607	0	0	510	0	0	2097
NRG	1985	0	1383	603	0	0	0
EquiPower	1880	1880	0	0	0	0	0
TransCanada	1210	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)

Table 1: Generation Mix Differences: Major Firms

shock which shows to what extent the cost shock was passed on to output 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.

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 pre-existing 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.

Generation mix differences   Electricity generating firms in New England have different generation portfolio compositions. Table 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 signifi-

cantly 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 MWh 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 units. For example, Table 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.

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 (Indendent 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.

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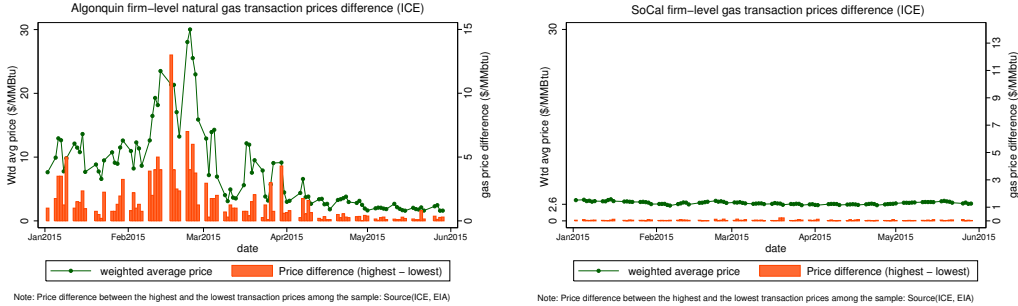
<table>
<tr><td>(a) Algonquin citygate</td><td>(b) SoCal citygate</td></tr>
</table>

Notes: Data source is over-the-counter individual transaction-level gas spot prices at two citygate 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.

Figure 2: Over-The-Counter Gas Spot Prices: Year 2015

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.[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.

Other sources: long-term contract and spot gas price volatility 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] 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

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[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 purchase.(EIA-923)

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 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 citygates, Algonquin and SoCal, are plotted against time.[8] Algonquin is a citygate in New England where severe gas price shocks occurred in the winter (Jan. - Mar.) due to pipeline congestion, whereas SoCal is a citygate in California without any pipeline congestion. Large dispersion in Over-the-counter gas prices in New England compared to an absence of dispersion 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]

2.3   Data vs. Estimation: 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

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[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.

[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.

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 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.

3   Strategic Responses to Cost Shocks: Markup Adjustments

Strategic markup adjustments in auctions   A firm's incentive to increase or decrease markups in the presence of cost shock is affected by several factors including the (1) shape of the demand curve (2) cost shock of the firm (3) cost shocks of competitors, and (4) nature of competition among firms.[12]

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[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.

[11]The ICE over-the-counter gas price data which I used to generate graphs in Table 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.

[12]The list of these factors is taken from Fabra and Reguant (2014).

While, in general, we must consider all these factors to understand strategic incentives of firms, we can rule out the demand side channel (factor (1)) in our study of wholesale electricity market because the demand for electricity in this market is considered almost completely price inelastic. Inelastic demand results because the demand side auction participants, who are the load-serving companies, 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 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.

Heterogeneous impacts at the margin   I use a simple example to explain the intuition behind how having heterogeneous (rather than homogenous) impacts on their costs gives firms incentives to adjust markups. Here, I consider firms, and electricity generating units of them that are close to setting the price of the auction (marginal unit) because strategic manipulation of price bids occurs only when a firm has an *ex-ante* positive chance of setting an auction price.

Figure 3 provides a graphical illustration of the situations where different types of shocks are given to the price bids of three units, A, B, and C. Units A and B are owned by firm 1, and unit C is owned by firm 2. Suppose that currently firm 1 is a price setter where the price bid of its unit B intersects with the market demand curve (not shown in the graph). Firm 1 faces competition from firm 2 that tries to underbid unit B to make its unit C to be the price setter and be accepted in the auction. Bold lines show the distribution of price bids before the shock where firms have already optimized, and colored lines are the price bids adjusted by the size of the cost increase following the shock. 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 3 illustrates a situation where all three units are affected homogenously by a shock; the price bid of each unit increases by equal size cost shock. In this case, distribution of bids (slopes of supply-offer curves) after the shock is the same as the one before the shock, implying that firms lack further incentives to adjust their markups in response to the shock.

Panels (b) and (c) illustrate a different situation where costs of firms are affected heterogeneously by the shock. First, in panel (b), the cost increase of unit B is larger than that of unit C. In this case, firm 1 has an incentive to raise the price bid of its marginal unit B further by adding a markup over the cost increase, without losing its current position as a price setter. This is possible because firm 1 understands that competitor (firm 2) will have to raise price bid of unit C at least by the size of its cost increase that is larger than the cost increase of firm 1s unit B. On the other hand,

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[13]Load serving companies are those that sell and deliver electricity to retail consumers. They have obligations to meet the (forecasted) demand which makes their demand in the wholesale market to be almost perfectly inelastic.

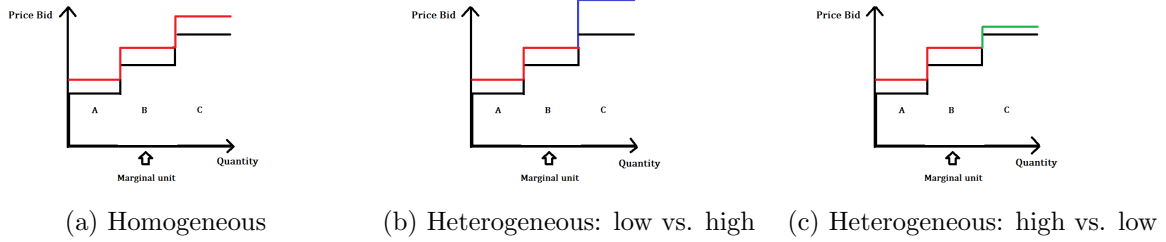(a) Homogeneous   (b) Heterogeneous: low vs. high   (c) Heterogeneous: high vs. low

Figure 3: Graphical Illustration of Different Types of Cost Shocks

Firm 1 has different incentives in the situation illustrated in Panel (c), where unit B's cost increases by more than that of unit C. Unit B faces a tradeoff because if it increases the bid too much, the dispatch orders of units B and C may be reversed and unit B may not even be accepted in the auction.[14] Now, firm 1 has incentive to add zero or negative markups to avoid this and secure the dispatch of its marginal unit B.

