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

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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 the existing heterogeneous impacts fails to reflect the change in competition arising from the shock, and is, on average, underestimated.

1 Introduction

It is important from an economic policy perspective to understand how a 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 cost 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 cost shock to the industry 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 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 others have incentives to raise markups, while the highly-impacted firms 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.[1] This implies that a market analysis that fails to account for the existing heterogeneous feature of the shock will not capture the meaningful changes in competition, thereby undermining the role of competition in shaping the pass-through.

This argument applies more generally in the context of any policy, regulation, or even mergers. For instance, industry-based regulation – though imposed uniformly across firms – could affect firms to different extents.[2] A merger that only lowers the cost of a merged firm results in different cost impacts across firms. If such heterogeneous impacts occur in an environment characterized by imperfect competition, these could induce strategic behavior which ultimately affects the overall impact of regulation and price effects of merger.

Despite its importance, the major empirical challenge is the difficulty in uncovering this heterogeneous transmission channel, as it is often unobserved from the data. 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 obtain from the data in general. This is

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[1]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.

[2]For example, Lyubich, Shapiro, and Walker (2018) show that due to substantial heterogeneity in energy and CO_2 productivity, plants may have different impacts from an industry-level emissions regulation.

particularly so when the source and the destination of the impact is unclear and the nature and the intensity of the shock frequently changes over time. Given that markup analysis must be based on the correct assessment of cost, this also implies that uncovering the change in strategic incentives is a challenge.

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 in which 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 structurally estimate the precise cost information – at a daily frequency – from the data on bids and use it instead of the limited cost data.

Besides, analyzing the event itself is policy relevant due to its strong impact on the New England electricity market. During the period of the 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 exercise of market power, as the electricity market is characterized by imperfect competition.

Exploiting these features within a structural framework, I develop a method to precisely identify the heterogeneity in the impacts of the gas price shock on the costs of electricity-generating firms. Then, with a detailed analysis of markups, I show that firms' incentives to adjust markups critically depend on the extent of heterogeneity in the cost impacts. I then obtain pass-through rates that fully account for the heterogeneous transmission channel, and find that markup adjustments are important determinants of pass-through. While the empirical setting and methodology of this paper makes it possible to uncover the underlying heterogeneity, even acknowledging the presence of it – in order to adapt the empirical strategy accordingly – is difficult in general. For this reason, it is important to ask whether and by how much the pass-through estimate could be inaccurate when we omit the heterogeneous transmission channel (when it is present) in the analysis. To show this, I implement a pass-through estimation that disregards the heterogeneity, and find that the estimate is significantly underestimated by almost one half, on average. Despite the fact that a large variation in firms' markup and pricing incentives arising from the heterogeneity are not captured, a more troubling finding is that even the aggregate implications of the cost shock on the market price could be incorrect when the existing heterogeneity is not properly accounted for.

One of the main contributions of this paper is to show that a simple enough industry-wide cost shock, combined with firm heterogeneity, can be a source of market power which leads to firms strategically adjusting their markups. This markup mechanism appears to be the main driver of the bias found in the pass-through estimate when disregarding the heterogeneous impacts. As shown in the analysis, markups are induced and more actively adjusted as the degree of the cost

impact heterogeneity increases. Thus, the estimation that overlooks such heterogeneity on the cost side is downplaying the markup's role in increasing the prices, particularly so when the adjustments in markups are most active and largest in magnitude, thereby underestimating the pass-through. This finding may appear to be alarming: it is often the case that pass-through estimated exclusively from data – which, in some cases, may not be precise enough to capture the different firm-level responses to the cost shock – complements the analysis of market competition and assists policy decisions.

The main analysis begins by empirically identifying the heterogeneity in the impacts of the gas price shock, which arises from firms having different sets of generating assets and technology.[3] 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 this context because the highly aggregated fuel price data is not precise enough to quantify the exact firm-level impacts on cost.[4] Another factor complicating the measurement of cost is the presence of a dual unit generator 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 its opportunity cost 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 costs from the bidding data, utilizing the standard methodologies developed in the auction literature (Reguant, 2014; Hortaçsu and McAdams, 2010). The estimation of marginal costs, however, is not sufficient for the identification, given that the 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.[5] 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 within the same estimation, from different samples – days with and without the shock – exploiting the fact that efficiency is invariant to 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

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[3]For example, if firms do not operate gas generation or have the option to shift production to generators using different fuels, their costs will be unaffected, or affected less, by the gas price shock compared to others.

[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.

[5]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.

and prices that result from the shock alone, I conduct a simulation (Jaffe and Wyle, 2013; Fabra and Reguant, 2014) where every other factor except for the shock is controlled. 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 the 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 a 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 even 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 adjustments vary across firms, and that the identity of a price-setting firm changes across auctions.[6] Therefore, I simulate the auction-level pass-through rates and find these rates to be 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 implement a pass-through estimation that does not account for the heterogeneous impacts of the cost shock, in a reduced form set up which is more common in the literature. I regress electricity prices on costs observed from the aggregate data – the gas price index – which departs from the true cost shock of each firm when heterogeneous impacts are present. By using this näive cost measure, the regression is treating the impacts of the cost shock to be homogeneous across firms. I find that the pass-through rate is underestimated in this case – close to 50 percent, on average – compared to the almost complete (97 percent) pass-through obtained from the simulation. However, when using the cost estimated from the model – which accurately represents a firm-specific cost shock and fully incorporates the differences in the impacts across firms – the reduced form pass-through estimate becomes close to complete. This confirms that the primary cause of the bias we find in the näive pass-through estimates is the measurement error in the cost arising from omitting the heterogeneous impacts. That is, the näive cost variable generated

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[6]The wholesale electricity market uses the multi-unit uniform auction where the final market clearing price of the auction is determined by a single firm.

with the average data overstates the actual sizes of cost shocks of low-impacted firms which make up a large proportion of the price setting firms in my sample. Overstating the impact on the cost side, in turn, implies that the contribution of markups in raising the price is understated, resulting in a lower than actual pass-through rate.

This paper contributes to the literature on market power as well as the empirical pass-through literature, and makes a connection between the two with respect to firm heterogeneity. Despite the extensive literature on market power, there remains a lack of studies that explore cost shock as a source of market power. To the best of my knowledge, this paper is amongst the first to empirically investigate the link between heterogeneous cost responses and strategic markup adjustment. In particular, due to the empirical setting, this paper relates to the literature that studies market power in the electricity market setting where forward contracting (Bushnell et al., 2008), transmission constraints (Borenstein et al., 2000; Ryan, 2014), and dynamic cost (Reguant, 2014) have been introduced as important determinants of market power.

The pass-through literature has evolved in such a way so as to address the relative importance of how each of these factors (such as markups and cost transmission) has contributed to pass-through. A stream of literature shows that markup adjustment is an important determinant of pass-through and is the cause of incomplete pass-through, which prevails especially in the trade and macro literature (Nakamura and Zerom, 2010; Goldberg and Hellerstein, 2013, Fabra and Reguant, 2014, Amiti, et.al, 2014, De Loecker et.al, 2016). On the cost transmission part, Goldberg and Hellerstein (2013) show that the part of the cost that is unaffected by the shock (non-traded cost) is the main source of incomplete pass-through. This paper fills in the gap in the literature, first by introducing the concept of heterogeneous cost transmission which stems from firm heterogeneity, and considers it explicitly in the pass-through context. Secondly, instead of examining the relative importance of markup adjustment and heterogeneous cost transmission channels, this paper explores the endogenous link between these factors and its relationship to the pass-through. Finally, the paper shows that a non-careful estimation of pass-through – especially with regard to the measurement of the cost shock – could potentially explain why a large proportion of literature reports incomplete pass-through.

It is worth emphasizing that the main message of this paper is the need for a careful consideration of the underlying features of the shock, by showing that the strategic incentives and pass-through could be sensitive to these features. The paper does not claim that heterogeneous impacts are present in all cases. The emissions cost shock to electricity firms as shown by Fabra and Reguant (2014) in their careful analysis, is an example of where the industry is heterogeneous but the impact of the shock is fairly homogeneous across firms. In addition, the paper does not advocate the use of structural analysis in all cases, rather that the use of structural methods and micro-level data may be useful in cases where the heterogeneous transmission is not transparent from the data (Goldberg and Hellerstein (2013) and Nakamura and Zerom (2010) also recover precise cost from the structural analysis).
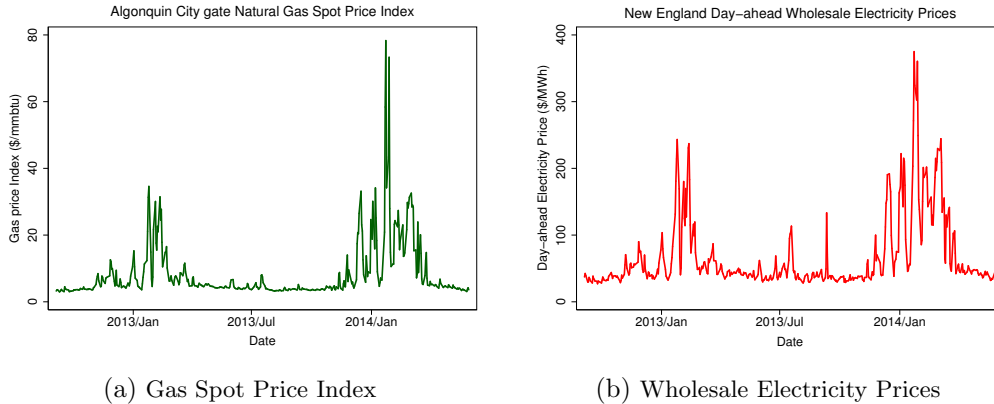
(a) Gas Spot Price Index
(b) Wholesale Electricity Prices

Notes: Sample from September 2012 to March 2014. Gas spot price index (source: NGI) and the day-ahead market Locational Marginal Price (LMP) averaged across nodes and hours (source: ISO-NE) are shown in the graph.

Figure 1: Natural Gas Price Shock and Wholesale Electricity Prices

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.[7] Panel (a) of Figure 1 shows an increase in the spot gas 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 the usual level.

As a result, 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]

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[7]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.

[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 of the electricity market demand can be found in Appendix A.6.2.

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| | Generation Capacity (MW) | | | | | |
Firm	Total	Gas	Oil	Dual	Coal	Hydro	Nuclear
Exelon	4,747	3,300	267	1,179	0	0	0
GDF Suez	2,649	1,210	22	0	124	1,293	0
Dominion	2,607	0	0	510	0	0	2,097
NRG	1,985	0	1,383	603	0	0	0
EquiPower	1,880	1,880	0	0	0	0	0

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

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 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, where 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 results in them having different impacts from the shock. Therefore, the impact of the shock on the costs 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, as shown in Table 1, while Exelon had approximately

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[9]As I will address later, how the gas price shock affects the cost of generators that have the possibility of setting the market price (being ex-ante marginal) is important for firms' markup adjustment incentives. When firms have a differing composition of generation assets, the fuel types of (ex-ante) marginal generators of firms would differ, which results in firms' costs at the margin being impacted differently by the gas price shock. For instance, in an extreme case where all firms only operate the gas-fired generators, every firm's ex-ante marginal unit will be the gas-fired generator, thus a lesser variety exists in the shock's impacts across firms at the margin. Further, how the costs of the firms' entire generation changes with the gas price shock is also relevant for strategic incentives, because firms 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.

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 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 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.

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.[10] 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.[11]

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.[12] Figure 2 shows the existence of such heterogeneity in spot 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.[13] 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 those at a city gate in California where the shock did not occur. The gap between the minimum and maximum

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[10]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.

[11]See Appendix A.3.2 for more discussion on the relationship between long-term contract price and the spot price of gas.

[12]See Appendix A.3.2 or Online Appendix B.2 for more discussion on why the timing of gas procurement may differ even among generators operated by the same firm.

