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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 behaviour 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 behaviour of firms participating in RGGI auctions. We then analyse data from 58 RGGI auctions to assess the relevant parameters, employing machine learning and three different 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).

In a landmark move toward greenhouse gas regulation, the Regional Greenhouse Gas Initiative (RGGI) stands out as a forerunner cap-and-trade program in the United States, specifically designed to reduce carbon emissions.[1] RGGI's framework, detailed in Figure 1, involves a coalition of twelve states in the Northeast and Mid-Atlantic regions, all committed to systematically lowering greenhouse gas emissions. Each state has crafted a unique cap-and-invest strategy, under which emissions caps are enforced and firms must acquire corresponding permits to produce CO2 emissions. RGGI's innovative model not only addresses climate change but also inspires other regions to consider similar paths. According to Analysis Group's independent evaluation, RGGI has notably decreased carbon emissions by 46%, accrued \$3.8 billion from the sale of emissions permits, and ultimately delivered \$5.7 billion in net economic benefits over a twelve-year period.[2]

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 behaviour 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 behaviour 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 behaviour of polluting firms that bid in a 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.

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

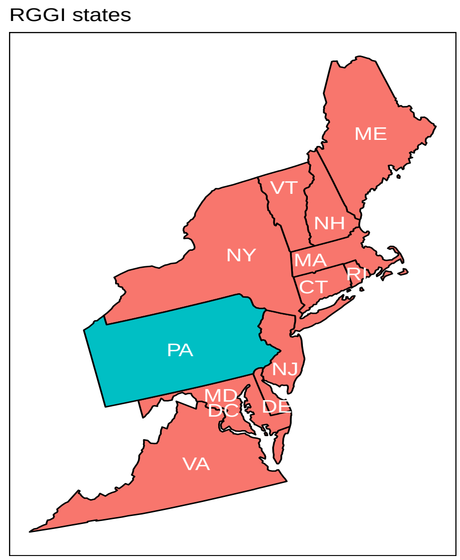


Figure 1: The map of participating states in RGGI. Pennsylvania joined the program in 2022

Thus, the contribution of this paper is twofold. First, we present a theoretical model that analyses the bidding behaviour of firms in RGGI's auctions, considering a setup that reflects relevant 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 one of major policies implemented in RGGI auctions, called the Cost Containment Reserve (CCR),[3] would reduce the extent of untruthful bidding in the auction and could 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 employs diverse methods, including linear and nonlinear regression models, as well as panel regression and machine learning models, to deeply analyse the distinct effects of auction parameters and policy changes on RGGI. We introduced the concept of the concentration of large-scale bidders (LSB) and investigated its effect on the auction clearing price. Furthermore, we scrutinized the impact of various variables on the clearing price of auctions using these methods.

We initiate our empirical analysis with a preliminary examination, evaluating key factors that influence clearing prices and analyzing the effects of policy interventions on auction outcomes. Indeed, we conduct a preliminary analysis to identify significant variables and their relationships with clearing prices. This crucial step helps us determine whether these variables exert a linear or nonlinear influence on clearing prices. Subsequently, utilizing machine learning models, specifically the Random Forest and Gradient Boosted Trees (GB) algorithms, we investigate the relationships between variables without making any prior assumptions about the linearity or nonlinearity of these connections. The insights from the Random Forest model indicate that the most significant factors affecting the auction clearing price include the trigger price, GDP, Emission Containment Reserve (ECR), and the Cost Containment Reserve (CCR). We then use visualization techniques to pinpoint significant variables and to understand their impact on auction prices more clearly. Drawing

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

insights from this wide ranging analysis, we then explore various methods to discern how different factors influence auction clearing prices. Applying these diverse models allows us to investigate their robustness across alternative analytical approaches.

Our findings indicate that irrespective of the use of nonlinear or linear models and whether the approach is policy-centered or variable-focused, the core results are consistent. Notably, key variables identified in the machine learning analysis, consistently show significance and similar direction in both model types, highlighting their substantial influence on auction clearing prices. The findings of this study collectively validate the strength of the relationships we have identified and highlight the consistency of our results across different analytical methods, thereby boosting the credibility of our conclusions.

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 model is presented, and four 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 commences with preliminary analysis and visualization, proceeding to unveil the outcomes derived from employing both (non)linear regression methods, as well as machine learning techniques. Then, provides some further analysis and discussion of the results. Finally, Section 6 provides concluding remarks.

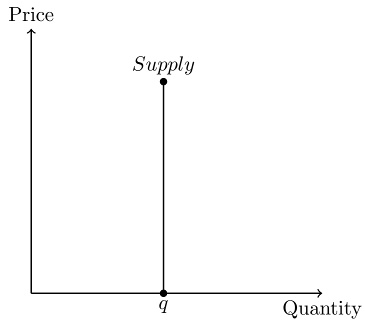
2 Background and previous literature

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.

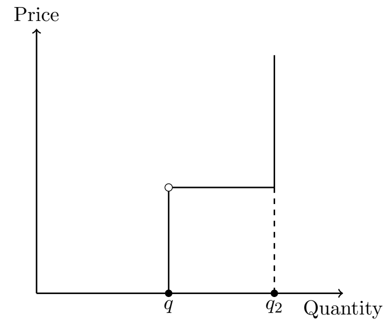
The uniform-price auction is the most commonly used auction format in cap-and-trade markets due to its desirable features such as price discovery and simplicity of rules (Khezr and MacKenzie, 2018b). However, it is well-established in the literature that this type of auction does not result in truthful 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.[4] 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. Therefore the market has two main mechanisms for the allocation and reallocation of permits:

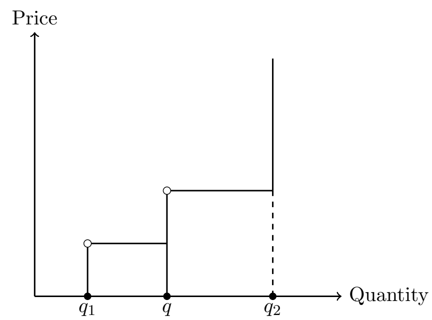
[4]Note that Pennsylvania was not formally added to RGGI for the data studied in this paper. Also, Virginia was included in RGGI from auction 51.



(a) Original Supply



(b) CCR introduced



(c) ECR introduced

Figure 2: Three different supply schedules implemented by RGGI

auctions for the initial allocation, and trade of permits for the secondary market.

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). As some of the most prominent policies implemented in RGGI are CCR and ECR, there are several papers that investigate the effect of such price caps on equilibrium prices. These studies usually make distinct modelling assumptions concerning firms' values for permits, abatement costs, the timing of the model and whether it is a multi period or a single shot game. Some papers focus on bidding behaviour and strategic interactions in the auction and abstract from the multi stage game. For example, Khezr and MacKenzie (2018b) presents a static setup that attempts to replicate the CCR within a uniform-price auction using common values for permits. They show that, if the overall cap is fixed after the introduction of the reserve allowance, the CCR cannot lower the auction clearing price, as in any new equilibrium of the auction with increasing supply, the price is at least as high as the price with a vertical supply.[5] Therefore, based on their conclusions one would expect CCR to probably increase the auction clearing price and the cost of permits if the total cap remains constant after the introduction of CCR.

Furthermore, there is another type of studies which abstract from bidding behaviour in the auction and try to model the dynamics of the game. For instance, Salant et al. (2022) develop an infinite-horizon model to study the effects of nonbinding price floors. They show that introducing a price floor below the initial market value can lead to an increase in price under certain conditions. They further noted that this increase is more significant when a rigid price floor is implemented, as opposed to a flexible one. Based on their conclusions one would expect a policy like ECR would increase the auction clearing price.

We note that due to the complexity that arises from the existence of multiple equilibria, there are no studies that investigate both the bidding behaviour in the auctions and the dynamics of a multi-stage game at the same time. In this paper, we took the former approach and study a single shot auction game. 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. As with any other theoretical model, our model has limitations in addressing some realistic aspects of the RGGI. However, we make sure to investigate these limitations in the theoretical section and further discuss how they influence our results.

