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

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ONLINE APPENDIX

A Model

First-order condition The original version of the necessary first-order condition shown in equation (2) is as follows:

$$\mathbb{E}_{-it}\left[\frac{\partial P_{ht}}{\partial b_{ijkht}}\Big[\,(Q_{iht}(P_{ht})-\nu_{iht})\;+\;\big(P_{ht}-\;C^{'}_{ijt}\big)\,\frac{\partial Q_{iht}(P_{ht})}{\partial P_{ht}}\,\Big]\right]=0 \tag{A.1}$$

As implied by the market clearing condition, the quantity supplied by firm i equals the residual demand of the firm, i.e., $Q_{iht} = RD_{iht}$. Therefore, we can replace Q_{iht} in equation (A.1) with RD_{iht}. Also, P_{ht} is interchangeable with b_{ijkht} because the first-order condition holds for the ex-ante marginal unit, the price bid of which is the market clearing price, i.e., $P_{ht} = b_{ijkht}$. The final expression of the first-order condition after replacing these variables is shown in equation (2).

Constant marginal cost specification Using a constant marginal cost specification is justified when the number of steps of a unit accepted in the auction are small, which is the case of the New England electricity market. That is, more than half of the units participating in the auction submit a single step supply bid, and about 90 percent of units submit bids less than five steps (see Table H.2 for details). Ryan (2014) also justifies his use of a constant marginal cost specification with the fact that most of the units cleared two to maximum four steps in the Indian electricity market.

Dynamic component of the cost Wolak (2003) and Reguant (2014) discuss the importance of dynamic cost components such as start-up costs and ramping costs. However, because my study focuses on the cost differences across two different sample periods – days with and without the shock – any change in firm's decision that comes from the dynamic component will be consistent across these samples, and will not critically affect my analysis.

Despite this, I also estimated the cost with quadratic and ramping cost terms included in it as a robustness check and found minimal changes in the analysis result. 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 on the cost changes of gas-fired generators, I disregard quadratic, ramping, or dynamic costs throughout the analysis.[1]

B Estimation

Resampling The empirical analogue of the first-order condition (shown in equation (2) of a firm involves expectation over others' bid, $\mathbf{b}_{-it}$. In order to deal with the expectation term, I adopt the resampling methodology that is commonly used in the literature (Hortaçsu, 2002; Hortaçsu

[1]However, there are some generators that submit excessively high price bids compared to the others, and they quickly supply electricity only when the demand is high, by ramping up fast. For these units, I included the ramping cost term in order to avoid heat rate parameter being overestimated.

	Resampling $\mathbf{b}_{-it}$ 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 $m \neq i$ from the pool of days that are similar to day t. That is, if the similar days of day t are $T_t = \{t_1, t_2, \ldots, t_6\}$, randomly sample one day from the set T_t for each firm m.
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 set of market price, $P_{t,s} = \{p_{1t,s} \ldots, p_{24t,s}\}$.
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 $P_{t,i} = \{P_{t,i,1}, \ldots, P_{t,i,S}\}$
Step 4:	Going through Steps 1-4 gives a set of resampled prices for firm i, i.e., $P_{t,i}$. Now repeat steps 1-4 for each firm in the sample, $i \in F$ and get $P_{t,i}$ for $i \in F$

Table B.1: Resampling Procedure

and McAdams, 2010; Kastl, 2011; Hortaçsu and Kastl, 2012; Reguant, 2014 ; Ryan, 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 the resampling method can be extended to allow for the ex-ante observable asymmetries between days by performing the resampling within the ex-ante symmetric group of days, i.e., *Similar days*. I adopt this and select similar days for each day t in the sample based on the following criteria: demand forecast, peak temperature, weekday, and gas market conditions. The values of each criterion of *Similar days* are similar to those of day t. I also find that bidding patterns of firms on similar days closely resemble those of day t. In the main estimation, I used six similar days when resampling. As a robustness check, I also resampled with different numbers of similar days, and the parameter estimates were not qualitatively different from the estimates obtained from the resampling with six similar days.[2]

Resampling procedure is as follows. First, we need to resample firm i's beliefs about its competitors' bids, $\mathbf{b}_{-it}$, on day t, by randomly drawing sets of bids from the ex-post realized bids of *Similar days* of day t. I resampled $S = 100$ sets of bids for each firm i and obtained a market clearing prices for each resampled set of bids. The market is cleared at which point the supply bid curve constructed with the resampled bids intersects with the ex-post realized demand bid curve of day t. Conducting the clearing process for the entire resampled draws gives a distribution of market prices that is expected by firm i in ex-ante, which can be used to construct the ex-ante expected first-order condition of firm i. More details of the procedure, which is similar to that of Hortaçsu (2002) and Reguant (2014), are provided in Table B.1.

Note that the identity of each firm is fixed within the resampling process, which was also the case in Reguant (2014). This approach is different from the one implemented in Hortaçsu and McAdams (2010) where the firms were treated ex-ante symmetric, and thus randomization occurs over firms (N) and auctions (T). In my analysis, randomization occurs across auctions ($T = \{t_1, \ldots, t_6\}$).

From a bidder i's point of view, we need to resample the distribution of $\mathbf{b}_{-i} = \{b_1, \ldots, b_{n-1}\}$. Suppose $r = \{1, 2, 3, 4, 5, 6\}$ is a random variable (each number indexes the selected similar days), and r_j^{bs} denotes the random variable selected by firm j ($j \neq i$) for a bs^{th} bootstrap draw. Below

[2]There is a possibility that the ex-ante similar days we have chosen may have some unobserved heterogeneity components which could bias our cost estimates, especially for extremely high shock days where we cannot find days that are ex-ante similar. One way to address this problem is to use the method of Cassola, Hortaçsu and Kastl (2013), where resampling randomization occurs over bidders having fixed the day. However, this method faces a tradeoff because it requires a symmetry of firms (at least within each firm block) which is a more problematic assumption than the symmetry of days as the focus of our study is to explore heterogeneity across firms.

shows the randomly selected auctions (t) for each bootstrapped sample:

$$bs = 1: \quad \{t_{r_1^1}, t_{r_2^1}, \ldots, t_{r_{n-1}^1}\}$$

$$\vdots$$

$$bs = S: \quad \{t_{r_1^S}, t_{r_2^S}, \ldots, t_{r_{n-1}^S}\}$$

Then, the resampling process is completed once we select the bid of firm j ($i.e., b_j$) of the selected day $t_{r_j^{bs}}$.

Despite having a small number of T, we have enough variation by having a large number of bidders (N) by randomizing in the fashion described above (T^N is a sufficiently large number). The randomizing process used here is similar to the wild bootstrapping, while in the standard example of wild bootstrap, r is $r = \{-1,\ 1\}$. Our example is similar to a wild bootstrap with r dimension of the number of similar days (six in this case). Since the dimension of T is equal to the dimension of r, it is also important to ensure that T is not too large as the convergence speed must be greater for N than for T. Therefore, having a large number of T is not necessary to get a consistent estimate in my empirical set up.

Endogenous residual demand slope Firm-specific unobserved cost shock could shift the firm's bid up, resulting in a larger slope of residual demand. Failing to account for such unobserved 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 (2014), I instrumented the slope of residual demand in the estimation. As for the Sample 0 estimation, I used hourly forecasted demand and the daily forecasted temperature, both of which exogenously shift the endogenous slope variable, but are not correlated with the unobserved supply shock, as instruments. For the Sample 1 estimation, I used forecasted demand error (i.e., actual demand - forecasted demand) to eliminate the dependency of moments across hours.