[13]The firm-level natural gas transaction prices at the ICE are not publicly available, in general. From 2015, the EIA started publishing the summary statistics of the transaction prices offered by the ICE, which unfortunately does not cover our sample period (from 2012 to 2014). Although not completed in this paper, extending analysis to the year 2015 sample and comparing the implied gas price estimates to the range of ICE gas transaction prices would be a good external validation for our empirical analysis.
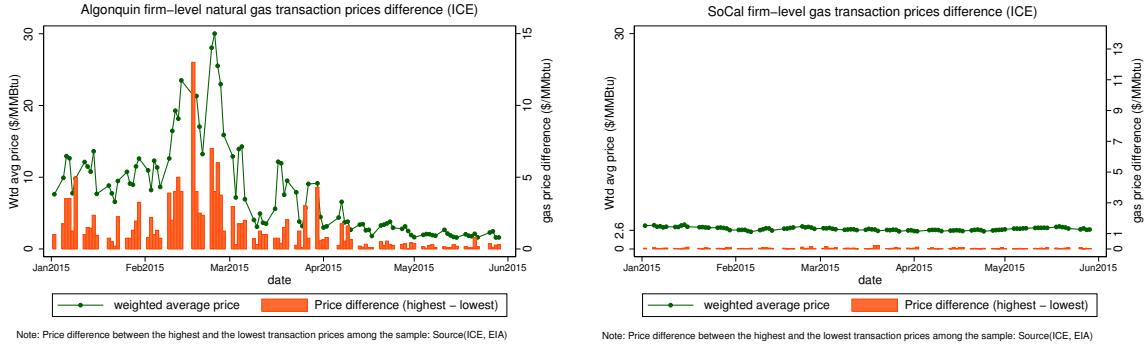
(a) Algonquin city gate   (b) SoCal city gate

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

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 that are reflected in firms' costs to differ.

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).[14] 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 volatility in spot gas prices, as the average value cannot capture such dispersion at the individual firm level.

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.[15] 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 suitable especially in this context where capturing the cost impact heterogeneity among firms is essential for the analysis.

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[14]The gas price index is generated by companies such as *Platts*, *SNL*, and Natural Gas Intelligence (NGI), where individual firm-level gas transaction prices are collected at the spot market each day and a single index value is measured by taking a weighted-average or median value out of the collected information. I obtain the gas price index data from NGI where they use the weighted average methodology to calculate the index. However, some companies use the median value for the index in order to lessen firms' incentives to overstate (misreport) their actual gas procurement prices in an attempt to manipulate the index value.

[15]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.

To overcome this empirical challenge, I utilize 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 by submitting supply bids for each of their generating units. 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.[16] The single market price applies to all infra-marginal suppliers who sell electricity in this market, making this auction a uniform price auction.

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 marginal is uncertain at the time of bidding because firms submit bids simultaneously without knowing how others will bid. Thus, 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.

While the shape of the demand curve also affects a firm's incentive to adjust markups, 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.[17] 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.[18]

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[16]The market organizer, the Independent System Operator (ISO) of New England, constructs the curves and clears the market. The market clearing price referred to is the energy component price (system price) of the daily auction, which is the single price that clears the entire system.

[17]This is because the demand side tends to submit price insensitive bids in the auction. Fabra and Reguant (2014) indeed 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.

[18]The binding constraints on the transmission line is another important factor of market power in the wholesale electricity market (Borenstein, Bushnell and Stoft, 2000; Joskow and Tirole, 2000; Ryan, 2014). Transmission constraints have not been incorporated in this analysis for two reasons. First, it is difficult to model the transmission congestion in the auction model as the actual market clearing process of the ISO (market organizer) is not reconstructed (where a special algorithm is used to clear the market, fully accounting for transmission constraints). Second, any presence of the transmission congestion, if binding, must be revealed in the difference between the Energy Component Price (the market clearing price of the entire system, i.e., the system marginal price) and the Locational Marginal Price (LMP). This is because the additional cost related to the congestion (i.e., the congestion component), which represents the price of congestion for binding constraints, is added to the energy component price
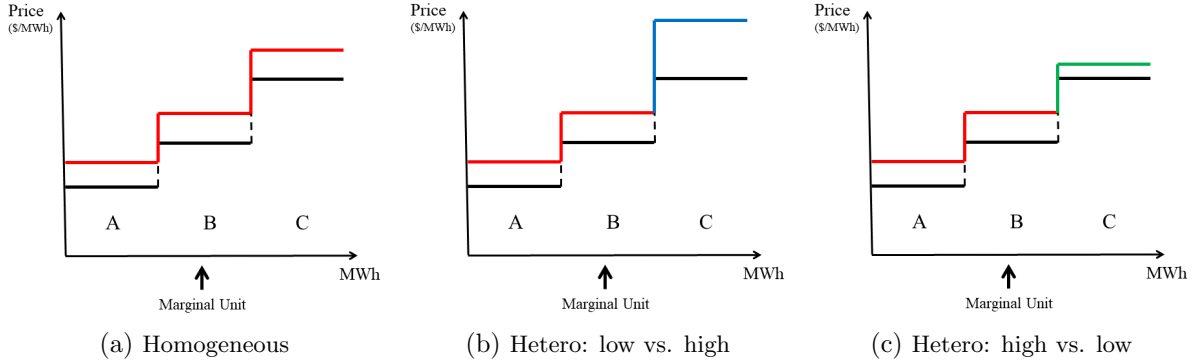
Figure 3: Graphical Illustration of Different Types of Cost Shocks

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, the costs of all three units are affected homogenously by the shock, and the price bid of these units increases by the same size accordingly. In this case, the distribution of bids (slope of the bid curve) before and after the shock are the same. Given that firms were already optimizing before the shock, no change in the bid distribution after internalizing the cost 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 1's unit B increases by less than that of Firm 2'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 increase, which is bigger than 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 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.[19]

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when calculating the final locational marginal price (source: ISO-New England). Over the period of study, locational marginal prices at nodes in the New England grid did not depart much from the energy component price, implying that transmission constraints were not binding.

[19]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

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 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.[20] Without the shock, the spot gas prices are around \$4/MMBtu, which is substantially lower than the spot oil prices that range between \$18 – \$22/MMBtu. 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 and oil units. Especially when the post-shock gas price lies within the range of spot oil prices, the marginal cost of the gas unit is comparable to that of an oil unit which is unaffected by the shock. In this case, a gas unit is likely to be in a situation shown in Panel (c) of Figure 3, where it lacks an incentive to increase the markup at the margin. In contrast, the oil unit, which was previously left out of competition, behaves more strategically by adding markups under a large-sized shock.[21]

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 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).[22] 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. In the daily auction, a firm submits hourly price bids (b) and quantity bids (q) – which consist of multiple steps (k) of

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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.

[20] As shown in Figure A.5 in Appendix A.7, 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.

[21] This is a result of the high gas prices creating a situation in which the oil units could compete with highly impacted gas units, and because the chance of oil 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.

[22] The specification of profit in my model is slightly different from the one in Reguant (2014), where a firm is assumed to maximize the sum of hourly profits of the day. This was necessary as the main focus of Reguant (2014) is to estimate dynamic cost parameters (ramping cost, start-up cost) which requires the firms' quantity decisions to be dependent across hours. Because the dynamic parameters are not the central focus of my paper, I assume firm optimization to be independent across hours. Therefore, firms in my model maximize hourly profits independently.

bids – for each of its generating units. Therefore, the kth step of a bid submitted for firm i's unit j in the auction held at hour h of day t is $\text{b}_{ijkht} =< b_{ijkht}, q_{ijkht} >$. Given the market clearing price P_{ht}, the (ex-post) profit function of firm i in the hourly auction (ht) is shown below:

$$\pi_{iht}(\text{b}_{iht}, \mathbf{b}_{-iht}) = P_{ht}(\text{b}_{iht}, \mathbf{b}_{-iht}) \left(Q_{iht}(P_{ht}(\text{b}_{iht}, \mathbf{b}_{-iht})) - \nu_{iht} \right) - \sum_{j=1}^{J_i} C_{ijt}(q_{ijht}(P_{ht}(\text{b}_{iht}, \mathbf{b}_{-iht})))$$

(1)

Q_{iht} is the sum of quantity generated by the entire dispatched units of firm i, and q_{ijht} is the quantity generated by firm i's unit j, in the hour h day t auction. Also, b_{iht} is the vector of bids of the entire units operated by firm i, and $\mathbf{b}_{-iht}$ is a collection of bid vectors of all other firms. The market clearing price is a function of the bid distribution, i.e., $P_{ht}(\text{b}_{iht}, \mathbf{b}_{-iht})$, because the price depends on the full 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 is a function of the bid distribution, shown as $Q_{iht}(P_{ht}(\text{b}_{iht}, \mathbf{b}_{-iht}))$ and $q_{ijht}(P_{ht}(\text{b}_{iht}, \mathbf{b}_{-iht}))$, respectively.

I assume that the electricity generation cost of unit j of firm i is linear in quantity, i.e., $C_{ijt}(q_{ijht}) = mc_{ijt} \ q_{ijht}$; 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, ν_{iht}, is not affected by the market price, and must be subtracted from the total quantity, Q_{iht}. I estimate ν_{iht} within the model similar to Reguant (2014), due to the difficulty in obtaining data on the forward contracts.[23] I assume that firms forward contract a certain percentage, γ_{ih}, of their hourly output production and that this forward contract rate is constant over time.[24] The specification for the forward contracted quantity of firm i for the hour h of the day t is, therefore, $\nu_{iht} = \gamma_{ih} Q^*_{iht} + \varepsilon_{iht}$, where Q^*_{iht} is the actual quantity of electricity generated by firm i in auction ht, which is observed in the data. Within the model,

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[23]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.

[24]The constant forward contract rate assumption is common in the wholesale electricity market studies, as seen in Bushnell, Mansur and Saravia (2008) and Reguant (2014). The fact that the constant rate specification is used even in Bushnell et al. (2008), where the researchers had access to confidential information of the firm's forward contracts, gives justification to our assumption. As forward contracts derive from vertical intergration between the supply and retail companies, forward contracted quantity would have to be adjusted flexibly to the changes in retail customer demand. In this respect, it is reasonable to assume that suppliers contract a fixed *rate* of their daily generation over time, than a fixed amount, given that the total market demand from the retail sector changes every hour and day. Note that a bias in the forward contract rate estimate will not critically affect our main results because the rate is estimated to be the highest (and positive) during off-peak hours when baseload generation are mostly marginals. The marginal cost of gas-fired units, which is the primary focus of our analysis, is estimated mostly from the peak-hour sample when forward contract is small and close to zero. Therefore, the maginal cost estimates used in the main analysis of this paper are not be sensitive to the bias in forward contract rate estimates.

Q_{ht}^* is treated as exogenous, where the value is fixed for the given hour.[25]

Firms have uncertainty over the bids of competitors ($\mathbf{b}_{-it}$) as they submit bids simultaneously in the auction. Thus, a firm must form a belief about the distribution of others' bids ($\widetilde{\mathbf{b}}_{-it}$) 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 $\widetilde{\mathbf{b}}_{-it}$:

$$\max_{b_{it}} \ \mathbb{E}_{-it}[\ \pi_{it}(b_{it}, \widetilde{\mathbf{b}}_{-it})\ ]$$

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.[26] 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).[27]

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

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 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.).[28] The marginal cost of generation

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[25]While Q_{iht} varies as the marginal unit (j) and bid step (k) change within the model, the ex-post quantity generated by firm i, Q_{iht}^*, does not vary.

[26]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.

[27]See Appendix A.1 for more details concerning the derivations of the condition.

[28]These 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.
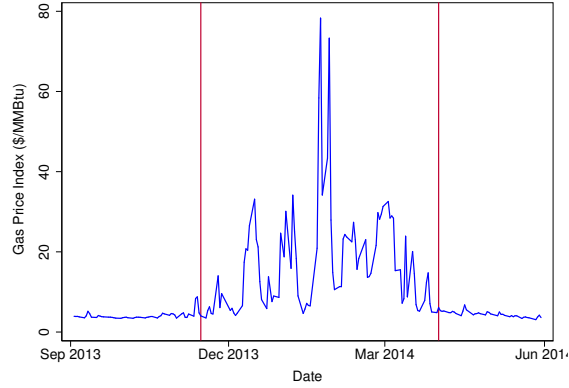
Figure 4: Sample 0 and Sample 1

mc_{ijt} can be decomposed further into two parts: fuel costs and emissions 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:

$$mc_{ijt} = hr_{ij} \left(FP_{ijt} + \tau_t \, e_{j,fuel} \right) \tag{3}$$

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 (τ_t) 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. 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.

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

The fact that gas prices are stable across days in 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 *data* ($FP_{index,t}$) in place of the fuel price component of the marginal cost of a gas-fired unit j, i.e., FP_{ijt}, for Sample 0 observations. To summarize, I am implicitly assuming in Sample 0 that: $FP_{ijt} \approx FP_{lkt} \approx FP_{index,t}$ ($i \neq l$, $j \neq k$).

