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

Harim Kim*

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Abstract

Industry-wide shocks can have heterogeneous impacts on firms’ costs due to different firm characteristics. The heterogeneity in these impacts is crucial for understanding the pass-through of the shock, because of its implications on strategic competition. In the context of the gas price shock in the electricity market, I develop a method to identify heterogeneous impacts of the shock and show with a structural analysis that the heterogeneous feature of the shock induces markup adjustments of firms. Pass-through that is estimated without incorporating heterogeneous impacts fails to reflect the change in competition arising from the shock, and is, on average, underestimated.

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1 Introduction

Many significant economic events take the form of a shock. Therefore, it is important from an economic policy perspective to understand how the shock is transmitted to the industry, and further, to important variables of the market, such as the market price. The focus of this paper is on the transmission of the shock to the industry, with respect to firm heterogeneity which is a distinctive feature of many industries. When the industry is composed of heterogeneous firms, the transmission of the shock to the industry – in particular, the cost shock – could be heterogeneous as well. That is, some firms have characteristics that are less susceptible to the shock than others, and such a difference in these characteristics may lead to firms experiencing varying degrees of cost increase from the industry-wide cost shock.

Such heterogeneous impacts of the shock have important implications on strategic competition between firms in the industry. Intuitively, what governs a firm’s strategic decision in response to a cost shock is whether a firm’s cost increases by more or less than its competitors. When the impact of the cost shock is homogeneous, firms lack incentives to adjust markups, as the costs of all firms increase by similar amounts. On the other hand, with heterogeneous impacts, firms are likely to change their strategic incentives; low-impacted firms whose cost increase is smaller than the others have incentives to raise markups, while the highly-impacted firms that experience a large increase in costs may decrease markups to compete with the low-impacted firms.

In this paper, I show that the heterogeneity in the impacts of the cost shock is crucial for understanding the complete picture of how the cost shock is transmitted to the market price – cost pass-through – because of its implications on strategic competition. Because the extent of cost pass-through is determined by the price setting firm’s adjustment of markup in addition to the cost shock, getting the right picture of the change in competition arising from the shock is necessary to obtain the correct pass-through, and vice versa. This implies that a market analysis that fails to account for the heterogeneous feature of the shock will not capture the meaningful changes in competition, thereby undermining the role of competition in shaping

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1 This was the case of the emissions cost shocks studied by Fabra and Reguant (2014).
2 Markup adjustment is viewed as an important determinant of pass-through in empirical pass-through literature, including De Loecker et al. (2016), Fabra and Reguant (2014), Goldberg and Hellerstein (2013), and many others.
the pass-through.

Despite the importance, empirical studies that explore this heterogeneous transmission channel are scarce because of the major empirical challenge: to show how the opportunity costs of firms increase to different extents as a result of a shock, detailed and high-frequency information on firm-level costs is required, which is difficult to get from the data in general.

In this respect, the natural gas price shock event that occurred in New England, which is the empirical setting of this paper, provides attractive features that allow us to overcome this challenge. Because gas is a key input for generating electricity in the New England wholesale electricity market, exogenous shocks to the gas prices affected the costs of electricity-generating firms, but to different extents, due to substantial heterogeneity among firms. This feature makes the event an ideal setting to explore the heterogeneous transmission of the shock. Another attractive feature is that the high-frequency bidding data is available in this electricity market because the market is organized as auctions. Since firms reveal their opportunity costs of electricity generation to the bid, we can extract the precise cost information from the data on bids and use it instead of the limited cost data.

Exploiting these features within a structural framework, I develop a method to identify the heterogeneity in the impacts of the gas price shock on the costs of electricity-generating firms. I then examine the changes in firms’ strategic incentives that arise from the heterogeneous feature of the shock, and explore how these changes are reflected in the pass-through rate of the gas price shock to electricity prices. Finally, to illustrate the importance of accounting for the heterogeneous impacts, I conduct a pass-through estimation that disregards the heterogeneous transmission channel.

The findings of this paper provide empirical evidence to an intuitive, yet often disregarded, view that a cost shock can be a source of market power if transmitted heterogeneously across firms; the adjustments in markups are induced by the shock, indicating a change in firms’ strategic incentives. Strikingly, the pass-through rate estimated without accounting for the heterogeneous transmission channel does not reflect this change in markups and is significantly underestimated, on average. This finding is alarming because often pass-through estimated exclusively from data, which may not be precise enough to capture the different firm-level responses to the
shock, complements the analysis of market competition and assists policy decisions.\(^3\)

In relation to these points, analyzing the gas price shock event itself is policy relevant due to its strong impact on the New England electricity market; during the period of shock, the price of electricity was up to six times the usual level. It was the focus of regulators, therefore, to understand the pass-through of this shock, while considering the possibility of the market power that may have been exercised, as the electricity market is characterized by imperfect competition.

The main analysis begins with empirically identifying the heterogeneity in the impacts of the gas price shock, which arises from firms having different sets of generating assets and technology. For example, the costs of firms that do not operate gas generation or have the option to shift production to generators using different fuels will be unaffected, or affected less, by the gas price shock compared to those of other firms. However, the aforementioned empirical challenge is still present in this market because of the incomplete cost data. While measuring the cost using fuel price data is common in the studies of electricity market, this approach is not suitable in our context because the highly aggregated fuel price data is not precise enough to quantify the exact firm-level impacts on cost.\(^4\) Another factor further complicating the measurement of cost is the presence of a specific type of generator called a dual unit which can switch its fuel from gas to oil when gas prices are high so that its cost does not significantly increase. However, a dual unit’s fuel switch decision at the time of production is typically unobserved, making it difficult to measure the opportunity cost of the unit from the data.

I take a number of unique approaches to overcome this empirical challenge. First, instead of relying on the limited cost data or measuring the costs, I estimate firm-and generator-level marginal cost from the bidding data, utilizing the standard methodologies developed in the auction literature (Reguant, 2014; Hortacsu and

\(^3\)For example, in many fields of economics, pass-through is increasingly being used as a sufficient statistic for welfare analysis (Weyl and Farbinger, 2012; Chetty, 2009). Also, since obtaining pass-through rate from available data is relatively easier than conducting a full structural analysis, the estimated or calculated pass-through rate complements the analysis of market power, and is used to infer underlying market structure (Atkin and Donaldson, 2015; Bergquist, 2017). Finally, pass-through is widely being used by regulators and policy makers to assess the influence of the economic event on market outcomes.

\(^4\)Measuring the cost of electricity generation is possible because of the simple production technology, which enables decomposition of the cost into fuel price, emissions price, and heat rate. See Wolfram (1999) and Borenstein, Bushnell, and Wolak (2002) for an example.
McAdams, 2010). The estimation of marginal costs, however, is not sufficient for the identification, given that marginal cost of generating electricity using gas is a combination of (i) the price of gas and (ii) the (physical) efficiency of a generator. Since the gas price shock affects the cost of a generator through the gas price component – which I term implied gas prices – the variation in the implied gas prices across firms and generators more precisely reveals the heterogeneity that results from the shock alone. Besides, the implied gas prices can be used to identify the fuel switch decisions of the dual units, which is an important source of the impact heterogeneity. Thus, the additional step is to obtain the implied gas prices from the estimated marginal costs by partialling out the efficiency. To do so, I develop a novel approach where I estimate both implied gas price and efficiency from different samples, within the same estimation. Exploiting that efficiency is invariant to shock, I estimate generator efficiencies from sample days without the shock, and use these to separate out the implied gas prices from the marginal costs estimated from sample days that experienced shock. From the estimates, I document substantial heterogeneity in the impacts and find that the degree of heterogeneity increases as the market is hit by a larger gas price shock.

In the second half of the analysis, I obtain markups and pass-through rates in order to relate these to the documented heterogeneous impacts. Since our analysis involves changes in markups and prices that result from the shock alone, I conduct a simulation (Jaffe and Wyle, 2013; Fabra and Reguant, 2014) where I can control for every other factor except for the shock. That is, by imposing a small counterfactual cost shock, I can simulate the adjustments in markups and prices that result exclusively from the shock.

The markup analysis reveals that the heterogeneous feature of the gas price shock induces strategic adjustment of markups, but the pattern of adjustment differs across firms depending on their impacts from the shock; the hard-hit firms, the cost of which is affected more by the shock, added smaller and more negative markups compared to the firms that received a low impact from the shock. Interestingly, the difference in adjustment patterns becomes more distinct as the overall size of the shock increases. This result is consistent with the fact that the hard-hit firms that are gas-intensive in their generation face more intense competition under larger shock than under a small shock. For instance, while gas units compete with the similarly-impacted gas units when the shock is small, they now compete with both gas and
oil units under a sufficiently large shock, which pushes the cost of gas units closer to that of oil units. Having to compete with a larger pool of competitors, including oil units that are unaffected by the shock, the hard-hit firms behave more competitively, lowering markups further.

To explore how these firm-level markup adjustments are reflected in the pass-through, the need for a more disaggregated and higher-frequency pass-through rate arises, especially given that the size and the direction of the markup adjustment vary across firms and that the identity of a price-setting firm changes across auctions. Therefore, I simulate the auction-level pass-through rates and find that those rates are heterogeneous as well. That is, pass-through rates are lower in auctions where a hard-hit firm – which is not capable of adding large markups – is a price setter, than in auctions where less-impacted firms set the price. Despite this variation across auctions, the mean of pass-through rates is 97 percent, implying a near complete pass-through of the shock to electricity prices, on average.

Lastly, as a comparison, I conduct a reduced-form pass-through estimation that does not properly account for the heterogeneous impacts of the shock. I regress electricity prices on cost variable measured with aggregate fuel price data – the gas price index – which is not precise enough to reflect the differences in costs 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 which is obtained from the simulation. Underestimation resulted because the costs of low-impacted firms, which takes up a large proportion of price setting firms in my 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 resulted from markup adjustments, the naïve regression with the imprecise cost measure misleadingly attributes the increase in price more to the increase in costs, thereby underestimating the pass-through rate. However, when instead using the cost variable measured with the implied gas price, which captures the heterogeneity of the impacts, the reduced-form pass-through estimate is again close to complete.

Since the paper analyzes the changes in strategic competition in the electricity market, it relates to the stream of literature that studies market power in the electricity market setting. In addition to forward contracting (Bushnell et al., 2008),

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5The wholesale electricity market uses the multi-unit uniform auction where the final market clearing price of the auction is determined by a single firm.
transmission constraints (Borenstein et al., 2000; Ryan, 2014), and dynamic cost (Reguant, 2014), I introduce fuel cost shock, with an emphasis on its heterogeneous transmission as a source of market power in the electricity market. The paper also contributes to a large body of literature that studies the pass-through of the shock in a variety of market settings. In relation to methodology and the industry being studied, this paper is closest to Fabra and Reguant (2014), which explores pass-through of emissions cost shocks in the Spanish electricity market. The paper can also be linked to the set of papers that use structural analysis and micro-level data to study the pass-through (Nakamura and Zerom, 2010; Goldberg and Hellerstein, 2013). Although the concept of heterogeneous impacts is similar to the non-traded cost that is found to be an important source of incomplete pass-through, in Goldberg and Hellerstein (2013), I focus more on how the presence of the part of the cost that is irresponsive to the shock induces strategic adjustment of markups, and its relation to the pass-through. In general, the paper contributes to the pass-through literature by showing that non-careful implementation of the estimation, especially regarding the measurement of the cost shock, could lead to finding incomplete pass-through, which currently prevails in the literature.

