POLLUTION PERMIT CONSIGNMENT AUCTIONS: THEORY AND EXPERIMENTS[†]

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Noah C. Dormady[*] & Paul J. Healy[**]

Abstract:

Unlike other auction-based climate change markets, California's AB32 market utilizes a consignment auction design in which utilities are allocated a share of emissions permits that they must sell into the uniform-price auction. Auction revenue is returned to the consignee, which creates an incentive to increase the auction clearing price through strategic bidding. In a simple theoretical example, we show that consignees will accomplish this by overstating their quantity demanded in the auction, since this increases the probability that the auction clears at a positive price. This results in inefficient allocations and inflated auction prices. We test this consignment mechanism through a series of lab experiments and confirm these predictions. We also find that overall firm profits are lower in a consignment auction than in a non-consignment auction market, and that firms are more likely to not receive the quantity of permits they need for program compliance in the auction.

Keywords: Carbon Auction; Consignment Auction; Cap and Trade; Experimental Economics; Energy Policy; Environmental Policy; Auction Design

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[*]Assistant Professor, John Glenn School of Public Affairs, The Ohio State University, 1810 College Rd., Columbus OH 43210, Email: dormady.1@osu.edu, Phone: (614) 688-1668, Fax: (614) 292-1868.
[**] Associate Professor, Department of Economics, The Ohio State University, 1945 N. High St., Columbus OH 43210, Email: healy.52@osu.edu, Phone: (614) 247-8876.

1. Introduction

Throughout the past four decades, scholars have studied market-based approaches to environmental policy, or 'emissions trading.' Much of the early work focused on tradeoffs between the various price-based approaches and standard regulatory approaches (Dales, 1968; Montgomery, 1972; Tietenberg, 2006). Since then, a number of inefficiencies associated with market-based approaches have been discovered. These include inefficiencies from political misallocation of emissions permits (Dewees, 2008; Ellerman et al., 2000), distortionary influences from regulatory governance (Arimura, 2002; Averch and Johnson, 1962), inefficiencies due to imperfect competition and market power (Hahn, 1984; Malik, 2002; Misiolek and Elder, 1989; Van Egteren and Weber, 1996), and distortionary interactions with deregulated electricity markets (Joskow and Kahn, 2002).

Recently, the question of efficiency in the initial allocation has featured prominently in this literature. Early markets required the regulator to allocate the initial endowment of permits among existing firms (i.e., "grandfathering"), which created a complicated and contentious political process (Ellerman et al., 2000). More contemporary implementations use auctions to overcome these issues. It is argued that auctions are more efficient, reduce tax distortions, provide more flexibility in the distribution of costs, provide greater incentives for abatement innovation, are fairer and, thus, reduce politically contentious arguments (Burtraw and Sekar, 2014; Cramton and Kerr, 2002).

Here we caution that auctions can generate inefficiencies when designed poorly. If the regulator is willing to keep the revenues collected from the auction, then efficiency is not difficult to achieve: A sealed-bid auction with Vickrey pricing (or the ascending-clock variant of Ausubel 2004) gives full efficiency in equilibrium. A reasonable (though not fully efficient) alternative is to use uniform pricing, since it is transparent and sets a clear signal of the value of permits going forward.[1] But if the regulator is constrained to collect zero revenues (meaning revenues cannot be used to fund government activities or

[1] Studies of inefficiencies in emissions trading auctions have mainly been focused on strategic demand reduction under uniform pricing and imperfect competition (Ausubel and Cramton, 2002; Dormady, 2013; 2014; List and Lucking-Reilly, 1998; Weber, 1997).

reduce taxes or instead are statutorily required to be returned to electric utilities), how should such an auction be modified? A naïve solution is to redistribute the collected revenue back to the bidders, as is done in the consignment process. But doing so can distort bidders' incentives and can generate serious allocation inefficiencies in the auction. In general, any firm that will receive consignment revenues from more units than they plan to purchase for themselves becomes a 'net seller' of permits and therefore has an incentive to increase the clearing price in the auction through bid manipulations. Symmetrically, any firm receiving sales revenues from fewer units than they plan to purchase for themselves becomes a 'net buyer' and has an incentive to decrease the clearing price through bid manipulation.

Today's carbon markets in the U.S. utilize auctions for the initial allocation of tradeable permits, rather than grandfathering. The European ETS markets will also be required to utilize auctions going forward, and a number of other international carbon markets are considering the utilization of auctions. Since 2008, nine East-coast states operate an auction-allocated carbon market known as the Regional Greenhouse Gas Initiative (RGGI) (see Dormady, 2013; RGGI, 2010). RGGI, which covers only the electricity sector, utilizes a non-consignment auction for the initial allocation of nearly 100 percent of its carbon permits. Revenues from the auction are used to either backfill state deficits or are invested in energy efficiency and renewable energy programs at the discretion of the state government. That revenue is not returned to the utilities or independent power producers (IPPs) that purchase the permits. Utilities pass through any permit acquisition costs in their rate base subject to commission approval, and IPPs pass through costs indirectly to utilities through wholesale markets.

Since 2012, California has been operating the Assembly Bill 32 (AB32) market in which consignment auctions are used quarterly to initially allocate permits to the electricity, natural gas and oil-refining sectors. To prevent energy cost increases during a fragile recovery, California pre-allocates a fixed and significant quantity of permits to the main power distributors at zero cost. This is much like grandfathering, *except* these firms are then required to consign, or sell, all allocated permits into the quarterly permit auctions. IPPs, along with the utilities that are consigning permits, purchase the permits that they need for program compliance in the auction. Revenue from the sale of consigned permits is returned to the consigning utilities at the price at which the auction cleared, and is required to be used to benefit ratepayers in their respective service territories. Revenue from the sale of permits sold by the regulator for permits that are under the cap but not allocated to consigning utilities, is returned to the state's general fund.

This format of auction is a modified revenue neutral auction, similar to the Hahn and Noll (1983) auction, with the key difference being that only certain bidders (utilities) are allocated units to consign. The divergence in auction design between the RGGI and AB32 markets has raised some new questions of efficiency in auction design more generally, and auctions as an allocative mechanism for emissions trading markets more specifically. Both markets utilize a second price uniform-price sealed bid auction format, but only the AB32 market uses consignment.

The efficiency implications of this consignment auction mechanism are presently unclear. Whereas in a typical uniform-price carbon auction, such as utilized in the RGGI market, it is clear that all firms have an incentive to bid strategically to acquire their emissions permits at the lowest possible cost, in a consignment auction it is not as clear cut. Those firms that consign a larger share of emissions permits than they demand in the short run, become net sellers of emissions permits in the market. Their incentives in the auction can be distorted, so standard models of bidding behavior would not directly apply.

This design question has also featured prominently in the current regulatory debate. In June of 2015, the U.S. Environmental Protection Agency (EPA) released rules to regulate greenhouse gases at the national level under the framework of the Clean Air Act. Under the Act, states are the compliance entities. The rules allow significant flexibility of approach, however they recommend carbon markets first above all other compliance approaches. These recommendations not only mention, but are based upon the existing structural designs of the RGGI and AB32 markets. There is significant national debate presently regarding which auction design is a model for the rest of the nation in compliance with the new rules. In addition, the European Union recently announced a directive to use auctions to allocate permits in all of its carbon markets going forward. Thus, it is imperative that we understand what auction designs are most efficient in this setting, and what pitfalls must be avoided.

In this paper we investigate the efficiency implications of this consignment auction design. We first design an experiment that tests how consignment alters behavior in the uniform-price auction mechanism for allocating permits. We then solve for equilibria in this experiment to identify exactly what types of inefficiencies are predicted due to the consignment. Then we see whether these predictions are borne out in the data.

Our main treatment conditions compare the standard uniform-price auction to the uniform-price auction utilizing consignment. Our treatments also include differentiated production consisting of high and low emissions-intensity producers, allowing us to simulate alternative regulatory contexts to approximate East-coast and West-coast market conditions generally. We find that the consignment mechanism results in significantly higher auction-clearing prices across the board, as predicted by the theory. We also find that the consignment mechanism results in significantly lower efficiency, and that it is actually injurious to the profit of consigning firms which is contrary to the narrative put forth by the major utilities.