After inserting the index data for FP_{ijt} and placing in the emissions cost measured from the data (both τ_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).

$$mc_{ijt} = \mathbf{hr}_{ij} \left(FP_{index,t} + \tau_t \, e_{j,fuel} \right) \qquad\qquad t \in \text{Sample 0} \qquad\qquad (4)$$

Therefore, I can estimate the heat rates of each unit separately from the marginal cost, from the Sample 0 observations. I can estimate heat rates of other fuel type generators – such as coal or oil – in a same way, by plugging in the price index data of these fuels in place of FP_{ijt}, because spot prices of these fuels are also stable over Sample 0. 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.[29] 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

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[29]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.

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.

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 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, $\widehat{mc_{ijt}}$. Separating the implied fuel price from the marginal cost estimate is possible because I have the unit-specific heat rates estimated from Sample 0, $\widehat{hr_{ij}}$, 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.

$$\widehat{mc_{ijt}} = \widehat{hr_{ij}} \left(\mathbf{FP}_{ijt} + \tau_t e_{j,fuel} \right) \qquad\qquad t \in \text{Sample 1} \qquad\qquad (5)$$

This methodology can be applied to dual units as well because dual unit's heat rate does not change significantly between burning gas and burning oil.[30] More discussion of the dual unit's heat rate is provided in Appendix A.6.1.

Forward contract parameter   I restrict the forward contract rate, γ_{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.[31]

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 ($\mathbf{b}_{-it}$) that are uncertain

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[30] As dual units can use different types of fuel, it is important to check whether the heat rate of the dual unit differs when burning gas versus burning oil. With the actual data of heat rates available from the EPA CEMS (Continuous Emission Monitoring Systems) data, I find that the heat rate change is minimal for dual units when fuels are switched. In my sample, some dual gas units that generated electricity using gas on Sample 0 days have switched to using oil on Sample 1 days. Even in this case, I can use the heat rate estimated from Sample 0 for the estimation in Sample 1.

[31] 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).

to firm i. I approximate the expectation term following the method developed by Hortaçsu 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, $\widetilde{\mathbf{b}_{-it}}$, by resampling from the observed bids. The analytical expressions of $\frac{\partial P_{ht}}{\partial b_{ijkht}}$ and $\frac{\partial RD_{iht}}{\partial P_{ht}}$, 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:

$$m_{ijkht}^T(\theta_{\mathbf{T}} \; ; S) = \frac{1}{S}\sum_{s=1}^{S} \frac{\partial \widehat{P_{ht}^s}}{\partial b_{ijkht}}\Big((Q_{iht}^s - \nu_{iht}(\gamma_{ih})\,) \; + \; (b_{ijkht} - mc_{ijt}\,)\,\frac{\partial \widehat{RD_{iht}^s}}{\partial P_{ht}}\Big) \qquad (6)$$

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.[32] I instrument the slope of the residual demand, $\frac{\partial \widehat{RD_{iht}^s}}{\partial P_{ht}}$, which is subject to potential endogeneity, with the hourly forecasted demand, the daily forecasted temperature (Sample 0), and the forecasted demand error (Sample 1).[33]

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

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

$$\sum_{h=1}^{H}\sum_{k=1}^{K} Z'_{1,ht}\, m_{ijkht}^1\,(mc_{ijt} \mid \widehat{hr_{ij}}, \widehat{\gamma_{ih}}) = 0, \quad \forall j \qquad (8)$$

Identification and Inference Identification of both heat rate and forward contract parameters in the Sample 0 estimation is possible by imposing reasonable restrictions on parameters, and the identification strategy is similar to that of Reguant (2014). First, the heat rate parameter (hr_{ij}) 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 (γ_{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.[34]

In order to identify forward contract parameter γ_{ih}, I need an exogenous variation in quantity (Q_{iht}) and slope of residual demand (RD'_{iht}), 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

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[32]The wide hat denotes the kernel smoothed values. Smoothing of the curve is necessary to obtain derivatives. See Appendix A.2.

[33]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.

[34]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.

identify γ_{ih}. Similarly, the identification of the heat rate (hr_{ij}) 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.[35] I use bidding data from October 2012 to March 2014, excluding samples from the spring/summer period.[36] The supply bids come from *Energy Offer* data, and for the demand bids I use *Demand bids* data.[37] 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, 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.[38] 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.[39]

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[35]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.

[36]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.

[37]I provide more details on the additional bids – import/export bids, financial bids, etc. – in Section B.4 of the Online Appendix.

[38]The number of bid steps of generating units is summarized in Table B.1 in the Online Appendix.

[39]The spot gas price index data is acquired from *Natural Gas Intelligence* and *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 *EIA* and *SNL energy*. Emissions permit prices are taken from *EPA RGGI* auctions data. More details on the fuel price data and the emissions permit data can be found in Section B.3 of the Online Appendix.

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

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

5 Estimation Results: Documenting the Heterogeneous Impacts

5.1 Heat rates and forward contract rates

Table 2 reports the average of the estimated unit-specific heat rates, separately by the fuel types of generating units.[40] The estimates are close to the heat rates reported by the EIA (Energy Information Administration), where the average of gas-fired unit's heat rate lies between 7.6 and 11.3 and that of oil-fired units lies between 9.9 and 13.5.[41]

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.6 of Appendix A.7, 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.

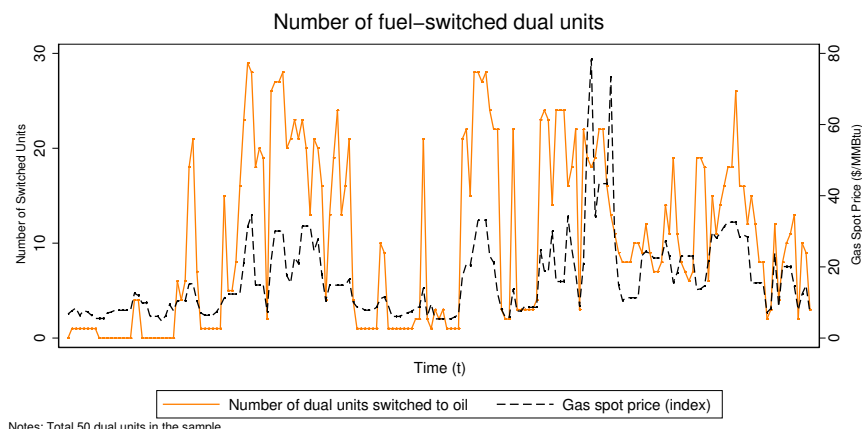### 5.2 Implied fuel price estimates

I document the heterogeneity of the impacts of the gas price shock with estimates of 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.

I first estimated the unit-specific marginal costs of electricity generation $(\widehat{mc_{ijt}})$ for each day in Sample 1 where gas prices are volatile, and summarized them in Figure A.1 of Appendix A.3. Using $\widehat{mc_{ijt}}$ along with heat rate estimates, I 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.[42] Figure 6 presents the implied fuel price estimates 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.

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[40]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.

[41]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.

[42]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.

Number of fuel−switched dual units

Notes: Total 50 dual units in the sample

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 5: Dual Unit's Fuel Switch Decision Identified

The graphs of the three selected firms are useful to demonstrate the existence of the heterogeneous impacts, as well as to explain how to identify the dual unit's fuel switch decision. Panels (a), (b), and (c) of Figure 6 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 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 a 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 only the spot price of gas fluctuates over the period of shock, when the prices of other fuels are stable, is useful for detecting the fuel switch.

Panel (c) of Figure 6 illustrates 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.[43]

In this way, I identify the fuel switch decisions of all dual units, for each day in the sample. Figure 5 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. As shown in the graph, more fuel switches occur as the gas price increases, which corresponds to the cost-minimizing behavior.

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[43]More details of how I identified the fuel switch decision of dual units, especially when the spot gas prices are similar to the oil price, are provided in the Appendix A.3.3.

However, not all of the dual units switch fuels according to such behavior, even on days when the gas prices are substantially higher than the spot oil prices, indicating that some heterogeneity exists in the way firms make their switch decisions. The identified fuel switch decisions are an important source of the heterogeneity in the impacts, 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 implied gas prices vary substantially across units and firms, even within a single day. This is shown in Panels (b) and (c) of Figure 6 where I plot implied gas prices of gas units operated by Firm 9 and Firm 33 (green lines), together with the gas price index data which serve as a reference point. While the implied gas prices of Firm 9's units track the gas price index data closely, those of Firm 33 differ from the index values. Implied gas prices are even different among gas units operated by the same firm, shown by the dispersion in the paths of the estimates of Firm 33 in Panel (c). More discussion of why implied gas prices could vary within a day and even within the firm is provided in Appendix A.3.2.

Another interesting finding 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 7 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 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 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 index data 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 classify 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.[44] 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.[45]

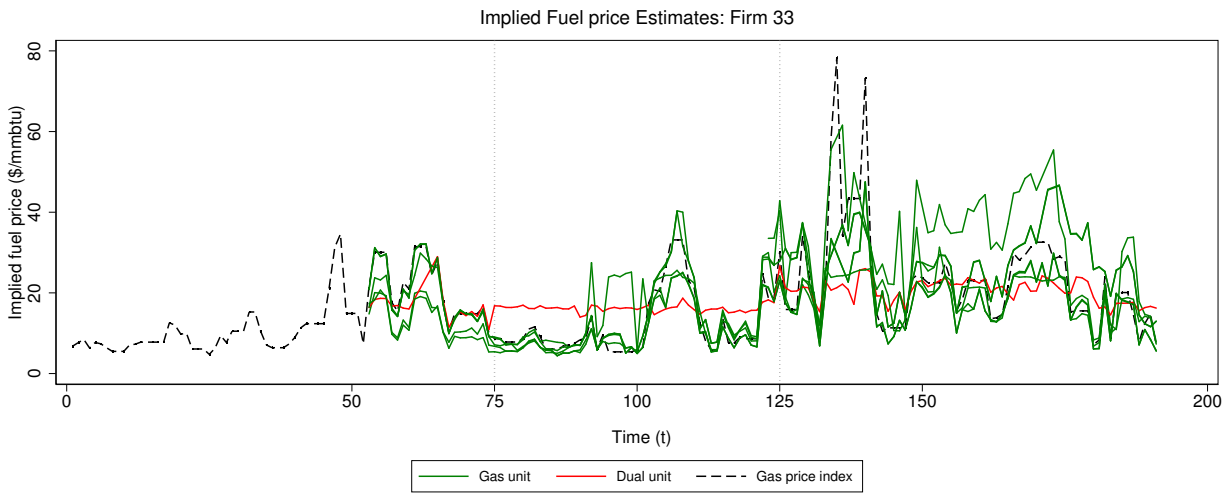[44]I drop dual gas units when calculating the capacity of gas generation.