2 Gas Price Shocks and the Sources of Heterogeneous Impacts

2.1 Gas price shocks in the New England wholesale electricity market

Natural gas is the key input for electricity generation in the New England wholesale electricity market, where the industry’s reliance on gas has increased from 15 percent of total generation in the year 2000 to almost 50 percent by the year 2015 (ISO-NE). In the winters of 2013 and 2014, a series of severe natural gas price shocks occurred in New England. The main cause of the shocks was the congestion in the gas pipelines caused by unusually cold weather, which makes the shock exogenous to the electricity market. Panel (a) of Figure 1 shows an increase in the spot gas

\[ \text{In contrast to the gas price shock, the impacts of emissions cost shocks across firms are homogeneous and thus did not give firms the incentives to adjust markups, which is one of the reasons why the authors find complete pass-through of emissions cost shock.} \]

\[ \text{The gas pipelines that deliver natural gas into the region almost always run close to the maximum capacity. The New England winters of 2013 and 2014 experienced particularly record-low cold weather, which worsened the congestion of pipelines because of the increased use of gas for residential heating. The gas demand from the electricity generators did not significantly increase during this period which makes the shock exogenous to electricity market.} \]
prices (gas price index) at one of the major city gates in New England. While the spot gas prices were stable at around $4/MMBtu on normal days without congestion, spot gas prices increased substantially over the winters of 2013 and 2014, frequently rising above $20/MMBtu which was almost five times more than normal.

As a result of these gas price shocks, the wholesale electricity prices in the New England electricity market increased substantially, as shown in Panel (b) of Figure 1. The fact that wholesale electricity prices moved together with the spot gas prices (see Panel (a)) indicates that the gas price shock – an input cost shock on the supply side – was, in this case, the major driver of the fluctuations observed in the output electricity prices.\(^8\) However, the transmission of the gas price shock to the cost of electricity generation, and further on to the electricity prices, is not as straightforward as it appears in the graphs due to the heterogeneous feature of the gas price shock, which I describe in the following section.

2.2 Why are the impacts of cost shocks across firms heterogeneous?

While all of the electricity generating firms in New England were subjected to the gas price shock, the actual impact of the shock on the cost of each firm differed due to their heterogeneity regarding generation mix, generation technology and gas procurement channels. The goal of this section is to provide potential sources that

\(^8\)Since the electricity demand shocks were not present over this period, I can rule out the demand side as a cause of the increase in electricity prices. More details can be found in Section B.1 of the Online Appendix.
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Notes: The capacities of five 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 Dual category.

Table 1: Generation Mix Differences: Major Firms

may cause such different impacts from the shock, which I will later verify with the empirical analysis of the costs.

**Generation mix differences** Table 1 shows the generation capacities of major firms in the New England electricity market, by energy source. The percentage of gas generation, as part of the total generation capacity, differs significantly across firms. For example, EquiPower’s generation capacity consists entirely of gas-fired units, whereas NRG has a high percentage of oil generation which more than doubles the percentage share of gas generation. Because the gas price shock increases the generation costs of the gas-fired units only, having different shares of gas generation in the total capacity results in them having different impacts from the shock. Therefore, the impact of the shock on the costs of firms would be greater for firms with a larger share of gas generation than for those with a larger share of oil and coal units in their generation.9

**Dual gas units** Some of the gas-fired units are equipped with dual generation technology that enables the generation of electricity with fuels other than gas, called dual gas units. More than 28 percent of gas generators in New England were dual units (as of 2014), and each firm had a different share of dual gas units. For example,

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9How the costs of the firm’s entire generation changes with the gas price shock is relevant in my context because the firms in this market compete in a specific type of auction called the multi-unit uniform auction. That is, a firm’s strategic decision at the margin is affected by how much in total it can sell in the market (see Ausubel and Cramton (2002) for a summary), which is affected by the overall changes in costs of the entire generation set.
as shown in Table 1, while Exelon had approximately a quarter of its gas generation coming from dual gas units, EquiPower did not operate any dual gas units.

Dual units use gas on normal days when gas prices are low but can switch to using oil when gas prices are too high, in order to avoid a greater impact on costs. For example, if the spot gas price increases to $25/MMBtu, which is more expensive than the price of oil (e.g., price of No.2 oil is $21/MMBtu), a dual unit has the option to switch fuel to oil, which is cheaper than gas. However, the non-dual gas unit that is not equipped with the technology to switch will have to continue using gas at a high price; hence, the cost of a dual gas unit increases by less than that of a non-dual gas unit, especially on days with a large shock.

Although it may seem that the decision to switch the dual unit’s fuel supply is driven by cost minimizing incentives, not every dual unit behaves in this way. Whether they switch fuels depends on the availability of on-site oil fuel stock, as well as a firm’s generation decision that involves the entire generating assets.\(^\text{10}\)

**Long-term contract and spot gas price volatility** Even among the non-dual gas units, the extent of cost increases due to shocks can differ because firms can purchase gas from two different channels (i) from the daily spot gas market, or (ii) through a long-term contract with a gas supplier. Firms that enter into a long-term contract with gas suppliers can secure gas at the contracted price. Unlike spot gas prices that change every day and moment based on the gas market condition, the pre-committed contracted price is not affected by day-to-day spot gas market conditions.\(^\text{11}\) Therefore, especially on days with severe gas price shocks, the cost difference between gas units that purchase gas via a long-term contract and those buying from the spot market could be substantial.

The increased volatility of the spot price of gas is another source of heterogeneous impacts. When the spot gas market is under shock (caused by severe pipeline congestion), the gas spot prices vary throughout the day by fluctuating over time, even within a single day. Since the timing of gas procurement differs across firms, significant fluctuations in spot gas prices over time results in differing firm- and unit-level gas prices. Figure 2 shows the existence of such heterogeneity in spot

\(^{10}\)Source: ISO-NE Winter Reliability Program (2015/2016)

\(^{11}\)Since the contract decisions are made in advance, given the longer time frame, a firm cannot set up a contract immediately as a response to a high spot gas price. This makes the variation in procurement channels across firms exogenous.
Notes: Data source is over-the-counter individual transaction-level gas spot prices at two city gate points, provided by Intercontinental Exchange (ICE). The line in the figure shows the weighted average values of transaction-level gas prices, and the bars show the difference between the highest and the lowest among transaction-level gas prices. Only the subset of transactions is available as data.

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

gas prices at the firm level, where the minimum and maximum of daily firm-level spot gas prices at two city gates are plotted against time. Panel (a) shows the spot gas prices at a city gate in New England where severe gas price shocks occurred in the winter, while Panel (b) shows spot gas prices at a city gate in California where the shock did not occur. The gap between the minimum and maximum measures the dispersion of spot gas prices among firms. I observe a large dispersion in Panel (a), but no dispersion in Panel (b). This provides evidence that spot gas prices are volatile within the same day when the gas market is under shock, and that increased volatility causes firm-level spot gas prices to be different.

Data vs. estimation: which better captures heterogeneity? The empirical challenge arises given the difficulty in observing heterogeneous cost responses from data due to the general unavailability of detailed cost information. In studies of the electricity market, the cost of generating electricity using gas is measured with the gas price index data, which is a weighted-average value of firm-level spot gas prices (Wolfram, 1999; Borenstein et al., 2002). When spot gas prices do not significantly fluctuate, the index data is a reasonably accurate measure of the firm-level gas price because the firm-level gas price is close to the average value. However, using index data becomes problematic when firm-level gas prices are dispersed due to increased.

12The gas price index is generated by companies like Platts and SNL, where they collect individual firm-level gas transaction prices at the spot market each day and measure a single, weighted-average index value out of the collected information.
volatility in spot gas prices, as the average value cannot capture such dispersion at the individual firm level. Moreover, the gas price index could significantly overstate gas prices paid by firms that procure gas by long-term contract because the contract price is not even included when generating the index measure.

Even if the high-frequency firm-level gas prices are available, the cost measure generated with these gas prices may not reflect the true opportunity cost of electricity generation. For example, the opportunity cost of dual gas units that considers switching fuel to oil cannot be measured with the spot gas price, because whether they have decided to switch at the time of the supply decision is typically unobserved. Therefore, measuring cost from data is not appropriate, especially in my context, where capturing the cost heterogeneity among firms is essential for my analysis. To overcome this empirical challenge, I rely on the high-frequency data of bids which is available in this electricity market, and estimate the marginal cost that rationalizes the firms’ bids, which is the real opportunity cost that is internalized by the firms in their bids.

3 Strategic Response to Cost Shocks: Markup Adjustments

Since the wholesale electricity market uses a multi-unit uniform auction to clear the market, electricity generating firms compete for sales in the auction. Firms submit supply bids, which consist of a price bid and a quantity bid, for each of their generating units. The price bid reflects a unit’s marginal cost of electricity generation, plus the additional part – the markup – that results from strategic consideration. The demand side, the load-serving companies, submits bids that are insensitive to the price in order to secure a certain amount of electricity in the market, thus making the demand almost perfectly inelastic. A single market clearing price of the auction is determined at the intersection of aggregate supply and demand curves, which implies that a price bid of the unit located at the intersection (i.e., marginal unit), will be the market clearing price. The single market price applies to all infra-marginal suppliers who sell electricity in this market, making this auction a uniform price auction.

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13 This is also in line with the argument by Fabra and Reguant (2014) that a shock observed in the data cannot always be the actual shock internalized by the firms.

14 The market organizer, the Independent System Operator (ISO) of New England, constructs the curves and clears the market.
The price-setting *marginal* unit is pivotal because a firm can manipulate the market price by adjusting the price bids of the marginal unit. Therefore, while firms may not strategically bid for their infra-marginal units, they have the incentive to do so for the marginal units. However, which unit will be the marginal unit is uncertain at the time of bidding because firms submit bids simultaneously without knowing how others will bid. Consequently, the strategic incentive to adjust bids occurs to those units that are *expected* to be the marginal unit, that is, the ex-ante marginal units.

A firm’s incentive to increase or decrease markups in the presence of a cost shock is affected by the shape of the demand curve as well. I can rule out the demand side channel in my study because the demand for electricity in the wholesale electricity market is considered almost perfectly price inelastic.\(^{15}\) That is, the ability of a firm to adjust markups is restricted by the demand only when it is elastic, in which case raising the price through an additional markup adjustment leads to a reduction in the quantity demanded. Therefore, any adjustment in markups following a cost shock considered here is the result of strategic considerations related to how the shock affects the costs of firms relative to their competitors as well as the nature of competition among firms.

Heterogeneous impacts and markup adjustments at the margin  I use a simple example to explain the intuition behind how a shock that has heterogeneous impacts on firms’ costs provides them the incentives to adjust markups. I consider units that are or near the *marginal* units. Figure 3 illustrates the situations in which I give different types of shocks to three units, A, B, and C. The units A and B are operated by Firm 1, and unit C is operated by Firm 2. Suppose that currently, unit B is the marginal unit of this 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 that the final adjustment of the price bid following a cost shock can be decomposed into a shift according to the size of the cost shock, and a subsequent shift according to the size of the markup adjustment.

In Panel (a) of Figure 3, all three units are affected homogenously by the shock;

\(^{15}\)Fabra and Reguant (2014) find lack of demand response to price changes in the Spanish wholesale electricity market and show that demand does not restrain firms’ ability to adjust markups.
the price bid of the units increases by the same-sized cost shock. In this case, the distribution of bids (slope of the bid curve) after the shock is the same as before the shock. Because firms were already optimizing before the shock, no change in the bid distribution after the shock implies that firms lack incentives to further adjust bids by adding markups. Panels (b) and (c) illustrate a different situation where the costs of firms are affected heterogeneously by the shock. In Panel (b), the cost of Firm 2’s unit B increases by more than that of Firm 1’s unit C, in which case Firm 1 has an incentive to raise the price bid of its marginal unit B further by adding a markup, without losing its status as a price setter. This is possible because Firm 1 understands that the competitor (Firm 2) will have to raise the price bid of unit C at least by the size of the cost shock which is bigger than the cost shock of its own. On the other hand, Firm 1 has a different incentive in a situation illustrated in Panel (c), where the cost of unit B increases by more than that of unit C. Now it becomes difficult for Firm 1 to add markups because the further increase in price bids may reverse the dispatch orders of units B and C, in which case the unit B may not be accepted in the auction. In this case, Firm 1 has the incentive to lower the price bid by adding zero or negative markups.  

I can extend this logic to the case of multiple firms by using residual demand. In general, a firm’s incentive to adjust markups in response to a cost shock – either raising or lowering – depends on whether or not the slopes of the residual demand...