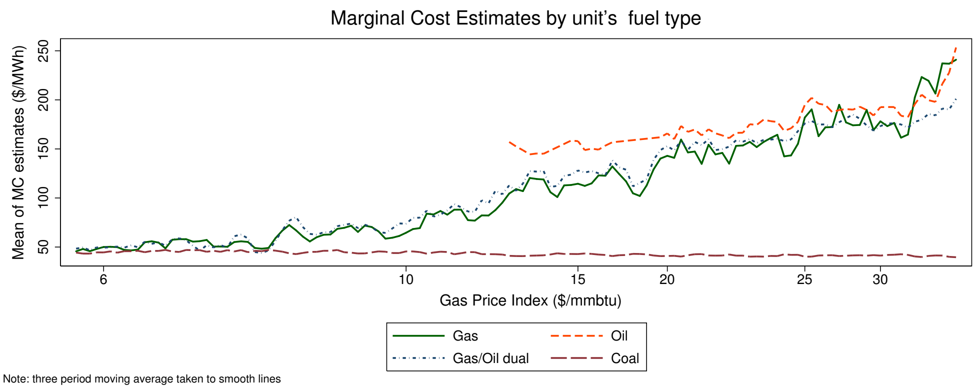
Smoothed supply bid, residual demand and weight The derivatives of the supply offer curve and the residual demand curve of each firm enter the empirical analogue of the first-order condition. Since these curves are submitted as step functions, I first smooth the curves using the normal kernel smoothing approach following Wolak (2007), using a bandwidth of \$3/MWh for the Sample 0 estimations and \$6/MWh for the Sample 1 estimations. 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.

Let firm i's unit j's step k bid to be $\mathrm{b}_{ijkht} =< b_{ijkht}, q_{ijkht} >$. Suppose the market clearing price at hour h is P_{ht}. Note that $\mathcal{K}$ and κ are the CDF and pdf of a normal distribution. Then, the smoothed supply bid curve of firm i using the bandwidth bw is represented as below:

$$\widehat{Q}_{iht}\left(P_{ht}, \mathbf{b}_{iht}\right) = \sum_{j \in J_i} \sum_{k} q_{ijkht}\, \mathcal{K}\Big(\frac{P_{ht} - b_{ijkht}}{bw}\Big)$$

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

$$\widehat{RD}_{iht}\left(P_{ht}, \mathbf{b}_{-iht}\right) = D_{ht} \ - \sum_{m \neq i} \sum_{j \in J_m} \sum_{k} q_{mjkht}\, \mathcal{K}\Big(\frac{P_{ht} - b_{mjkht}}{bw}\Big)$$



Notes: Unit-specific marginal cost estimates of days in Sample 1 are averaged within each fuel type categories: gas, oil, dual, and coal. The set of units included in the calculation of the average value changes over time. Averaged estimates are plotted against the gas price index values of the days in the sample.

Figure C.1: Estimated Marginal Generation Costs by Fuel Type: Averaged Across Firms

Then the derivative of the residual demand curve is:

$$\frac{\partial \widehat{RD}_{iht}}{\partial P_{ht}}(P_{ht}, \mathbf{b}_{-iht}) = -\frac{1}{bw} \sum_{m \neq i} \sum_{j \in J_m} \sum_{k} q_{mjkht}\, \kappa\Big(\frac{P_{ht} - b_{mjkht}}{bw}\Big)$$

Finally, the expression of the weight, which is the probability of bid step b_{ijkht} being the marginal unit, is shown below (Wolak, 2007):

$$\frac{\partial P_{ht}}{\partial b_{ijkht}} = \frac{\partial \widehat{Q}_{iht}(P_{ht})}{\partial b_{ijkht}} \Big/ \Big(\frac{\partial \widehat{RD}_{iht}(P_{ht})}{\partial P_{ht}} - \frac{\partial \widehat{Q}_{iht}(P_{ht})}{\partial P_{ht}}\Big)$$

Inference Standard errors of the heat rates and forward contract rates estimated from Sample 0 are constructed using a bootstrap method. Although I do not incorporate generating units' dynamic decisions (dynamic parameters) in my model, I implement the block bootstrap method in order to generate standard errors, addressing the possibility of the temporal dependence in the underlying data process (see Reguant (2014) for details). Standard errors of Sample 1 marginal cost parameters are generated using a GMM standard error formula. Because this Sample 1 GMM estimation is indeed a linear IV estimation, I use IV standard errors. Alternatively, we could also bootstrap the standard errors. In this case, block bootstrapping is not necessary as the temporal dependence disappears by our selection of instrument (demand forecast error that is *i.i.d.* across hours).

C Estimation Results

C.1 Marginal cost estimates by fuel types

I first estimate the unit-specific marginal costs of electricity generation ($\widehat{mc_{ijt}}$) for each day in Sample 1 where gas prices are volatile. In Figure C.1, I take the daily cross-sectional average of the estimates separately by fuel type – coal, gas, dual and oil units – and plot them against the gas price index value for each day, which proxies for an overall size of a gas price shock. Not surprisingly, the average of the marginal cost of gas-fired units increases with the overall size of the

Year	Plants (N)	Gas Procurement Channels (plant level) Contract	Spot Market	Max. # of spot gas suppliers
2013	38	19 %	81 %	6
2014	39	12 %	88 %	9

Data source: EIA-923 Schedule 2

Table C.1: Percentage of Firms Procuring Gas from Long-term Contract vs. Spot Market (Plant Level)

shock, while that of coal and oil units does not change much in the sample.[3] The average of the gas units' marginal costs becomes similar to that of oil units when the daily gas price lies between the range of oil prices ($18 - 25/MMBtu), and becomes the highest among all fuel types when the gas price exceeds the level of the oil price. This finding suggests that the cost advantage of a gas-fired unit relative to other fuel type units changes with the intensity of the gas price shock.

C.2 Exploring the dispersion in the implied gas price estimates

The sources of heterogeneous impacts discussed earlier in Section 2 could potentially explain our main findings from the estimation of implied gas prices: (i) dispersion in the firm- and generator-level implied gas prices, which exists even within a day, and (ii) the dispersion increases with the overall size of the daily gas price shock. Here, I validate my estimates from the bid data by comparing them with information obtained from the external sources - the EIA-923 form.[4] Note that the comparison provided here is incomplete as the EIA-923 dataset does not cover the entire sample.

Does a firm with a long-term contract have a lower estimated implied gas price? In Table C.1, I summarized percentages of gas-fired power plants in New England that purchase gas through the long-term contract and from the spot market, using power plants that appear in the EIA-923 data. Although the sample size is small, about 20 percent of the power plants purchase gas through long-term contracts, and the rest of the plants purchase gas at the spot market from various different gas suppliers.

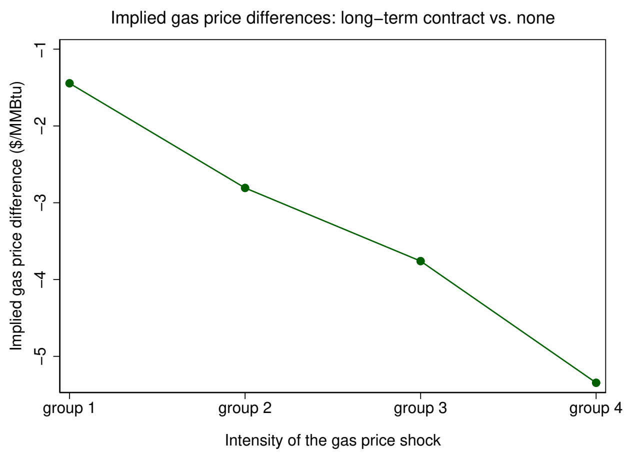
By cross-comparing the EIA-923 data with my estimates, I identified the firms in my bidding data that procure gas through a long-term contract.[5] In order to verify whether firms with a long-term gas contract would have implied gas price estimates that are lower than those without the contract, I regressed implied gas prices on a dummy variable assigned to firms identified as having a long-term contract.[6] Additionally, to see how the difference in implied gas prices between those

[3]The slightly increasing path of the average of the marginal cost of oil units is a result of having more high-cost oil units included in the sample when taking the average.

[4]EIA-923 Schedule 2 (mandatory collection of data by U.S. Energy Information Administration) contains information on fuel receipts (including the cost and the quality of fuel) as well as whether plants purchased gas at the spot market or through the long-term contract. However, starting from 2013, only the plants of sizes greater than 200 MW are required to submit the information to the EIA, and only the regulated firms and plants have an obligation to disclose the fuel cost information. Furthermore, since all of the information is reported at a monthly level, conducting an analysis on a daily basis using this dataset is not possible. Finally, matching the generating units that appear in the bidding data to the plants (which consists of several generating units), that appear in the EIA-923 data is difficult as they use different IDs.

