Strategic Uncertainty, Competition and Asymmetric Pass-Through

Harim Kim*

March 20, 2025

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Abstract

Asymmetric cost pass-through refers to the widely documented phenomenon where prices rise faster when costs increase but decrease more slowly when costs drop. Despite its prevalance across various industries and markets, establishing the general cause of this asymmetry has been challenging. The most widely accepted explanation emphasizes the role of consumers, where search costs prevent them from acquiring price change information, or focuses on supplier-specific costs such as inventory and price adjustment costs. In this paper, I document asymmetric pass-through in a unique empirical setting where these potential causes of asymmetry are absent, suggesting that such asymmetry can arise solely from the strategic responses of suppliers. Leveraging this setting, I employ a test of asymmetric cost responses that is free from the challenges typically associated with estimating asymmetric pass-through. Using rich bidding data, I show that firms adopt different strategies when costs decrease, and I structurally estimate their ex ante beliefs about competitors' strategies that rationalize their best reponse bidding. The findings reveal that beliefs are systematically different and more dispersed in the cost-decreasing case, supporting the idea that a broader strategy set in this phase may increase uncertainty over rivals' behavior (strategy), resulting in prices not falling in line with cost decreases.

*Department of Economics, University of Connecticut, Email: harim.kim@uconn.edu. I would like to thank Alex Imas, Joel Flynn, Steve Cicala, Steven Puller, Gordon Leslie for helpful comments.

1 Introduction

Asymmetric price response to cost changes, often termed the rockets and feathers effect, are pervasive across many industries and markets, making it an important feature of price dynamics. While this asymmetry in cost pass-through has been studied most extensively in the gasoline market (Borenstein et al. (1997)), Peltzman (2000) provides empirical evidence of its presence across a wide range of product markets. Beyond product markets, asymmetric pass-through has also been documented and analyzed in value-added tax transmission (Benzarti et al. (2020)), exchange rates (Pollard and Coughlin (2004)), bank deposit rates (Neumark and Sharpe (1992)), and municipal bonds (Green et al. (2010)).

Despite being widely documented, this asymmetry is puzzling because standard price theory (or comparative statics of price theory) treats cost increases and decreases symmetrically, implying equal price responses in both directions. As a result, research has focused on exploring and identifying conditions under which the asymmetry naturally arises. The most widely accepted explanation emphasizes the role of consumers, citing that inattention or search costs prevent them from obtaining information about cost decreases, thereby weakening competitive pressure to lower prices and leading to slower price adjustments (Yang and Ye (2008); Tappata (2009); Lewis (2011)). Other potential explanations include inventory effects, non-linear price adjustment costs (menu costs), and tacit collusion, though their relevance may depend on specific market context.

In this paper, I provide evidence that asymmetric price responses to cost changes occur even in the absence of many conditions previously proposed as potential sources of asymmetry, exploiting a unique empirical setting in the wholesale electricity market that allows testing for asymmetry with minimal assumptions and structural constraints. The market I study has a simple structure in which all previously identified sources of asymmetry – especially consumer inattention and search costs – cannot explain the documented asymmetry. This finding suggests that asymmetry can naturally emerge from strategic interactions among suppliers, independent of consumer-side factors.

Leveraging firm-level bidding data, which reveals firms' strategic decision-making, I show that underlying strategies of firms also exhibit asymmetry, differing significantly between samples with similar fundamentals (e.g., cost and demand conditions) but opposite cost-change directions. The key insight behind this finding is that a firm's decision to adjust prices in response to a cost decrease is driven solely by strategic considerations – namely, whether competitors will also lower prices. As a result, firms face greater uncertainty over competitors' strategies in cost-decreasing situations than in cost-increasing cases, where raising prices by at least the amount of cost increase is necessary to sustain per-unit profits. This is evidenced by the significantly different bidding patterns documented in the analysis.

To further verify this, I employ a structural estimation of firms' beliefs about competitors' bids that rationalize their best-response bidding and find that belief distributions become more dispersed and shift in specific ways for certain types of competitors. By identifying the role of strategic interactions between suppliers as a source of asymmetry – often difficult to isolate from consumer-side factors - this finding contributes to the literature by showing an additional mechanism through

which asymmetry can arise.

The main empirical analysis in this paper utilizes a unique cost variation in the electricity market driven by natural gas prices, which enables a more proper empirical strategy to test for asymmetry. Natural gas prices exhibit upside volatility, creating an environment where the generation costs of power plants to rise sharply and decreases back to pre-increase levels within a short window of several days. As discussed in Benzarti et al. (2020), such cost variation provides an ideal setting for examining asymmetry in pass-through, as it ensures perfect symmetry in the cost range over which pass-through rates are averaged. In my empirical analysis, I compare electricity prices between samples before and after the cost increase event – referred to as the pre-increase and post-increase samples – to test whether prices return to pre-increase levels. As these two samples are not fundamentally different with market conditions affecting the equilibrium prices being similar, prices should return to the original level if adjustment to cost change is symmetric. However, I find that prices in the post-increase sample are about 7% higher than in the pre-increase sample, suggesting that output prices do not fully revert to their initial levels immediately, indicating asymmetric pass-through. The empirical setting of this paper differs from the standard asymmetric pass-through literature, which typically examines both upward and downward price variations without constraining the range of costs analyzed.

The major advantage of the wholesale electricity market is that it is free from known causes of asymmetric pass-through, suggesting the presence of other possible sources. First, the demand side (i.e., consumers) is absent in this market. Electricity demand in the wholesale market comes from large utility companies and is perfectly inelastic, ruling out the standard search-cost explanation for asymmetric price responses. In other words, there are no consumers incurring search costs to learn about cost changes and to adjust demand accordingly. Second, supply side firms sell and price their outputs daily and hourly, leaving little incentive to delay price or production adjustments to test the market. Because firms must compete and make swift decisions in daily markets, they respond immediately to exogenous market variables such as fuel prices and demand, which change daily. This feature ensures that firms' strategic decision-making remains static. Moreover, since firms are obligated to participate in daily markets and prices are determined each day, output price adjustments to input cost changes (i.e. gas prices) occur instantaneously. This allows me to rule out alternative explanations for price asymmetry, such as price adjustment frequency (Gopinath and Itskhoki (2010)) or the cost of price adjustment (i.e. menu costs). Third, because the empirical analysis compares samples that have similar features except for the direction of cost change (cost movement history), we can eliminate asymmetry in market power exertion or supply curve convexity as primary drivers of asymmetry. Lastly, information about fundamental market conditions – such as fuel prices – is transparent, updated daily, and available to all suppliers, as they procure inputs daily based on immediate needs. This rules out information asymmetry between firms, particularly regarding costs, as well as the inventory effect that could delay price responses (Borenstein et al. (1997)).

Therefore, the asymmetric price responses documented in this paper cannot be explained by

widely known sources of asymmetry. To further investigate these findings, I leverage the high-frequency bidding data at the firm and generating unit levels, which is available due to the market being cleared via multi-unit uniform auction. I observe bids submitted by all firms at hourly frequency, which reveal the strategies underlying firms' optimal supply decisions and ultimately determine the equilibrium price. I examine bidding patterns between the pre- and post-increase samples and find evidence of systematically higher bids in the post-increase sample. Importantly, I also find that the stylized peak-hour bidding pattern typically observed in this market – where strategic firms bid higher in peak hours than in off-peak hours – is absent in the post-increase sample; price bids in the post-increase sample are more dispersed around a higher level than in the pre-increase sample. The disappearance of this pattern, along with higher bids submitted, suggests that firms adopted different bidding strategies in the post-increase sample. These differences in bidding strategies vary across firms with different strategic positions and are particularly pronounced for certain types of firms – especially those that engaged in more strategic bidding in the pre-increase sample.

Given that there are no fundamental differences in market variables between these samples besides the direction of cost change, the change in bidding strategies suggests a possible change in the firm's expectations (beliefs) about competitors' bids. To explore this further, I employ a structural estimation of the ex-ante expected belief distribution that rationalizes the bids submitted by each firm. I parameterize each firm's expected bid distribution for its competitors and leverage the first-order condition of optimal bidding to estimate the distribution parameters that minimize the difference between observed bid markup and those generated from the parameterized bid distribution. This estimation allows me to assess whether there are systematic differences in expected bid distributions between the pre- and post-increase samples. The results show that firms' belief distributions about their competitors' price bids shifted slightly to the right (an increase in the mean) in the post-increase sample than in the pre-increase sample. More importantly, the distributions became more dispersed, with the standard deviation parameter increasing for the majority of firms. This change is more pronounced during peak hours, though a considerable change also occurs in off-peak hours, explaining the more dispersed bidding pattern observed in the bid data analysis. However, the exact pattern and direction of change vary across firm types as well as the type of competitors.

Literature Review The asymmetric price responses to input cost changes has been observed in many different markets. While extensively documented in the gasoline market (Borenstein et al. (1997); Eckert (2002) and etc.), asymmetric price responses are also prevalent across a wide range of product markets (Peltzman, 2000). This phenomenon has been analyzed in municipal bonds market (Green et al. (2010)) and in studies of value-added tax incidence (Benzarti et al. (2020)), and monetary policy transmission (Karadi and Reiff (2019); Perez-Orive, Timmer, and van der Ghote (Perez-Orive et al.)).

Several explanations have been proposed for this phenomenon, explicitly regarding the asym-

metry, with the most widely accepted being the search cost explanation. Many studies on gasoline markets show that search costs of demand side are significantly higher following a negative cost shock than a positive one, leading to lagged price adjustments on the supply side (Yang and Ye (2008); Tappata (2009); Lewis (2011)). Other potential explanations include non-linearity in price adjustment costs and inventory effects (Borenstein et al. (1997)), market power (Neumark and Sharpe (1992), Borenstein and Shepard (2002)).

This paper offers another possible source of asymmetry, in addition to these widely accepted explanations. The contribution of this paper is to document price response asymmetry in a simple setting where all potential sources posited by the literature can be excluded and analyze the sources of this asymmetry as part of firms' strategic decisions in response to increased uncertainty over competitors' strategies. I achieve this by leveraging high-frequency microdata at the firm level, which allows me to uncover the uncertainty embedded in firms' decision-making.

While not explicitly studying asymmetry, an extensive body of literature has examined incomplete pass-through as an explanation for price rigidities, which is an important topic in international macroeconomics. For example, studies have explored price adjustment frequency (Gopinath and Itskhoki (2010)), price adjustment costs (Nakamura and Steinsson (2008)), and markup adjustments (Goldberg and Hellerstein (2013); Amiti et al. (2019)). If these sources of incomplete pass-through differ depending on the direction of the cost change, they could explain asymmetric pass-through. However, my empirical setting is free from these aforementioned sources and provides a more explicit test of asymmetry.

The closest study to this paper is Benzarti et al. (2020), which examines VAT pass-through using a tax increase and decrease of equal size in the Finnish hairdressing industry – an empirical setting similar to the one used in this paper. However, this paper differs from theirs in key aspects. First, Benzarti et al. (2020) observe only one such tax increase-decrease pair, limiting statistical analysis. Moreover, since the tax changes occur five years apart, differences in economic conditions make an apples-to-apples comparison difficult. While they supplement their analysis with VAT pass-through estimates from multiple EU countries and industries, these tax changes are neither precisely equal in magnitude nor fully controlled for cross-country, industry, and tax-type differences. In contrast, the empirical setting in this paper allows for the observation of multiple cost increase-decrease pairs within a short timeframe (several days). Furthermore, rather than pooling industries with varying characteristics, this study focuses on a single market, analyzing firm-level strategies to provide a micro-founded explanation for asymmetric pass-through.

2 Conceptual Background and Empirical Strategy

2.1 Testing the effect of the cost change direction on pass-through

Asymmetric response to cost shocks is inherently related to the concept of cost pass-through. The cost pass-through rate ρ, defined as the response of prices to a *marginal* change in the cost, is a function of the current state in which the marginal change is evaluated at. This implies that

the pass-through rate is heterogeneous and is not a constant parameter in general (Benzarti et al. (2020); Kim (2022)). For instance, the marginal pass-through rate in response to a very small change in the cost could be differerent when the marginal pass-through was evaluated at the cost level of $c_0 = 5$ and at $c_1 = 10$. In other words, $\rho(c_0) \neq \rho(c_1)$.

Since the marginal pass-through rate is a point on a $\rho(\cdot)$ function, this rate itself does not vary with the direction of the cost change from the point evaluated, meaning that marginal rate ρ cannot be asymmetric in principle. Therefore, as demonstrated in Benzarti et al. (2020), testing the price response asymmetry involves using the average pass-through, an average of ρ evaluated over a range of cost values. In our context, for a cost change from c_1 to c_2, the average pass-through is represented as:

$$\bar{\rho} = \frac{1}{c_2 - c_1} \int_{c_1}^{c_2} \rho(c) dc$$

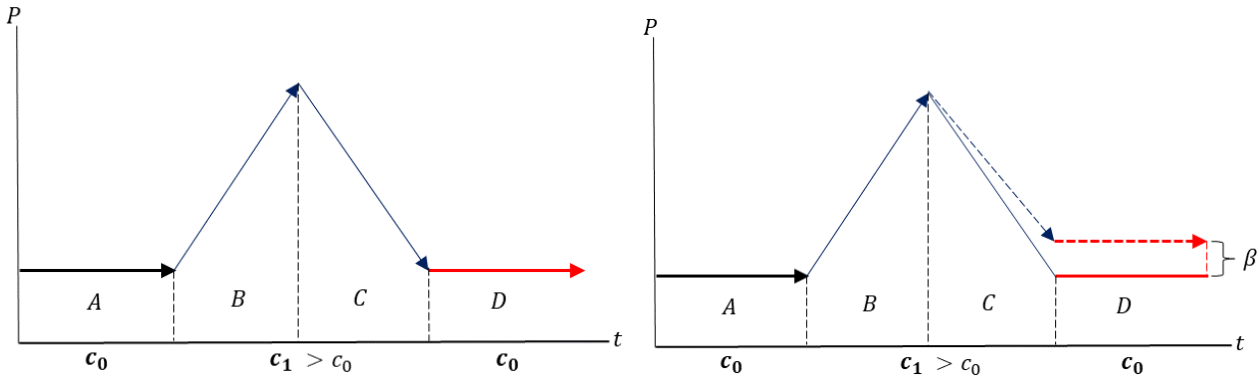
This expression clearly shows that the average pass-through rate varies with the range of costs as well as the start and end points of the range in which the non-constant marginal pass-through ρ is averaged. Different size of $\Delta c = c_2 - c_1$ results in different levels of $\bar{\rho}$, and even with the same Δc, if the set includes different points of c_t, the ρ value differs.

Therefore, to properly test for the asymmetry, the range of cost change in both directions should be the same and the range itself also has to be symmetric; with cost-increase and cost-decrease ranges being $[c_1, c_2]$ and $[c_2, c_1]$, respectively. A simple comparison of pass-throughs estimated within subsamples that differ in the direction of cost change but having different set of cost values, may not capture the true asymmetry as these average rates should be different by construction.[1]

To address this problem, one needs to observe an ideal setting in which the cost change in one direction is followed by the equivalent-sized cost change in the opposite direction. For instance, Benzarti et al. (2020) studies the asymmetric tax incidence, using the equivalent-sized tax rate changes in Finland, which was decreased by 14 pp from the baseline rate τ_0 to τ_1, and later increased by the same magnitude of 14 pp, bringing tax rate back to the original level τ_0. They compare the average pass-through rates estimated separately for two period within each period, leveraging the feature that the range of tax changes are the same between the decrease ($\tau_0 \to \tau_1$) and increase ($\tau_1 \to \tau_0$) periods, and the ρ s are integrated over the same range of τ changes.

Figure 1 describes the subsequent cost change events ideal for testing asymmetry. Figure shows the changes in the output prices when the cost, which used to be at c_0, increases to c_1 (in block B) and then decreases to c_0 (block C). Since the range of cost change as well as the end points of these ranges are the same between the blocks B and C, one way to test asymmetry is to compare the average pass-through rates obtained from each block to see if they differ – test if $\bar{\rho}_B = \bar{\rho}_C$. If $\bar{\rho}$ s are the same, as depicted in Panel (a), it indicates that the price response is symmetric. On the other hand, Panel (b) depicts the case where $\bar{\rho}$ s are different, with price change in block C shown in a dashed line is smaller than that in block B (i.e., $\bar{\rho}_B > \bar{\rho}_C$) which corresponds to asymmetric pass-through.

[1]Despite this limitation and concerns, we have ran the pass-through regression, shown in Table A7 in Appendix.



(a) Symmetric Case (b) Asymmetric Case

Figure 1: Price and Cost Relationship: symmetric vs. asymmetric price adjustment cases

However, finding an empirical setting for a proper test of price response asymmetry is challenging in general. One of the major challenges is to ensure that other factors that may affect the pass-through are held constant between the cost-increase and cost-decrease events so that the only difference between these samples are the direction of the cost (tax) change. For instance, one major concern in Benzarti et al. (2020) analysis was that the timing between the decrease and increase events were many years apart (e.g. five years), thus there was no assurance that economic conditions between two time periods were the same. Because of this issue, a direct comparison of the pre tax-decrease equilibrium prices to the post tax increase equilibrium prices within the industry were not possible, and instead the prices of the adjacent product not subject to the tax changes were used as a comparison. Moreover, observing many such unique events of in real data is rare, often not enough variation to conduct a statistical analysis, which was another major concern in Benzarti et al. (2020) as they observed only one such ideal tax change event.

Empirical Strategy To overcome the challenges described in Section 2.1, I take a different approach to test the asymmetry in price response, leveraging the unique empirical setting and data. First, instead of focusing on blocks B and C shown in Figure 1, I focus on blocks A and D, testing whether the price comes back to the same level as before once the cost decreases to c_0. That is, assuming other conditions being the same between time block A and D, if the price response is symmetric, the prices in blocks A and D should be the same as the costs in both blocks are the same at c_0, as depicted in Panel (a). If the price response to cost change is asymmetric, prices don't fall back to the same level as before the cost increase – prices in block D would be higher than the prices in block A, implying that the price does not return to the previous level despite the cost decreasing back to the previous level. The extent of asymmetry is then captured by the difference in the price levels between the pre-increase and post-increase samples (block A and block B), represented as parameter β in Panel (b).

Therefore, while the costs of blocks are the same, these two samples differ in the movements of the costs. The cost c_0 in the post-increase sample (block D) is along the movement of cost coming down,

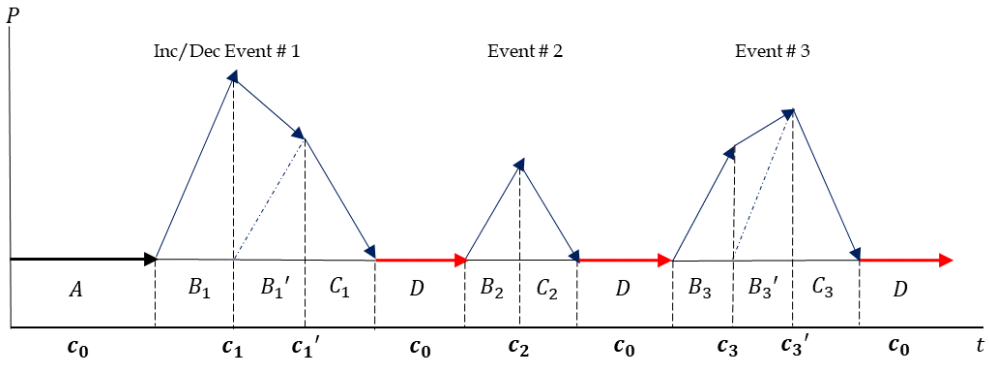


Figure 2: Example of the Events in the Sample: Symmetric Case

which does not apply to the cost c_0 in the pre-increase sample. Focusing on these pre- and post-increase sample has advantages in that we can obtain a more homogenized samples to use for the test (e.g., both samples having the same cost and other fundamentals) which increases observations and statistical power. If focusing on blocks B and C, even if we have multiple observations of such event, the extent of cost change, $c_1 - c_0$, may not be the same across events which could further complicate the empirical analysis. Moreover, by focusing on more homogenized samples excluding the shock period, we do not have to control for the shock period's market condition where many things change.

Empirical Setting: Natural Gas Price Variation and Electricity Prices The natural gas price variation I use in the analysis is very similar to this ideal setting of testing the impact of the difference in the direction of the cost change, which was described in the previous section. Since natural gas is an essential input of electricity generation, a change in the level of natural gas prices implies a cost change, thereby affecting the output electricity prices. The cost pass-through in the electricity market setting has been studied extensively in the literature (Fabra and Reguant (2014); Kim (2022), and etc.).

A unique feature of this natural gas price variation is that the price is subject to an upside volatility mainly caused by the weather-related pipeline congestion. Absence of the shock, the gas price stays around the normal range which is fairly constant and stable over time. Therefore, the cost to the electricity generators stays constant with almost no change across days and hours, similar to a situation described in block A in Figure 1 where the cost is at c_0. When the congestion occurs, the gas price increases above the usual level, raising the cost to c_1 and also increasing the price, as depicted in block B of the figure. Once the pipeline congestion disappears, the gas price drops down to the normal range – the level same as before the congestion happens – and the cost of generation goes back to c_0, as depicted in block C of the figure. Therefore, the cost fluctuations in the electricity market caused by the upside volatility of the gas prices creates an environment similar to the ideal setting to test the asymmetry of output price responses. In principal, there must not be a significant differences in prices between phase A and phase D.

While the general pattern of the data is similar to that described in Figure 2, there are some differences from that described in Figure 1. First, the events in my data do not exhibit a cost increase followed directly by an equal amount of cost decrease. Instead, there are multiple rounds of higher cost days (with $c > c_0$) before the cost drops to the original level of c_0, as described in Figure 2. That is, as shown in the Event 1, the costs are c_1 and then c_1' (blocks B_1 and B_1') before dropping to c_0 (block C_1), and in the Event 3, the costs are c_3 and c_3' (blocks B_3 and B_3') before dropping to c_0 (block C_3). Second, I observe multiple cases of such cost increase-decrease event pairs (e.g., 20 events in the sample), whereas Benzarti et al. (2020) observes only one pair of such event (one-time tax decrease and increase). The bigger number of events, which also increases the block A and D sample days surrounding the event, enables statistical inference on the extent of asymmetry, β, estimated as the difference in the prices between pre- and post- samples, A and D.[2]

The critical condition that leads to identifying the effect of direction of price change was that sample A and D periods – denoted as pre-increase and post-increase samples – are not fundamentally different, having similar market conditions and differs only in the direction of the cost change from the previous period. The major advantage of my setting is that the duration of the event of price increase and decrease is very short, happening over several days windows, with the frequency of cost change at the *daily* level. Also the information about the gas price level which applies to the firm and its competitors, is available to all participants in the market. Once the gas market turbulence caused by the pipeline issue is resolved, the electricity generators will immediately learn that by observing the price in the gas spot market. Moreover, it is a common knowledge that the difference in individual spot gas prices is very little when the gas market is liquid (see Kim (2022), for details). This feature gurantees that firms have little uncertainty over whether the cost of generating using natural gas has come down, as well as its levels.

To summarize, all other fundamentals are transparent to all participants and same across the samples. If we find a significantly different prices between the samples, despite the observed equivalence in the data, the difference can be attributed to an unobserved source that causes difference in the price responses between when cost goes up and goes down.