Our findings highlight leading empirical analyses of revenue neutral auctions. Prior work by Franciosi et al. (1993) and Ledyard and Szakaly-Moore (1994) reported on controlled laboratory experiments investigating the revenue neutral auction design. This work occurred during the design debates surrounding the use of auctions for small allocations of sulfur dioxide permits under the U.S. Acid Rain Program (Title IV) of the Clean Air Act.

Ledyard and Szakaly-Moore compare a revenue neutral auction to a double auction and find that the revenue neutral auction is less efficient than the double auction, and that it results in lower auction-clearing prices. When a monopolist is endowed with all available permits—and is therefore guaranteed to be a net seller—the revenue neutral auction continues to be less efficient than the double auction but now generates higher clearing prices. This finding is consistent with the intuition in our theoretical model, and broadly consistent with our experimental results.

Franciosi et al. compare the revenue neutral auction to a standard uniform-price auction and find that the revenue neutral auction results in higher auction-clearing prices; however their results do not hold at a high degree of statistical significance. And in stark contrast to the results presented here, they find the revenue neutral auction to be more efficient than the standard uniform-price auction. One possible reason for the difference in results is that our firms have a constant marginal value for permits (equal to the non-compliance penalty). And consistent with the AB32 market, our firms know with certainty whether they will be net buyers or net sellers. These differences stem from the fact that we take a short-run view in which firms cannot adjust pollution output or abatement (which are inherently longer run) in response to permit prices, while these other papers implicitly assume they can. How our theory would extend to the Franciosi et al. environment is not immediately obvious.

To allow us to focus on the bidding incentives of firms in an in-depth manner, our analysis takes an explicitly short-run view of a single quarterly auction. We do not consider the re-trading of permits, or the impact of permit prices on pollution abatement. Within this time frame it is infeasible for firms to adjust their production levels or abatement technologies, so their value for a permit is simply the non-compliance penalty it avoids. A longer-run analysis would study whether or not re-trading solves initial auction inefficiencies, and how auction design might impact abatement innovation and pollution outputs, but is beyond the scope of our current work. Our goal is instead to highlight the short-run permit allocation inefficiencies that can occur when auction revenues are refunded to bidders via the consignment process. Moreover, secondary market corrections for inefficient auction allocations are not costless to firms or society. They impose transaction costs—through brokerage fees, consultancy services and insurances—and they subject firms to short-run permit uncertainty. And more importantly, because the auction phase is the most important price signal for the trading market in auction-based systems, inflated prices arising from strategic overbidding can substantially affect system-wide price signals and exchange benchmarks in the secondary trading market.

2. Experimental Design

The experiment is designed to test the efficiency of the consignment mechanism as utilized in a carbon auction, in comparison to a traditional non-consignment auction mechanism. We begin with a description of the consignment mechanism.

2.1 The Consignment Mechanism

In a traditional Coasian market (see Fig. 1) the regulator sets a target annual emissions cap at the socially-efficient emissions level. That cap usually decreases annually at a fixed rate until the statutory target is achieved within a reasonable planning horizon. The regulator issues tradeable property rights (e.g., permits, credits, allowances) matching that annual cap, typically such that one emissions permit allows the holder to emit 1,000 tons of carbon dioxide equivalent (CO2e).

Auctions for the initial allocation of permits all utilize a non-discriminatory auction format: the uniform-price sealed bid auction, in which firms place a bid for both a price and a quantity of emissions permits. Bids are ranked by price from highest bid to lowest bid, and when the quantity of price-ranked bids meets the quantity of permits auctioned, permits are awarded to winning bidders at a uniform auction-clearing price. That uniform price is typically analogous to the second price auction rule (the highest losing bid). The revenue generated by the auction of these emissions permits is equivalent to the uniform auction-clearing price multiplied by the quantity of permits awarded. For a detailed description of the uniform price auction, see Milgrom (2004), Krishna (2009), and Dormady (2013).

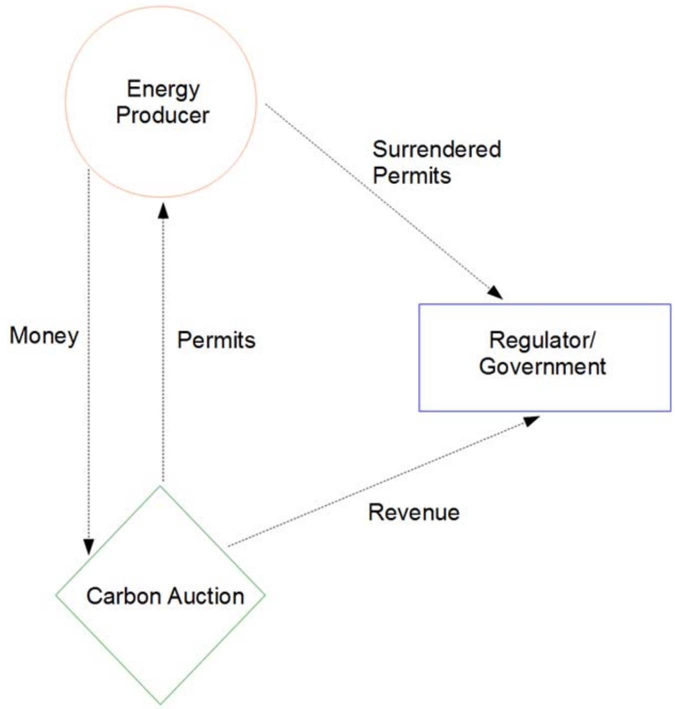


Figure 1. A Traditional Carbon Auction Design
(RGGI Inc., Waxman-Markey, Kerry-Boxer)

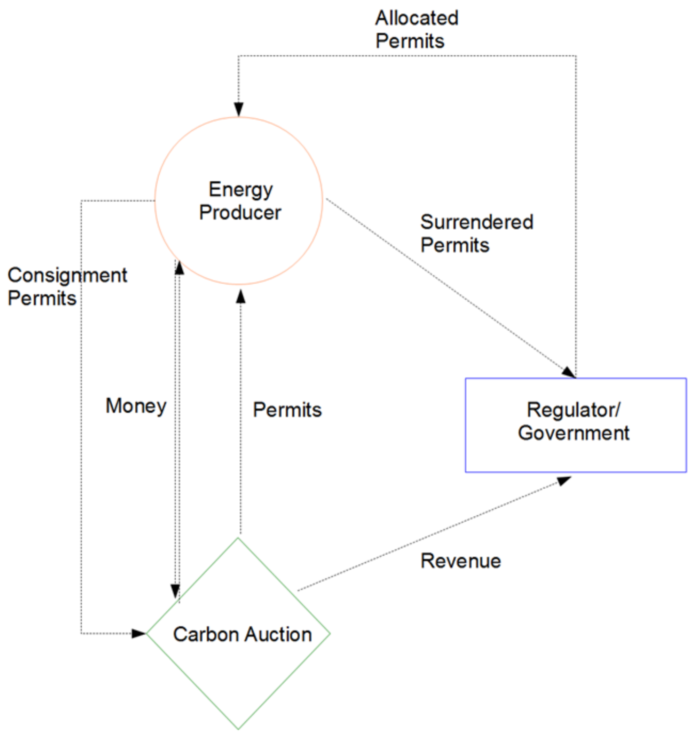


Figure 2. A Carbon Auction with Consignment
(California AB32)

Under a consignment mechanism, the emissions permits are freely allocated to the utilities *before the auction* (see Fig. 2). The utilities are then required to consign, or sell, all of those allocated permits into the quarterly auction. The utilities then keep the revenue from the sale of those emissions permits. Firms purchasing emissions permits, including the consigning utilities, purchase emissions permits which they consigned, or which other utilities consigned. The revenue from consignment roughly offsets the cost of permit acquisition, so utility consumers see no cost pass-through. There are also typically other emissions permits sold in the auction by the regulator, from which the revenue goes to the state government. This is consistent with the accounting of emissions, as utility emissions are not the only emissions counted in the aggregate socially-efficient economy-wide cap.

2.2 Experiment Setup

The lab experiment simulates a Coasian permit auction under stochastic permit demand and a variety of treatment conditions. All treatments utilized the uniform-price sealed bid auction. In each session, 16 subjects participate for two practice periods and 51 actual periods, though they were not informed of the total number of periods.