[5]Unfortunately, matching data at the generator level was not possible because the identity of the plant is masked in the bidding data.

[6]I included in the regression the time (t) fixed effect so that the variation used in the estimation is the cross-firm variation within a day.



Notes: The graph shows the average differences (represented by the coefficients of the "gas procurement contract" dummy) in implied gas prices between firms that purchase gas via long-term contract and on the spot market. *Group* variable refers to subsamples that are selected based on different levels of daily gas price shocks. Group 1 has the smallest-sized shock and the intensity of the shock increases along the axis.

Figure C.2: Difference in Implied Gas Prices: Firms with and without the Long-Term Gas Procurement Contract

with and without the long-term contract varies with the overall size of the gas price shock, I ran regressions separately on subsamples that vary in sizes of gas price shocks. Figure C.2 shows the estimated coefficients. The negative coefficient estimates indicate that the implied gas prices are, on average, lower for firms that purchase gas via the long-term contract than those that do not. Also, the magnitude of coefficient estimates increases as the overall size of the shock increases, which corresponds to the fact that the difference between the long-term contracted price and the spot price of gas becomes larger as the gas price shock increases considerably. Therefore, the existence of a long-term gas contract explains the dispersion that we find in the implied gas price estimates.

Why do estimated implied gas prices of generators vary within a firm? One particularly interesting finding is that the implied gas prices differ across generators operated by the same firm. Indeed, uncovering the true source of such a dispersion is extremely challenging, but several factors may explain the dispersion in the estimates. A firm's generation portfolio consists of several different power plants that are in some way operated independently. While the management and bidding for these plants are done by a single entity, the fuel procurement channels could vary significantly across plants and even across generators.

Since we know that spot gas prices can vary within a day, power plants ordering gas at different time points could lead to different gas prices across plants and generators, even if all of them purchase gas on the spot market. One possible explanation for such a procurement practice is the dispatch uncertainty in the day-ahead electricity auction. In general, firms do not know at the time of the bidding which of their generating units will finally be accepted in the auction so that they could actually generate electricity in the market. Thus, purchasing gas for all of their generating units at the time of the bidding is risky for firms. Instead, firms will purchase gas in advance only for those units that are most likely to generate electricity in the market, and postpone purchasing for the rest of the uncertain units. The fuel price implied in the bids of these postponed generators could be the expected price of gas at the time of the gas use, which could differ from the spot price at the time of bidding. Such gas procurement and bidding practices are evidenced by the Market

Gas procurement channels	# of firms purchasing gas from: 2013	2014
Spot gas market only	16	14
Long-term contract only	3	1
Both spot and long-term contract	2	5
More channels than above	0	1
Total # of firms in the sample	21	21

Table C.2: Summary of the Number of Gas Procurement Channels (Firm Level)

rule published by the ISO-NE.[7]. These behaviors, combined with the increase in the volatility of the spot gas prices, result in a dispersion in implied gas prices across generators. Also, the fact that volatility increases more as the gas price shock becomes larger could potentially explain why the dispersion among generators increases with the overall size of the shock.

Also, when some of the firm's generating units purchase gas through a long-term contract, while others purchase from the spot market, the implied prices could vary across units. In Table C.2, I summarize the number of gas procurement channels from which each firm purchases gas, which shows that some firms indeed rely on both spot market and long-term contracts.[8]

Is opportunity cost of gas always the spot price of gas? One may argue that, even if the long-term contracted prices of gas are lower than the daily spot prices, the opportunity cost of gas is always the spot price when considering the resale option in the secondary gas market. In this case, the existence of the long-term contract cannot explain the dispersion in the estimates.

The above argument may be true when the gas market is under normal conditions – thus, fully liquid – which supports the use of single gas price index value for constructing costs of all gas generators in Sample 0 estimation. Since the opportunity cost of gas would be close to the spot gas price regardless of the gas procurement channel – whether they purchase gas from forward or from spot – the cost generated with the gas price index represents the true opportunity cost of gas for each firm. In this case, the bias of using index data may exist, but is significantly less pronounced than in a volatile period.

However, when the gas market is under stress that is mainly caused by the congestion in pipelines, the transportation cost of gas may become too high, and the resale of gas becomes less attractive as the gas market is not fully liquid (see Borenstein, Busse and Kellogg (2012) for more details of illiquid gas market). Moreover, the primary goal of firms in the wholesale market is to generate and sell electricity; thus the gas resale option may receive less priority in their decision. When the long-term contracted price of gas of a generating unit is lower than the spot prices at the time, and if the unit is close to being a marginal price setter, the firm may form the bid of this marginal unit based on the actual contracted price. This is because, if the firm instead submits a higher bid for this unit based on the spot price of gas at the moment, the chance of this unit being accepted in the auction will be forgone, as well as the positive profit that would have been earned from the

[7] For the purpose of monitoring market participants' bids, market monitors sometimes require a market participant to submit a fuel price whenever the market participant's expected price to procure fuel for the unit will be greater than that used by the Internal Market Monitor – the gas price index. It is stipulated in the Market Rule that firms may submit "a price from a publicly available trading platform or price reporting agency, demonstrating that the submitted fuel price reflects the cost at which the Market Participant "expected" to purchase fuel for the operating period covered by the Supply Bid, as of the time that the Supply Bid was submitted, under an arm's length fuel purchase transaction (ISO-NE Market Rule, Appendix A: Fuel Price Adjustments)."

[8] The number of firms that rely on both channels could be large in the total sample because EIA-923 is not representative of all firms that participate in the auction.

unit's electricity sale.

Any possibility of optimization error? The final point to address is whether the dispersion we observe in our estimates is a result of an optimization error that may arise from firms not bidding strategically according to the first-order condition. This is certainly an issue for small fringe suppliers that are far from being marginal, as pointed out in Hortaçsu and Puller (2008). However, in the estimation, we included only those units close to being marginal, thus firms that do not have the incentive to bid optimally, as well as the units of firms far from being marginals, have been taken out at the estimation stage. Even if optimization error exists, the dispersion becoming larger – as we look at the sample with larger gas price shock – is hard to explain only with the error. That is, such findings could be rationalized only if firms behave less optimally when gas prices become higher, which cannot be supported by any theoretical or empirical evidence. Moreover, we find that the dispersion in the bids (of strategic bidders) increases as the shock becomes more intense. Since bids observed in data are not subject to any optimization error, dispersion in bids implies the existence of the dispersion in either costs or markups, or both.

C.3 More on dual unit's fuel switch identification

Here I provide a more detailed explanation of how I identified the dual gas unit's fuel switch decision. Detecting the fuel switch of a dual gas unit is possible by comparing its implied fuel price estimate to the data on spot prices of gas and oil (index values). Note again that both the level and volatility of spot prices are useful for the identification. That is, the spot oil prices are stable over the entire sample, which makes the oil price revealed in the marginal costs of the generator – if they had used oil for generation – to be close to the spot oil price observed from the data. If the estimated fuel price of a dual unit differs from the level of spot oil price, or if it fluctuates over the sample following the path of a volatile spot gas prices, we can conclude that the dual unit did not use oil but used gas for generation. For example, the estimated fuel price of $12/MMBtu or $30/MMBtu indicates a use of gas by the unit because these levels differ significantly from the oil price, i.e. $18 - 22/MMBtu.

The most problematic price range is where the spot gas prices are similar to the oil price, i.e., between $18 - 22/MMBtu, as it is hard to determine whether the estimated fuel price corresponds to oil or gas. To precisely identify the fuel switch of dual units over this price range, I first checked the overall pattern of the estimated fuel prices together with the pattern of daily spot gas price data. If the fuel switch from gas to oil occurs, the estimates of fuel price will stay constant around the level of spot oil price, while the spot gas price of the time continuously increases. Even if this flat part does not continuously appear over the sample period, observing at least one flat portion is indicative of the fuel price at which the switch occurs for this dual unit, which can be used as a reference level.