[45]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.
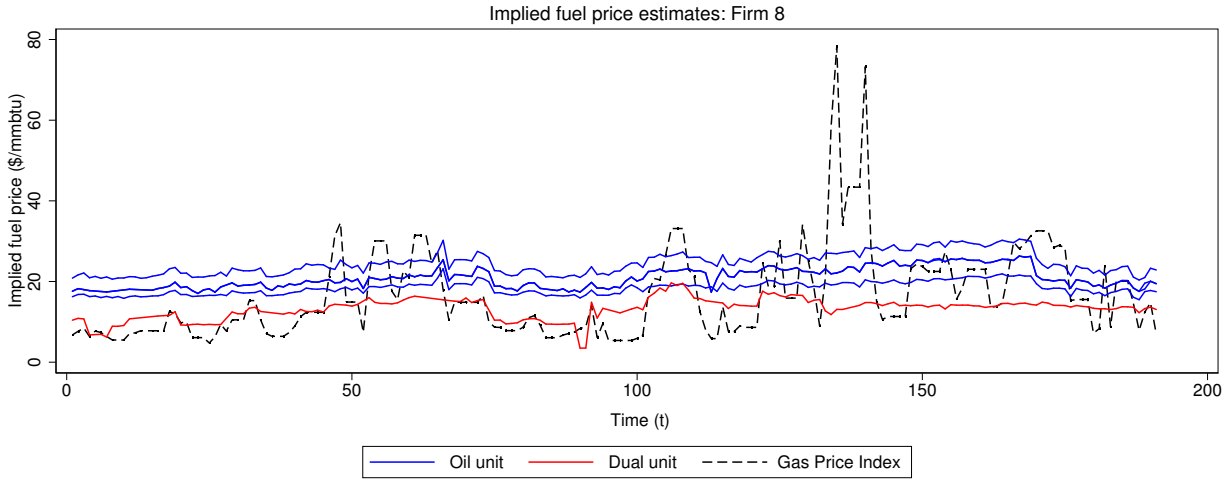
(a) Firm 8
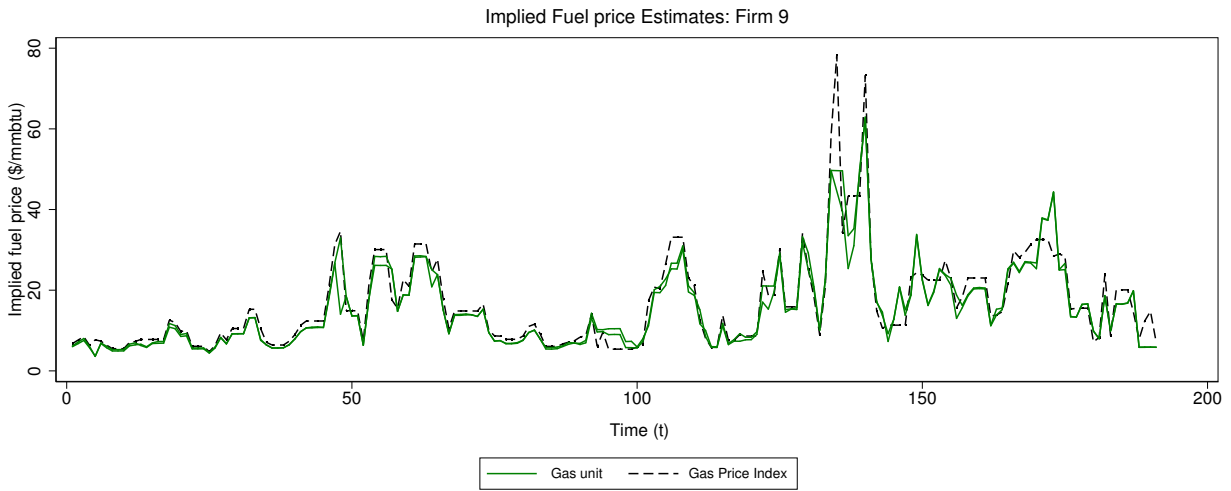
(b) Firm 9

(c) Firm 33

Notes: Implied fuel price estimates of non-dual gas units (green line), dual gas units (red line), and oil units (blue line) are plotted over time. The black dashed line shows the gas price indices (data) for the corresponding days. I report only the estimates that are statistically significant.

Figure 6: Implied Fuel Price Estimates

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Note: excludes dual units that switched
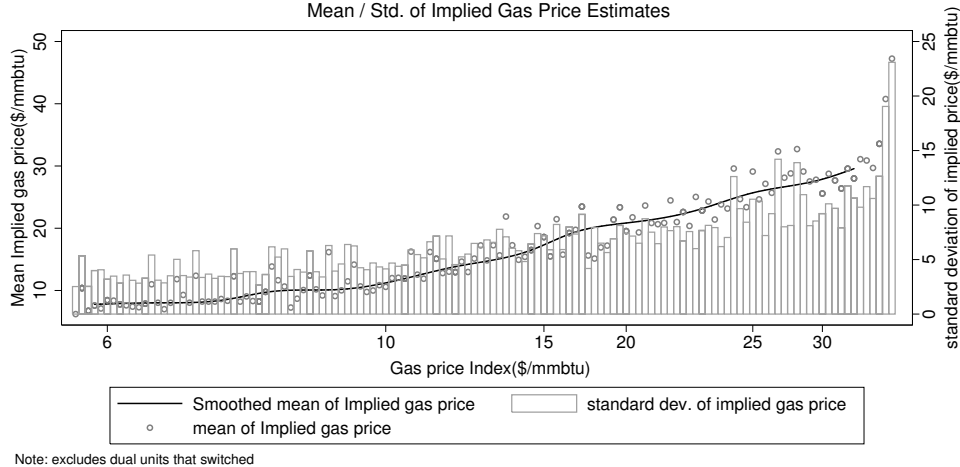
Notes: The graph contains the mean and standard deviation of the estimated implied gas prices of all gas units in the sample. Statistics are plotted against daily gas spot price indices.

Figure 7: Estimated Implied Gas Prices: Mean and Standard Deviation

6 Markup Analysis

The objective of this section is to explore how firms' markup adjustments 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. Simulated markup reveals the marginal incentives for markup adjustment that arise purely from the cost shock, thus, more relevant for pass-through analysis.
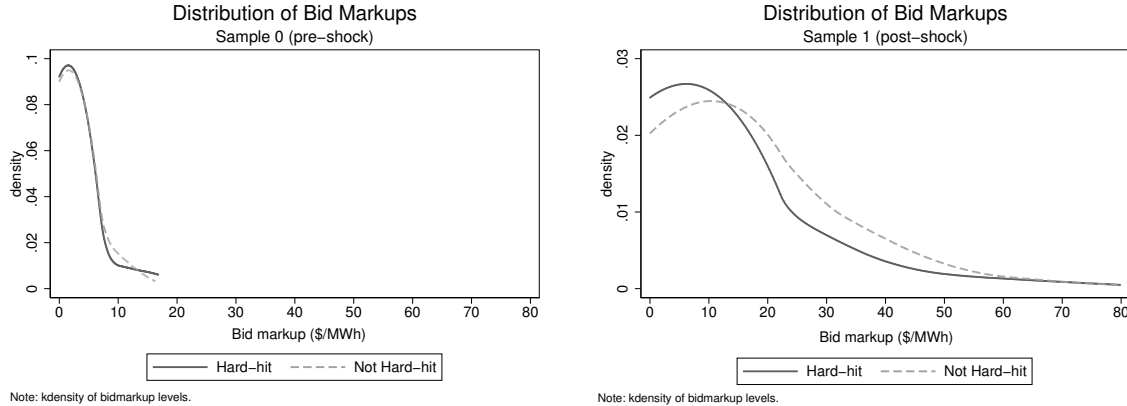
6.1 Bid markup analysis

The price bid of a firm can be decomposed into a part that reflects marginal costs and the part related to the strategic decision, which I denote as the bid markup.[46] Bid markups can be calculated directly from the first-order condition shown in equation (9), as we have estimates of the marginal cost and data on price bids.[47]

$$
\text{bid } \widehat{\text{markup}}_{iht} = b_{ijkht} - \widehat{mc_{ijt}} \ = \ \frac{\mathbb{E}_{-it}[\, Q_{iht} - \nu_{iht} \,]}{\mathbb{E}_{-it}[\, \partial RD_{iht}/\partial P_{ht} \,]}
\tag{9}
$$

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 separately by the hard-hit firm group

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[46]The bid markup is related to the degree of competition faced by a firm in a market. 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.

[47]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. Equation (9) 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.

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Distribution of Bid Markups
Sample 0 (pre–shock)

Distribution of Bid Markups
Sample 1 (post–shock)

Note: kdensity of bidmarkup levels.

Note: kdensity of bidmarkup levels.

(a) Sample 0 Bid Markup Distribution

(b) Sample 1 Bid Markup Distribution

Notes: Kernel densities of the levels of bid markups (*unit*: $/MWh) of firms are plotted. Panel (a) is for Sample 0, where there was no gas price shock, and Panel (b) is for Sample 1 where the gas price shock was present. The bold line is the density of "hard-hit" firm group, and dashed line is the density of those "not hard-hit".

Figure 8: Bid Markup Distributions: Hard-Hit vs. Not Hard-Hit Firms

and the not hard-hit group, shown in Panels (a) and (b) of Figure 8, respectively.[48]

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 those in Panel (a), which are concentrated around 0.[49] A comparison of the mean of distributions of hard-hit firms and not hard-hit firms across panels shows that, on average, markups increase less for the hard-hit firms than for those less affected by the shock.

6.2 Markup simulation: first-order approach

With bid markups, how a shock affects markups can be examined by comparing 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, because the presence of the shock is not the only difference between the samples. Other factors that affect firm's strategic decision, such as the aggregate market demand, also differ across these samples.[50]

To tackle this problem, I implement a simulation where the firm-specific markup responses to a small counterfactual cost shock are measured at each auction. Since the only factor 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. Moreover, how the markup *marginally* responds to the cost shock would be more relevant for the analysis of pass-through which aims to capture the marginal response of the market price to the cost change. The simulation is based on the first-order approach (Jaffe and Weyl, 2013; Fabra and Reguant, 2014) where I give a small cost perturbation

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

[49]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.

[50]Also, a simple comparison of the 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 the entire system (market) and then simulate the endogenous changes in markups of each firm implied by the first-order condition.

Note that a small cost perturbation elicits markup adjustment incentives of firms at the current equilibrium, *given* the characteristics of the equilibrium. Suppose we simulate markups by imposing a small cost shock to the system of a sample day when the actual gas price shock was large (e.g., a day when gas price (index) value is \$20/mmbtu). Then, the simulated markups reveal the incentives of firms when the market is affected by a large-size gas price shock, not by the additional small cost shock which only serves as a means of perturbing the system. That is, the variables that change when the size of a gas price shock is large compared to when it is low are the distribution of the bids, the location of each firm's bids relative to others (thus, the set of competitors), and most importantly the degree of heterogeneity in the impacts, as documented in the previous section. The simulated marginal incentive, therefore, is a function of these characteristics associated with a large-sized gas price shock, along with the realized market demand.

Thus, 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. In this respect, this simulation 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).[51]

I impose a gas price shock of size \$0.1/MMBtu in the simulation, which increases the generation costs of gas-fired units by the size of approximately \$1/MWh. The size of the cost perturbation is zero for generators unaffected by the shock: coal unit, oil unit and dual gas units that switch fuel to oil. In this way, the simulation accounts for the different marginal impacts across firms and generators from the cost perturbation.[52]

Equation (10) explains the idea behind the simulation.

$$\Delta pbid_{ij} \quad = \quad \underbrace{mc_j'(q_j) - mc_j(q_j)}_{\text{direct cost shock}} \quad + \quad \underbrace{|\frac{\partial p'(q_i')}{\partial q_i'}| \, \tilde{q}_i' - |\frac{\partial p(q_i)}{\partial q_i}| \, \tilde{q}_i}_{\text{Markup Change}} \tag{10}$$

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 adjustment associated with that cost change. $\Delta pbid_{ij}$ 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

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[51]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.

[52]Table A.4 in Appendix A.4 summarizes the sizes of cost perturbations of all generating units. 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 impact from the shock as measured by the estimated implied gas price. More details about this perturbation are provided in Section B.7 of the Online Appendix.

cost perturbation, which results in a change in the entire distribution of price bids.[53] The change in the distribution affects the variables 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 of these variables before and after the perturbation are observed within the simulation, thus the endogenous *markup change* component is measured directly.[54]

Result Firm-level markup adjustments are simulated for each hour-day (ht) auction in the sample. I generate a daily measure by taking an average of the hourly simulated markups across hours.[55] Note that markup is reported only for the ex-ante marginal firms (with a positive probability of being a marginal price setter) because firms have incentives to adjust markups only when they expect to influence the market price.[56]

I exclude the fringe firms from the analysis because they lack incentive to adjust markup upon cost shock. That is, the simulated markups of fringe firms are small, below 1 % of the size of their cost perturbations. This finding is in line with the findings from other electricity market studies showing that small fringe firms do not behave strategically in contrast to large-scale strategic firms (Borenstein et al., 2002; Bushnell et al., 2008). All markup adjustment graphs presented in Figure 9 are of large-scaled firms.[57]

In Figure 9, I plot the density of simulated changes in markups separately for hard-hit firms and not hard-hit firms. To control for the intensity of the gas price shock which is an important determinant of the degree of heterogeneity in the impacts, I plot the 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.[58]

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

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[53]Note that this method can be understood as breaking down the complete process of adjusting price bids, according to the first order condition, into two parts: first, the part reflecting cost change of its own; and second, the part reflecting markup change that results from cost changes of competitors. Note that the process does not assume markup adjustments to be fixed. This resembles any decision process made at the margin, and the intuition is similar to Figure 3 presented in Section 3.

[54]Because 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.

[55]Note 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.

[56]The simulated markup of firms having zero probability of becoming marginal, i.e., $\frac{\partial p}{\partial b} = 0$, is assigned to zero.