We can extend this logic by using residual demand to the case of multiple firms. In general, a firm's incentive to adjust markups - either raising or lowering- depends on the changes in the slopes of residual demand curve 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 incentive to adjust markups. The steeper (more inelastic) that a curve becomes, the greater the ability of a firm to raise markup. Exactly to what extent markups are adjusted is an empirical matter.

Size of the shocks: different impacts across fuel types   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 increases the marginal costs of gas units only.[15] Note that the sizes of gas price shocks differ across days in the sample depending on the extent of pipeline congestion of each day. As shown in Figure 4, spot prices of other fuels – coal and oil – do not change with the shock while the spot price of gas fluctuates due to different sized shocks.

Without the shock, gas prices are around $4/mmbtu, which is substantially lower than oil prices that range between $18/mmbtu and $22/mmbtu. Such difference in fuel prices makes marginal costs of electricity generation to differ across fuel types. Unless the gas price shock is large enough to make the daily gas price to exceed the level of oil price, marginal costs of generating with gas is smaller than that of generating with oil. When the size of the gas price shock is small, or the shock does not exist, gas unit competes with other gas units that have marginal costs close to its own.

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

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[14]Markup adjustments considered here is the additional changes in markups in response to the shock, which will be added over the existing bid markup of each firm (and unit) that is a non-negative value. If a firms unit is not accepted in the auction, firm forgoes positive bid markups that could have been earned from the lost unit, which leads to a loss in its profit.

[15]Since the cost of coal units is below the cost of gas units regardless of the size of the shock, competition between coal and gas units is not the main consideration here.
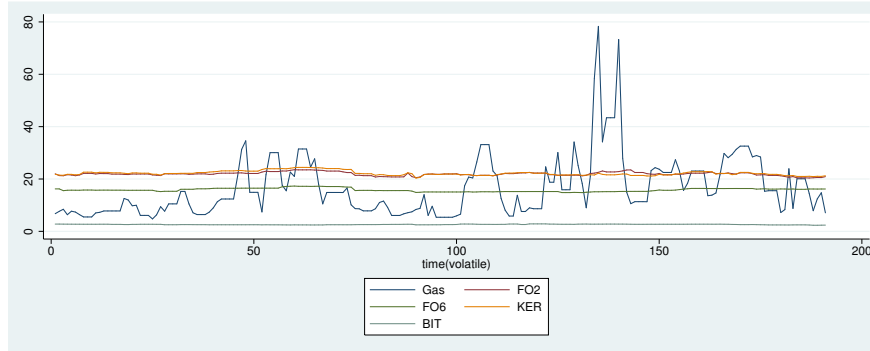
Notes: The graph above shows the spot prices of each fossil fuel over the period of days when gas price shocks were present. For gas price, I used daily day-ahead Gas Spot price *index* at Algonquin citygate (source: NGI, SNL), and prices of petroleum liquid (FO2, FO6, KER) and coal (BIT) are the daily spot price index taken from EIA and SNL. Price indices are converted to \$/MMBtu.

Figure 4: Spot Fuel Prices of Days when Gas Shocks were Present

and oil units. This happens when the post-shock gas price lies within the price range of \$18/mmbtu and \$22/mmbtu. In this case, a gas marginal unit is surrounded by and must compete with dual and oil units whose costs are relatively impacted less and unaffected by the shock. Thus, gas units are likely to be in a situation shown in Panel (c) of Figure 3, where the gas unit (unit B) has an incentive to add markups smaller than before (of zero or negative value) to behave competitively.

On the other hand, an increase in the overall size of the shock gives oil and dual units incentives to add markups that are larger than before, because now they compete with gas units whose costs are affected hard by the shock. This is similar to a situation depicted in Panel (b) of Figure 3. Moreover, the chance of dual and oil units becoming the marginal price setting unit increases with the size of the shock as well, giving them incentives to behave more strategically under cost shocks. High-cost dual and oil units are able to set the price in the auction more often when the shock's size is large, because an increase in the marginal costs of gas units results in higher market clearing prices.

4   Institutions and Data

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.[16] In this paper, I focus entirely on the generation side of the market, i.e.

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[16]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.

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

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).[17] 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 B.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.

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

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[17]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.

by finding the price at which aggregate supply and demand curves intersect, accounting for the transmission constraints and other dynamic cost parameters.[18] 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.[19] 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.

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.[20] 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.[21] 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 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

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

[19]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.

[20]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.

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

year.[22]

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.

5   Model and Empirical Strategy

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 $i = \{1, \ldots, N\}$ 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 $j = \{1, \ldots, J_i\}$. 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 $k = \{1, \ldots, 10\}$. Therefore, bids submitted for firm i's unit j of segment k at hour h is $< b_{ijhk}, q_{ijhk} >$.[23]

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.[24] Given this market clearing price, firm i's (ex-post) profit function is shown below:

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

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

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[22]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.

[23]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}.

[24]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.

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(2) shows the maximization of the expected profit. Notice that the expectation is taken over the belief of the bids of other firms, $\widetilde{\mathbf{b}}_{-i}$:

$$\max_{\mathbf{b}_i} \ \mathbb{E}_{-i}[\ \pi_i(b_i, \widetilde{\mathbf{b}}_{-i})\ ] \tag{2}$$

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 (3) is the final first-order condition that will be used for the estimation.

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

$$\Leftrightarrow\ \ \mathbb{E}_{-i}\left[\frac{\partial P_h}{\partial b_{ijkh}}\ \big[\ (Q_{ih}(P_h) - \nu_{ih})\ +\ \big(P_h - C'_{ij}(Q_{ih}(P_h))\big)\ \frac{\partial Q_{ih}(P_h)}{\partial P_h}\ \big]\right] = 0 \tag{3}$$

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 dyanamic 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.[25] Despite this, I tried estimating with different cost specifications as a robustness check, by specifying quadratic and ramping cost terms.[26]

I assume forward contract size to be the percentage of their expected hourly output, following Reguant (2014).[27] 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

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[25]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.