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16 The markup adjustment considered here is the additional change in markups that is added to the non-negative bid markup that firms were already earning. Although earning a negative bid markup in total by bidding below the cost is not reasonable, an additional negative markup adjustment on top of a positive bid markup is possible as long as the bid markup after the adjustment is not negative.
curve change after the shock.

**Size of the shock and the different impacts across fuel types** The overall size of the gas price shock is an important factor that changes the intensity of the competition between gas units and oil units because the shock increases the marginal costs of gas units only. Without the shock, the spot gas prices are around $4/MBtu, which is substantially lower than the spot oil prices that range between $18 – $22/MBtu. Therefore, unless the gas price shock is large enough to make the daily gas price to exceed the level of the oil price, the marginal cost of gas units is smaller than that of oil units. As a result, when the size of the gas price shock is small, gas units compete only with the other gas units that have similar marginal costs.

As the size of the gas price shock increases, the marginal cost of a gas unit approaches that of an oil unit, forcing gas units to compete with both gas units and oil units. Especially when the post-shock gas price lies within the range of spot oil prices, the marginal cost of the gas-fired unit is comparable to that of an oil-fired unit which is unaffected by the shock. In this case, a gas-fired unit is likely to be in a situation shown in Panel (c) of Figure 3, where it does not have an incentive to increase the markup at the margin. On the other hand, a large-sized shock induces oil-fired units that were previously left out of competition to behave more strategically by adding markups, which is similar to the situation depicted in Panel (b) of Figure 3.18

4 Model, Empirical Strategy, and Data

4.1 Multi-unit uniform auction model

Because of the difficulty in identifying the heterogeneity in the impacts of the shock from the data and the need for a thorough analysis of firms’ markups, we

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17 As shown in Figure A.3 in Appendix A.6, spot prices of other fuels (coal and oil) do not change with the shock, whereas the spot price of gas fluctuates due to differently sized shocks.

18 This is a result of the high gas prices creating a situation in which the oil-fired units could compete with highly impacted gas-fired units, and because the chance of oil-fired units becoming marginal units increases with higher levels of gas prices. High-cost oil units can set the price in the auction more often when the size of the shock is large, because an overall increase in the marginal costs of gas units results in higher market clearing prices.
need a model that explains the strategic decisions of electricity generating firms. I present a model that describes the bidding decisions of the firm in a multi-unit uniform auction, and the model setup is similar to Reguant (2014). Suppose there are $i = \{1, \ldots, N\}$ firms that each operates $J_i$ number of units, indexed by $j = \{1, \ldots, J_i\}$, that can generate electricity using multiple energy sources. A firm submits hourly price bids ($b$) and quantity bids ($q$) for each of its generating units. Since firms are allowed to submit multiple steps of bids for each unit, I denote the step with $k$. Therefore, the $k^{th}$ step of a bid submitted for firm $i$’s unit $j$ at hour $h$ of day $t$ is $b_{ijkht} = < b_{ijkht}, q_{ijkht} >$. Given the market clearing price $P_{ht}$, firm $i$’s (ex-post) profit function on day $t$ is shown below:

$$\pi_{it}(b_{it}, b_{-it}) = \left( \sum_{h=1}^{24} P_{ht}(b_{iht}, b_{-iht}) \left( Q_{iht}(P_{ht}(b_{iht}, b_{-iht})) - \nu_{iht} \right) \right) - \sum_{j=1}^{J_i} C_{ijt}(q_{ijt}(P_{t}(b_{it}, b_{-it}))) \right)$$

(1)

$Q_{iht}$ is the quantity generated by the entire dispatched units of firm $i$ at hour $h$, and $q_{ijt}$ is the quantity generated by firm $i$’s unit $j$ on day $t$, where the hourly generations are aggregated across hours. Also, $b_{iht}$ is the bid vector of firm $i$ that includes the bids of the entire unit operated by the firm at hour $h$, and $b_{-iht}$ is bid vectors of all other firms. The market clearing price is a function of the bid distribution, i.e., $P_{ht}(b_{iht}, b_{-iht})$, because the price depends on the entire distribution of supply bids submitted by firms. How many units of a firm will be accepted in the auction depends on the final price, thus the total quantity supplied by firm $i$ and its unit $j$ are functions of the bid distribution, shown as $Q_{iht}(P_{ht}(b_{iht}, b_{-iht}))$ and $q_{ijt}(P_{t}(b_{it}, b_{-it}))$, respectively.

I assume that the electricity generation cost of unit $j$ of firm $i$ is linear in quantity, i.e., $C_{ijt}(q_{ijt}) = mc_{ijt} q_{ijt}$; thus, the marginal cost of electricity generation is constant over quantity, i.e., $C'_{ijt}(q_{ijt}) = mc_{ijt} + \epsilon_{ijkht}$. While dynamic cost is also an important component of the electricity generation cost (Wolak, 2003; Reguant, 2014), I did not include it in the main cost specification. Further discussion about the cost specification can be found in Appendix A.1.

It is common for electricity generating firms to engage in a forward contract where they sell a certain amount of electricity to the demand side at a committed price in advance of the auction. Therefore, the forward contracted quantity is exogenous at the time of the bidding and is not affected by the market price. For this reason, I
subtract this quantity, $\nu_{iht}$, from the total quantity supplied, $Q_{iht}$. I estimate $\nu_{iht}$ within the model similar to Reguant (2014), due to the difficulty of obtaining data on the forward contracts.\(^{19}\) I assume that firms forward contract a certain percentage, $\gamma_{ih}$, of their expected hourly output. The specification for the forward contracted quantity of firm $i$ for the hour $h$ of the day $t$ is, therefore, $\nu_{iht} = \gamma_{ih}Q_{iht} + \varepsilon_{iht}$.

Firms have uncertainty over the bids of competitors ($b_{-it}$) as they submit bids simultaneously in the auction. Thus, a firm must form a belief about the distribution of others’ bids ($\tilde{b}_{-it}$) and choose the optimal bid, $b_{it}$, that maximizes its ex-ante expected profit given this belief. The maximization problem of firm $i$ is described below where the expectation is taken over $\tilde{b}_{-it}$:

$$\max_{b_{it}} \mathbb{E}_{-it} \left[ \pi_{it}(b_{it}, \tilde{b}_{-it}) \right]$$

Because firms lack incentives to bid strategically when they do not have any control over the price, the optimality condition holds only for the ex-ante marginal unit of a firm that has a positive probability of setting the market price.\(^{20}\) Although only one unit sets the price ex-post, there are multiple ex-ante marginal units in a single auction due to uncertainty over how others would bid and what the market clearing price would be. Given that $k^{th}$ step of firm $i$’s unit $j$ is ex-ante marginal unit of auction $ht$, the necessary first-order condition with respect to the price bid $b_{ijkht}$ is shown in equation (2).\(^{21}\)

$$\mathbb{E}_{-it} \left[ \frac{\partial P_{ht}}{\partial b_{ijkht}} \left[ (Q_{iht}(P_{ht}) - \nu_{iht}) + (b_{ijkht} - C'_{ijt}) \frac{\partial RD_{iht}}{\partial P_{ht}} \right] \right] = 0 \quad (2)$$

### 4.2 Empirical strategy

In this section, I explain the samples, the decomposition of a marginal cost and the assumptions that enable the estimation of the additional parameters: implied fuel price and heat rate. The key parameter is the implied fuel price which is the

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\(^{19}\)Bushnell, Mansur, and Saravia (2008) have shown that electricity generating firms in the New England wholesale electricity market indeed enter a forward contract with the demand side. As they had access to confidential information of firm-level forward contracts, they did not estimate the forward contracted quantity in the analysis.

\(^{20}\)I take the analytical expression of this ex-ante probability of price setting, $\frac{\partial P_{ht}}{\partial b_{ijkht}}$, from Wolak (2003) in order to calculate the probabilities and to sort out the ex-ante marginal units. The expression can be found in Appendix A.2.

\(^{21}\)See Appendix A.1 for more details concerning the derivations of the condition.
fuel price component of a unit’s marginal cost of electricity 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 a firm’s cost by separately backing out the
implied fuel price parameters from the marginal cost estimates. To separate out the
implied fuel price from the marginal cost, I first need to estimate the unit-specific
heat rate, which is the physical efficiency of the unit.

Marginal cost decomposition The additional parameters, the heat rate and the
(implied) fuel prices, appear in the marginal cost decomposition which is commonly
used in the studies of electricity markets (Wolfram, 1999; Borenstein et al., 2002,
etc.). The marginal cost of generation $mc_{ijt}$, which is assumed to be a constant
value over quantity, can be decomposed further into two parts: fuel costs and emis-
sions costs. Since each part contains the heat rate (physical efficiency), the final
expression of marginal cost becomes the heat rate multiplied by the sum of the fuel
price and emissions price. Equation (3) shows the decomposed marginal cost of unit
$j$ operated by firm $i$ on day $t$:

$$mc_{ijt} = hr_{ij} (FP_{ijt} + \tau_{t} e_{j,fuel})$$

$FP_{ijt}$ is the price of a fuel used by firm $i$’s unit $j$ on day $t$, and $\tau_{t} e_{j,fuel}$ is the
part of the emissions cost where the emissions permit price ($\tau_{1}$) is multiplied by the
emissions factor ($e_{j,fuel}$). The heat rate of unit $j$, shown as $hr_{ij}$, does not vary across
days because the physical efficiency of a generator does not change over time.

Samples used in the estimation I exploit two different samples that enable the
estimation of a different set of parameters; sample days without the gas price
shock, which I denote as Sample 0, and days with the gas price shock, denoted as
Sample 1. Figure 4 shows the parts of days and the gas price index values over these
samples.

The key difference between these samples is the presence of the gas price shock.

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22These studies exploit the decomposition to calculate the marginal cost of electricity generation
using data on fuel price, heat rates, and emission costs. Separating out the components of the
marginal cost is not an easy task within other industries where various inputs and technologies
are used for producing goods. Electricity generation, on the other hand, has a simple production
technology with fuel being the only major variable input, which enables the decomposition of the
marginal cost.
Notes: Days in between the red vertical lines are part of Sample 1 which is a collection of days that experienced gas price shock. Days outside of the lines are part of Sample 0 when the gas price shock was not present. Sample days are taken from the fall/winter periods (from September to March) of 2012-2013 and 2013-2014.

Figure 4: Sample 0 and Sample 1

In the absence of severe pipeline congestion, the gas price usually stays around $4/MMBtu without any significant fluctuation. However, the gas price rises above $4/MMBtu when the pipeline is severely congested, which I define as a shock event. The exact levels of the daily post-shock gas prices would depend on the degree of congestion on the day, causing the gas prices to fluctuate substantially within Sample 1, as shown in Figure 4. Therefore, I have grouped the normal days, for which gas price index values are around $4/MMBtu, into Sample 0, and have grouped the days for which gas price index values rises above $4/MMBtu into Sample 1.

Heat rate parameter From Sample 0, I estimate the heat rate parameter of each unit, \( h_{rij} \), which shows up in the marginal cost expression in equation (3).

The fact that gas prices are stable across Sample 0 enables estimation of the heat rate. That is, when gas prices do not fluctuate across hours within a day, the firm- and unit-specific spot gas prices, which will eventually be reflected in the price bids, do not greatly differ across firms and units. In this case, the gas price index, which is a weighted-average of individually reported spot gas prices, is a good measure of the firm-unit-level gas prices. Therefore, I can use the gas price index \( F_{\text{index},t} \) in place of the fuel price component of the marginal cost of a gas-fired unit \( j \), i.e., \( F_{ij,t} \), for Sample 0 observations. To summarize, I am implicitly assuming in Sample 0 that: \( F_{ij,t} \approx F_{lk,t} \approx F_{\text{index},t} \) \((i \neq l, j \neq k)\).

