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Abstract

The Regional Greenhouse Gas Initiative (RGGI), as the largest cap-and-trade system in the United States, conducts quarterly auctions to distribute emissions permits to firms. This study examines the behavior of firms and the performance of RGGI auctions from both theoretical and empirical perspectives. We begin by providing a theoretical model that offers insights regarding the optimal bidding behavior of firms participating in RGGI auctions. We then analyze data from 58 RGGI auctions to assess the relevant parameters, employing panel random effects and machine learning models. Our findings indicate that most significant policy changes within RGGI, such as the Cost Containment Reserve, positively impacted the auction clearing price. Furthermore, we identify critical parameters, including the number of bidders and the extent of their demand in the auction, demonstrating their influence on the auction clearing price. This paper offers valuable policy insights for all cap-and-trade systems that allocate permits through auctions, as it substantiates the efficacy of policies and the importance of specific parameters using data from an established market.

Keywords: Emissions permit; auctions; uniform-price; RGGI.

JEL Classification: D22; C5; Q5; D44.

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1 Introduction

Carbon neutrality represents a significant challenge of the current century. Governments worldwide have tackled the issue of reducing carbon emissions by implementing caps through cap-and-trade markets, such as Europe's EU-ETS, the US's Regional Greenhouse Gas Initiative, and California/Quebec's AB-32. A cap-and-trade market is a system that restricts the total quantity of pollutants that can be emitted, allowing firms to buy and sell allowances for those emissions. The primary objective of a cap-and-trade market is to decrease overall pollution levels by establishing a cap on emissions and fostering a market for companies to trade emission allowances. A well-implemented cap-and-trade market yields substantial socio-economic benefits. Furthermore, previous research demonstrates that an efficiently designed emissions market can accomplish the goal of emissions reduction at the lowest possible cost (Coase, 2013; Montgomery, 1972; Lopomo et al., 2011).

Marking a significant milestone in the control of greenhouse gases, the Regional Greenhouse Gas Initiative (RGGI) has emerged as a forerunner in the United States, implementing a market-based cap-and-trade program aimed at curbing carbon emissions.[1] The cooperative endeavor of RGGI, as depicted in Figure 1, involves twelve Northeastern and Mid-Atlantic states, united under the collective ambition of placing a cap on, and systematically diminishing, carbon dioxide emissions originating from the power sector.[2] The program has gained widespread recognition for its innovative approach to addressing climate change, setting a precedent for other states to follow. RGGI has brought substantial economic benefits to all participating states. For instance, an independent report issued by Analysis Group reveals that over its 12-year history, RGGI has driven a 46% reduction in carbon emissions, generated \$3.8 billion in allowance proceeds, and produced \$5.7 billion in net economic benefits.[3]

Through the establishment of a cap on carbon dioxide emissions, RGGI has created a market-based mechanism for reducing greenhouse gas emissions by initially allocating permits via uniform-price auctions. The effectiveness of such auctions in achieving the policy goals of reducing emissions and promoting energy efficiency depends on various factors, including the bidding behavior of firms and the design of auction parameters. Therefore, a theoretical and empirical study of auctions in RGGI is crucial to better understand the mechanisms behind the auction outcomes and to identify ways to improve the design of future auctions. By analyzing the bidding behavior of firms and testing the effectiveness of various auction parameters, such a study can provide important insights and policy recommendations for not only RGGI but also other cap-and-trade systems that use auctions to allocate permits.

This paper aims to investigate the auctions conducted by RGGI since the inception of the program. It examines the effects of changes in auction rules and parameters on auction outcomes, providing evidence of the effectiveness of various policies implemented by RGGI. Initially, we develop a theoretical model that offers insights into the behavior of polluting firms that bid in a

[1] The first major market-based cap-and-trade program in the United States was the Acid Rain Program, which was established by Title IV of the 1990 Clean Air Act Amendments. The program aimed to reduce sulfur dioxide (SO2) emissions, which were a major contributor to acid rain. The Acid Rain Program was successful in reducing SO2 emissions and laid the groundwork for subsequent cap-and-trade programs, such as RGGI.

[2] Note that in regions covered by RGGI, a cooperative effort has been undertaken to reduce carbon dioxide (CO2) emissions from the power sector. This initiative involves each participating state developing its own cap-and-invest program to cap and reduce emissions over time. The cap-and-invest program sets a cap on the total amount of CO2 emissions that are allowed in each state and requires power generators to hold permits, or allowances, equal to their emissions.

[3] The Economic Impacts of the Regional Greenhouse Gas Initiative on Ten Northeast and Mid-Atlantic States, White Paper, May 2023.

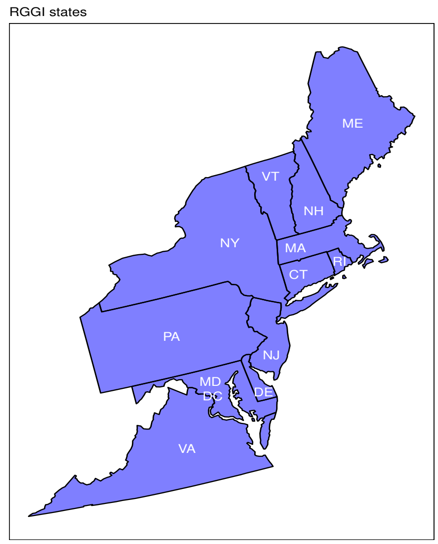


Figure 1: The map of articipating states in RGGI

uniform-price auction to acquire emissions permits. Our analysis also explores the implications of modifications made to RGGI auctions over time. Subsequently, we utilize data from RGGI auctions to empirically test the hypotheses posited by our theoretical model. This research stands among the few studies that employ both auction theory and empirical analysis to investigate auctions in a cap-and-trade market.

Thus, the contribution of this paper is twofold. First, we present theoretical results that analyze the bidding behavior of firms in RGGI's auctions, considering a setup that reflects real-world parameters in those auctions. Second, we provide empirical evidence based on available data regarding the effectiveness of the implemented changes in auction parameters. Our theoretical model contemplates a scenario where firms have private abatement costs and submit a schedule of bids in a uniform-price auction. We show that the Cost Containment Reserve (CCR)[4] would reduce the extent of untruthful bidding in the auction and increase the auction clearing price, *ceteris paribus*. Furthermore, we demonstrate that the scale of demand by bidders is a crucial parameter for the auction clearing price; with large-scale bidders, we anticipate a decline in the auction clearing price due to an increase in bidders' monopsony power.

Our empirical approach starts with the analysis of data structure as a fundamental step in both machine learning and conventional statistical models. Panel regression models, like other statistical models, are based on a mathematically proven theoretical foundation, but require certain assumptions, such as the random utility maximization theory, to be satisfied by the input data (Ben-Akiva et al., 1985). In contrast, popular machine-learning methods, including random forest which support vector machine and neural networks, are non-parametric and rely on computers to explore the data structure without a preconceived notion of what it should look like. This flexibility in modelling structures is useful but often neglected in the analysis of behavioral outputs such as elasticity. Policymakers require knowledge not only of the determinants of mode choice but also of their direction and magnitude of influence, and they often apply elasticities to inform policy. Therefore, to assess the credibility of machine learning in policy-choice modeling, it is necessary to evaluate its ability to generate reliable behavioral outputs. This study conducts such an analysis by comparing machine-learning models with classic panel regression models.

[4]Later, in Section 2, we delve into more detail regarding the CCR and its operation within RGGI auctions.

Therefore our study employs an empirical approach that encompasses both panel regression and machine learning models to analyze the distinct effects of auction parameters and policies of RGGI. We introduced the concept of concentration of large-scale bidders (LSB) and investigated its effect on the auction clearing price. Furthermore, we scrutinized the impact of diverse variables on the clearing price of auctions using two statistical and machine learning approaches.

Specifically, we initiated the investigation with a panel random effects model to assess the significance of critical parameters. Our findings indicate that the concentration of LSB has a direct effect on the clearing price, and as this ratio increases, the clearing price decreases. Additionally, the number of bidders has a positive effect on the clearing price. Moreover, both the Cost Containment Reserve (CCR) and Emission Containment Reserve (ECR) exhibit a significant effect on the clearing price, as expected, and are positively correlated with it. Finally, we extended our empirical analysis to machine learning analysis by employing the Random Forest and Gradient Boosted Trees (GB) algorithms to overcome the multicollinearity problem that might arise in a panel regression involving some variables. The results obtained from the Random Forest model suggest that the most significant variables that impact the clearing price are the trigger price, GDP, ECR, and CCR.

Another objective of this study is to assess the influence of GDP, gas price, the number of bidders, and trigger prices on the clearing price in carbon permit auctions. To achieve this goal, we provide arc elasticity analysis for the mentioned critical variables. Our results indicate that GDP significantly affects the clearing price as an exogenous variable, with a 1% increase in GDP leading to a 1.45% increase in the clearing price. Moreover, the results suggest that the number of bidders also significantly impacts the auction clearing price. Our analysis demonstrates that the behavioral examination of auction markets can offer valuable insights into the relationships between various auction attributes and carbon emissions permit policies. Overall, our study highlights the importance of bidding behavior of firms and the merit of integrating panel and machine learning approaches to gain a comprehensive understanding of the effects of different variables on auction outcomes.

This paper is structured as follows: Section 2 provides a detailed explanation of the literature review and background of the study. In Section 3, a theoretical study is presented, and three distinct propositions are discussed. Section 4 examines the RGGI auction data and introduces two new concepts, namely, large-scale bidders and concentration ratios. Section 5 presents the results obtained from the estimation of panel regression and machine learning approaches, followed by an elasticity analysis of the results. Finally, Section 6 provides concluding remarks.