[26]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.

[27]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.
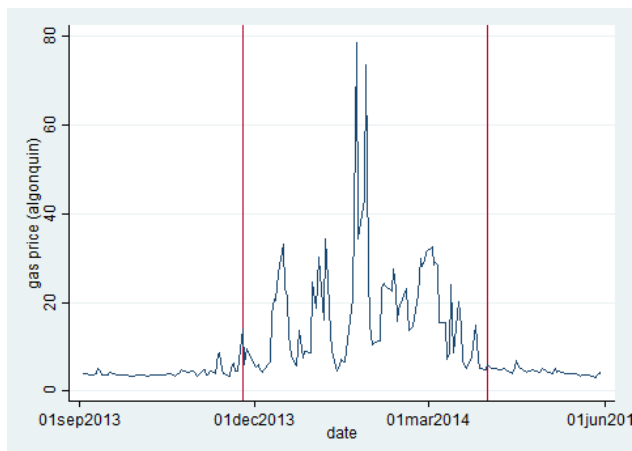
Notes: Days in between red lines are part of Sample 1 which is a collection of days when gas price shock was present. Days outside of red lines are part of Sample 0 where gas price shock was not present.

Figure 5: Illustration of Sample 0 (stable) and Sample 1 (volatile)

section.

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

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 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,

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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 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.

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.[28] Equation (4) shows the decomposition of day t's marginal cost of unit j of firm i:

$$mc_{ijt} = hr_{ij} \left(FP_{ijt} + \tau_t \, e_{j,fuel} \right) \tag{4}$$

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(4) enters the first-order conditions of both sample 0 and sample 1, differernt 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(4). Heat rate represents the physical efficiency of a generating unit in converting fuel to electricity; heat rate is invariant to any shocks or changes in

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[28]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).

market conditions.[29] 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 (4).[30] In sum, here I am implicitly assuming that;

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

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 (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:

$$mc_{ijt} = \mathbf{hr}_{ij} \left(FP_{index} + \tau_t \, e_{j,fuel} \right) \qquad\qquad t \in \text{Sample 0} \qquad\qquad (5)$$

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 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 (4).

There are several advantages of using the implied fuel price over using the marginal cost term, particulary for gas-fired units. Firstly, implied gas price estimates allow me to identify the actual

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[29]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 fastly, which I do not consider in my model.

[30]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 furture 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.

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(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.[31] Therefore, the invariance of heat rate across Sample 0 and Sample 1 is the key feature that enables extraction of implied fuel price. The equation(6) below shows the marginal cost expression for Sample 1, where the implied fuel price parameter is shown in boldface type:

$$\widehat{mc_{ijt}} = \widehat{hr_{ij}} \left(\mathbf{FP}_{ijt} + \tau_t \, e_{j,fuel} \right) \qquad\qquad t \in \text{Sample 1} \qquad\qquad (6)$$

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

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[31]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 fastly, 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 2: Resampling Procedure

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.

5.3 Estimation

Resampling: treatment of the expectation term For the estimation, I need to derive an empirical analogue of the first-order condition shown in equation (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 assymmetries 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.

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 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.[32] Functional forms of the smoothed residual demand and supply offer curves are provided in the Appendix.

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:

$$m_{ijkht}^T(\theta_{\mathbf{T}}\,; bw, S) = \frac{1}{S} \sum_{s=1}^{S} \frac{\partial \widehat{P_{ht}^s}}{\partial b_{ijkht}} \Big((Q_{ikht}^s - \nu_{iht}(\gamma_{ih})\,) \; + \; (b_{ijkht} - mc_{ijt}\,) \frac{\partial \widehat{RD_{iht}^s}}{\partial P_{ht}} \Big) \qquad (7)$$

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 (8) and (9):

$$\sum_{t=1}^{T} \sum_{k=1}^{K} Z'_{0,ht} m_{ijkht}^0(hr_{ij}, \gamma_{ih}) = 0, \quad \forall j, h \qquad (8)$$

$$\sum_{h=1}^{H} \sum_{k=1}^{K} Z'_{1,ht} m_{ijkht}^1(mc_{ijt}; \hat{hr}_{ij}, \hat{\gamma}_{ih}) = 0, \quad \forall j \qquad (9)$$

5.4 Identification and inference

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}

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[32] 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.

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.[33]

To understand from which variations the parameters are identified, I provide a simplified version of the first-order condition below.[34]

$$b_{ijkth} = hr_{ij}(FP_{ij} + \tau e) + \frac{Q_{ijkth}}{RD'_{ith}} - \frac{\gamma_{ih}Q_{ith}}{RD'_{ith}} \tag{10}$$

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.[35]

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.

6   Estimation Results

6.1   Heat rates and forward contract estimates

In Table 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 dual units is 11.01.[36] Note that heat rates estimated from the model does not necessarily have to equal the

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[33]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.

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

[35]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.

[36]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 technolgy at then was inefficient steam turbine, dual units in my sample tend to be old and thus inefficient than other gas generators.

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.[37]

Fuel	Average of unit-specific heat rates (MMbtu/MWh)
Gas units	9.09
Oil units	12.39
Dual units	11.01

Notes: Estimated unit-specific heat rates are averaged within each fuel type categories: gas, oil, and dual gas units. *Gas units* sample excludes gas units that have dual technology installed.

Table 3: Heat Rate Estimates

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.

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.