To our knowledge, there is no paper that empirically investigates the auction parameters and the bidding behaviour 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 behaviour. Given that most of the 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; Salant et al., 2023). 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. Salant et al. (2023) study the theoretical findings of Salant et al. (2022) and support these finding. They show in a laboratory experiment that prices respond to nonbinding price floors.

[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.

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 $A(c_i)$.[8] 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 $\sum_i \lambda_i > Q$. In our theoretical model we abstract from the secondary market mainly for tractability reasons. If one assumes the expectation regarding the secondary market is fixed and ex-ante identical for all firms, it is plausible to conclude that the secondary market cannot influence the bidding behaviour of firms. We later show in the empirical analysis that auctions are usually the mechanisms to provide price signals for the secondary market and not vice versa.[9] In particular, we examine the mutual influence of auction clearing prices and secondary market prices. The Granger causality test indicates no statistical significance for secondary market prices predicting future clearing prices, while historical clearing price changes significantly forecast future secondary market prices. We provide more explanation in Section 4.

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.[10] 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 all bidders are in non-increasing orders. 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 part of the aggregate demand curve with a random marginal allocation rule.[11]

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.[12]

[8]In our theoretical model, we assume that firms are compliance entities. Although the majority of firms in real-world markets are polluting entities, there may also be other participants, such as speculators, active in these markets. We abstract from these entities for simplicity.

[9]Moreover, in the empirical analysis we control for the trade in the secondary market by including the trade volume and price in the secondary market.

[10]We assume that the size of λ_i is restricted so that it does not exceed a quarter of the total permits available. Although this assumption does not meaningfully affect our results, it aims to align with RGGI's rules, which prohibit firms from submitting bids for more than 25% of the total available allowances.

[11]We note that in practice, there are multiple methods for randomly allocating excess demand. For instance, in RGGI, each bidder is assigned a random number from 1 to n, where n represents the total number of bidders whose bids are on the flat part of the aggregate demand curve. Allocation begins with bidder 1 and continues until the supply is exhausted. Other rationing rules are also possible. For example, California employs a pro-rata rationing rule to allocate the supply of allowances when there is excess demand at the margin.

[12]In a scenario where banking of permits is allowed, the banked permits would be subtracted from the total emissions, with e representing the net level of emissions.

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.[13]

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

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 any possible 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

[13] Note that by incorporating a secondary market into the game, any surplus can only transfer from one bidder to another. Therefore, maximizing the surplus in the auction becomes a more crucial objective.

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 behaviour.

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 behaviour by bidders changes with the above change in the supply.

Proposition 2. *With an increasing supply, the equilibrium demand schedules submitted by firms are at least as high as the ones 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.*

There is a nuanced yet very crucial point regarding how we model the CCR and the result mentioned above. In our model, we assume the total number of permits available (the cap) is fixed at Q. So, if the CCR is implemented, the cap remains unchanged at Q, and at some quantity lower than the cap, the supply of permits would decline for prices below the trigger price. An alternative perspective on CCR exists. One can define a quantity of permits equal to $\omega > 0$ and adjust the total cap to $Q + \omega$ after the implementation of CCR, where the supply increases by ω for prices above the trigger price. In the case of RGGI, it is not easily verifiable which of the two methods was implemented in practice. The cap was reduced by 50% (from about 153 million tons to 72 million tons) at the same time the CCR was established. The CCR contains around 10 million tons to be added to the cap should the price trigger be exceeded. Therefore the total number of permits available, including the CCR is significantly below the amount before the policy was implemented. While our empirical analysis accounts for these factors, in the theoretical model, we assume the total number of permits to be distributed is fixed at Q, with CCR included in that quantity.

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 could 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 behaviour 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.

One important aspect of allowance allocation in RGGI is the option of banking. It is crucial to recognize that the game described in this section is a single-shot static game. In a one-shot game, allowance banking could be considered merely a fixed endowment and would not significantly influence the results. A more realistic approach would involve a scenario where firms bid in multiple stages and bank extra allowances. With the introduction of banking, various motivations can arise. For example, consider the primary motivation to be the uncertainty regarding future demand for permits. If firms are assumed to have unbiased expectations about their future demand, it seems reasonable to consider the banking of allowances as an endowment for the firm at any given auction. It is important to acknowledge that there could be other motivations, such as inter-period price trade-offs, and that simplifying the model to a single-shot game might overlook some significant dynamic effects. However, as detailed in the background section, due to the presence of multiple equilibria, extending the model to a multi-period setting is an exceedingly complex challenge and beyond the aim of this research's theoretical section. Our primary objective here is to construct a theoretical model that can yield insights into the behaviour of firms in the auction, insights we plan to later test using empirical methods.

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.[14] 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 modelling. 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 depicts the carbon allowance prices in RGGI auctions from 2008 to 2022, alongside the weighted prices of carbon allowances traded in the secondary market. 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

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

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.

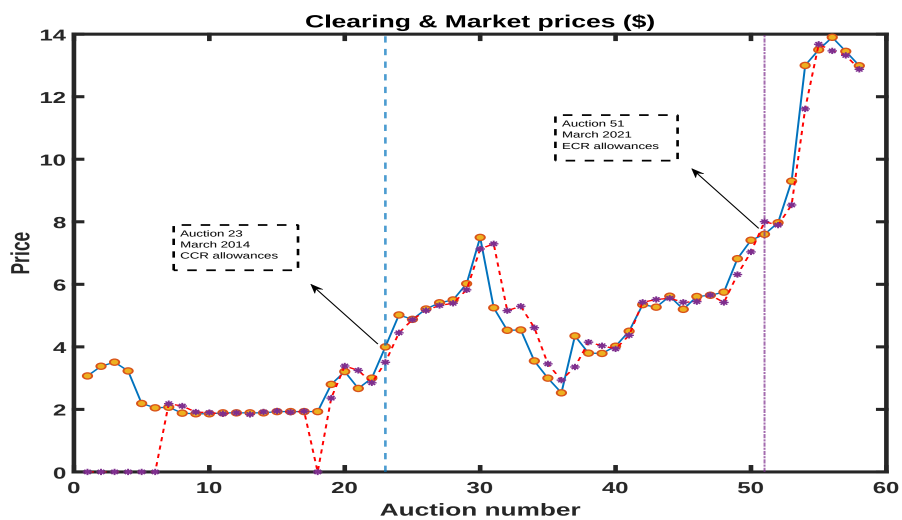


Figure 3: Clearing price in RGGI auctions.

We statistically examine the impact of auction clearing prices on future secondary market weighted prices to gain insights into their relationship. The Granger causality results show that auction clearing prices can significantly influence secondary market prices, evidenced by a very low p-value (0.0008). This indicates that historical changes in auction clearing prices offer meaningful insights for forecasting future prices in the secondary market. This initial test is conducted to demonstrate that auctions provide statistically significant price signals for the secondary market.

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 known 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).

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 1, 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 Definition 1 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 behaviour 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 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

In this section, we present the empirical methodology employed to evaluate the key factors influencing clearing prices and to analyse the effects of policy interventions on auction outcomes. We begin by conducting a preliminary analysis to identify significant variables and their relationship

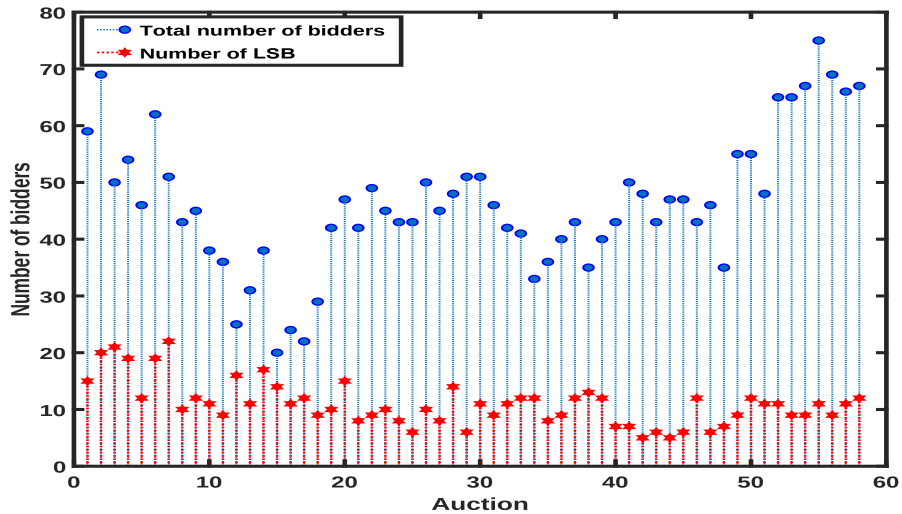


Figure 4: Number of Bidders and Large-scale Bidders in RGGI Auctions (Auctions 1-58).