2 Background and previous literature

Since the introduction of cap-and-trade markets there has been a debate regarding the initial allocation of emissions permits. Cramton and Kerr (2002) were one of the first to discuss the advantages of auctions for initially allocating licenses, as opposed to free allocations (also known as grandfathering). They argue that, when designed appropriately, auctions are more effective at allocating permits to firms that assign the highest value to them. Furthermore, auctions can generate revenue for regulators, which can potentially be utilized to offset the adverse social externalities of pollution. Consequently, auctions have become the most prominent and widely employed mechanism in nearly all cap-and-trade systems today.

The uniform-price auction is the most commonly used auction format in cap-and-trade markets due to its desirable features such as price discovery and simplicity of rules (Khezr and MacKenzie, 2018b). However, it is well-established in the literature that this type of auction does not result in truthful bidding, as bidders are incentivized to under-report their true values (Back and Zender, 1993; Ausubel et al., 2014; Khezr and Cumpston, 2022). This issue is referred to as demand reduction (Ausubel et al., 2014). Some studies propose alternative supply strategies as a means of reducing or eliminating demand reduction (Back and Zender, 2001; McAdams, 2007). For example, McAdams (2007) suggests that not committing to a fixed supply at the ex-ante level could decrease the likelihood of demand reduction.

RGGI commenced in 2008 with 10 participating states: Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, and Vermont. Later Virginia and Pennsylvania joined the program in 2020 and 2022, respectively. RGGI employs quarterly uniform-price auctions to allocate emissions permits to firms. From its inception in 2008 through the first quarter of 2023, RGGI has conducted 58 quarterly auctions and distributed billions of CO2 permits to firms in the US. Although all permits are initially allocated through auctions, firms are allowed to trade these permits in the secondary market to address demand uncertainty.

There have been several modifications to the RGGI auction rules since 2008 to accomplish various policy objectives. The first major change was the introduction of the CCR during the third compliance period, which began in January 2014. The CCR was devised to help regulate the cost of allowances in RGGI's quarterly auctions by making additional allowances available if the auction clearing price surpassed a predetermined price threshold. This price threshold is referred to as the trigger price, which was initially set at $4 in 2014 and has been adjusted over time to account for inflation and alterations to the program.

Another significant alteration to the RGGI auction was the introduction of the ECR, which stemmed from the 2017 program review and was implemented in 2021. According to the ECR rules, participating states withhold a portion of allowances from the auction if the clearing price falls below a specified threshold. The ECR aims to offer additional flexibility and control over emissions by ensuring that the market price of allowances remains sufficiently high to incentivize emission reductions.

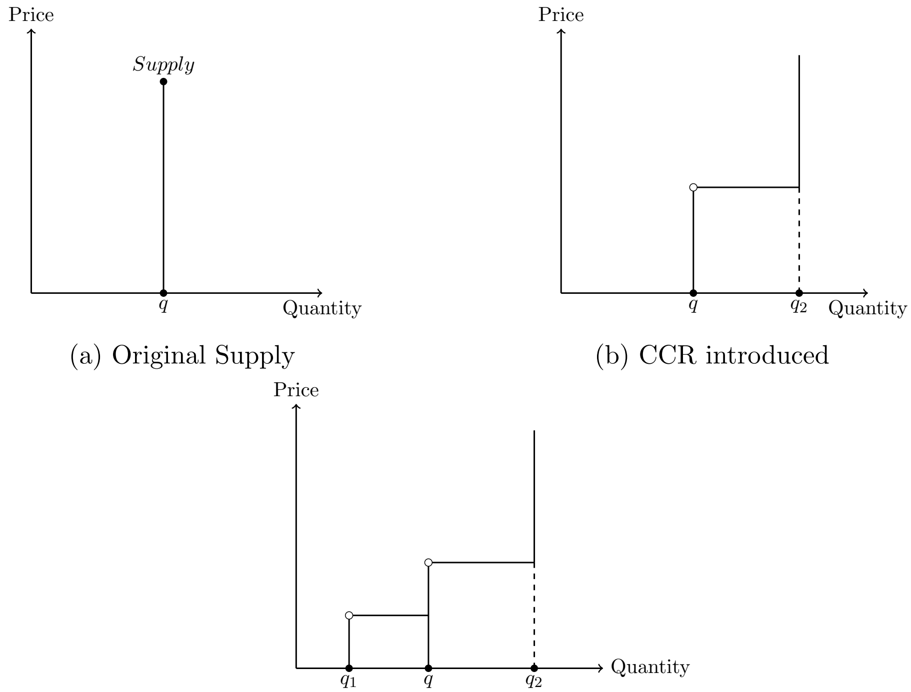
The uniform-price auction is a critical component of RGGI's permit allocation mechanism. Numerous studies investigate the performance of uniform-price auctions within the context of cap-and-trade markets (Kline and Menezes, 1999; Khezr and MacKenzie, 2018b,a). Each of these papers makes distinct modeling assumptions concerning firms' values for permits and abatement costs. For example, Khezr and MacKenzie (2018b) presents a common value setup and attempts to replicate the CCR within a uniform-price auction. They demonstrate that the CCR cannot lower the auction clearing price, as in any new equilibrium of the auction with increased supply, the price is at least as high as the price with vertical supply.[5] Therefore, CCR would probably increase the auction clearing price and the cost of permits. Our theoretical model differs from the one in Khezr and MacKenzie (2018b) as in our model we assume firms have private information regarding their abatement costs.

To our knowledge, there is no paper that empirically investigates the auction parameters and the bidding behavior in RGGI.[6] However, there is a class of literature that study the uniform-price auction empirically.[7] For instance, Kastl (2011) studies the uniform-price auction's performance using a data from Czech Treasury auctions. Kastl (2011) suggests the uniform-price auction works well both in terms of revenue generation and efficient allocation of units. He suggests bidding in the uniform-price auction is closely related to oligopolistic behavior. Given that most of the

[5]The issue of cost containment has been identified as a challenge for regulatory bodies in cap-and-trade markets. Traditionally, approaches used to address this issue involve implementing price caps on permits or establishing reserve supply mechanisms to regulate price fluctuations (Murray et al., 2009; Fell et al., 2012; Kollenberg and Taschini, 2016).

[6]There are papers that empirically investigate other aspects of RGGI. For instance, see Fell and Maniloff (2018) and Chan and Morrow (2019).

[7]See Khezr and Cumpston (2022) for a comprehensive review of these studies.



(a) Original Supply

(b) CCR introduced

(c) ECR introduced

Figure 2: Three different supply schedules implemented by RGGI

papers that empirically study uniform-price auctions use data from treasury auctions, and there are clear differences between treasury and emissions permit markets, there is an important gap in the literature regarding the empirical analysis of uniform-price auctions employed in cap-and-trade markets.

Finally there are several papers that use laboratory experiments to study uniform-price auctions that are employed in cap-and-trade markets (Shobe et al., 2010, 2014; Holt and Shobe, 2016; Perkis et al., 2016; Friesen et al., 2022). For example, Friesen et al. (2022) demonstrates the existence of focal points where dual allowances are employed in a uniform-price auction. Their model, which attempts to mirror both cost and emission containment reserves in RGGI, incorporates a supply curve featuring two steps. They show that the two trigger prices responsible for releasing the reserves play a pivotal role in determining the final auction clearing price.

3 Theoretical model

A regulator would like to allocate Q number of emission permits to $n > 1$ firms indexed by $I = 1, ..., n$. Each firm $i \in I$ has a non-decreasing and continuous abatement cost function $A(c_i)$. We assume parameter c_i is private information of firm i. However, it is common knowledge that c_i is distributed according to some distribution function $F(.)$ on $[\underline{c}, \bar{c}]$, which is continuous and differentiable with density $f < \infty$. Moreover, suppose each firm has a capacity equal to λ_i, which indicates the maximum number of permits they demand with no abatement cost. To avoid trivial cases, we assume $\sum_i \lambda_i > Q$.

The regulator uses a standard uniform-price auction to allocate the Q permits to firms. In the auction, each bidder i submits a schedule of sealed bids for up to λ_i units. Denote $\mathbf{b_i}$ as the bid schedules submitted by firm i, which determines the maximum price they are willing to pay for each permit. Without loss of generality, we assume bid schedules for each bidder are in non-increasing order. The regulator aggregates all the bids, sorting them from the highest to the lowest, and clears the market by allocating all the quantity Q. The price for all the units is set at the intersection of aggregate demand and supply, where the bids on the left-hand side of the intersection are winning bids. If there are multiple bids with the same price at quantity Q (the demand is flat), then the price is determined at the flat with a random marginal allocation rule.

To be able to define each firm's demand for permits we need to further specify the marginal abatement cost (MAC) function. In particular, suppose the MAC function of each firm i is defined as follows:

$$MAC(c_i, e) = c_i - \alpha e \tag{1}$$

where c_i is firm i's private information as described above, e is the level of emissions, and α is a positive constant.

We use Equation (1) to derive each firm's demand for permits. First, note that the level of emissions that makes the MAC equal to zero is equal to the firm's capacity λ_i, that is, $\lambda_i = \frac{c_i}{\alpha}$. Further, note that at any price $p < c_i$, the quantity demanded for permits is given by:

$$q_i = \frac{c_i}{\alpha} - \frac{1}{\alpha} p \tag{2}$$

Therefore, each bidder i who wins x_i units in the auction at a clearing price equal to p receives the following surplus.

$$\pi_i = \int_0^{x_i} (c_i - \alpha x) dx - p x_i \tag{3}$$

Next, we are going to investigate the bidding strategies of firms in the auction. Firms submit demand schedules to the auctioneer. The auctioneer computes the aggregate demand and clears the market until the quantity Q is sold. As mentioned before, the price is determined at the intersection of aggregate demand and Q. We define the bidding process as follows. Each firm i submits a bid schedule $\mathbf{b}_i(c_i)$ which determines their maximum willingness to pay for permits. Denote the inverse of bid schedule, $x_i(b)$ as the submitted demand schedule by firm i and $X = \sum_i x_i$ as the aggregate submitted demand.

The following proposition shows firms have incentives to under-report the true value of c_i in every equilibrium.