[57]As the fringe (small-scaled) firm's adjustment is very small regardless of the shock intensity, their markup densities would degenerate around zero.
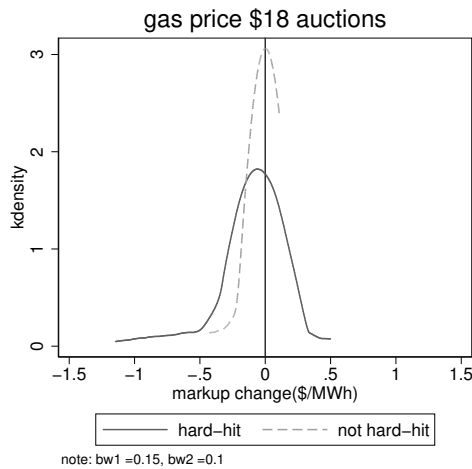
[58]Among those selected days, I again chose days having similar levels of electricity demand, daily peak-temperature, and spot gas market conditions, to ensure that any other factor that may affect markups has been controlled for. More details on the selection of similar days are provided in Appendix A.2.
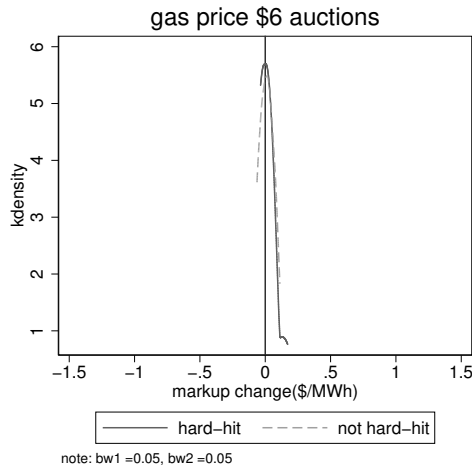
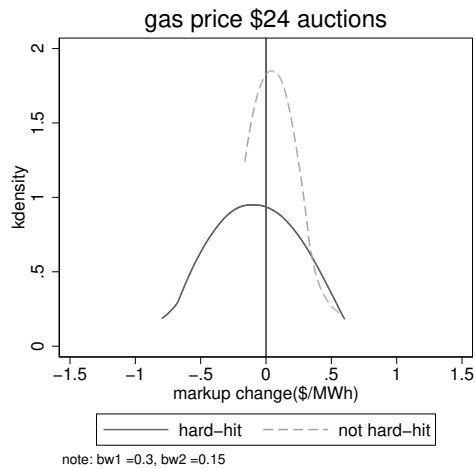(a) Gas price index $6/MMBtu
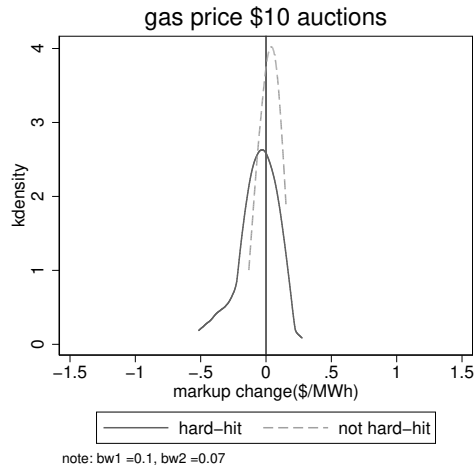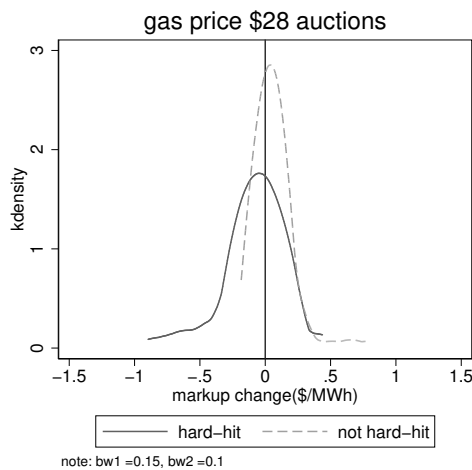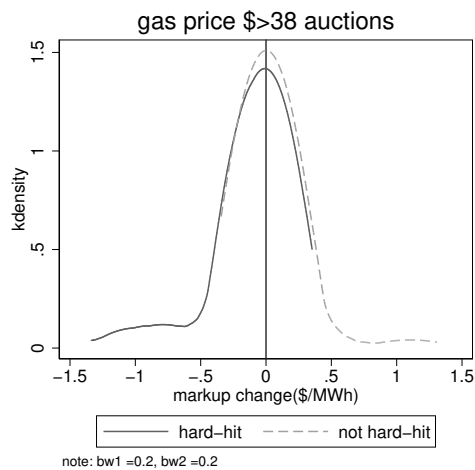
(b) Gas price index $10/MMBtu

(c) Gas price index $18/MMBtu

(d) Gas price index $24/MMBtu

(e) Gas price index $28/MMBtu

(f) Gas price index > $38/MMBtu

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 9: Simulated Markups: Hard-hit vs. Not Hard-hit Firms

(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 affected by the shock.

Interestingly, the pattern of markup adjustments differs by 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.[59] 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 competition 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

A question relevant to policy-making is to ask not by how much the market price has increased after the cost increase, but, whether the price has increased proportionally to the cost increase, i.e., cost pass-through. This section studies the pass-through, demonstrating in particular that a careful examination of markups – which must be based on a correct assessment of the extent of cost increase – is essential for obtaining accurate pass-through rates.

So far, we have documented the heterogeneous responses of costs and markups to the gas price shock, with the aid of a structural estimation that enabled us to capture this rich pattern. Extending this structural framework, I implement a unique approach by simulating the auction-level pass-through rates that are constructed based on the estimated costs and markups, thus fully accounting for the heterogeneous impacts. Such high-frequency pass-through rates are useful for 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 auctions.

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[59] One may wonder if the differing markup adjustment pattern is a result of firms having a different probability of being marginal price setters. While it is possible, it is not necessarily a critical determinant of the density pattern for the following reasons. First, great care has been taken of non-marginal price setters (having a non-positive probability weight of setting the price) by assigning zero to the markups of these firms. Second, because I am using only the large-scale strategic firms that operate multiple units when plotting density, it is highly likely that at least one of their units will be an ex-ante marginal unit (having a positive probability weight). These firms are not ranked or re-weighted using the probability of becoming marginal when simulating the markup. This is due to the concern that while we can clearly tell which firms' units are closer to the margin in ex-post, it is difficult for firms to expect their rank in ex-ante – when strategic decisions arise – due to uncertain nature of the auction.

In general, this type of simulation that requires a structural approach is not easy to implement. Instead, a standard way of estimating pass-through is to explore a reduced-form relationship of prices and costs, using available data. The accuracy of such reduced-form estimation critically depends on the underlying feature of the shock's transmission. That is, if the shock's transmission to firms' costs is heterogeneous, the estimation faces a challenge, as different responses of firm-specific costs to the shock may be difficult to measure from the data only (especially so when only the aggregated-level data are available). If the data on firms' costs is rich enough, or otherwise, the feature of the shock makes aggregate cost data sufficient enough for representing firm-level cost responses – such as in the case of having homogeneous impacts from the shock – the reduced-form estimate of pass-through must yield similar results as in the structural set up.

Nevertheless, it is difficult to even acknowledge the presence of the heterogeneous impacts unless we structurally uncover the underlying heterogeneity as done in this paper or get access to rich data. This, in turn, implies that examining whether the cost variable used in the regression is prone to measurement issues or not is difficult as well, which brings concerns over the regression analysis of pass-through when the heterogeneous impacts are present. To illustrate this challenge and to quantify the bias arising from omitting heterogeneity, I estimate pass-through rates from a naïve regression that does not properly account for the heterogeneity in the impacts, and compare these to the simulated pass-through rates that fully incorporate it.

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.[60] 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 the size of the cost perturbation given to the marginal unit j of auction ht is known, as is 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 ρ_{ht} in equation (11).[61]

$$\rho_{ht} = \frac{\Delta p_{ht}}{\Delta \mathrm{mc}_{j,ht}} \quad \text{where} \quad \Delta p_{ht} = \Delta b_{j,ht} = \Delta \mathrm{mc}_{j,ht} + \widehat{\Delta \mathrm{markup}}_{i,j,ht} \tag{11}$$

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

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[60]More details on the selection of ex-post units are in Appendix A.5.

[61]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.

Summary statistics	Simulated pass-through rates, ρ_{ht}
Mean	0.974
Min	0.004
Max	2.198
S.d.	0.204
N	2,661

Notes: Pass-through rates of each hourly auction (ht) at which gas units are marginal units are used in the regression. Outliers above and below the 98th and 2nd percentiles, respectively, are dropped.

Table 3: Summary of Simulated Cost Pass-through Rates

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 electricity 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.7). This implies that even if the same-size cost shock is imposed on the marginal units of hard-hit and not 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

A more common form of estimation is a simple reduced-form regression which identifies a single, average pass-through rate using cross-auction (section) variations in prices and costs, both observed from data.[62] The standard regression specification for estimating the pass-through in the electricity market setting is shown in equation (12), which is similar to that used in Fabra and Reguant (2014):

$$p_{ht} = \rho \, hr_{ht}G_{ht} + \beta_0 \mathbf{X}_{ht}^D + \beta_1 \mathbf{I}_{ht} + \epsilon_{ht} \tag{12}$$

ρ is the parameter of interest which captures the average rate of cost pass-through.[63] Dependent variable p_{ht} is the electricity price that cleared the auction held on day t at hour h.[64] The key variable is $hr_{ht}G_{ht}$ which measures the generation 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,

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[62]Due to the lack of cost data, one could use either a variable that is a good proxy of cost or that is correlated with the variation in cost. However, it is not uncommon to use the cost measure estimated from a structural model (see Ganapati, Shapiro and Walker (2018), for example).

[63]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 *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.

[64]I use the day-ahead electricity auction's energy component price for p_{ht}, which is published daily by ISO-NE.

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. More details about the regression such as the descriptions of other variables and the endogeneity problem are provided in Appendix A.5.

To demonstrate the challenges that a regression analysis faces when the shock's impacts on the costs of firms is heterogeneous, I estimate three variants of regressions that differ in how the gas cost term, $hr_{ht}G_{ht}$, is constructed (results of each are shown in Table 4). First two specifications, shown in columns (1) and (2), are näive regressions in the sense that we use a cost measure that a researcher not carefully taking into account the heterogeneous impacts would use: the cost variable constructed with the highly-aggregated gas price index data. Specifically, for the cost variable in column (1) specification, I use the average heat rate ($\bar{hr}$) for hr_{ht} and the gas price index data ($\bar{G}_{ht}$) for G_{ht}.[65] Since both the heat rate and the gas price index are average values, the gas cost variable of regression (1) implicitly assumes the impacts of the cost shock to be homogeneous across firms and units. The cost variable of the column (2) specification is slightly better than the one in column (1) as it is constructed with unit-specific heat rates ($\widehat{hr_{ij}}$) estimated earlier from the model, which reflect the differences in efficiencies across units. However, the variable is still inaccurate because the aggregate gas price index data ($\bar{G}_{ht}$) is used for G_{ht}.

On the other hand, the cost variable used in the specification shown in column (3) is accurate as it is constructed based on the estimates from the structural model. That is, the unit-specific implied gas price ($\widehat{FP_{ijt}}$) is used for G_{ht} and the unit-specific heat rate ($\widehat{hr_{ij}}$) is used for hr_{ht}, both of which are estimated at the generating unit level. Therefore, the cost variable used in (3) precisely represents the firm- and generator-level marginal costs, and fully accounts for the differences in the gas price shock's impacts on costs across firms and units.

I 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 in order 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 or not 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, ρ, can be compared with the *mean* of the simulated pass-through rates (ρ_s).[66]

Results   The first row of Table 4 reports the result of *full sample* regressions. Comparsion of (1) and (2) shows the importance of incorporating heterogeneity in heat rates. The difference in

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[65]EIA 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 $\bar{hr}$ (source: EIA report, 2015).

[66]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.

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

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 droped 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

estimates are not substantial, being 0.481 in (1) and 0.457 in (2), which indicates that omitting the heterogeneity in heat rates (efficiency) does not critically affect the pass-through estimates. Both specifications, however, yield pass-through rates that are below 0.5 (50 percent), which is significantly different from, and smaller than, the close to complete pass-through rate of 0.974 (97 percent) obtained from the simulation (shown in Table 3). That is, the average pass-through estimate is underestimated when the differences in the extent of cost increases from the shock are not properly accounted for in the regression.

On the other hand, the pass-through estimate is close to the mean of simulated pass-through rates when the cost measure used in the regression fully accounts for the differences in impacts, 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 in the differences across units, this finding confirms that omitting the heterogeneity in the firm-level cost resulting from different exposure to gas price shock is the primary source of the underestimation.