At the start of the session, half of the subjects are randomly assigned to be a 'High' type, and the other half are assigned to be a 'Low' type. This type assignment remains fixed across all periods. In each period, the subjects are randomly matched into four groups of four, such that each group contains two High types and two Low types. Subjects are not aware of the identities of their competitors at any time; they only know that they are in a randomly-drawn group of four consisting of two High types and two Low types.

At the start of each period, each subject is randomly (and independently) assigned a production level of either 4, 5, or 6 units of energy, and are told that their firm must produce exactly this many units of energy. These values are broadly representative of low, intermediate and peak levels of energy demand in the field.[2] Subjects receive revenue from their production: For every unit of energy they produce, they receive $100 experimental. As such, in any period, subjects receive a fixed 'endowment' of production revenue that can be $400, $500, or $600 experimental. Again, subjects have no choice in production; it is entirely exogenous and thus consistent with short-run emissions.

Production also creates pollution, and subjects need to purchase permits to cover the pollution they produce. The difference between High types and Low types is in the units of pollution emitted per unit of energy. High types emit two units of pollution for each unit of energy produced. Low types emit only one unit of pollution for each unit of energy produced. Thus, High types will demand twice as many permits as Low types for a given production level. These two types are broadly representative of coal and natural gas generation, respectively, which are the two main carbon-emitting sources of power generation today.[3] We refer to 'High' and 'Low' as the firm's *pollution type*, and 4, 5, or 6 as their *production type*. We view pollution types as publicly observable, while production types are private information. Note that pollution types are fixed throughout, that production types are redrawn each period, and that there is no correlation between pollution types and production types.

In each period, pollution permits are sold via the uniform price auction. Given the range of possible pollution types and production types, the aggregate permit demand in any period ranges from 24 to 36 permits. The aggregate supply of emissions permits sold at auction in any period is always 30 permits. Given the fixed supply of emissions permits, this design allows us to test our hypotheses for cases in which the permit demand exceeds, and is exceeded by, permit supply.

Subjects could bid for any quantity of emissions permits, irrespective of their individual pollution output. A subject holding a deficit of emissions permits at the end of the period incurs a non-compliance penalty of $50 experimental for each unit of pollution output greater than their number of permits on hand. Subjects face limited liability: if they lose money in a given period, their final profit for that period

[2] Peak production may also be broadly representative of low-hydro years in California, in which full generation output from fossil units is required to clear aggregate system-wide demand.
[3] Coal production is approximately twice (1.6 times depending on technology) as carbon-intensive as natural gas production.

is adjusted to zero. These two design parameters allow us to focus exclusively on the auction phase of emissions trading while avoiding conflating effects of risk aversion, while at the same time adhering to institutional review board (IRB) preferences against unnecessary subject exposure to financial losses.

As stated above, we study here the short-run setting where firms are essentially locked in to their exogenously-given production and pollution levels. Abatement and production adjustments, if they were to occur, would be realized across periods and are therefore not included in our experimental design.

2.3 Treatments

The experiment includes four treatments (See Table 1) that generalize common auction-based market designs and regional production portfolios. The control treatment is a baseline treatment in which no permit consignment is introduced. The remaining treatments include permit consignment that depends on firms' pollution types. Permit consignment consists of a pre-auction allocation of a fixed quantity of emissions permits to certain subjects, and entitles the allocated subject to the revenue from the sale of those permits at the auction's clearing price. In the main treatment of interest, all subjects are required to consign an allocated quantity of emissions permits. For robustness, we also study treatments in which only the High pollution types or only the Low pollution types consign permits.

In the main treatment group in which all subjects consign permits, High pollution types are allocated 10 permits and Low pollution types are allocated 5 permits. These are also the average permit demand for each pollution type. The firms are forced to sell their allocated permits in the auction (keeping the resulting revenue) and must purchase for program compliance any permits that they wish to use to cover their pollution output.

Table 1. Experiment Treatment Parameters

Treatment	Bidder (Type)	Energy Production	Permits Needed	Permits Allocated
Control - No Consignment	1 - Low 2 - Low	~U{4,5,6}	1 x Production	0
	3 - High 4 - High		2 x Production	
Treatment - All Consign	1 - Low 2 - Low	~U{4,5,6}	1 x Production	5
	3 - High 4 - High		2 x Production	10
Treatment - Low Consign	1 - Low 2 - Low	~U{4,5,6}	1 x Production	5
	3 - High 4 - High		2 x Production	0
Treatment - High Consign	1 - Low 2 - Low	~U{4,5,6}	1 x Production	0
	3 - High 4 - High		2 x Production	10

With consignment, firms' incentives can vary widely depending on their production type. A firm with only 4 units of energy production receives more permits than they need, and therefore becomes a *net seller* of permits in the auction. They clearly prefer a higher auction price. A firm with 6 units of production does not have enough permits and becomes a *net buyer*, clearly preferring a lower auction price. A firm with 5 units is allocated exactly the number of permits that they need for their pollution output and are *net neutral*. By allowing production types to vary, we can study the impact these differential incentives have on bidding behavior.

In the treatment in which only Low pollution types consign permits, each Low type subject is allocated 5 permits. In the treatment in which only High pollution types consign permits, each High type subject is allocated 10 permits. Again, this creates net buyers and net sellers, depending on the realized energy production levels. Any bidder that is not consigning permits can also be thought of as a net buyer, which is the case in our control group in which no consignment occurs.

In each of the three consignment treatments, if the total quantity of permits sold at auction is less than the number consigned, then subjects receive the revenue from a quantity of permit sales equal to their proportional share of the total quantity consigned.

The High-only and Low-only treatments are broadly representative of markets with merchant gas and merchant coal production, respectively. These are also broadly representative of East Coast and West Coast markets, respectively. In a very broad and general sense, East Coast markets tend to consist of utilities generating native load mainly from coal power, with IPPs supplying generally from gas. The opposite is generally true in West Coast markets, in which utilities tend to generate more from gas than coal. Because our explicit focus is the bidding incentives of the auction phase, we do not simulate much granularity in generation portfolios of firms, and moreover, that would add unnecessary complexity to an already detailed lab experiment.

In actual permit markets the auction only determines an initial allocation of permits; firms are free to trade subsequently through bilateral exchange. Mutually beneficial trades may arise in practice as firms' production and pollution levels change over time. In our static setting, however, such trades would only be possible if the auction outcome is inefficient. Thus, we do not allow post-auction permit trading in our experimental design, and instead measure directly the frequency with which inefficient allocations obtain.[4]

2.4 Recruitment and Sampling

The experiments were conducted at the [redacted] University Experimental Economics Laboratory. Subjects were recruited by an email solicitation through the experimental economics subject pool. Subjects consisted entirely of undergraduate students in economics, as well as other majors across campus in the physical and natural sciences, and other social science disciplines. Subjects were randomly matched to experimental sessions dependent upon their availability, and treatments were assigned randomly to scheduled sessions.

[4] One potential weakness of our design is that, in practice, firms' expectations of re-trading may alter their bidding behavior. This depends on whether firms expect to make a profit in equilibrium through re-trades, which in turn is sensitive to things like bargaining power that are beyond the scope of our study. We therefore leave this as a topic for future work. This problem is mitigated by the fact that, under AB32, all consignment permits must be auctioned first, and cannot be sold directly into the secondary market.

2.5 Experiment Operation

We conducted eight 2.5 hour (approx.) experimental sessions, excluding pilot sessions. Of these eight, we conducted two 2.5 hour (approx.) experiment sessions for each of our four treatments. Each session began with a set of written subject instructions (see Appendix) and a walk-through of the user interface. Experimental software was programmed using the Zurich Toolbox for Readymade Economic Experiments (Z-TREE) and its companion client software application Z-leaf (Fischbacher, 2007). Subjects received two handouts consisting of the written instructions and a payment form, as well as consent forms.

3. Theoretical Predictions and Hypotheses

3.1 Theoretical Predictions

We use computational methods to find a Bayes-Nash equilibrium for our experimental market. We were unable to find a pure-strategy equilibrium for the *No Consign*, *Low Consign*, and *High Consign* treatments.[5] In the *All Consign* treatment, we were able to identify a pure-strategy equilibrium that highlights the intuitive distortions we describe above. We also confirm that bidding truthfully is not an equilibrium; net sellers have an incentive to manipulate the expected clearing price by increasing their quantity bids while net buyers have a countervailing incentive to decrease their quantity bids.