Proposition 1. *In a symmetric equilibrium, it is optimal for firms to under-report their types c_i.*

Proof. See Appendix 6.

The above proposition suggests that firms have clear incentives to not reveal their true demand in the auction. The result of this proposition is aligned with many other results in the literature that show the uniform-price auction has the problem of demand reduction (Krishna, 2009). The intuition behind this result is that firms know that their submitted demand influences the aggregate demand and consequently the price for all the units. Therefore, lowering the submitted demand schedule, at least partly, would reduce the expected clearing price of the auction and increase their expected payoff. Moreover, there are papers that highlight possible equilibria with very low prices, particularly where firms learn to lower their demand such that all units are sold at the lowest possible price. For instance, Back and Zender (1993) suggests that the lowest price equilibrium is Pareto dominant for buyers. Based on the above result, as well as the support from the literature, we construct the following claim.

Claim 1. *We hypothesize that the initial implementation of a vertical supply of permits by RGGI would result in low equilibrium prices within the auction framework.*

There are several studies that investigate different design changes in the uniform-price auction to reduce or eliminate the demand reduction problem (Back and Zender, 2001; McAdams, 2007; Damianov and Becker, 2010; Khezr and Menezes, 2020). One suggested method, initially discussed by McAdams (2007), is to use an increasing supply rather than a vertical supply. Since the introduction of the CCR, RGGI essentially used this method and changed the supply of permits to an increasing supply as a step function. Next, we would like to investigate how this simple change in the supply would alter bidding behavior.

Suppose the regulator uses the following supply schedule. For prices below p', only δQ permits are available, where $0 < \delta < 1$. If the auction clearing price is at or above p', then all the Q units will be available to potential buyers. In our model, p' is equivalent to the trigger price that was introduced in 2014 by RGGI. The following proposition shows how bidding behavior by bidders changes with the above change in the supply.

Proposition 2. *With an increasing supply, the equilibrium demand schedules submitted by firms is at least as high as the one submitted with a vertical supply.*

Proof. See Appendix 6.

The result of Proposition 2 suggests that an increasing supply would reduce firms' incentives to under-report their types relative to a vertical supply. The intuition behind this result is straightforward: when supply is increasing, larger quantities of supply would be available at higher prices conditional on demand. This is in contrast with a vertical supply where all units are available even if aggregate demand and supply intersect at the lowest possible price. Therefore, lower bids would be punished by a lower quantity of supply. This simple adjustment would incentivize firms to bid larger relative to the case with a vertical supply.

Based on this result, we can conclude that the implementation of CCR by RGGI was a proper approach if the aim was to reduce or eliminate the demand reduction problem. Therefore, we expect to see evidence of a price increase in our empirical investigation of auctions after the implementation of CCR, *ceteris paribus.*

Claim 2. *We hypothesize that the implementation of CCR increased the auction clearing prices in RGGI, ceteris paribus.*

It is straightforward to assert that a similar claim is applicable to the ECR. In fact, technically speaking, the ECR is akin to the CCR in the sense that it adds a step to a vertical step function. Consequently, one can conclude that the implementation of the ECR would increase the auction clearing prices in RGGI.

Another crucial variable influencing the auction outcome is the number of bidders. There are two important points related to the number of bidders. First, it seems intuitive that when the number of bidders increases, we expect higher equilibrium prices, *ceteris paribus.* For instance, one approach is to show that if one more bidder is added to the auction, the price in any new equilibrium is at least as large as in the case with one fewer bidder. Second, keeping the total demand fixed, the scale of each bidder's demand could also alter the auction outcome. When one or few bidders demand a larger amount of the total available units, they possess higher monopsony power in the auction (Baisa and Burkett, 2018; Hortaçsu and Puller, 2008).

First we show increasing the number of bidders would have an upward effect on the auction clearing price. Denote $n' > n$ as the new number of bidders. The following proposition summaries the result.

Proposition 3. *When the number of bidders increases the auction clearing price would also increase, ceteris paribus.*

Proof. *See Appendix 6.*

The above result is quite intuitive. With more bidders in an auction, assuming all else is equal, the aggregate demand will increase, leading to an increase in the auction clearing price. In the context of RGGI, this means that with more firms participating in the auction, we can expect to see higher permit prices, all else being equal. The following claim summarizes this result.

Claim 3. *We hypothesize that when the number of bidders in RGGI auctions increases the auction clearing price increases, ceteris paribus.*

Next, we introduce additional notations to consider the scale of bidders. To facilitate a reasonable comparison with our basic model, suppose there exists a large bidder l that combines $l < n$ bidders from the original model into a single bidder. As a result, we now have $n - l + 1$ bidders in the game, where l is a positive integer greater than one, and bidder l has a larger capacity than other bidders given a specific type. The quantity of demand for bidder l is given by:

$$q_l = \frac{lc_l}{\alpha} - \frac{l}{\alpha}p \tag{4}$$

It is evident from the above equation that, given a fixed type, the large bidder has l times more demand than a regular bidder. One conjecture is that higher monopsony power could increase demand reduction and lower the auction price. The subsequent proposition demonstrates that, in the presence of one large bidder, demand reduction could become more pronounced.

Proposition 4. *With a large bidder the auction clearing price is less than the case without a large bidder, ceteris paribus.*

Proof. *See Appendix 6.*

The result of Proposition 4 suggests that when the scale of demand by a firm increases in the auction, while keeping everything else constant, we expect the auction price to decline. The intuition behind this result is closely related to the increased incentives for demand reduction. When a firm has a larger demand relative to others, there is more room for manipulation of the submitted demand schedule. Consequently, we expect a firm to reduce its demand below its actual demand more extensively if it has a larger scale. The following statement encapsulates the findings derived from the above result within the context of RGGI.

Claim 4. *Large scale bidders in RGGI auctions would lower the auction clearing price, ceteris paribus.*

The above four claims attempt to highlight the effects of some of the most important parameters in RGGI auctions. In Section 5, we strive to present evidence supporting the above claims using data from 58 RGGI auctions. It is important to note that, as with any theoretical model, the one proposed here has some limitations. For instance, we abstain from considering the secondary market for the sake of tractability. Incorporating a secondary market would undoubtedly have implications for bidding behavior in the auction. However, assuming fixed price expectations in a secondary market, and with all other variables remaining constant, our results would still hold true and maintain their validity.

In the next section, we provide additional details about the data available from the 58 auctions and define two key variables that will enable us to test the theoretical claims.

4 Data description

In this section, a preliminary analysis will be conducted on the dataset gathered from 58 auctions executed in the RGGI regions.[8] The objective is to identify and establish two critical definitions that would aid in understanding the data more accurately and would help testing important variables in the empirical model. These definitions are: first, the concept of large-scale bidders, which refers to the scale of demand of participating firms in the auction; and second, the concentration of bids, which describes the distribution of winning bids across the different bidders. These concepts will be utilized in the next step, empirical modeling. By examining these two definitions, we can gain a deeper understanding of the auction dynamics, which would be valuable for policymakers and stakeholders in carbon trading markets.

Figure 3 illustrates the carbon allowance prices in RGGI auctions between 2008 and 2022. It also depicts the auctions in which CCR and ECR where introduced. Between 2008 and 2013, the carbon allowance prices remained relatively low, fluctuating between \$1.86 and \$3.21 per allowance. In fact, in the majority of auctions, the clearing price was equal or very close to the reserve price. During this period, neither the CCR nor ECR policies were in place. In 2014, the CCR policy was implemented. The CCR Trigger prices are as follows: \$4 in 2014, \$6 in 2015, \$8 in 2016, and \$10 in 2017. Starting from 2018, the CCR trigger price increased 2.5% annually until the end of 2020. Then in 2021, in the new compliance period the CCR trigger price increased to \$ 13 with an annual increase of 7% for future years. Since the implementation of CCR from auction 23 to auction 30, we observe a sharp increase in prices. However, after auction 31, there is a sharp decline in the auction clearing price until auction 36, where we observe a price equal to \$2.53. Since then, the prices have mainly increased, particularly from auction 51 when the ECR was implemented. From this point on, the carbon allowance prices experienced a significant increase, reaching a peak of \$13.50 per allowance in Q1 of 2022. Moreover, the ECR trigger price was initially established at \$6.00 in 2021, and it increased with an annual increment of 7 percent for subsequent years.

As identified in the theoretical section, there are two important variables that influence auction prices, namely the number of bidders and the number of Large Scale Bidders (LSB). The number of bidders is observed in every auction. However, to identify the number of LSB, we need further analysis. The relationship between the number of large bidders and the auction clearing price in uniform-price auctions is not necessarily straightforward. It is widely believed that if there are one or just a few bidders with significant demand, they could exercise monopsony power and drive down the auction clearing price (Kagel and Levin, 2016). However, if there are many large bidders, they may engage in intense competition that prevents the price from decreasing. In fact, beyond a certain threshold, the presence of more large bidders can trigger a bidding war that pushes the final price upwards. The effect of large bidders on auction prices is a complex, nonlinear, and nuanced issue that can depend on a variety of factors (Kagel and Levin, 2016).

[8] The data we used for this paper is publicly available on RGGI's website: `https://www.rggi.org/Auctions/Auction-Results/Prices-Volumes`.