2.2 Market features that rule out alternative sources of asymmetry

The wholesale electricity market offers an ideal setting in which commonly discussed sources of asymmetry can be ruled out.

A large number of studies document and explore the causes of asymmetric pass-through, i.e., the rockets-and-feathers effect, with the most popular explanation being consumer search costs on the demand side (Yang and Ye (2008); Tappata (2009); Lewis (2011), etc.). The wholesale electricity market does not have an active demand side that responds to prices. That is, electricity in this market is purchased by companies such as electric utilities or retail electricity providers, which do

[2]This was not possible in Benzarti et al. (2020)'s Finnish VAT experiment setting because they observe only one event. To complement the drawback, Benzarti et al. (2020) conducted a separate analysis using the VAT changes implemented across EU countries.

not react to prices, making demand almost perfectly inelastic. As there are no proper consumers whose consumption decisions are affected by information about cost changes on the supply side, this feature of the market allows us to exclude all explanations involving consumer search or demand-side reactions. In other words, there are no consumers who respond differently to prices between a cost-increasing phase and a cost-decreasing phase. This means that any documented evidence of price asymmetry in this market cannot be attributed to the demand side.

Another advantage of this electricity market setting is that the market operates every day with market clearing happening regularly at an hourly frequency. The firms must compete and make swift production decisions in daily markets, taking the market condition of that day into account, by submitting their bids simultaneously.[3] This implies two things. First, price adjustment happens every day, with no adjustment costs, as firms are forced to compete every day, namely in a high-frequency market, and receive the profits for their sales that day once the market clears. This makes this electricity market free of other possible sources causing a lack of price responses, importantly the price adjustment frequency (Gopinath and Itskhoki (2010)) or the cost of price adjustment (i.e. menu cost). Thus, the difference in price adjustment frequencies or price adjustment costs between the cost-increase and decrease situations cannot be a source of asymmetric pass-through, as there is no systematic difference in these measures between the cost-increase and decrease situations.

Second, as firms must compete and profit in daily markets, market competition and equilibrium price formation do not involve dynamics, with firms' objectives being maximize static profits. The static nature of pricing and competition implies that firms have no incentives to choose actions today to influence competitors' future strategies. Moreover, the fundamental market variables relevant to firms' pricing and decision-making, such as natural gas prices and electricity market demand, change daily and are are exogenously determined.[4] There is no systematic evolution of these exogenous market variables, which are critical for firm's decision-making, and no feedback loop between firms' actions and these variables.

For example, natural gas prices, which form the basis of a firm's marginal cost, are determined in a separate gas market that operates independently of electricity market.[5] Furthermore, when making production decisions for the contemporaneous market, the only relevant gas price is today's spot market price due to the just-in-time nature of natural gas supply.[6] Power generators must purchase gas for daily use in the spot market, meaning that while gas prices may appear similar across days, this does not imply that a fixed price is maintained throughout the sample. Instead,

[3]To be precise, the clearing for all hours within a day happens altogether at once on the day before the actual market, upon observing projections of hourly market variables along with spot gas prices at the time.

[4]While the prices of other fossil fuels are also subject to change, they are usually supplied to power generators through long-term contracts. Procurement of natural gas, on the other hand, relies more on spot market trading and is thus exposed to exogenous shocks.

[5]The natural gas spot market is competitive. Even when gas prices increase, the primary driver is not higher electricity consumption. Thus, these two markets can be considered independent.

[6]An exception applies to firms purchasing gas through long-term contracts, where forward prices remain fixed throughout the sample period. However, the majority of gas generators procure gas through the spot market. Additionally, even if gas prices do not change daily, other fundamental factors, such as market demand, may fluctuate. Thus, even these generators make decisions in a static manner.

gas prices appear to be stable due to spot gas prices staying at a competitive level with minimal disruption.

Additionally, market demand in this wholesale market is exogenously determined, as it depends on retail consumers' consumption needs rather than wholesale market conditions. Retail electricity consumption is driven by household activities and external factors such as weather conditions, with retail consumers being unaware of conditions in the wholesale generation sector. This disconnect between the retail and wholesale sectors makes wholesale sectors makes wholesale electricity demand exogenous. While similar demand patterns and levels emerge throuhgout the day, they remain random and vary across days. are still random and varies across days.[7]

Because of the aforementioned features unique to this market, regarding nature of market clearing and the absence of systematic evolution in exogenous market variables, there is no intertemporal dependency to deem this market to be characterized as an example of dynamic competition, and the form of competition can be considered being static. Due to market fundamentals changing every time before a simulataneous competition takes place, the competition does not either fit into repeated games nor sequential games. Thus, the dynamic pricing incentive rarely exists in this market, which, if present, could slow down the price adjustment to cost changes (MacKay and Remer (2022)). The just-in-time nature of natural gas, with storage not being a viable option for firms, also implies that the inventory effect is absent, thus dynamic considerations that may arise from motive to manage inventory is not present.[8] Further explanation of why the dynamic does not apply to my setting can be found in Appendix **??**.

While the competition in this market is not dynamic in the sense that there is no dynamic feed loop between actions and state variables, there is a dynamic element in terms of the belief formation. Although market fundamentals of the previous stage does not constitute a state space as these are not directly used in today's pricing, the belief about opponnent's strategy set today is affected by the past period's state variable common to all firms (specifically, the gas price) which gives information about the direction of the cost change. Therefore, the intertemporal aspect manifests only through the evolution of beliefs rather than direct strategic adjustments based on historical fundamentals. I elaborate more on this in the next section.

2.3 Conceptual Framework: Asymmetric Price Responses and Strategy

Direction of the cost change and the different importance of strategic component As discussed in the Section 2.2, the empirical setting of this paper enables exclusion of many potential factors that could cause an asymmetric response. Therefore, if any difference in price reponses exists, it can be attributed to supply-side behavior arising in a non-cooperative strategic environment. To understand this phenomenon, I focus on the differences in strategy sets between

[7]There is a possibility of dynamic production decisions across hours due to fixed costs, but this generally does not create dynamic dependencies across days. A discussion of the dynamic operation of certain power plants and its impact on our results is provided in the robustness section.

[8]Note that production lags and finite inventories along with asymmetric inventory adjustment costs has been named as one possible explanations for finding asymmetric pass-through in gasoline prices in Borenstein et al. (1997).

cost-increase and cost-decrease cases.

When market fundamentals and the competitive environment change, firms must revise their expectations about how their competitors will behave. As a result, uncertainty regarding strategies of other competitors – strategic uncertainty – can increase following a change in environment.[9] For example, Doraszelski et al. (2018) studies how the introduction of a newly deregulated market creates strategic uncertainty – uncertainty regarding what their rivals would do – among firms in the UK electricity system. Similarly, a policy change can change firms' beliefs about competitors' behavior, making some firms less certain about the probability of others continuing with the same strategy played before the policy change. In an entry/exit game, a firm may face greater uncertainty regarding the entry decisions of firms located farther away from its own network than those competing in an adjacent market (Aguirregabiria and Magesan (2020)).

Similar to the examples mentioned above, an exogenous shock that changes input costs represents another form of change in competitive enviroment. A cost decrease, in particular, tends to be associated with greater strategic uncertainty than a cost increase. This is because, as I argue, a firm's payoffs depend more critically on competitors' strategies when costs decrease than when they increase, leaving firms with a wider set of strategies to consider, which in turn leads to greater strategic uncertainty.

To fix ideas, consider a simple setting in which firms have an initial markup of zero and all firms face the same cost increase, Δc. When the cost increases, it is common understanding that every firm needs to increase the price by at least the size of the cost increment Δc to avoid profit losses and maintain per-unit profit. Note that the profit loss from not increasing prices by the size of cost increase is the production-side profit loss. Thus, the price adjustment to cost increase is largely independent of competitors' pricing strategies, meaning it requires little strategic consideration.

On the other hand, when costs decrease, whether firms lower their prices in response is entirely a strategic decision, not driven by the need to minimize losses from input cost changes, because the profit of firms increase in this case if everything else remains constant. Firms will lower their prices only if they believe (or expect) that their competitors will do so, in which case the profit loss occurs due to reduced (residual) demand. The threat of not being able to produce due to competitor lowering its price would drive firms to lower their prices as well.

I further elaborate on the difference between the two cases. Suppose a firm initially charges a price of P_0 and faces a cost increase of Δc, thereby having to choose a price from a strategy set, $P \in [P_0, \infty)$. Any price below $P_0 + \Delta c$ can be rationally excluded from the firm's strategy set because such prices are not sufficient to cover the increased costs. Competitors would also rationally expect this firm to raise its price by at least Δc to maintain profitability per unit of sales. Any additional price adjustments beyond $P_0 + \Delta c$ fall within the firm's rationalizable strategy set and are solely based on strategic considerations. Given this strategy set, firms are likely to pass on the cost increase either fully or to a large extent by choosing strategies beyond this threshold.

[9] Strategic uncertainty can affect market outcomes, particularly in cases where multiple equilibria exists. For further discussion, see Moris and Shin (2002), Brandenburger (1996), Van Huyck et al. (1990), Besanko et al. (2013) and etc.

Now, suppose a firm's current price is $P_0 + \Delta c$, and the cost decreases by Δc. Unlike in the cost-increase case, the cost reduction itself does not directly drive the price down, as the firm's profit does not decrease when the cost decreases – in fact, the profit increases unless competitors lower their prices. Thus, the expected payoffs (profits) associated with prices (strategies) between $P_0 + \Delta c$ and P_0 (the full cost pass-through level) depend critically on competitors' pricing strategies. Depending on firms' beliefs about competitors' strategies, setting a price within $P_0 + \Delta c$ and P_0 is not rationally excluded from the firm's strategy set, which corresponds to incomplete pass-on of the cost decrease.

In this context, the relative importance of strategic considerations in price adjustments to cost changes differs between cost-increase and cost-decrease situations. When decomposing the price change into two components – purely cost-driven and strategic – the strategic component carries more weight in the cost-decreasing case. Moreover, the set of rationalizable strategies varies depending on the direction of the cost change.

Equilibrium Concepts Baysian Nash Equilibrium (BNE) framework can be applied to explain the empirical findings considered in this paper, as firms, without observing their competitors' strategies, must choose strategies that maximize their expected profits given their beliefs. We can maintain the assumption that BNE is played in both cost-increasing and cost-decreasing cases and instead focus on the differences in belief sets. Each firm chooses optimal bid that maximizes its expected profit which is based on the firm's belief about expected residual demand. However, ex-ante residual demand does not necessarily equal ex-post residual demand. In other words, the expected bids of competitors, which firms use to form expected residual demand, do not have to be the same as the ex-post equilibrium bids of competitors.

3 Empirical Analysis

3.1 Data

The main dataset used in the analysis is from the New England wholesale electricity market (ISO-NE). This market allocates electricity through hourly auctions, providing high-frequency bidding data as well as price and production data. Since the market is held and cleared every hour, the price and bidding analysis is conducted at the hourly level. On the supply side, power-generating firms operate power plants that use various types of fuels, such as natural gas, coal, oil, hydro, and renewables.[10] There are a total of 85 firms, including 12 large-scale firms, with the remainder being fringe firms, collectively operating 360 power generators. Demand side participants are retail companies or elecitric utilities that submit price-insensitive bids for electricity, making demand perfectly inelastic. As a result, only the level of demand is relevant for the analysis. The data used includes supply-side energy offer bids from the day-ahead wholesale electricity market, demand offer bids, and system clearing prices (i.e., energy component) spanning the years 2012 to 2014.

[10] Note that the generation share of renewables for this time period was very small.

The analysis focuses on sample days from October to April – the winter season – when natural gas price variation is most pronounced.

For the analysis, I use the natural gas price index data (from *Natural Gas Intelligence*), a commonly used daily measure of natural gas spot prices.[11] The heat rates (physical efficiency) of each generator are obtained from a separate estimation, which is detailed in the Appendix. The gas price index data and the generator heat rates are then used to construct the marginal cost of the generators.

3.2 Samples

3.2.1 Pre-Increase and Post-Increase Samples

As previously explained, natural gas prices in the New England region exhibit upside volatility, creating a unique event where a cost increase is followed by a cost decrease within a relatively short time frame. This pattern is illustrated in Figure 3, which plots the daily natural gas price (index) in New England. I define the base-level gas prices as the reference level that prevails when there is no exogenous shock to the gas spot market, approximately \$4/MMBtu (ranging from \$3.5 to \$4.5/MMBtu). As shown in the figure, while spot gas prices are typically set around this base level, we observe a series of events where gas prices increase above the base level, fluctuate over time, and then decrease back to the base level. Since changes in gas prices lead to immediate changes in the cost of generating electricity with gas-fired generators, the generation costs for these generators follow the same pattern shown in the figure.

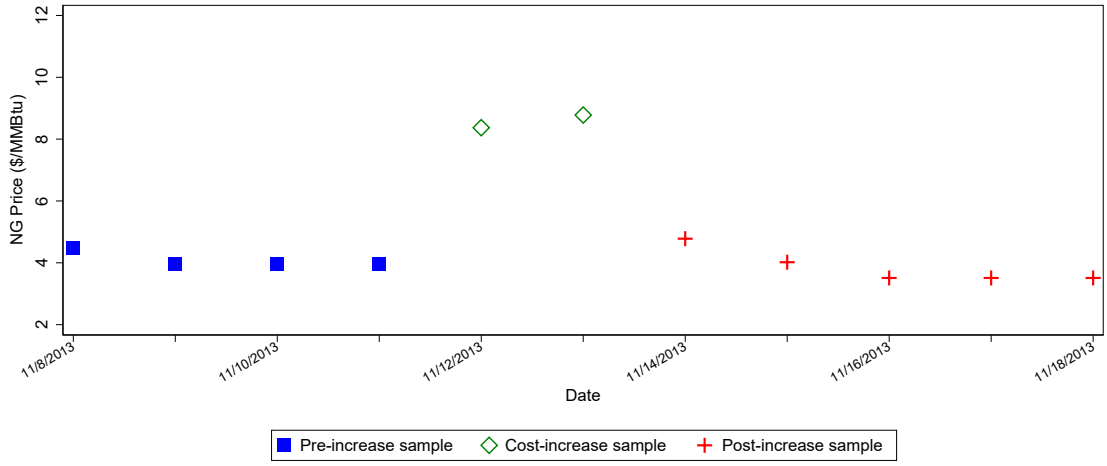
The sample is divided into three parts: Pre-Increase, Cost-Increase (cost shock), and Post-Increase samples. This division is based on the direction and levels of gas price changes, which are critical for identifying the asymmetric price response to input cost changes. Note that the empirical analysis utilizes only the Pre-increase and Post-increase samples. The cost increase events are used solely to divide the sample into pre- and post-increase samples.

The division of these samples is exogenous, as natural gas price increases occur for reasons independent of electricity market conditions. The congestion driving sharp gas price spikes is primarily due to higher residential heating demand during cold weather, rather than increased demand from the power generation sector.[12] Spot gas prices are determined exogenously in the commodities market, and power generators observe these prices when making production decisions.

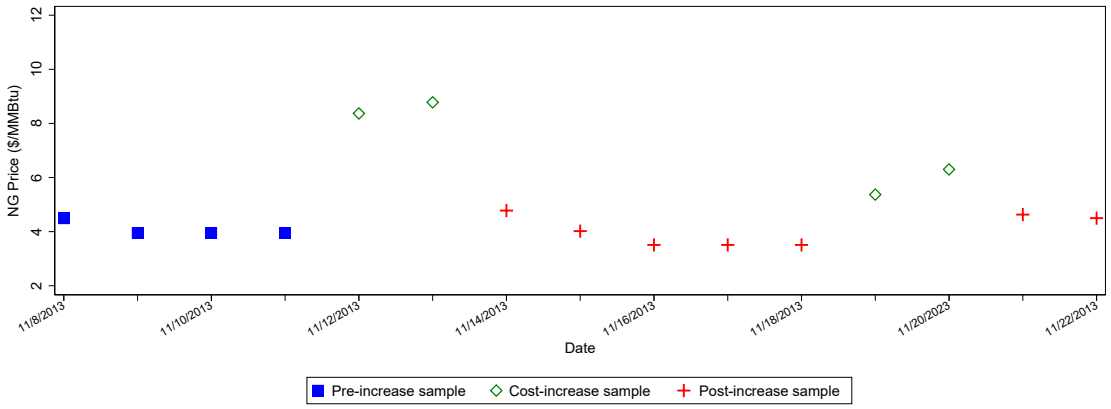
Figure 3, Panel (a) presents a simplified visualization of the sample days divided into three main parts, illustraing the samples and their categorization. The first block, denoted as the *Pre-Increase* sample (labeled A in the figure), includes consecutive days with stable gas prices around the lowest base level, approximately \$4/MMBtu. This pre-increase block consists of consecutive days of the

[11] The index data for other fossil fuels, such as petroleum products and coal, was also used, although these fuels are not the primary focus of the analysis.

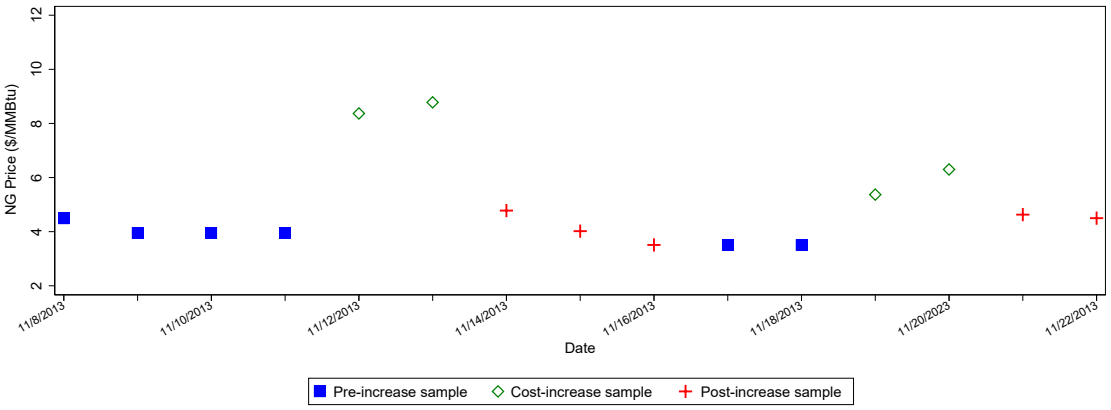
[12] While cold weather may raise electricity use among residential customers, the increase is not large enough to cause congestion. Additionally, daily electricity demand levels on congestion days are not significantly higher than on other winter days.



(a) Pre-increase, Cost-increase, and Post-increase Samples



(b) Main Sample Division



(c) Alternative Sample Division

Figure 3: Visualization of Sample from Data

lowest base-level gas prices, before any significant gas price increase event occurs, with no significant cost increase event in between (resulting from the gas price shock).

The second block, the *Cost-Increasing* sample, follows the pre-increase sample and includes

days when gas prices increase above the base level. These higher-than-base level days may vary in duration, from a single day to several consecutive days, and gas price levels within this period can vary.[13] I group these consecutive days of higher-than base level gas prices into the same block, each representing a cost-increase event.

Finally, the third block, the *Post-Increase* sample, consists of days when gas prices decrease back to the base level after an increase in the second block. This block includes consecutive days with base-level gas prices, following a cost increase event and preceding another cost increase event. Since the data includes multiple cost-increase events, there are several post-increase blocks. These blocks are grouped together in my analysis. Thus, the post-increase sample comprises days with base-level gas prices situated between cost-increase events.

In an alternative categorization, I divided the post-increase sample into pre- and post-shock samples by reclassifying some of the days before a subsequent cost increase event – originally part of the post-increase sample – as part of the pre-increase sample. While this alternative division presented challenges, such as the short length of post-increase blocks and the difficulty of choosing the number of days for the reclassified sample, the results were qualitatively similar to the original categorization. In some cases, the alternative categorization even yielded stronger results, which will be discussed in Section 3.3.3.

Adjustments were made to better align gas price levels between the pre-increase and post-increase samples. The pre-increase sample, being larger and containing more lower-range base-level prices than the post-increase sample, had a slightly lower average gas price. To address this, I removed very low gas price days from the pre-increase sample to better match the post-increase sample's gas price distribution. While this adjustment does not affect the qualitative results, it enhances comparability of samples, which is crucial for identifying asymmetry. This adjusted sample selection is the default for all analyses in this document.

3.2.2 Peak and Off-Peak Hours

With 24 hourly markets cleared each day, we have market outcomes for every hour. Each market in the sample is indexed by (t, h), indicating the market for hour h on day t. The number of hours within the pre- and post-increase sample days is equally balanced.

It is well-known that in the wholesale electricity market, competition levels and pricing strategies vary across different hours. During the early hours when electricity demand is low – known as *off-peak* hours – there is typically more competition due to the large idle capacity available. In these hours, aggregate demand for electricity is much smaller than the available capacity, and low-cost baseload generators are already serving the demand. Therefore, off-peak hours are characterized by low market power, providing less opportunity for firms to behave strategically to increase their profits.

On the other hand, *peak* hours are when strategic play and the exercise of market power are

[13] The gas price levels could vary depending on the severity of pipeline congestion, which proportionally increases the illiquidity of natural gas supplies in the spot market.

Sample	Stats	NG price ($/MMBtu)	Electricity Price ($/MWh)	MC ($/MWh)	Demand (MW)
Pre-Increase	Mean	4.30	37.9	37.5	13,269
($D_t = 0$)	Med	4.27	37.5	37.7	13,424
	Min	3.90	19.3	24.1	6,197
	Max	5.18	74.3	70.0	23,049
	SD	0.27	8.2	6.9	3,428
	N	1,324			
Post-Increase	Mean	4.55	40.9	39.3	13,385
($D_t = 1$)	Med	4.64	39.1	40.1	13,178
	Min	3.51	22.1	22.1	6,092
	Max	5.16	97.5	73.8	23,081
	SD	0.37	9.1	7.2	3,163
	N	1,509			

Notes: The entire sample is divided into Pre-Increase, which includes days before or long after the shock period, and Post-Increase sample that contains days with normal range of natural gas prices in between the shock samples. Electricity price refers to the hourly day-ahead electricity price (energy component) that clears the entire system. MC refers to marginal cost of marginal units. Demand refers to the hourly net demand faced by the supply-side generators in this market, excluding demand met by net interchange or demand responses. The sample includes day-hour pairs where non-dual natural gas generating units set the market price.

Table 1: Summary Statistics: Pre-Increase and Post-Increase Samples

more pronounced. During these hours, overall electricity demand is high, and idle capacity is much lower than during off-peak hours. This allows firms, especially those with considerable scale and generation available at the hour, to increase their markups by bidding strategically. Therefore, peak hours are when firms may strategically utilize their generation assets to gain extra profits.[14]

I leverage the well-known differences between off-peak and peak hours to examine bidding patterns – typically more pronounced during peak hours – vary between the pre- and post-samples and contribute to asymmetric price responses. I define peak hours as 8 AM to 11 PM and off-peak hours as 12 AM to 7 AM.[15]

3.3 Main Analysis

3.3.1 Price difference between pre- and post-increase samples

The first set of analyses examines whether there is a statistically significant difference in equilibrium prices between the *pre-increase* and *post-increase* samples. Both samples have base-level gas prices but differ in whether they precede or follow a cost-increasing event. Note that observations from the cost-increasing sample are not used in the analysis.