I further verified the identified fuel switch decisions of dual units over this problematic price range using the EPA emissions data (CEMS). The CEMS data contains the daily emissions rate of a generator which can be used to tell the type of fuel used by the generator, since burning gas and oil generate different emission rates. However, the emissions rate data exists only for those that actually generated electricity in the market (by being accepted in the auction), thus the dataset does not include all of the dual units and days in our sample. This is one of the reasons why I instead identified the fuel switch decisions mainly from the fuel price estimates in this paper. At least for generators that appear in the CEMS data, I verified my fuel switch decision to be consistent with what the emissions rate data suggests.

D Markup Simulation

Sizes of cost perturbation imposed in the simulation Sizes of cost perturbation resulting from the counterfactual gas price shock of 10 cents differ across units because each unit uses different types of fuels and has different heat rates. The generation cost of only the gas-fired units will be perturbed by the gas price shock, and the sizes of perturbations vary among gas-fired units due to differences in heat rates, though not substantial. Also, because firms have different proportion of gas-fired generation in their generation set, sizes of cost perturbations at firm-level would vary as well. Therefore, we can say that the heterogeneity in the impacts from the gas price shock has been accounted for at the cost perturbation stage. Table D.1 summarizes the sizes of marginal cost perturbation at both the unit- and firm-level. I also implemented a cost perturbation that incorporates the differences in implied gas prices across firms and units. More description can be found in Section G.5.

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. Includes generators of all fuel types.

Table D.1: Summary of Sizes of Marginal Cost Perturbations to a Gas Price Increase of $0.1/MMBtu

E Pass-through

Identifying the ex-post marginal units from data I identified ex-post marginal units from two data sources: hourly day-ahead electricity auction bids (supply offer bids) and the hourly equilibrium market clearing prices (Energy Component price), both obtained from the ISO-NE website. Among the submitted supply offer bids (which consists of price bids and quantity bids), I found the price bid that equals the equilibrium market clearing price, and identified the unit that submitted the selected price bid as a marginal unit of the auction.

More on pass-through specification and endogeneity of $hr_{th}G_{ht}$

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

As described earlier, p_{ht} is the electricity price and $hr_{ht}G_{ht}$ is the gas cost variable. I also specified $\mathbf{X}^D_{ht}$ which is the demand side control variable where I used peak-time temperature data. Fixed effects, $\mathbf{I}_{ht}$, are specified as well including month, day of the week, hour fixed effects.

The gas cost component, $hr_{ht}G_{ht}$, is subject to potential endogeneity. Because the identity of the marginal unit is determined by the electricity market equilibrium which is affected by the unobserved demand and supply side factors, the heat rate of the marginal unit, hr_{ht}, suffers from endogeneity. Therefore, I instrumented the gas cost term with the gas price index, $\bar{G}_{ht,index}$, which is exogenous to electricity prices as it is determined by the conditions of the spot gas market, but correlated with the gas cost term. The selection of instrument is similar to that of Fabra and Reguant (2014).[9]

[9]Note that it is possible that an increase in the electricity generation could affect the gas market through an increased demand for the gas from the electricity generators, in which case our instrument would not be valid. However, I find that the variation in electricity generation (resulting from increased demand for electricity) is not

Exploring the cause of underestimation To investigate why the näive regression underestimates the pass-through, I checked percentage of marginal units whose costs measured with the index data overstate their actual costs, shown in Table E.1. That is, for each gas-fired marginal unit, I compared $\widehat{hr}_{ij}\ \bar{G}_{ht,index}$ with $\widehat{hr}_{ij}\ \widehat{F_{ijt}}$, and selected those units with $\widehat{hr}_{ij}\ \bar{G}_{ht,index} > \widehat{hr}_{ij}\ \widehat{F_{ijt}}$. Note that $\widehat{F_{ijt}}$ is the implied fuel prices of the unit estimated earlier from the model.

		N	%	% w.r.t
(1)	Gas marginal units in total	3,129	100	-
(2)	Marginal units with overstated cost measure	2,076	66.34	to (1)
(3)	Dual marginal units among overstated units	615	29.62	to (2)

Notes: If a unit's marginal cost measured with the gas price index data is greater than that measured with the implied gas price estimate, I categorized the unit as having an overstated cost measure. First row (1) shows a total number of marginal units used in the regression, and row (2) shows how many among them have overstated cost measure. Row (3) shows how many of the units in (2) are dual gas units that switched fuel from oil to gas on the day. Percentage is calculated with respect to the sample shown in column % w.r.t.

Table E.1: Marginal Units with Overstated Cost Measure

The first row (1) of Table E.1 shows the total number of gas-fired marginal units in the sample used for the pass-through estimation, and the second row (2) shows how many of them have the overstated cost measures. I find that, for 66 percent of the marginal units in the sample, the costs measured with the gas price index were greater than the costs implied by the unit-specific implied gas price estimates. The fact that a substantial portion of marginal units have overstated cost measures explains the finding of underestimation of pass-through parameters in näive regressions.

Also, among those marginal units with the overstated cost measure, almost 30 percent (29.62 %) of them are dual units that switched fuel from gas to oil. Note that the measurement error of the inaccurate cost variable is substantially larger for these fuel-switched dual units than units that relied on gas for generation.

Measurement error and the bias The instrument used in the main regression is for addressing the endogeneity of the identity of the marginal unit. That is, the unobserved demand and supply factors in the error term could affect which type of units become marginal – price setter – in the auction. For instance, when the electricity demand is low, the generating units with lower heat rates or gas prices are likely to be marginal, and vice versa when the demand is high.

To correct for this type of endogeneity of the gas cost term of the ex-post marginal unit, I used the gas price index ($\bar{G}_{ht}$) as an instrument. However, this instrument cannot correct the measurement error arising from omitting heterogeneous impacts. To explain this, I provide a more general formulation of the problem which is described below. Denote the näive measure of the marginal cost as $\widetilde{X}_{ht}(=\widehat{hr}_{ij}\bar{G}_{ht})$. Then $\widetilde{X}_{ht}$ can be decomposed into roughly three parts:

$$\widetilde{X}_{ht} = X^*_{ht} + \mu_{ht} + \upsilon_{ht}$$

X^*_{ht} is the true value of the unit's marginal cost, μ_{ht} is the measurement error, and υ_{ht} is the endogenous part that is correlated with the unobserved demand and supply factors. Since the instrument Z $(= \bar{G}_{ht})$ used in the regression is chosen to correct for the endogenous part, υ_{ht}, it satisfies the condition $E(Z'\upsilon_{ht}) = 0$.

If Z is also exogenous to the measurement error part μ_{ht}, then the pass-through rate can be estimated without the measurement error bias, even in näive regressions. However, as shown in the

correlated with the variation in gas prices. Instead, an increased demand for gas from the residential heating sector was the primary cause of the variation in gas prices.

plot provided in Figure E.1 of the online Appendix E, the chosen instrument Z is correlated with the measurement error, i.e., $E(Z'\mu_{ht}) \neq 0$.

More details on how I generated the graphs in Figure E.1 are as follows. First, the measurement error (μ_{ht}) is obtained by taking a difference between a näive marginal cost (i.e., $\widehat{hr}_{ij}\bar{G}_{ht}$) and the marginal cost generated with the estimated implied fuel prices ($\widehat{hr}_{ij}\widehat{FP}_{ijt}$). Then, the measurement error variable ($\mu_{ht} = \widehat{hr}_{ij}\bar{G}_{ht} - \widehat{hr}_{ij}\widehat{FP}_{ijt}$) is plotted against the instrument used in the regression, i.e., the gas price index ($Z = \bar{G}_{ht}$). As shown in Figure E.1, the instrument variable is positively correlated with the measurement error; the measurement error tends to increase in magnitude as the instrument value increases. Such positive correlation can be explained by our findings from the cost analysis; since the dispersion in firms' costs increases with the size of the gas price shock (as measured by the gas price index value), the measurement error generated from using the average value for firm-specific cost increases with the gas price shock as well.