Table 2. Equilibrium Bidding Strategies in the *All-Consign* Treatment

Firm Type	Permits Consigned	Permits Needed	Quantity Bid	Price Bid
Low Net Seller	5	4	4	$50
Low Zero Net	5	5	5	$50
Low Net Buyer	5	6	6	$50
High Net Seller	10	8	**9**	$50
High Zero Net	10	10	10	$50
High Net Buyer	10	12	**11**	$50

[5] The best responses in these games are highly cyclic, with players' price bids cycling while quantity bids remained equal to the quantity needed. We conjecture that a complex mixed-strategy equilibrium exists in which players choose a mixture of price bids but submit truthful quantity bids. But we have been unable to find such a mixed-strategy equilibrium to date.

The equilibrium bids for each type are shown in Table 2. Specifically, with consignment, all firms submit a price bid of $50. As for quantity bids, the low types that have pollution levels of 4, 5, and 6 bid truthful quantities of 4, 5, and 6 permits, respectively. The high types that have pollution levels of 8, 10, and 12 distort their quantities, bidding 9, 10, and 11 respectively. Intuitively, the high-type net sellers overbid on quantity by a small amount to try to increase the chance that the good is rationed and sold for a positive price. Similarly, the high-type net buyers underbid on quantity to decrease the chance of positive price. Low-type net sellers and net buyers have similar pressure, but for a low-type net seller a one-unit increase in their quantity bid turns them into a zero net demand agent, which then eliminates the incentive to overbid the quantity. Similarly, a low-type net buyer who tries to underbid the quantity turns themselves into a zero net demand agent, eliminating the underbidding incentive. High types, on the other hand, can manipulate their bid by one unit without changing whether they are a net buyer or net seller. Thus, we see quantity manipulation by high types, but not low types.

These quantity manipulations lead to potential inefficiencies in auction allocations. For example, if one high type is a net buyer and one is a net seller, then the net buyer will end up with one permit less than its requirement (forcing it to pay $50 in non-compliance penalties) while the net seller will end up with an extra permit it does not need (which also wasted $50 due to the permit's purchase price in the auction). This is a $50 inefficiency ex-post, since the net seller could sell her extra permit to the net buyer at any price between $0 and $50 and both would be made better off.

With types being uniformly distributed, the probability of having a high-type net seller and a high-type net buyer is 2/9. These are exactly the scenarios when inefficiencies are generated, so we expect to see an average inefficiency of $50*2/9 = $11.11 in the market.[6]

Although the quantity manipulations are symmetric—the high net seller overbids by one unit while the high net buyer underbids by one unit—the effect on the clearing prices is actually asymmetric, leading to an overall increase in the expected clearing price. In equilibrium the clearing price is $50 in 50

[6] When the low-types are both net sellers then the high-types are sometimes rationed, distorting slightly the cases where inefficiencies arise. But these distortions exactly "offset", and in fact the expected inefficiency per period is exactly $11.11. The actual calculation is available upon request.

of 81 possible type profiles, giving an expected clearing price of \$50*50/81 = \$30.86. If instead all bidders bid truthfully the clearing price would be \$50 in only 47 of 81 possible type profiles, dropping the expected clearing price by \$1.85 down to \$29.01.

3.2 Hypotheses

We would like to use the theory to generate testable hypotheses about our experiment, but we are limited by the fact that we were able to find an equilibrium only in the *All Consign* treatment. Based on our analysis of the other treatments, however, we can conjecture that quantity bids will be truthful in all cases because our computerized iteration of best response calculations never deviated from that strategy; it is the equilibrium prices that cycled indefinitely among prices below \$50. Thus, we proceed (tentatively) by assuming truthful quantity bids and random price bids at or below \$50 in all treatments except *All Consign*.

Under this assumption,our first testable hypothesis is that consignment should lead to rationing more often, meaning the clearing price is more likely to be positive. Second, when the clearing price is positive, we expect it to be \$50 under consignment but much less without consignment, due to price mixing.

H1a: $Pr(Price>0)_{AllConsign} > Pr(Price>0)_{OtherTreatments}$

H1b: $Avg.\ Price_{AllConsign}\ if\ (Price > 0) > Avg.\ Price_{OtherTreatments}\ if\ (Price > 0)$

Next, we expect quantity manipulations by high-type net buyers and net sellers.

H2a: *Net sellers inflate their quantity bids in the All Consign treatment.*

H2b: *Net buyers deflate their quantity bids in the All Consign treatment.*

Finally, we predict that the manipulated quantity bids in the *All Consign* treatment will generate greater inefficiencies and greater non-compliance penalties in that setting.

H3a: $Inefficiency_{AllConsign} > Inefficiency_{OtherTreatments}$

H3b: $E[non\text{-}compliance\ penalty]_{AllConsign} > E[non\text{-}compliance\ penalty]_{OtherTreatments}$

4. Results

We report the results of eight sessions in total, two in each of the treatments. Each session ran for approximately 2.5 hours including subject instruction time, and all sessions ran for 51 bidding periods in total. Data in early periods are noisier due to subjects' learning, so we restrict all analyses to the final 25 periods in which behavior stabilizes more. In our appendix, we provide a replication of all results tables including all paid periods as a robustness check for interested readers.

4.1 Auction-clearing Prices

Our first hypothesis is that the *All Consign* prices will be higher, and will be positive more frequently. In Table 3 we show these averages by treatment. As predicted, the average auction prices are substantially higher when all firms consign, but they are also high when only the inefficient high types (i.e., higher pollution per unit of energy output) consign permits. We find a slight decrease in average prices when only the efficient low types consign permits.

Table 3. Auction Clearing Price Summary Statistics

	Auction Clearing Price		
Treatment	Overall Average	% Periods With Price = 0	Avg. Price When Price > 0
Control (No Consign)	6.74	40.9%	11.39
Treatment (All Consign)	24.17	25.0%	32.23
Treatment (High Consign Only)	15.36	24.5%	20.35
Treatment (Low Consign Only)	5.86	35.1%	9.02

To test whether the differences in clearing prices are significantly different between treatments, we regress auction clearing price against dummy variables for each treatment (Table 4). We use a Tobit regression because auction prices are censored below zero, we control for aggregate permit demand, and cluster errors by session. The omitted category is the control treatment without consignment. We find a significant increase in clearing price when all agents consign, and a marginally significant increase when only high types consign. The effect of the Low consignment treatment is insignificant, though positive once we control for aggregate permit demand. Similar results obtain when limiting to only periods with a positive price, though significance is reduced in all cases due to the smaller size of this subsample. A logistic regression (also clustered by session and controlling for aggregate demand) reveals that all three treatments have a significantly lower chance of generating a zero clearing price, with *p*-values all less than 0.01.