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

Discussion: The cause of underestimation Generally speaking, the bias we find in the naïve regressions in columns (1) and (2) of Table 4 is driven by the measurement error that arises from using the cost variable generated with an aggregate-level data. Note again that when the shock homogeneously affects the costs of firms and generators, the cost shock observed from the aggregate data is close to the true cost shock that each firm faces. When the shock's impact is heterogeneous, however, the cost shock observed from the data departs from the true cost shock, thereby generating the measurement error, as extensively documented from our cost estimates. In other words, having a measurement error in the cost indicates that the markup adjustment channel, which plays an increasingly important role in the pricing as the heterogeneity in the impact increases, is largely neglected in the estimation. This implies that the underlying degree of competition, as revealed in the markups, that we infer from the pass-through rate could be misleading if the estimation is not carefully implemented.

More specifically, the underestimation of pass-through in these naïve regressions is a result of having a large portion of low-impacted marginal units in our sample. While the costs of these units increase relatively less than the others, the cost measured with the average gas price index data overstates the actual sizes of cost increases of these units. Overstating the impact on cost side, in turn, implies that the contribution of markups in raising the price is understated, resulting in a lower than actual pass-through rate.[67]

One way to correct for such a measurement error is to use an instrument. However, the instrument used in our regression, which is similar to the one used in Fabra and Reguant (2014), is not intended to correct for the measurement error originating from omitting the heterogeneous impacts.[68] That is, the instrument we use only addresses the endogeneity of the cost variable that results from the unobserved demand and supply factors. While this instrument assures that the variation of marginal cost across auctions (ht) is exogenous, the measurement error is still present with the instrument. Since the measurement error arising from omitted heterogeneity is not present in the cost variable used in the regression (3), the difference in the pass-through estimates between (2) and (3) represents the attenuation bias arising from the measurement error.[69] General formulation of the problem and more discussion of the measurement error can be found in Appendix A.5.

Such a measurement error can be corrected if another valid instrument which specifically targets this type of error is found. However, finding a valid instrument to target firm-specific measurement errors that persist across auctions, along with the model endogeneity, is challenging and is beyond the scope of this paper. On the whole, by showing the existence of the systematic bias originating from the heterogeneity in the cost responses, our result demonstrates why it is important for researchers to carefully examine the feature of the shock and its transmission when developing their empirical methodology and choosing proper instruments.

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[67]More information of marginal units with overstated cost measure is provided in Appendix A.5.

[68]This was not a concern in their estimation as the impact of the emissions price increase on costs were homogeneous so that the emissions cost constructed from the data were accurate measures of firm-level emissions cost.

[69]The fact that our estimate shown in (3) is close to the average of pass-through rates obtained from a completely different methodology (simulation) gives an external validation to this argument.

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.

In addition to the general implications, 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.

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A Appendix

A.1 Model

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

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

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]

A.2 Estimation

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

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

Each resampled set of bids represent one possible realization of the ex-ante expected bids. Thus, a collection of resampled bids will approximate the ex-ante expected bid distribution of a firm.

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

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

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

From a bidder i's point of view, we need to resample the distribution of $\mathbf{b}_{-i} = \{b_1, \ldots, b_{n-1}\}$. Suppose $r = \{1, 2, 3, 4, 5, 6\}$ is a random variable (each number indexes the selected similar days), and r_j^{bs} denotes the random variable selected by firm j ($j \neq i$) for a bs^{th} bootstrap draw. Below shows the randomly selected auctions (t) for each bootstrapped sample:

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

$$\vdots$$

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

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

Despite having a small number of T, we have enough variation by having a large number of bidders (N) by randomizing in the fashion described above (T^N is a sufficiently large number). The randomizing process used here is similar to the wild bootstrapping, while in the standard

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

example of wild bootstrap, r is $r = \{-1, 1\}$. Our example is similar to a wild bootstrap with r dimension of the number of similar days (six in this case). Since the dimension of T is equal to the dimension of r, it is also important to ensure that T is not too large as the convergence speed must be greater for N than for T. Therefore, having a large number of T is not necessary to get a consistent estimate in my empirical set up.

Endogenous residual demand slope Firm-specific unobserved cost shock could shift the firm's bid up, resulting in a larger slope of residual demand. Failing to account for such unobserved shock will misleadingly conclude that a firm behaves less competitively by adding higher markup when actually the higher bid is a reflection of unobserved cost shock. Therefore, following Reguant (2014) and Ryan (2014), I instrumented the slope of residual demand in the estimation. As for the Sample 0 estimation, I used hourly forecasted demand and the daily forecasted temperature, both of which exogenously shift the endogenous slope variable, but are not correlated with the unobserved supply shock, as instruments. For the Sample 1 estimation, I used forecasted demand error (i.e., actual demand - forecasted demand) to eliminate the dependency of moments across hours.

Smoothed supply bid, residual demand and weight The derivatives of the supply offer curve and the residual demand curve of each firm enter the empirical analogue of the first-order condition. Since these curves are submitted as step functions, I first smooth the curves using the normal kernel smoothing approach following Wolak (2007), using a bandwidth of \$3/MWh for the Sample 0 estimations and \$6/MWh for the Sample 1 estimations. As a robustness check, I tried different bandwidths to see how sensitive the derivatives are to the bandwidth selection. Results are quite robust across bandwidths except for some days when electricity prices are extremely high.

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

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

	Resampling $\mathbf{b}_{-it}$ of firm i on auction day t:
Step 1:	Fix the bids of firm i to its actual ex-post observed bids of day t
Step 2:	Randomly sample the bids of each firm $m \neq i$ from the pool of days that are similar to day t. That is, if the similar days of day t are $T_t = \{t_1, t_2, \ldots, t_6\}$, randomly sample one day from the set T_t for each firm m.
Step 3:	Clear the market using the supply offer curve constructed using the resampled bids from steps 1-2, and the ex-post demand bid curve of day t. Market clearing yields one set of market price, $P_{t,s} = \{p_{1t,s} \ldots, p_{24t,s}\}$.
Step 4:	Step 1-3 is for one resampled draw, i.e. s = 1. Thus, repeat the steps 1-3 for S = 100 times, and get $P_{t,i} = \{P_{t,i,1}, \ldots, P_{t,i,S}\}$
Step 4:	Going through Steps 1-4 gives a set of resampled prices for firm i, i.e., $P_{t,i}$. Now repeat steps 1-4 for each firm in the sample, $i \in F$ and get $P_{t,i}$ for $i \in F$

Table A.1: Resampling Procedure

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

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

Then the derivative of the residual demand curve is:

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

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

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

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 GMM standard error formula. Because this Sample 1 GMM estimation is indeed a linear IV estimation, I use IV standard errors. Alternatively, we could also bootstrap the standard errors. In this case, block bootstrapping is not necessary as the temporal dependence disappears by our selection of instrument (demand forecast error that is *i.i.d.* across hours).

A.3   Estimation Results

A.3.1   Marginal cost estimates by fuel types

I first estimate the unit-specific marginal costs of electricity generation $(\widehat{mc_{ijt}})$ for each day in Sample 1 where gas prices are volatile. In Figure A.1, I take the daily cross-sectional average of the estimates separately by fuel type – coal, gas, dual and oil units – and plot them against the gas price index value for each day, which proxies for an overall size of a gas price shock. Not surprisingly, the average of the marginal cost of gas-fired units increases with the overall size of the shock, while that of coal and oil units does not change much in the sample.[3] The average of the gas units' marginal costs becomes similar to that of oil units when the daily gas price lies between the range of oil prices ($18 - 25/MMBtu), and becomes the highest among all fuel types when the gas price exceeds the level of the oil price. This finding suggests that the cost advantage of a gas-fired unit relative to other fuel type units changes with the intensity of the gas price shock.

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

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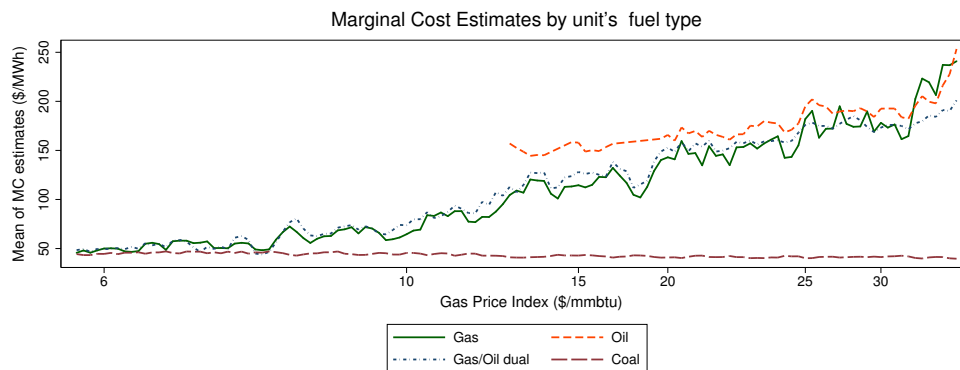
Notes: Unit-specific marginal cost estimates of days in Sample 1 are averaged within each fuel type categories: gas, oil, dual, and coal. The set of units included in the calculation of the average value changes over time. Averaged estimates are plotted against the gas price index values of the days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

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

A.3.2 Exploring the dispersion in the implied gas price estimates

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

Does a firm with a long-term contract have a lower estimated implied gas price?
In Table A.2, I summarized percentages of gas-fired power plants in New England that purchase gas through the long-term contract and from the spot market, using power plants that appear in the EIA-923 data. Although the sample size is small, about 20 percent of the power plants purchase gas through long-term contracts, and the rest of the plants purchase gas at the spot market from various different gas suppliers.

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

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

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

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

Data source: EIA-923 Schedule 2

Table A.2: Percentage of Firms Procuring Gas from Long-term Contract vs. Spot Market (Plant Level)

a long-term contract.[6] Additionally, to see how the difference in implied gas prices between those with and without the long-term contract varies with the overall size of the gas price shock, I ran regressions separately on subsamples that vary in sizes of gas price shocks. Figure A.2 shows the estimated coefficients. The negative coefficient estimates indicate that the implied gas prices are, on average, lower for firms that purchase gas via the long-term contract than those that do not. Also, the magnitude of coefficient estimates increases as the overall size of the shock increases, which corresponds to the fact that the difference between the long-term contracted price and the spot price of gas becomes larger as the gas price shock increases considerably. Therefore, the existence of a long-term gas contract explains the dispersion that we find in the implied gas price estimates.

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

Since we know that spot gas prices can vary within a day, power plants ordering gas at different time points could lead to different gas prices across plants and generators, even if all of them purchase gas on the spot market. One possible explanation for such a procurement practice is the dispatch uncertainty in the day-ahead electricity auction. In general, firms do not know at the time of the bidding which of their generating units will finally be accepted in the auction so that they could actually generate electricity in the market. Thus, purchasing gas for all of their generating units at the time of the bidding is risky for firms. Instead, firms will purchase gas in advance only for those units that are most likely to generate electricity in the market, and postpone purchasing for the rest of the uncertain units. The fuel price implied in the bids of these postponed generators could be the expected price of gas at the time of the gas use, which could differ from the spot price at the time of bidding. Such gas procurement and bidding practices are evidenced by the Market rule published by the ISO-NE.[7]. These behaviors, combined with the increase in the volatility of

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

[7]For the purpose of monitoring market participants' bids, market monitors sometimes require a market participant to submit a fuel price whenever the market participant's expected price to procure fuel for the unit will be greater than that used by the Internal Market Monitor – the gas price index. It is stipulated in the Market Rule that firms may submit "a price from a publicly available trading platform or price reporting agency, demonstrating that the submitted fuel price reflects the cost at which the Market Participant "expected" to purchase fuel for the operating period covered by the Supply Bid, as of the time that the Supply Bid was submitted, under an arm's length fuel
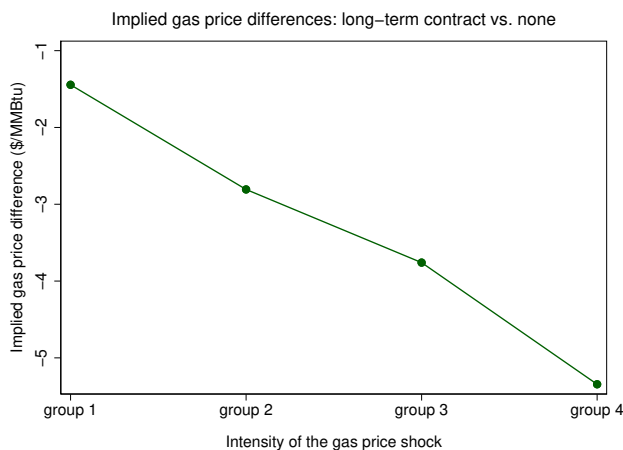
Notes: The graph shows the average differences (represented by the coefficients of the "gas procurement contract" dummy) in implied gas prices between firms that purchase gas via long-term contract and on the spot market. *Group* variable refers to subsamples that are selected based on different levels of daily gas price shocks. Group 1 has the smallest-sized shock and the intensity of the shock increases along the axis.