After inserting the index data for \( F_{ij,t} \) and placing in the emissions cost mea-
sured from the data (both $\tau_t$ and $e_{j,fuel}$ are available as data), the only remaining parameter is the unit-specific heat rate $hr_{ij}$, as shown in equation (4).

$$mc_{ijt} = hr_{ij} (FP_{index,t} + \tau_t e_{j,fuel}) \quad t \in \text{Sample 0}$$ (4)

Therefore, I can estimate the heat rates of each unit separately from the marginal cost, from the Sample 0 observations.\(^{23}\) Note that estimation of the heat rate is only possible in Sample 0 because I cannot use the gas price index data in place of $FP_{ijt}$ in Sample 1. This is because the index data is not a good measure of unit-level gas prices when the dispersion in gas prices increases. Instead, I estimate $FP_{ijt}$ from Sample 1 observations, which I term the *implied* fuel price.

**Implied fuel price parameter** The main parameter estimated from Sample 1 is the implied fuel price parameter, $FP_{ijt}$, which is the fuel price component of the marginal cost of generation shown in equation (3).

There are several advantages to using the implied fuel price over the marginal cost, in particular for gas-fired units. First, the implied gas price estimates allow me to identify the actual impact of the gas price shock on the unit’s marginal cost, as measured by the gas prices reflected in firms’ bids, net of unit-specific heat rates. By partialing out the heat rate component, I have a clearer picture of the heterogeneous impacts resulting solely from the gas price shock.\(^{24}\) Second, I can utilize the implied fuel prices of dual gas units to identify whether or not they switched fuels to oil on a given day. The idea is that, if a dual gas unit switches to using oil, the estimated implied fuel price of the unit will correspond to the price of oil, rather than the price of gas. Therefore, the fuel switch decision of the dual unit is identified by comparing its implied fuel price with the gas price and oil price data. Finally, implied gas prices, which are estimated at a unit-level, offer more accurate and high-frequency information than the gas price index data. I can overcome the limitation of not having data for firm- and unit-level gas prices by using the estimated implied gas prices.

\(^{23}\)Since I can use the index values in place of $FP_{ijt}$ for other fuel types such as coal or oil – the spot prices of which are also stable over Sample 0 – I can estimate the heat rates of all units that generate electricity using fossil fuel.

\(^{24}\)Even if I observe variations in the marginal costs across firms and units, such variations cannot be attributed solely to the differences in the impacts from the shock because of the pre-existing heterogeneity in the heat rates.
To obtain $FP_{ijt}$ of Sample 1, I first estimate the unit-specific marginal costs of each day in Sample 1, shown as $mc_{ijt}$ in equation (5) for each $t \in$ Sample 1. Because the levels of gas prices vary substantially across days in Sample 1, the marginal costs of gas-fired units are also different across days, implying that a unit-specific marginal cost parameter must be estimated per day.

I then go a step further and back out the implied fuel price $FP_{ijt}$ from the marginal cost estimates, $\hat{mc}_{ijt}$. Separating the implied fuel price from the marginal cost estimate is possible because I have the unit-specific heat rates estimated from Sample 0, $\hat{hr}_{ij}$, as well as the data on emissions cost, $\tau_t e_{j,fuel}$. Since the heat rate – which is a physical efficiency of a generating unit – is invariant to shocks or any changes in the market conditions, I can use the heat rates estimated from Sample 0 in the Sample 1 observations. Therefore, the invariance of the heat rate across Sample 0 and Sample 1 is the key feature that enables the extraction of the implied fuel price from the marginal cost, as shown in equation (5) below.

$$\hat{mc}_{ijt} = \hat{hr}_{ij} \left( FP_{ijt} + \tau_t e_{j,fuel} \right) \quad t \in \text{Sample 1} \quad (5)$$

**Forward contract parameter** I restrict the forward contract rate, $\gamma_{ih}$, to be a constant value over the sample in order to better identify the parameter. Thus, a single set of forward contract parameters, $\{\gamma_{ih}\}_{h=1,24}$, is assigned to each firm and does not vary across days. I estimate forward contract parameters only from Sample 0, because it is practically infeasible to simultaneously identify and estimate forward contract parameters in Sample 1, together with the marginal cost which will be estimated on a daily basis. In the Sample 1 estimation, I plug in the forward contract rates that are estimated from Sample 0, exploiting the assumption that forward contract rates do not vary across days.

---

25 Some dual gas units may use gas to generate electricity in Sample 0 days, but switch to oil instead on Sample 1 days. Even in this case, I can use the heat rate estimated from Sample 0 for the estimation in Sample 1 because the heat rate of a dual unit does not change with the fuel switch. More details can be found in Section B.1 of the Online Appendix.

26 Specifically, if the observation from Sample 1 is from the winter season of 2013, I use the forward contract rate estimated from days in Sample 0 that belong to the same time frame (season).
4.3 Estimation

To estimate parameters, I need to derive an empirical analogue of the first-order condition shown in equation (2), which includes an expectation over the bids of other firms \((b_{-i})\) that are uncertain to firm \(i\). I approximate the expectation term following the method developed by Hortacsu and McAdams (2010), which has been applied to the electricity auction settings in Reguant (2014). The key idea of this method is to approximate firm \(i\)'s expectation of others' bids, \(\tilde{b}_{-i,j}\), by resampling from the observed bids. The analytical expressions of \(\frac{\partial \hat{P}_{ht}}{\partial b_{ijkht}}\) and \(\frac{\partial \hat{RD}_{ht}}{\partial P_{ht}}\), which appear in the first-order condition, are taken from Wolak (2003). Specific details of how I implement the resampling and obtain the derivatives of the curves are provided in Appendix A.2.

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

\[
m_{ijkh}^T(\theta_T ; S) = \frac{1}{S} \sum_{s=1}^{S} \frac{\partial \hat{P}_{ht}^s}{\partial b_{ijkht}} \left( (Q_{iht} - \nu_{iht}(\gamma_{ih})) + (b_{ijkht} - m_{ijht}) \frac{\partial \hat{RD}_{ht}^s}{\partial P_{ht}} \right) \tag{6}
\]

where \(T\) denotes the Sample, i.e., \(T \in \{0, 1\}\), subscript \(s\) denotes the resampled value, and \(S\) is the total number of resampled observations.\(^{27}\) I instrument the slope of the residual demand, \(\frac{\partial \hat{RD}_{ht}^s}{\partial P_{ht}}\), which is subject to potential endogeneity, with the hourly forecasted demand, the daily forecasted temperature (Sample 0), and the forecasted demand error (Sample 1).\(^{28}\)

The final empirical moment conditions used in the estimation are shown below in equations (7) and (8):

\[
\sum_{t=1}^{T} \sum_{k=1}^{K} Z'_{0,ht}^t m_{ijkh}^0 (hr_{ij}, \gamma_{ih}) = 0, \quad \forall j, h \tag{7}
\]

\[
\sum_{h=1}^{H} \sum_{k=1}^{K} Z'_{1,ht}^1 m_{ijkh}^1 (mc_{ijht} | hr_{ij}, \gamma_{ih}) = 0, \quad \forall j \tag{8}
\]

Identification and Inference Identification of both heat rate and forward contract parameters in the Sample 0 estimation is possible by imposing reasonable re-

\(^{27}\)The wide hat denotes the kernel smoothed values. Smoothing of the curve is necessary to obtain derivatives. See Appendix A.2.

\(^{28}\)Endogeneity of the slope of the residual demand arises if unobserved firm-specific cost shock is present (Reguant, 2014; Ryan, 2015). See Appendix A.2 for more details on the instruments.
strictions on parameters, and the identification strategy is similar to that of Reguant (2014). First, the heat rate parameter \( h_{rij} \) is assigned to each generating unit \((ij)\) and is assumed to be constant across hours and days in Sample 0, which is a reasonable assumption as the heat rate is a physical efficiency of a generator. On the other hand, the forward contract rate \( \gamma_{ih} \) is assigned to each firm \((i)\) and constant across days in Sample 0, but differs across hours \((h)\). Thus, each firm has 24 hourly forward contract rate parameters.\(^{29}\)

In order to identify forward contract parameter \( \gamma_{ih} \), I need an exogenous variation in quantity \( Q_{ihst} \) and slope of residual demand \( RD'_{ihst} \), while fixing the forward contract rate. Thus, having fixed the hour to \( h \), observing firm-specific variations in bids across steps, units and days would identify \( \gamma_{ih} \). Similarly, the identification of the heat rate \( h_{rij} \) is possible by observing a unit-specific variation in bids across hours and days because the heat rate parameter is assumed to be constant across hours and over the sample period.

Because I use the forward contract rates estimated from Sample 0 in the Sample 1 estimation, the identification of the marginal cost parameter in Sample 1 is straightforward as it is the only parameter estimated from this sample. In other words, it becomes similar to a situation whereby a researcher has data on forward contracts, in which case the marginal cost is immediately identified (Wolak, 2000).

I use bootstrap method to obtain standard errors. More on parameter inference can be found in Appendix A.2.

### 4.4 Data

Since this paper studies strategic bidding and market outcomes in the day-ahead auction, I use day-ahead wholesale electricity auction data published by ISO-NE which is publicly available on their website.\(^{30}\) I use bidding data from October 2012

\(^{29}\)Restricting forward contract rates to be different across hours is reasonable because firms usually report their contracted amounts to ISO-NE on an hourly basis. Moreover, the assumption that the contract rates do not vary across days within the sample corresponds to a common practice in the electricity market where firms set up a forward contract with the demand side in the long term, which may last for a season.

\(^{30}\)While there are two major auctions held in the wholesale electricity market, which are the day-ahead auctions and the real-time auctions, it is common in the electricity market literature (Borenstein et al., 2002; Wolak, 2003; Reguant, 2014; Ryan, 2014) to study the strategic behavior of firms in the day-ahead market. More discussions can be found in the Online Appendix.
to March 2014, excluding samples from the spring/summer period.\textsuperscript{31} In terms of
the supply bids, I use the \textit{Energy Offer} data, and for the demand bids I use \textit{Demand
bids} data.\textsuperscript{32} Supply bids are the most important data set as I focus primarily on the
bidding of electricity generating firms. A total of 86 firms, including 32 small fringe
suppliers that operate a single generating unit, together submit bids for a total of
305 generating units. While firms are allowed to bid up to 10 steps, more than
half of the units submit a single step supply bid, and about 90 \% of units submit
bids less than five steps.\textsuperscript{33} The data on hourly cleared prices (Energy Component
Price) is also available from ISO-NE website, which I later use in the pass-through
analysis. Finally, I obtained data on fuel prices and emissions permit prices from
various sources.\textsuperscript{34}

5 Estimation Results

5.1 Heat rates and forward contract rates

<table>
<thead>
<tr>
<th>Fuel</th>
<th>Average of unit-specific heat rates (MMBtu/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gas units</td>
<td>9.09</td>
</tr>
<tr>
<td>Oil units</td>
<td>12.39</td>
</tr>
<tr>
<td>Dual units</td>
<td>11.01</td>
</tr>
</tbody>
</table>

\textit{Notes:} The estimates of unit-specific heat rates are averaged within each
fuel type category: gas, oil, and dual gas units. The gas-fired unit sample
excludes those that are dual units at the same time.

Table 2: Heat Rate Estimates

Table 2 reports the average of the estimated unit-specific heat rates, separately
by the fuel types of generating units. I find that average of the heat rates of gas-

\textsuperscript{31}I excluded the spring/summer (April - August) samples because the firm-level forward contract
parameters are likely to be different between fall/winter and spring/summer seasons.
\textsuperscript{32}I provide more details on the additional bids – import/export bids, financial bids, etc. – in
Section B.4 of the Online Appendix.
\textsuperscript{33}The number of bid steps of generating units is summarized in Table B.1 in the Online Ap-
pendix.
\textsuperscript{34}The spot gas price index data is acquired from \textit{Natural Gas Intelligence} and \textit{SNL Energy}. The spot prices of other fossil fuels, such as coal (Bituminous coal (BIT)) and various oil products
(No.2, Kerosene, etc.), are obtained from \textit{EIA} and \textit{SNL Energy}. Emissions permit prices are taken
from \textit{EPA RGGI} auction data. More details on the fuel price data and the emissions permit data
can be found in Section B.3 of the Online Appendix.
fired units is 9.09, oil-fired units is 12.39, and dual gas units (gas/oil) is 11.01.\footnote{The heat rates of the dual gas units are higher than those of the non-dual gas units, because the dual technology was actively installed in the early 2000s when the inefficient (higher heat rate) steam turbine was the most common type of turbine used by gas generators.} The estimates are close to the heat rates reported by the EIA (Energy Information Administration), where the average of the heat rates of gas-fired units lies between 7.6 and 11.3 and the average of oil-fired units lies between 9.9 and 13.5.\footnote{EIA reports the average of heat rates separately by types of fuel as well as types of turbines used in a generator. I report the range of average heat rates for each fuel type as the turbine technologies differ across generating units of the same fuel type.}

The firm-specific hourly forward contract rates estimated from Sample 0 vary substantially across firms and hours. The average taken across hours and firms is around 47 percent. In Figure A.4 of Appendix A.6, I take an average of the hourly contract rates across firms and plot this against hours to see how contract rates change across hours. The graph shows that firms tend to forward contract a larger portion of their generation during off-peak hours compared to peak hours when firms sell less than 20 percent of the hourly generation forward, on average.