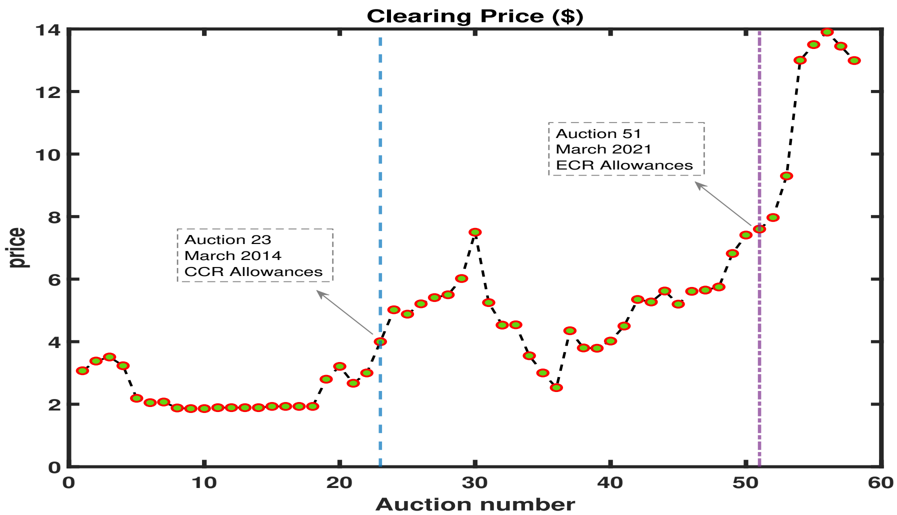


Figure 3: Clearing price in RGGI auctions.

In our data, we observe the total permits won by each firm in every auction. As identified in our theoretical model, the number of permits won in the auction has a positive and monotonic relationship with the actual demand for permits. Therefore, it is reasonable to use the number of permits allocated to each firm in the auction as a variable that represents the scale of bidders. Thus, we define LSB as follows:

Definition 1. *LSB is generated by a cutoff rule with* $(\mathcal{B}_1, \mathcal{B}_2, \cdots, \mathcal{B}_n) \in \mathcal{R}^n$ *if* $\mathcal{D}(\mathcal{B}_i) > 0$ *for* $i = 1, \cdots, n$ *where*

$$\mathcal{D}(\mathcal{B}_i) = \sum_{j=1}^{n} (\mathcal{B}_i - \mathcal{B}_j), \tag{5}$$

where B_i *is the total permits won by firm* i *and* n *is the total number of bidders in an auction.*

To understand the concept of the above definition, let us consider an example with three bidders denoted by $\mathcal{B}_1 = 5$,$\mathcal{B}_2 = 7$, and $\mathcal{B}_3 = 2$. For each bidder, we calculate the sum of the differences between their winning bids and the winning bids of the other two bidders which gives, $\mathcal{D}(\mathcal{B}_1) = 1$, $\mathcal{D}(\mathcal{B}_2) = 7$ and, $\mathcal{D}(\mathcal{B}_3) = -8$. According to Definition , when the sum is positive, we consider that bidder as an LSB bidder. Thus in this example bidder 1 and 2 are defined as LSB. Note that the computation of LSB is not symmetric, and by definition, the bidder that won the highest number of permits is always an LSB. Of course, LSB by itself is not the best measurement of the scale of a bidder relative to the other bidders. Therefore, in the next definition, we introduce a concentration ratio to address these shortcomings.

Definition 2. *Suppose the number of LSB in an action is represented by* $n' < n$*. We define the concentration of LSB based on the following formula:*

$$\mathcal{C} = \frac{\sum_{k=1}^{n'} \mathcal{B}_k}{\sum_{j=1}^{n} \mathcal{B}_j}, \tag{6}$$

For the above example the concentration ratio is equal to $\frac{12}{14}$ which demonstrates a high monopsony power of the two bidders.

Figure 4 depicts the total number of bidders and the number of large scale bidders based on the above definition in all 58 auctions held in the RGGI. As shown in the figure, the number of large-scale bidders ranges from a minimum of 5 to a maximum of 22, while the number of bidders ranges from a minimum of 20 to a maximum of 75. Furthermore, there seems to be some correlation between the number of large-scale bidders and the number of bidders, as auctions with a higher number of large bidders also tend to have a higher number of bidders in general. The data presented in this plot is important for understanding the dynamics of RGGI auctions and the behavior of market participants. The number of large-scale bidders in an auction is a good indicator of the level of competition for carbon allowances, as large-scale bidders typically have a significant impact on auction outcomes. In addition, the number of bidders can also provide insight into market participation and the overall demand for carbon allowances.

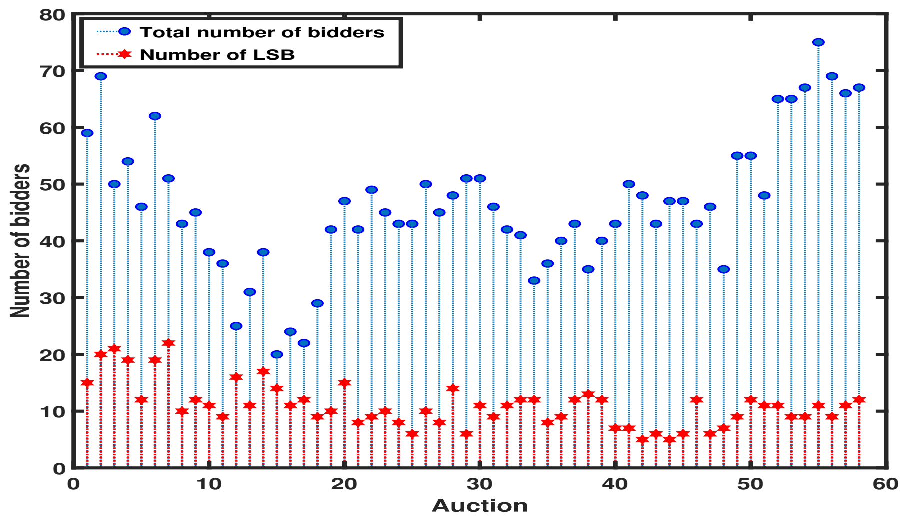


Figure 4: Number of Bidders and Large-scale Bidders in RGGI Auctions (Auctions 1-58).

Figure 5 shows the histogram and kernel density estimation of the concentration of large-scale bidders in all 58 RGGI auctions. The average concentration is approximately 80%, indicating a high concentration of demand for large-scale bidders. Therefore, we expect the concentration of large-scale bidders to be an essential variable in our empirical analysis in the next section.

5 Empirical approach

This section outlines the empirical strategy employed to assess the impact of the policy on auctions. Two distinct approaches will be compared in the analysis: Random effects and machine learning. Although machine learning techniques are not primarily designed to generate precise parameter estimates, they can identify intricate data patterns that were not predetermined (Mullainathan and Spiess, 2017). This is possible because machine learning methods facilitate the selection of variables from a vast set of covariates.

5.1 Panel random effects

In order to analyze the impact of changes in auction rules on outcomes, such as the addition of the CCR, we evaluate different formulations of statistical models and then use various diagnostic tests

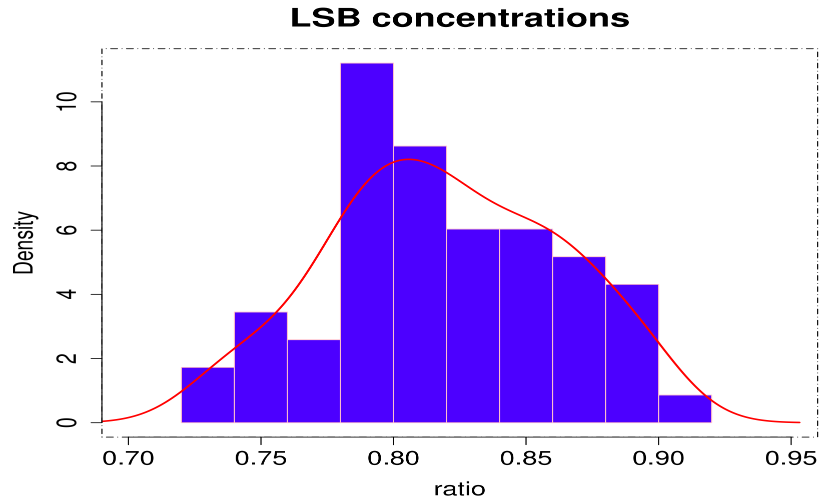


Figure 5: Distribution of concentration of LSB among 58 auctions in RGGI.

to check for autocorrelation. In this analysis, we consider three different models: the least-squares model (Pooled OLS), the fixed-effect model (FE), and the random-effect model (RE).

The following panel formula is used to explain the dependent variables by using independent ones across all auctions:

$$Y_{it} = \sum_{j \in J} \alpha_i X_{it}^j + u_i + \gamma_t + \epsilon_{it}, \tag{7}$$

where

Y_{it}: the dependent variable, which is the clearing price in the first model, and the logarithm of the clearing price in the next two models;

X_{it}^j: the j^{th} independent variable, with i representing the i^{th} auction and t representing time from September 2008 to December 2022;

α_i: the coefficient for the respective independent variable;

u_i: captures the individual-specific random effects of i^{th} auctions;

γ_t: captures the time-specific random effects;

ϵ_{it}: the error term.

Linear models like panel regression have a limitation of multicollinearity among variables, which restricts the inclusion of certain variables in a given model. To mitigate the issue of collinearity, we split variables into two different models with distinct foci. The first model is centred on variables such as the number of bidders, concentration ratios, and exogenous variables such as GDP and gas prices. On the other hand, the second model emphasizes policy actions such as ECR availability and the trigger price. The approach is adopted to control multicollinearity among variables and ensure a more reliable estimation of the regression coefficients.

Model 1: We consider a formula that includes the dependent variables of GDP, Gas price, the concentration of LSB, number of bidders (NoB), CCR and ECR. Specifically, we use the following equation:

$$P_{it} = \alpha_0 + \alpha_1 GDP_{it} + \alpha_2 GAS_{it} + \alpha_3 ConLSB_{it} + \alpha_4 NoB_{it} + \alpha_5 CCR_{it} + \alpha_6 ECR_{it} + u_i + \gamma_t + \epsilon_{it}, \quad (8)$$

where P_{it} represents the clearing price, i represents the auction number, and t represents time. Note that $ConLSB$ is the concentration ratio which is defined in Definition 2, NoB is the number of bidders in each auction and all α's are fixed unknown parameters. Further, CCR and ECR are dummy variables for both policies in RGGI. u_i captures the individual-specific random effects, γ_t captures the time-specific random effects. Finally, ϵ denotes the error terms.