The unit of observation is at the hourly level because the electricity market clears every hour (h) of the day (t), whereas the categorization of samples is done at the daily level (t). The main

[14]The exercise of market power during peak hours is viewed as necessary, unless excessive, for generating firms to gain profits to use for investment or cover fixed costs. However, market power always have a risk of resulting in a significant price hikes, harming consumer welfare, as experienced in the CA electricity crisis.

[15]Additionally, I use an alternative categorization that further divides peak hours into 8 AM to 3 PM and 4 PM to 11 PM, with the latter considered more peak. The results are qualitatively similar.

specification is shown below in equation (1):

$$P_{th} = \alpha + \beta \text{ Post-Increase}_t \ + \gamma X_{th} + \eta + \varepsilon_{th} \tag{1}$$

P_{th} is the equilibrium wholesale price that clears the entire system (i.e., energy component price), which does not reflect the local transmission congestion cost. The control variables X_{th} include market variables that affect equilibrium price determination, such as hourly aggregate demand (Demand_{th}) and the marginal cost of the *marginal* unit clearing the market ($mc_{i,th}$).[16] Note that demand used here is different from a typical consumer demand, as these are an aggregate level of demand requested by retail companies, without any price specified for the quantities. Year and hour fixed effects are specified in η. Therefore, the specification controls for all possible observabe factors that could affect equilibrium electricity prices.

The main variable of interest is the indicator Post-Increase_t assigned to the pre- and post-increase samples. Specifically, $\text{Post-Increase}_t = 1$ if t belongs to the post-increase sample and $\text{Post-Increase}_t = 0$ if t belongs to the pre-increase sample. The regression tests whether output electricity prices differ significantly between these samples after controlling for all other observable factors influencing equilibrium prices. A statistically significant and sizable β_1 would indicate a systematic difference in pricing behavior attributable to the direction of the cost change, which is the only distinguishing factor between the samples. The empirical design aligns with the concept illustrated in Figure 1. I estimate equation (2) using a simple regression where the standard errors are clustered at day (t) and hour (h) level to address for potential within-day and across-day correlations.

Although relevant market variables are controlled for, it is important to assess the balance of control variables between the pre- and post-increase samples. Table 1 presents summary statistics for spot natural gas prices, day-ahead wholesale electricity prices, and aggregate market demand (equivalent to net generation met by internal supply-side generation), separately for pre- and post-increase samples. The two samples are well balanced, exhibiting nearly idential distributions across key variables.

Table 2, column (1), presents the estimation results of equation (1). The price difference between the two samples is statistically significant, as indicated by a positive and significant $\hat{\beta}_1$, after controlling for fundamental market variables such as demand and marginal costs (gas prices). On average, prices in the post-increase sample are approximately \$3.17/MWh higher than in the pre-increase sample, representing a 7.2% difference, as shown in the logged values regression in column (2). This difference is substantial, given the overall similarity in other market conditions affecting both samples.

I examine how the β_1 estimate differs between peak and off-peak hours, as shown in columns (3)-

[16] The equilibrium market price is determined by the price bid of the last generating unit, located at the intersection of the system's supply and demand curves, denoted as the *marginal* unit. Therefore, I specify only the marginal cost this marginal unit in the regression, as it is relevant for the equilibrium price. Nevertheless, the entire distribution of marginal costs is also important, as it determines the shape of the supply bid curve. The changes in this distribution will be explored further by examining the bid distributions of all firms.

	(1)	(2)	(3)	(4)	(5)
		Full Sample		Off-peak	Peak
	P_{th}	log (P_{th})	P_{th}	P_{th}	P_{th}
Post-Increase$_{t,h}$	3.170***	0.072***	2.599***	2.739***	3.697***
	(0.480)	(0.011)	(0.452)	(0.373)	(0.542)
$Peak$			−0.918		
			(0.674)		
Post-Increase$_{t,h} \times Peak$			0.940**		
			(0.395)		
Hour FE	✓	✓	x	✓	✓
Year FE	✓	✓	✓	✓	✓
N	2,833	2,833	2,833	1,114	1,719

Notes: Standard errors in parentheses. * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$. Standard errors are clustered at day(t) and hour(h) level. The sample consists of markets where non-dual natural gas-fueled generating units are marginal.

Table 2: Main Price Analysis Results

(5) of Table 2. The price differences between the post- and pre-increase samples are pronounced in both off-peak and peak hours, particularly larger during peak hours, which is demonstrated clearly in the subsample regressions shown in columns (4) and (5), where I run the regression seperately on off-peak hours and peak hours sample. This suggests that the factor driving asymmetric price responses, if any, is present in both off-peak and peak hours but slightly more pronounced during peak hours when strategic decision-making plays a greater role in price determination.

3.3.2 Markup difference

As an important driver of price changes, aside from costs, is markup, firms not lowering prices to the decreased marginal cost level is analogous to not restoring their markups to their pre-increase levels. In a simple theoretical framework, conditioned on all market conditions being the same, there is no clear reason why firms would not revert to their previous markup levels once the cost decreases. While the literature citing consumer inattention and weak demand response as a source of asymmetry finds that firms may exploit delayed or muted consumer reactions to sustain higher markups in the cost-decreasing situation, consumers and information frictions are absent in our empirical setting.

While the main analysis indirectly captures the markup component by examining price differences conditional on marginal costs, we explicitly check how markups of the price-setting marginal units differ across samples by running a variant of equation (2) with markup as a dependent variable. The markup used in this analysis is the *market-level* markup which is equivalent to bid markup, $b_{ijt} - mc_{ijt}$, of marginal firm-unit (i, j) that determines the equilibrium price of a market in day t, hour h.

Table 3, column (1), shows that average markups at the margin are higher in the post-increase

	(1) Full sample	(2) Off-Peak	(3) Peak
		Markup_{th}	
Post-Increase_t	1.373^{**}	0.934^{**}	1.924^{***}
	(0.479)	(0.376)	(0.627)
Demand_{th}	0.0015^{***}	0.0006^{***}	0.0018^{***}
	(0.0001)	(0.0001)	(0.0001)
Hour FE	✓	✓	✓
Year FE	✓	✓	✓
N	2,833	1,114	1,719

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at day level (newey-west standard errors). Using only when the non-dual natural gas units are marginal. The unit of demand is MWh.

Table 3: Marginal Markup Analysis Result

sample than in the pre-increase sample. When further dividing the sample into off-peak and peak hours, as shown in column (2) and (3), the markup of marginal units increased more in the peak than in off-peak hours, though the extent of increase in off-peak hours is also noticeable.

The finding that the average markup difference between the pre- and post-increase samples is smaller than the price difference suggests that the shift in the bid distribution is not uniform. If all previously marginal firms in the pre-increase sample had uniformly raised their markups in the post-increase sample, the overall bid distribution and the composition of marginal units would have remained unchanged, thereby having the markup difference similar to the price difference. Thus, the smaller difference in markups is a result of a non-uniform shift in the firm-level bid markup distribution, as well as the changes in the identity and composition of firms near the margin. For instance, Figure A1 in the Appendix shows that the composition of marginal units changed considerably between the pre- and post-increase samples.[17]

The *market-level* markups used in this analysis do not capture overall picture of competition, as they reflect only the ex-post marginal player's markups, which depend on both exogenous market demand and the bid distribution of all potentially marginal firms. Therefore, it is crucial to examine bidding strategies across the full set of firms with a more micro-level analysis of firm-specific pricing (bidding) behavior, which follows in Section 4.

3.3.3 Dynamic price pattern within the post-increase sample

Asymmetry in the speed of price adjustment or in the size difference? The estimate β_1 captures the *average* price difference between two samples that differ only in the direction of cost changes, controlling for relevant market conditions. A natural question, however, is whether

[17]Figure A1 was generated by assigning unique IDs to ex-post marginal units and plotting their percentage occurences as marginal units in the pre- and post-increase samples. These graphs were created separately of off-peak and peak hours, and in both cases, we observe shifts in the composition of marginal price setters. A similar analysis at the firm level, shown in Figure A2 in the Appendix, indicates composition changes, though they are less pronounced than at the unit level.

prices in the post-increase sample gradually return to levels closer to the pre-increase sample, relating to the broader literature on the *speed* of convergence. Studies on asymmetric pass-through, particularly in gas station pricing, suggest that price asymmetries gradually disappear (Borenstein et al. (1997), Lewis and Noel (2011); Peltzman (2000)). Their notion of asymmetry refers to slower price declines than increases, namely the difference in the adjustment speed. Other studies quantify the extent of asymmetry using level differences in prices or pass-through estimates. For instance, Benzarti et al. (2020) provide evidence that in the case of a VAT change in Finland, price asymmetries persist, with prices failing to return to their original levels. Thus, it is important to distinguish whether the asymmetry found in my analysis pertains to the speed of adjustment or the magnitude of price differences.

I argue that quantifying the price asymmetry in my empirical setting captures both the magnitude of asymmetry and the asymmetry in the speed of response. Specifically, the observed price level difference between the two samples in this market setting is analogous to difference in adjustment speed. This analogy holds because the market operates continuously – clearing every hour – and fundamental cost levels, which firms use for decision-making, are updated daily. In such a setting, if prices following a cost decrease do not return to pre-increase levels despite firms optimizing on the day of the cost decrease, this implies a delayed response, or asymmetry in adjustment speed.

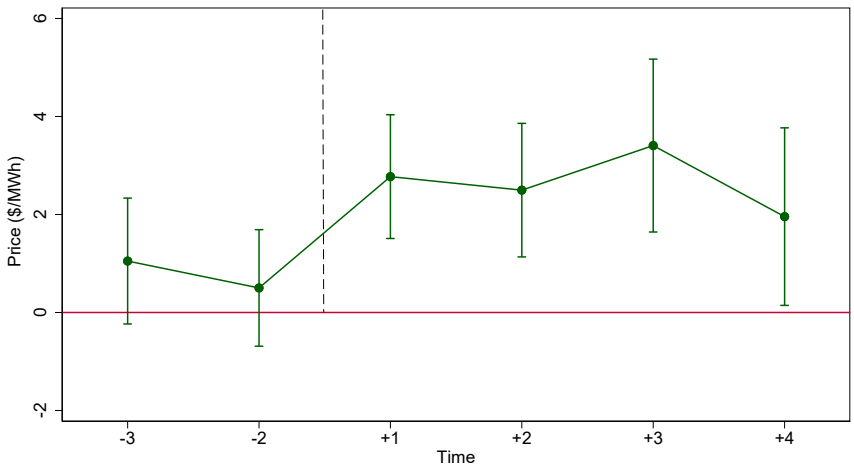
For example, consider three consecutive time periods, $t-1$, t, and $t+1$, where t represents a cost-increase event, and costs at time $t-1$ and $t+1$ are identical. If prices at $t+1$ remain higher than at $t-1$, despite firms having adjusted, it indicates that the price adjustment to a cost decrease is not immediate. In contrast, in industries where price and cost changes occur infrequently, a delayed downward price adjustment months after a cost decrease is considered a slow response. In my setting, where price adjustments happen immediately by market design (due to peculiarity of market operation), observing persistently higher prices after a cost decrease suggests a lagged response akin to that in less frequently adjusting market.

Thus, the concept of adjustment speed is not solely dictated by the physical time frame but also by how pricing behavior aligns with market dynamics. Nontheless, I conduct additional analyses to examine price adjustments over time, which, while not part of the main specification, are presented in the next subsection.

Do prices in the post-increase sample decrease over time? I employ empirical analysis to examine a dynamic price convergence pattern over time in an event-study analysis, where the event is the cost-increase events.[18] I run the following specification:

$$P_{th} = \Big(\sum_{k \in \{-m,\ldots,+n\}} \beta_k D_{t-k} \Big) + \gamma X_{th} + \mu_h + \eta_t + \varepsilon_{th} \tag{2}$$

[18] Unlike other studies, such as Borenstein et al. (1997) and Lewis (2011), which examine the lagged response of a cost change in time t – specifically, the effect of Δc_t on $[\Delta P_t, \Delta P_{t+1}, \ldots, \Delta P_{t+n}]$ – there is no lag in production response to the cost at time t due to frequent market clearing and non-storability of inputs for output production.



Notes: The graph shows the price each period $\hat{\beta}_{1,k}$ for *Time* $k = \{-3, -2, +1, +2, +3, +4\}$ relative to a baseline comparison period $k = -1$. Confidence intervals are computed using Newey-west standard errors (5% significance level).

Figure 4: Event study: Price change $\pm k$ days since the cost-increase event

I set $m = 3$ and $n = 4$, with the baseline at $k = -1$. Since the cost-increase event itself ($k = 0$) is not included in the analysis, it is excluded from this analysis as well. The coefficients for $k > 0$ capture the dynamic price pattern following the cost increase relative to the $k = -1$ (the day before the event, part of the pre-increase sample). The coefficients for $k < -1$ show price levels in the pre-increase sample before the event occured.

Figure 4 present these estimates, which reflect price changes conditioned on observables relative to $k = -1$. The estimates β_k for $k > 0$ are significantly positive, with a slight downward trend over time, while those for $k < -1$ are not statistically significant. This indicates that post-event prices remain significantly higher than pre-event prices, declining over time – though not monotonically for $k \leq 3$ days – before showing a clearer downward trend after $k \geq 3$ days. In contrast, no significant price difference is observed in the pre-event sample. These results reinforce the presence of a systematic price difference between the pre- and post-event samples, even when analyzed in shorter time windows.

While not the primary focus, this event study helps determine how long the characteristics of the post-increase sample persist. Based on these findings, I use $k = 2$ and $k = 3$ to define the alternative post-increase sample categorization discussed in Section 3.2.1.

3.3.4 Incorporating cost-increase period information

The cost-increase (shock) sample serves solely as an exogenous event for dividing the data. While firms' optimization is not dynamic, their strategies post-shock may depend on the nature of the cost-increase period. For instance, firms' expected strategies in the post-increase sample could differ based on whether a cost decrease follows a higher or lower starting point. To assess whether price analysis results are influenced by the characteristics of the cost-increase period, I incorporate

the magnitude and timing of cost declines into the main analysis. I find that a cost decline from a higher level results in higher post-increase prices and that post-increase prices are higher when the cost decrease is immediate rather than gradual. Details along with the results are provided in Appendix A.1.

3.3.5 General applicability of results: comparing single market price and firm-level pricing

The pricing mechanism in this market differs from a typical setting in which firms set their own product prices. Instead, the market clears through a unitform-price auction, resulting in a single market price for all firms. Consequently, the price analysis in this paper does not involve firm-level prices. Given this unique mechanism, it is important to examine how the absence of firm-specific pricing affects the analysis and how adopting a single market price aligns with standard practices in pricing research to ensure broader applicability.

A key distinction between uniform and firm-level pricing is that, while firms in firm-level pricing cases receive the prices they set, firms in a uniform price auction receive the market-clearing price, which may differ from their price bids. However, the price bids of interest in this analysis are those from firms expecting their bids would set the price which they eventually receive (i.e., ex-ante marginal bids). Thus, the market setting is not fundamentally different from one where firms set prices to maximize their ex-ante expected profit, making the uniform-price mechnism comparable to firm-level pricing strategies.

Furthermore, using a single market price in the analysis is comparble to using representative price indices, a common approach in price analysis studies. The uniform price in an auction-based market, despite being a single value, indirectly reflects individual firm-product prices, much like a price index, as both are shaped by the distribution of individual-level prices. Moreover, markets often feature numerous firms, variety of products, and a wide range of prices, making firm-level price data impractical for analysis. Consequently, even in markets with firm-level pricing, most empirical studies of price movements or pass-through effects rely heavily on aggregate or average price measures. In particular, pass-through analyses involving cost variations over time frequently use aggregated prices or sales-weighted average price indices to capture meaningful price variations. This approach is also prevalent in macroeconomics and trade economics research on price adjustments.[19]

3.3.6 Robustness checks

The crucial condition leveraged in the analysis is that the samples before and after the cost increase, namely the pre- and post-increase samples, have the same market environment besides the direction of cost change. I undergo several robustness checks to ensure this, further investigating if any systematic differences in the operation enviornment are present between the pre- and post-increase samples due to the cost-increase period's market condition carried over. For example,

[19] See Goldberg and Hellerstein (2013) for a review.

a strained supply of natural gas to power generators during the gas increase period could have resulted in these generators continue operating in a way as they did during the gas price increase phase.

The first robustness check is to redo the price and markup regression using a modified sample where I drop the first day of the post-increase sample, to address the possibility that generators may find it difficult to return to their usual operation and bidding manner immediately on the first day of gas price decrease. Especially since we use the day-ahead market data, the bidding of which happens approximately a day before the actual generation happens, one may worry that the information revealed in the bids and thus prices may not fully reflect the change in the gas market's condition. While this is not true since tradings at the gas market occur in a day-ahead timeline as well, matching electricity market operation schedule, I further examine whether the results hold when excluding the first day of each post-increase sample blocks. Column (1) and (2) of Table 4 shows the results of Table 2 when the first days of the post-increase sample are dropped, where I find the estimate to be even larger than in our main result, indicating that our finding is not driven by a lagged response on the generators side.

The second robustness check addresses the fact that gas prices in the pre- and post-increase samples are not exactly the same. Since we have controlled for the marginal cost of the marginal unit in our main regression, the price difference that we document is not attributable to the cost difference resulting from a small difference in gas prices across these samples.[20] Despite this, as a robustness check, I further restricted both samples to select days and hours that are closest match to the days in the sample. Specifically, for each day in the post-increase sample, I find the most similar day in terms of several categories such as gas price, demand, daytime, and etc, among the pre-increase sample. I do the same process for each day in the pre-increase sample to assure homogeneity between the pre- and post-increase samples. The main specification is then implemented using the restricted sample, results of which are shown in Column (3) and (4) of Table 4. Although the sample size is small, we find estimates $\hat{\beta}$ that are even larger and significant when samples are restricted to the most similar days, despite having more similar average gas prices than before in the pre- and post-increase samples, as reported in the summary statistics in Table 5; the average gas price is \$4.45/MMBtu for the pre-increase, and \$4.43/MMBtu for the post-increase sample

Column (5) and (6) shows the result where both the first and second robustness checks are combined; using the matched sample and with the first day of the post-increase sample dropped. Noticeably, when applying such adjustment, the average gas prices of the post-increase sample is lower than that of the pre-increase sample, as shown in the row (c.) of Table 5, while it was slightly larger before in the main sample. Despite having even lower gas prices, with average gas price of \$4.45/MMBtu for the pre-increase and \$4.39/MMBtu for the post-increase, the equilibrium prices in the post-increase sample is even higher than in the main results – positive and large estimates

[20] What we did not account for is the entire distribution of firms' marginal costs. But, the difference among gas-fired generators is very small when the gas price returns back to normal.

for the Post-Increase$_t$ variable as shown in Table 4 columns (5) and (6).

Lastly, I also check whether generation at the power plant level is comparable between the pre- and post-increase samples, addressing broadly two concerns related to the preceding high gas price period. First, since the surge in gas price is caused by the pipeline capacity congestion, one concern may be that the gas shortage during the high gas price period persists and causes gas-fired power plants to generate and bid differently in the post-increase period. However, the gas shortage or the cut in gas supplies to gas-fired generators were not a major issue during the shock period as the congestion does not imply a block in gas supply, but only reflects the scarcity value of the pipeline capacity. While the suspension of gas supplies is not a problem, a fuel switching decisions among some of the gas power plants equipped with dual generation technology during the high gas price period. That is, an increase in gas price can alter the generation pattern of some of the dual gas generators, which can switch to burning oil when the gas becomes more expensive than oil (Kim (2022)). If these dual generators continued using oil even after the gas price falls back to the low level due to congestion problem being resolved, we may observe a different generation/bidding pattern in the post-increase sample which is influenced by the cost-increase sample's operation decisions.

To address all of these concerns, I checked whether gas-fired and dual gas generators' operation patterns in the post increase sample differ significantly from those in the pre-increase sample.[21] I used generator-level electricity generation amount implied by the quantity bids accepted in the day-ahead market auction. Columns (7) and (8) of Table 4 presents the result of the regression of generator-level quantities on the post-increase sample indicato, where column (7) regression used generation amount (quantities) of gas/oil dual units, and column (8) restricts the sample to the pure gas units. From column (7), we find that there is no significant change in dual generators' generation across samples, indicating that possible fuel switching during the high gas price phase were not carried over to the post-increase period. Column (8) results show that there is a small decrease in pure gas generators' generation amount, but the change is small and not strongly significant. Histogram plots of generation quantities of the selected generators – presented in the Appendix Figure A3 – also confirms that there is no significant generation differences between the pre- and post-samples.

In Section A.2, I provide several additional robustness checks of the main regression. Among those checks, I estimated the same equation 1 using an alternative post-increase indicator – which was explained in Section 3.2.1– the results of which are shown in Table A4 with details provided in Appendix A.2.1. The alternative post-increase indicator was constructed by further dividing the initial post-increase sample: for days within the initial post-increase sample, I grouped first n days into the alternative post-increase sample and the remaining days ($K - n$ where $k \leq K$) into the pre-increase sample of the subsequent cost increase event. Results hold under these different robustness checks, with details of the analysis and results provided in Appendix A.2.

[21] However, note that the amount of generation cannot be exactly the same since we document a change in bidding behavior in the post-increase sample. This robustness check is to detect a significantly different structural change in the generation pattern.

	a. First-day Dropped		b. Sample Matched		c. Both a. and b.		Generator q_{ijt}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	P_{th}	log (P_{th})	P_{th}	log (P_{th})	P_{th}	log (P_{th})	Dual	Gas
Post-Increase$_{t,h}$	3.081^{***}	0.069^{***}	3.627^{***}	0.086^{***}	3.350^{***}	0.079^{***}	-0.319	-7.371^{*}
	(0.491)	(0.012)	(0.680)	(0.017)	(0.666)	(0.017)	(1.529)	(4.284)
Hour FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	2,543	2,543	481	481	421	421	45,516	62,208

Notes: Standard errors in parentheses. * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$. Newey-west standard errors with lag $m = 22$. Price regressions in columns (1)-(6) use market outcomes when the non-dual natural gas units are marginal. Columns (7)-(8) presents generating-unit level quantity regressed on the post-increase indicator. These regressions use day-ahead accepted quantities of generators owned by major firms, where column (7) use gas/oil dual generators only and column (8) use pure gas generators.

Table 4: Robustness Checks: main price regression

Adjustment	Variable	Sample	Mean	Median	S.D.	min	max	Obs
a. Sample Matched	gas price	pre-	4.44	4.49	0.26	4	5.18	173
		post-	4.43	4.50	0.29	4.02	5.16	313
c. Sample Matched + first day dropped	gas price	pre-	4.44	4.49	0.27	4	5.18	173
		post-	4.39	4.41	0.27	4.02	5.16	253
a. Sample Matched	demand	pre-	13550	14033	3446	6617	21505	173
		post-	13260	13511	2955	6529	21113	313
c. Sample Matched + first day dropped	demand	pre-	13550	14033	3446	6617	21505	173
		post	13133	13367	3012	6648	20583	253

Table 5: Summary Statistics: Robustness Checks

4 Investigating the difference in the bidding strategy

The previous section documents systematic differences in prices between the pre- and post-increase samples. Since the market operates through a multi-unit uniform auction, a single uniform price – determined by participants' bids in equilibrium – applies to all firms and generators accepted in the auction. Therefore, in this market, each firm-plant does not set its own price but instead adjusts its bids to influence the equilibrium price ex ante. As explained in Section 3.3.5, this differs from many other markets in which each firm would set and receive a price for its own product. Nevertheless, competition in this setting is similar to price competition, as firms choose price bids that maximize their profits from an ex ante perspective, anticipating that they will receive that price in the equilibrium.[22]

To further investigate these differences, I examine whether there were any differences in strategic bidding behavior between the two samples. A key advantage of the dataset is that I observe the

[22]It could also be viewed as quantity competition, as a firm can adjust its price bid to adjust the quantity it supplies in equilibrium.

optimal bidding decisions of all firms at an hourly frequency, which allows me to investigate changes optimal bidding strategies at both the firm and generating unit levels. This micro-level analysis further links the documented changes in bidding strategies to the equilibrium price differences between the samples, as discussed in Section 3.