5.2 Documenting the heterogeneous impacts on costs

In this section, I characterize the heterogeneity of the impacts of the gas price shock on the costs of firms, with estimates of marginal costs and implied fuel prices. Additionally, I discuss how implied fuel prices can be used to identify a dual unit’s fuel switch decision, and document the identified switch decisions.

5.2.1 Marginal cost estimates by fuel types

From Sample 1, where gas prices are volatile due to shocks, I estimate the unit-specific marginal costs of electricity generation ($\hat{mc}_{ijt}$) for each day in the sample. In Figure 5, 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. Thus, the horizontal axis values are increasing with the 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 shock, while that of coal and oil units do not change much in
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 5: Estimated Marginal Generation Costs by Fuel Type: Averaged Across Firms

The average marginal costs of all three fuel types become similar when the daily gas price lies between $20 - 25/MMBtu, which is the approximate range of oil spot prices in the sample period. Also, the marginal cost of gas units becomes the highest among the three fuel types when the gas price exceeds that price range. 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.

5.2.2 Implied fuel price estimates

I have obtained implied fuel price estimates of all thermal units – gas, coal, oil, and dual units regardless of their switch decisions – for each day in Sample 1. Here I present the estimates of the units of three firms – Firm 8, Firm 9 and Firm 33 – that have different generation fuel mixes. That is, Firm 8 operates oil and dual gas units; Firm 9 operates only the non-dual gas units; and Firm 33 operates both dual and non-dual gas units. The graphs of the three firms selected help to illustrate the heterogeneity in the impacts from the shock, as well as how to identify the dual unit’s fuel switch decision. Panels (a), (b), and (c) of Figure 7 show the implied fuel prices of each of their generating units. I distinguish fuel types by different colors and, additionally, plot the gas price index data in the same panel to create a point

37 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.

38 Note that the implied fuel prices can be estimated only for those units that have positive ex-ante probability of being a marginal unit of the auction.
Notes: The solid (orange) line shows the number of dual gas units that switched to oil for electricity generation, which is identified from the implied fuel price estimates. The black dashed line shows the gas price index data. Both lines are plotted over days when the gas price shock occurred (Sample 1).

Figure 6: Dual Unit’s Fuel Switch Decision Identified

of reference against which the estimates can be compared.

Identifying dual unit’s fuel switch decision Fuel switch decisions of dual units at the time of production are not observed, and no single, consistent rule governs their switch decisions. The estimated implied fuel price of a dual gas unit reveals the type of fuel used by the unit, which enables identification of its fuel switch decision. For example, if the estimated fuel price of the dual unit is close to the price of oil rather than the price of gas, this implies that the dual unit was planning to use oil for electricity generation at the time of bidding, indicating a switch of fuel from gas to oil. Also, the fact that price fluctuations caused by the shock occur only for gas is useful for the identification. Panel (c) of Figure 7 aids comprehension of the idea behind the identification. While the spot gas prices (index value shown by the dashed line) and implied fuel prices of gas units (green line) fluctuate within the period between t=75 and t=125, dual unit’s implied fuel prices (red line) are stable at a level around $20/MMBtu, which is the spot price of oil at the time. This indicates that the dual unit did not use gas for generation within this period, implying a switch of fuel from gas to oil.

In this way, I identify the fuel switch decisions of all dual units, for each day in the sample. Figure 6 shows the total number of dual units that switched fuels from gas to oil, plotted alongside the daily gas price index which proxies the intensity of the gas price shock. The graph suggests that the number of dual units that
switch fuel to oil increases as the gas price increases, which corresponds to the cost-minimizing behavior. However, not all of the dual units in the sample switch fuels, even on days when the gas prices are substantially above the level of spot oil prices, indicating that some heterogeneity exists in the way firms make the switch decision. The fuel switch decisions identified from the estimates are an important source of the heterogeneity in the impacts on firms’ costs and will be used in the subsequent analysis of markup and pass-through.

**Differences in implied gas prices** Now I limit my analysis to the implied fuel prices of gas-fired units, which I term implied gas prices. The estimated implied gas prices vary substantially across units and firms, even within a single day. This is shown in Panels (b) and (c) of Figure 7 where I plot implied gas prices of gas units operated by Firm 9 and Firm 33 (green lines), together with the gas price indices which serve as a reference point. While the implied gas prices of Firm 9’s generating units track the gas price indices closely, those of Firm 33 differ from the gas price index. Implied gas prices are even different among gas units operated by the same firm, shown by the variation in the paths of the estimates of Firm 33 in Panel (c).

Another interesting observation is that the cross-firm and cross-unit dispersion in implied gas prices increase with the overall size of the shock. This is shown in Figure 8 where I plot the means and standard deviations of daily unit-specific implied gas prices of all gas-fired units in the sample, excluding dual units. The graph shows that the dispersion in the estimates, as measured by the standard deviation, increases with the size of the shock that is represented along the horizontal axis.

Overall, the results indicate that the impacts of the shock on gas-fired units, as captured by the implied gas prices that are revealed in their bids, are heterogeneous. In Appendix A.3, I have explored how the sources of heterogeneous impacts which I discussed earlier in Section 2 are related to these findings. Apart from that, my finding that the estimated implied gas prices do not always equal the gas price index data also demonstrates that the gas price index cannot be an accurate measure of unit-level gas prices. This again supports the claim that constructing a generator-level cost with the gas price index data may be misleading in this case.

**Grouping firms: “hard-hit” vs. “not hard-hit”** For the subsequent markup analysis, I will analyze markups by a group of firms rather than individually. I clas-
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 dashed line shows the gas price indices (data) for the corresponding days.

Figure 7: Implied Fuel Price Estimates
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.

Figure 8: Estimated Implied Gas Prices: Mean and Standard Deviation

sify firms into two different groups based on their impacts from the shock. Firms whose costs are identified as being highly impacted by the gas price shock are grouped as “hard-hit” firms, and the rest are grouped as “not hard-hit” firms. If more than 80 percent of a firm’s generation capacity is a gas-fired generation, I classified this gas-intensive firm as a hard-hit firm.\textsuperscript{39} Gas-intensive firms are hit relatively hard by gas price shocks because their generation capacity is comprised of fewer dual and oil units, the costs of which are not (or less) affected by the shock.\textsuperscript{40}

6 Markup Analysis

The objective of this markup analysis section is to explore how markup adjustments that firms make in response to the gas price shock differ across firms, and by the impacts they receive from the shock. To do so, I measure two different types of markups that reveal similar, but slightly different information: bid markups and simulated markups. While bid markups can be measured directly from the marginal cost estimates, I conduct a separate simulation semi-counterfactually in order to obtain the simulated markups.

Although a bid markup – a strategic component of a price bid – is a measure

\textsuperscript{39}I drop dual gas units when calculating the capacity of gas generation.

\textsuperscript{40}I also group firms using the cross-sectional distribution of implied gas prices, the details of which are provided in Section B.5 of the Online Appendix.
commonly used in the auction literature, it is not suitable for measuring the *change* in markups that result solely from the cost shock. On the other hand, a simulated markup reveals the endogenous changes in markups that arise purely from the cost shock, because the only variable perturbed in the simulation is the cost shock. Simulated markups are, therefore, more relevant for pass-through analysis, which will be further discussed in the next section.

6.1 Bid markup analysis

The price bid of a firm can be decomposed into a part that reflects marginal costs of supplying the product and the additional part related to the strategic decisions of firms, which I denote as the bid markup. The bid markup is related to the degree of competition faced by a firm in a market. Bid markups can be calculated from the first-order condition of optimal bidding, shown in equation (9), and the calculation is straightforward as we have estimates of the marginal cost and data on price bids.

$$\text{bid markup}_{iht} = \hat{b}_{ijkht} - \hat{mc}_{ijt} = \frac{\mathbb{E}_{-it}[Q_{iht} - \nu_{iht}]}{\mathbb{E}_{-it}[\partial RD_{iht}/\partial P_{ht}]}$$ (9)

I measure firm-specific bid markups for each day in the sample without the gas price shock (Sample 0) and with the shock (Sample 1), and plotted distributions of these separately by the hard-hit firm group and the not hard-hit group, which are shown in Panels (a) and (b) of Figure 9, respectively.

A comparison between panels (a) and (b) shows that firms have added, on average, larger bid markups when the gas price shock is present, regardless of the firm groups. That is, the distributions in Panel (b) is located more to the right (higher mean) and spread out than the distributions in Panel (a), which are concentrated around 0.

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41 Ideally, under perfect competition, firms would not add any markups over their marginal costs, while under imperfect competition, firms that expect to be the price setter (in ex-ante) add bid markups so as to raise the market price and increase their profits.

42 Since the first-order condition holds for ex-ante marginal units, I can obtain bid markups of not only the ex-post marginal unit but all ex-ante marginal units. The above bid markup expression is conditioned on $k^{th}$ step bid of firm $i$’s unit $j$ is the ex-ante marginal unit of the auction held at hour $h$ of day $t$.

43 I measured firm-specific bid markups for each hour-day auction and took average across hours to obtain a daily measure.

44 Increased dispersion in bid markups in Sample 1 indicates substantial heterogeneity in the adjustments of bid markups across firms. I explore this more in detail in Section B.6 of the Online Appendix.
A comparison of the distributions of hard-hit firms and not hard-hit firms across panels shows that the mean of the distribution increases more after the shock for the not hard-hit firm group than for those in hard-hit firm group. This suggests that, on average, firms whose costs are affected less by the shock increase their markups more in response to the gas price shock, compared to those affected greatly by the shock. However, a simple comparison of the markup distributions across samples does not reveal the change in markups that are due solely to the shock, as discussed in the next section.

6.2 Markup simulation: first-order approach

With bid markups, the only possible way to examine how a shock affects markups is to compare bid markups across a no-shock period (Sample 0) and a shock period (Sample 1). However, this comparison does not properly reveal the markup adjustment that results solely from the change in the cost caused by the shock, because the presence of the shock is not the only difference between the samples. Other factors, such as the aggregate market demand that affect strategic decisions of firms, also differ across these samples.45

45Also, a simple comparison of the distributions of bid markups across samples is problematic as we cannot properly control for the differences in overall sizes of the shock across days in Sample 1, which is an important factor of markup adjustment.
To tackle this problem, I implement a simulation where, at each auction, I measure the firm-specific markup responses to a small counterfactual cost shock. Since the only factor that is perturbed in the simulation is the cost – with other conditions unchanged – this is a better means of analyzing the markup response to a change in the cost. The simulation is based on the first-order approach (Jaffe and Weyl, 2013; Fabra and Reguant, 2014) where I give a small cost perturbation to the entire system (market) and then simulate the changes in markups of each firm implied by the first-order condition.