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 estimated 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 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

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

Marginal Cost Estimates by unit's fuel type
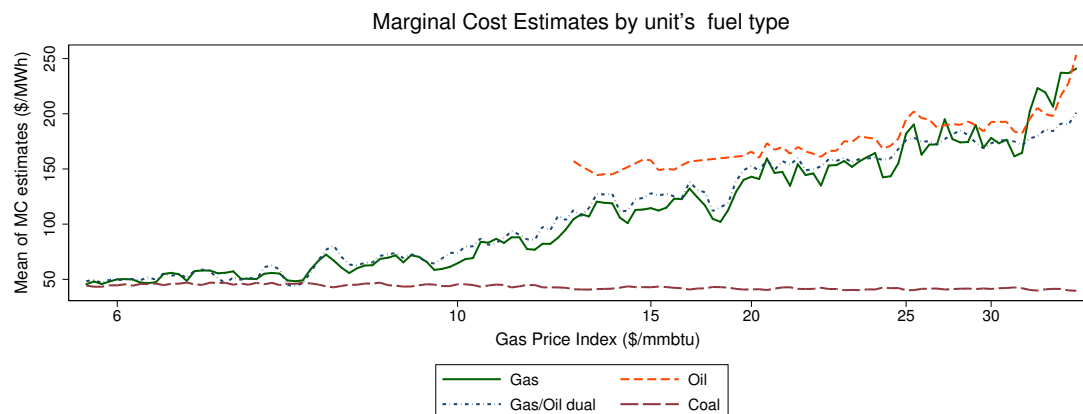
Note: three period moving average taken to smooth lines

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.

Figure 6: Estimated Marginal Generation Costs by Fuel Type: Averaged across Firms

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.[38] 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.[39] Also, 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 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.

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

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[38]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.

[39]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 threshold.

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 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 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 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[40]. Figure 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 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
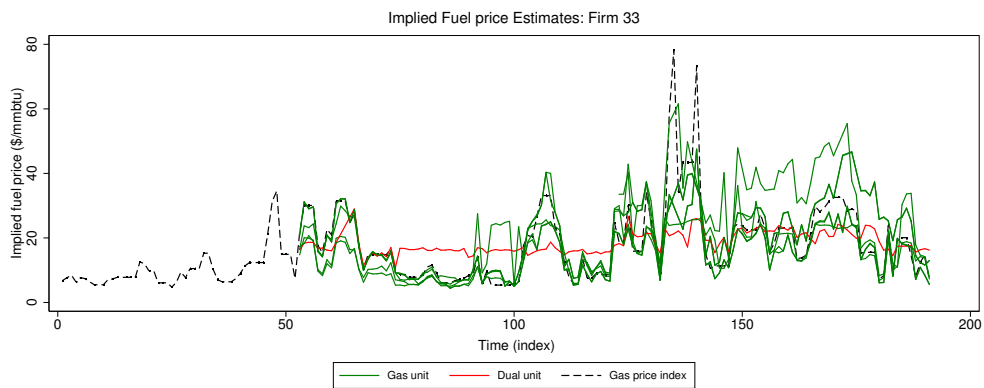
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[40]Only for those units with heatrate estimates and volatile sample marginal cost estimates
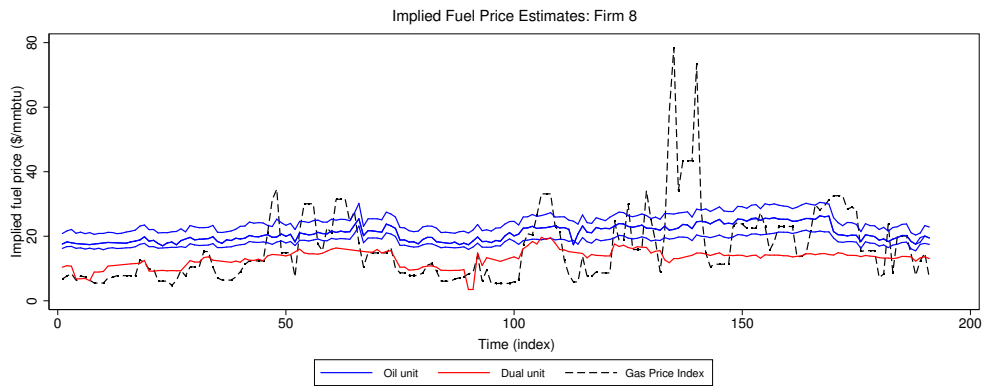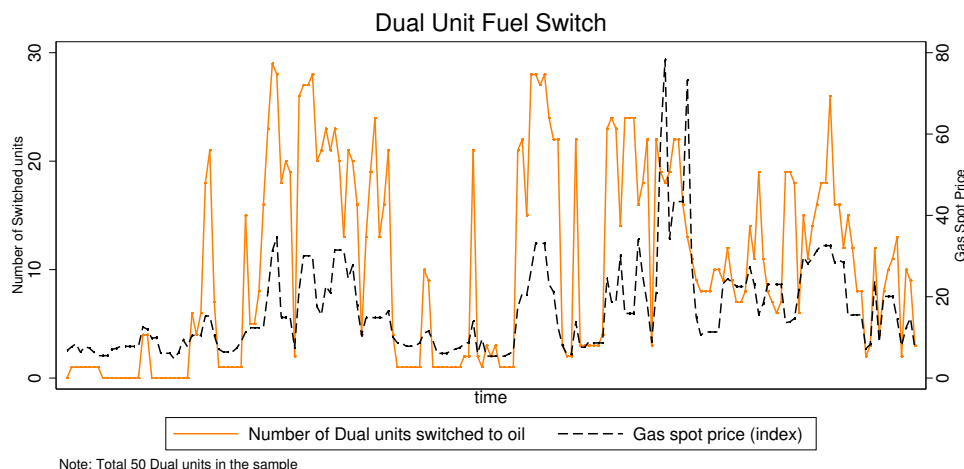
(a) Firm 8
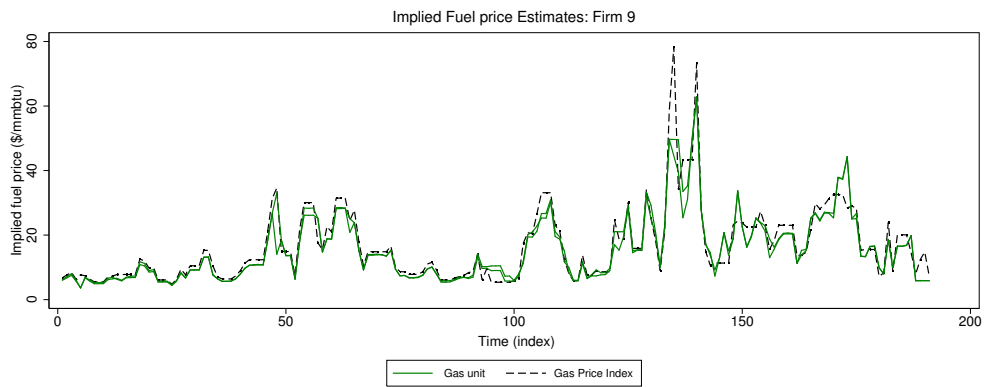
(b) Firm 9

(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 7: Implied Fuel Price Estimates

Figure 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 occured.

implied gas prices of units differ across the two firms. Furthermore, the implied gas price estimates even differ across gas 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 9. Figure 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.[41] 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

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[41]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.