4.1 Description of Bidding

In the market indexed by (t, h), firm i $(i = 1, \ldots, N)$ submits a bid schedule, $< b_{ijkth}, q_{ijkth} >$, which includes the price bid b_{ijkth} and the quantity bid q_{ijkth} for each of its unit j $(j \in \mathcal{J})$. Each unit's bid can have multiple steps, denoted by k. The bid reflects the willingness to supply q_{ijkth} at a price greater than or equal to b_{ijkth}. In this auction, quantity bids are typically fixed, and firms primarily adjust the price bid b_{ijkth} to respond strategically. [23] Firms submit bids that maximize their expected profits while considering their expectations about the bids of competitors.

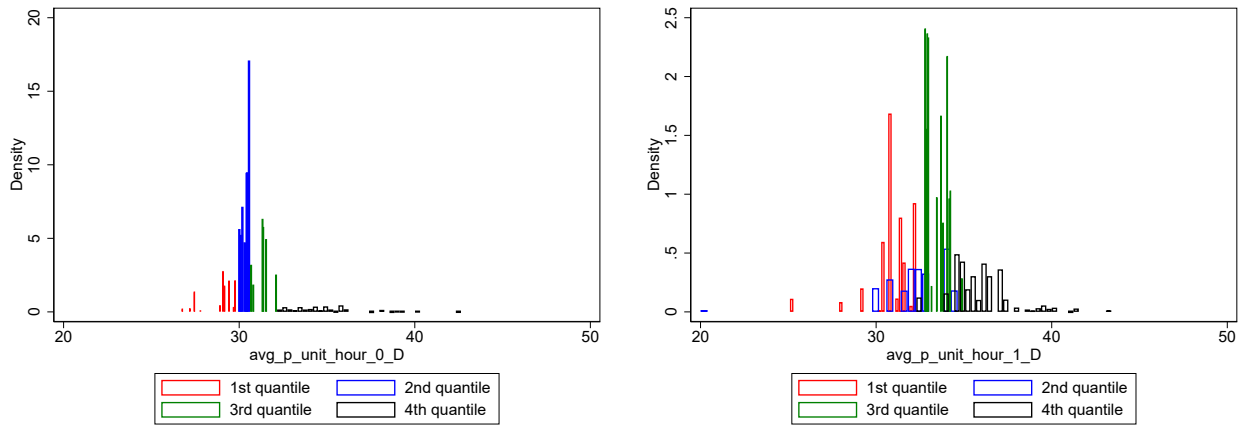
Although I observe all bids submitted by participating firms and their generating units, only the bids with a positive probability of setting the market price (*i.e.*, ex-ante marginal bids) are considered strategically relevant in a multi-unit uniform auction. Therefore, I focus on examining the bids of potentially marginal units – those with price bids within a close range around the ex-post equilibrium price (e.g., the ± \$5/MWh), most of which are natural gas-fired generators.[24] A firm may use multiple marginal units for strategic bidding, with larger firms typically employing more. Since firms consider all such units in their bidding decisions, I allow firms to have multiple marginal units in the analysis. However, for each generating unit, I retain only the step bid (k) closest to the ex-post equilibrium price.

Bid distribution change An initial examination of the bidding data suggests a change in bidding patterns. I compare the distribution of price bids, b_{ijkth}, between the pre- and post-increase samples, as shown in Figure 5. Price bids of generating units j of the pre-increase sample are ranked in increasing order, and index values from 1 to 4 are assigned to units in each quartile, separately for each demand group (e.g., low to high demand).[25] I then plot the bid distributions of these units for the post-increase sample in increasing order and examine whether their quartile indices match those of the pre-increase sample. Panels (a) and (b) show the distributions for the lowest-demand subsample (e.g., off-peak hours), while panels (c) and (d) correspond to the highest-demand subsample (e.g., peak hours).

[23] Since firms can own multiple units, their submitted bids are often referred to as supply schedules, $S_{ith}(p_{th}, q_i)$. This notation follows Wilson (1979) and Hortaçsu and Puller (2008), though I use a slightly different notation throughout this paper.

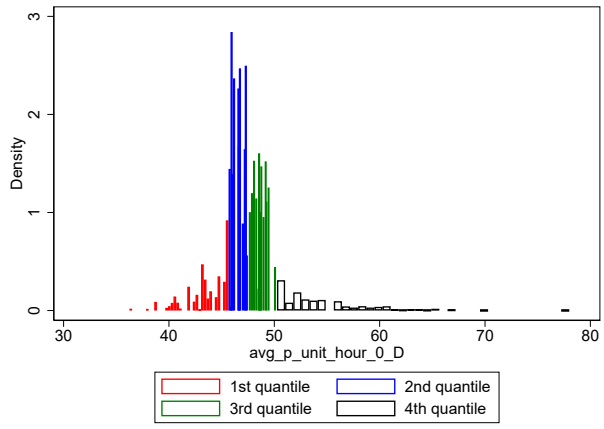
[24] I tried two similar approaches to select the marginal units. First, I selected units with price bids within a close range around the ex-post equilibrium price (e.g., the ± \$5/MWh). Second, I compute the probability of being marginal for each firm (i) and generating unit (j), $\frac{\partial p_{th}}{\partial b_{ijkth}}$, by construcing each firm-generator's residual demand curve using ex-post observed bids. Since both approaches yield a similar set of marginal units, I opt for the simpler method in the main analysis. While both approaches have limitations – neither fully captures the ex-ante probability based on each firm-unit's residual demand distribution – they help identify most close-to-marginal units.

[25] I also tried an alternative method of using the price bid of a single closest-to-marginal step bid of each unit j instead of the volume-weighted bids, where I find qualitatively similar graphs.

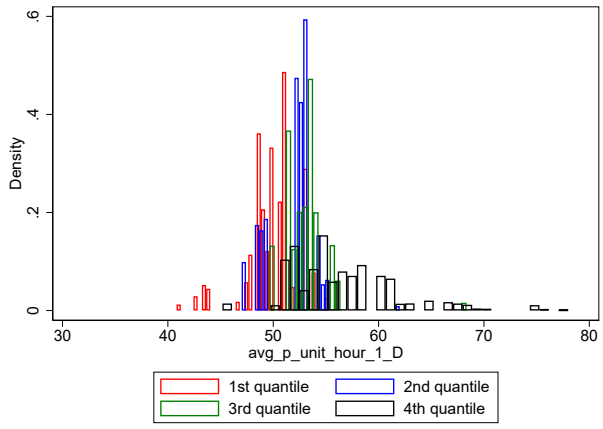


(a) Pre-increase: Low Demand (gr 1)

(b) Post-increase: Low Demand (gr 1)



(c) Pre-increase: High Demand (gr 4)



(d) Post-increase: High Demand (gr 4)

Figure 5: Distribution of (volume-weighted) price bids of pre- and post-increase samples: by demand

If bidding strategies were consistent across the pre- and post-increase samples, the bids in panels (b) and (d) would be expected to align with those in panels (a) and (c). However, the distributions do not preserve their original order: units in the first and second quartiles of the pre-increase sample tend to bid higher, and bids are more dispersed across all quartiles in the post-increase sample. This suggests that the original bid rankings are not preserved – previously low-bidding units no longer bid the lowest, and vice versa. The mixing of quartile groups indicates that firms may be employing different bidding strategies in the post-increase sample.

4.2 Bid markup Analysis: Difference between pre- and post-increase samples

The graph above is only suggestive in that the factors that could result in differences in bids are not controlled for. Thus, I bring this to a regression setting, with the bid markup ($b_{ijth} - mc_{ijt}$) of potentially marginal units as main dependent variable. The bid markup contains useful information about a firm's strategy, and is measured as a difference between the price bids of firm i's unit j

	(1)	(2)
	$b_{ijth} - mc_{ijt}$	
Post-Increase$_t$	1.024**	0.552*
	(0.350)	(0.321)
Peak$_h$		−0.110
		(0.372)
Post-Increase$_t$ × Peak$_h$		0.784**
		(0.340)
Demand$_{th}$	0.0017***	0.0017***
	(0.0001)	(0.0001)
constant	0.667*	0.727**
	(0.334)	(0.343)
Hour FE	✓	x
Year FE	✓	✓
Firm FE	✓	✓
N	55,214	55,214

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors clustered at the day (t) and firm (i) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (*i.e.*, marginal) are used for estimation. Demand variable is demeaned (unit: MWh).

Table 6: Bid markup regression: Full sample

and the marginal cost of the unit.[26] I run the following regression shown in equation (3), the specification of which is similar to that in equation (1):

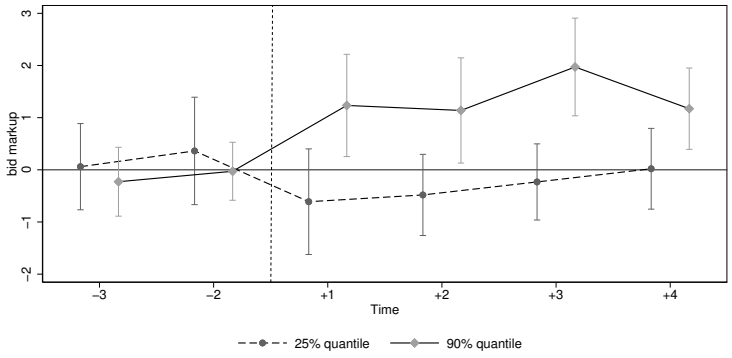
$$b_{ij,th} - mc_{ij} = \alpha + \beta \text{ Post-increase}_t + \gamma \text{ Demand}_{th} + \eta + \varepsilon_{th} \tag{3}$$

To ensure consistency with the price regression, the analysis uses bid markups from day-hour markets (t, h) where a (non-dual) natural gas unit sets the equilibrium price.[27] I included bid markups from firm i's generating unit j only if unit j is a gas-fired generator. In other words, the analysis focuses on bids and bid markups from generating units whose marginal costs were affected by changes in gas prices.

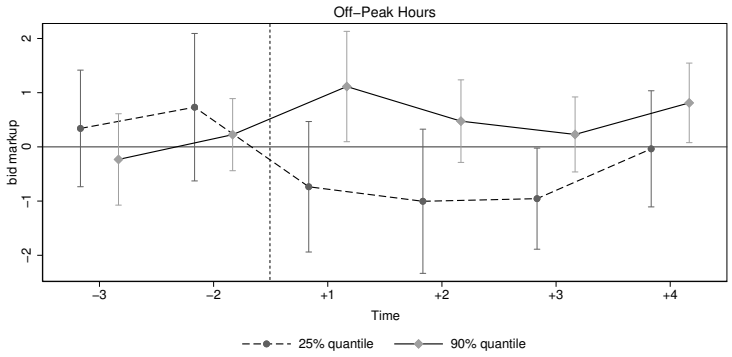
Table 6 column (1) shows the result, which presents a positive and significant coefficient for the post-increase sample (Post-Increase$_t$), indicating that there is a systematic overbidding (bid markup increase) compared to the pre-increase sample. In column (2), I break the sample into peak hours and off-peak hours. I find that increased bid markups in the post-increase sample is more pronounced during the peak hours, indicated by the coefficient estimate of the interaction variable. However, note that this regression only verifies the average difference in the first-order

[26] The reason why specifying the marginal cost as a control variable is not suitable here is because marginal cost of a unit j does not change across hours within a day. Thus, if specifying the marginal cost as a control, it is equivalent to specifying a day (t) fixed effects. In the price regression this was not an issue because the price and the identity of the marginal unit, as well as its marginal cost, changes across hours within a day.

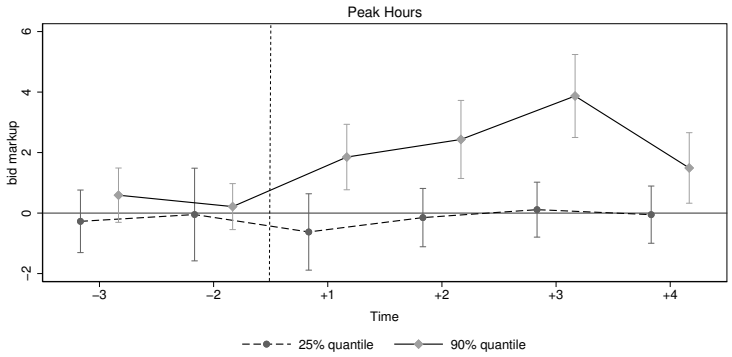
[27] I also conducted a similar analysis using the bids, b_{ijth}, as the dependent variable, with marginal costs specified as a control variable, which yielded qualitatively similar results.



(a) Total sample



(b) Off-Peak Hours



(c) Peak Hours

Figure 6: Event study of bid markup: total, off-peak, peak hours

moments of bid markups (of marginal firms and units) between the samples.

The change in bidding pattern is shown in the event study analysis as well. I implement an event study type regression of quantiles of bid markup variables, similarly as in the price regression, using the day before the cost-increase event (last day of the pre-increase sample) as a baseline. The pattern of estimates are similar to that of price regression, as shown in Figure 6. Since the bid markup regression includes a set of bid markups of potential marginal units, I check the estimates for 90 percent and 25 percent quantiles of bid markups. [28] I also check this pattern separately for

[28]I chose 25 percentile because 10 percent quantile has large confidnce intervals while having a similar path of

	(1)	(2)	(3)	(4)
	< 100	[100, 500)	[500, 1000)	> 1000
	fringe	small	med	large
	$b_{ij,th}$	$b_{ij,th} - mc_{ij,th}$		
Post-Increase$_t$	0.240	1.080^{***}	0.917^{**}	1.034^{***}
	(0.741)	(0.378)	(0.399)	(0.333)
Demand$_{th}$	0.0011^{***}	0.0015^{***}	0.0018^{***}	0.0017^{***}
	(0.0002)	(0.0001)	(0.0000)	(0.0000)
Hour FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
N	333	10,632	14,132	29,468

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Dependent variable used for fringe firms (column (1)) is the price bid, b_{ijk}, not the bid markup since we cannot accurately estimate heat rates for fringe suppliers. Demand variable is demeaned within each firm group (unit: MWh).

Table 7: Bid markup regression: firm group by size

off-peak hour and peak hour samples.

One interesting finding from this result is that bid markups do not differ much across days within the pre-increase sample – days before the cost-increasing event – and both 25th and 90th quantiles show similar pattern. However, after the event, 90th and 25th quantile values diverge; the high-quantile bid markup values are significantly higher than the pre-increase baseline level, whereas the low-quantile bid markup does not significantly differ from the pre-increase sample values. Such diversion implies an increase dispersion in bidding strategies across firms in the post-increase sample compare to those in the pre-increase sample. These patterns are consistent across samples, including total, peak and off-peak hour samples. The divergence of bid markups is most pronounced in peak-hour samples, the hours in which strategic consideration is most in effect.

4.3 Bidding Differences by firm group

To further examine how bidding patterns differ by firm type, I examine the difference in bid markups between pre- and post-increase samples by grouping firms based on (i) total capacity (size) and (ii) generation mix and dominant fuel type.

Firm grouping by size First, I categorize firms into four groups based on their total generation capacity and the number of generating units.[29] *Fringe* firms operate a small-scale generation unit, with nameplate capacity not exceeding 100 MW in most cases. Their bidding behavior does not appear strategic, as most fringe units submit a single-step constant bid that does not vary signifi-

estimates compared to the 25th quantile.

[29] Generation capacity data comes from ISO-NE *SCC*– Seasonal Claimed Capability

	(1)	(2)	(3)	(4)	(5)
	Heavybase	Gaslarge	Gas/oil mix	Other mix	Peaker
			$b_{ij,th} - mc_{ij,th}$		
Post-Increase$_t$	0.416	0.952^{***}	1.314^{***}	1.008^{**}	2.914^{**}
	(0.470)	(0.315)	(0.429)	(0.429)	(1.076)
Demand$_{th}$	0.0014^{***}	0.0016^{***}	0.0017^{***}	0.0022^{***}	0.0031^{***}
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Hour FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
N	4,665	19,210	10,381	7,671	499

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable is demeaned within each firm group sample (unit: MWh).

Table 8: Bid markup regression: firm group by generation mix

cantly across days and hours.[30] *Small* firms include those with a reported total capacity between 100 MW and 500 MW.[31] A key distinction between *small* and *fringe* firms is that small firms operate multiple units and submit multi-step bids. *Medium* firms have capacities between 500 MW and 1,000 MW, and *Large* firms include those with total capacity exceeding 1,000MW, up to 4,000 MW.

Firm grouping based on generation composition While firm size is the most frequenty used indicator of firm strategy and market power, firm characteristics other than size may also affect strategic decisions. Therefore, I categorize firms based on their generation mix or the types of fuels used by their generating assets. I exclude small-scale fringe firms and focus only on firms with substantial scale and mulitple generating units.[32]

Heavy base firms are those operating large-scale nuclear generation. In addition to their low-marginal cost nuclear power plants, which run continously as baseload, they also own some marginal units with positive marginal costs that can be utilized strategically. However, the share of capacity that can be used strategically is smaller than that of other firm types. The *Gas Large* group includes large firms operating only natural gas-fired units. Since natural gas is the marginal fuel in almost every hour, these firms actively engage in strategic bidding, submitting multi-step bids (at least five and up to ten steps) for all of their units. Almost all of their generating units are potentially marginal at all times. The *Gas/Oil Mix* group consists of firms with generation portfolio including

[30]For fringe firms, I use bids b_{ijth} instead of bid markups in the analysis due to the small sample size and lack up bid markup variation, which makes estimating heat rates (marginal cost) difficult.

[31]Some firms in this category report capacity close to 500 MW but have idle or extremely high-cost capacity, making their effective capacity lower than the reported capacity.

[32]The importance of generation mix to better understand firms' strategic interactions in the wholesale market has been emphasized in Kim (2024) and Fabra and Llobet (2024).

	(1)	(2)	(3)	(4)
	< 100	[100, 500)	[500, 1000)	> 1000
	fringe	small	med	large
	$b_{ij,th}$		$b_{ij,th} - mc_{ij,th}$	
a. Off-Peak Hours				
Post-Increase$_t$	-0.106	0.554	0.172	0.488^{*}
	(0.595)	(0.331)	(0.315)	(0.261)
b. Peak Hours				
Post-Increase$_t$	0.999	1.254^{**}	1.736^{***}	1.484^{***}
	(1.436)	(0.459)	(0.573)	(0.452)
Hour FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
N(offpeak)	200	2,549	6,288	12,542
N(peak)	133	8,083	7,844	16,926

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at day (t) and firm (i) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable (demeaned within each firm group, unit MWh) is also specified but not reported in this table.

Table 9: Bid markup regression: peak vs. off-peak, firm group by size

only natural gas- and oil-fired plants. Since natural gas is typically less expensive than oil, these firms primarily rely on natural gas-fired generators, using oil-fired units only during peak hours. The *Other Mix* group includes firms with a diverse fuel mix, including natural gas. These firms have a relatively balanced mix of base generation (e.g., biomass, waste or coal fired) and marginal generation (e.g., natural gas or oil). The key distinction between Gas/Oil Mix and Other Mix firms is that the former lacks base generation, whereas the latter owns a considerable share of base generation. Similarly, while both Heavy Base and Other Mix firms operate baseload units, the proportion of marginal capacity (e.g., gas-fired generation) is larger for Other Mix firms. I also identify a group of *Peakers*, firms that operate peaking plants only during peak hours. These firms rely on peak-hour operations to collect scarcity rents necessary to recover the high fixed start-up or ramping costs of running their generators. Peakers are considered as being the most strategic type, as they mainly operate during peak hours when the bidding decisions are driven more by strategic considerations than by generation costs.

Results: Full sample by firm group Having estsablished the firm group categories, I first run separate regressions of equation (3) for each firm group. Table 7 presents the results for firm groups based on firm size, showing that bid markups are higher in the post-increase sample for all firm groups except fringe firms, as indicated by the positive and significant estimates for the Post-Increase$_t$ variable. The higher bid markups observed for small-scale firms are primarily driven by the inclusion of peaker firms in this category, highlighting the need for generation-mix-based

	(1)	(2)	(3)	(4)	(5)
	Heavybase	Gaslarge	Gas/oil mix	Other mix	Peaker
			$b_{ij,th} - mc_{ij,th}$		
a. Off-Peak Hours					
Post-Increase$_t$	-0.079	0.601^{**}	0.775^{*}	-0.374	–
	(0.354)	(0.231)	(0.374)	(0.625)	–
b. Peak Hours					
Post-Increase$_t$	1.950^{*}	1.611^{***}	1.478^{**}	1.341^{**}	3.521^{**}
	(0.920)	(0.508)	(0.515)	(0.491)	(1.266)
Hour FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
N (offpeak)	2,721	10,614	2,414	1,650	–
N (peak)	1,944	8,596	7,967	6,021	486

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at day (t) and firm (i) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable (demeaned, unit MWh) is also specified but not reported in this table.

Table 10: Bid markup: peak, off-peak subsample, firm group by generation mix

firm groupings.

Table 8 presents the results for firm groups based on generation mix, revealing more diverse patterns in bid markup differences. On average, all firm groups except the heavy base group exhibit higher bid markups in the post-increase sample compared to the pre-increase sample.

Results: Off-peak and peak sample by firm group I also examine how bidding strategies in the post-increase sample differ between off-peak and peak hours by running equation (3) regression on subsamples of off-peak and peak hours. Tables 9 and 10 present the results for firm size group and generation-mix groups, respectively, further breaking down the sample by peak and off-peak hours.

Table 9 reports results by firm size groups. In off-peak hours, only large firms have higher bid markups in the post-increase sample. However, in peak hours, all firm types except fringe firms exhibit higher bid markups in the post-increase sample.

Table 10 presents results for the generation-mix based firm groups. Gas large firms and gas/oil mix firms apply higher bid markups in both off-peak and peak hours, with the extent of increase greater in peak hours. Since gas generation serves as the lowest-cost base generation for these firm types, they use these assets for bidding in off-peak hours. Heavy base and other mix firms have higher bid markups in the post-increase sample, mainly in peak hours. These firms have a considerable share of base generation other than gas, utilizing gas generation mainly as a strategic asset during peak hours. Lastly, peaker firms, which operate primarily in peak hours, also exhibit

	(1)	(2)	(3)	(4)	(5)
	full Sample	Sub Sample: by Firm Size (MW)			
		< 100	[100, 500)	[500, 1000)	> 1000
		Fringe	Small	Medium	Large
	$b_{ij,th} - mc_{ij,t}$	$b_{ij,th}$	$b_{ij,th} - mc_{ij,t}$		
Pre-Increase					
Peak_h	0.786^{*}	0.743	0.689^{*}	0.599	0.898^{**}
	(0.389)	(0.905)	(0.382)	(0.486)	(0.352)
Post-Increase					
Peak_h	-0.103	-2.158	0.637	-0.014	-0.467
	(0.364)	(1.579)	(0.434)	(0.385)	(0.314)
Hour FE	x	x	x	x	x
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
N (Pre-Increase)	27,585	203	5,249	7,082	14,749
N (Post-Increase)	27,629	130	5,383	7,050	14,719

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Column (2) – fringe – uses the price bids ($b_{ij,th}$) as a dependent variable due to the difficulty of estimating marginal cost (heat rates) for these units. Standard errors for regression (1) are clustered at the day (t) and firm (i) level, and standards errors for the subsample regressions (2)-(5) are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable (demeaned within each firm group, unit MWh) is also specified in the regression but not reported.