with clearing prices. Subsequently, we employ a range of analytical approaches, including nonlinear modelling, linear regression, and panel regression models, to investigate the specific impacts of auction parameters and the policies implemented within the RGGI framework. In particular, in the main empirical analysis, we examine six distinct models. In Models 1, 3, and 5, we investigate the impact of various essential variables including two main policy variables of interest 'CCR' and 'ECR' which we later define in subsection 5.2. In Models 2, 4, and 6 we use similar essential variables except that we substitute 'CCR' and 'ECR' with the trigger prices. Following this, we will explore the intricacies of these relevant models in the subsequent subsections. The main reason for not concurrently considering policy variables with trigger prices is rooted in statistical concerns, primarily the potential for collinearity. In particular, the simultaneous inclusion of these variables in one model may result in collinearity issues, as evidenced by statistical tests such as the Variance Inflation Factor (VIF).

5.1 Preliminary machine learning analysis

Our empirical analysis begins with an essential preliminary step: examining the data structure. This foundational process is critical for both machine learning and traditional statistical models. To identify the most significant variables influencing the dependent variable, namely the clearing price, we utilize the Random Forest model. Known for its ability to handle nonlinearity and mitigate multicollinearity, the Random Forest model employs bootstrap sampling techniques. This approach systematically explores various combinations of variables, treating each as a distinct model and assigning them unique sets of data points. For more information, see (Mullainathan and Spiess, 2017). Through this method, we aim to uncover and highlight the key variables that drive the clearing price.

The results of the Random Forest algorithm are shown in Figure 6 for different variables. The left plot in Figure 6 illustrates the stabilization of the mean of squared residuals at approximately 0.4731 after roughly 400 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 weighted price, GDP, Year as a proxy for trend, CCR trigger price, the number of bidders, policy

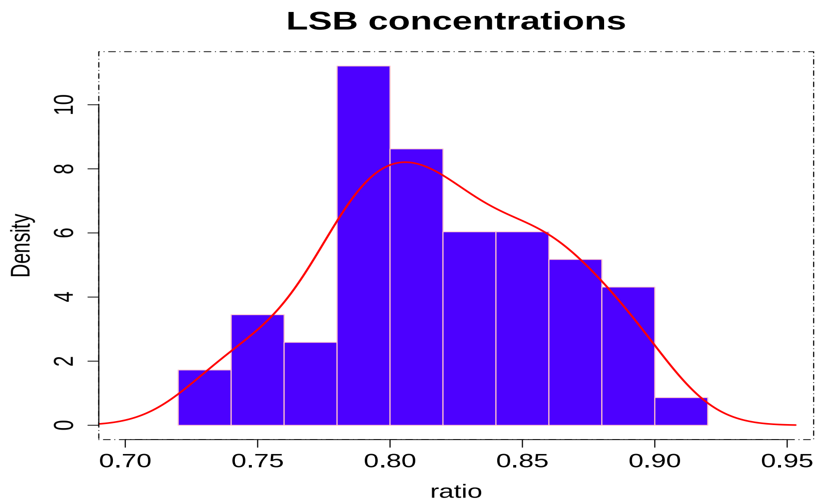


Figure 5: Distribution of concentration of LSB among 58 auctions in RGGI.

and Quantity sold (QS).[15]

Apart from 'GDP' as an exogenous variable and variable 'Year' which acts as a proxy for trend, 'weighted price', the 'trigger price', the 'number of bidders', 'CCR' and 'ECR' emerge as the most critical factors in shaping 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.

[15]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.

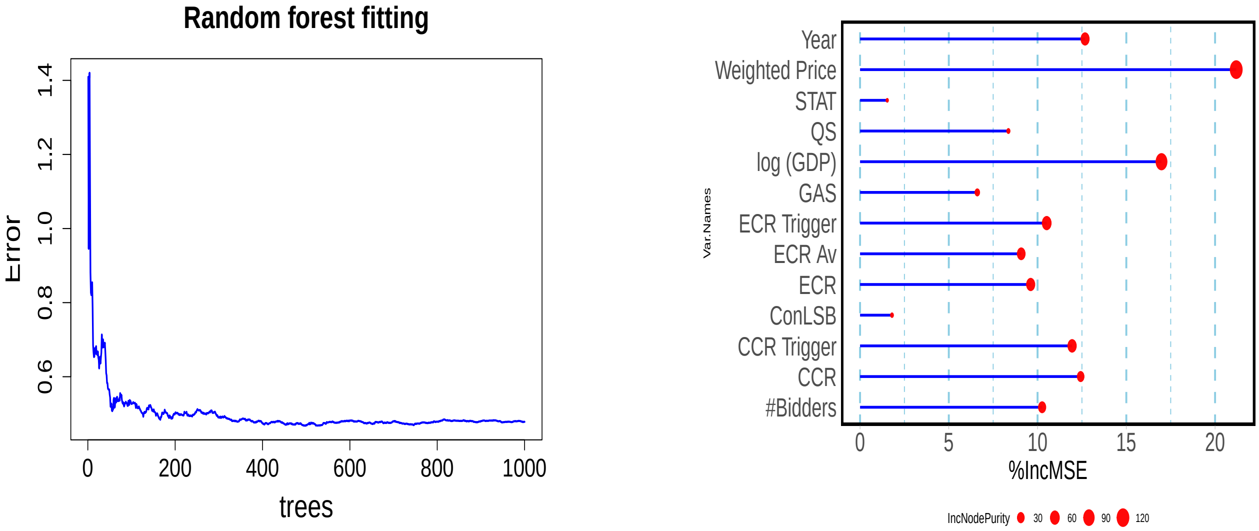


Figure 6: Plots from parameter tuning in Random Forest algorithm determine the optimal number of trees and variables. 'LSB Con' refers to the LSB concentration, 'No. Of Bidders' is the number of bidders.

Figure 7 illustrates the most significant variables determined by node purity, corroborating our earlier findings in the Random Forest analysis. In this method, Weighted Price, GDP, CCR Trigger, and Trend emerge as the most influential variables, while ConLSB and STAT exhibit comparatively lower significance.[16]

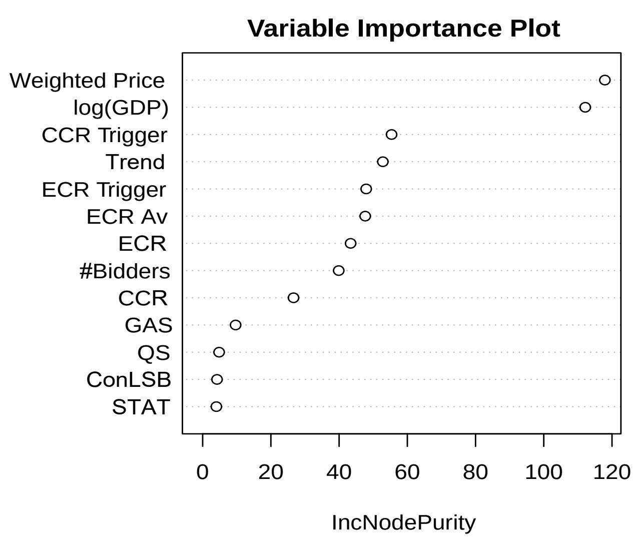


Figure 7: Variable importance in the model is determined by estimating node purity using the random forest algorithm.

[16]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.