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Mean / Std. of Implied Gas Price Estimates
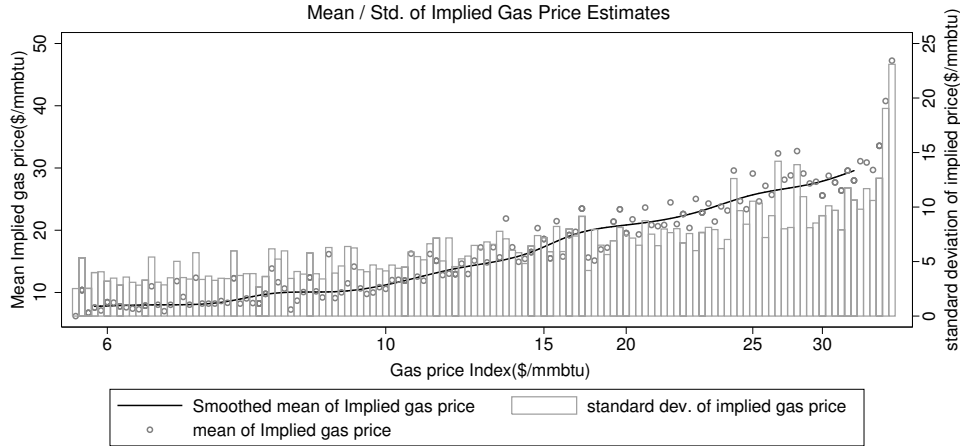
Note: excludes dual units that switched

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.

Figure 9: Estimated Implied Gas Prices: Mean and Standard Deviation

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 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 verifying 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.[42] 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 based generation when the shock is severe.[43]

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.[44] 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.[45] Therefore, I will mainly use the *gas intensive* grouping throughout the markup analysis section when reporting the results.

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.

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

[43]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 baseload units (hydro and nuclear).

[44]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.

[45]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.

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 (11):

$$b_{ijkht} - mc_{ijt} \; = \; \frac{\mathbb{E}_{-i}[\, Q_{ijkht} - \nu_{iht}\,]}{\mathbb{E}_{-i}[\, \partial RD_{iht}/\partial p_{ht}\,]} \tag{11}$$

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. $b_{ijkht} - \widehat{mc_{ijt}}$.[46]

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, $\partial p_{ht}/\partial b_{ijkht} > 0$.[47] To measure bid markup, we need unit-level price bids. More details on how I selected price bids is explained in the Appendix.

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 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 10 also shows how bid markup adjustments are different across two different groups of firms. Figure 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

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[46]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

[47]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.
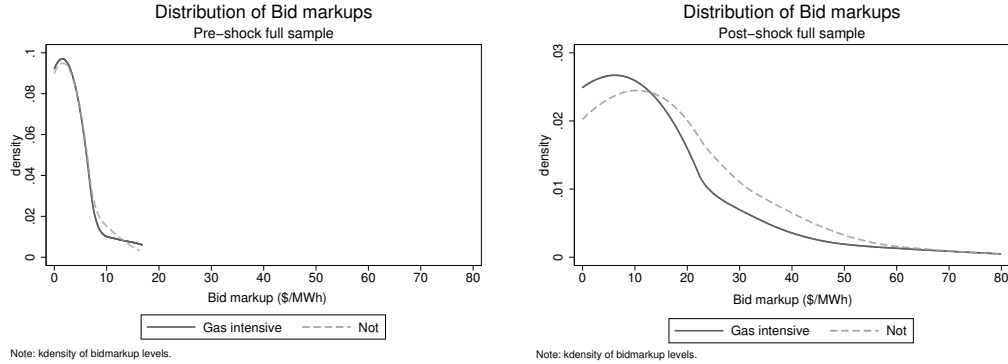
(a) Pre-shock Bid Markup Distribution   (b) Post-shock Bid Markup Distribution

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.

Figure 10: Bid Markup Distributions: Gas Intensive vs. Non-Intensive Groups

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 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 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 bidmarkups including all strategic firms. Table B.2 in Appendix shows the results.

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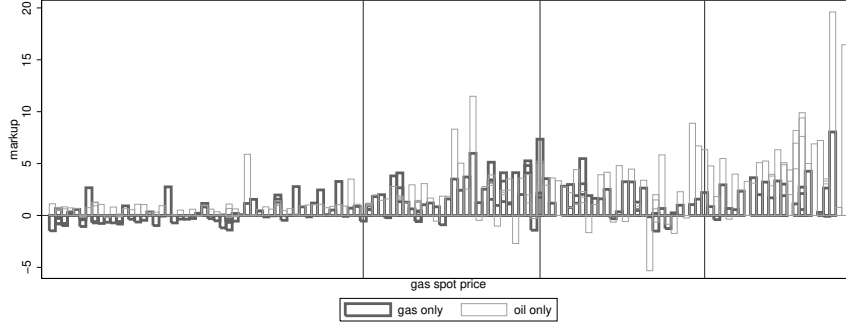
Note: The graph shows daily bid markups of two specific firms, firm 9 and 53,
plotted against the gas price indices of a given day. Thus, overall size of the gas
price shock increases along the x-axis. Firm 9 is gas intensive, and firm 53 is not
gas intensive. Three vertical lines show gas spot index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

Figure 11: Bid Markups of Two Firms: Volatile Sample 1

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.