Table 11: Bidding differences: peak-hour bidding, by firm size group

higher bid markups in the post-increase sample.

4.4 Bidding differences across hours: peak-hour bidding by firm type

Another way to verify differences in firms' bidding strategies between the pre- and post-increase samples is to examine whether the typical hourly bidding pattern observed in this market is preserved in the post-increase sample. To do so, I compare bidding patterns between peak and off-peak hours separately for the pre- and post-increase samples. As discussed in Section 3.2.2, peak hours are when strategic considerations play a greater role in pricing and firms are most capable of exercising market power by increasing markups, whereas off-peak hours have much lower strategic capability. Therefore, firms – especially those engaging in strategic bidding – typically submit higher bids in peak hours than in off-peak hours.

I run equation (4) separately for pre- and post-increase samples, and by firm group, to check the general pattern of bid markups across hours within each sample. Only the bid markups of potentially marginal units were used, similarly as before.

$$b_{ij,th} - mc_{ij} = \alpha + \beta \ \text{Peak}_h \ + \gamma \ \text{Demand}_{th} + \eta + \varepsilon_{th} \tag{4}$$

Table 11 presents the results for firm size categories, showing that firms' bidding strategies across

	(1)	(2)	(3)	(4)	(5)
	Full Sample	Sub Sample: by Firm Size			
		Heavy Base	Gas Large	Gas/Oil Mix	Other Mix
	$b_{ij,th} - mc_{ij,t}$	$b_{i,th} - mc_{ij,t}$			
Pre-Increase					
Peak_h	0.786^{*}	-0.205	1.049^{***}	0.732^{*}	0.727^{*}
	(0.389)	(0.760)	(0.379)	(0.396)	(0.401)
Post-Increase					
Peak_h	-0.103	0.457	-0.335	0.204	0.040
	(0.389)	(0.518)	(0.310)	(0.393)	(0.454)
Hour FE	x	x	x	x	x
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
N (Pre-Increase)	27,585	2,207	8,972	5,510	4,206
N (Post-Increase)	27,629	2,458	10,238	4,871	3,465

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors for regression (1) are clustered at the day (t) and firm (i) level, and standards errors for the subsample regressions (2)-(6) are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable (demeaned within each firm group, unit MWh) is also specified in the regression but not reported.

Table 12: Difference in the bidding strategies: peak vs. off-peak, by firm hetero

hours differ significantly different between the two samples. In the pre-increase sample (first row), overall bid markups are higher in *peak* hours, as shown in column (1). Within firm groups (columns 2-5), *large* (column 5) and *small* firms (column 2) apply significantly higher markups in peak hours than in off-peak hours. This pattern aligns with the typical strategic bidding behavior documented in this wholesale electricity market, though peak-hour strategic bidding is not perfectly correlated with firm size (medium-sized firms do not exhibit a distinct bidding pattern).

However, bidding strategies in the post-increase sample, shown in the second row of Table 11, deviate from this pattern, as peak-hour strategic bidding is no longer evident. Both large and small firms that bid higher in peak hours now exhibit no clear difference in bid markups between peak and off-peak hours, shown by estimates in the second row being insignificant for all firm categories. This suggests a substantial change in firms' bidding strategies in the post-increase sample, particularly among the largest firms, which have the greatest capability/ability to behave strategically. Notably, this difference emerges despite having similar market conditions.

A more pronounced difference in bidding patterns emerges when using firm group categories based on generation mix, as shown in Table 12. In the pre-increase sample (first row, columns 2-5), Gas Large, Gas/Oil Mix, and Other Mix firms tend to add higher bid markups during peak hours, which corresponds to the typical strategic bidding pattern in this market. This peak-hour strategy is most pronounced among Gas Large firms, which have sufficient gas generation capacity available during high-demand hours that can be utilized stragetically.

Interestingly, these patterns disappear in the post-increase sample, as shown in the second row

of columns (2)-(5) in Table 12. The firm groups that previously increased markups in peak hours no longer exhibit this behavior in the post-increase sample. While overall markup levels may be higher across firm groups in the post-increase sample compared to the pre-increase sample, the distinct peak-hour bidding patterns observed in the first-row results are absent. The absence of peak-hour strategic bidding suggests that firms' bidding and pricing strategies are more dispersed across hours. This finding indicates that the bidding strategies employed by firms in the post-increase sample differ significantly from those in the pre-increase sample. Despite market fundamentals – such as demand, marginal costs, and the set of competitors – being similar across the samples, firms are not bidding as they did before, implying a fundamental shift in firms' bidding behavior.

4.5 Summary: Which firms show a change in bidding behavior?

I summarize the types of firms that bid differently in the post-increase sample. First, by firm size, all firm types except for fringe suppliers submit higher price bids – reflected in higher bid markups – in the post-increase sample than in the pre-increase sample (Table 7). Large firms raise price bids in both off-peak and peak hours, whereas small and medium-sized firms increase mainly in peak hours (Table 9).

By generation mix, all firm types except heavy base firms submit higher price bids in the post-increase sample (Table 8), but at different hours (Table 10). Gas large and gas/oil mix firms bid higher in both off-peak and peak hours, suggesting that their bidding strategy has leveled out across hours at a higher level. Other mix firms (base/gas mix) submit higher price bids mainly in peak hours, with little change in off-peak hours. Peaker firms, operating primarily in peak hours, submit significantly higher bids in the post-increase sample. Heavy base firms show only a slight, insignificant increase in peak-hour bids.

A more striking evidence of the shift in strategy is revealed through the peak-hour bidding pattern within each sample – specifically, whether firms continue the typical strategic bidding of adding higher markups in peak hours compared to off-peak hours in the post-increase sample. The change in bidding pattern is most pronounced for large firms and, to a lesser extent, for small firms (Table 11). Among these large-scale firms, peak-hour bidding patterns differ the most for gas large firms, as shown in Table 12, as well as for gas/oil and other mix firms. That is, the peak-hour strategic bidding previously observed in the pre-increase sample no longer exists in the post-increase sample, despite overall increase in bid markups in the post-increase sample.

There are two key takeaways from these findings. First, the increase in price bids in the post-increase sample is more concentrated in peak hours, when strategic considerations play a greater role in price bid formation. Second, the distinct peak-hour bidding patterns observed in the pre-increase sample disappear in the post-increase sample, despite the overall increase in price bids. Instead, bid dispersion across hours and firms increases. This suggests that firms' bidding strategies in the post-increase sample are not only systematically different from those in the pre-increase sample but also characterized by greater variation in how firms adjust their bids.

Since market fundamentals, cost structures, and firm-specific strategic abilities remain un-

changed across samples, the observed changes in bidding behavior likely reflect changes in firms' expectations about their competitors' bidding strategies. In particular, firms may face greater uncertainty about how competitors will bid, leading them to anticipate a broader range of potential competitor strategies, including the possibility of higher price bids than in the pre-increase sample, as discussed in Section 2.3. As a result, firms may adjust their own bidding approaches, contributing to both the increased dispersion in bids and the overall rise in price bids.

4.6 Discussion: Other possible causes

Markup adjustment being the cause of the difference? In relation to the extensive pass-through literature, which finds incomplete pass-through and attributes it primarily to markup adjustment (e.g., exchange rate pass-through literature), it is natural to interpret asymmetric price responses as another realization (result) of firms' markup adjustment.

While markups inherently explain why prices exceed costs, this paper questions why markups would be higher in the post-increase sample than in the pre-increase sample. For instance, if two days, $t-1$ and $t+1$, have the same marginal costs and other market conditions held fixed, firms should apply the same markup on both days. In other words, any incentive to add a certain markup on the post-increase day $(t+1)$ should also exist on the pre-increase day $(t-1)$, leading to identical prices on both days. Explaining the observed asymmetry in prices through markup adjustment alone requires justifying why markups increase only in the post-increase sample and not in the pre-increase sample – an aymmetry in markup adjustment incentives that is difficult to rationalize without further explanation.

Tacit collusion Another possible explanation is tacit collusion, mentioned as one of the hypotheses in Borenstein et al. (1997). That is, prices may be sticky downward because the past prices serve as a focal point for oligopolistic sellers, as firms need not immediately adjust their prices to a negative cost shock. Thus, coordination may emerge naturally and persist until a firm observes a deline in sales or a price drop below the trigger level.

Based on the understanding of how tacit collusion emerges and is sustained, I argue that my empirical setting is unlikely to support its formation. In the data, the post-increase period is relatively short – averaging only four days – thus, insufficient for tacit collusion to develop. Moreover, firms do not immediately observe competitors' bids in previous periods, as such data is released four months later. While equilibrium price and quantity data is immediately available, this information alone does not reveal competitors' strategies in this uniform-price auction setting.[33] Additionally, price leadership is difficult to emerge, as firms submit their bids simultaneously each day rather than sequentially. Even if some firms attempt to lead by raising price bids, others cannot observe these changes, making it difficult to distinguish strategic pricing from fluctuations in market fun-

[33] Firms receive daily notifications of their dispatched quantities and market prices after the market clears but do not see competitors' bids or generated quantities. The bids submitted by firms are released four months later per FERC regulations.

damentals.[34] Lastly, the market variables being stochastic within the sample further complicates formation of a focal point.

The results of my analysis further support the claim that the observed patterns are not driven by tacit collusion. If firms were attempting to collude to increase market power, they would do so more effectively when collusion is less likely to be detected and when their relative market power is greater. This suggests that we should observe coordination towards high prices particularly during peak hours, which would result in intensifying differences between peak and off-peak bidding patterns. However, I find the bidding pattern between peak and off-peak hours being less distinct in the post-increase sample, with firms submitting high prices not only in peak hours but also in the off-peak hours. Moreover, the bidding pattern is far from coordinating on a particular focal point as the price bids in the post-increase sample became more dispersed across firms and hours. Furthermore, the price difference between pre- and post-increase samples is not large enough to support collusion.

Forward contract Electricity-generating firms often set up forward contracts with the demand side (retail companies), which can make them less responsive to wholesale market conditions and less strategic when forward obligations are binding (see Bushnell, Mansur, and Saravia (2008) for further discussion).

One might question whether the documented differences between samples could have resulted from forward contracts. However, this can be ruled out, as forward contract terms should be the same for sample days that differ only in cost direction. Since firm-level forward contract rates are typically fixed for at least a season, they do not change over short periods. Given that the pre- and post-increase samples in our analysis are at most a month apart, the forward contract rate can be assumed constant.[35]

5 Model: estimating the belief

The regression indicates that there is a systematic difference in the bidding between the samples, even within the same firm (category). Since other fundamentals such as market demand, set of competitors, the marginal cost of generation are not substantially different between the samples, the difference in bidding could be caused by the difference in the beliefs about the strategy of competitors.

To better understand the bidding decision of a firm, I present a model that describes the bidding

[34] For instance, Byrne and De Roos (2019) show that in the retail gasoline market, where price adjustments are publicly visible, reaching a focal point can take over a year of repeated interactions, with with price leadership playing a crucial role. Identifying tacit collusion empirically remains challenging, particularly in determining which price becomes the focal point and how firms coordinate.

[35] Using the rate instead of the actual amount of forward contracts is not an issue. Even if the rates are proportional to production, total hourly output remains nearly the same in both samples after controlling for marginal cost, demand, and other market conditions.

decisions of the firm in a multi-unit uniform auction (Kim (2022); Ryan, 2021; Reguant, 2014).[36] 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 bids – for each of its generating units. Therefore, the k^{th} step of a bid submitted for firm i's unit j in the auction held at hour h of day t is $\mathrm{b}_{ijkht} =< b_{ijkht}, q_{ijkht} >$. Given the market clearing price P_{ht}, the (ex-post) profit function of firm i in the hourly auction (ht) is shown below:

$$\pi_{iht}(\mathrm{b}_{iht}, \mathbf{b}_{-iht}) = P_{ht}(\mathrm{b}_{iht}, \mathbf{b}_{-iht}) \left(Q_{iht}(P_{ht}(\mathrm{b}_{iht}, \mathbf{b}_{-iht})) - \nu_{iht}\right) - \sum_{j=1}^{J_i} C_{ijt}(\, q_{ijht}(P_{ht}(\mathrm{b}_{iht}, \mathbf{b}_{-iht}))\,) \quad (5)$$

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., $P_{ht}(\mathrm{b}_{iht}, \mathbf{b}_{-iht})$, 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 $Q_{iht}(P_{ht}(\mathrm{b}_{iht}, \mathbf{b}_{-iht}))$ and $q_{ijht}(P_{ht}(\mathrm{b}_{iht}, \mathbf{b}_{-iht}))$, respectively. It is generally asuumed in the literature 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., $C'_{ijt}(q_{ijt}) = mc_{ijt} + \epsilon_{ijkht}$.[37]

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 $\widetilde{\mathbf{b}}_{-it}$:

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

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.[38] 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

[36] 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.

[37] 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 the online Appendix A.

[38] 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 the online Appendix B.

marginal unit of auction ht, the necessary first-order condition with respect to the price bid b_{ijkht} is shown in equation (6).

$$\mathbb{E}_{-it}\left[\frac{\partial P_{ht}}{\partial b_{ijkht}}\left[\left(Q_{iht}(P_{ht})-\nu_{iht}\right)+\left(b_{ijkht}-C'_{ijt}\right)\frac{\partial RD_{iht}}{\partial P_{ht}}\right]\right]=0 \tag{6}$$

Rearranging Equation (6) gives the following expression, shown in equation (7), which is similar to a general expression of a firm's markup. Although the expression contains the price bid b_{ijkht} instead of the market price P_{ht}, the necessary condition of each firm applies to firms in an ex ante manner where the firm anticipates its bid b_{ijkht} to be a market clearing price. The condition shows that 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.[39]

$$b_{ijkht}-mc_{ijt}=-\frac{\mathbb{E}_{-it}[\frac{\partial P_{ht}}{\partial b_{ijkht}}\left(Q_{iht}-\nu_{iht}\right)]}{\mathbb{E}_{-it}[\frac{\partial P_{ht}}{\partial b_{ijkht}}\,\partial RD_{iht}/\partial P_{ht}]} \tag{7}$$

The bid markup is, therefore, a function of expected quantity and the slope of the firm's residual demand, both of which are dependent on others' bids, $\widetilde{\mathbf{b}}_{-it}$. Residual demand is aggregate demand excluding the supply by other competitors. If we denote the supply of firm i as $S_{ith}(P_{ht})$, then;

$$D_{ht}(P_{ht})+\varepsilon_{th}=\sum_{i=1}^{N}S_{it}(P_{ht})$$

must hold in equilibrium, and how much the firm i can supply and whether or not firm can adjust the market price P_{ht} through its bid adjustment depends on others' strategies.

From Equation (7) which guides the bidding decision of firms, we know that the bid markup is determined based on firm i's ex ante belief about the distribution of competitors' bids. Therefore, any differences in $b_{ijk,th}$ or $b_{ijk,th}-mc_{ij,th}$ across samples that arise despite having the same $mc_{ij,th}$ and market fundamentals may result from the difference in the distribution of bids $\mathbf{b}_{-it}$ that determines the expectation terms, $E_{-it}(\dot{)}$. Therefore, estimating the distribution of bids implied by firms' bidding decisions would identify the role of different strategy sets in causing the asymmetry in price responses.

5.1 Ex-ante expectation and ex-post realizations

As a preliminary check before estimating beliefs, I computed the bid markup using the *ex post* optimal bid – what would have been optimal if the firm had known ex ante uncertain information about $\mathbf{b}_{-it}$, following Doraszelski et al. (2018). Specifically, I calculate the bid markup using equation (7), substituting realized competitors bids $\mathbf{b}^*_{-it}$, which firms do not observe at the time

[39]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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Sub Sample: by Firm Type					
		med	large	Heavybase	Gaslarge	Gas/oil mix	Other Mix
		$\mathbf{1}(\Delta\text{bidmarkup})$					
Pre-Increase							
Peak_h	0.038	-0.074^{**}	0.063^{**}	-0.071^{**}	0.098^{***}	-0.024	0.056^{*}
	(0.037)	(0.027)	(0.025)	(0.029)	(0.033)	(0.020)	(0.032)
constant	0.265^{***}	0.257^{***}	0.253^{***}	0.171^{***}	0.282^{***}	0.150^{***}	0.227^{***}
	(0.048)	(0.030)	(0.020)	(0.034)	(0.022)	(0.022)	(0.032)
Post-Increase							
Peak_h	-0.003	0.001	-0.004	0.003	0.008	-0.003	0.037
	(0.022)	(0.021)	(0.017)	(0.023)	(0.019)	(0.020)	(0.033)
constant	0.268^{***}	0.111^{***}	0.292^{***}	0.073^{***}	0.291^{***}	0.116^{***}	0.323^{***}
	(0.025)	(0.017)	(0.017)	(0.016)	(0.018)	(0.020)	(0.037)
Hour FE	x	x	x	x	x	x	x
Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
N (Pre-Increase)	15,074	2,588	12,370	2,150	7,807	1,734	3,251
N (Post-Increase)	15,979	2,752	13,129	2,458	9,198	1,208	3,013

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors for regression (1) are clustered at the day (t) and firm (i) level, and standards errors for the subsample regressions (2)-(5) are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Generating units with positive marginal probability (ex post) included in the sample. Demand variable (demeaned within each firm group and sample, unit is MWh) is also specified in the regression but not reported.

Table 13: Probability of occurence of ex-post, ex-ante bidmarkup difference

of bidding. Thus, the ex post bid markup serves as an upper bound on the value of information acquisition (Doraszelski et al., 2018). [40]

The ex post bid markup, $\text{bidmarkup}^{*}_{ith}$, differs from the observed bid markup, $[b_{ijkht} - mc_{ijt}]^{obs}$. The difference reflects how firms' expected bid distributions deviate from the perfect information case, on average.[41] I examine the sign of this markup difference to assess whether firms perceived residual demand as more inelastic or elastic relative to the ex post bid distribution. A positive difference suggests the firms expected weaker competition – implying relatively inelastic residual demand – and the negative is for the opposite. Comparing markup differences across the Pre-Increase and Post-Increase samples allows us to assess whether firms' belief sets differ, using the ex post optimal level as a reference. More details are in Appendix A.3.2.

Table 13 presents the probability of a positive bid markup difference, analyzed separately for the pre- and post-increase samples. Using the dependent variable $\mathbf{1}(\Delta\text{bidmarkup}_{ith})$, this regression

[40] Since firms correctly observe the bid distribution, this calculation assumes no uncertainty. Computation details are provided in Appendix A.3.2.

[41] Since firms maximize ex ante expected profits, their actual bids may not be ex post optimal. The difference between ex ante and ex post implied bid markups, often called ex post regret, serves as an upper bound on markup adjustments due to information acquisition (Doraszelski et al., 2018; Hortaçsu and Puller, 2008).

captures the likelihood of a positive bidmarkup difference and how it varies between peak and off-peak hours.[42] I estimate this separately for the pre- and post-increase samples to explore cross-hour patterns within each sample.

While the overall estimates are nearly identical between samples (column 1) differences emerge across firm types. When grouped by size (columns 2-3), medium-sized firms show a lower probability of a positive difference in peak hours in the pre-increase sample, suggesting they perceived stronger competition in peak hours. On the other hand, large firms exhibit a higher probability, implying they perceived residual demand more inelastic in peak hours. However, these patterns disappear in the post-increase sample. Columns (4)-(7) report results by firm characteristics. In the pre-increase sample, Gas Large and Other Mixed firms have larger coefficients for peak hours, indicating they perceived more inelastic demand in peak hours – consistent with their typical bidding patterns. Conversely, heavy base firms show lower coefficients, suggesting they perceived to have faced more elastic residual demand in peak hours, likely due to owning fewer strategic peak-hour assets. In the post-increase sample, these distinct peak vs. off-peak patterns disappear across all groups, with no significant differences in occurence probabilities. This aligns with findings from the bidding pattern analysis, suggesting that firms' average perceptions of competitors' bid distributions (residual demand) become more evened out across hours in the post-increase period.

5.2 Estimation of beliefs about the competitors' bids

Now, we examine the change in firms' beliefs by estimating the ex-ante bid distribution that rationalizes the observed bid markups. The analysis of ex post bids in the earlier section suggests that changes in ex ante beliefs may explain the change in bidding patterns as well as market outcomes in the post-increase sample. Estimating the ex ante belief distribution of competitors' bids, which rationalizes these differences in bidding behavior, allows us to confirm that a cost-decreasing environment creates a different strategic setting than in the pre-increase sample. Additionally, this estimation helps verify changes in location and dispersion of the belief distribution, which can be linked to uncertainty over strategies.

I do this in the context of BNE, imposing less restrictive assumption on the equilibrium of the post-increase sample, and compute the bid distribution that fits the residual demand slope the best, which approximates the ex ante belief of close competitors' bids ($\mathbf{b}^e_{-it}$) that satisfies the best response of each firm. While we do not rule out the possibility of this outcome being generated from an equilibrium different than BNE, the post-increase sample outcomes could be one of the equilibrium points among multiple equilibria which is possible in our setting due to having distribution of beliefs. If so, this can be analyzed within BNE framework, only with a different belief set, and we do not necessarily have to treat this outcome as a disequilibrium or out-of-path equilibrium and try to explain this outside of the standard nash equilibrium framework.

[42] A linear probability model is preferrable here since the main indendent variable is a binary indicator, making probit and logit estimations less suitable.

Selection of a Competitor Set The analysis relies heavily on not parameterizing the set of potential competitors, instead use the information observed from the other day that shows the greatest resemblance with the candidate day (t, h). Although strategic uncertainty involves uncertainty regarding which firms the firm would compete against, I treat this piece of information as being fairly predictable.[43] I select similar day-hour $((\bar{t}, \bar{h})$ market among the pre-increase day sample, implicitly assuming that firms form belief based on the past day in which the conditions of the market is most similar to the market it is facing in time (t, h). Similar day of sample $(t, h) \in$ Post Increase is selected from the pre-increase sample days, and the similar day of sample $(t, h) \in$ Pre-Increase is also selected within the pre-increase sample, but only from days prior to the target day and hour (t, h) (i.e., $\bar{t} \leq t$). Markets with similar charateristics as the candidate day (t, h) market are selected based on the closeness of the daily gas prices, daily demand, hour, real time demand, and daytime.[44]

The selection of close competitors of each candidate market (t, h) is done as follows. For the chosen similar day-hour market $(\bar{t}, \bar{h})$ of the pre-increase sample, I generate each firm i's residual demand curve $RD_{i\bar{t}\bar{h}}$ using the ex post bids of the market $(\bar{t}, \bar{h})$. I then selected the close competing units m of firm i, denoted as $u_{m,ith} = \{f, j, k\}$ $(m = 1, \ldots, M,\ f \neq i)$, which is a combination of firm (f)-generator(j)-step(k) that are closely located around the ex-post equilibrium point of the residual demand curve $RD_{i\bar{t}\bar{h}}$. Since the smallest unit of bidding is the 'step', I treat each $\{f, j, k\}$ as an independent unit when selecting the close competitors. I select $M = 5$ number of close competing units of firm i for the candidate market (t, h) in the analysis.