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

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

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

the spot gas prices, result in a dispersion in implied gas prices across generators. Also, the fact that volatility increases more as the gas price shock becomes larger could potentially explain why the dispersion among generators increases with the overall size of the shock.

Also, when some of the firm's generating units purchase gas through a long-term contract, while others purchase from the spot market, the implied prices could vary across units. In Table A.3, I summarize the number of gas procurement channels from which each firm purchases gas, which shows that some firms indeed rely on both spot market and long-term contracts.[8]

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

The above argument may be true when the gas market is under normal conditions – thus, fully liquid – which supports the use of single gas price index value for constructing costs of all gas generators in Sample 0 estimation. Since the opportunity cost of gas would be close to the spot gas

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purchase transaction (ISO-NE Market Rule, Appendix A: Fuel Price Adjustments)."

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

price regardless of the gas procurement channel – whether they purchase gas from forward or from spot – the cost generated with the gas price index represents the true opportunity cost of gas for each firm. In this case, the bias of using index data may exist, but is significantly less pronounced than in a volatile period.

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

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

A.3.3 More on dual unit's fuel switch identification

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

The most problematic price range is where the spot gas prices are similar to the oil price, i.e., between $ 18 - 22 /mmbtu, as it is hard to determine whether the estimated fuel price corresponds

to oil or gas. To precisely identify the fuel switch of dual units over this price range, I first checked the overall pattern of the estimated fuel prices together with the pattern of daily spot gas price data. If the fuel switch from gas to oil occurs, the estimates of fuel price will stay constant around the level of spot oil price, while the spot gas price of the time continuously increases. Even if this flat part does not continuously appear over the sample period, observing at least one flat portion is indicative of the fuel price at which the switch occurs for this dual unit, which can be used as a reference level.

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

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 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 Section B.5 of the Online Appendix.

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

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

Table 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 from two data sources: hourly day-ahead electricity auction bids (supply offer bids) and the hourly equilibrium market clearing prices (Energy Component price), both obtained from the ISO-NE website. Among the submitted supply offer bids (which consists of price bids and quantity bids), I

found the price bid that equals the equilibrium market clearing price, and identified the unit that submitted the selected price bid as a marginal unit of the auction.

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

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

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

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

Exploring the cause of underestimation   To investigate why the näive regression underestimates the pass-through, I checked percentage of marginal units whose costs measured with the index data overstate their actual costs, shown in Table A.5. That is, for each gas-fired marginal unit, I compared $\widehat{hr}_{ij} \ \bar{G}_{ht,index}$ with $\widehat{hr}_{ij} \ \widehat{F}_{ijt}$, and selected those units with $\widehat{hr}_{ij} \ \bar{G}_{ht,index} \ > \ \widehat{hr}_{ij} \ \widehat{F}_{ijt}$. Note that $\widehat{F}_{ijt}$ is the implied fuel prices of the unit estimated earlier from the model.

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

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

Table 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 näive regressions.

Also, among those marginal units with the overstated cost measure, almost 30 percent (29.62 %) of them are dual units that switched fuel from gas to oil. Note that the measurement error of

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[9]Note that it is possible that an increase in the electricity generation could affect the gas market through an increased demand for the gas from the electricity generators, in which case our instrument would not be valid. However, I find that the variation in electricity generation (resulting from increased demand for electricity) is not correlated with the variation in gas prices. Instead, an increased demand for gas from the residential heating sector was the primary cause of the variation in gas prices.

the inaccurate cost variable is substantially larger for these fuel-switched dual units than units that relied on gas for generation.

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

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

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

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

If Z is also exogenous to the measurement error part μ_{ht}, then the pass-through rate can be estimated without the measurement error bias, even in näive regressions. However, as shown in the plot provided in Figure A.3 of Appendix A.5, the chosen instrument Z is correlated with the measurement error, i.e., $E(Z'\mu_{ht}) \neq 0$.

More details on how I generated the graphs in Figure A.3 are as follows. First, the measurement error (μ_{ht}) is obtained by taking a difference between a näive marginal cost (i.e., $\widehat{hr}_{ij}\bar{G}_{ht}$) and the marginal cost generated with the estimated implied fuel prices ($\widehat{hr}_{ij}\widehat{FP}_{ijt}$). Then, the measurement error variable ($\mu_{ht} = \widehat{hr}_{ij}\bar{G}_{ht} - \widehat{hr}_{ij}\widehat{FP}_{ijt}$) is plotted against the instrument used in the regression, i.e., the gas price index ($Z = \bar{G}_{ht}$). As shown in Figure A.3, the instrument variable is positively correlated with the measurement error; the measurement error tends to increase in magnitude as the instrument value increases. Such positive correlation can be explained by our findings from the cost analysis; since the dispersion in firms' costs increases with the size of the gas price shock (as measured by the gas price index value), the measurement error generated from using the average value for firm-specific cost increases with the gas price shock as well.

## A.6   Data

A.6.1   Dual units

Dual generation technology Installing dual-generation technology to electricity generator is not too difficult as one needs to change the nozzles, install the equipment that handles fuel supply and modify the control system (EPA-CHP Combustion Technology Report, 2015; Power Engineering, 2004). Once the technology has been installed, gas turbines can quickly switch from using gas to using another fuel, without much interruption. Although the installation is not difficult, not every gas unit is equipped with the technology because of the environmental regulations (on
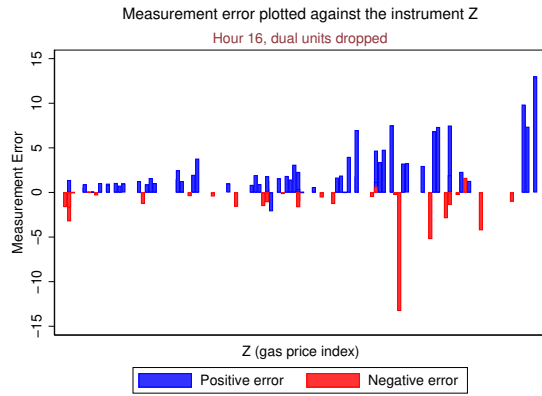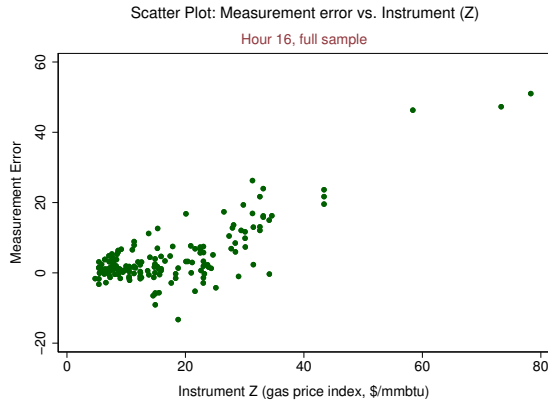
(a) Measurement error vs. instrument Z – dual units dropped
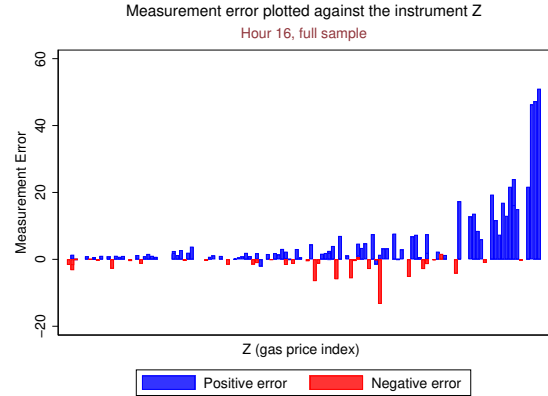
(b) Measurement error vs. instrument Z – dual units dropped
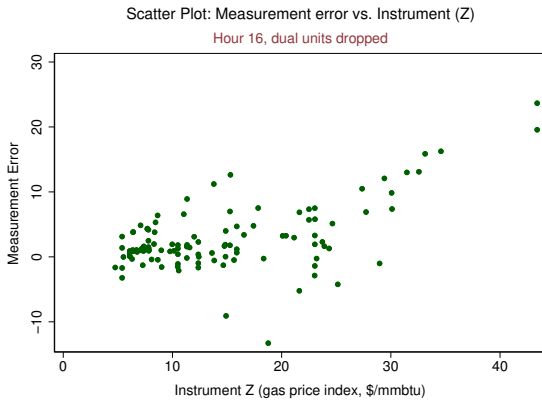
(c) Scatter plot : measurement error vs. instrument Z – dual units dropped

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

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

Figure A.3: Correlation between the measurement error of the marginal cost variable and the instrument variable used in the regression (gas price index)

burning oil) and lack of incentives to install technology during the period with low gas prices. Most of the existing dual units were constructed or converted in either 1980s or early 2000s when natural gas was relatively more expensive than other fuels (Power Engineering, 2004).

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

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

A.6.2   Electricity demand

Aggregate demand is another important factor that determines the market price in the wholesale electricity market, and it is natural to ask whether demand shocks contributed to a surge in wholesale electricity prices during the period of gas price shocks. I find that demands were not unusually higher during the period when electricity prices surged than on normal days when electricity prices were within a reasonable range. Moreover, while the electricity demand was on average higher in December 2013 than in January 2014, the electricity prices were much higher in January 2014. Given that gas prices were higher in January 2014 than in December 2013, this implies that the demand-side shock did not play a significant role in increasing the prices, rather, the cost increase resulting from the gas price shock was the primary cause of the surge in electricity prices. The historical trend of the electricity demand, shown in Figure A.4, also reveals that no significant demand shocks were present in the winters of 2013-2014 compared to other years.

A.7   Additional Figures and Tables

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[10]The different heats of combustion result in slightly higher mass flows through the expansion turbine when liquid fuels are used, and may lead to a small increase in the generator's efficiency performance (EPA-CHP combustion technology report, 2015).
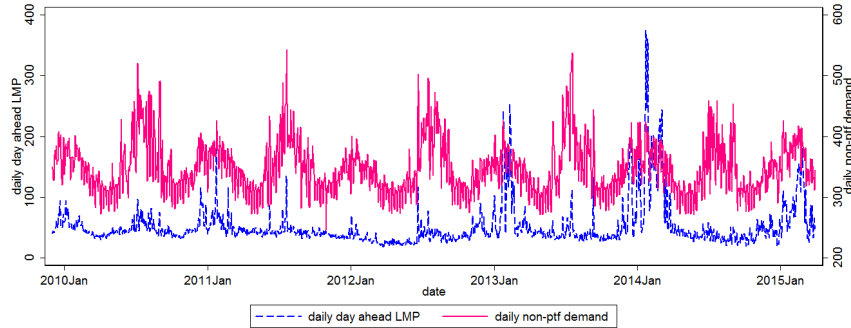
Notes: The daily day-ahead LMP is the daily average of the final wholesale electricity prices (locational marginal price) and daily non-ptf demand is the daily average electricity demand in the wholesale market.

Figure A.4: Daily Day-Ahead Electricity Demand: Years 2010 - 2015
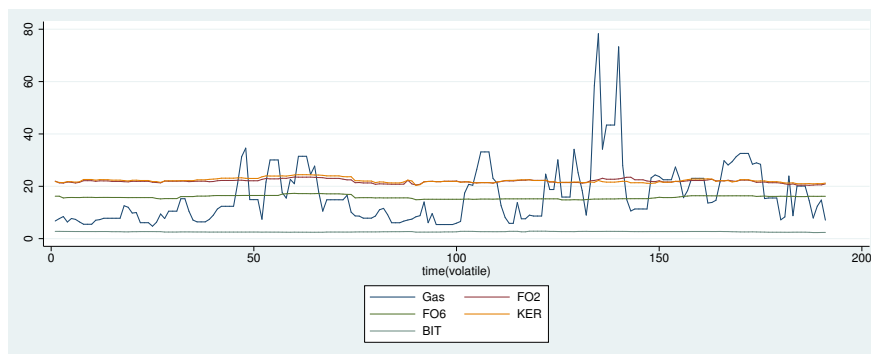
Notes: The graph shows the spot prices of each fossil fuel over the period when gas price shocks are present. For the gas price, I used daily day-ahead gas spot price *index* at Algonquin city gate (source: NGI, SNL), and for the petroleum liquid products (FO2, FO6, KER) and coal (BIT), I used daily spot price index available from EIA and SNL Energy. All price index values are converted to $/MMBtu.