F Data

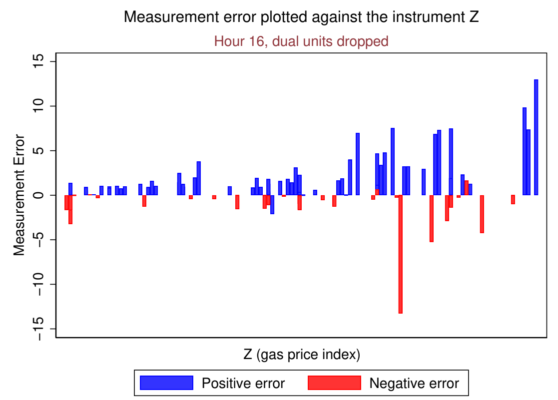
F.1 Dual units

Dual generation technology Installing dual-generation technology to electricity generator is not too difficult as one needs to change the nozzles, install the equipment that handles fuel supply and modify the control system (EPA-CHP Combustion Technology Report, 2015; Power Engineering, 2004). Once the technology has been installed, gas turbines can quickly switch from using gas to using another fuel, without much interruption. Although the installation is not difficult, not every gas unit is equipped with the technology because of the environmental regulations (on burning oil) and lack of incentives to install technology during the period with low gas prices. Most of the existing dual units were constructed or converted in either 1980s or early 2000s when natural gas was relatively more expensive than other fuels (Power Engineering, 2004).

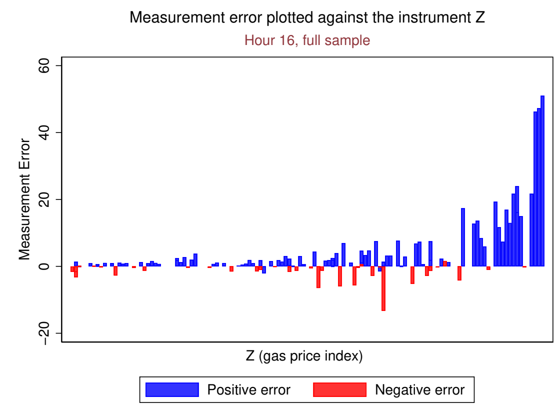
Heat rate of the dual gas unit Note that dual unit's heat rate does not change significantly between burning gas and burning oil. I have partially verified this with the actual heat rate component reported in the EPA CEMS (Continuous Emission Monitoring Systems) data. The CEMS (Continuous Emission Monitoring Systems) dataset contains information of heat content (MMBtu) and generation (MWh) of generators that enables calculation of their heat rates. However, the information of heat rates provided in CEMS data cannot be matched to the bidding data because the identify of firms and power plants are masked in the bidding data. Alternatively, I selected one dual unit from the CEMS dataset, and compared its heat rates on days when the unit was identified to have used gas versus days when it had switched to burning oil. Average of heat rates are 10.2 (MMBtu/MWh) when burning gas and 9.9 (MMBtu/MWh) when burning oil (diesel). Although slightly more efficient (lower heat rate) when burning oil, the difference is not substantial.[10]

Additionally, the heat rate defined in this paper aims to capture efficiency as a part of the cost that is invariant to the shock. Therefore, the heat rate I specify in my model could be conceptually slightly different from the one used by engineers measured by the thermal energy divided by the electricity.

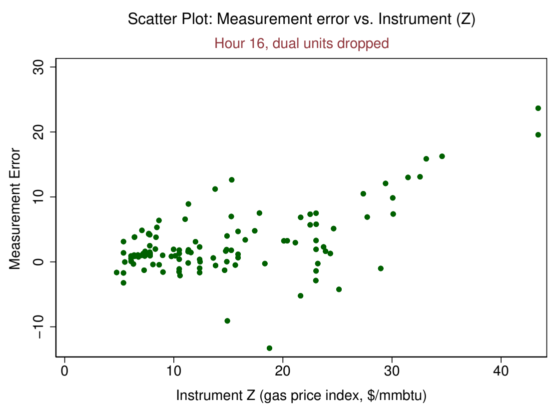
[10]The different heats of combustion result in slightly higher mass flows through the expansion turbine when liquid fuels are used, and may lead to a small increase in the generator's efficiency performance (EPA-CHP combustion technology report, 2015).



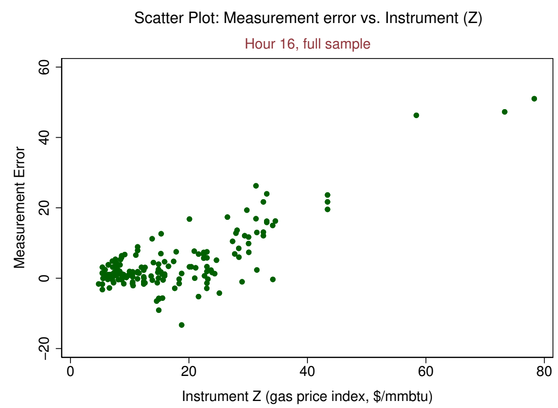
(a) Measurement error vs. instrument Z – dual units dropped



(b) Measurement error vs. instrument Z – dual units dropped



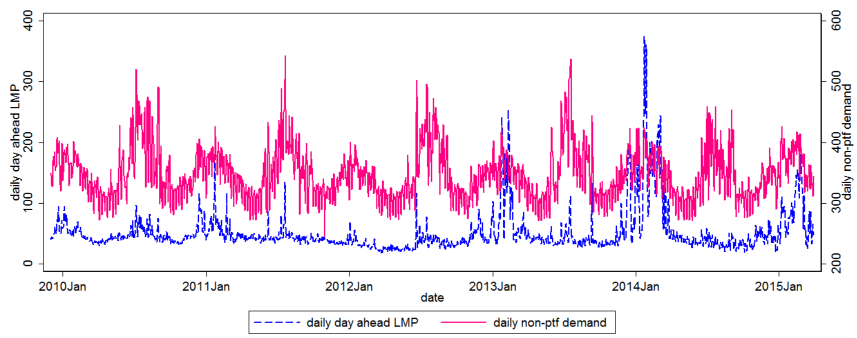
(c) Scatter plot : measurement error vs. instrument Z – dual units dropped



(d) Scatter plot : measurement error vs. instrument Z – full sample

Notes: The measurement error (μ_{ht}) is constructed by taking a difference between the näive cost measure and the accurate cost measure, i.e., $\mu_{ht} = \widehat{hr}_{ij}\bar{G}_{ht} - \widehat{hr}_{ij}\widehat{FP}_{ijt}$. The graph above shows the measurement error plotted against the instrument used in the regression, i.e., the gas price index ($\bar{G}_{ht}$), where the sample is restricted to hour 16 (4 pm) observations. I also plotted the graph for different hours and found similar patterns across hours. In panels (a) and (c) the dual-technology marginal units are dropped from the sample, whereas in (b) and (d), those are included. When dual units are included in the sample, the magnitude of the measurement error is bigger especially when Z is large. The correlation coefficient of the measurement error and the instrument is 0.34 (for hour = 16 and dual units dropped), and 0.57 (for hour = 16 and when dual units are included– full sample).

Figure E.1: Correlation between the measurement error of the marginal cost variable and the instrument variable used in the regression (gas price index)



Notes: The daily day-ahead LMP is the daily average of the final wholesale electricity prices (locational marginal price) and daily non-ptf demand is the daily average electricity demand in the wholesale market.

Figure F.1: Daily Day-Ahead Electricity Demand: Years 2010 - 2015

F.2 Electricity demand

Aggregate demand is another important factor that determines the market price in the wholesale electricity market, and it is natural to ask whether demand shocks contributed to a surge in wholesale electricity prices during the period of gas price shocks. I find that demands were not unusually higher during the period when electricity prices surged than on normal days when electricity prices were within a reasonable range. Moreover, while the electricity demand was on average higher in December 2013 than in January 2014, the electricity prices were much higher in January 2014. Given that gas prices were higher in January 2014 than in December 2013, this implies that the demand-side shock did not play a significant role in increasing the prices, rather, the cost increase resulting from the gas price shock was the primary cause of the surge in electricity prices. The historical trend of the electricity demand, shown in Figure F.1, also reveals that no significant demand shocks were present in the winters of 2013-2014 compared to other years.

G Additional

G.1 New England Wholesale Electricity Market

Day-ahead electricity market New England wholesale electricity market supplies electricity to the region's 6.5 million households and businesses (ISO - NE *Market overview*, 2014). The market is operated by ISO-New England, a non-profit company that clears the market. Electricity is supplied by firms that own generating assets, and is demanded by the local utilities and distribution companies (LDCs) that offer retail electricity services to the residential customers.