Table 4. Auction Clearing Price Regression

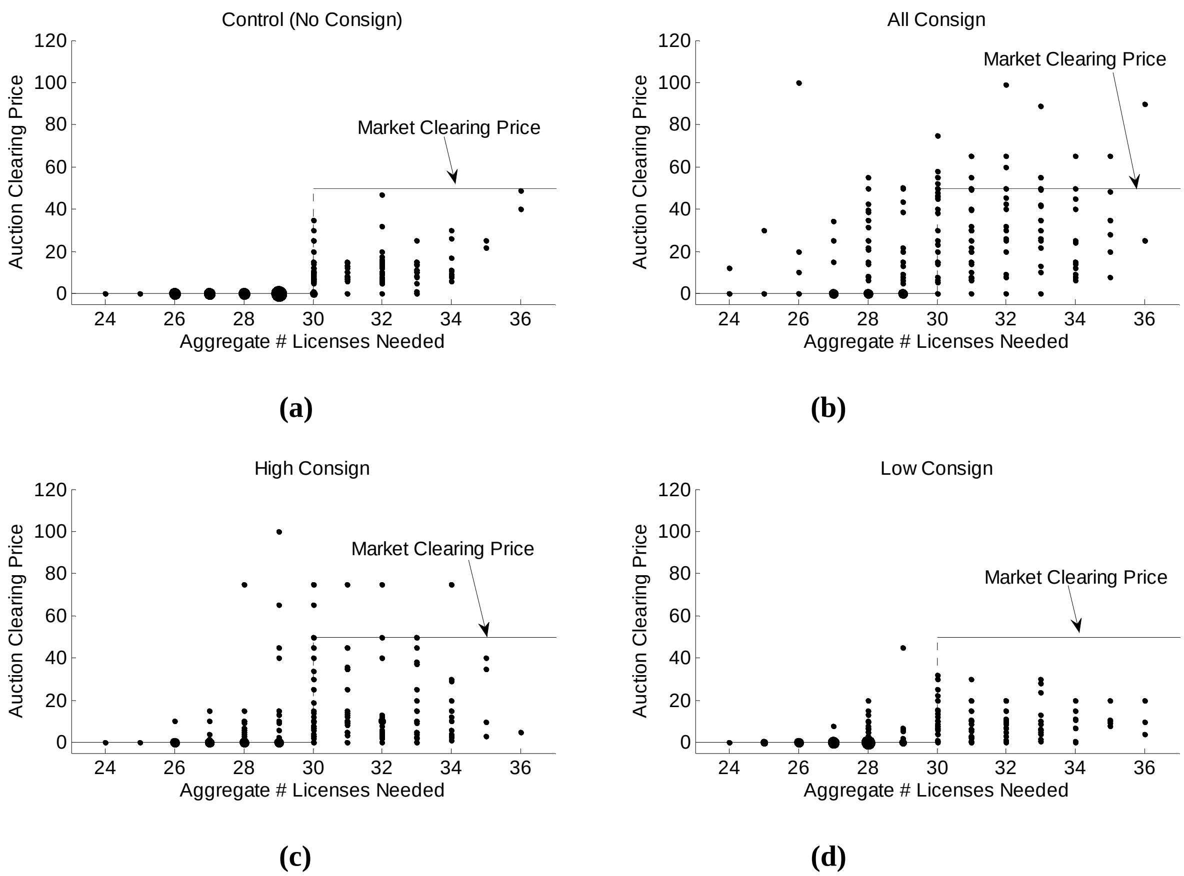
	Auction Clearing Price		
Independent Variable	Coefficient		Std. Err.
Treatment (All Consign)	22.73	**	7.63
Treatment (High Consign Only)	12.43	*	7.06
Treatment (Low Consign Only)	1.73		2.15
Aggregate Permit Demand	5.10	***	1.13
Constant	-155.48	***	36.02
N	832		
F-statistic	7.08	***	
McFadden's Pseudo R^2	0.07		

**** p<0.001 ** p<0.01 * p<0.1, robust std. errors clustered by session*

We also confirm this with two-sample non-parametric hypothesis tests (Wilcoxon tests) of treatment equality. We can safely reject auction clearing price equality with our control treatment in our *All Consign* treatment (*p<0.001*) and *High Consign* treatment (*p<0.001*). Also consistent with our regression analysis, we are not able to reject the null, however, for our *Low Consign* treatment (p<0.72).

Theses treatment differences are also visible in scatter plots of auction clearing prices versus aggregate demand (Figure 3). Recall that there is a fixed supply of 30 permits. Firms' marginal value for permits is $50 if they are facing non-compliance penalties and $0 if they have sufficient permits to avoid these penalties. Thus, the market clearing price is $0 when less than 30 permits are needed in the aggregate, and $50 when 30 or more permits are needed. With no consignment (panel a), auction prices are most often zero when demand is less than 30, and well below the market clearing price when demand is greater than 30. This is consistent with our assumption of truthful quantity bids and low price bids. With consignment by all firms (panel b) or high-type firms (panel c), auction prices frequently exceed the market clearing price, both when demand is low and high. In equilibrium firms should only submit price bids of \$50, which we clearly reject here since actual clearing prices are often different than \$50. When only low pollution types consign (panel d), some increase in low-demand clearing prices is observed, though no clear difference is seen for high-demand periods.

Figure 3a-d: Auction Clearing Prices for Each Treatment



In summary, we broadly confirm our hypothesis that consignment leads to higher clearing prices and a greater frequency of positive prices, though these effects appear insignificant when only low types (i.e., low emissions generation) consign permits for the reasons explained above

4.2 Price Bids

In theory, we expect all price bids to be $50 under consignment. Without consignment, we conjecture that bidders will play a mixed strategy, submitting bids substantially below $50. Table 5 provides the actual averages from the experiment. Although the point predictions of the theory are not borne out (due in part to several bidders submitting very high bids), we do see higher average price bids in the *All Consign* and *High Consign* treatments, but not in the *Low Consign* treatment. Low pollution types also submit substantially higher bids than the High pollution types. Finally, net sellers bid higher than net buyers or those with zero net demand.

Table 5: Average Price Bids

		Mean Bid Price		
Treatment	Type	Net Buyers	Zero Net Demand	Net Sellers
Control (No Consign)	*Low*	60.08	-	-
	High	33.59	-	-
Treatment (All Consign)	*Low*	126.55	165.47	278.32
	High	72.14	82.21	94.67
Treatment (High Consign Only)	*Low*	107.57	-	-
	High	70.73	88.92	92.97
Treatment (Low Consign Only)	*Low*	59.83	66.29	84.29
	High	23.26	-	-

To see whether these differences are significant, we regress the bid price on dummy variables for treatments (excluding no consignment), production type (net buyer or net seller), and pollution type.[7] The results are show in Table 6. The regression confirms that *All Consign* generates substantially higher bid prices, both in magnitude and significance. The effect of *High Consign* is also fairly large but significance is marginal. The *Low Consign* bid prices are indistinguishable from the *No Consign* treatment. Net sellers clearly submit higher bids, and high pollution types submit significantly lower bids.

[7] The effect of aggregate permit demand is insignificant because it is not observable by subjects when placing bids. Thus, we do not include it in these bid regressions.

Table 6: Regression of Bid Prices

Independent Variable	Bid Price Coefficient		Bid Price Std. Err.
Treatment (All Consign)	82.45	***	27.21
Treatment (High Consign Only)	45.59	*	24.46
Treatment (Low Consign Only)	-4.59		17.92
Treatment Net Buyer	-16.12		11.87
Treatment Net Seller	40.42	**	19.16
High Type	-50.39	***	17.77
Constant	72.03	***	16.72
N	3328		
F-statistic	5.80	***	
McFadden's Pseudo R^2	0.01		

**** p<0.01 ** p<0.05 * p<0.1, robust std. errors clustered by subject*

4.3 Quantity Bids

Our theoretical prediction is that, in the *All Consign* treatment, net sellers should submit quantity bids greater than their actual permit demand. We show the average amount by which quantity bids exceed permit requirements (*i.e.*, pollution output) in Table 7. In the control (*No Consign*) treatment, 97.2% of quantity bids are truthful—meaning they exactly equal the number of permits needed by the firm—so average overbidding levels are essentially zero for both pollution types. In the *All Consign* treatment only 78.4% of quantity bids are truthful, while 18.0% of bids are for more units than needed. The percentage of quantity overbids in the *High Consign* and *Low Consign* treatments are similar at 16.3% and 16.7%, respectively. Though we see positive overbidding on average for all types, the net sellers and those with a zero net demand have higher average levels of overbidding.