It is important to make the size of the shock imposed in the simulation small, so that the equilibrium after the perturbation does not depart greatly from the current equilibrium. This contrasts with the full counterfactual simulation that requires the computation of a new equilibrium, which is challenging in the multi-unit uniform auction setting due to the multiple equilibria problem (Klemperer and Meyer, 1989). I impose a gas price shock of size $0.1/MMBtu in the simulation, which results in an increase in generation costs of gas-fired units by the size of approximately $1/MWh. The size of the cost perturbation is zero for coal, oil and dual gas units that switch fuel to oil because they do not use gas for generation. In this way, I account for the different impacts of this counterfactual cost shock in the simulation. Table A.4 in Appendix A.4 summarizes the sizes of cost perturbations of all generating units, which shows that actual sizes of cost perturbation vary across units. Equation (10) below explains the idea behind the simulation.

$$\Delta \text{p}_{bidij} = mc_j'(q_j) - mc_j(q_j) + \left[ \frac{\partial p'(q_i')}{\partial q_i'} \right] \tilde{q}_i' - \left[ \frac{\partial p(q_i)}{\partial q_i} \right] \tilde{q}_i$$

When a cost shock hits a firm, the price bid of the firm will adjust by an amount that is equivalent to the combination of the marginal cost increase and the markup change.

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46 Given that the post-perturbation equilibrium is still close to the local equilibrium, we can use information on the current equilibrium in our simulation.

47 Also, because the estimation of this paper exploits the necessary condition of optimal bidding, I do not build a full structural model that describes how firms form their bids. The absence of a complete model of bidding makes it difficult to conduct a full counterfactual analysis, and therefore the semi-counterfactual simulation using the first-order approach is especially useful in our auction setting.

48 I also implement a slightly different version of perturbation as a robustness check, where I impose gas price shocks that are proportional to the firm’s actual shock as measured by the estimated implied gas price. More details about this perturbation are provided in Section B.6 of the Online Appendix.
adjustment associated with that cost change. $\Delta \text{p} \text{bid}_{ij}$ is the change in the price bid of firm $i$’s ex-ante marginal unit $j$. The direct cost shock captures the change in marginal cost due to shock, where $mc_j(q_j)$ and $mc_j'(q_j)$ denote the marginal cost of unit $j$ before and after the shock. The markup change captures the change in the markup where $\frac{\partial p(q_i)}{\partial q_i} \tilde{q}_i$ and $\frac{\partial p'(q_i')}{\partial q_i'} \tilde{q}_i'$ denote markups of firm $i$ before and after the shock, respectively.

I assume that each firm initially adjusts the price bid of its shock-affected units by the size of the cost perturbation, which results in a change in the entire distribution of price bids. The change in the distribution will change the values such as infra-marginal quantity and the slope of the residual demand that enter the markup expression, thereby changing the markup of each firm as captured by markup change in equation (10). Both infra-marginal quantities and slopes of residual demand curves before and after the perturbation are observed within the simulation, thus the endogenous markup change component is measured directly. The markups simulated in this way reflect a firm’s marginal incentive to adjust markups to a cost shock, around the current equilibrium.49

Result Firm-level markup adjustments are simulated for each hour-day ($ht$) auction in the sample. I generate a daily measure of these markups by taking an average of the hourly simulated markups across hours.50 Studies in the electricity market find that small fringe firms do not behave strategically in contrast to large-scale strategic firms (Borenstein et al., 2002; Bushnell et al., 2008). In line with these studies, I also find that simulated changes in the markups of fringe firms are below 1% of the size of their cost perturbations, which implies that they lack the incentive to adjust markups upon cost shock. Since the objective of the markup analysis is to show the change in the strategic incentives of firms, I exclude the fringe firms from the analysis.

In Figure 10, I plot the cross-sectional density of simulated changes in markups separately for hard-hit firms and not hard-hit firms. The intensity of the gas price

49Because this simulation utilizes the first-order condition that holds in ex-ante, a more accurate simulation requires a perturbation of ex-ante supply bid curves. More details of the simulation are outlined in Section B.6 of the Online Appendix.

50Note that the simulated markups are presented in levels ($$/MWh). For example, a markup adjustment of 0.5 means an increase in any additional markup by the size of $0.5/MWh in response to a cost increase that is approximately $1/MWh, on average.
Notes: Levels of the changes in markups ($/MWh) to cost shocks of approximately $1/MWh are plotted across days with different levels of gas spot price indices.

Figure 10: Simulated Markups: Hard-hit vs. Not Hard-hit Firms
shock, which differs across days, is another important determinant of markup adjustments; therefore it must be controlled for when plotting the graphs. I plot the markup densities of two firm groups separately by groups of days that have different levels of gas price shocks. Specifically, I select days on which the gas price index is $6, $10, $18, $24, $28 and greater than $38/MMBtu. Note that the heterogeneity of the shock’s impacts on the costs increases with the severity of the gas price shock, as documented earlier.

I first find that the markup adjustments constantly depart from zero as the intensity of the gas price shock increases. With a small-size shock, which is the case of the Panel (a), the densities are centered on zero for both groups of firms. I find that the lack of adjustment is convincing since the heterogeneity in cost impacts is not severe enough to change the competition when the shock is small. However, the markup densities become more dispersed across panels from (b) to (f) where the size of the shock increases. For instance, in Panel (f) where the gas prices are above $38/MMBtu, markup adjustments range from -1.5 to 1.5 and are not so centered on the value of zero. Since the extent of cost increases become considerably heterogeneous across firms as the intensity of the shock increases, I observe more active adjustments in the markups in this case as an indication of firms’ strategic incentives being changed by the shock.

The pattern of markup adjustments differs in relation to the firm’s impacts on costs, and the difference becomes more evident as the intensity of the shock increases, shown by a comparison of densities of the two firm groups across panels. As the shock becomes larger, moving from panels (a) to (f), the density of the hard-hit firms shifts more to the left, while the density of the not hard-hit firms shifts more to the right. Especially in Panel (f), I observe a stark difference in the densities of two firm groups. The distribution of the hard-hit group is located more in a negative range (approximately from -1.5 to 0.3), while that of the not hard-hit group is located more in a positive range (approximately from -0.5 to 1.3). This finding confirms that hard-hit firms, whose costs are affected more by the shock than not hard-hit firms, are not capable of adding large markups due to increased compe-

51 Among those selected days, I again chose days having similar levels of electricity demand, daily peak-temperature, and spot gas market conditions, to ensure that any other factor that may affect markups has been controlled for. More details on the selection of similar days are provided in Appendix A.2.
tion from the others. This is especially so because increasingly more dual units switch to oil and the oil units that were previously left out of the competition start competing with gas units as the size of the shock gets bigger. Thus, the hard-hit firms that are gas intensive in their generation face more intense competition in this case.

7 Cost Shocks and Market Price: Pass-Through Analysis

In this section, I explore how the heterogeneous responses of costs and markups to the gas price shock are reflected in changes to electricity prices. Since the increase in cost caused by a shock leads unavoidably to an increase in the output electricity price, it is a question relevant to policy-making to ask not by how much the price has increased, but whether the price has increased proportionally to the cost shock. Thus, I study how much of the cost shock is passed on to the output price (i.e., the cost pass-through), demonstrating in particular that a careful examination of markups, which must be based on a correct assessment of the extent of the cost increase, is essential for obtaining accurate pass-through rates.

I take a unique approach of simulating the auction-level pass-through rates, which is constructed based on costs and markups obtained from the structural set up that fully accounts for the heterogeneous impacts. Such high-frequency pass-through rates are more useful in analyzing the importance of the markup adjustment as a determinant of pass-through, especially in this situation where markups and costs vary across firms and over time.\(^{52}\) In general, this type of simulation is not straightforward to conduct, as it requires a structural model to implement. A standard way of estimating the pass-through is to run a simple regression using data on prices and costs. However, the regression analysis faces a challenge when heterogeneity is present in the impacts of the cost shock, because it is hard to incorporate into the analysis the richness of the adjustment of costs and markups that result from the shock, with only the data.

\(^{52}\)Strategic markup adjustment is an important determinant of the pass-through outcome, which has been addressed in the pass-through literature (De Loecker et.al, 2016; Fabra and Reguant, 2014; Amiti et.al, 2014; Goldberg and Hellerstein, 2013; Nakamura and Zerom, 2010)
7.1 Simulated pass-through

I adopt the same simulation method used in the markup analysis in order to simulate pass-through rates. Note that the market clearing price of an auction is equal to the price bid submitted by the ex-post marginal unit that sets the price.\textsuperscript{53} Thus, the simulated price bid change of the ex-post marginal unit in response to a small unit-size cost shock ($1/MWh) imposed in the simulation can approximate the pass-through rate of the auction, because by definition, pass-through is $\partial p/\partial c$. Since I know the size of cost perturbation given to the marginal unit $j$ of auction $ht$, as well as the size of the simulated markup of the firm $i$ that operates that unit, I can simulate the price bid change by summing these values together, as described in equation (11). As the size of the cost perturbation given to each marginal unit is not exactly $1/MWh$, I divide the simulated price bid change by the size of the unit’s cost perturbation to get the change in the price bid per unit-size cost increase, i.e., the pass-through rate of the auction $ht$, shown as $\rho_{ht}$ in equation (11).\textsuperscript{54}

$$\rho_{ht} = \frac{\Delta p_{ht}}{\Delta mc_{j,ht}} \quad \text{where} \quad \Delta p_{ht} = \Delta b_{j,ht} = \Delta mc_{j,ht} + \Delta \text{markup}_{i,j,ht}$$ \hspace{1cm} (11)

\textbf{Results} Table 3 provides a summary of the simulated pass-through rates of a total of 2,661 hourly auctions. The mean of the pass-through rates is 0.974, which is close to 1, suggesting a near complete pass-through of the cost shocks, on average. However, the pass-through rates range from 0.004 to 2.198 with a standard deviation of 0.204, indicating that considerable heterogeneity exists in the rates. Therefore, although firms completely pass on cost shocks to prices on average, the pass-through rates vary significantly across auctions. Heterogeneous pass-through rates may result from each auction having different marginal units, thereby having different incentives to adjust markups at the margin. To verify this, I run a simple regression and find that pass-through rates are on average lower by the size of 0.041 in auctions when hard-hit firms are at the margin, compared to when not hard-hit firms are at the margin (results are shown in Table A.6 of Appendix A.6). This implies that even if the same-size cost shock is imposed on the marginal units of hard-hit and not

\textsuperscript{53}More details on the selection of ex-post units are in Appendix A.5.

\textsuperscript{54}Because pass-through is not defined if the marginal unit’s cost perturbation is zero, I can simulate pass-through rates only for auctions where the marginal unit is gas-fired units, including the dual gas units that did not switch fuels.
hard-hit firms, the difference in their markup adjustments leads to different extents of pass-through rates at the margin.

7.2 Reduced form pass-through regression: concerns and limitations under heterogeneity

Instead of simulating, we could implement a simple regression which identifies a single (average) pass-through rate using cross-auction variations in prices and costs, both obtained from data.\(^5\) However, the pass-through estimate that relies only on information obtained from data may not be accurate, especially when the shock’s transmission to the costs of firms is heterogeneous. I demonstrate this by running three specifications of pass-through regression that differ in the measurement of cost shocks, and by comparing the estimates to the simulated pass-through rates.

The specification used for estimating the pass-through rate is shown below in equation (12), which is similar to that used by Fabra and Reguant (2014):

\[
p_{ht} = \rho hr_{ht} G_{ht} + \beta_0 x_{ht} + \beta_1 I_{ht} + \epsilon_{ht}
\]  

(12)

where \(\rho\) is the parameter of interest which captures the average rate of cost pass-through.\(^5\) Dependent variable \(p_{ht}\) is the electricity price that cleared the auction held on day \(t\) at hour \(h\).\(^5\) The key variable is \(hr_{ht} G_{ht}\) which measures the generation

\(^{5}\)Because the changes in cost values from one auction to the other are interpreted as cost shocks, the regression allows the estimation of only the \textit{average} of pass-through rates, and is not suitable for estimating high-frequency auction-level pass-through rates. This is in contrast to the simulation method where I impose small counterfactual cost shocks on each auction to simulate the auction-level pass-through rates.

\(^{5}\)Having \(\rho\) estimated close to 1 indicates a complete pass-through, \(\rho\) substantially less than 1 indicates an incomplete pass-through, and \(\rho\) greater than 1 indicates a more than complete pass-through.