Both the supply and demand sides participate in the day-ahead electricity market, which is held one day prior to the day of actual electricity generation, to sell and purchase electricity in advance. Another type of market exists in the wholesale electricity market, which is the real-time electricity market held on the day when actual generation occurs. This paper focuses on the firm behavior and market outcomes in the day-ahead electricity market, for the following reasons. First, more than 95 % of the electricity supplied during the next day is scheduled in the day-ahead auction (ISO-NE EMM Report, 2015). Second, the day-ahead auction offers a more favorable set-up by which to study 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, which are mainly caused by unexpected real-time market conditions (e.g., transmission line congestion).

Market clearing electricity prices The New England grid adopted the Locational Marginal Price (LMP) system, where the final market prices differ across pricing nodes after the single, system-clearing price (Energy Component Price, ECP) is adjusted by the size of the congestion cost that varies across nodes. As LMP depends on the hourly grid conditions at pricing nodes, it is difficult to use LMP in the analysis without having detailed information and understanding of ISO's market clearing algorithm. Therefore, I disregard the regional variation in prices across nodes and use the single price that clears the entire system – the Energy Component Price (ECP)– for the analysis. In fact, the LMPs do not differ much across nodes, and from the ECP, in my sample.

G.2 Natural Gas Price Shocks and the Spot Gas Market

Natural gas price shocks in New England New England does not have sufficient gas pipeline capacity, and as a result, the gas spot prices in New England is the highest in the U.S. Two major gas pipelines that deliver most of the gas into the region are Algonquin Gas Transmission pipeline (AGT) and Tennessee Gas Pipeline (TGP). The total capacity of these two pipelines combined is 3.5 bcf/day (EIA report, 2014), which runs very close to the total gas demanded in the region.[11] Since the pipeline congestion problem is unique to New England, severe shocks to gas prices during the winters of 2013 and 2014 occurred only in New England and other Northeastern regions, including New York. In fact, the highest gas spot price at Henry Hub which offers a starting point for all regional gas spot prices at various trading locations was $8/MMBtu in the winters of 2013-2014. This implies that the congested pipelines that deliver gas from Henry Hub to New England were the main cause of the gas price shocks that impacted New England.

Long-term contract and firm-level gas spot prices A long-term gas supply contract is defined as receiving gas under a purchase order with a term of one year or longer. Any contract with a duration less than a year is considered a spot purchase (EIA-923). While it is difficult to obtain specific details of long-term contracts as the information is confidential, the existence of the long-term contract is reported in various data sources. For example, EIA-923 data contains some basic information about whether a firm purchases gas in the spot market or through a long-term contract. However, the EIA-923 does not disclose the exact prices that firms paid at the spot market and for contracts unless the firm is regulated. Furthermore, the reported prices of those regulated are the monthly average values, which are not precise enough to use in our analysis.

The spot market price of gas at the local trading hub, the city gate, reflects all charges incurred for the acquisition, storage, and transportation of gas; it is the total price paid by the end user, the electricity generating firms. Most of the spot gas purchase occurs through a broker (e.g., ICE (Intercontinental Exchange)). After the acquisition of gas, firms must request (nominate) pipeline capacity to the pipeline companies, in order to secure the delivery of the purchased amount to their generation site. In New England, a problem occurs at the pipeline nomination stage as the capacity is constrained, which drives up the spot gas prices at the Algonquin city gate.

It is difficult to acquire firm-level spot gas prices, namely the over-the-counter spot gas prices. The ICE (International Commodity Exchange) over-the-counter gas price data, which I used for

[11] Other than these major pipelines, Massachusetts's Everett liquefied natural gas (LNG) terminal also supplies natural gas to the region and is connected with the AGT and TGP pipelines. Also, Canaport LNG import terminal sends gas into the region through Maritimes & Northeast pipeline.

generating graphs in Figure 2, is disclosed based on an agreement between EIA (Energy Information Administration) and ICE, starting from year 2015. However, the data set discloses only the summary statistics (average, minimum, and maximum) of the firm-level transaction prices and does not cover the sample period (2012 to 2014) used in my analysis.

Dispatch uncertainty and firm's gas procurement behavior Although the bulk of gas trading occurs in the morning of the day-ahead market (a day before the actual generation day), gas can be traded at different points of time both on the day before and during the operating day. The problem is that bidding in the electricity auction must be completed before noon of the day before the generation. In the day-ahead electricity auction, auction participants (both supply and demand) must submit bids for the next day between 10:00 am and 12:00 pm of the day before the generation. The outcome of the auction, such as which suppliers will be dispatched in the next day generation, is released at 4:00 pm. The uncertainty about which of their generating units will be accepted in the auction gives firms incentives to hold on gas procurement for their gas units that are less likely to be dispatched. Indeed, it is common among generators to acquire some additional gas after the auction result has finally been released. In this case, the bids they submit for those units may be based on their estimates of gas prices at the expected time of purchase.

G.3 Cost of Electricity Generation

Marginal fuel cost The unit of heat rate is MMBtu/MWh, and the unit of gas price is \$/MMBtu. Hence, the marginal fuel cost of electricity generation using gas (\$/MWh) is the heat rate multiplied by the gas price. In order to compute the fuel cost of oil-fired units, we must first convert the unit of oil spot prices, such as \$/gallon or \$/barrel, into \$/MMBtu. To do so, I divided the oil spot prices by the heat conversion rate taken from the EIA report (2013); 1 gallon of oil is equivalent to 138,690 Btu (for diesel fuel and heating oil), and 1 barrel of crude oil is equivalent to 5,800,000 Btu. Then, the marginal fuel cost of electricity generation using oil products is obtained by multiplying the converted oil prices with the heat rate.

Marginal emissions cost We can calculate the amount of CO_2 produced per kWh for specific fuels and for different types of generators, by multiplying the CO_2 emissions factor (or emissions rate) with the heat rate. Data on CO_2 emissions factor (lb CO_2 /MMBtu) for different types of fuels (gas, coal, oil and etc.) and different types of generators (e.g., combustion cycle) come from the EIA (2013). Then, the emissions cost of a generator can be calculated by multiplying the emissions permit price (Environmental Protection Agency (EPA) RGGI auction clearing price) to the amount of CO_2 produced by the unit.

Emissions regulation in New England The Northeast regions (New England) is and was subject to the following regulations: RGGI (Regional Greenhouse Gas Initiative), Ozone Transport Region (OTR) NO_x Cap and Allowance Trading Program, and Clean Air Interstate Rule (CAIR) (only MA and CT). OTR trading program is an implementation of emissions trading that primarily targets coal-burning power plants, allowing them to sell and buy emissions permits of SO_2 and NO_x. OTR trading program was replaced by Cross-state Air Pollution Rule (CSAPR) starting from year 2011, and the Northeast regions (all states in New England) are exempted from the new regulation. CAIR (Clean Air Interstate Rule) is a program that aims to reduce ozone level by suppressing SO_2 and NO_x emissions in 28 eastern states. All affected states chose to meet their emission reduction requirements by controlling power plant emissions through three separate interstate cap and trade programs: CAIR SO_2 annual trading program,NO_x annual trading program, and NO_x ozone season trading program. CAIR was again replaced by Cross-state Air Pollution Rule, as of January, 2015. The permit trading programs were temporarily reinstated until EPA could issue its new CSAPR rule.

In this study, I omit the NO_x and SO_2 permit prices when calculating the emissions cost because these pollutants are mostly regulated during the summer season, which starts from May 1 until Oct. 1. In fact, all the past NO_x and SO_2 regulations were effective only during this time period. The sample period that I use in the analysis is from October to March and does not include the period where any existing NO_x and SO_2 regulation might be effective. Therefore, the only effective emissions regulation during the study period that we must consider when calculating emissions costs is the RGGI (carbon permit trading).

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 CO_2 emissions where the capped amount decreases every year. It requires fossil fuel-fired electric power generators with a capacity of 25 MW or greater to hold allowances equal to their CO_2 emissions over a three-year control period. And then, the state allocate CO_2 allowances via quarterly, regional CO_2 allowance auctions. There were total 29 auctions as of September of 2015. Market participants can purchase CO_2 allowances at the quarterly allowance auctions or in the secondary market, such as the ICE and NYMEX Green Exchange, or via over-the-counter transactions.