Table 7: Average Quantity Overbidding

Treatment	Type	Net Buyers	Zero Net Demand	Net Sellers
	Mean Quantity Overbid (Quantity Bid - Permits Needed)			
Control (No Consign)	*Low*	0.02	-	-
	High	-0.01	-	-
Treatment (All Consign)	*Low*	0.11	0.54	0.27
	High	0.52	0.94	1.22
Treatment (High Consign Only)	*Low*	1.81	-	-
	High	0.24	0.27	0.63
Treatment (Low Consign Only)	*Low*	0.16	0.35	0.62
	High	0.44	-	-

Figure 4. Histogram of Overbidding (Net Sellers versus Net Buyers)

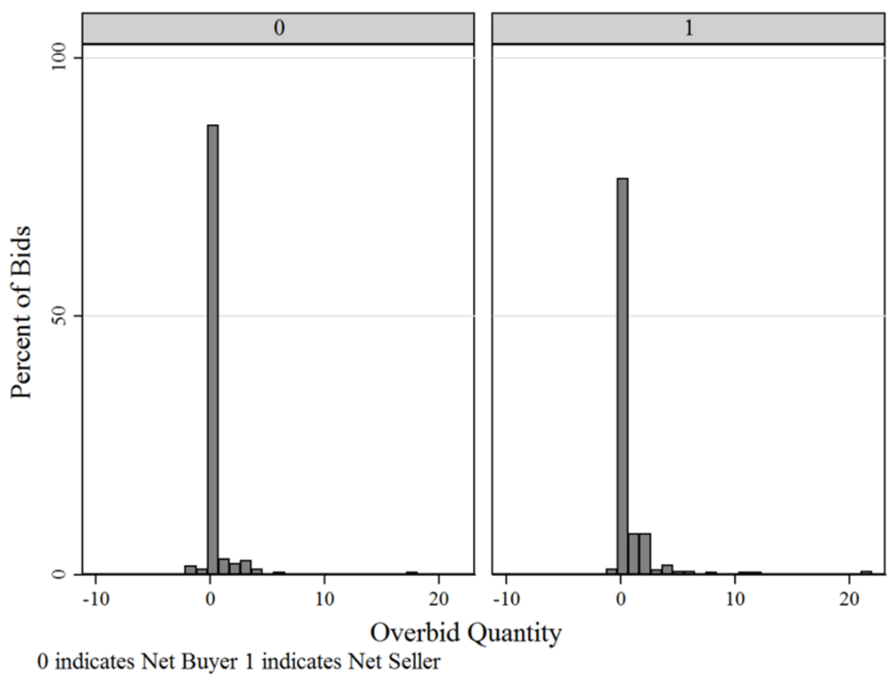


Figure 4 provides a graphical assessment of overbidding by net sellers. It provides a histogram of the percentage of bids that are overbids (bid quantities exceeding permit demand). Figure 4 includes all treatments and excludes zero net demand bidders, though the histograms look similar to figure 4 when limited to any single treatment group. Notably, the vast majority of bids are truthful for both types, though the percentage doing so is far less for net sellers. Most notably however, are the right tails of the distributions, which indicate clearly that net sellers engaged in overbidding far more frequently.

We confirm these insights with a Tobit regression of bid quantities on permits needed, treatments, and bidder types. We use cluster-robust standard errors, clustering by subject. The results appear in Table 8. The coefficient on permits needed is slightly greater than one, but not significantly so (*p*-value 0.161). This enables us to view the remaining coefficients as a rough measure of the magnitude of quantity overbidding. Such overbidding is significant in all three treatments with consignment.

The theory predicts that overbidding should be related to the bidder's production type (net seller versus net buyer) but not their pollution type (high versus low). The latter result obtains: High types are not more likely to overbid their quantities. The net buyers do tend to bid for lower quantities, as predicted, though net sellers do not overbid any more than those with zero net demand. The difference between the net buyer and net seller coefficients is highly significant (*p*-value of 0.002).

Table 8: Regression of Bid Quantities

	Bid Quantity	
Independent Variable	Coefficient	Std. Err.
Permits Needed	1.08 ***	0.06
Treatment (All Consign)	0.85 ***	0.33
Treatment (High Consign Only)	1.21 **	0.58
Treatment (Low Consign Only)	0.56 ***	0.17
Treatment Net Buyer	-0.72 **	0.34
Treatment Net Seller	-0.08	0.22
High Type	-0.60	0.54
Constant	-0.28	0.19
N	3328	
F-statistic	558.55 ***	
McFadden's Psuedo R^2	0.15	

**** p<0.01 ** p<0.05 * p<0.1, robust std. errors clustered by subject*

These results on production type do not appear robust to the exclusion of outliers; if we exclude the 2.4% of bidders whose quantity bid was (weakly) more than twice the number of permits needed, then the regression coefficients for net buyers and net sellers become insignificant at the 10% level, while all other results remain unchanged. Thus, we view our results on overbidding by production types as fairly weak and obscured by significant noise.

4.4 Permit Allocation Inefficiency

Quantity manipulation should lead to permit allocation inefficiencies. Bidders that inflate their bid quantity end up receiving more emissions permits than they need in the short run, while bidders that deflate their quantity end up paying non-compliance penalties. We define an "inefficiency" as occurring if one emissions permit was sold to a bidder in excess of his permit demand *and*, at the same time, another bidder received a non-compliance penalty for being short by a single permit. We then count the number of such inefficiencies observed in each period. For example, if one firm has two extra permits while two firms each are paying one non-compliance penalty, we count that as two inefficiencies. On the other hand, if a bidder received a non-compliance penalty for being short a single permit, and all other bidders did not acquire permits in excess of their permit demand, then we identify that auction as having no inefficiencies.

Without consignment, inefficiencies are very rare, averaging 0.02 per period. In other words, we see roughly one inefficiency for every 50 periods of play. In no period were more than two inefficiencies observed, and this happened in only one period. The low rate of inefficiency follows because 97% of quantity bids are truthful, as we assumed they would be in the theory. With consignment, however, inefficiencies are much more common. The average number per period in the *All Consign*, *High Consign*, and *Low Consign* treatments are 0.95, 0.53, and 0.65, respectively. Since each inefficiency represents a social loss of $50, these correspond to per-period welfare losses of $47.50, $26.50, and $32.50, respectively, compared to only $1.00 without consignment. Using a dummy variable regression with cluster-robust standard errors (clustering by session) as a robustness check (table excluded for simplicity), we find that each of these is significantly greater than the *No Consign* treatment, with *p*-values of 0.043, 0.001, and 0.002, respectively. Comparing among the three consignment treatments yields no significant differences, with Wald test *p*-values all greater than 0.31.

The increase in inefficiencies is not only due to them being more common; we also see greater numbers of inefficiencies when they occur. If we look only at periods with at least one inefficiency, the mean number of inefficiencies per period is 1.33 in the *No Consign* treatment, but jumps to 3.40, 2.68, and 2.65 in the *All Consign*, *High Consign*, and *Low Consign* treatments, respectively.

In our experiment, non-compliance penalties (NCPs) can come from two sources: inefficient outcomes, and markets where permit demand is greater than supply. The latter occurs randomly and is unaffected by subjects' decisions. Even if every period's outcome was efficient, each person would still pay an average of $12.96 per period in NCPs. Thus, we calculate the actual average per period and subtract $12.96 to give a measure of NCPs paid due to inefficiencies.

As expected, the results are perfectly in line with the inefficiency measure above. Without consignment subjects pay an average of $0.32 per period in excessive NCPs. In the *All Consign*, *High Consign*, and *Low Consign* treatments, this increases to $14.50, $8.61, and $7.47, respectively. These are all significantly different than without consignment.