We note that there are other machine learning approaches for the verification of the consistency of the results, such as Extra Trees,[17] AdaBoost methods,[18] and Gradient Boosted Trees. We report findings derived from the Gradient Boosted Trees algorithm (GB), a widely utilized ensemble method renowned for its effectiveness in both classification and regression tasks. This algorithm adeptly amalgamates numerous weak models to form a robust and powerful model.[19] 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, the first four important variables are 'weighted price', 'CCR', 'GDP', and 'Year' which exhibit the greatest impact on our model. The summary of this model fitting is presented in Figure 8.

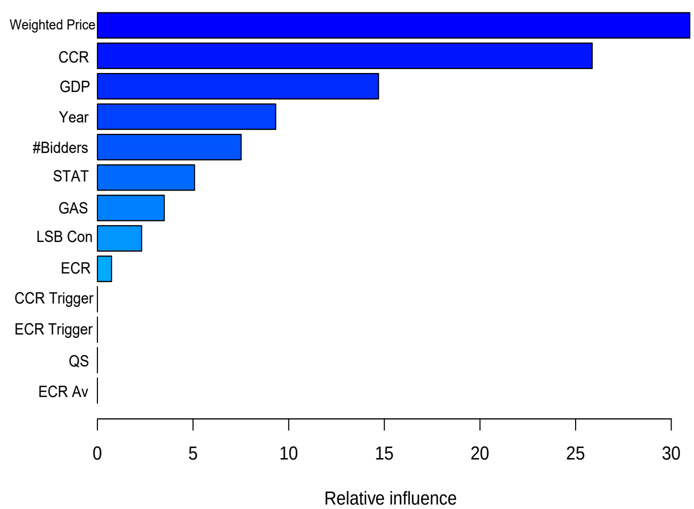


Figure 8: The importance of variables in the model based on GB algorithm.

In the subsequent phase of our analysis, building upon insights gained from the machine learning analysis, we show the relationships between crucial factors such as 'weighted price', 'log(GDP)', 'Year', and '# Bidders' with the dependent variable 'clearing price'. This visualisation provides a deeper understanding of model fitting and address the question of whether nonlinear models offer superior suitability for our modelling endeavours.

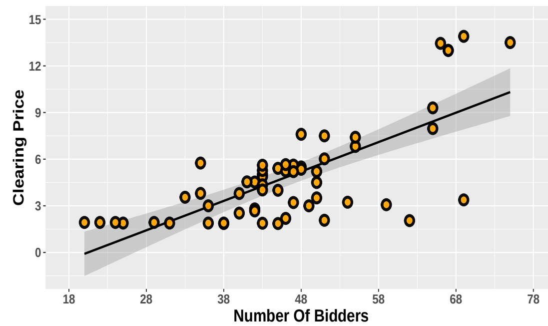
We present a series of scatterplots in Figures 9a to 9d to give a visual reference as to how these key variables and auction clearing prices are linked with each other. Figure 9a showcases the scatterplot depicting the relationship between the 'Year' of auctions as a proxy for temporal trends and the 'clearing price'. Notably, this plot does not exhibit a linear relationship with the dependent variable, 'price'. Instead, it reveals two distinct peaks in the middle of the dataset, occurring in 2015

[17] 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).

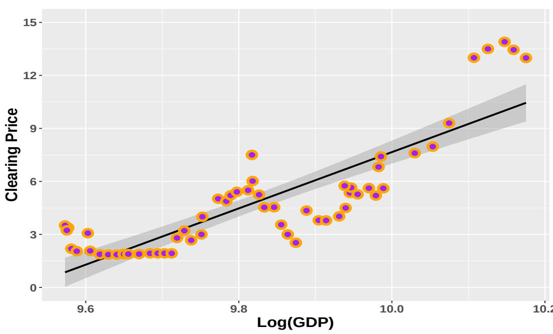
[18] AdaBoost - This model is an iterative algorithm that combines multiple weak classifiers into a single strong classifier. The weak classifiers are usually decision trees with a single split. More detail is available in Bonaccorso (2017).

[19] For more details see Natekin and Knoll (2013).

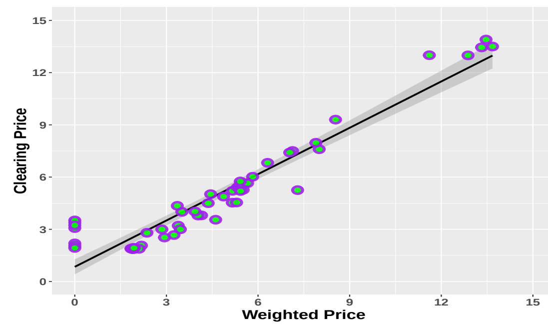
(a) Scatterplot for 'Year' & 'Clearing Price'



(b) Scatterplot for '#Bidders' & 'Clearing Price'



(c) Scatterplot for 'log(GDP)' & 'Clearing Price'



(d) Scatterplot for 'Weighted Price' & 'Clearing Price'

Figure 9: Univariate scatter plots: Auction clearing price and regressors

and the final year of our study, 2022. A similar pattern is also observed in Figure 9c. Conversely, Figure 9b displays a different pattern, with the primary concentration of data points occurring in the middle range. Finally, Figure 9d demonstrates a relatively linear relationship between weighted price and clearing price. This finding aligns with our prior expectations, as we anticipated that the most influential factor in determining the weighted price in the secondary market would be the auction clearing price. This highlights the notion that purchasers of carbon emission allowances typically submit their bids closely aligned with the previous auction's clearing price, with minimal deviation.

Through our preliminary analysis, we show a nonlinear and intricate relationship between the clearing price and other variables. To effectively capture this complexity, we have chosen the GAM as a main modelling approach. While recognizing the appeal of Linear Regression models in the literature, we include them in our analysis to offer comparative insights, acknowledging the simplicity they bring to understanding the relationships in the data.

5.2 Nonlinear analysis: Generalised Additive Model (GAM)

We used Generalized Additive Models (GAMs) as nonlinear models for their versatility in capturing intricate relationships, managing nonlinearity, interactions, and non-parametric elements. GAMs are adept at adapting to shifting trends and capturing time-varying effects.[20]

[20] GAMs outperform OLS models in two ways. Firstly, they excel at adapting to changing trends and capturing time-varying effects, unlike OLS models reliant on fixed linear relationships. Secondly, GAMs exhibit robustness against outliers, making them suitable for real-world datasets with anomalies or extreme values, adapting without strict data distribution assumptions. For more details about the application of GAM, see Wood (2017).

The nonlinear analysis aims to conduct a thorough investigation into the impact of a variety of variables, which we categorise into three distinct groups: auction-related variables including 'Weighted Price', '#Bidders', 'CCR', 'ECR', and 'ConLSB'; economic variables (essential exogenous factors) encompassing 'GDP', 'Gas price' and a trend.[21] Importantly, to account for the impact of the secondary market in the auction, we introduce two variables: 'Weighted Price' and 'Sum Total Allowances Transacted, (STAT)'. We calculate the Weighted Price for time step t based on the average weighted price of STAT in the secondary market from the previous auction at time $t-1$ up to one day before the new auction at a time t. Additionally, we define two variables, $CCR = log(QS) \times D_{CCR}$ and $ECR = log(QS) \times D_{ECR}$ where both D_{ECR} and D_{ECR} are dummy variables representing the introduction of two policies, CCR and ECR, within the RGGI framework.

Model 1: In the first model, non-periodic splines are employed to capture the nonlinear relationship between the auction clearing price and the following independent variables: CCR, ECR, Gas price, GDP, LSB concentration, $\#Bidders$ (number of bidders), STAT, and Weighted price.

$$\begin{aligned} P_t &= \alpha_1 CCR_t + \alpha_2 ECR_t + \alpha_3 \text{Weighted Price}_t + \alpha_4 \text{STAT}_t + f_1(log(GDP_t)) \\ &+ f_2(GAS_t) + f_3(Trend_t) + f_4(\#Bidders_t) + f_5(ConLSB_t) + +\alpha_5, \end{aligned} \tag{7}$$

where P_t represents the clearing price, in time t. The functions f_1, f_2, $\cdots$, f_5 are assumed to be smooth and will be estimated using a cubic regression spline. The coefficients $\alpha_1, ..., \alpha_5$ are unknown parameters.