Table 14 shows the competing units summarized by their firm type. In summarizing I grouped firm i into four types, using the same category as for the firms of competing units. Overall, the Gaslarge firm types most frequently appear as competitors of most type of firms. Table 15, which is a summary by peak and off-peak hours, shows that the relative share of Gaslarge type competitors is lower in the peak hours than in the off-peak hours, and increasingly more of mixed type firms (both gas/oil and base/gas) become competitors during peak hours, indicating that firms are slightly more likely to face the gaslarge firm type as a competitor in the off-peak hours.

	Competing Firm Type (share)			
Firm Type	Heavy Base	Gas Large	Gas/Oil Mix	Base/Gas Mix
Heavy Base	0.08	0.49	0.17	0.11
Gas Large	0.12	0.43	0.18	0.11
Oil/Gas Mix	0.12	0.48	0.14	0.11
Base/Gas Mix	0.12	0.48	0.17	0.07
Total	0.11	0.47	0.16	0.10

Table 14: Competitor Firm Type Share: Total

[43] Unless competing firms set price bids that are unusually higher or lower than the normally chosen levels, the set of competitors are fairly stable across days, which I summarize later.

[44] Depending on the order of priority given to these criteria, we get different sets of similar days. I put gas price level as the first criterion for selecting similar days. Prices are more of equilibrium outcome so I did not prioritize this value when selecting similar days.

Firm Type	Competing Firm Type (share)			
	Heavy Base	Gas Large	Gas/Oil Mix	Base/Gas Mix
	Off-Peak Hours			
Heavy Base	0.08	0.55	0.14	0.08
Gas Large	0.12	0.48	0.14	0.08
Oil/Gas Mix	0.11	0.54	0.11	0.08
Base/Gas Mix	0.11	0.54	0.13	0.05
Total	0.11	0.53	0.13	0.08
	Peak Hours			
Heavy Base	0.08	0.46	0.19	0.12
Gas Large	0.13	0.40	0.19	0.12
Oil/Gas Mix	0.12	0.45	0.16	0.12
Base/Gas Mix	0.12	0.45	0.19	0.09
Total	0.12	0.44	0.18	0.12

Table 15: Competitor Firm Type Share: Off-Peak and Peak Hours

5.3 Estimation method

I employ a simulated method of moments estimation leveraging rich set of hourly-daily bidding data and a measure of marginal cost. Based on the first-order condition of optimal bidding, the condition shown in equation (7), I construct the moment condition where expected difference between the observed and simulated markups is equal to zero. Since the moment contains expected values taken over competitors' ex-ante uncertain bids, we must approximate the expectation term via simulation, which makes this a simulated method of moments estimation (Pakes and Pollard, 1989).

The goal is to estimate parameters of the belief distribution of competitors' bids that rationalize firm i's optimal bids, from the perspective of firm i that is potentially marginal unit in the candidate day t hour h market of the post-increase sample. Belief distribution of each competing unit m is parameterized as a log-normal distribution, with logged bid values follow a normal distribution $N(\mu_m, \sigma_m)$, which are to be estimated. The belief distribution can be assigned at the unit level, regardless of their ownership.[45] To reduce the computational burden, I assume there is no correlation between competitors' bid belief distributions. This assumption is reasonable as indenpendency of bids are an assumption commonly imposed in the private value auction setting. Furthermore, as only one generating unit of a firm is included in the set of competitors for each market (t, h), correlation of bids among multiple units owned by the same firm is not a major concern. Lognormal distribution is often used as a statistical model for bids in the literature (Cantillon and Pesendorfer (2006)). The specification is further supported from visualization of bids data, shown in Figure A4 in the Appendix, where the log transformed bids (price bids) of a firm's generating unit are distributed close to a normal form.

While non-parametric techniques are often used in the literature to approximate the expected distribution of bids, they require a large number of similar-day data points (e.g., Guerre, Perrigne

[45] While the bidding strategy may be correlated for step bids that belong to a common owner, usually a single step bid appears as a competitor of firm i for the given (t, h) market.

and Vuong, 2000; Hortaçsu and McAdams (2010)). This approach is not feasible given the limited size of the post-increase sample, which makes it difficult to find sufficient number of similar days of the post-increase sample days. Therefore, I employ a parameteric approach.

In each market (t, h), firm i faces a set of competing units, $u_{m,ith} = \{f, j, k\}$, where competitors indexed by $m = 1, \ldots, M$. The estimation relies on fixing the set of competing units to those appear in data, as described in the previous subsection. Given M number of selected competitors of firm i for the market (t, h), the price bids of competitors of firm i is, $\mathbf{b}_{-it} = \{b_1, b_2, \ldots, b_M\}$ with corresponding quantity bids, $\{q_1, q_2, \ldots, q_M\}$. Throughout the analysis, we fix the quantity bids to the levels observed in (t, h) market data, as participants do not adjust quantity bids when bidding, rather changes prices bids.

The uncertainty about competitors' strategies (bidding) implies that each firm i forms a distribution of $\mathbf{b}_{-it}$. That is, the distribution of $\mathbf{b}_{-it}$ for $s = 1, \ldots, S$ is:

$$\begin{bmatrix} \mathbf{b}^1_{-it} \\ \mathbf{b}^2_{-it} \\ \vdots \\ \mathbf{b}^S_{-it} \end{bmatrix} = \begin{bmatrix} b^1_1, b^1_2, \ldots, b^1_M \\ b^2_1, b^2_2, \ldots, b^2_M \\ \vdots \\ b^S_1, b^S_2, \ldots, b^S_M \end{bmatrix} \tag{8}$$

Assuming no correlation across bids, I let each competitor bid, b_m, to follow a log normal distribution, $ln(b_m) \sim N_m(\mu_m, \sigma^2_m)$. This means that firm i expects the bid of competitor m to be drawn from a distribution, which arises due to being uncertain of others' strategy. The more dispersed the distribution is – higher σ_m – bigger the uncertainty, in general. By modeling each argument of $\mathbf{b}_{-ith}$ to have a distribution, the $\mathbf{b}_{-ith}$ also has a distribution (multivariate normal with no covariance across arguments).[46]

Then, the bid vector of competitors generated from the s^{th} draw from each $ln(b_m)$ distribution is:

$$\tilde{\mathbf{b}}^s_{-ith} = [\exp(\mu_1 + \sigma_1 Z^s_1), \ldots, \exp(\mu_m + \sigma_m Z^s_m), \ldots, \exp(\mu_M + \sigma_M Z^s_M)].$$

where $\mathbf{Z}^s = \{Z^s_1, \ldots, Z^s_M\}$ is drawn from a standard normal distribution. Randomly drawing $\mathbf{Z}^s$ and generating $\tilde{\mathbf{b}}^s_{-it}$ gives one realization of $\{b^s_m\}$ for $m = 1, \ldots, M$, where competitor m's bid drawn from the parameterized log normal distribution with parameter (μ_m, σ_m).

For each $\tilde{\mathbf{b}}^s_{-ith}$ generated from s^{th} draw from the bids' distribution, I compute the bid markup implied by the first-order condition of profit maximization, using the condition shown in equation (7) which is conditioned on firm i believing its marginal unit to set the ex-post market price. Specifically, bids $< b^s_m, q_m >$ are aligned in an increasing order of its price bid value b^s_m, while fixing the quantity bids to the observed level. I then compute the slope of firm i's residual demand curve RD'^s_{ith} and total generation quantity Q^s_{ith} conditioned on its marginal bid setting the price

[46] This condition may be violated if more than one bids are drawn from the same firm.

ex post (i.e., $p_{th} = b_{ith}$, where b_{ith} is observed from data):[47]

$$RD'(\tilde{\mathbf{b}}^s_{-ith}; p_{th} = b_{ith}), \quad Q_{ith}(\tilde{\mathbf{b}}^s_{-ith}; p_{th} = b_{ith})$$

This process is done separately for each simulation draw s, for a total of S number of draws, $\{\mathbf{Z}^1, \ldots, \mathbf{Z}^S\}$, from which the bid distribution $\{\tilde{\mathbf{b}}^1_{-ith}, \ldots, \tilde{\mathbf{b}}^S_{-ith}\}$ is generated. Given the distribution, the bid markup of firm i in (t, h) market is computed as follows:

$$\text{bid markup}^{sim}_{ith} = \frac{E_{-it}[Q_{ith}(\tilde{\mathbf{b}}^s_{-ith}; p_{th} = b_{ith})]}{E_{-it}[RD'(\tilde{\mathbf{b}}^s_{-ith}; p_{th} = b_{ith})]} \tag{9}$$

where the expectation terms are approximated as follows:[48]

$$E_{-it}\big[RD'(\tilde{\mathbf{b}}_{-ith})\big] = \int_0^\infty \ldots \int_0^\infty RD'(\tilde{\mathbf{b}}_{-ith})\ \phi_1 \ldots \phi_M\ db_1 \ldots db_M \approx \frac{1}{S}\sum_{s=1}^{S} RD'(\tilde{\mathbf{b}}^s_{-ith})$$

and,

$$E_{-it}\big[Q_{ith}(\tilde{\mathbf{b}}_{-ith})\big] = \int_0^\infty \ldots \int_0^\infty Q_{ith}(\tilde{\mathbf{b}}_{-ith})\ \phi_1 \ldots \phi_M\ db_1 \ldots db_M \approx \frac{1}{S}\sum_{s=1}^{S} Q_{ith}(\tilde{\mathbf{b}}^s_{-ith})$$

, where $\dot{\phi_m}()$ denotes the belief distribution of bid b_m.

Estimation The moment condition used for estimation is the difference between the simulated bid markup shown in Equation (9) and the observed bid markup of firm i in (t, h) market, denoted as bid markup$^{obs}_{ith}$. The sample mean of the difference averaged across days ($t = 1, \ldots, T$) for a given hour h is:

$$\bar{g}^h_{i,T}(\theta_i) = \frac{1}{T}\sum_{t=1}^{T}\big[\text{bid markup}^{sim}_{ith}(\theta_i) - \text{ bid markup}^{obs}_{ith}\big]$$

where $g^h_{i,t}(\theta_i = [\text{bid markup}^{sim}_{ith}(\theta_i) - \text{ bid markup}^{obs}_{ith}]$ is averaged across days to form $\bar{g}^h_{i,T}$.

I estimate the parameters of the belief distributions for a subset of competitors, denoted as $u_{l,ith} = \{f, j, k\}$ (where $l = 1, \ldots, L$, and $f \neq i$), that most frequently appear as firm i's competitors throughout the day (t) and hour (h) sample. A different set of estimable competitor sets are selected among the most frequent competitors, where I select $L_{\text{off-peak}} = 4$ and $L_{\text{peak}} = 5$ number of competitors for off-peak and peak hours, respectively.

[47] Note that RD' is computed by fitting the logged values of price bid points ($ln(b_{m,th})$) and quantity bids ($q_{m,th}$) using a linear specification. The linear curve offers the best fit since we restrict the marginal competitors to a small number, average of five units, which makes the slope to be local. Also, to ensure that marginal bid of firm i is close to the ex-post equilibrium price, I restrict the (t, h) of firm i to those markets in which the marginal bid of firm i is within a close range (± \$5/MWh) of the ex-post equilibrium price.

[48] Since we are taking an average similarly as Monte Carlo, each realization s receives an equal weight. Therefore, there is no need to compute the weight when taking average, and the sample average gives an unbiased estimate of an expected value.

While each (t, h) market has M selected competitors (units) for each firm i, denoted as $U_{ith} = \{u_{1,ith}, \ldots, u_{M,ith}\}$ for $t = 1, \ldots, T$ and $h = \{h_1, \ldots, h_H\}$, only a fixed set of competitors, $U_i = \{u_{1,i}, \ldots, u_{l,i}, \ldots, u_{L,i}\}$, appearing most frequently across the $T \times H$ market sample, is parameterized and estimated for each firm i. For competitors whose bids are not parameterized, I use bid data from a similar market of th market (e.g., (t_{sim}, h_{sim})), implicitly assuming that firm i's beliefs about these unparameterized firms are known with certainty (and degenerate at their ex-post bids).[49]

Therefore, if the distributions of L competitors are parameterized, the parameter set for firm i is given by $\theta_i = \{\mu_1, \ldots, \mu_L, \sigma_1, \ldots, \sigma_L\}$, resulting in a total of $2L$ parameters to be estimated for each firm i. I estimate parameters that minimize the difference between the simulated and observed bid markups. The moment conditions and objective functions are as follows:

$$\bar{g}_{i,T}(\theta_i) = \begin{bmatrix} \bar{g}_{i,T}^{h_1}(\theta_i) \\ \bar{g}_{i,T}^{h_2}(\theta_i) \\ \vdots \\ \bar{g}_{i,T}^{h_H}(\theta_i) \end{bmatrix}$$

and,

$$\hat{\theta}_i = \underset{\theta_i}{\operatorname{argmin}} \;\; \bar{g}_{i,T}(\theta_i)' \, W_T \, \bar{g}_{i,T}(\theta_i)$$

where W_T is chosen as an identity matrix.

I estimate θ_i for the same set of competitors separately for the pre-increase and post-increase samples. Within each sample, I further divide the hours into off-peak (from 11 pm to 8 am) and peak (9 am to 10 pm) groups, estimating parameters seperately for each group. Therefore, four sets of parameters are estimated across the four different samples: $t \in \{\text{Pre-increase}, \text{Post-increase}\}$ and $h \in \{\text{off peak}, \text{peak}\}$, thereby estimating $\{\theta_{i,pre}, \theta_{i,post}\}_{h \in \text{offpeak}}$ and $\{\theta_{i,pre}, \theta_{i,post}\}_{h \in \text{peak}}$.

I use $S = 500$ draws to construct the simulated expectation terms in bid markup$_{ith}^{sim}$, which enters the sample moment condition. As the dimension of the moment vector corresponds to the number of hours (H) in which the bids of parameterized competitors exist in markets, the total number of estimable parameters from this moment condition does not exceed H. Note that H and the number of days (T) vary across firms and samples, as they depend on the number of markets in which the parameterized competitors appear.

Identification Several assumptions we make enables identification of parameters. First, we restrict the number of competitors that would be drawn from parameterized distributions. This is to satisfy the order condition, where the number of parameters must not exceed the total number

[49] To elaborate, suppose four units, $\{u_{a,i}, u_{b,i}, u_{c,i}, u_{d,i}\}$, are selected for estimation, but they do not always appear as competitors in every (t, h) market. For example, in the ($t = 10$, $h = 12$) market, firm i may face competitors $U_{i,(10,12)} = \{u_{1,ith}, \ldots, u_{2,ith}, u_{a,i}, u_{4,ith}, u_{c,i}\}$, with corresponding bids $\{b_{1,ith}, \ldots, b_{2,ith}, b_{a,i}, b_{4,ith}, b_{c,i}\}$. In this case, only two of the parameterized units ($u_{a,i}$ and $u_{c,i}$) appear as competitor in this market, thus the parameter of b_a and b_c (e.g., $\{\mu_a, \mu_c; \sigma_a, \sigma_c\}$) are relevant. For competitors that are not parameterized, I use their observed bids instead. Since different markets contain different combinations of parameterized and non-parmeterized bids, I leverage this variation to identify the parameters.

of hours that appear in the sample. Therefore, for the peak-hour sample estimation, I estimate distribution parameter (μ, σ) of total $L_{peak} = 7$ competitors, i.e. $U^i_{\text{peak}} = \{u^i_1, \ldots, u^i_{L_{\text{peak}}}\}$, and total $L_{\text{off-peak}} = 5$ number of competitors for the off-peak hour sample, i.e. $U^i_{\text{off-peak}} = \{u^i_1, \ldots, u^i_{L_{\text{off-peak}}}\}$. Since each distribution has two parameters, the total number of parameters to be estimated becomes 14, and 10, respectively. For those non-parameterized competitors, we assume that there is no uncertainty in firm i's belief; being decentralized around the observed bids. To incorporate the sense of ex-ante nature, we use the bids of a similar day of our target day-hour (t, h).

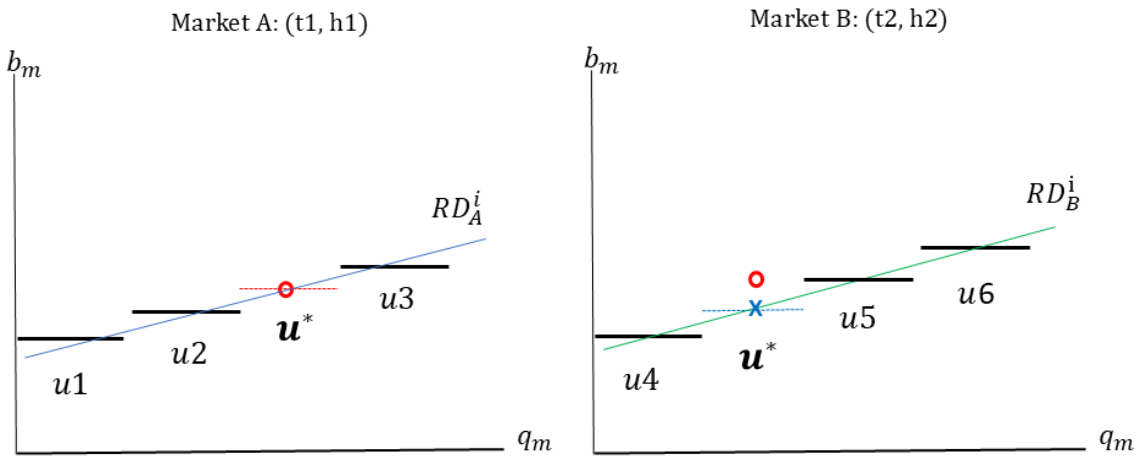
Second, we assume that firm i's belief distribution for the parameterized competing unit, $u^i_l = \{f, g, k\}$, is the same throughout the sample, i.e. same over time and hour. This assumption leverages the fact that days within the sample are homogeneous in terms of fundamentals such as marginal cost, and as long as the cost and demand are the same, the expectation of competitors' bids should not be significantly different within the sample. To ensure the homogeneity in beliefs, we dvided samples into a more homogenized ones, which are pre-increase/off-peak, pre-increase/peak, post-increase/off-peak, post-increase/peak, and estimate parameters separately within the sample which are assumed to be fixed within the sample.

Third, we assume that the set of close competitors a firm confronts in (t, h) market mimic those of a similar day in the past. Instead of using the ex-post close competitors of the target day, we construct a residual demand for the similar day of the candidate day and extract the list of close competitors. This mimics the firm's belief formation process where they use past market's competitor information when making bidding decisions.

Identification relies on observing variations in bid markups of firm i, along with the variation in the set of competitors $U^i_{th} = \{u^i_{1,th}, \ldots, u^i_{m,th}, \ldots, u^i_{M,th}\}$ and their bid values (b_{mth}) varying across day(t) and hour(h) markets in which the parmeterized competitor u^i_l appears as a close competitor.

The variation in bid markups of firm i reveals variation in the expected residual demand slopes, which is an averaged outcome of the belief about competitors' expected bids. Identifying the mean (i.e., μ) and dispersion (i.e., σ) of the belief distribution of u^i_l requires observing variations in bid markups of firm i across the markets where the same competitor u^i_l appears as a competitor of firm i as part of U^i_{th}, but with a different set of competitors other than u^i_l. Having a random variation in the set of competitors other than the parameterized unit, $u^i_{m,th}$ $(m \neq l)$ where $u^i_l \in U^i_{th}$ is particularly important.

We use a simple example to explain the idenfication strategy. Figure 7 shows the bids (price and quantity bids) of firm i's (reversed) residual demand curve, where the bids of competing units of firm i are aligned to match the slope of the residual demand RD^i that is implied by the observed bid markup of firm i in the (t, h) market. Among these competitors, unit u^* is the only competing unit whose belief about its bids is drawn from the parameterized distribution, and we assume expected bids of other units are equal to the observed bids of a similar day. Panels (a) and (b) presents competitor sets and residual demands of different day-hour markets, which we denote market A (of day $t1$ and hour $h1$) and market B (of day $t2$ and $h2$). Note that residual demand observed is the expected value taking into account the distribution of competitors' bids (ex ante beliefs about



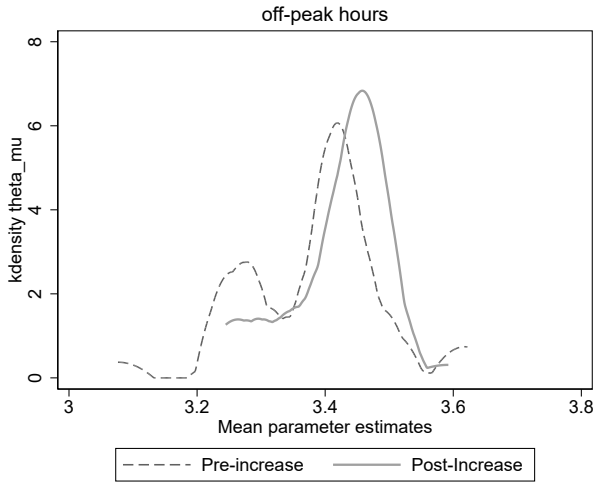
(a) Market A: (t1,h1) observation

(b) Market B: (t2,h2) observation

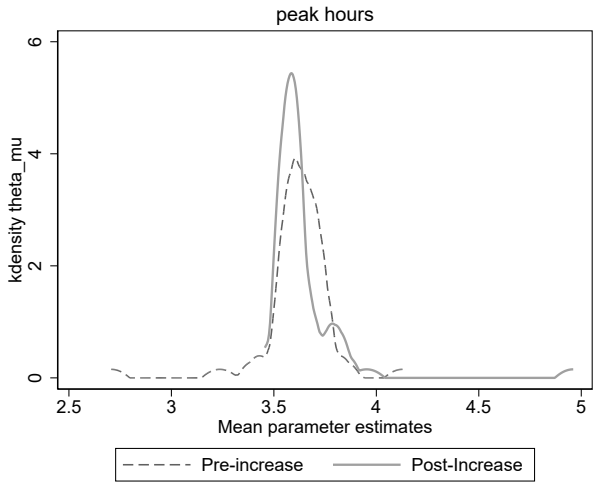
Figure 7: Identification: Variation in Residual Demand and Competitors

competitors' bids) from the perspective of firm i.