Table 9. Average Non-Compliance Penalties in Periods with Inefficiencies

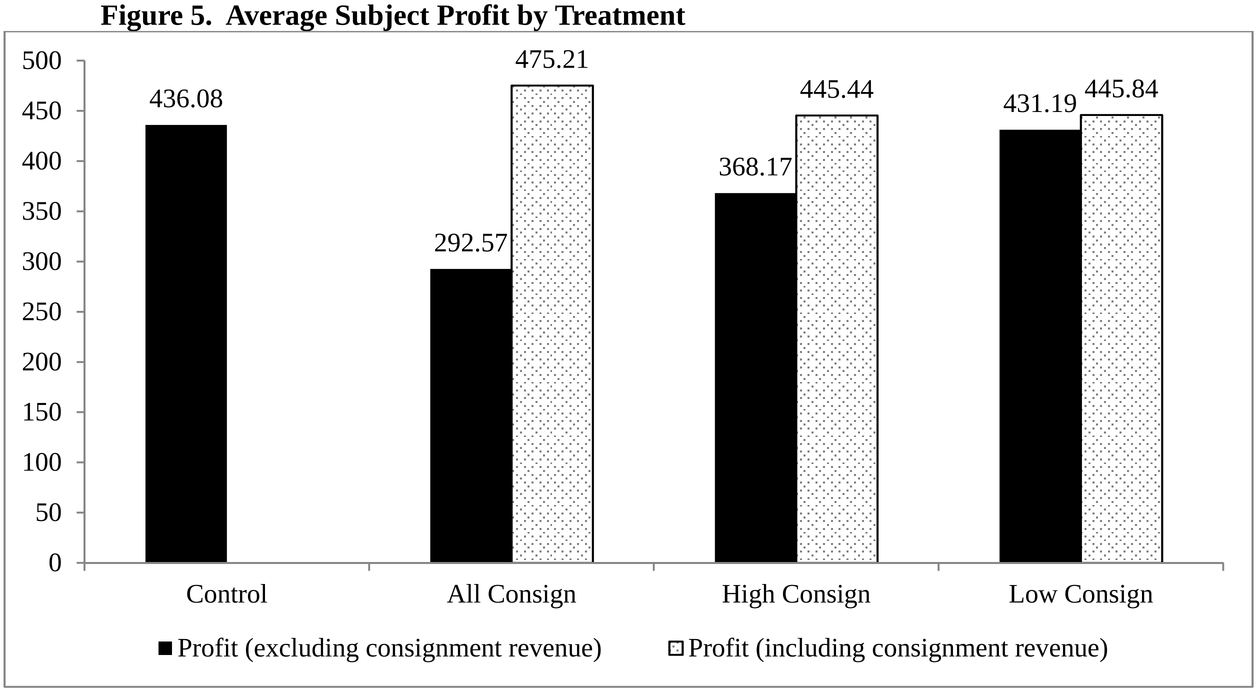
Treatment	Net Buyer NCPs	Zero Net Demand NCPs	Net Seller NCPs
Treatment (All Consign)	82.93	50.00	33.59
Treatment (High Consign)	76.92	46.98	15.91
Treatment (Low Consign)	33.33	63.26	3.03

Our theory makes a specific prediction about how inefficiencies should arise: Net sellers buy too many units while net buyers buy too few. Thus, if we only look at periods with inefficiencies, we should see net buyers paying all the NCPs. The actual results (Table 9) are not quite that stark, but clearly show that net buyers in fact pay substantially more NCPs. To test significance, we regress NCPs on treatment and production type, clustering by individual. We find no treatment differences among the three treatments with consignment (all p-values greater than 0.45), and no difference between net buyers and those with zero net demand (p-value 0.407), but that net sellers do pay significantly fewer NCPs than those with zero net demand (p-value <0.001) and fewer than the net buyers (Wald test p-value 0.001).

4.5 Profit

The inefficiency from the quantity bid distortions under consignment is also injurious to subject-level profit. In Figure 5 we provide the mean subject-level profit by treatment group. We define profit as the net of energy production revenue, non-compliance penalty and permit expenditures. We include bars for measures of profit that exclude consignment revenue so that it can be compared easily to the control group, and we also include bars for profit that includes consignment revenue adjacent to those.

Figure 5. Average Subject Profit by Treatment



In the control group, the mean profit is approximately \$436 experimental. It is \$293 in the treatment in which all subjects consign, excluding consignment revenue. We conduct non-parametric hypothesis tests of mean subject profit and find that we can safely reject the null hypothesis of mean profit equality in the *All Consign* and *High Consign* treatments, at the $p<0.001$ levels. We cannot safely reject this for the low consignment case, as the mean subject profit is approximately that of the control group. Furthermore, roughly the same effects hold when these values are decomposed by permit demand level, not reported here for simplicity.

In Table 10 we report mean profit by treatment group and by permit demand. And, we provide these same values including consignment revenue in Table 11. The results in Table 10 provide evidence that profit for net sellers is consistently lower than profit for net buyers, bidders with zero net demand, and also lower than all bidders in the control treatment without consignment.

Table 10. Average Profits

	Profit (excluding consignment revenue)		
	Net Buyers	Zero Net Demand	Net Sellers
Control (No Consign)	436.08	-	-
Treatment (All Consign)	305.05	297.03	274.79
Treatment (High Consign)	357.49	382.49	313.90
Treatment (Low Consign)	542.40	417.17	376.37

Table 11. Average Profits (Including Consignment Revenue)

	Profit (including consignment revenue)		
	Net Buyers	Zero Net Demand	Net Sellers
Control (No Consign)	436.08	-	-
Treatment (All Consign)	534.19	479.68	409.00
Treatment (High Consign)	540.23	429.08	414.12
Treatment (Low Consign)	579.77	422.98	400.17

It should be noted, however, that net sellers should ultimately receive a lower profit than net buyers by virtue of their lower production in the product market, all else being equal. That is, net buyers are producing more in the product market (energy) and receiving a larger quantity of production revenue. As detailed above, this was operationalized in this experiment as a production of either 4, 5 or 6 units in the product market, with corresponding production revenues of $400, $500 and $600 experimental, respectively. Because permit allocations are fixed, all bidders with production of 4 units are net sellers, and all bidders with production of 6 units are net buyers. We would expect profit, therefore, to be approximately $200 larger for net buyers than net sellers. This is clearly mitigated by inefficiencies due to the distortion of consignment that results in higher permit prices, overspending on permits by net sellers, and more frequent non-compliance penalties by net buyers.

We provide additional insight into these results with a Tobit regression of subject-level profit, provided in Table 12. We regress profit (excluding consignment revenue for comparison) on our treatment dummies, our dummies for net buyers and net sellers, and production type. The regression utilizes cluster robust standard errors, clustered by subject. The results provide robust evidence that subjects received significantly lower profits in treatments with consignment than in the *No Consign* control group, which is reference variable in the regression. Each treatment dummy is significant at the $p<0.01$ level, except the treatment in which only the low type subjects consign. The results also provide robust evidence that net sellers receive significantly lower profit than bidders with zero net permit demand. And, the results provide robust evidence that net buyers receive significantly larger profits than bidders with zero net permit demand. And finally, the results indicate that high types (who need twice as many permits) incur significantly less profit than low types.

Table 12. Regression of Profit

	Profit	
Independent Variable	Coefficient	Std. Err.
Treatment (All Consign)	-139.67 ***	16.19
Treatment (High Consign Only)	-66.52 ***	13.30
Treatment (Low Consign Only)	-1.97	7.61
Treatment Net Buyer	29.87 **	14.93
Treatment Net Seller	-43.10 ***	13.99
High Type	-78.97 ***	9.24
Constant	475.57 ***	7.05
N	3328	
F-statistic	67.04 ***	
McFadden's Psuedo R^2	0.02	

**** p<0.01 ** p<0.05 * p<0.1, robust std. errors clustered by subject*
D.V. excludes revenue from consigned permits

5. Conclusions

This paper has provided a theoretical and experimental analysis of the use of the consignment mechanism in carbon auctions. The results have provided rather robust evidence that the consignment mechanism, when compared against the standard uniform-price auction, results in significantly higher auction-clearing prices and substantial permit misallocation. In auction-based cap-and-trade programs (which is all greenhouse gas markets in the U.S., and will be all greenhouse gas markets in the E.U.) because the auction is crucial to influencing the market price as a benchmark and price signal, an inflated auction price due to the consignment mechanism can potentially result in systemic efficiency loss, misallocation, and misinformed abatement behavior.

The debate surrounding the efficient design of carbon auctions has tremendous currency in both the U.S. and international policy context. In light of the European Union's directive for all member states to move toward auction-based allocation for their Europe-wide carbon market, and in light of the EPA's final rules to reduce greenhouse gases under the Clean Air Act, these results have broad policy implications. While it is the regulator's aim to effectively balance the social cost of emissions with the economic impacts to businesses and households of pricing those emissions, our findings would suggest that the regulator may not be able to balance the two with a simple revenue adjustment like a consignment mechanism.

Furthermore, our findings have potentially significant implications for electric distribution firms (i.e., public utilities) that receive a pre-auction endowment of permits to consign. The argument among utilities, and the California regulator (CARB) is that the revenue from the sale of consigned emissions permits will offset cost increases that pass through in the wholesale price of power. Our findings on the other hand, provide evidence that the overbidding incentive inherent to the consignment auction reduces the profits of consigning firms. In other words, we find that while utilities are making the argument that consignment will be more profitable, to the benefit of ratepayers, the bidding incentives of the consignment auction are deleterious to profit because they inflate the cost of compliance. This is a striking irony.