	Estimate	Std.Error	tvalue	Pr(> $\|t\|$)	
(Intercept)	0.656	0.072	9.090	0.000	***
CCR	0.086	0.017	5.151	0.000	***
ECR	0.023	0.028	0.806	0.425	
Weighted Price	0.746	0.048	15.648	0.000	***
STAT	0.000	0.000	-2.146	0.037	*
Approximate significance of smooth terms:					
	edf	Ref.df	F	p-value	
$f_1(log(GDP))$	1.961	6.000	2.193	0.000	***
$f_2(GAS)$	0.963	0.969	0.236	0.635	
$f_3(Trend)$	1.725	2.030	45.062	0.000	***
$f_4(\#Bidders)$	1.275	1.625	15.594	0.000	***
$f_5(ConLSB)$	2.244	2.315	5.308	0.005	**
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
R^2(adj) = 0.976, Deviance explained = 98.1%					
GCV = 0.3181, Scale est. = 0.2477, n =58					

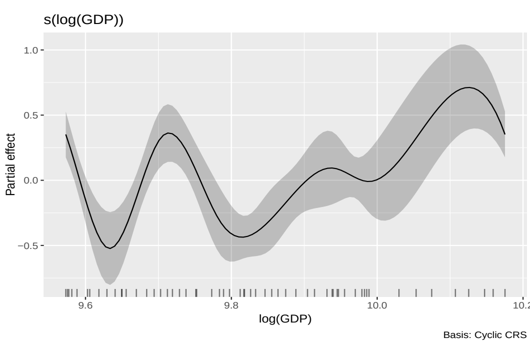
Table 1: Parameter estimation for nonlinear **Model 1**, Equation 7.

The results from our nonlinear regression model (GAM model), presented in Table 1, offer valuable insights into the factors that significantly influence auction clearing prices. We bring forward some important variable discussion. First, 'Weighted Price' emerges as a highly significant

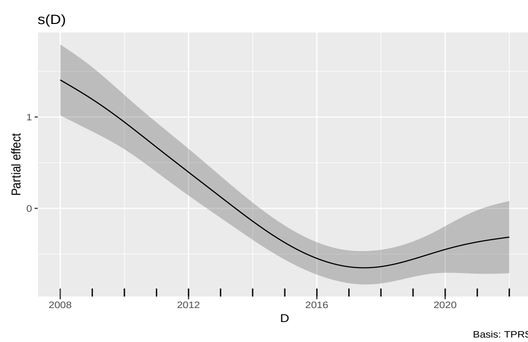
[21] It is worth noting that we opt for the log transformation of GDP rather than using GDP directly for several reasons. Firstly, this logarithmic transformation helps in mitigating heteroscedasticity, stabilizing the variance of the error term. Moreover, it contributes to normalizing the distribution of residuals, a crucial assumption for hypothesis testing and constructing confidence intervals.

determinant with a substantial positive effect on clearing prices (Estimate = 0.746, p-value < 0.001). This implies that there is a positive relationship between the weighted price of allowances in the secondary market clearing prices during auctions. Next, the logarithm of GDP is revealed to have a statistically significant impact on clearing prices, (p-value < 0.001), where its dynamic value is depicted in 10a. This nonlinear relationship suggests that changes in GDP do not have a uniform linear effect on clearing prices. Instead, they exhibit a complex association, where variations in GDP can approximately positively affect clearing prices.

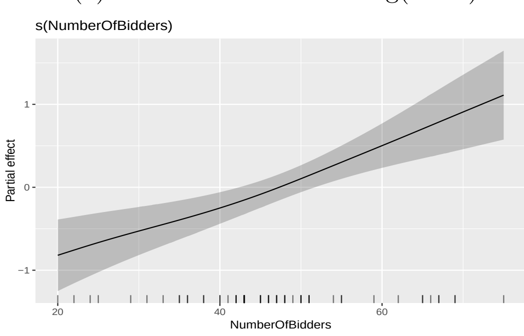
Moreover, the variable 'Trend' demonstrates a statistically significant impact on clearing prices (p-value < 0.001). This nonlinear pattern highlights the importance of temporal trends in auction outcomes, as shown in Figure 10b. The auction trend exerts a significant influence on clearing prices, with notable fluctuations observed in the middle years of the dataset, notably in 2015 and 2022. Additionally, the number of bidders, represented as '#Bidders' is found to be a substantial and statistically significant factor affecting clearing prices (p-value < 0.001). This positive linear relationship, as can be seen in Figure 10c suggests that an increase in the number of bidders in the auction leads to higher clearing prices. Notably, the complex nonlinear dynamics of 'LSB Con' with respect to the 'Clearing price' are revealed in 10d. The graph indicates a positive trend at lower concentrations, approximately around 75%, but interestingly transitions to a negative trend at higher concentrations, ranging from 90% to 95%. This finding reflects the competitive dynamics of the auction process.



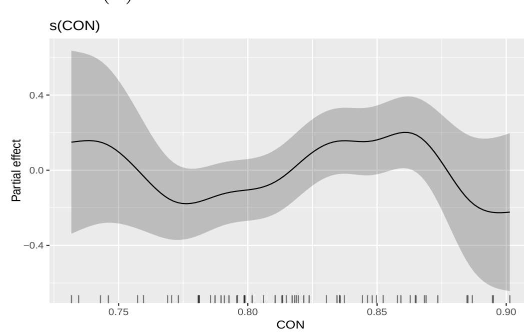
(a) Smooth function for 'log(GDP)'



(b) Smooth function for 'Trend'



(c) Smooth function for '$\#Bidders$'



(d) Smooth function for 'LSB Con'

Figure 10: Smooth functions of model in Equation 7 for four important variables.

Model 2: This model is structured to encompass the nonlinear relationship among the dependent variables: CCR Trigger, ECR Trigger, GDP, Quantity sold, STAT, the number of bidders, Trend, and weighted price. The equation, emphasizing RGGI policy analysis, is given by the following equation:

$$\begin{aligned} P_t &= \alpha_1 \text{CCR Trigger}_t + \alpha_2 \text{ECR Trigger}_t + \alpha_3 \text{Weighted Price}_t + \alpha_4 \text{STAT}_t \\ &+ f_1(QS) + f_2(Trendt) + f_3(log(GDP_t)) + f_4(\#Bidders_t). \end{aligned} \tag{8}$$

Results of **Model 2**, Equation 8, are reported in Table 2. As anticipated, the CCR Trigger has a coefficient of 0.011 with a p-value of less than 0.001, indicating a statistically significant positive impact on the dependent variable. Similarly, the ECR Trigger exhibits a coefficient of 0.010, and it, too, has a statistically significant positive effect on the dependent variable. In summary, both CCR and ECR triggers positively impact the dependent variable, with CCR Trigger showing a slightly stronger influence, as evidenced by its higher coefficient and lower p-value, signifying greater statistical significance. This indicates that both ECR or CCR trigger prices have a significant positive effect on the auction clearing price. In other words, keeping everything constant, a higher ECR or CCR trigger price would increase the auction clearing price one average. These results demonstrate the importance of CCR and ECR triggers, as well as the weighted price, in explaining the variations in the dependent variable in RGGI auctions. The adjusted R-squared value of 0.981 indicates that the model explains a substantial amount (98.5%) of the variance in the dependent variable, making it a good fit for the data. Further, we can see the consistency of results compared with results in Table 1. Next, we consider Equation 7 in the linear format as follows.

	Estimate	Std.Error	tvalue	$\Pr(>\lvert t\rvert)$	
(Intercept)	0.609	0.052	11.787	0.000	***
CCR Trigger	0.011	0.001	7.500	0.000	***
ECR Trigger	0.010	0.003	3.357	0.002	**
Weighted Price	0.698	0.039	18.104	0.000	***
STAT	0.000	0.000	-2.374	0.022	*
Approximate significance of smooth terms:					
	edf	Ref.df	F	p-value	
$f_1(QS)$	3.947	10.000	3.064	0.000	***
$f_2(Trend)$	0.597	0.598	276.118	0.000	***
$f_3(log(GDP))$	2.437	6.000	1.859	0.000	***
$f_4(\#Bidders)$	0.873	0.873	24.275	0.000	***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
R sq.(adj) = 0.981 Deviance explained = 98.5%					
GCV = 0.2418 Scale est. = 0.1909 n =58					

Table 2: Parameter estimation for nonlinear **Model 2**, Equation 8.