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 (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 inframarginal quantity of firm i net of forward contracted amount. Dashed

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variables denote post-shock values, and non-dashed variables denote pre-shock values. Therefore, the first part of equation (12) represents the size of the direct cost shock, and the second part shows the change in markups.

The principles of equation (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 (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.

$$\Delta pbid_{ij} \;\; = \;\; \underbrace{mc'_j(q_j) - mc_j(q_j)}_{\text{direct cost shock}} \;\; + \;\; \underbrace{|\frac{\partial p'(q'_i)}{\partial q'_i}|\,\tilde{q}'_i \; - \; |\frac{\partial p(q_i)}{\partial q_i}|\,\tilde{q}_i}_{\text{Markup Change}} \tag{12}$$

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 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 (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.

Simulated endogenous changes in markups measure firms' incentives to adjust their price bids
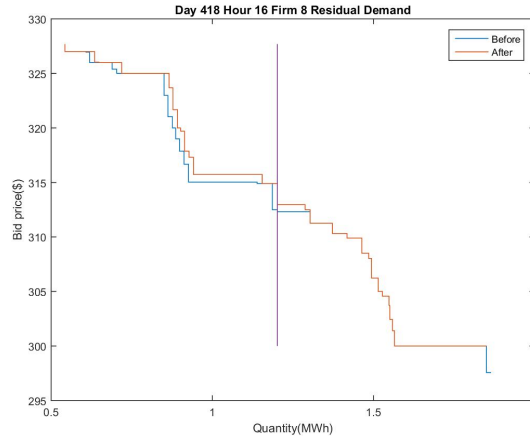
Figure 12: Example of a Shift of a Residual Demand After the Perturbation

further after raising their price bids by the size of the cost shock. Therefore, the final simulated price bid adjustment $\Delta pbid$ in equation (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.

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.[48] 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 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 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.

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[48]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 8.

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 cost change is $/MWh

Table 4: Summary: Changes in Marginal Cost to a Gas Price Increase of $0.1/MMBtu

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).[49]

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 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.
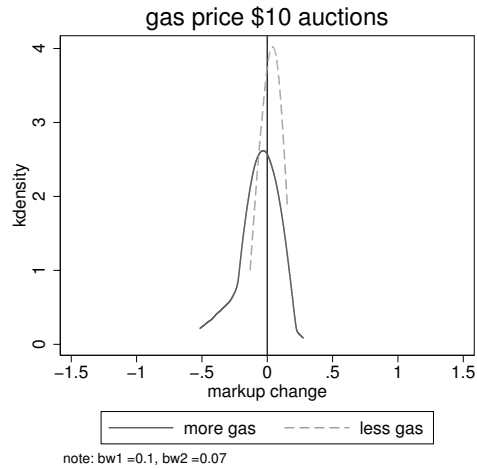
"Hard-hit" firms vs. "Not" In order to explore how strategic markup adjustments that are made by firms are related to their impacts from the cost shock, in Figure 13 I plotted the cross-sectional density of endogenous changes in markups separately for two different groups of firms: *gas intensive* and *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

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[49]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.
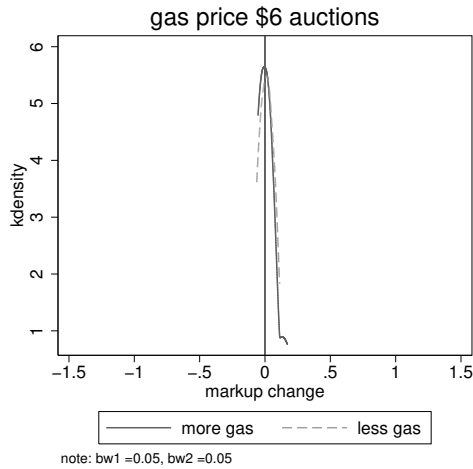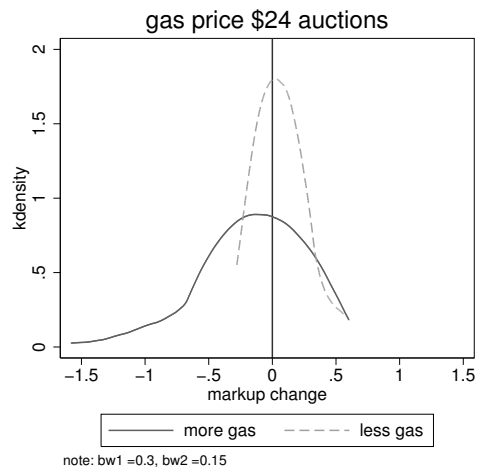
(a) Gas price index $6/MMbtu days   (b) Gas price index $10/MMbtu days
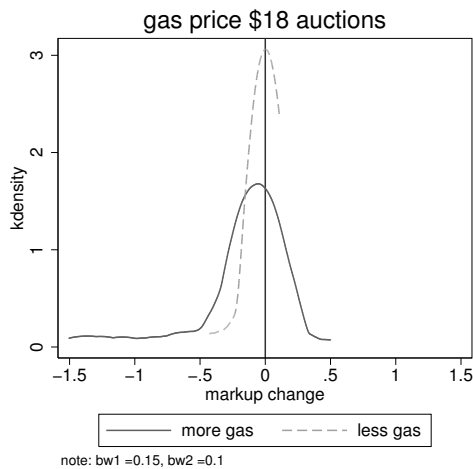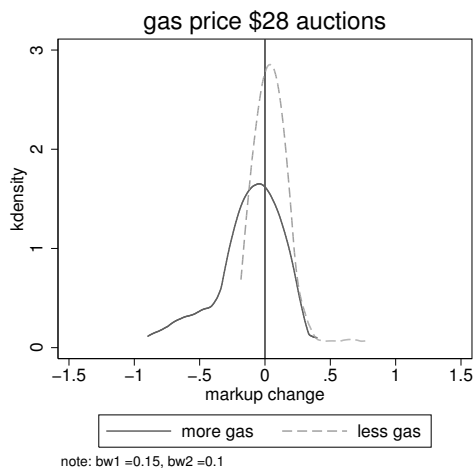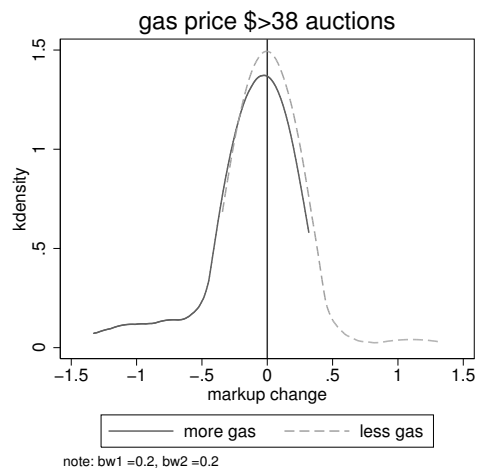
(c) Gas price index $18/MMbtu days   (d) Gas price index $24/MMbtu days

(e) Gas price index $28/MMbtu days   (f) Gas price index > $38/MMbtu days

Note: 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.