Remark 1. *We incorporate time as one of the random effects, accounting for unobserved, time-specific factors that may influence the dependent variable. By treating time as a random effect, we recognize the presence of time-specific characteristics or trends that affect the outcome variable but are not captured by fixed effects or observed covariates. Estimating time as a random effect enables us to identify unique time-specific variations and control for unobserved time-specific factors. This approach helps distinguish the impact of fixed effects from the random effects associated with each specific year, thereby providing a more comprehensive analysis of the relationship between the variables and the dependent variable over time.*

After fitting the model based on different approaches, the random effects model was chosen as the most appropriate model (Table 1). Looking at the table, we can see that the coefficients represent the estimated effects of each variable on the outcome variable, clearing price. The estimate column provides the point estimates for each coefficient, which represents the average change in the outcome variable for a one-unit increase in the predictor variable, holding all other variables constant. For example, the estimated coefficient for GDP is 0.0004, which means that, on average, for each unit increase in GDP, the outcome variable is expected to increase by 0.0004 units, holding all other variables constant.

The p-values column in the table indicates the statistical significance of each coefficient. Specifically, it shows the probability of obtaining a test statistic as extreme as the one observed, assuming that the null hypothesis is true. In this case, a p-values less than 0.05 is considered statistically significant, which means that there is strong evidence to reject the null hypothesis and conclude that the coefficient is significantly different from zero. Looking at the p-values column, we can see that all of the coefficients, except for CCR, have a p-value less than 0.05, which suggests that they are statistically significant. This means that we can be confident in the estimates of these coefficients and their effects on the outcome variable.

Further, to understand which of the random effects regression and a simple OLS regression is suitable we use a statistical test of Breusch-Pagan Lagrange Multiplier (LM).[9] The results of this test reveal that the null hypothesis is rejected, and it can be concluded that the random effects method is a more appropriate model for the analysis. It is important to note that in macro panels with long time series, serial correlation in panel models is a major concern, as it can lead to bias in the test results Baltagi and Baltagi (2008). We utilized the Breusch-Godfrey/Wooldridge test to examine the presence of serial correlation within the dataset. The results of the test indicate that the null hypothesis concerning the non-existence of serial correlation cannot be rejected, with a corresponding p-value of 0.0667.

Moreover, we examined the issue of multicollinearity in the model by computing the variance inflation factor (VIF) and tolerance factor - 1/VIF, which are presented in Table 2. This table

[9]The null hypothesis LM test posits that the variances across entities are equal to zero, indicating an absence of significant differences across units, and thus, no panel effect.

Coefficients:	Estimate	Std.error	z-value	Pr(> $\|z\|$)	
(Intercept)	-3.5335	1.5646	-2.2584	0.0239	*
GDP	0.0004	0.0001	3.3040	0.0010	***
GAS	0.2392	0.0989	2.4202	0.0155	*
ConLSB	-4.0934	1.9613	-2.0871	0.0369	*
Number Of Bidders	0.0515	0.0157	3.2875	0.0010	**
CCR	1.1393	0.6755	1.6866	0.0917	.
ECR	2.9939	0.9146	3.2736	0.0011	**
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Total Sum of Squares: 151.43					
Residual Sum of Squares: 27.005					
R^2: 0.8217					
Adj. R^2: 0.8015					
Chi sq: 244.192 on 6 DF, p-value: < 2.22e-16					

Table 1: parameter estimation based on the random effect of panel data.

variable	VIF	1/VIF
GDP	10.784	0.093
GAS	2.798	0.357
ConLSB	6.837	0.146
Number Of Bidders	3.234	0.309
CCR	2.413	0.414
ECR	2.130	0.470
Mean	4.699	0.298

Table 2: Multicollinearity test for **Model 1**.

presents the variance inflation factor (VIF) and its reciprocal, 1/VIF, for each variable in the model. The VIF measures how much the variance of the estimated regression coefficient is increased due to collinearity among the predictor variables. In this case, the variables with the highest VIF values are GDP, ConLSB, and Number of Bidders, indicating some level of collinearity. The mean VIF is 4.699, which is somewhat good, and does not cause for concern. The reciprocal of the VIF is also shown, which is sometimes used as a measure of tolerance, or how much of the variation in a variable is not explained by the other predictor variables. A value of less than 0.1 for tolerance is generally considered to indicate high collinearity, but in this case, all variables have a tolerance greater than 0.1.

Next, we investigate the results from the panel analysis for Model 1 and our claims in the theoretical section. According to Claim 1 and 2, we expect that once the CCR was implemented, the prices of auctions would increase, ceteris paribus. Given that the coefficient of CCR is both positive and significant (Table 1), our evidence suggests this claim is correct. In fact, our analysis demonstrates that, once we control for other important variables, the price of auctions increased after the implementation of CCR.

Moreover, we used the Mann-Whitney U non-parametric test to determine if the auction prices for auctions 1 to 22 are statistically the same as the reserve prices. The results indicated that there is a significant difference between the two sample distributions, and the prices are not statistically the same as the reserve prices. However, this result could partly be the outcome of a low number of observations. As shown in Figure 3, in most auctions before CCR, the price is either identical or marginally above the reserve price, which indicates that a vertical supply scheme could result in the lowest possible equilibrium price.

Our results also show that Claim 3 is correct. The number of bidders has a positive and significant effect on the auction clearing price. Finally, Claim 4 is also proven by the result of Model 1, as the coefficient for the concentration of LSB is negative and significant. This indicates that when the concentration of bidders increases, the auction clearing price declines.

Model 2: The second model, which is focused on policy analysis, examines the relationship between the dependent variables ECRTrigger, CCRTrigger, Quantity sold (QS), the price of natural gas, the number of bidders and Concentartion of large scale bidders, ConLSB. The model is specified as follows:

$$\begin{aligned} P_{it} &= \alpha_0 + \alpha_1 \text{ECRTrigger}_{it} + \alpha_2 \text{CCRTrigger}_{it} + \alpha_3 QS_{it} \\ &+ \alpha_4 GAS_{it} + \alpha_5 NoB_{it} + \alpha_6 ConLSB_{it} + u_i + \gamma_t + \epsilon_{it}. \end{aligned} \tag{9}$$

The results of the second model are presented in Table 3.

Coefficients:	Estimate	Std.error	z-value	$Pr(>\|z\|)$	
(Intercept)	0.8126	2.3945	0.3393	0.7343	
ECR Trigger	0.5529	0.1772	3.1202	0.0018	**
CCR Trigger	0.2653	0.0738	3.5937	0.0003	***
Quantity of Sold	-0.0067	0.0222	-0.3032	0.7617	
GAS	0.2646	0.1333	1.9843	0.0472	*
Number Of Bidders	0.0637	0.0195	3.2599	0.0011	**
ConLSB	-2.5119	2.7287	-0.9205	0.3572	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Total Sum of Squares: 108.25					
Residual Sum of Squares: 29.435					
R^2: 0.7280					
Adj. R^2: 0.6961					
Chisq: 136.56 on 6 DF, p-value: < 2.22e-16					

Table 3: parameter estimation based on the random effect of panel data.

Table 3 shows the estimation results of the Eq 9. The intercept is estimated to be 0.8126, indicating that when all predictor variables are set to zero, the response variable has an average value of 0.8126. Of particular importance are the estimated coefficients for the ECR Trigger price (0.5529) and the CCR Trigger price (0.2653). These coefficients suggest that a one-unit increase in either trigger price leads to a corresponding increase of 0.5529 and 0.2653 units in the response variable, the clearing price, while holding all other variables constant. Notably, both trigger prices (ECR and CCR) are statistically significant at the 0.01 and 0.001 levels, respectively. Additionally, the variables "Quantity of sold" and "GAS" have estimated coefficients of -0.0067 and 0.2646, respectively. The latter has a p-value of 0.0472, indicating that the relationship between the variable and the response variable is statistically significant at the conventional level of 0.05. Finally, in terms of sign of coefficients of the number of bidders and ConLSB show consistency with the result of model in the Table 1.

The significance of the variables is denoted by asterisks in the table, with three asterisks indicating a highly significant relationship (p-value < 0.001), two asterisks indicating a significant relationship (p-value < 0.01), and one asterisk indicating a marginally significant relationship (p-value < 0.05).

In addition, the Breusch-Godfrey test was employed to test for serial correlation in the dataset which produced a p-value of 0.0973. These results suggest that the null hypothesis of the absence of serial correlation can be accepted. Regarding multicollinearity, the variance inflation factor (VIF) and tolerance factor (1/VIF) are presented in Table 4. The results indicate an average multicollinearity of 1.568 among the variables in the model, suggesting the absence of detrimental multicollinearity.

variable	VIF	1/VIF
ECR Trigger	2.025	0.494
CCR Trigger	2.084	0.480
Quantity of sold	1.425	0.702
GAS	1.306	0.766
Number Of Bidders	1.504	0.665
ConLSB	1.064	0.940
mean	1.568	0.638

Table 4: Multicollinearity test for **Model 2**.

Note that due to collinearity concerns, we were unable to include more exogenous variables such as GDP, and inflation together in one equation. If we were to include these variables in a single equation, the VIF test would reveal a significant level of collinearity, which can have serious implications for our regression model. Additionally, other variables such as oil price in West Texas Intermediate (WTI), electricity price, and the Consumer Price Index (CPI) were tested, but the results, based on this specific dataset, indicate their lack of statistical significance. It is essential to reiterate that random effects were specified on time in order to account for unobserved heterogeneity among entities. This modelling approach aligns with theoretical expectations that the price series should exhibit a trend, specifically an upward trajectory, over time.

To address the above limitation, we intend to employ a machine learning model that can identify the most influential variables with the greatest impact on the clearing price. By leveraging this approach, we aim to overcome the challenges posed by collinearity and determine the most significant factors affecting the clearing price.

