The Consignment Mechanism in Carbon Markets: A Laboratory Investigation[†]

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Abstract: Unlike other auction-based carbon emission markets, California's carbon market (AB32) 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 numerical example, we identify the incentive that consignees have to overstate their quantity demanded in the auction, since this increases the probability that the auction clears at a higher price. This results in inefficient allocations and inflated auction prices. We test this effect through a series of laboratory experiments and confirm these predictions. Findings indicate 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. We conclude with implications for the design and modification of future Coasian markets.

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1. Introduction

Throughout the past four decades, research evaluating market-based approaches to environmental policy has proliferated. 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 (Dormady, 2013; Joskow and Kahn, 2002).

The importance of an efficient initial allocation of permits has featured prominently in recent debates. Early market designs 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), resulting in environmental "hot spots" and other social equity concerns (Ringquist, 1998). 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 reduce taxes and 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 Emissions Trading System (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, does not utilize a consignment mechanism in its 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 state governments. That revenue is not returned to the utilities or wholesale generators that purchase the permits. Regulated utilities pass through any permit acquisition costs in their rate base subject to commission approval, and independent power producers who participate in regional ISO/RTO markets pass through costs indirectly to utilities through wholesale markets (e.g., the day-ahead market).

[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, 2000; Weber, 1997).

Juxtaposed to RGGI, California has been operating the Assembly Bill 32 (AB32) market since 2012, in which consignment auctions are used to initially allocate permits to the electricity, natural gas and oil-refining sectors. California pre-allocates a fixed and significant quantity of permits to the main distribution utilities at zero cost. This is similar to grandfathering, *except* these firms are then required to consign, or sell, all allocated permits into the auctions. All firms in applicable sectors are then required to purchase the permits that they need for program compliance in the auction. The revenue that distribution utilities obtain from the sale of consigned permits is returned to them at the marginal price at which the auction cleared. It is then required to be used to benefit ratepayers in their respective service territories, broadly defined. Revenue from the sale of any additional permits sold by the regulator (i.e., the California Air Resources Board) for permits that are under the cap but not allocated to consigning utilities is returned to the state's general fund. This auction format is a modified revenue-neutral auction, similar to the Hahn and Noll (1983) auction, with the key difference being that only certain bidders (i.e., distribution utilities) are allocated units to consign. The divergence in auction design between the RGGI and AB32 markets has raised 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 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 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 and the importance of a laboratory investigation becomes much clearer. Moreover, there are important policy implications at both the state and regional levels. Inefficiencies in permit allocation associated with distortions in auction design can potentially result in adverse societal, environmental and financial consequences. It is imperative that we understand what auction designs are most efficient for the initial allocation of tradeable permits, and what pitfalls can be avoided.

In this paper we study how consignment affects behavior in uniform price auctions. We consider a setting with no consignment (e.g., RGGI) and compare it to three different levels of consignment—one in which all firms are consigned permits to sell, one in which only low-emissions firms are consigned permits, and one in which only high-emissions firms are consigned permits. We show that, in theory, firms who are consigned units have an incentive to distort their bids, leading to inefficiencies. We then observe actual behavior in an experimental setting to see whether these distortions and inefficiencies are in fact realized.

More specifically, 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 both high and low emissions-intensity producers. This allows us to simulate two common generalizable regulatory contexts, such as merchant gas and coal wholesale producers. Experimental results indicate that the consignment mechanism results in significantly higher auction-clearing prices across the board. We also find that the consignment mechanism results in significantly lower efficiency, and that it can be financially injurious to the profit of consigning firms.

1.1 Comparison to Existing Empirical Approaches

This paper highlights 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 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. They find that 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 broadly consistent with our experimental results—although we do not explicitly model monopoly. On the other hand, 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 divergent results is that we allow for scenarios in which the emissions cap can be binding (i.e., the supply of permits is exceeded by demand). When this occurs, firms have a constant marginal value for permits (equal to the non-compliance penalty). Consistent with insights gained through the empirical literature on cheating behavior in emissions markets (Malik, 2002; Misiolek and Elder, 1989; Van Egteren and Weber, 1996), firms have no direct incentive to pay a higher marginal price to acquire a permit in an auction if that price exceeds the marginal price of the non-compliance penalty. And, consistent with the AB32 market design, our firms know with certainty whether they will be net buyers or net sellers as actual firms operating in these markets do. 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. We highlight the practical applicability of a more short-run auction experiment—carbon prices are a relatively small component of firms' production costs and very unlikely to modify production behavior (e.g., quantity of petroleum refined in Southern California) in the short-run (Newbery, 2016).