\(^{5}\)I use day-ahead electricity auction’s energy component price, which is published by ISO-NE.
cost of the ex-post marginal unit of auction $ht$. Since we need cross-sectional variation in the cost that is primarily due to the gas price shock, I restrict observations to auctions in which gas units (including dual gas units) are the marginal units. Therefore, $hr_{ht}$ is the heat rate of the marginal $gas$ unit of this auction, which I multiply by the price of the gas used by this unit ($G_{ht}$) to construct the $gas cost$ variable. Descriptions of other variables and how I managed the endogeneity of the cost variable is provided in Appendix A.5.

I implement three variants of regressions that differ in how the gas cost term, $hr_{ht}G_{ht}$, is constructed. Table 4 presents the estimates of $\rho$ under each specification. In column (1) specification, I use the average heat rate ($\bar{hr}$) as $hr_{ht}$ and the gas price index data as $G_{ht}$.

Since both measures do not reflect the heterogeneity, the gas cost variable used in this naïve regression treats impacts from the cost shock as homogeneous across firms and units.

In the next two specifications (columns (2) and (3)), I use unit-specific heat rates, $\hat{hr}_{ij}$, estimated earlier in the model, which reflect differences in efficiencies across units. Two specifications are different in that I use the gas price index data as $G_{ht}$ in (2), while I use the estimated implied gas price of the marginal unit, $\hat{FP}_{ijt}$, as $G_{ht}$ in (3). Because implied gas prices are estimated at a generating unit-level, they capture the differences in the impacts on costs across firms and units that originate from the gas price shock. Therefore, while the specification of column (2) regression incorporates heterogeneity in the heat rates only, the specification in (3) incorporates heterogeneity in both heat rates and gas prices.

I also run these specifications on different samples. While the full sample includes the entire observations, I drop observations of auctions where the marginal unit is a dual unit that switched fuel to oil to construct the duals dropped sample that overlaps more with the sample used in the pass-through simulation. Lastly, I run specifications on subsamples that are constructed based on the overall size of the gas price shock in order to verify whether the pass-through rate is indeed homogeneous across different parts of the sample.

I then compare the reduced form pass-through estimates with the simulated pass-through rates to verify the accuracy of the estimates. The (average) pass-through rate

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58EIA reports average of the heat rates of generators by fuel types and turbine technology. I take an average of the heat rates of gas-fired units across different turbine technologies to construct $\hat{hr}$ (data source: EIA report, 2015).
<table>
<thead>
<tr>
<th>Sample</th>
<th>$\hat{h}_r$ = Average heat rate</th>
<th>$\hat{h}_r$ = Estimated heat rate</th>
<th>$G_{ht}$ = Gas index</th>
<th>$G_{ht}$ = Gas index</th>
<th>$G_{ht}$ = Implied gas price</th>
</tr>
</thead>
<tbody>
<tr>
<td>full sample</td>
<td>0.481 (0.042)</td>
<td>0.457 (0.052)</td>
<td>1.118 (0.040)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>duals dropped</td>
<td>0.585 (0.063)</td>
<td>0.531 (0.086)</td>
<td>1.085 (0.046)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>below $$15</td>
<td>0.833 (0.085)</td>
<td>0.882 (0.068)</td>
<td>0.979 (0.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>btw $$15 and $$25</td>
<td>0.606 (0.119)</td>
<td>0.520 (0.096)</td>
<td>1.007 (0.052)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>above $$25</td>
<td>0.306 (0.069)</td>
<td>0.302 (0.070)</td>
<td>1.498 (0.216)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N (full sample)</td>
<td>3,129</td>
<td>3,129</td>
<td>3,110</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: 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 dropped those switched dual units from the sample. All standard errors are clustered at firm, hour level. F-stats of the full sample first stage regression shown in each column are (1) 535.0, (2) 147.1, and (3) 191.4, respectively.

Table 4: Reduced-Form Pass-through Estimation: Three Specifications

The rate parameter, $\rho$, can be compared with the mean of the simulated pass-through rates ($\rho_s$). 59

Results  The first row of Table 4 reports the result of full sample regressions. Comparison of (1) and (2) shows the importance of incorporating heterogeneity in heat rates. Although estimates are slightly different, being 0.481 in (1) and 0.457 in (2), the difference is not substantial, which implies that heat rate is not a critical factor that causes the differences in the pass-through estimates. Both specifications, however, yield pass-through rates that are below 0.5 (50 percent), implying an incomplete pass-through, which is significantly different from, and smaller than, the close to complete pass-through rate of 0.974 (97 percent) obtained from the sim-

59 Although our findings from the simulation suggest that pass-through rates are heterogeneous across auctions, the average of these rates conveys useful information of the overall incidence of a cost shock.
ulation (shown in Table 3). This finding suggests that the average pass-through estimate is inaccurate – and underestimated in my case – when I do not properly incorporate into my regression the differences in the extent of cost increases from the shock.

Interestingly, the pass-through estimate becomes close to the mean of simulated pass-through rates when the regression accounts for heterogeneity in both heat rates and gas prices, as shown in column (3). The full sample estimate is 1.118, and when regressed on the *duals dropped* sample that overlaps more with the sample used in the simulation, the pass-through rate is 1.085, which is even closer to the complete pass-through implied by the simulation. Since the only difference between specifications (2) and (3) is whether the gas price variable $G_{ht}$ reflects heterogeneity, this finding confirms that neglecting the difference in the way that firm-unit-level costs are affected by the shock leads to the underestimation of pass-through.

The last three rows of Table 4 show the results of subsample regressions. I find different pass-through estimates across subsamples, which corresponds to the earlier finding that the pass-through rate itself is not homogeneous over the sample and, instead, depends on state variables that govern the price setter’s incentive to adjust markups.

The underestimation of pass-through in naïve regressions has resulted primarily from having a large portion of low-impacted marginal units in our sample. While the costs of these units increases relatively less than the others, the cost measured with the weighted-average gas price index data overstates the actual sizes of cost increases of these units. Therefore, by using an inaccurate cost measure that overstates the impact of the shock on the cost side, a naïve pass-through estimation understates the contribution of strategic markup adjustments in raising the price, leading to a conclusion of the lower pass-through rate. Note that the direction of bias may differ depending on how the sample is comprised. If the majority of auctions included in the regression have high-impacted marginal units – the costs of which increased by more than a naïve cost measure would suggest – we may end up overestimating the pass-through.

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60 Table A.5 in Appendix A.5 summarizes the number of units whose actual cost increase, as implied by the estimated costs, is smaller than what is measured by a naïve gas cost variable used in specification (1).

61 I provide graphical illustration of the mechanism behind the underestimation in Appendix A.5.
8 Conclusion

While firm heterogeneity has been emphasized in the literature as an important feature of many industries, much less attention has been paid to how firm heterogeneity leads to heterogeneous transmission of the shock, especially in the empirical context. This paper empirically verifies the heterogeneous impacts of the shock across firms costs and shows that such impact heterogeneity affects strategic competition between firms and the subsequent pass-through outcome.

The findings of this paper have important implications for regulators of the market. First, from the analysis of strategic competition, it is implied that regulators must consider not only the scale of firms, but also other characteristics of firms that determine their exposure to gas price shocks, in order to better understand the competition in the market. Another important finding is that the same level of gas price shock could lead to different sizes of electricity price increases, depending on which type of firms (and their generators) are at the margin. Understanding this result is useful for implementing policy instruments that aim to prevent electricity prices from surging to excessive levels and to curb the price volatility, both of which the New England electricity market experienced during the shock event.

As an incidence measure, pass-through is used in many markets to understand the consequences of the shock, which thus becomes the basis of policy decisions. In this respect, my finding that the pass-through rate could be inaccurate when not properly accounting for the heterogeneity is troubling. For example, while the true average pass-through of 97 percent suggests that firms in the market were fully passing on the cost burden to electricity prices at least on average, the inaccurate pass-through rate of less than 50 percent tells a different story where firms do not pass through the cost, possibly to stay competitive. Therefore, a correct estimation of pass-through must be the priority in order to prevent misguided policy decision-making.

References


A Appendix

A.1 Model

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

\[ E_{it} \left[ \frac{\partial P_{ht}}{\partial b_{ijkht}} \left[ (Q_{iht}(P_{ht}) - \nu_{iht}) + (P_{ht} - C'_{ijt}) \frac{\partial Q_{iht}(P_{ht})}{\partial P_{ht}} \right] \right] = 0 \]  

(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 Online Appendix 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

¹However, 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.
A.2 Estimation

Resampling The empirical analogue of the first-order condition (shown in equation (2)) of a firm involves expectation over others’ bid, \( b_{-i,t} \). In order to deal with the expectation term, I adopt the resampling methodology that is commonly used in the literature (Hortaçsu, 2002; Hortaçsu 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 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 the 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 resembles 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.

Resampling procedure is as follows. First, we need to resample firm \( i \)’s beliefs about its competitors’ bids, \( b_{-i,t} \), 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. Market is cleared at which 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 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 A.1.

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
Table A.1: Resampling Procedure

Resampling \( b_{-i,t} \) 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, \( P_{t,s} = \{ p_{1,t,s}, \ldots, p_{24,t,s} \} \).

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 \( i \in F \).

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 \( b_{ijkht} = < b_{ijkht}, q_{ijkht} > \). Suppose the market clearing price at hour \( h \) is \( P_{ht} \). Note that \( \mathcal{K} \) and \( \kappa \) 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:

\[
\hat{Q}_{iht}(P_{ht}, b_{ih}) = \sum_{j \in J_{i}} \sum_{k} q_{ijkht} \mathcal{K}(\frac{P_{ht} - b_{ijkht}}{bw})
\]

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

\[
\hat{RD}_{iht}(P_{ht}, b_{-iht}) = D_{ht} - \sum_{m \neq i} \sum_{j \in J_{m}} \sum_{k} q_{mjkht} \mathcal{K}(\frac{P_{ht} - b_{mjkht}}{bw})
\]

Then the derivative of the residual demand curve is:

\[
\frac{\partial \hat{RD}_{iht}}{\partial P_{ht}}(P_{ht}, b_{-iht}) = -\frac{1}{bw} \sum_{m \neq i} \sum_{j \in J_{m}} \sum_{k} q_{mjkht} \kappa(\frac{P_{ht} - b_{mjkht}}{bw})
\]
Finally, the expression of the weight, which is the probability of bid step \( b_{ijkht} \) being the marginal unit, is shown below (Wolak, 2007):

\[
\frac{\partial P_{ht}}{\partial b_{ijkht}} = \frac{\partial \hat{Q}_{ihht}(P_{ht})}{\partial b_{ijkht}} \left( \frac{\partial \hat{R}D_{ihht}(P_{ht})}{\partial P_{ht}} - \frac{\partial \hat{Q}_{ihht}(P_{ht})}{\partial P_{ht}} \right)
\]

**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 standard GMM standard error formula. Because this Sample 1 GMM estimation is indeed a linear IV estimation, I use IV standard errors.

**A.3 Estimation Results**

**Exploring the dispersion in the implied gas price estimates** The sources of heterogeneous impacts discussed earlier in Section 2 explain findings of (i) dispersion in implied gas prices and (ii) the dispersion increasing with the overall size of the shock. Here, I supplement my findings with the EIA-923 dataset to relate these sources to my estimates. However, the analysis presented here is incomplete as the EIA-923 dataset covers only a small part of the entire sample and the information contained in it is limited.