5.2 Machine learning analysis

As explained before, one limitation of linear models such as panel regression is the presence of multicollinearity among variables. This limitation necessitates the exclusion of certain variables from a given model. In contrast, Random Forest is a non-linear classification algorithm that uses bootstrap sampling to mitigate the effects of multicollinearity. The method considers various combinations of variables as separate models, each of which receives a unique set of data points. The results in Figure 6 demonstrate the outcomes of the Random Forest algorithm using different variables. In Figure 6, the left plot illustrates the stabilization of the mean of squared residuals at approximately 0.6942 after roughly 500 iterations, while the right plot showcases the weights of variables and their proportional impact on MSE. As expected, the variables that are most critical to this method are GDP, trigger price, the number of bidders, ECC policy and Quantity sold.[10]

Apart from GDP as an exogenous variable, the trigger price, the number of bidders, CCR and ECR are the most critical variables in determining auction clearing prices. This is supportive of our claims and the analysis of the theoretical section as we suggested the supply change and the number of bidders are important determinants of the auction clearing price in a uniform-price auction.

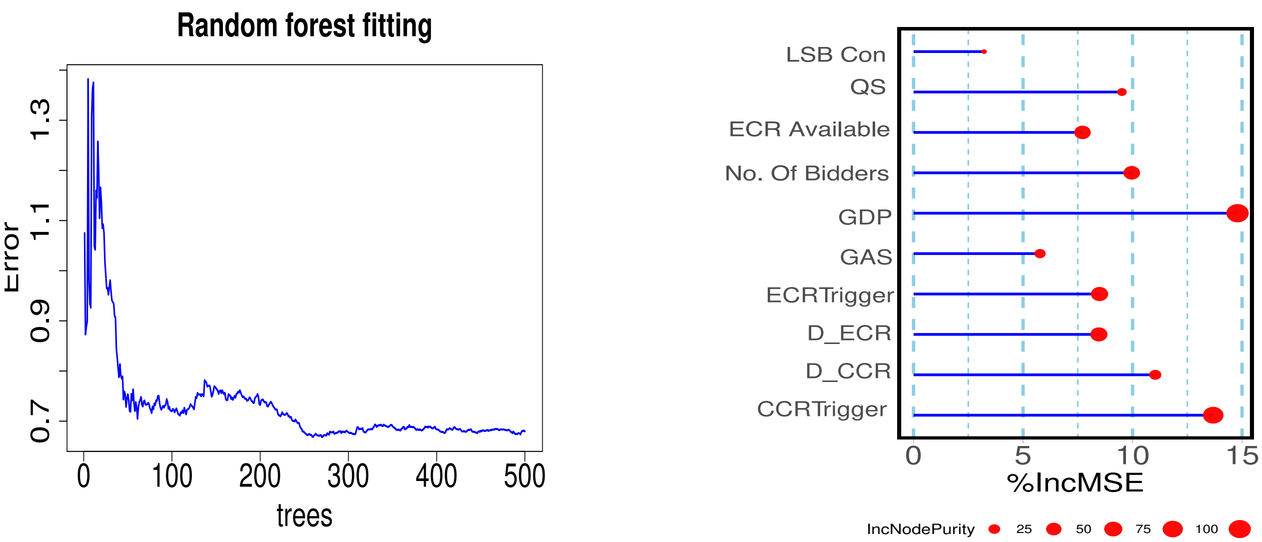


Figure 6: Plots from parameter tuning in Random Forest algorithm determine the optimal number of trees and variables. 'LSB Con' refers to the LSB concentration, 'No. Of Bidders' is the number of bidders.

Figure 7 depicts the most significant variables based on node purity,[11] which reinforces our previous result that GDP, number of bidders, trigger price, GDP, ECR and CCR are the most effective policy variables in this method.

We note that there are other machine learning approaches for the verification of consistency of the results, such as Extra Trees[12], AdaBoost methods[13], and Gradient Boosted Trees. In this study, we report results based on the Gradient Boosted Trees algorithm (GB), which is a popular

[10]Note that the Random forest regression models do not provide coefficients in a similar way as simple regression models. Unlike simple linear regression models, where the coefficients of the linear equation that links the response variable to the predictors are estimated, random forest regression models are made up of a collection of decision trees. Each tree is constructed utilizing a random subset of the predictors. Hence, instead of estimating a single set of coefficients, random forest regression models estimate a set of weights that correspond to the significance of each predictor in the model. It is worth mentioning that Random Forest is associated with a lower risk of overfitting and is less sensitive to outliers.

[11]Node purity is a measure of how well the samples in a node belong to a single class, and it is used as a stopping criterion in decision trees, including those used in Random Forest.

[12]Extra Trees (or Extremely Randomized Trees) - This model is similar to Random Forest, but the selection of the split point is done randomly, without considering the optimal threshold value for each feature. For more details, see Bonaccorso (2017).

[13]AdaBoost - This model is an iterative algorithm that combines multiple weak classifiers into a single strong classifier. The weak classifiers are usually decision trees with a single split. More detail is available in Bonaccorso (2017).

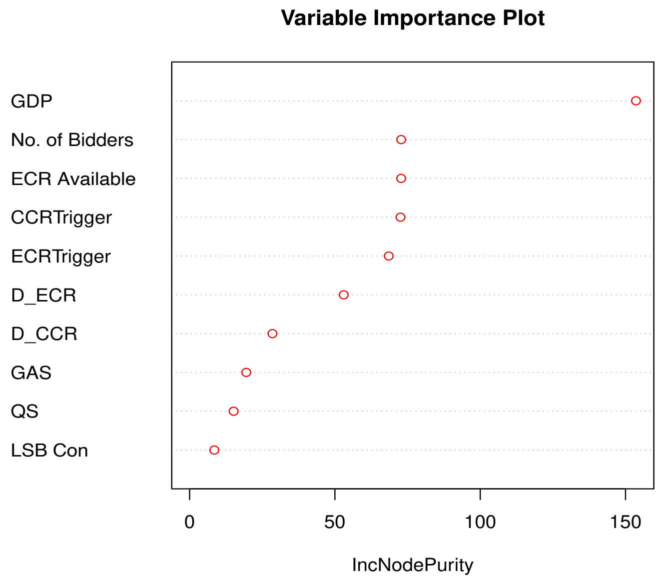


Figure 7: Variable importance in the model is determined by estimating node purity using the random forest algorithm.

ensemble method commonly used for classification and regression tasks. Natekin and Knoll (2013) This algorithm combines multiple weak models to create a strong model. The learning rate and the number of trees are controlled by hyperparameters, with a learning rate of $\lambda = 0.01$, 10,000 trees, and a depth of 8 for each tree, although the results are not highly sensitive to these parameters. Similar to the Random Forest model, GDP, the Trigger Price and GDP, number of bidders exhibit the greatest impact on our model. The summary of this model fitting is presented in Figure 8.

The RF and GB models both indicate that the trigger price is a highly significant variable in determining the clearing price in RGGI auctions. The trigger price serves as a safety valve to control the supply of allowances in the market. If the clearing price falls below the trigger price, then the allowance reserve will not be offered in the auction, which reduces the total supply of permits. Therefore, if firms are willing to release the reserve supply, or in other words, if the demand is high enough such that the reserve supply is demanded by firms, then they must at least pay the trigger price for all the permits. This highlights the importance of the trigger price in determining the auction clearing price (Friesen et al., 2022).

5.3 Arc elasticity analysis

Interpreting the results of panel regression and machine learning models is generally straightforward and intuitive. As with any statistical model, we can easily analyze the sign, magnitude, and statistical significance of the model coefficients. However, these models also provide a unique opportunity to conduct more nuanced analyses, such as calculating marginal effects and elasticities. These analyses allow us to compare the effects of different variables on the dependent variable, accounting for the complex dependencies and interactions that may be present in the data. Importantly, these analyses are based on explicit mathematical formulations and derivations, which ensure the transparency and rigor of the findings. By conducting these types of analyses, researchers can gain a deeper understanding of the factors driving the outcomes observed in their data and make informed decisions based on their findings.

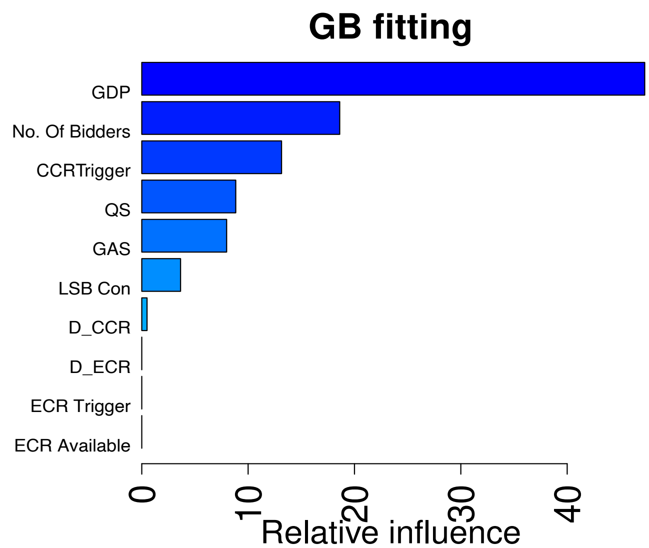


Figure 8: The importance of variables in the model based on GB algorithm.

In this subsection, we take into account the exogeneity of the variables to estimate the price elasticities. Despite being distant from a formal price estimation analysis, we posit that this approach could enhance the comparability of the outcomes to prior research and thereby prove advantageous for policy assessment and guidance.

In the first step of analyzing price elasticity, we examine the impact of the concentration ratio of LSB on price. We assume that the vector of all variables in the main model remains constant, and only the ConLSB variable in Model 1 varies from 33% less than the current value to 33% higher. The coefficients of this variable in the model are reported on the left side of Figure 9. It can be observed that as the concentration ratio increases, the coefficient value decreases, indicating a negative effect on the clearing price, as expected and explained in Proposition 4. Furthermore, we illustrate the significance of this variable on the right side of Figure 9.