Figure A.5: Spot Fuel Prices of Days when Gas Price Shocks were Present

Firm–level, hourly, forward contract rate estimates (mean and std)
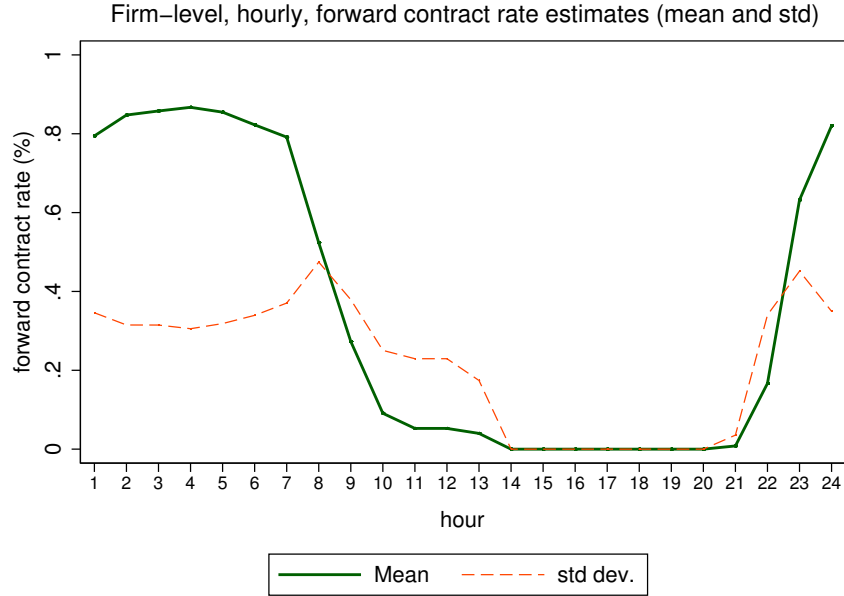
Note: estimates of 19 major firms included in the sample

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

Figure A.6: Forward Contract Rates: Summarized Across Firms

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

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

Table 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.

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.[1] 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.

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

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_2 produced per kWh for specific fuels and for different types of generators, by multiplying the CO_2 emissions factor (or emissions rate) with the heat rate. Data on CO_2 emissions factor (lb CO_2 /MMBtu) for different types of fuels (gas, coal, oil and etc.) and different types of generators (e.g., combustion cycle) come from the EIA (2013). Then, the emissions cost of a generator can be calculated by multiplying the emissions permit price (Environmental Protection Agency (EPA) RGGI auction clearing price) to the amount of CO_2 produced by the unit.

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

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

RGGI is the first market-based regulatory program in the U.S. to reduce greenhouse gas emissions (RGGI.org). All states in the New England region, along with NY and MD, participate in this program. RGGI caps the CO_2 emissions where the capped amount decreases every year. It requires fossil fuel-fired electric power generators with a capacity of 25 MW or greater to hold allowances equal to their CO_2 emissions over a three-year control period. And then, the state allocate CO_2 allowances via quarterly, regional CO_2 allowance auctions. There were total 29 auctions as of September of 2015. Market participants can purchase CO_2 allowances at the quarterly allowance auctions or in the secondary market, such as the ICE and NYMEX Green Exchange, or via over-the-counter transactions.

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

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

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

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

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.

4

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.8, I also present the simulated markups plotted separately by firms grouped under "high-impact" and "low-impact" categories, shown in Figure B.4.

B.6 Bid markup

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

Dispersion in post-shock bid markups Another important observation from Figure 8 is that the post-shock bid markup distribution is more dispersed than the pre-shock bid markup distribution. Such dispersion implies that firm-level bid markups in the post-shock period were substantially heterogeneous.

To explore this, I plotted in Figure B.1 the firm-level bid markups of two firms, Firm 9 (*gas only*) and Firm 53 (*oil only*). The size of the bid markup increases along the horizontal axis for both firms, which indicates that both added larger bid markups, on average, as the size of the gas price shock increased. The interesting pattern arises within the competitive range of gas prices when daily gas index values are between \$15 and \$25/MMBtu. While bid markups of *gas-only* firm start decreasing within the competitive range, bid markups of *oil-only* firms increase constantly. This implies that firms adjust bid markups according to different patterns depending on their impacts received from the gas price shock. Therefore, the increased dispersion in post-shock bid markup distribution is a combination of having different impacts on costs across firms and having different levels of gas prices across days.
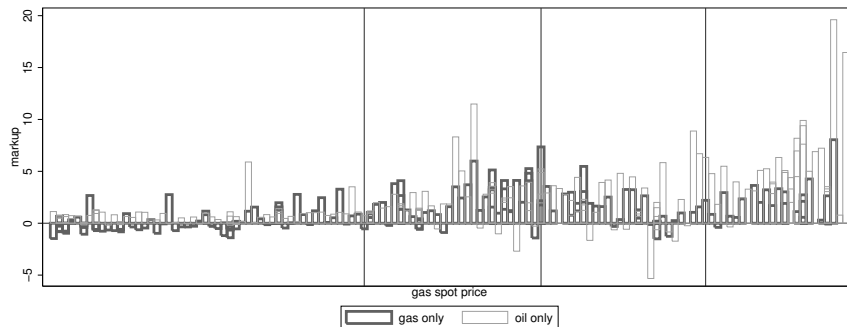
Notes: The graph shows daily bid markups of two specific firms, Firm 9 and Firm 53, plotted against the gas price index values of days in the sample. Thus, overall size of the gas price shock increases along the x-axis. Firm 9 is a gas-intensive firm, and Firm 53 is an oil-intensive firm. Three vertical lines are drawn at gas price index levels of \$15, \$20, and \$25, respectively.

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

B.7   Markup Simulation

Simulation of the ex-ante first-order condition   The bids of competitors observed in the auction ex-post is not the information that a firm used when making bidding decisions in ex-ante. That is, a firm chooses its optimal bid based on its expectations of bids of competitors. To tackle this, I exploited the resampling technique that is similar to the one used in the parameter estimation in order to construct the average supply offer curve out of the set of resampled supply offer curves. This average curve mimics the supply offer curve that the firm expected in ex-ante. I perturbed this average curve and measured the resulting endogenous changes in markups separately for each firm, because different ex-ante expected supply offer curves apply to each firm as they have different set of beliefs of others' bids. This method is a slight extension of Fabra and Reguant(2014)'s first order approach simulation where they perturbed ex-post realized bids for the simulation.

I resampled each observation randomly from a pool of similar days. The results reported in this paper are based on random draws from three similar days. Because it is practically challenging to take an average of curves and then perturb it again, I instead took a weighted average of the markups obtained from the perturbation of the each resampled supply curve. I used the probability of becoming marginal unit, $\frac{\partial p_h}{\partial b_{ijkh}}$, as a weight for calculating the weighted average.

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

Simulation with different sizes of gas price perturbation   Instead of imposing the equal size of 10 cents to all gas units in the simulation, I conducted another simulation where I imposed a gas price shock weighted by the actual impact as captured by the implied gas price estimates. For example, if the gas price index of the day is \$20/MMBtu and a unit's implied gas price is \$ 18/MMBtu, I imposed a gas price shock equivalent to $(18/20) * 0.1 = 0.09$ (9 cents) to this unit. The final increase in the marginal cost of this unit is $hr * 0.09$. This type of cost perturbation more precisely incorporates the heterogeneity in the impacts among gas-fired generators, as measured by the implied gas prices across units. The results based on the alternative simulation were qualitatively similar to the result from the main analysis.
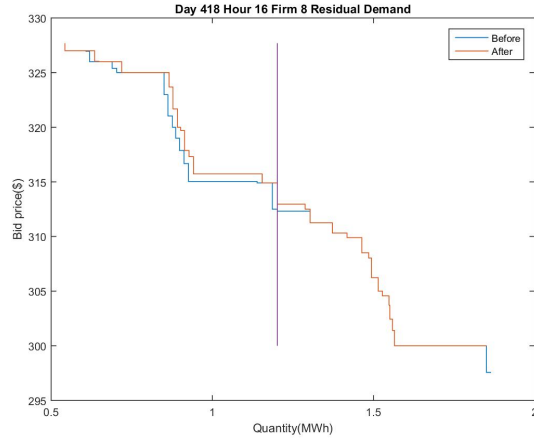
B.8   Additional Figures and Tables

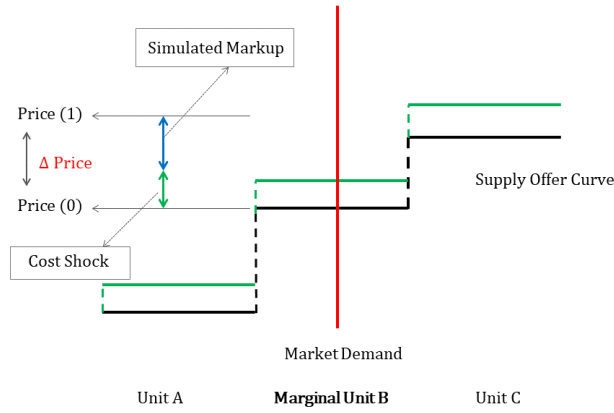Figure B.2: Example of a Residual Demand Shift After the Perturbation

Figure B.3: Graphical Illustration of the Pass-Through Simulation

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

Notes: Number of steps submitted by generators is summarized in this table. *Number of Generators* shows how many generators submitted bids with steps shown in *Number of Steps* column. *Percentage* is the percentage of generators submitted the step out of a total 305 generators.
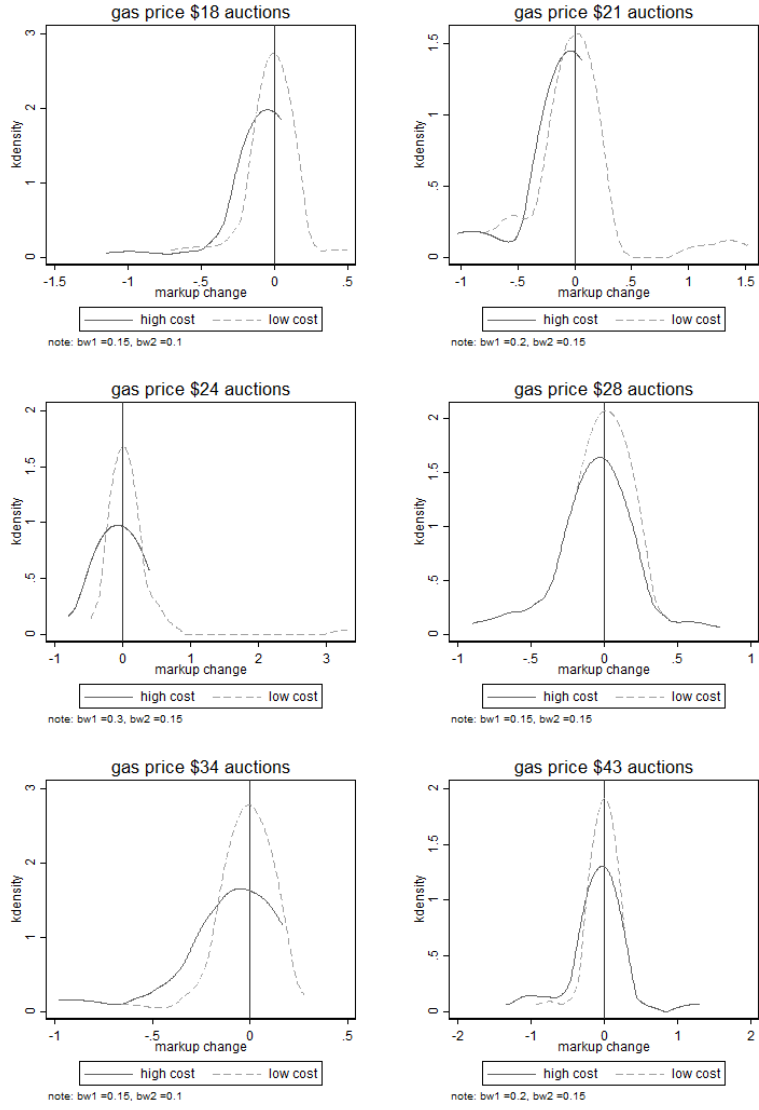
Table B.1: Summary of Number of Bid Steps

Figure B.4: Simulated Markups of High-Impact vs. Low-Impact Firms