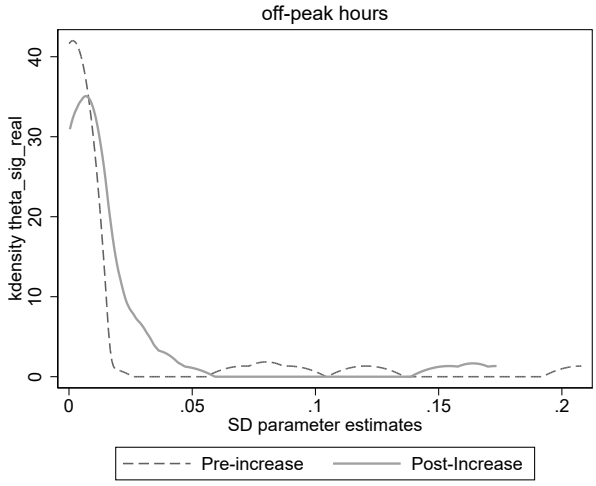
Suppose we observe competitor set $U_A^i = \{u_1, u_2, u_3, u^*\}$ and firm i's residual demand RD_A^i from $(t1, h1)$ market. We can pin down the average value of the unit u^*'s price bid value b_A^* (shown in red circle "$\circ$" in panel (a)) by finding the value that fits the slope of the residual demand (RD_A^i). In other words, the ordering of units and the average value of the parameterized unit's average bid would minimize the difference between the slope of the residual demand implied by the observed bid markup and that constructed from the model. If the mean of the distribution, μ, is the only parameter of our interest, we can identify μ from this single market observation. However, our interest is in estimating mean and variance of the belief distribution (μ, σ), and uniquely identifying each of the parameters from a single observation is not feasible as there could be different combinations of μ and σ pairs that could yield the same expected value pinned down by the observed residual demand (bid markup). For instance, the identified value from a single market observation can be rationalized by distributions with parameters $(\mu, 0)$ or (μ, σ). This problem can be resolved if we observe another market outcome in which firm i faces a different competitor set in which the parameterized unit u^* still appears as one of the competitors, as shown in Panel (b) of Table 7. Given this competitor set now containing units $U_B^i = \{u_4, u_5, u_6, u^*\}$, and with different values of their bids along with firm i's bid markup (residual demand), we can find the average value, b_B^* (shown in cross mark in panel (b)), that fits the residual demand RD_B^i the best, thereby minimizing the slope difference between the observed and model-constructued residual demands. Intuitively, if the distribution with parameter $(\mu,\ 0)$ that rationalizes market A's moment condition would imply a point (red-colored marker "$\circ$") in panel (b) instead of the actual fitted value shown in a blue-colored cross marker ("$\times$"), this second observation identifies the existence of the σ parameter as well as its size. Observing multiple markets in which u^* appears as a competitor, but with different set of other competing units, allows us to uniquely identify μ and σ parameters.



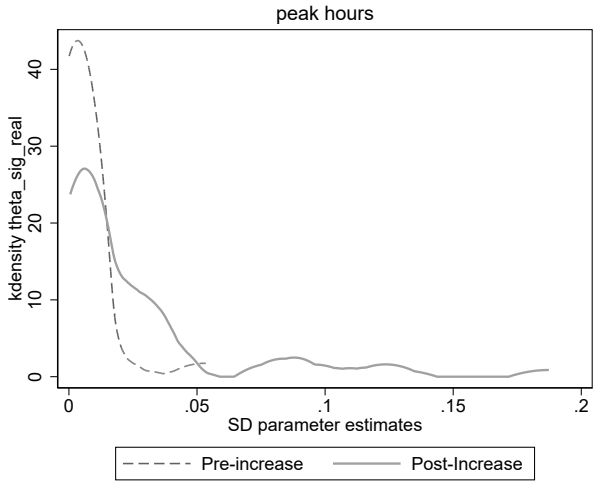
(a) μ parameter estimates: off-peak hours



(b) μ parameter estimates: peak hours



(c) σ parameter estimates: off-peak hours



(d) σ parameter estimates: peak hours

Figure 8: Mean and Standard Deviation Estimates: Pre- and Post-Increase Samples

Therefore, conditioned on assumptions demonstrated before, a random variations in the set of competitors of firm i other than the parameterized units, their bid values, and firm i's optimal bid markups across hours and days would identify the parameters of the belief distribution of the parameterized firm-unit-step.[50] The electricity market offers this random variation because hourly demand levels vary exogenously determined outside of the wholesale market and such exogenous variation in hourly demand levels creates variation in the competitor sets as well. Moreover, even though hourly market environment varies due to demand changes, it is possible to find a marginal unit of firm i and its optimal bid markup in any demand level because firm i can utilize multiple units for strategic bidding.

[50]Note that a variation across h, given the t is more important than the variation across t within a fixed h.

5.4 Results

I estimate separate set of parameters for each firm i, $\theta_i = \{\mu_1, \ldots, \mu_L; \sigma_1, \ldots, \sigma_L\}$, for the pre- and post-increase samples, and for off-peak and peak hours. Figure 8 presents the distribution of estimates $\hat{\theta}_{i,\text{Pre}}$ and $\hat{\theta}_{i,\text{Post}}$, plotted separately for off-peak and peak hours.

As shown in panels (a) and (b), the mean parameter estimates of firms' belief distributions are slightly larger in the post-increase sample than in the pre-increase sample for both off-peak and peak hours, indicated by a rightward shift in the parameter density plots. In the off-peak hour sample, the increase in μ primarily occurs at the lower end, while the overall range remains similar. In the peak hours, μ parameter distribution is shifted to the right, covering a higher value range than in the pre-increase sample.

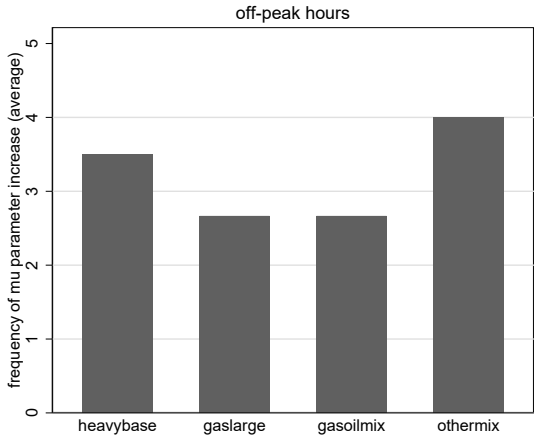
A more distinct difference is observed in the standard deviation parameter estimates, shown in panels (c) and (d). The distribution of $\hat{\sigma}$ in the pre-increase sample is more concentrated around lower values in both off-peak and peak hours, indicating little dispersion in firms' belief distributions. However, in the post-increase sample, the estimates are more spread out toward higher values, particularly during peak hours. This suggests that belief distributions in peak hours are more dispersed in the post-increase sample than in the pre-increase sample.

Figure 9 shows the frequency of the direction changes in μ and σ, summarized by firm i's type. The direction of parameter changes between the pre- and post-increase samples is measured and categorized by firm group. For the off-peak hour sample, the parameters of all four firm types exhibit increases, as shown in panels (a) and (d). In peak hours, the increase in $\hat{\mu}$ is most pronounced for gas large firms, while the $\hat{\sigma}$ increases more distinctly for gas large and base/gas mix (or other mix) firms.

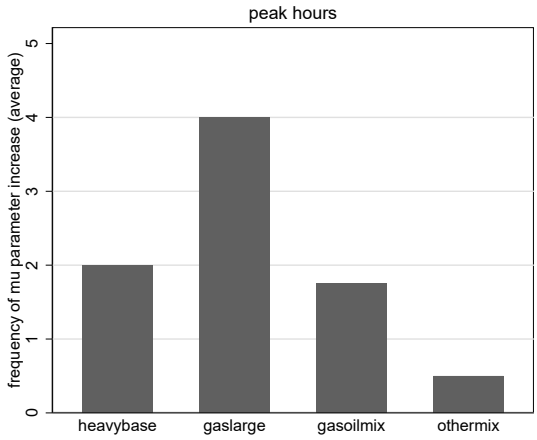
Overall, we observe considerable changes in both parameters not only in the peak-hour but also in off-peak hours, with the most noticeable change occuring in the σ parameter in peak hours, though the estimated magnitude of standard deviations is not too large in general.

6 Conclusion

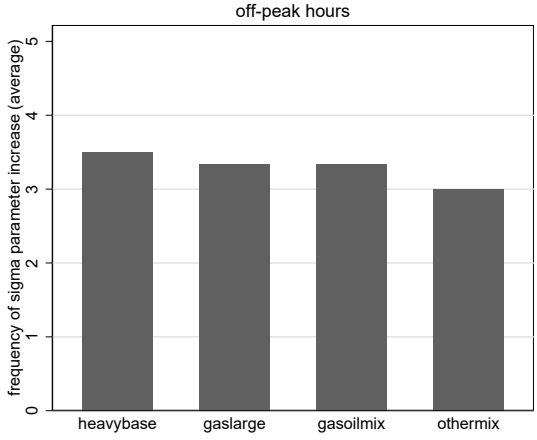
Asymmetric price responses to cost changes, particularly the sluggish adjustment to cost decreases, are a widespread phenomenon documented across many industries and product markets. Despite its prevalence, understanding the source of such asymmetry has been challenging. In this paper, I find evidence of asymmetric price responses to cost changes in a unique empirical setting where all previously studied sources of asymmetry are absent, suggesting that this asymmetry may result from firms adopting different strategies. Specifically, the cost-decreasing situation leaves firms with a broader strategy set than the cost-increasing case, a claim supported by the analysis of bidding strategies and the structural estimation of underlying beliefs that rationalize ex-post bids. The findings of this paper contribute to the literature on asymmetric pass-through by demonstrating that asymmetric responses to cost decreases can arise solely from strategic considerations when uncertainty over competitors' strategies increases.



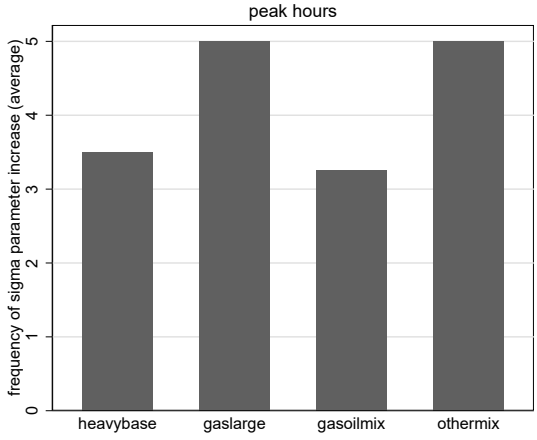
(a) Frequency of increase in μ: Off-peak Hours



(b) Frequency of increase in μ: Peak Hours



(c) Frequency of increase in σ: Off-peak Hours



(d) Frequency of increase in σ: Peak Hours

Figure 9: Firms with increased μ and σ in the post-increase samples: by bidder firm type

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A Appendix

A.1 Incorporating the cost-increase period information

The cost-increase (shock) sample serves solely as an exogenous event for dividing the data. While firms' optimization is not dynamic, their strategies post-shock may depend on the nature of the cost-increase period. For instance, firms' expected strategies in the post-increase sample could differ based on whether a cost decrease follows a higher or lower starting point.

To assess whether price analysis results are influenced by the characteristics of the cost-increase event, I examine the magnitude and timing of cost declines. The first variable, gp_{t-1}, represents the gas price on the last day of the cost-increase sample – before the price returned to the post-increase range at time t. However, in some cases, the gas price declined gradually rather than immediately. For example, as seen in Inc/Dec Event #1 (Figure 2), the price dropped over multiple rounds before stabilizing at the lowest level. I define gp_{lastInc} as the gas price on the last day before this decline began and introduce an indicator, Im_dec, to capture whether the return to the lowest level was immediate.[51] Since these variables are undefined for days before the cost-increase event, I assign them a value of zero in the pre-increase sample. The Post-Increase$t$ indicator is excluded from this analysis, as these variables vary only within the Post-Increase$t = 1$ sample.

Table A1 shows that a higher gp_{lastInc} significantly increases post-increase prices, suggesting that a cost decline from a higher level leads to higher subsequent prices. However, $gp_{\text{t-1}}$ has no significant effect, likely due to limited variation within the sample and the dissipation of effects across multiple rounds of cost declines. The coefficient on Im_dec indicates that post-increase prices are higher when the cost decrease is immediate rather than spread over several rounds.

	(1)	(2)	(3)	(4)	(5)
			P_{th}		
gp_{t-1}	0.172			-0.00711	
	(0.242)			(0.265)	
gp_{lastInc}		0.108***			0.120***
		(0.0369)			(0.0373)
Im_dec			1.467**	1.474***	1.592***
			(0.580)	(0.564)	(0.603)
N	2,833	2,833	2,833	2,833	2,833

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A1: Price regression: with characteristics of the cost-increase period

A.2 Robustness Checks

I have conducted several additional robustness checks to verify that the significant price difference between the samples is meaningful.

[51] Pre-increase sample days are assigned $Im_dec = 0$, assuming a sufficiently long gap since the last cost increase.

A.2.1 Refining the pre- and post-increase sample divisions

In addition to the division of pre- and post-increase samples explained in Section 3.2.1, I also tried a slightly different division of the pre- and post-increase samples by further dividing the post-increase sample days into pre- and post-shock samples. Previously, all base-level gas price days between two cost-increase events were grouped into the post-increase sample. In this new categorization, I reclassified n days before the next cost increase event, previously part of the post-increase sample, into the pre-increase sample. For example, if a post-increase sample block consists of K days followed by another cost increase event, the previous categorization assigned all K days to the post-increase sample. However, since a few days before another cost increase event can be viewed as a pre-increase sample, I tried assigning the first n days as the post-increase sample and the next $K - n$ days as the pre-increase sample of the subsequent cost increase event.

This alternative categorization presents challenges. The number of base-level gas price days in each post-increase block (under the original categorization) averages only 5 days. Given this relatively short length of the post-increase sample block, the underlying structure of these days within the original block may not differ significantly. Additionally, determining the valid n cannot be done arbitrarily. I discuss how I determine the size of n in the dynamic price pattern and event-study section 3.3.3. Despite these challenges, I find qualitatively similar results when trying $n = 2, 3, 4$, with even stronger results under this alternative categorization, which I discussed in Section 3.3.3. The results for the $n = 4$ case is presented in Table A4.

A.2.2 Price regression only with the pre-increase sample

First, I generated a hypothetical post-increase sample selected from the days in the pre-increase sample. For each day in the original post-increase sample, I selected a most similar day having the closest features regarding the following market variables; daily maximum demand, daily average demand, peak hour maximum and average demand, and gas price levels. Since gas price levels are similar across pre- and post-increase samples, the priority is given to the similarity in demand levels – the maximum and average demand of the peak hours – when selecting similar days. In this way, I have generated counterparts of post-increase sample days among the pre-increase days, and assigned a hypothetical post-increase sample indicator, Hy. Post-Increase$_t$, to this sample. Then, the original post-increase sample was dropped in the analysis.[52]

Table A2 shows the results of this first robustness check, where the specifications are the same as in Table 2. Despite choosing the most similar days of the original post-increase sample among the pre-increase sample, none of the estimates are significantly different from zero. This suggests that the original post-increase sample has some structurally different strategic environment that is not present in the pre-increase sample.

[52]Note that several days in the post-increase sample can have the same pre-increase sample day as a best counterpart. Therefore, the correspondence between the hypothetical and the original variables is not one-to-one, and the total sample size of the hypothetical sample is smaller than that of the original sample.

	(1) P_{th}^{da}	(2) log (P_{th}^{da})	(3) P_{th}^{da}
Hy. Post-Increase$_t$	0.376	0.010	0.524
	(0.59)	(0.015)	(0.533)
Peak$_h$			0.824
			(0.541)
Hy. Post-Increase$_t$ × Peak			−0.189
			(0.625)
Hour FE	✓	✓	x
Year FE	✓	✓	✓
N	1,236	1,236	1,236

Notes: Standard errors in parentheses. * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$. Newey-west standard errors with lag $m = 17$. Using only when the non-dual natural gas units are marginal.

Table A2: Robustness Check: using hypothetical post-increase variable

A.2.3 Price regression with subsample: post-increase days with lower-gas prices

The original inbetween sample's average gas prices are slightly higher on average, by about \$0.2/MMBtu. However, this small discrepancy in average gas prices between the samples is a natural variation as data points cannot be identical. Since the upside volatility feature of the gas prices enables clear identification of pre- and post-shock samples, which ensures our categorization of post-increase and pre-increase samples is valid.

While this small discrepancy does not violate our assumption nor weakens the credibility of our analysis, it is worth examining whether the effect we find in the main analysis is critically affected by the average gas prices of the sample. Thus, I construct a subsample of the original post-increase sample by selecting days with a lower average gas price that is lower than the pre-increase sample. I selected subsample, in an ad-hoc way, to make the new subsample to have a lower average gas prices. Now, the average gas prices are \$4.29/MMBtu for the pre-increase sample and \$4.17/MMBtu for this post-increase sample.[53]

If the positive coefficient we found is driven by higher gas prices, we should not find a positive and significant $\hat{\beta}$ coefficient when running the regression on this subsample. However, Table A3 shows that the coefficient is still positive and significant for the post-increase sample, despite the gas prices being lower on average and also the demand being lower in the newly selected post-increase sample. This suggests that the result we find is not simply driven by small discrepancies in the market-level characeteristics (variables). Nevertheless, please note that the selection of sub sample is not executed in a sophisticated way, thus the result should be interpreted with caution.

[53] Because I had to select days to shift the average gas prices, the demand becomes more unbalanced between the samples, though not significantly. That is, the new sample has an average demand of 12,801 MWh, lower than that of not-inbetween sample's 13,255 MWh.

	(1) P_{th}^{da}	(2) log (P_{th}^{da})	(3) P_{th}^{da}
Post-Increase$_{t,h}$	1.440**	0.030*	1.309**
	(0.584)	(0.016)	(0.553)
Peak			0.313
			(0.403)
Post-Increase$_{t,h}$ × Peak			0.256
			(0.510)
Hour FE	✓	✓	x
Year FE	✓	✓	✓
N	1,774	1,774	1,774

Notes: Standard errors in parentheses. * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$. Newey-west standard errors with lag $m = 17$. Using only when the non-dual natural gas units are marginal.

Table A3: Robustness Check: sub sample of the post-increase sample

A.2.4 Price regression: Placebo Analysis

As an extension of the robustness check in Appendix A.2.2, I conducted a placebo analysis to check whether our estimate $\hat{\beta}$ can also be estimated if we choose any time block sample within the pre-increase sample. I created a hypothetical indicator of post-increase sample by randomly selecting days randomly drawn from the pre-increase sample – days that were originally assigned Post-Increase$_t = 1$ – but keeping the number of observations assigned to this hypothetical indicator variable the same as in the original categorization.

Then, I run the same regression as in 1 using the hypothetica indicator, excluding the original post-increase sample from the analysis.[54] I repeated this random drawing process for $S = 200$ times. In about 90% of the cases among a total of 200 placebo regressions, the estimate β is insignificant at the 5% level. Among the significant estimates, the average value of estimates is about $\bar{\beta}_s = 0.75$ with minimum -0.92 and maximum 1.48. The fact that we cannot reject $\beta_s = 0$ in this simulation indicates that our original post-increase variable has a significant explanatory power compared to a randomly drawn dummy. Thus we can conclude that our post-increase sample has some feature/element that has some explanatory power against the prices.

A.2.5 Pass-through rate estimation

I also estimated a variant of Equation 1 which attempts to capture the difference in the pass-through rates between the pre- and post-increase samples. The problem of this specification is that the marginal cost value does not vary much within the sample, which is not an ideal setting to estimate the pass-through rate that exploits variation in marginal costs. Nevertheless, as a robustness check, and also since the specification shown in Equation 10 is more commonly used

[54] Excluding the the original post-increase sample for this placebo analysis is necessary because we have already verified that the original post-increase sample has significantly higher prices than in pre-increase, thus including the original sample may always lead to a significantly negative estimate of β.

form of specification in the literature, I estimate ρ_1.

$$P_{th} = \beta_0 + \rho_0\, mc_{th} + \ \rho_1 mc_{th}\, D\ + \gamma X_{th} + \mu_h + \eta_t + \varepsilon_{th} \tag{10}$$

Results are shown in Table A6. As can be seen from the estimates, the rate is estimated to be too low, though the pass-through is higher in the post-increase sample.

Second, I implemented a standard pass-through specification by estimating the rate of price increase relative to the marginal cost change, separately for the sample where cost is increasing and decreasing, using the cost-increase sample days instead of using samples before and after the cost-increase event. Table A7 presents the results where I find that the estimated rate is lower for the cost-decreasing sample than in the cost-increasing sample, though the sample size is small and this estimation is still prone to problems discussed in Section 2.1.

A.3 Model

A.3.1 Smoothed supply bid, residual demand, and weight

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

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

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

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

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

Then the derivative of the residual demand curve is:

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

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

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

A.3.2 Ex-ante expectation and ex-post realizations

This section details the analysis presented in Section 5.1. I computed the bid markup using the *ex post* optimal bid, which would have been optimal if the firm had known information that were ex ante uncertain, such as $\mathbf{b}_{-it}$, similarly as in Doraszelski et al. (2018). Specifically, I generate the right hand side of the equation (7) using the distribution of firm i's competitors' bids obseved in data, $\mathbf{b}^*_{-it}$, and compute the bid markup using this distribution. These ex post realized bids of competitors are never observed at the time of bidding, thus the ex post bid markup offers an upper bound of what a firm can earn in terms of information acquisition (Doraszelski et al., 2018). As firms correctly observe others' bid distribution, there is no uncertainty over bids in this calculation, thus the $\mathbf{b}^*_{-iht}$ is fixed (and degenerated) to a single vector of observed bids of firm i's competitors and expectation term disappearing from the bid markup expression, as shown in equation (11).[55]

$$\text{bidmarkup}^*_i = [b_{ijkht} - mc_{ijt}]^* = -\frac{Q_{iht}(\mathbf{b}^*_{-iht}) - \nu_{iht}}{\partial RD_{iht}(\mathbf{b}^*_{-iht})/\partial P_{ht}} \tag{11}$$

I computed this measure separately for each firm i in the sample, only for its generating units j that are close to being marginal, and for each day (t) and hour (h). The ex-post bid markup measure, bidmarkup^*_i, differs from the actual bid markup calculated using the observe bid of firm i, $[b_{ijkht} - mc_{ijt}]^{obs}$, shown in equation (7), with the difference between these measures reflecting how the expected belief of firm i differs from the ex post optimal belief.

Therefore, I take a difference between the observed bid markup and the ex post optimal bid markup, shown in equation (12).

$$\Delta\text{bidmarkup}_i = [b_{ijkht} - mc_{ijt}]^{obs} - [b_{ijkht} - mc_{ijt}]^* \tag{12}$$

The sign of this bid markup difference indicates whether the expected residual demand based on firm i's expected belief about competitors' bids, denoted $\mathbf{b}^{ex}_{-iht}$, was relatively more inelastic or elastic than what is implied by the residual demand constructed from the ex post realized bid distribution, denoted $\mathbf{b}^*_{-iht}$. Therefore, a positive bid markup difference implies the following inequality:

$$\Delta\text{bidmarkup}_i > 0 \;\; \Rightarrow \;\; \frac{E_{it}[Q(\mathbf{b}^{ex}_{-it})]}{E_{-it}[RD'(\mathbf{b}^{ex}_{-it})]} > \frac{Q(\mathbf{b}^*_{-iht})}{RD'(\mathbf{b}^*_{-it})} \tag{13}$$

[55] Note that the probability, $\partial p/\partial b$ that enters equation (7) is canceled out in this ex-post realization case as the expectation term given the realization of ex-post bid distribution.