Figure 13: Simulated Markups: Gas Intensive vs. Non-Intensive Groups

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.[50] 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 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 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 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 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 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 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

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[50]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)

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.

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.[51] 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

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[51]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.

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 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.[52] 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.[53]

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.

$$\Delta p_s = \Delta b_{s,margin} = \Delta \mathrm{mc}_{s,margin} + \Delta \widehat{\mathrm{markup}}_{s,f,margin} \tag{13}$$

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[52] 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.

[53] 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.

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.

Table 5: Summary Statistics: Simulated Cost Pass-through Rates

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

Results and analysis   Table 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 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 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

	(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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Simulated Pass-through Regressed on Cost Impacts and Gas Price Index Variables

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 6, and leads to a 0.076 rate drop for high impact firms set auctions as reported in (2) of Table 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.

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.[54] 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

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[54]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.

shocks of the same size on each auction.[55]

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.

Regression specifications   Conventional approach to measuring cost pass-through run the following regression provided in equation (14) below:[56]

$$p_{th} \;= \rho \; hr_{th}G_{th} \;+\; \beta_0 \mathbf{X}_{th}^{D} \;+\; \beta_1 \mathbf{I}_{th} \;+\; \epsilon_{th} \tag{14}$$

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 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.[57] 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,

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

[56]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.

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

$hr_{th}G_{th}$, is constructed. Table 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 homogenous 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.[58]

In the next two specifications that are shown in columns (2) and (3) of Table 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) incorporates heterogeneity in both heatrates 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.

Results   The first row of Table 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 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

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[58]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 heatrate for all non-dual gas units and GT heatrate 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 heatrate is 11.5 on average. These heatrate values are used in Specification (1) when generating gas cost

	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.

Table 7: Reduced Form Pass-through Regression: Three Specifications

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 7 are similar to *full sample* estimates. In specifications (1) and (2) of Table 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 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.[59] 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.

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 es-

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[59]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

timated 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 7 to the *mean* of simulated pass-through rates across auctions reported in Table 5 which is 0.974, a value close to 1. Note that ρ estimates from Specifications (1) and (2) of Table 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.

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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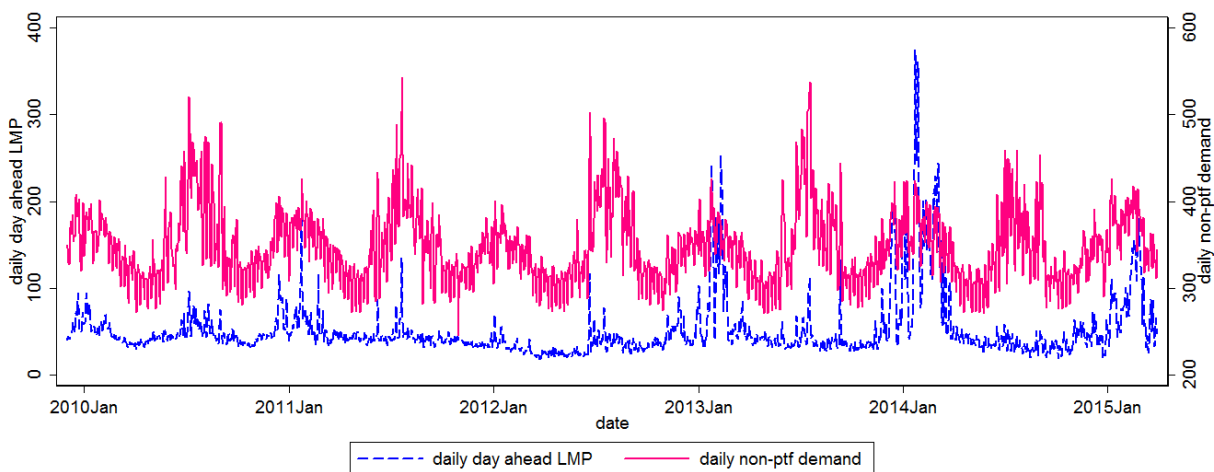
Appendix