The GAM models 1 and 2 yield promising results that align well with theoretical expectations, affirming their suitability for examining relationships in RGGI auctions. Nevertheless, in the following subsection, we broaden our analysis to enhance the robustness of our findings by incorporating linear regression models. This additional exploration aims to validate the consistency of our results and provide a comprehensive understanding of the dynamics at play in the next subsection, where we introduce two linear regression models.

5.3 Linear analysis

In this stage, we conduct an empirical analysis using linear regression Models 3 and 4. These models are evaluated by comparing their fit against the previously obtained results. **Model 3**: This model is a linear representation derived from the first nonlinear model using a linear Regression approach. The corresponding equation is as follows:

$$\begin{aligned} P_t &= \beta_1 CCR_t + \beta_2 ECR_t + \beta_3(log(GDP_t)) + \beta_4(Trend_t) + \beta_5(\#Bidders_t) \\ &+ \beta_6(ConLSB_t) + \beta_7\text{Weighted Price}_t + \beta_8\text{STAT}_t + \beta_9 GAS_t + \beta_{10}, \end{aligned} \tag{9}$$

where the coefficients $\beta_1, ..., \beta_{10}$ are unknown parameters.

	Estimate	Std.Error	tvalue	$\Pr(>\|t\|)$	
(Intercept)	0.000	0.000	-6.017	0.000	***
CCR	0.024	0.019	1.238	0.222	
ECR	0.064	0.030	2.167	0.035	*
Trend	-0.001	0.000	-3.368	0.001	**
Weighted Price	0.663	0.064	10.333	0.000	***
STAT	-0.000	0.000	-1.457	0.151	
#Bidders	0.051	0.011	4.795	0.000	***
log(GDP)	0.013	0.001	10.090	0.000	***
GAS	0.132	0.080	1.655	0.104	
ConLSB	-0.001	0.000	-3.822	0.000	***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
R sq.(adj) = 0.95 Deviance explained = 96.2 %					
GCV = 0.49652 Scale est. = 0.43659 n =58					

Table 3: Parameter estimation for linear **Model 3**, Equation 9.

The results obtained from our linear regression model, as presented in Table 3, offer valuable insights into the determinants of auction clearing prices. Several critical variables stand out as significant contributors to these prices. Notably, 'Weighted Price' exhibits a highly significant positive impact on clearing prices (Estimate = 0.663, p-value < 0.001). Furthermore, 'log(GDP)' displays a statistically significant positive effect (Estimate = 0.013, p-value < 0.001), emphasizing that changes in the logarithm of GDP positively affect clearing prices. Additionally, the number of bidders, represented as '#Bidders', significantly affects clearing prices with a positive coefficient (Estimate = 0.051, p-value < 0.001).

It is worth noting that in both (non)linear models, 'Weighted Price' consistently shows a highly significant and positively associated variable with clearing prices. Furthermore, 'log(GDP)' consistently shows a significant positive impact, suggesting that economic growth, as represented by GDP, positively influences clearing prices, while in both models 'GAS' price is not statistically significant. Moreover, the number of bidders, denoted as '#Bidders', consistently displays a significant positive association with clearing prices in both models, highlighting the competitive nature of auctions and how increased bidder participation tends to drive up prices. Finally, the consistent treatment of policy variables, 'CCR' and 'ECR' in the nonlinear and linear models, demonstrates their respective impacts on clearing prices, underscoring the importance of regulatory policies in shaping auction dynamics.

	Estimate	Std.Error	tvalue	Pr(> $\lvert t \rvert$)	
(Intercept)	-0.001	0.000	-2.540	0.014	*
CCR Trigger	0.385	0.183	2.104	0.040	*
ECR Trigger	0.128	0.055	2.309	0.025	*
Quantity Sold	-0.020	0.011	-1.843	0.071	.
Trend	-0.000	0.000	-5.128	0.000	***
log(GDP)	0.049	0.018	2.748	0.008	**
#Bidders	0.064	0.009	7.020	0.000	***
Weighted Price	0.659	0.063	10.440	0.000	***
STAT	-0.000	0.000	-1.670	0.101	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
R sq.(adj) = 0.95 Deviance explained = 95.5 %					
GCV = 0.500 Scale est. = 0.457 n =58					

Table 4: Parameter estimation for linear model **Model 4**, Equation 10.

Model 4: In this model, we explore the linear relationship between the following dependent variables: CCR Trigger, ECR Trigger, GDP, Number of bidders, QS, STAT, Trend, and Weighted price. The model is specified as follows:

$$\begin{aligned} P_t &= \beta_1 \text{CCR Trigger}_t + \beta_2 \text{ECR Trigger}_t + \beta_3 \text{QS}_t + \beta_4 (\#Bidders_t) \\ &+ \beta_5 \text{Weighted Price}_t + \beta_6 \text{STAT}_t + \beta_7 (log(GDP_t)) + \beta_8 (Trend_t) + \beta_9. \end{aligned} \tag{10}$$

Table 4 shows results for linear regression model 10. In the analysis, both the CCR Trigger and ECR Trigger demonstrate statistically significant positive impacts on the dependent variable, with coefficients of 0.385 and 0.128, and corresponding p-values of 0.040 and 0.025, respectively. While the CCR Trigger exhibits a stronger effect, both contribute positively to the outcome, underscoring their importance in the model. In terms of the Quantity Sold, it has a coefficient of -0.020 with a p-value of 0.071. Although the p-value is slightly above 0.05, denoted by '.', suggesting marginal statistical significance, the negative coefficient suggests that the Quantity Sold has a somewhat negative effect on the dependent variable, as we normally expected.

5.4 Further analysis and discussion

In this subsection, we continue our empirical investigation by applying panel regression analysis. Panel data analysis provides a valuable framework for capturing time specific effects and trends, which is crucial for accommodating changes and developments over time. Secondly, it offers a robust solution for addressing unobserved or time invariant heterogeneity by incorporating fixed effects or random effects tailored to individual entities, effectively controlling for variations in the data. Lastly, when dealing with individuals or entities exhibiting evolving characteristics and behaviours over time, panel data models excel at accounting for this dynamic individual heterogeneity. Therefore, we adopt the assumption of grouping auctions by year within the RGGI context and implementing panel regression models. This choice is underpinned by two primary rationales. Firstly, temporal dynamics and time dependent patterns. The relevance of grouping auctions by year is contingent upon the existence of temporal dynamics or time-dependent patterns within the data. Factors such as seasonal variations, cyclical trends, or recurring events may exert distinct influences on auction dynamics in each year. Further, the chosen grouping strategy establishes a framework conducive to capturing and accommodating these time-specific influences on auction outcomes. Secondly, the economic fluctuations. Economic conditions are subject to change over time, with periods of growth or recession potentially impacting the demand for emission allowances and, by extension, influencing auction prices. Moreover, grouping auctions by year facilitates the recognition and examination of shifts in economic conditions, allowing the panel regression model to account for these temporal variations in the determination of auction outcomes. Thus this assumption ensures a comprehensive framework for capturing and addressing these time-specific influences on the observed auction outcomes.

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

$$Y_{it} = \sum_{j \in J} \alpha_i X_{it}^j + u_i + \gamma_t + \epsilon_{it}, \tag{11}$$

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.

In the subsequent two models, we examine the validity of grouping auctions by year and employing panel regression models. This methodological approach is grounded in an awareness of the varying temporal dynamics, time-dependent patterns, and economic fluctuations that might exert disparate influences on auction dynamics across different periods.