A related seminal paper utilized a laboratory experiment to test auction performance between a standard uniform-price auction and the eventual EPA Title IV market design—a double auction with some unique design characteristics (Cason and Plott, 1996). While their results find that the uniform-price auction is more efficient and generally outperforms the EPA auction design, their paper does not utilize a revenue-neutral or consignment component and is not directly instructive. It is noteworthy nonetheless that they similarly find the uniform-price auction to be superior for trading emissions permits, which further motivates our methodological approach and experimental design—described in the next section—in terms of testing against the standard uniform-price auction as a control, or base, case.

In the sections to follow, we detail our experimental design and four major treatment conditions, identify core hypotheses to be tested in the experiment, and present detailed analyses of our results at the aggregate (market) and individual (firm) levels.

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 non-consignment auction mechanism. We begin with a description of the consignment mechanism.

2.1 The Consignment Mechanism

In a traditional Coasian market 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.[2] 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. 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. Surrendered permits (i.e., permits

[2] It is important to note that in operating emissions markets in the U.S. firms do not submit a schedule of bids, and instead submit a single price-quantity bid.

used for program compliance) are returned, or electronically cancelled, by the regulator. For a detailed description of the uniform price auction, see Milgrom (2004), Krishna (2009), and Dormady (2013).

Under a consignment mechanism, emissions permits are freely allocated to the utilities *before the auction*. 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 permits. Firms purchasing emissions permits, including the distribution utilities that are themselves consigning permits, purchase from the pool of permits that includes those that they consigned. Additional (non-consigned) permits are included in the pool of permits. These additional permits are sold by the state and generate additional revenue. 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, detailed below. All treatments utilized the uniform-price sealed bid auction. In each session, 16 subjects (4 groups of 4) participated for two practice periods and 51 actual periods, though they were not informed of the total number of periods.

At the start of each period, each subject was randomly and independently assigned a production level of either 4, 5, or 6 units of energy. This broadly represents quarterly consumption levels for a distribution utility or output from a wholesale generator, for example. The levels are representative of low, intermediate and peak levels of energy demand in regional energy markets.[3] Subjects received fixed revenue from their production of energy: for every unit of energy they produced, they receive $100 experimental.[4] As such, in any period, subjects received a fixed 'endowment' of production revenue, $400, $500 or $600 experimental.

[3] Peak production may also be broadly representative of months during low-hydro years in California, in which full generation output from fossil units is required to clear aggregate system-wide demand and reserve margins.

[4] At the end of the session, all experimental currency was exchanged for US$ at the rate of $1 for every $1,000 experimental.

Production also creates pollution, and subjects need to purchase permits to cover the pollution they produce. At the start of the session, half of the subjects were randomly assigned to be a 'High' type, and the other half were assigned to be a 'Low' type. This type assignment remained fixed across all periods. In each period, the subjects were randomly matched into four groups of four, such that each group contained 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. Also, because the auctions were sealed bid, subjects could not see the bids of others bidding against them.

The difference between High types and Low types is in the units of pollution emitted per unit of energy produced (i.e., emissions factor). 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 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 predominant carbon-emitting sources of power generation today.[5] 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 ranged from 24 to 36 permits. The aggregate supply of emissions permits sold at auction in any period was always 30 permits. Given the fixed supply of emissions permits, this design allows us to test our hypotheses both for cases in which the permit demand exceeds, and is exceeded by, permit supply.

[5] Coal production is approximately twice (1.6 times depending on technology) as carbon-intensive as natural gas production. For simplicity and ease of subject understanding, we simplified this to an emissions factor ratio of 2:1.