A   Graphs

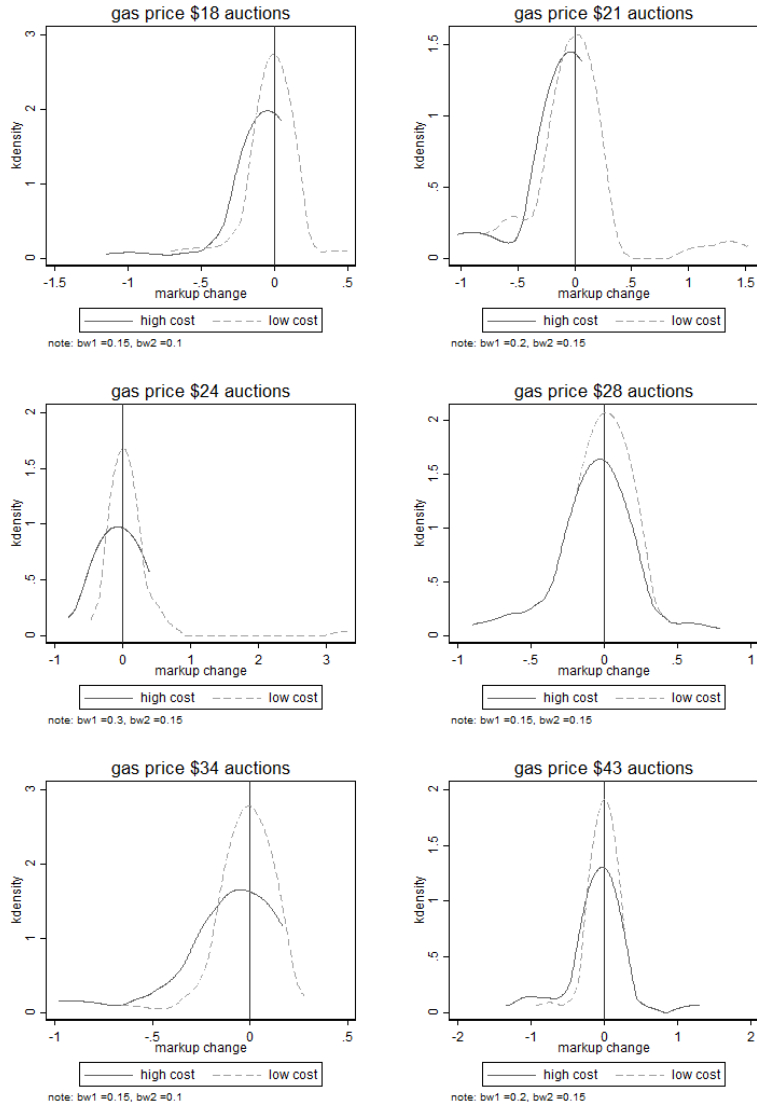Figure A.1: Daily Day-Ahead Electricity Demand: year 2010 - 2015

Figure A.2: High vs. low implied gas cost, by gas level

B   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

Table B.1: Bid steps in the data

| | 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

Estimated hourly bidmarkups are averaged across hours to construct a daily bidmarkup measure. P_{gas} is the spot gas price index and *gas/oil* is the relative share of gas capacity, i.e. $Q_{gas}/(Q_{gas} + Q_{oil})$ where Q_{gas} includes dual gas units.

Table B.2: Regression of Bidmarkup on log Gas Spot prices(size of the shock)

C   Others

C.1   Emissions cost and fuel cost

Emissions cost   Northeast region (New England) is under the following regulations: RGGI (Regional Greenhouse Gas Initiative), Acid Rain Program (under regulation of EPA NE), CAIR (only MA and CT). Acid Rain program is an implementation of 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 Northeast region (all states in New England) is exempted from the new regulation. CAIR(Clean Air Interstate Rule) is a program that aims to reduce ozone level by supressing SO2 and NOx emissions in 28 eastern states. This program was replaced by Cross-state Air Pollution

Rule, as of January, 2015. All affected states chose 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 allowances issued under this program will become invalid effective January 1st, 2012 (ICAPEnergy, Schmalensee and Stavins, 2013). Therefore, the only effective emissions cost during the study period would be RGGI carbon permit.

EPA's Regional Greenhouse Gas Initiative (RGGI) RGGI is the first market-based regulatory program in the U.S.to reduce greenhouse gas emissions (RGGI.org). All states in the New England region, along with NY and MD participate in this program. RGGI caps the CO2 emissions where the capped amount decreases 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 quarterly allowance auctions or in the secondary market, such as the ICE and NYMEX Green Exchange or via over-the-counter transactions.

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. CO2 emissions factor(lb CO2/MMbtu) information is taken from EIA (2013). Emissions factor is in other words, emissions rate.

Calculating the marginal fuel cost The unit of heat rate is MMBtu/MWh and the unit of gas price is \$/MMBtu. Hence, the marginal cost of gas 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 oil spot prices are reported in \$/gallon or \$/barrel. In order to convert this price into a price per MMbtu, I divided oil spot prices by the heat conversion rate which is published by EIA (2013); 1 gallon of oil is equivalent to 138690 Btu (diesel fuel and heating oil) and 1 barrel of crude oil is equivalent to 5800000 Btu.

C.2 Dispatch uncertainty and Gas procurement behavior

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.

C.3   Treatment of Import/Export and Financial Bids

About 10 percent of New England's electricity demand is met by imports from Canada. As imported and exported amount of electricity depend on transmission constraints which I do not have data on, it is hard to incorporate these import/export bids into the model. Instead, I use the hourly net interchange data, which is the actual 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 consists 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 these bids and modeled them as a non-strategic, price takers.

C.4   Smoothed Supply bid curve, Residual demand curve, and Weights

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:

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

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

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

Then the derivative of the residual demand curve is:

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

Finally, the expression of the weights of the first-order condition is shown below (Wolak, 2007):

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

C.5   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.

C.6 Selection of Unit-specific price bids for the bid markup measurement

If most of the generating units submit single step(or $k = 1$) bids, the bid of that first step can be used for bid markup measurement. However, if a unit submits multiple steps of supply bids, which step to use as bid is not straightforward. To tackle this problem, I used quantity-weighted price bids that are often reported and used for markup calculations in multi-unit auction literature (Wolfram(1999); Cassola et.al (2013); Ryan(2015)). This measure is an average of price bids of multiple steps of a unit, weighted by the quantity bid sizes of each step.Here, I included all steps below and including the highest weight step l, i.e. $k \le l$, in q-weighted bid generation, so $K = l$ in this case. Expression of this weighted price bid is shown below:

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

As a robustness check, I also generated price bids using the highest probability weight bids and the highest marginal cost among positive weight bids. All three specifications give qualitatively similar results.

C.7 Different perturbation used for the simulations

Instead of imposing the equal size of 10 cents to all gas units, I imposed a gas price shock weighted by the actual impact that applies to each unit. For example, if the gas price index of the day is \$20/MMbtu and a unit's implied gas price is \$ 18/MMbtu, then I imposed $(18/20) * 0.1 = 0.09$(9 cents)of gas price shock on this unit, so the final gas cost increase will be $hr * 0.09$. This second perturbation incorporates the heterogeneity in implied gas prices across firms and units.

C.8 Ex-ante First-order condition treatment

Competitors' bids realized in the auction ex-post is not the information that a firm had used when optimizing its bids 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 $\frac{\partial p_h}{\partial b_{ijkh}}$.