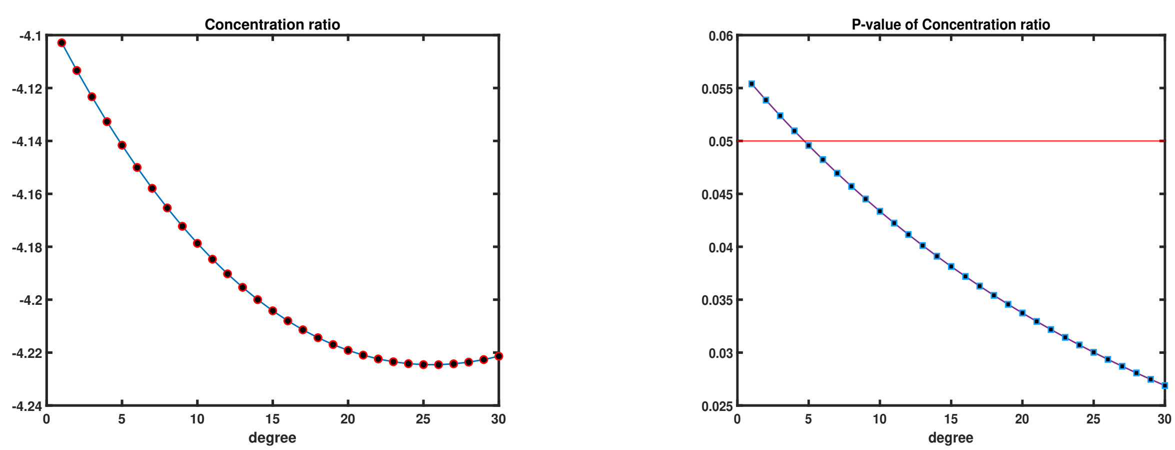


Figure 9: Left plot shows coefficient for clearing price $\sim$ concentration ratio and right plot shows the corresponding p-value.

To compute the elasticity we consider the following steps. Firstly, the average values of the variables of interest are computed. Then, based on the estimated coefficients from Model 1, the elasticity of the clearing price (y_{avg}) with respect to the main variables (e.g., number of bidders, NoB) is computed using the formula: $elasticity = \alpha_4 * (NoB_{avg}/y_{avg})$.

According to results in Table 1, the analysis of Elasticity and the marginal effect of the number of bidders on clearing price reveals that the elasticity of clearing price with respect to the number of bidders is estimated as 0.4879. This implies that a 1% increase in the number of bidders is associated with a mere 0.4879% increase in the clearing price.[14] Similarly elasticities of clearing price with respect to GDP and gas price are 1.4532% and 0.2354% respectively. As hypothesized and confirmed by the machine learning implementation, the empirical results reveal that GDP has a statistically significant impact on the clearing price as an exogenous variable. Specifically, a one percent increase in GDP is associated with a 1.4532 percent increase in the clearing price. Finally, in terms of Trigger price which is one of the most significant and important variables among all others, based on both RF and GB models, elasticity is equal to 0.4741%.

6 Conclusive remarks and policy recommendations

In this paper, we studied RGGI auctions both theoretically and empirically. We constructed a theoretical model that mirrors the auctions in RGGI and provided a set of claims regarding the auction characteristics and the clearing prices. In our empirical analysis, we employed panel random effects models and machine learning models to test the hypotheses provided. The outcomes indicate that our theoretical predictions align with the empirical results. In particular, CCR and the number of bidders are among the most important determinants of the auction clearing price. Additionally, when the concentration of bidders' demand increases to a few bidders, the auction clearing price is expected to decrease due to the monopsony power of bidders. We further identified other important variables that influence the price of auctions in RGGI auctions.

Understanding firm behavior in strategic settings such as multi-unit auctions is crucial for achieving an effective and efficient allocation of goods or services. For instance, in cap-and-trade markets, understanding firm behavior is pivotal for the effectiveness of policies implemented by regulators. Without a clear understanding of these behaviors and what motivates firms to act in a particular way, a policy could have unintended consequences, which usually come at significant costs for taxpayers. Therefore, policy lessons learned based on both theoretical insights and empirical evidence could play a unique role in addressing issues related to firm behavior.

This paper offers several important policy lessons for cap-and-trade systems that use uniform-price auctions for the initial allocation of emissions permits. The evidence suggests that bidders can easily learn to collude and reduce their demands if the regulator provides a vertical supply of permits. However, a simple increasing supply such as CCR can significantly increase their bids and alleviate the demand reduction problem. Our results show that the trigger price is a significant variable influencing the auction clearing price. Therefore, regulators must carefully adjust such prices as they are some of the most important policy variables that determine the auction clearing price. Moreover, regulators must be aware of the concentration of bidders in the auction, as greater concentration can enhance monopsony power, which consequently reduces the auction clearing price.

[14] Elasticity greater than 1 indicates high responsiveness of y to changes in x, while elasticity less than 1 indicates low responsiveness. An elasticity of 1 indicates perfect responsiveness. Indeed, for example, if the elasticity is greater than 1, it means that a one percent increase in x leads to a greater than one percent increase in y, indicating that y is highly responsive to changes in x.

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Appendix 1: Additional tables

The tables 5 and 6 show data related to 58 auctions for the sale of carbon allowances that took place from September 2008 to Dec 2022. The auctions were organized by the RGGI, a cooperative effort among twelve US Northeastern and Mid-Atlantic states to reduce greenhouse gas emissions from the power sector. The auctions took place approximately every three months, with some variations. The table contains information about a series of auctions for CCR and ECR allowances. The auction number and date are listed for each auction. The CCR and ECR Allowances Sold columns represent the number of allowances sold at each auction for each type of allowance. The Quantity Sold column shows the total number of allowances sold, regardless of type, at each auction. Looking at the data, we can see that there were no CCR or ECR allowances sold or available for most of the dates listed. However, on March 5th, 2014, 5,000,000 CCR allowances were sold, and on September 9th, 2015, 10,000,000 CCR allowances were sold. On December 1st, 2021, 3,919,482 CCR allowances were sold. Finally, in the most recent data point on March 3rd, 2021, there were 11,307,333 ECR allowances available. Finally, the Clearing Price column shows the price at which the allowances were sold.

Further the table 5 and 6 demonstrate that the number of allowances sold varied greatly from one auction to another, ranging from as little as 7,487,000 to as much as 40,685,585. We can also see that the clearing price varied over time, with the highest price being $7.50 per allowance in auction 30 and the lowest being $1.86 per allowance in auctions 9 and 10. In summary, this table provides a snapshot of a series of auctions for CCR and ECR allowances. It shows the number of allowances sold at each auction, the clearing price for each auction, and the date of each auction.

	Date	GDP	Quantity Sold	#Bidders	Clearing Price	$CCR_{Available}$	CCR Sold	$ECR_{Available}$	CCR Trigger	ECR Trigger
Auc 1	Sep-08	14806	12565387	59	3.07	0	0	0	0	0
Auc 2	Dec-08	14431	31505898	69	3.38	0	0	0	0	0
Auc 3	Mar-09	14371	31513765	50	3.51	0	0	0	0	0
Auc 4	Jun-09	14405	30887620	54	3.23	0	0	0	0	0
Auc 5	Sep-09	14490	28408945	46	2.19	0	0	0	0	0
Auc 6	Dec-09	14594	28591698	62	2.05	0	0	0	0	0
Auc 7	Mar-10	14851	40612408	51	2.07	0	0	0	0	0
Auc 8	Jun-10	15039	40685585	43	1.88	0	0	0	0	0
Auc 9	Sep-10	15205	34407000	45	1.86	0	0	0	0	0
Auc 10	Dec-10	15377	24755000	38	1.86	0	0	0	0	0
Auc 11	Mar-11	15515	41995813	36	1.89	0	0	0	0	0
Auc 12	Jun-11	15521	12537000	25	1.89	0	0	0	0	0
Auc 13	Sep-11	15611	7487000	31	1.89	0	0	0	0	0
Auc 14	Dec-11	15831	27293000	38	1.89	0	0	0	0	0
Auc 15	Mar-12	16057	21559000	20	1.93	0	0	0	0	0
Auc 16	Jun-12	16221	20941000	24	1.93	0	0	0	0	0
Auc 17	Sep-12	16366	24589000	22	1.93	0	0	0	0	0
Auc 18	Dec-12	16520	19774000	29	1.93	0	0	0	0	0
Auc 19	Mar-13	16635	37835405	42	2.80	0	0	0	0	0
Auc 20	Jun-13	16796	38782076	47	3.21	0	0	0	0	0
Auc 21	Sep-13	16946	38409043	42	2.67	0	0	0	0	0
Auc 22	Dec-13	17176	38329378	49	3.00	0	0	0	0	0
Auc 23	Mar-14	17196	23491350	45	4.00	5000000	5000000	0	4.00	0
Auc 24	Jun-14	17555	18062384	43	5.02	0	0	0	4.00	0
Auc 25	Sep-14	17742	17998687	43	4.88	0	0	0	4.00	0
Auc 26	Dec-14	17843	18198685	50	5.21	0	0	0	4.00	0
Auc 27	Mar-15	17988	15272670	45	5.41	10000000	0	0	6.00	0
Auc 28	Jun-15	18253	15507571	48	5.50	10000000	0	0	6.00	0
Auc 29	Sep-15	18362	25374294	51	6.02	10000000	10000000	0	6.00	0
Auc 30	Dec-15	18346	15374274	51	7.50	0	0	0	6.00	0

Table 5: This table shows the auction dates, offerings, quantities sold, final ratios of bids to supply, and clearing prices for 58 auctions held between 2008 and 2022.