Our results also provide an interesting complement to an existing problem in carbon markets in the U.S., and internationally. Because all of the firms purchasing emissions permits in carbon auctions have an incentive to lower compliance costs, the incentive to bid strategically to lower carbon auction clearing prices is ubiquitous. As a result, the problem of low price equilibria in auction-allocated carbon markets has been raised. The RGGI markets for example, saw carbon prices almost consistently near the price floor, or reserve price, for the first few years. In 2014, the member states cut the aggregate supply of emissions permits by 45 percent across the board, and prices have increased to approximately $5 per ton (from approx. $2 per ton) (RGGI, 2014). And every auction-based carbon market to date utilizes some form of reserve price (floor). Our finding that the consignment auction yields consistently higher auction clearing prices, except in contexts in which the energy demand is high and only low emissions-intensity firms are consigning permits, provides weak support for the assertion that consignment auctions might mitigate the problem of low price equilibria.

The problem of low price equilibria may be more significant than misallocation alone. In auction-allocated carbon markets, the auction price plays a critical and systemic role of providing a price signal to producers, particularly long-term decision-makers. Given that energy firms, in particular, have a planning horizon that exceeds, in many cases, a decade, the current carbon auction price can send a long-term production and abatement signal with long-lasting macroeconomic implications. This has long since been understood in the environmental economics literature, as firms make long-term abatement spending and capital decisions on the basis of their discounted expected future permit price (Stevens and Rose, 2002). Should a consignment mechanism provide an effective tool for mitigating the problem of low price equilibria in the short term, it may have long-standing implications for the cost-effectiveness and macro impacts of the emissions trading program.

There are two factors that we do not model in our laboratory experiments or in our theoretical analysis that may serve to mitigate the inefficiencies of the consignment auction that we find. The first is that we do not model banking. Banking is the ability of firms to store un-surrendered emissions permits for future use, a program design that is allowed in a majority of the world's carbon markets and serves to enhance temporal flexibility. Our finding that the inefficiency of the consignment auction is driven by the overbidding incentive of net sellers, which is also consistent with Ledyard and Szakaly-Moore (1994), may be less of a public policy problem in the long run in light of banking. That is, firms may be bidding for an additional quantity of emissions permits to increase the auction-clearing price, but that may not constitute a systemic inefficiency because firms can simply store those excess permits for future use.

The second is *ex-post* trading—the 'trade' in cap-and-trade. While our analysis does not model post auction transfers, strategic overbidding and underbidding can be balanced in post auction transactions bilaterally among firms, with the inherent (potentially high) transactions costs involved in the trading process. Although it would be more favorable from a public policy standpoint to avoid using secondary market trading to correct the sort of gross auction misallocations discovered in this empirical analysis, particularly when trading is not costless, it is important to note that relying solely upon secondary market trading as a corrective is a second best policy option.

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Appendix A. Results Including All Bidding Periods

In the preceding analysis, all results were provided with the first 25 bidding periods removed to allow for subject learning. Below, we provide all of the same results but include all bidding (except practice periods) periods as a robustness check.

Table A1. Auction Clearing Price Summary Stats (all periods)

	Auction Clearing Price		
Treatment	Overall Average	% Periods With Price = 0	Avg. Price When Price > 0
Control (No Consign)	7.69	39.2%	12.67
Treatment (All Consign)	21.08	22.8%	27.31
Treatment (High Consign Only)	15.51	21.6%	22.33
Treatment (Low Consign Only)	6.36	30.9%	9.19

Table A2. Auction Clearing Price Regression (all periods)

	Auction Clearing Price		
Independent Variable	Coefficient		Std. Err.
Treatment (All Consign)	17.95	**	6.51
Treatment (High Consign Only)	13.91	*	8.40
Treatment (Low Consign Only)	1.98		2.21
Aggregate Permit Demand	4.25	***	0.79
Constant	-127.83	***	-5.04
N	1632		
F-statistic	11.07	***	
McFadden's Pseudo R^2	0.05		

**** p<0.001 ** p<0.01 * p<0.1, robust std. errors clustered by session*

Table A3. Average Price Bids (all periods)

		Mean Bid Price		
Treatment	Type	Net Buyers	Zero Net Demand	Net Sellers
Control (No Consign)	*Low*	75.48	-	-
	High	40.88	-	-
Treatment (All Consign)	*Low*	100.22	135.6	228.39
	High	65.18	70.51	83.89
Treatment (High Consign Only)	*Low*	106.71	-	-
	High	75.21	83.66	89.82
Treatment (Low Consign Only)	*Low*	66.15	72.47	74.83
	High	24.39	-	-

Table A4. Regression of Bid Prices (all periods)

	Bid Price	
Independent Variable	Coefficient	Std. Err.
Treatment (All Consign)	48.78 **	24.86
Treatment (High Consign Only)	33.49	25.56
Treatment (Low Consign Only)	-14.31	19.89
Treatment Net Buyer	-10.71	11.63
Treatment Net Seller	31.99 *	16.38
High Type	-46.25 ***	16.92
Constant	81.17 ***	19.20
N	6528	
F-statistic	5.63 ***	
McFadden's Pseudo R^2	0.01	

**** p<0.01 ** p<0.05 * p<0.1, robust std. errors clustered by subject*

Table A5. Average Quantity Overbidding (all periods)

		Mean Quantity Overbid (Quantity Bid - Permits Needed)		
Treatment	Type	Net Buyers	Zero Net Demand	Net Sellers
Control (No Consign)	*Low*	0.13	-	-
	High	0.12	-	-
Treatment (All Consign)	*Low*	0.47	0.57	0.85
	High	0.69	1.45	1.2
Treatment (High Consign Only)	*Low*	1.98	-	-
	High	0.14	0.42	0.61
Treatment (Low Consign Only)	*Low*	0.37	0.58	0.63
	High	0.55	-	-

Table A6. Regression of Bid Quantities (all periods)

	Bid Quantity	
Independent Variable	Coefficient	Std. Err.
Permits Needed	1.02 ***	0.03
Treatment (All Consign)	1.07 ***	0.32
Treatment (High Consign Only)	1.22 **	0.58
Treatment (Low Consign Only)	0.58 ***	0.20
Treatment Net Buyer	-0.71 **	0.28
Treatment Net Seller	-0.25	0.25
High Type	-0.37	0.39
Constant	0.17	0.12
N	6528	
F-statistic	2025.77 ***	
McFadden's Psuedo R^2	0.12	

**** p<0.01 ** p<0.05 * p<0.1, robust std. errors clustered by subject*

Table A7. Average Non-Compliance Penalties in Periods with Inefficiencies (all periods)

Treatment	Net Buyer NCPs	Zero Net Demand NCPs	Net Seller NCPs
Treatment (All Consign)	96.68	58.77	48.46
Treatment (High Consign)	100.00	58.14	71.88
Treatment (Low Consign)	39.80	60.66	21.76

Table A8. Regression of Profit (all periods)

	Profit	
Independent Variable	Coefficient	Std. Err.
Treatment (All Consign)	-111.86 ***	14.23
Treatment (High Consign Only)	-83.90 ***	16.25
Treatment (Low Consign Only)	0.25	6.41
Treatment Net Buyer	33.71 *	13.41
Treatment Net Seller	-54.23 ***	12.82
High Type	-81.22 ***	10.02
Constant	467.23 ***	6.61
N	6528	
F-statistic	81.48 ***	
McFadden's Psuedo R^2	0.01	

**** p<0.01 ** p<0.05 * p<0.1, robust std. errors clustered by subject*

D.V. excludes revenue from consigned permits

Table A9. Average Profits (all periods)

	Profit (excluding consignment revenue)		
	Net Buyers	Zero Net Demand	Net Sellers
Control (No Consign)	426.68	-	-
Treatment (All Consign)	335.43	318.62	277.02
Treatment (High Consign)	324.69	366.83	280.22
Treatment (Low Consign)	536.70	407.71	369.91

Table A10. Average Profits (Including Consignment Revenue) (all periods)

	Profit (including consignment revenue)		
	Net Buyers	Zero Net Demand	Net Sellers
Control (No Consign)	426.68	-	-
Treatment (All Consign)	530.06	473.49	400.26
Treatment (High Consign)	531.64	417.62	401.03
Treatment (Low Consign)	574.53	415.02	396.20