G.4 Bidding Data

Import and export bids About 10 percent of electricity demand in New England is met by imports from Canada. Since the flow of imported and exported amount of electricity into the grid depends on the transmission constraints which I do not have information about, accounting for import/export bids together with the supply and demand bids when clearing the market is difficult. Instead, I use the hourly net interchange data, which is the final observed net flow of electricity into the grid measured by the difference in import and export. I subtracted the net interchange from the total electricity demand to generate the net demand that has to be met by the internal market supply.

Financial bids Besides supply and demand bids, financial traders can submit the virtual bids in the day-ahead electricity auction. Financial bids consist of a small portion of the day-ahead electricity transactions (about 1.5 %), and these bids are not associated with physical assets (ISO-NE EMM Report, 2015). I compared the outcomes with and without financial bids in the model and found no significant differences in the result. Despite this, I included financial bids in my analysis, treating them as a non-strategic, price takers.

Dynamic parameters of the auction Suppliers participating in the auction can submit the dynamic parameters, such as the must take capacity, minimum economic level of capacity and cold-start cost, etc., together with their quantity and price bids. Out of these dynamic parameters, I used the must-take capacity parameter, e.g., the minimum capacity a unit must dispatch in the auction, to detect the units that are unavailable for electricity generation. That is, setting the must-take capacity above the total capacity of a generator indicates that the unit cannot operate on a given day.

Identifying the masked information The identity of firms and generating units is masked, but I was able to identify most of the firms and some of their generating units by matching the information from bids data to other data sources such as the Seasonal Capacity Auction data. For those firms that I was unable to identify, at least the type of fuel used by their generating units was identified from the estimated implied fuel prices.

G.5 Estimation

Grouping of firms based on the estimated implied gas prices In the main analysis, I use the grouping of firms based on how intensive their generation is in gas-fired units. I also tried a slightly different grouping which is based on the cross-sectional differences in the estimated implied gas prices. For this second grouping, I look at the cross-sectional distribution of implied gas prices, for each day in the sample. I then classified firms that fall above the 50^{th} percentile of the distribution as being "high-impact" firms, and the rest as "low-impact" firms. I used weighted-average of implied gas prices for those firms that operate multiple gas units because the levels of implied gas prices differ across gas units operated by the same firm. This weighted-average value measures a firm's average exposure to the gas price shock. For example, the average measure of a firm that operates mostly dual gas units would be smaller than that of others, indicating that the firm's impact from the gas price shock is smaller than the others.

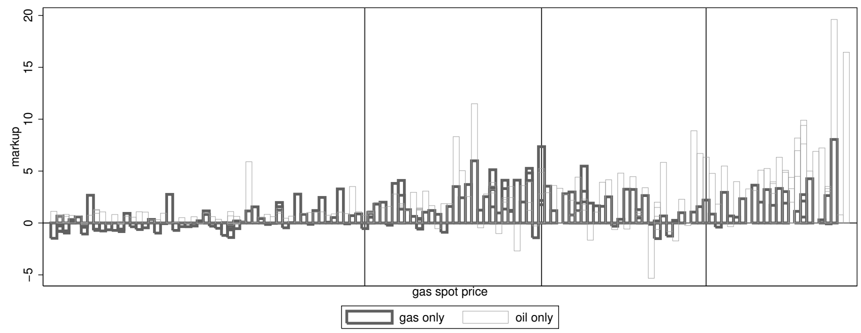
Two firm groupings are similar except that while a set of firms grouped under *Gas-intensive* category is fixed over time and across auctions, those grouped under *High-impact* category may change every day depending on the distribution of the implied gas prices. Since the firms classified based on two different measures overlap in most of the days in my sample, the results from each categorization are qualitatively similar. Therefore, I use the *Gas-intensive* grouping throughout the analysis of markups. However, I also present the simulated markups plotted separately by firms grouped under "high-impact" and "low-impact" categories, shown in Figure H.5.

G.6 Bid markup

Suppose that a kth step bid of firm i's generating unit j is the ex-ante marginal unit of the auction held at hour h of day t. After rearranging the first-order condition, the bid markup of this unit is expressed as in equation (9). Since we already have estimated the marginal cost of electricity generation, mc_{ijt}, the bid markup is measured by subtracting the marginal cost estimate $\widehat{mc_{ijt}}$ from the price bids data, i.e. $b_{ijkht} - \widehat{mc_{ijt}}$.

Dispersion in post-shock bid markups Another important observation from Figure 8 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 this, I plotted in Figure G.1 the firm-level bid markups of two firms, Firm 9 (*gas only*) and Firm 53 (*oil only*). The size of the bid markup increases along the horizontal axis for both firms, which indicates that both added larger bid markups, on average, as the size of the gas price shock increased. The interesting pattern arises within the competitive range of gas prices when daily gas index values are between \$15 and \$25/MMBtu. While bid markups of *gas-only* firm start decreasing within the competitive range, bid markups of *oil-only* firms increase constantly. This implies that firms adjust bid markups according to different patterns depending on their impacts received from the gas price shock. Therefore, the increased dispersion in post-shock bid markup distribution is a combination of having different impacts on costs across firms and having different levels of gas prices across days.



Notes: The graph shows daily bid markups of two specific firms, Firm 9 and Firm 53, plotted against the gas price index values of days in the sample. Thus, overall size of the gas price shock increases along the x-axis. Firm 9 is a gas-intensive firm, and Firm 53 is an oil-intensive firm. Three vertical lines are drawn at gas price index levels of $15, $20, and $25, respectively.

Figure G.1: Bid Markups of Two Firms: Sample 1

G.7 Markup Simulation

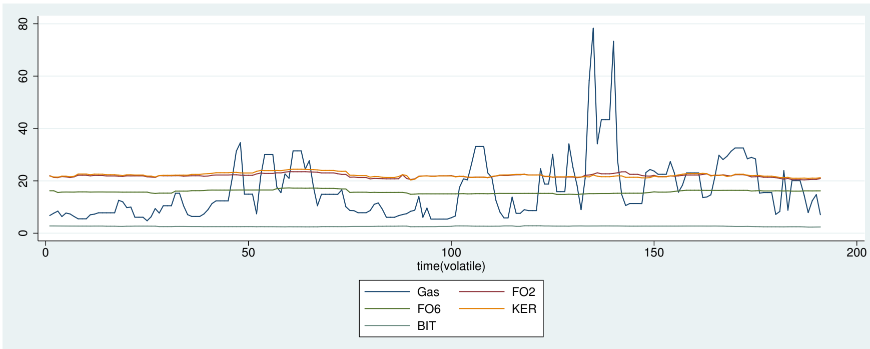
Simulation of the ex-ante first-order condition The bids of competitors observed in the auction ex-post is not the information that a firm used when making bidding decisions in ex-ante. That is, a firm chooses its optimal bid based on its expectations of bids of competitors. To tackle this, I exploited the resampling technique that is similar to the one used in the parameter estimation in order to construct the average supply offer curve out of the set of resampled supply offer curves. This average curve mimics the supply offer curve that the firm expected in ex-ante. I perturbed this average curve and measured the resulting endogenous changes in markups separately for each firm, because different ex-ante expected supply offer curves apply to each firm 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 resampled each observation randomly from a pool of similar days. The results reported in this paper are based on random draws from three similar days. Because it is practically challenging to take an average of curves and then perturb it again, I instead took a weighted average of the markups obtained from the perturbation of the each resampled supply curve. I used the probability of becoming marginal unit, $\frac{\partial p_h}{\partial b_{ijkh}}$, as a weight for calculating the weighted average.