Model 5: In this model similar to models 1 and 3, we consider a dynamic model to assess how the policy affects on auction clearing prices over time. The regression model is as follows:

$$\begin{aligned} P_{it} &= \eta_1 CCR_{it} + \eta_2 ECR_{it} + \eta_3 (GDP_{it}) + \eta_4 (Trend_{it}) + \eta_5 (\#Bidders_{it}) \\ &+ \eta_6 \text{Weighted Price}_{it} + \eta_7 \text{STAT}_{it} + u_i + \gamma_t + \epsilon_{it}, \end{aligned} \tag{12}$$

where the coefficients $\eta_1, ..., \eta_7$ are unknown parameters. Moreover, u_i captures the individual-specific random effects, γ_t captures the time-specific random effects. Finally, ϵ denotes the error terms. The reason that we do not consider $\log(GDP)$ instead of GDP in Equation (12) despite our use of the former in previous models lies in computational considerations. Specifically, the inclusion of $\log(GDP)$ results in singular outcomes, rendering the model unable to parameter estimations. 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 5). According to Table 5 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, ECR has a coefficient of 0.118, indicating that a one-unit increase in ECR is associated with an average increase of 0.118 units in the dependent variable. Its p-value of 0.021 suggests statistical significance. CCR also has a positive coefficient of 0.086, signifying that a one-unit increase in CCR corresponds to an average increase of 0.086 units in the dependent variable, with a significant p-value of 0.017. In contrast, Trend has a negative coefficient of -0.601, implying that a one-unit increase in Trend is linked to an average decrease of 0.601 units in the dependent variable. Its p-value of 0.019 indicates statistical significance. These results suggest that ECR and CCR positively influence the dependent variable, while Trend exerts a negative influence, and all three variables are statistically significant in explaining the variation in the dependent variable. The p-values column in the table indicates the statistical significance of each coefficient.

Coefficients:	Estimate	Std.error	z-value	$Pr(>\|z\|)$	
(Intercept)	1189.600	514.410	2.313	0.021	*
CCR	0.086	0.036	2.385	0.017	*
ECR	0.118	0.051	2.313	0.021	*
#Bidders	0.058	0.016	3.569	0.000	***
Trend	-0.601	0.257	-2.341	0.019	*
GDP	0.001	0.000	3.364	0.001	***
STAT	0.000	0.000	-0.344	0.731	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Total Sum of Squares: 578.89					
Residual Sum of Squares: 51.03					
R-Squared: 0.91185					
Adj. R-Squared: 0.90148					
Chisq: 527.555 on 48 DF, p−value: < 2.22e-16					

Table 5: Parameter estimation based on **Model 5**, Equation 12.

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).[22] 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 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

[22]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.

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.

Model 6: In this policy focused analysis, we explore the relationship between the following dependent variables: CCR Trigger, ECR Trigger, GDP, Quantity sold, STAT, Trend, and Weighted price. The model is specified as follows:

$$\begin{aligned} P_{it} &= \eta_1 \text{CCR Trigger}_{it} + \eta_2 \text{ECR Trigger}_{it} + \eta_3 \log(\text{QS}_{it}) + \eta_4 \text{Weighted Price}_{it} \\ &+ \eta_5 \text{STAT}_{it} + \eta_6 (GDP_{it}) + \eta_7 (Trend_{it}) + u_i + \gamma_t + \epsilon_{it}, \end{aligned} \tag{13}$$

Coefficients:	Estimate	Std.error	z-value	$Pr(>\lvert z \rvert)$	
CCR Trigger	0.011	0.005	2.025	0.049	*
ECR Trigger	0.006	0.008	0.755	0.454	
log(Quantity Sold)	0.237	0.399	0.595	0.554	
Trend	-0.659	0.197	-3.349	0.002	**
GDP	0.001	0.000	2.275	0.028	*
Weighted Price	0.731	0.089	8.186	0.000	***
STAT	0.000	0.000	-0.863	0.393	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Total Sum of Squares: 578.89					
Residual Sum of Squares: 31.167					
R^2: 0.94616					
Adj. R^2: 0.93471					
Chisq: 136.56 on 6 DF, p-value: $< 2.22\text{e-}16$					

Table 6: parameter estimation based on the **Model 6**, Equation 13.

Table 6 shows the estimation results of the Equation 13. Trend exhibits a significant negative impact with a coefficient of -0.659, indicating that for each unit increase in Trend, the dependent variable is expected to decrease by 0.659 units on average. The associated p-value is 0.002, signifying its statistical significance. CCR Trigger has a positive coefficient of 0.011, suggesting that a one-unit increase in CCR Trigger corresponds to an average increase of 0.011 units in the dependent variable, with a marginally significant p-value of 0.049. On the other hand, EER Trigger, with a coefficient of 0.006 and a p-value of 0.454, does not appear to have a statistically significant influence on the dependent variable. These findings indicate that Trend is a significant predictor, exerting a negative effect, while CCR Trigger has a positive, albeit marginally significant, influence on the dependent variable.

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.

The robustness and consistency of the results among the different models provide strong support for the reliability of the findings in this analysis. Despite employing various modelling techniques, including nonlinear (GAM) and linear (OLS) models, the main findings remain consistent. Specifically, the consistent significance and direction of key variables, such as 'Weighted Price', 'log(GDP)', 'Trend' and the number of bidders, in both nonlinear and linear models reinforce their substantial impact on auction clearing prices. Moreover, the consistent treatment of policy variables, 'CCR' and 'ECR', in the different models underscores their importance in shaping auction dynamics. For instance, the alignment in the treatment of policy variables, 'CCR' and 'ECR', is another noteworthy aspect of consistency. As per our preliminary analysis the nonlinear GAM analysis is the most suitable fit for the current data structure. Based on GAM results 'CCR' has resulted in an increase of the auction clearing price with a high level significance. The robustness of this result is evidenced by the significant coefficient of 'CCR' in the panel random effect regression. In all Models 2, 4 and 6, the CCR trigger price has a positive and statistically significant coefficient. This demonstrates the importance of the CCR trigger price in determining the auction clearing price. Moreover, the coefficient of 'ECR' despite being positive is not significant in the GAM model. However, in both linear and random panel regressions this variable has a positive and significant coefficient.

According to Claims 1 and 2, we expect that auction prices, ceteris paribus, were higher after the implementation of 'CCR'. Given that the coefficient of 'CCR' is both positive and significant (see Table 1), the evidence supports this claim. It is important to note that this result accounts for a significant reduction in the cap that occurred in the new compliance period starting with 'CCR'. In fact, our analysis demonstrates that, once we control for other important variables, auction prices on average increase after the implementation of 'CCR'.

Moreover, our empirical results support Claim 3, as the number of bidders is shown to have a positive and significant effect on the auction's clearing price (Tables 1-2). Finally, the results of Model 1 show a complex relationship between the concentration of LSB and the clearing price (Figure 10d). This supports our claim 4 where the intuition suggests that with a few number of large scale bidders, the auction clearing price declines due to high monopsony power. The result shown in Figure 10d supports this intuition as when the ratio is close to one (to the right of the figure) the value is at the lowest and negative. However, when the number of large scale bidders becomes larger their monopsony power declines as the function's value increases demonstrating higher auction clearing prices. The variation of the value declines for some lower ratios but with small variations and mostly positive. This indicates that when the concentration of bidders declines, the auction clearing price would mostly increase as the competition increases. These results collectively demonstrate the robustness of the identified relationships and highlight the stability of the findings across various analytical approaches, reinforcing the credibility of the conclusions drawn from the analysis. The agreement between results further strengthens the reliability of the insights gained in this study, providing a comprehensive and cohesive understanding of the factors influencing auction clearing prices.

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 various models to test the hypotheses provided. In particular, we use nonlinear, linear, and panel regression approaches, with two variations of models incorporating different variables. In most of our models, CCR had a positive and significant influence on the auction clearing price, robustly indicating that the CCR policy was indeed successful in lowering demand reduction. This finding aligns with our Claim 2 and some previous theoretical and experimental claims (Khezr and MacKenzie, 2018b; Friesen et al., 2022). Note that although there was a significant reduction in the cap at the time CCR was introduced, the auction clearing price declined significantly after auction 30. Therefore, it is not straightforward to conclude that the increase in auction clearing price after the introduction of CCR is solely due to cap reduction. Furthermore, in our models, we also control for the reduction in the cap, and therefore, based on our results, it is evident that the introduction of CCR increased the auction clearing price on average.