First, I check from the EIA data whether or not firms engage in different gas procurement behaviors; they can purchase gas from a long-term contract or the spot market. While the spot gas price increases with the shock, the long-term contract price does not significantly increase over the contract period, therefore widening the gap between the prices, especially when spot gas prices surge due to a severe shock. In Table A.2, I summarized the percentage of power plants that purchase gas through the long-term contract and from the spot market, as appears in the EIA-923 data. Although the sample size is small, I find a substantial portion of firms – about 20 percent – procuring gas through contracts. Despite this, the majority of plants purchase gas on the spot market, and from various spot gas suppliers. This is shown in the last column of the Table A.2 that reports

---

2EIA-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 obligation to disclose the fuel cost information. Furthermore, since all of the information is reported at a monthly level, conducting an analysis at 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.
the maximum number of spot gas suppliers from which each firm procured gas.\(^3\)

In order to verify how different the estimated implied gas prices of firms purchasing gas through a long-term contract are from those purchasing at the spot gas market, I run a simple regression of implied gas prices on a dummy variable that is assigned to firms identified as having a long-term gas procurement contract.\(^4\) I run regressions separately on subsamples that vary in sizes of gas price shocks, and plotted the coefficient estimates in Figure A.1. The negative coefficient estimates suggest that the estimated implied gas prices are lower for firms having the long-term gas procurement contract than those without, on average. Also, such difference in implied gas prices between firm groups increases as the overall size of the shock increases, which is shown by a decreasing path of estimates in Figure A.1 as we move towards subsamples having larger shocks. This finding verifies that the presence of a long-term gas procurement contract in this market is one of the sources of the dispersion that we find in the implied gas price estimates.

The gas procurement behavior may also vary between generating units owned by the same firm, which explains the dispersion in implied gas prices among units operated by the same firm. In Table A.3, I summarize the number of gas procurement channels from which firms purchase gas. While the majority of firms purchase gas only from the spot market, some firms rely on both spot market and long-term contracts to buy gas, implying that gas procurement channels differ among units owned by the same firm.

Finally, the increase in the volatility of spot gas prices can explain why I may find dispersion in implied gas prices, even if all units purchase gas on the spot market. Firms do not procure gas for the entire unit at the same time: more efficient units that have a higher chance of being accepted in the auction may have priority over others when purchasing gas.\(^5\) Such procurement behavior, combined with the increase volatility in the

---

\(^3\)Note that the actual number of spot gas suppliers from which plants procure gas could be bigger than the numbers reported here because some plants report supplier as “various suppliers”.

\(^4\)By cross-comparing the EIA-923 data to my estimates, I identified firms in the New England market that procure gas through a long-term contract. 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.

\(^5\)Firms engage in this behavior to minimize the risk of purchasing more gas than what they expect to use in the generation. Since firms do not know at the time of the bidding which units will finally be accepted in the generation, it is risky for them to purchase gas for all generating units.
Implied gas price differences: long-term contract vs. none

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 A.1: Difference in Implied Gas Prices: Firms with and without the Long-Term Gas Procurement Contract

spot gas prices, results in a dispersion in firm-level implied gas prices. Also, the fact that volatility increases more as the gas price shock becomes larger explains why the dispersion increases with the overall size of the shock.

A.4 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

<table>
<thead>
<tr>
<th>Gas procurement channels</th>
<th># of firms purchasing gas from:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2013</td>
</tr>
<tr>
<td>Spot gas market only</td>
<td>16</td>
</tr>
<tr>
<td>Long-term contract only</td>
<td>3</td>
</tr>
<tr>
<td>Both spot and long-term contract</td>
<td>2</td>
</tr>
<tr>
<td>More channels than above</td>
<td>0</td>
</tr>
<tr>
<td>Total # of firms in the sample</td>
<td>21</td>
</tr>
</tbody>
</table>

Table A.3: Summary of the Number of Gas Procurement Channels (Firm Level)

For this reason, firms have the incentive to purchase gas for units that are certain to produce in the market that opens the next day, and postpone purchasing for the rest of the uncertain units. One may argue that firms can resell the left-over gas, but only a small group of firms with a special contract with the pipeline companies can engage in reselling.
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 A.4 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 the Online Appendix.

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>min</th>
<th>max</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>s.d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generator-level</td>
<td>0.47</td>
<td>0</td>
<td>1.896</td>
<td>0</td>
<td>0</td>
<td>0.941</td>
<td>0.55</td>
</tr>
<tr>
<td>Firm-level</td>
<td>3.20</td>
<td>0</td>
<td>8.9</td>
<td>0.754</td>
<td>2.70</td>
<td>5.48</td>
<td>2.68</td>
</tr>
</tbody>
</table>

Notes: Unit of the cost change is $/MWh. Includes generators of all fuel types.

Table A.4: Summary of Sizes of Marginal Cost Perturbations to a Gas Price Increase of $0.1/MMBtu

A.5 Pass-through

Identifying the ex-post marginal units from data I identified ex-post marginal units, which will be used throughout the pass-through analysis, from 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. 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 $hr_{ht}G_{th}$

$$p_{ht} = \rho hr_{ht}G_{ht} + \beta_0 X_{ht}^{D} + \beta_1 I_{ht} + \epsilon_{ht}$$

As described earlier, $p_{ht}$ is the electricity price and $hr_{ht}G_{ht}$ is the gas cost variable. I also specified $X_{ht}^{D}$ which is the demand side control variable where I used peak-time temperature data. Fixed effects, $I_{ht}$, 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, $G_{ht}$, 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).

Exploring the cause of underestimation To investigate why the naïve 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 A.5. That is, for each gas-fired marginal unit, I compared $h_{rij} G_{t,index}$ with $h_{rij} \hat{F}_{ijt}$, and selected those units with $h_{rij} G_{t,index} > h_{rij} \hat{F}_{ijt}$. Note that $\hat{F}_{ijt}$ is the implied fuel prices of the unit estimated earlier from the model.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>%</th>
<th>% w.r.t</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>Gas marginal units in total</td>
<td>3,129</td>
<td>100</td>
</tr>
<tr>
<td>(2)</td>
<td>Marginal units with overstated cost measure</td>
<td>2,076</td>
<td>66.34</td>
</tr>
<tr>
<td>(3)</td>
<td>Dual marginal units among overstated units</td>
<td>615</td>
<td>29.62</td>
</tr>
</tbody>
</table>

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 of 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 A.5: Marginal Units with Overstated Cost Measure

The first row (1) of Table A.5 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 naïve 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.

Intuition behind the underestimation of pass-through parameter Figure A.2 illustrates the mechanism behind the underestimation. Although the final price increased by the marginal unit is the same in both cases, the pass-through estimate can be significantly different. If we use the cost measured with the gas price index data, as shown in (a), we may conclude that the price increase is attributed entirely to the cost increase which implies a complete pass-through. However, if the true size of the cost increase is indeed smaller than what the index would measure, as shown in Panel (b),
then a large part of the price increase has resulted from the markup adjustment of the marginal unit which implies a more than complete pass-through.\(^6\) Therefore, by using an inaccurate cost measure, a naïve regression is understating the contribution of strategic markup adjustments in the estimation, leading to a conclusion of the lower pass-through rate.

\[^6\text{Realizing its cost increase being smaller than that of a competitor, the marginal unit has an incentive to increase its price bid a little more without losing its position as a price setter, and this additional part is the result of strategic decision.}\]

**Figure A.2:** Description of the Mechanism Behind Underestimation of Pass-Through Rate

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Notes: The graph above shows the price bids of three units before and after the shock. The cost of the marginal unit is measured using the gas price index data in Panel (a), and measured using the implied fuel prices estimated from the model, in Panel (b). The bold black line shows the bids before the shock and bold colored lines are the bids after being adjusted by the cost increase resulting from the shock. Colored dashed line shows the bids after being adjusted by the size of the markup adjustment if it occurs. \(\Delta P\) is the size of the auction price increased due to shock, which is equivalent to the size of the price bid increased by the marginal unit B. The length of the solid arrow measures the size of the price bid increased due to an increase in the cost, and the length of the dashed arrow measures the size of the price bid increased due to markup adjustment.
A.6 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 A.3: 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, $\gamma_{ih}$, estimated from the model.

Figure A.4: Forward Contract Rates: Summarized Across Firms
Simulated pass-through rates

<table>
<thead>
<tr>
<th></th>
<th>( \rho_{ht} )</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Hard-hit firm</td>
<td>-0.041*</td>
<td>(0.0195)</td>
</tr>
<tr>
<td>Cost shock</td>
<td>-0.099*</td>
<td>(0.0464)</td>
</tr>
<tr>
<td>Hard-hit * Dgas</td>
<td>-0.0089***</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Dgas</td>
<td>0.00004</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.007***</td>
<td>(0.0427)</td>
</tr>
</tbody>
</table>

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 A.6: Regression of Simulated Pass-through Rates on Types of Price Setting Firms
B  Online Appendix (Not for Publication)

B.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.

**Electricity demand shock**  Aggregate demand is another important factor that determines the market price in the wholesale electricity market, and one may suspect that demand shock could have contributed to a surge in wholesale electricity prices during the period of gas price shocks. To verify this, I checked the patterns of aggregate electricity demand and electricity prices of the sample days and did not find any unusual pattern in daily demands over this period. Moreover, while electricity demands were high between December 2013 and early January 2014, electricity prices during this period were not as high as those of mid-January 2014 when the market suffered from the largest increase in
electricity prices. This implies that the demand-side shock did not play a significant role in increasing the electricity prices during the sample period. Also, historical trend of the electricity demand, shown in Figure B.1, reveals no significant demand shocks during the winters of 2013-2014 compared to other years.

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 (EPA-CHP Combustion Technology Report, 2015). 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 gas was relatively more expensive than other fuels (Power Engineering, 2004).

There is no substantial difference in general performance with either fuel. However, the different heats of combustion result in slightly higher mass flows through the expansion turbine when liquid fuels are used, and thus result in a small increase in power and efficiency performance. In addition, the fuel pump work with liquid fuel is less than with the fuel gas booster compressor, thereby further increasing net performance with liquid fuels. (EPA-CHP combustion technology report, 2015).

I additionally checked whether dual unit’s heat rate differs significantly when using different fuels, with data on heat rates of generators. The CEMS dataset contains information on heat rates of generators. The information of heat rates provided here, however, cannot be matched to the bidding data as the identities of the firms and the plants are masked in the bidding data. I chose one dual unit from the CEMS dataset sample and
compared its heat rates for days when the unit was identified to use gas and days when the
unit was identified to have switched to oil. Average of heat rates are 10.2 (MMBtu/MWh)
when burning gas and 9.9 (MMBtu/MWh) when burning oil (diesel). Although slightly
lower when burning oil, the difference is not substantial. Also, note that the concept of
physical efficiency defined in the paper and the engineering estimate of the heat rate are
slightly different. In this respect, it is reasonable to assume that dual unit’s heat rate does
not change with the type of fuel it uses.

B.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.\footnote{Other than these major pipelines, Massachusetts’s Everett liquefied natural gas (LNG) term-
inal 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.} 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 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.

**B.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\textsubscript{2} produced per kWh for specific fuels and for different types of generators, by multiplying the CO\textsubscript{2} emissions factor (or emissions rate) with the heat rate. Data on CO\textsubscript{2} emissions factor (lb CO\textsubscript{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.

B.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 electric-
ity 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.

**B.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 50th 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, in Appendix B.7, I also present the simulated markups plotted separately by firms grouped under “high-impact” and “low-impact” categories, shown in Figure B.5.

B.6 Markup

B.6.1 Bid Markup

Suppose that a \( k \)th 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 \( \hat{mc}_{ijt} \) from the price bids data, i.e. \( b_{ijkht} - \hat{mc}_{ijt} \).

Dispersion in post-shock bid markups Another important observation from Figure 9 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 B.2 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.

B.6.2 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
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 B.2: Bid Markups of Two Firms: Sample 1

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, \( \frac{\partial p}{\partial b_{ijkh}} \), 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. \( \Delta \text{markup}_s \) for \( s = 1 \ldots S \). The weighted-average of markups is generated with \( \Delta \text{markup}_s \), weighted by \( \frac{\partial p}{\partial b_{ijkh}} \).

**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/MBtu
and a unit’s implied gas price is $18/MMBtu, I imposed a gas price shock equivalent to \((18/20) \times 0.1 = 0.09\) (9 cents) to this unit. The final increase in the marginal cost of this unit is \(hr \times 0.09\). 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.
B.7 Additional Figures and Tables

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

Figure B.4: Graphical Illustration of the Pass-Through Simulation
Figure B.5: Simulated Markups of High-Impact vs. Low-Impact Firms
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<th>Number of Generators</th>
<th>Percentage (%)</th>
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</table>

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 B.1: Summary of Number of Bid Steps