The inequality above indicates that below holds:

$$|E_{it}[RD'(\mathbf{b}^{ex}_{-it})]| < |RD'(\mathbf{b}^{*}_{-it})|$$

suggesting that the expected residual demand a firm i generated from the expected distribution of competitors' bids takes into account when forming the bid was more inelastic than the actual ex-post residual demand evaluated at the observed distribution. [56]

Therefore, the sign of this bid markup difference indicates something about the difference in the firm's ex ante perception about competitors' bidding (pricing) and the ex-post realized competition. Positive sign indicates that a firm was perceiving the competition from others to be less fierce and thinking it has advantage over others – relative inelastic residual demand. The negative sign, on the other hand, indicates a firm perceived the competition to be fierce – its residual demand being relatively elastic. We can check if the bid markup difference measures, especially the signs, differ between the Pre-Increase and Post-Increase samples, which allows us to check whether the belief sets of firms are different by sample, using ex post optimal level as a reference point.

[56] However, note that here we are assuming that the quantities, Q, do not differ significantly from having different beliefs. Even if so, the identification of the sign (i.e., relative inelasticity) still holds for the following reason. The equilibrium property indicates that if the firm expects its residual demand to be inelastic, meaning $|RD'|$ being smaller, the expected quantity (sales) will be bigger under that expected bid distribution. Therefore, if $|E_{-it}[RD'(\mathbf{b}^{ex}_{-it})]| < |RD'(\mathbf{b}^{*}_{-it})|$ holds then $E_{-it}[Q(\mathbf{b}^{ex}_{-it})] \geq Q(\mathbf{b}^{*}_{-it})$ will also hold, thus the inequality condition is not violated even when allowing Q to differ by distribution.

A.4 Tables and Figures

	$n = 4$	
	P_{th}	$\log(P_{th})$
Post-Increase$_t$	3.222^{***}	0.0754^{***}
	(0.436)	(0.0110)
Hour FE	✓	✓
Year FE	✓	✓
N	2,106	2,106

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Newey-west standard errors used. Used markets in which the non-dual natural gas units are marginal. n days within the original post-increase sample are grouped into the new post-increase sample and the remaining days are grouped as part of pre-increase sample of the subsequent cost increase event.

Table A4: Main regression: alternative sample division ($n = 4$)

	mean	med	min	max	s.d.	N
Block's maximum k	5.05	4	1	10	2.99	19

Notes: Each block within the phase 2 have multiple days which I indexed by k. The table shows the summary of the block-level maximum k.

Table A5: Summary statistics of maximum of block-level day index, k

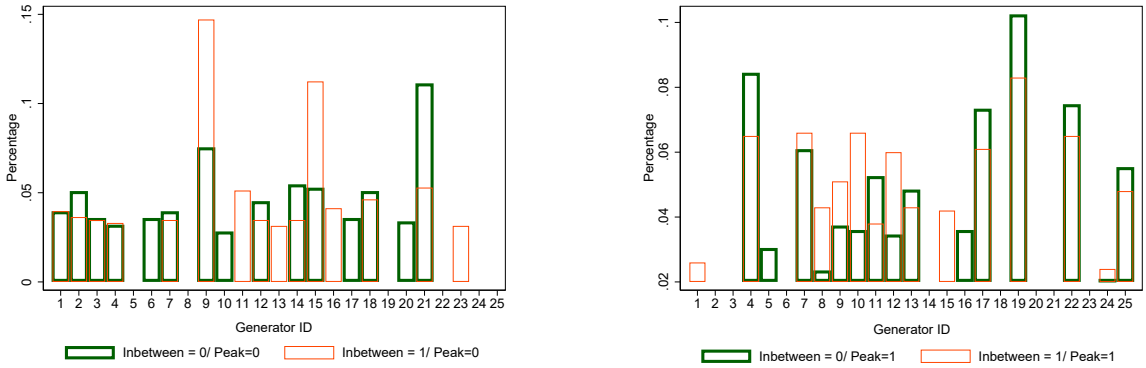
	(1)
	$P_{t,h}$
MC × Post-Increase	0.105^{**}
	(0.043)
Post-Increase	-1.102
	(1.721)
MC	0.105^{***}
	(0.034)
Hour FE	✓
Year FE	✓
N	2,833

Table A6: Pass-through difference: inbetween vs. not

	(1) $P_{t,h}$ (Inc)	(2) $P_{t,h}$ (Dec)
MC (implied cost)	1.096	0.997
	(0.069)	(0.025)
Month FE	✓	✓
Daytime FE	✓	✓
Hour FE	✓	✓
N	841	685

Notes: Standard errors in parentheses. Using only the sample when natural gas prices rise above the normal level (shock period). The sample consists of days when non-dual natural gas generating units are marginal. *Inc* sample includes days when natural gas price is in an increasing path and *Dec* sample includes days when the natural gas price is in a decreasing path. As in Kim (2022), the marginal cost estimated from the bids (implied marginal cost) is used for estimating the pass-through. Also, the marginal cost is instrumented with gas spot price.

Table A7: Pass-through: increasing and decreasing sample, IV regression



(a) Offpeak Hours (b) Peak Hours

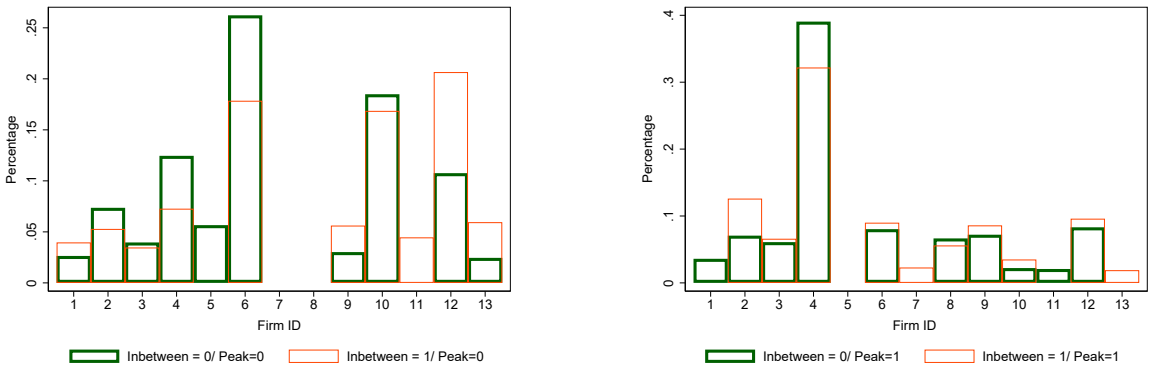
Notes: The graph shows the percentage of each unit's occurences as marginal power plant, taken separately by Pre-increase and Post-increase samples and Peak and Offpeak samples. Generation ID indicates an arbitrary index assigned to each generating unit.

Figure A1: Marginal Units: distribution by Pre- and Post-Increase and Peak/Offpeak

	(1)	(2)	(3)	(4)	(5)
	Full Sample	Sub Sample: by Firm Group			
		Group 1	Group 2	Group 3	Group 4
	$b_{i,th} - mc_{i,j}$	$b_{i,th} - mc_{i,j}$			
$\text{Inbetween}_{t,h}$	0.87^{**}	1.12^{*}	0.75^{**}	0.97^{**}	0.84^{**}
	(0.382)	(0.624)	(0.376)	(0.397)	(0.371)
constant	-26.3^{***}	-29.68^{***}	-15.6^{***}	-25.1^{***}	-53.0^{***}
	(1.486)	(2.266)	(1.339)	(1.269)	(1.854)
Hour FE	o	o	o	o	o
Year FE	o	o	o	o	o
Firm FE	o	o	o	o	o
N	62,299	2,683	15,902	16,470	27,246
R^2	0.613	0.558	0.710	0.677	0.534

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors for regression (1) are clustered at the day (t) and firm (i) level, and standards errors for the subsample regressions (2)-(5) are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Firm group is categorized based on the total capacity. Firm group 1 is the fringe suppliers operating a small scale single unit. Firm group 2 includes firms with total capacity less than 500MW and not fringe, firm group 3 includes firms with capacity between 500-1000 MW, and firm group 4 includes firms with total capacity above 1,000MW. The dependent variable $b_{i,th}$ is the firm-unit-day-hour level price bids that are close to being marginal (roughly ± \$5/MWh around the equilibrium price).

Table A8: Bid markup regression: bids close to marginal



(a) Offpeak Hours (b) Peak Hours

Notes: The graph shows the percentage of each firm's occurences as being a marignal price setter (by owning the marginal power plant), taken separately by Inbetween and Not-inbetween samples and Peak and Offpeak samples. Firm ID indicates an arbitrary index assigned to each firm.

Figure A2: Marginal Firms: distribution by Inbetween and Not-Inbetween and Peak/Offpeak

	(1)	(2)	(3)	(4)	(5)
	full Sample	Sub Sample: by Firm Group			
		Group 1	Group 2	Group 3	Group 4
	$b_{i,th} - mc_{i,j}$	$b_{i,th} - mc_{i,j}$			
$\text{Inbetween}_{t,h}$	0.49	0.62	0.58	0.47	0.54
	(0.345)	(0.682)	(0.372)	(0.343)	(0.360)
$\text{Peak}_{t,h}$	0.22	−0.33	0.34	−0.09	0.36
	(0.425)	(0.730)	(0.352)	(0.416)	(0.384)
$\text{Peak}_{t,h} \times \text{Inbetween}_{t,h}$	0.59	1.03	0.23	0.88*	0.50
	(0.369)	(0.836)	(0.357)	(0.462)	(0.365)
constant	−25.7***	−29.03***	−21.17***	−25.16***	−27.62***
	(1.383)	(1.753)	(1.19)	(1.009)	(0.839)
Hour FE	x	x	x	x	x
Year FE	o	o	o	o	o
Firm FE	o	o	o	o	o
N	62,299	2,683	15,900	16,470	27,246
R^2	0.611	0.552	0.708	0.673	0.530

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors for regression (1) are clustered at the day (t) and firm (i) level, and standards errors for the subsample regressions (2)-(5) are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Firm group is categorized based on the total capacity. Firm group 1 is the fringe suppliers operating a small scale single unit. Firm group 2 includes firms with total capacity less than 500MW and not fringe, firm group 3 includes firms with capacity between 500-1000 MW, and firm group 4 includes firms with total capacity above 1,000MW. The dependent variable $b_{i,th}$ is the firm-unit-day-hour level price bids that are close to being marginal (roughly ± \$5/MWh around the equilibrium price). If a unit has several step bids being marginal, I took an average of multiple-step bids within a unit. Peak hours is from 8AM to 10PM and the rest of the hours are grouped as off-peak.

Table A9: Bidmarkup regression: peak vs. offpeak, bids close to marginal

	(1)	(2)	(3)	(4)	(5)
	Full Sample	Sub Sample: by Firm Group			
		Group 1	Group 2	Group 3	Group 4
	$b_{i,th}$	$b_{i,th}$			
Inbetween$_{t,h}$	3.64^{***}	5.11^{***}	4.79^{***}	4.04^{***}	5.76^{***}
	(0.420)	(0.226)	(0.690)	(0.569)	(0.792)
constant	-5.08^{***}	-2.84	1.47	-1.24	2.43
	(1.741)	(1.675)	(2.789)	(2.321)	(1.679)
Hour FE	o	o	o	o	o
Year FE	o	o	o	o	o
Firm FE	o	x	x	x	x
N	67,243	4,570	20,933	16,289	25,515
R^2	0.783	0.753	0.709	0.738	0.732

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the day (t) and firm (i) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Firm group is categorized based on the total capacity. Firm group 1 is the fringe suppliers operating a small scale single unit. Firm group 2 includes firms with total capacity less than 500MW and not fringe, firm group 3 includes firms with capacity between 500-1000 MW, and firm group 4 includes firms with total capacity above 1,000MW. The dependent variable $b_{i,th}$ is the firm-unit-day-hour level price bids that are close to being marginal (roughly ± \$5/MWh around the equilibrium price). If a unit has several step bids being marginal, I took an average of multiple-step bids within a unit.

Table A10: (Before dropping gp below 3.9 sample) Bid regression: bids close to marginal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Sub Sample: by Firm Type					
		med	large	Heavybase	Gaslarge	Gas/oil mix	Other Mix
		$\mathbf{1}(\Delta\text{bidmarkup})$					
Post-Increase$_t$	11253.1^{**}	38169^{***}	18306^{*}	123986^{***}	33617^{**}	8389^{***}	9136
	(5615.3)	(7762)	(9661)	(22998)	(16360)	(2404)	(5567)
constant	130072^{***}	455103^{***}	97907^{***}	1412229^{***}	149946^{***}	19737^{***}	92943^{***}
	(356.2)	(7298)	(8601)	(20265)	(14818)	(2221)	(5050)
Hour FE	x	x	x	x	x	x	x
Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
N	7770	1690	1197	507	507	832	506

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the day (t) and firm (i) level. Dependent variable is the firm's daily profit (unit: \$).

Table A11: Daily Firm Profits: Pre- vs. Post-Increase Sample Comparison

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Sub Sample: by Firm Type					
		med	large	Heavybase	Gaslarge	Gas/oil mix	Other Mix
				$\mathbf{1}(\Delta\text{Profit}_{it})$			
Pre-Increase							
Peak_h	93.86	920.7^{**}	-164.0	1181.4	313.7	-195.3	-1385.0^{***}
	(191.2)	(369.9)	(500.7)	(816.3)	(784.3)	(176.6)	(369.2)
constant	6119.9^{***}	22341.2^{***}	3673.3^{***}	56725.0^{***}	5149.7^{***}	1347.3^{***}	4513.8^{***}
	(310.2)	(380.5)	(408.3)	(968.8)	(697.6)	(113.7)	(240.9)
Post-Increase							
Peak_h	-511.1^{***}	-704.3^{**}	-1449.8^{***}	-2708.6^{***}	1566.0^{***}	-474.6^{***}	-1852.5^{***}
	(158.8)	(312.6)	(401.6)	(760.9)	(574.7)	(137.0)	(282.5)
constant	7208.8^{***}	25514.3^{***}	5275.3^{***}	64595.7^{***}	7150.4^{***}	1942.3^{***}	5421.1^{***}
	(236.1)	(327.8)	(427.5)	(805.2)	(680.7)	(94.84)	(252.4)
Hour FE	x	x	x	x	x	x	x
Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
N (Pre-Increase)	50,182	10,111	7,955	4,020	3,887	3,877	3,323
N (Post-Increase)	55,186	11,708	8,969	4,551	4,466	4,325	3,835

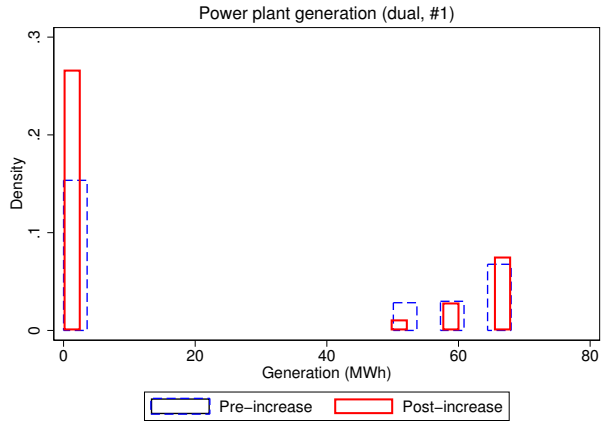
Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the day (t) and firm (i) level. Dependent variable is the firm's daily profit (unit: \$).

Table A12: Profit Pattern

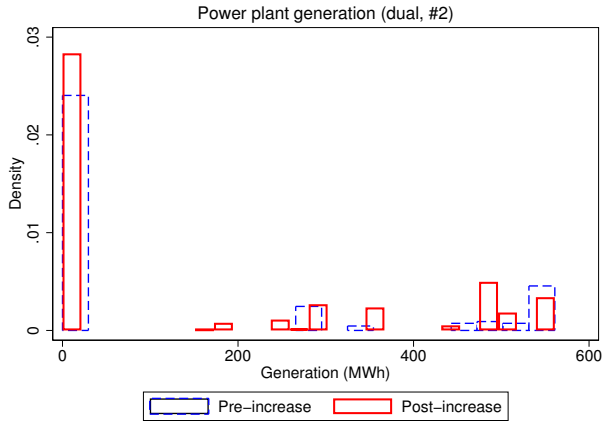
	(1)	(2)	(3)	(4)	(5)
	full Sample	Sub Sample: by Firm Group			
		Group 1	Group 2	Group 3	Group 4
	$b_{i,th}$	$b_{i,th}$			
$\text{Inbetween}_{t,h}$	3.05^{***}	4.18^{***}	4.01^{***}	3.69^{***}	4.97^{***}
	(0.375)	(0.210)	(0.743)	(0.544)	(0.744)
$\text{Peak}_{t,h}$	-0.07	-0.77^{***}	-0.85	0.48	-0.55
	(0.306)	(0.04)	(0.519)	(0.498)	(0.503)
$\text{Peak}_{t,h} \times \text{Inbetween}_{t,h}$	0.91^{***}	1.12^{**}	1.15^{**}	0.45	1.28^{***}
	(0.312)	(0.120)	(0.521)	(0.476)	(0.351)
constant	-4.43^{**}	-1.69	2.67	-1.03	3.19
	(1.725)	(1.419)	(2.296)	(2.465)	(1.718)
Hour FE	x	x	x	x	x
Year FE	o	o	o	o	o
Firm FE	o	x	x	x	x
N	67,243	4,570	20,933	16,289	25,515
R^2	0.781	0.744	0.706	0.727	0.729

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the day (t) and firm (i) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Firm group is categorized based on the total capacity. Firm group 1 is the fringe suppliers operating a small scale single unit. Firm group 2 includes firms with total capacity less than 500MW and not fringe, firm group 3 includes firms with capacity between 500-1000 MW, and firm group 4 includes firms with total capacity above 1,000MW. The dependent variable $b_{i,th}$ is the firm-unit-day-hour level price bids that are close to being marginal (roughly ± \$5/MWh around the equilibrium price). If a unit has several step bids being marginal, I took an average of multiple-step bids within a unit. Peak hours is from 8AM to 10PM and the rest of the hours are grouped as off-peak.

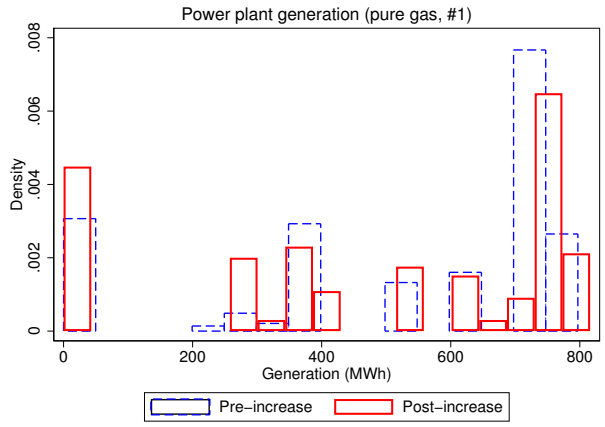
Table A13: (Before dropping gp below 3.9 sample) Bid regression: peak vs. offpeak, bids close to marginal



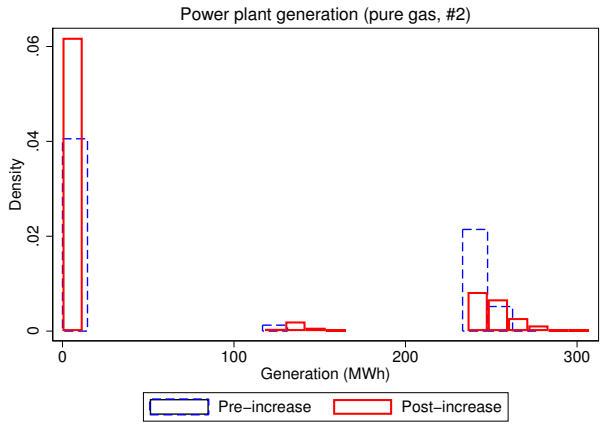
(a) Dual gas unit #1



(b) Dual gas unit #2

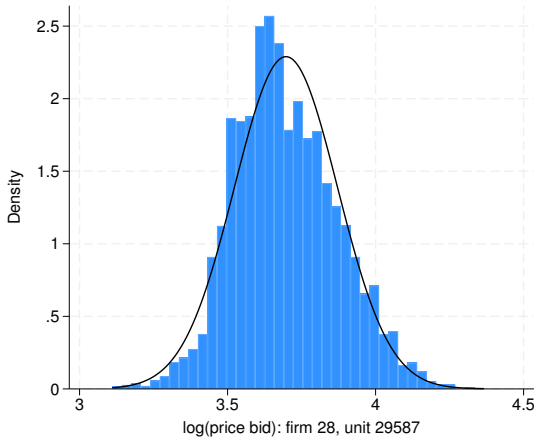


(c) Gas unit #1

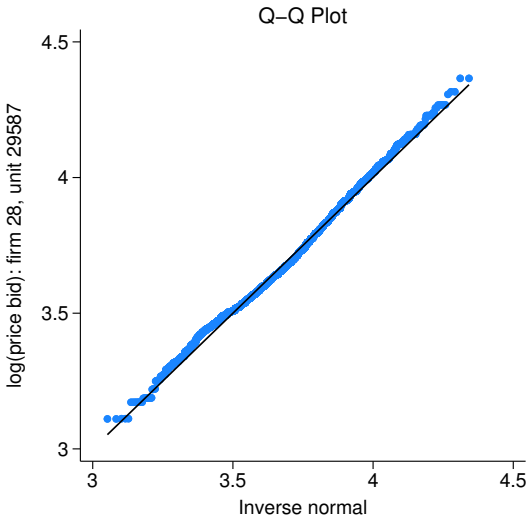


(d) Gas unit #2

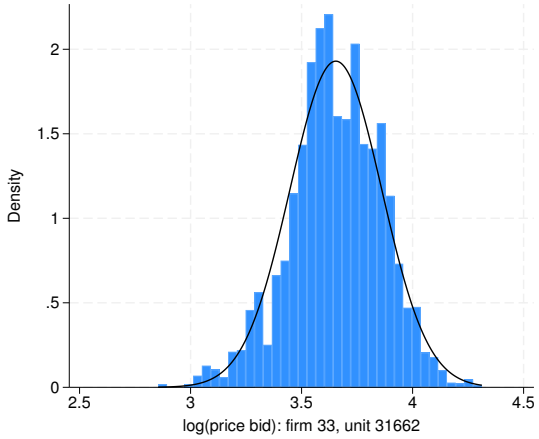
Figure A3: Histogram of generator-level quantity: pre-increase vs. post-increase



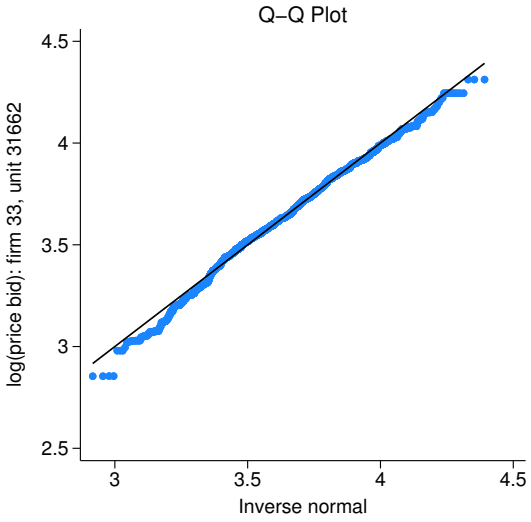
(a) Firm 28: distribution



(b) Firm 28: Q-Q plot



(c) Firm 33: distribution



(d) Firm 33: Q-Q plot

Figure A4: Log transformed Price Bids: single generating unit's of firm 28 and 33