	Date	GDP	Quantity Sold	#Bidders	Clearing Price	$CCR_{Available}$	CCR Sold	$ECR_{Available}$	CCR Trigger	ECR Trigger
Auc 31	Mar-16	18517	14838732	46	5.25	10000000	0	0	8.00	0
Auc 32	Jun-16	18645	15089652	42	4.53	10000000	0	0	8.00	0
Auc 33	Sep-16	18886	14911315	41	4.54	10000000	0	0	8.00	0
Auc 34	Dec-16	19061	14791315	33	3.55	10000000	0	0	8.00	0
Auc 35	Mar-17	19225	14371300	36	3.00	10000000	0	0	10.00	0
Auc 36	Jun-17	19430	14597470	40	2.53	10000000	0	0	10.00	0
Auc 37	Sep-17	19702	14371585	43	4.35	10000000	0	0	10.00	0
Auc 38	Dec-17	20019	14687989	35	3.80	10000000	0	0	10.00	0
Auc 39	Mar-18	20212	13553767	40	3.79	10000000	0	0	10.25	0
Auc 40	Jun-18	20561	13771025	43	4.02	10000000	0	0	10.25	0
Auc 41	Sep-18	20735	13590107	50	4.50	10000000	0	0	10.25	0
Auc 42	Dec-18	20850	13360649	48	5.35	10000000	0	0	10.25	0
Auc 43	Mar-19	21063	12883436	43	5.27	10000000	0	0	10.51	0
Auc 44	Jun-19	21375	13221453	47	5.62	10000000	0	0	10.51	0
Auc 45	Sep-19	21570	13116447	47	5.20	10000000	0	0	10.51	0
Auc 46	Dec-19	21781	13116444	43	5.61	10000000	0	0	10.51	0
Auc 47	Mar-20	20886	16208347	46	5.65	11800000	0	0	10.77	0
Auc 48	Jun-20	20707	16336298	35	5.75	11800000	0	0	10.77	0
Auc 49	Sep-20	21646	16192785	55	6.82	11800000	0	0	10.77	0
Auc 50	Dec-20	21713	16237495	55	7.41	11800000	0	0	10.77	0
Auc 51	Mar-21	22694	23467261	48	7.60	11976778	0	11307333	13.00	6.00
Auc 52	Jun-21	23234	22987719	65	7.97	11976778	0	11307333	13.00	6.00
Auc 53	Sep-21	23736	22911423	65	9.30	11976778	0	11307333	13.00	6.00
Auc 54	Dec-21	24520	27041000	67	13.00	11976778	3919482	11307333	13.00	6.00
Auc 55	Mar-22	24972	21761269	75	13.50	11611278	0	10961898	13.91	6.42
Auc 56	Jun-22	25521	22280473	69	13.90	11611278	0	10961898	13.91	6.42
Auc 57	Sep-22	25823	22404023	66	13.45	11611278	0	10961898	13.91	6.42
Auc 58	Dec-22	26246	22233203	67	12.99	11611278	0	10961898	13.91	6.42

Table 6: Between 2008 and 2022, a total of 58 auctions were held, with this table displaying crucial information such as auction dates, offerings, quantities sold, final bid-to-supply ratios, and clearing prices.

Appendix 2: Proof of Propositions

Proof of Proposition 1:

Focusing on symmetric equilibria $\mathbf{b}(c_i)$, we show that firms would always be better off by submitting types lower than c_i. First, suppose firm i with c_i submits a type $b_i > c_i$. Then, firm i's submitted demand schedule becomes,

$$x(b_i) = \frac{b_i}{\alpha} - \frac{1}{\alpha}p \tag{10}$$

Fix any auction clearing price p^*. At any p^*, the firm wins an extra quantity of permits equal to $x_i' = \frac{b_i - c_i}{\alpha}$, where the maximum willingness to pay for these permits is strictly below p^* according to the true demand function in Equation (2). Therefore, firm i's payoff is strictly larger when submitting their true type c_i compared to any $b_i > c_i$.

Next suppose firm i submits a type $b_i \leq c_i$. If all other firms except i submit their true types, then the auction clearing price is given by,

$$\mathbf{c}_{-i} + b_i - np^* = \alpha Q \tag{11}$$

where $\mathbf{c}_{-i}$ is the sum of all other types except for i. This gives the following equilibrium quantity for bidder i.

$$x_i^* = \frac{b_i}{\alpha} - \frac{\mathbf{c}_{-i} + b_i - \alpha Q}{n\alpha} \tag{12}$$

Now one can rewrite Equation (3) as follows.

$$\pi_i = \int_0^{x_i^*} (c_i - \alpha x)dx - \frac{1}{n}(\mathbf{c}_{-i} + b_i - \alpha Q)x_i^* \tag{13}$$

Differentiate the above with respect to b_i. We have,

$$\frac{\partial \pi_i}{\partial b_i} = \frac{dx_i^*}{db_i}(c_i - \alpha x_i^*) - \frac{1}{n}x_i^* - \frac{1}{n}(\mathbf{c}_{-i} + b_i - \alpha Q)\frac{dx_i^*}{db_i} \tag{14}$$

Substituting x_i^* from Equation 12 gives,

$$\frac{\partial \pi_i}{\partial b_i} = (\frac{1}{\alpha} - \frac{1}{n\alpha})(c_i - b_i + p^*) - \frac{1}{n}\frac{b_i}{\alpha} + \frac{1}{n}\frac{p^*}{\alpha} - (\frac{1}{\alpha} - \frac{1}{n\alpha})p^* \tag{15}$$

After some cancellations we have,

$$\frac{\partial \pi_i}{\partial b_i} = (\frac{1}{\alpha} - \frac{1}{n\alpha})c_i - \frac{1}{\alpha}b_i + \frac{1}{n}\frac{p^*}{\alpha} = 0 \tag{16}$$

It is routine to check that the above equation is negative at $b_i = c_i$ for any price lower than c_i. This concludes the proof.

Proof of Proposition 2:

We show in any new equilibia with increasing supply bidders would submit weakly larger bids compared to the case with vertical supply. Denote $\mathbf{b}(c_i)$ as any equilibrium submitted bid by bidder i in the auction with vertical supply. We want to show when the supply changes to an increasing one, the new equilibrium bid $b'(c_i)$ is at least as large as $b(c_i)$. Denote the new supply schedule formally as,

$$Supply = \begin{cases} \delta Q & \text{if} \quad p^* < p' \\ Q & \text{if} \quad p^* \geq p' \end{cases} \tag{17}$$

Suppose bidder i follows a symmetric equilibrium bidding strategy $\mathbf{b}(c_i)$ as previously defined. In this case there are two possibilities regarding the equilibrium clearing price. If the equilibrium clearing price $p^* \geq p'$ then the total available supply is the same as the previous case and $b(c_i)$ remains as the best response of i. However, if $p^* < p'$ the supply would reduce to δQ. This results to a reduction of x_i^* equal to $\frac{(1-\delta)Q}{n}$ and an increase in price equal to $\frac{\alpha(1-\delta)}{n}$. Therefore $\mathbf{b}(c_i)$ is not necessarily a best response of i in this situation. Next we show if $\mathbf{b}(c_i)$ is no longer a best response, and the only possibility for a new best response $b'(c_i)$ is to be larger than $\mathbf{b}(c_i)$. First, we show reducing the bid cannot be a best response. Rewrite Equation 15 as follows.

$$\frac{\partial \pi_i}{\partial b_i} = (\frac{1}{\alpha} - \frac{1}{n\alpha})c_i - \frac{1}{\alpha}b_i + \frac{1}{n}\frac{p^*}{\alpha} \tag{18}$$

It is clear from the above first-order condition that when price increases b_i can only increase to remain a best response. Second, there is an extra incentive to increase $b(c_i)$ as the payoff function now has a kink at p' and more unit will be available if the price goes above p'. In particular, if the price is arbitrary close to p', firms would have incentives to increase the price marginally and obtain further $\frac{(1-\delta)Q}{n}$ units as all the Q units become available and increase their overall payoff.

Proof of Proposition 3:

Rewrite the first-order condition for n' bidders.

$$\frac{\partial \pi_i}{\partial b_i} = (\frac{1}{\alpha} - \frac{1}{n'\alpha})c_i - \frac{1}{\alpha}b_i + \frac{1}{n'}\frac{p^*}{\alpha} = 0 \tag{19}$$

After some manipulations we have,

$$\frac{1}{\alpha}(c_i - b_i) - \frac{1}{n'\alpha}(c_i - p^*) = 0 \tag{20}$$

since $n' > n$, the b_i that solves the above equation must be strictly greater than the one that solves the original first-order condition with n bidders.

Proof of Proposition 4:

Following a similar analysis to the proof of Proposition 1 fixing the bidding strategy of all other bidders except l, when bidder l submits a bid b_l the market clearing rule gives,

$$\mathbf{c}_{-l} + lb_l - np^* = \alpha Q \tag{21}$$

where $\mathbf{c}_{-l}$ is the sum of all other types except for l which gives the following equilibrium quantity for bidder l.

$$x_l^* = \frac{lb_l}{\alpha} - \frac{l(\mathbf{c}_{-l} + lb_l - \alpha Q)}{n\alpha} \tag{22}$$

Now we can write the expected payoff of bidder l as follows.

$$\pi_l = \int_0^{x_l^*} (c_l - \frac{\alpha}{l}x)dx - \frac{1}{n}(\mathbf{c}_{-l} + lb_l - \alpha Q)x_l^* \tag{23}$$

Differentiating above equation with respect to b_l and after some cancellations we have,

$$\frac{\partial \pi_l}{\partial b_l} = l(\frac{1}{\alpha} - \frac{l}{\alpha n})(c_l - b_l) + l(\frac{1}{n}\frac{p^*}{\alpha} - \frac{1}{n}\frac{b_l}{\alpha}) = 0 \tag{24}$$

Now comparing the above with the first-order condition in the proof of Proposition 1, the first term on the right hand side, which is the positive term, is less for a large bidder l compared to the previous case while the second term on the right hand side is the same as before. Therefore the b_l that solves the above equation has to be lower than b_i.