There are significant policy implications regarding the above result. First, note that as suggested by its name, CCR was intended to contain costs for firms. Our evidence indicates that CCR, and similar ex-ante increasing supply schedules, do not reduce the auction clearing price. Second, despite CCR not being successful in reducing the auction price, there are still substantial benefits from such policies, including the elimination or alleviation of demand reduction in the auction, which could improve auction revenue and possibly efficiency.

Overall 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 behaviour 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 behaviour is pivotal for the effectiveness of policies implemented by regulators. Without a clear understanding of these behaviours 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 behaviour.

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. Consequently, most of the current cap-and-trade systems use various supply adjustment methods to ensure there is less room for bid manipulations. For instance, a simple increasing supply such as CCR can significantly increase 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. Some existing policies in RGGI are in place to address this issue. For instance, as state before a bidder cannot bid for more than a percentage of the total available allowances in each RGGI auction.

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Appendices

Appendix 1: Additional tables

The tables 7 and 8 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 7 and 8 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 7: 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 8: 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.

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.

Variable	**Min.**	**1st.Q**	**Median**	**Mean**	**3rd.Q**	**Max**	**std**
Clearing Price	1.86	2.57	4.19	4.89	5.62	13.90	3.19
GDP	14371	16098	18354	18782	20877	26246	3248.84
inflation	210.20	229.40	238.20	243.00	255.70	296.80	21.39
Gas	2.72	3.76	4.45	4.82	5.47	9.92	1.55
LTW	0.73	0.79	0.82	0.82	0.85	0.90	0.04
Number Of Bidders	20.00	40.25	45.50	46.34	51.00	75.00	12.09
ECR Available	0	0	0	1535810	0	11307333	3873596
CCR Available	0	0	10000000	5802625	10000000	11976778	5367435
Quantity Sold	7487000	14713820	18986342	21673774	26624324	41995813	8860635
Weighted Price	0.00	1.94	4.26	4.56	5.54	13.68	3.43
Allowances Transfer	0	993250	5045500	11044511	10976500	84395000	17172945

Table 9: Descriptive Statistics

In Table 9, the clearing Price represents the price at which carbon allowances were cleared in an auction. It has a median value of 4.19 and a mean of 4.89, indicating that, on average, allowances cleared at a price close to 4.89 units. The maximum clearing price observed was 13.90, while the minimum was 1.86. Further Weighted Price, on the other hand, represents the price of allowances in the secondary market, with a median of 4.26 and a mean of 4.56. This suggests that, on average, allowances in the secondary market had a similar price to those cleared in auctions. Further, the comparison between 'Clearing Price' and 'Weighted Price' indicates that, on average, prices in the secondary market are relatively close to clearing prices. Regarding the quantity of allowances, 'Quantity Sold' represents the total quantity of allowances successfully sold in auctions, with a median of 18,986,342 units and a mean of 21,673,774 units. On the other hand, 'Total Allowances Transferred' has a median of 5,045,500 units and a mean of 11,044,511 units. This data suggests that approximately 25% of the total allowances initially sold in auctions are subsequently transferred in the secondary market."

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,

$$x(b_i) = \frac{b_i}{\alpha} - \frac{1}{\alpha}p \tag{14}$$

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,

$$\mathbf{c}_{-i} + b_i - np^* = \alpha Q \tag{15}$$

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

$$x_i^* = \frac{b_i}{\alpha} - \frac{\mathbf{c}_{-i} + b_i - \alpha Q}{n\alpha} \tag{16}$$

Now one can rewrite Equation (3) as follows.

$$\pi_i = \int_0^{x_i^*} (c_i - \alpha x)dx - \frac{1}{n}(\mathbf{c}_{-i} + b_i - \alpha Q)x_i^* \tag{17}$$

Differentiate the above with respect to b_i. We have,

$$\frac{\partial \pi_i}{\partial b_i} = \frac{dx_i^*}{db_i}(c_i - \alpha x_i^*) - \frac{1}{n}x_i^* - \frac{1}{n}(\mathbf{c}_{-i} + b_i - \alpha Q)\frac{dx_i^*}{db_i} \tag{18}$$

Substituting x_i^* from Equation 16 gives,

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

After some cancellations we have,

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

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,

$$Supply = \begin{cases} \delta Q & \text{if} \quad p^* < p' \\ Q & \text{if} \quad p^* \geq p' \end{cases} \tag{21}$$

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 19 as follows.

$$\frac{\partial \pi_i}{\partial b_i} = (\frac{1}{\alpha} - \frac{1}{n\alpha})c_i - \frac{1}{\alpha}b_i + \frac{1}{n}\frac{p^*}{\alpha} \tag{22}$$

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.

$$\frac{\partial \pi_i}{\partial b_i} = (\frac{1}{\alpha} - \frac{1}{n'\alpha})c_i - \frac{1}{\alpha}b_i + \frac{1}{n'}\frac{p^*}{\alpha} = 0 \tag{23}$$

After some manipulations we have,

$$\frac{1}{\alpha}(c_i - b_i) - \frac{1}{n'\alpha}(c_i - p^*) = 0 \tag{24}$$

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,

$$\mathbf{c}_{-l} + lb_l - np^* = \alpha Q \tag{25}$$

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

$$x_l^* = \frac{lb_l}{\alpha} - \frac{l(\mathbf{c}_{-l} + lb_l - \alpha Q)}{n\alpha} \tag{26}$$

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

$$\pi_l = \int_0^{x_l^*} (c_l - \frac{\alpha}{l}x)dx - \frac{1}{n}(\mathbf{c}_{-l} + lb_l - \alpha Q)x_l^* \tag{27}$$

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

$$\frac{\partial \pi_l}{\partial b_l} = l(\frac{1}{\alpha} - \frac{l}{\alpha n})(c_l - b_l) + l(\frac{1}{n}\frac{p^*}{\alpha} - \frac{1}{n}\frac{b_l}{\alpha}) = 0 \tag{28}$$

Appendix 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 analyse 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 rigour 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.

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 11. 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 11.

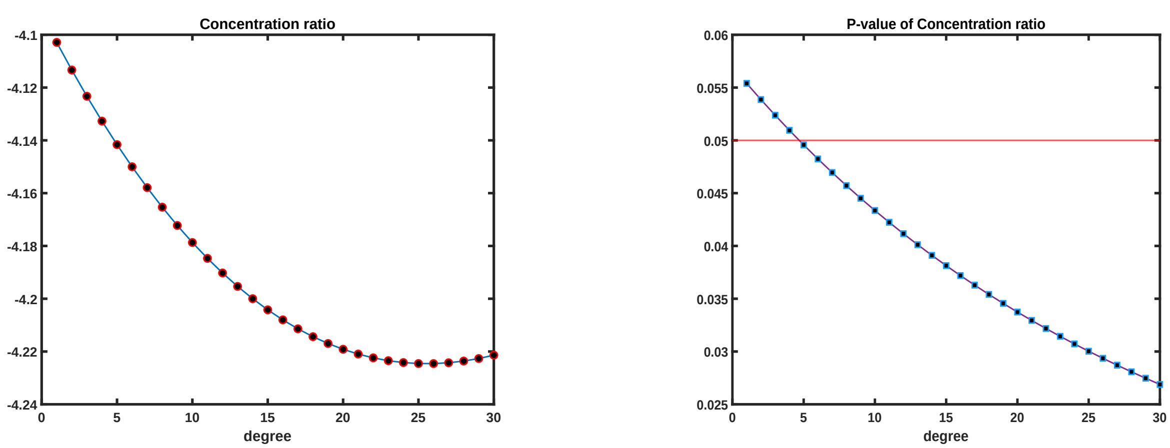

Figure 11: Left plot shows coefficient for clearing price $\sim$ concentration ratio and right plot shows the corresponding p-value.

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 5, the analysis of Elasticity and the marginal effect of the number of bidders on the clearing price reveals that the elasticity of the 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.[23] 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%.

[23] 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 unitary responsiveness.