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

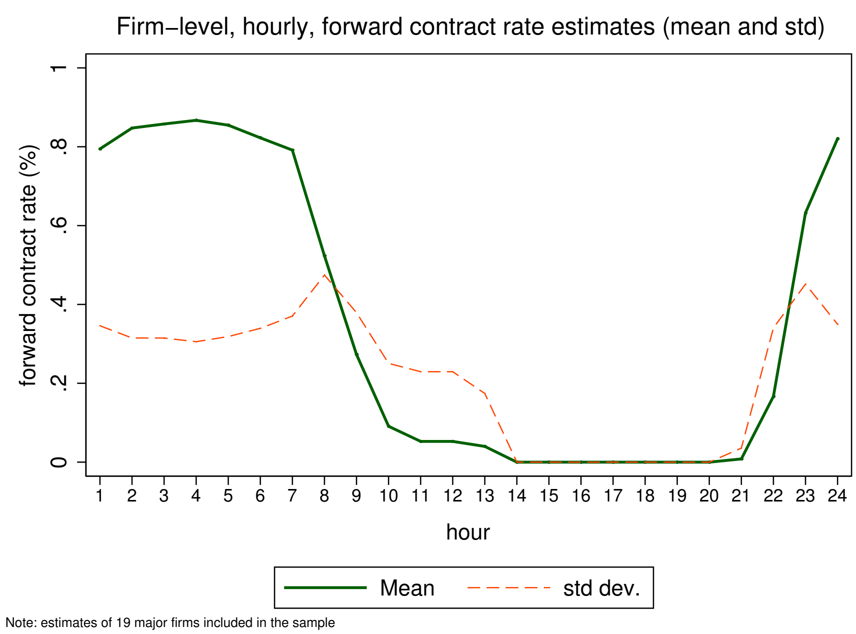
Simulation with different sizes of gas price perturbation Instead of imposing the equal size of 10 cents to all gas units in the simulation, I conducted another simulation where I imposed a gas price shock weighted by the actual impact as captured by the implied gas price estimates. For example, if the gas price index of the day is $20/MMBtu and a unit's implied gas price is $ 18/MMBtu, I imposed a gas price shock equivalent to $(18/20) * 0.1 = 0.09$ (9 cents) to this unit. The final increase in the marginal cost of this unit is $hr * 0.09$. This type of cost perturbation more precisely incorporates the heterogeneity in the impacts among gas-fired generators, as measured by the implied gas prices across units. The results based on the alternative simulation were qualitatively similar to the result from the main analysis.

H Additional Figures and Tables



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

Figure H.1: Spot Fuel Prices of Days when Gas Price Shocks were Present



Notes: The graph above shows the cross-sectional average and standard deviation of firm-level hourly forward contract rates, γ_{ih}, estimated from the model.

Figure H.2: Forward Contract Rates: Summarized Across Firms

	Simulated pass-through rates
	ρ_{ht}
Hard-hit firm	-0.041*
	(0.0195)
Cost shock	-0.099*
	(0.0464)
*Hard-hit * Dgas*	-0.0089***
	(0.002)
Dgas	0.00004
	(0.006)
Constant	1.007***
	(0.0427)
Observations	2,214

Notes: Auction-level pass-through rates (including only the auctions where gas units are marginal units) are regressed on several variables. The *hard-hit* variable is a group dummy assigned to firms grouped under the hard-hit category, and *Cost shock* is the size of the cost perturbation imposed in the simulation. *Dgas* is a difference between the gas price of the auction day and the average of gas prices over the sample which is around \$21/MMBtu. Outliers above and below 98th and 2nd percentiles are dropped. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table H.1: Regression of Simulated Pass-through Rates on Types of Price Setting Firms

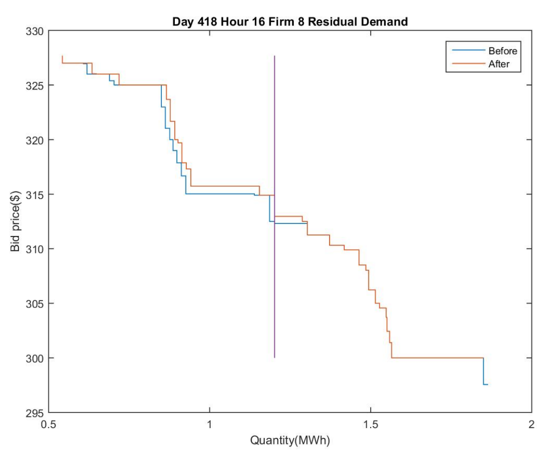


Figure H.3: Example of a Residual Demand Shift After the Perturbation

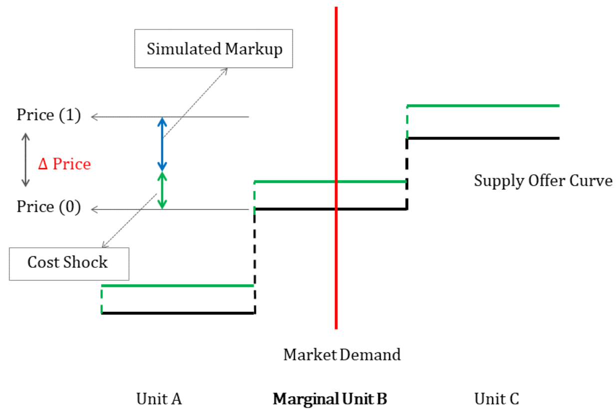


Figure H.4: Graphical Illustration of the Pass-Through Simulation

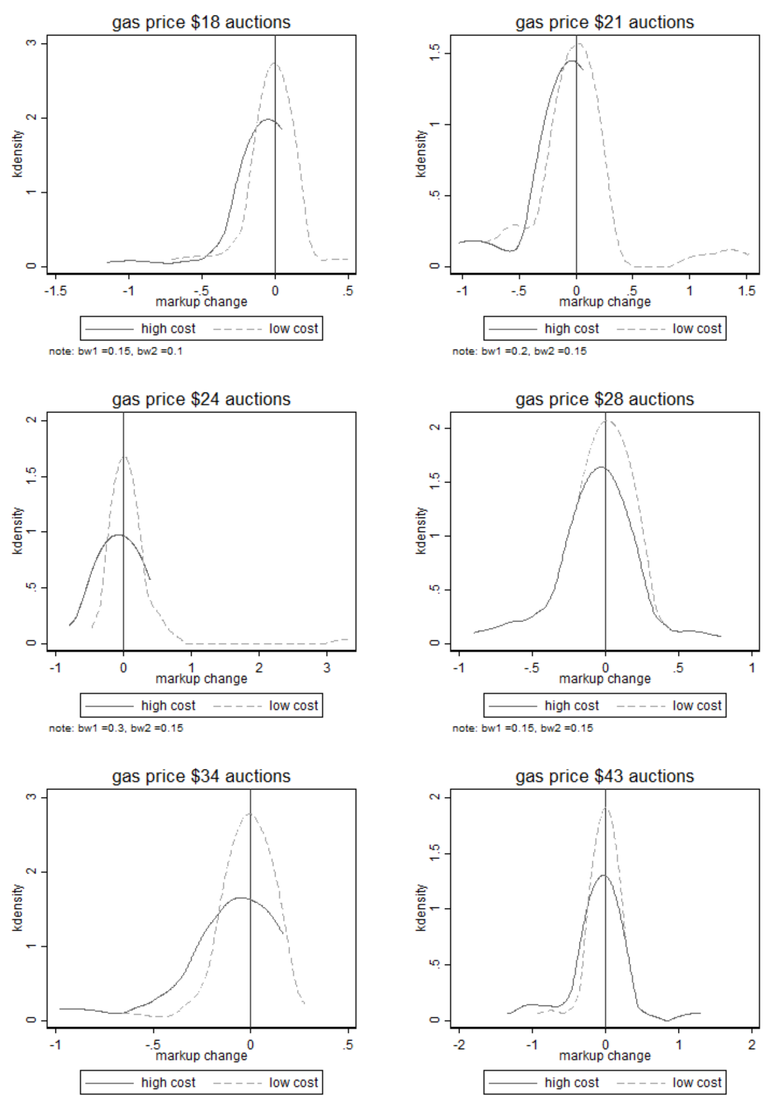


Figure H.5: Simulated Markups of High-Impact vs. Low-Impact Firms

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

Notes: Number of steps submitted by generators is summarized in this table. *Number of Generators* shows how many generators submitted bids with steps shown in *Number of Steps* column. *Percentage* is the percentage of generators submitted the step out of a total 305 generators.

Table H.2: Summary of Number of Bid Steps