Subjects could bid for any quantity of emissions permits, irrespective of their individual pollution output. Bids were placed in the form of a single price-quantity pair rather than a schedule of bids. A subject holding a deficit of emissions permits at the end of the period would incur 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 is adjusted to zero.[6]

2.3 Treatments

The experiment includes four treatments (see Table 1) that generalize common auction-based market designs and heterogeneous regional production portfolios. The control treatment provides a market with no permit consignment and all auction revenue is returned to the regulator. This is consistent with the system used in the RGGI market region (Northeastern US). 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, 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 these treatments, all auction revenue from the sale of consigned permits returns to the consignees, and the revenue from the sale of non-consigned permits returns to the regulator.

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. This is consistent with historical emissions-based allocation systems utilized in both California and RGGI. These are also the average permit demand for each pollution type. The firms are forced to sell their allocated permits into the auction (keeping

[6] The limited liability rule was not exercised much in this experiment, in total only 0.3% (26) of all observations. Its modal occurrence was in practice periods in which subjects were familiarizing themselves with the software.

the resulting revenue) and must purchase for program compliance any permits that they wish to use to cover their pollution output.

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.

Table 1. Experiment Treatment Parameters

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

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.

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 (or renewables) than coal. Because our explicit focus is the bidding incentives of the auction phase, we do not simulate numerous combinations of generation portfolios, and moreover, that would add unnecessary complexity to the experiment.

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 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.

2.5 Experiment Operation

We conducted eight 2.5-hour experimental sessions, excluding pilot sessions. Of these eight, we conducted two sessions for each of our four treatments. Each session consisted of four markets, or experiments, operating simultaneously. Each session began with a set of written subject instructions and a walk-through of the user interface. Experimental software was programmed using Z-TREE (Fischbacher, 2007). Subjects received two handouts consisting of the written instructions and a payment form, as well as consent forms.

In total, there were 16 subjects per session, consisting of four groups of four bidders each, and eight sessions in total, for a total of 128 subjects. On average, subject earnings were $32, including a ten-dollar show-up payment. The standard deviation in earnings was approximately $2.30, with a range between approximately $24.50 and $36.50.

3. Auction Predictions & Hypotheses

3.1 Auction Predictions

We use computational methods to find a Bayes-Nash equilibrium for our experimental market. We were able to identify a pure-strategy equilibrium in our main treatment, the *All Consign* treatment. We were unable to find a pure-strategy equilibrium for the *No Consign*, *Low Consign*, and *High Consign* treatments.[7] This equilibrium highlights the intuitive distortions from the utilization of the consignment mechanisms that 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

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, and 12 distort their quantities, bidding 9, 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

[7] 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.

net demand agent, eliminating the underbidding incentive beyond that point. 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 expect to see more 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.[8]

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 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 computational solutions just described 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 main treatment (*All Consign*). Based on our computational analysis of the other treatments, however, we

[8] 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.

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: *High type net sellers inflate their quantity bids in the All Consign treatment.*

H2b: *High type 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 (8.69)	40.9%	\$11.39 (8.64)
Treatment (All Consign)	\$24.17 (23.71)	25.0%	\$32.23 (22.13)
Treatment (High Consign Only)	\$15.36 (20.36)	24.5%	\$20.35 (21.16)
Treatment (Low Consign Only)	\$5.86 (7.90)	35.1%	\$9.02 (8.23)

Note: Standard deviations in parentheses.

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 (reference) 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. 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 clearing price of zero, with p-values all less than 0.01.

Table 4. Auction Clearing Price Regression

Independent Variable	Auction Clearing Price Coefficient (St. Err.)
Treatment (All Consign)	22.73**
	(7.63)
Treatment (High Consign)	12.43*
	(7.06)
Treatment (Low Consign)	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

Robust std. errors clustered by session. * *p<0.10,* ** *p<0.05,* *** *p<0.01*

These treatment differences are also visible in scatter plots of auction clearing prices versus aggregate demand (Figure 1). 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 predicted 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 predicted 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 only high-type firms (panel c), auction prices frequently exceed $50, both when demand is low and high. In equilibrium firms should only submit price bids of at most $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 are observed, and no clear difference are observed for high-demand periods.

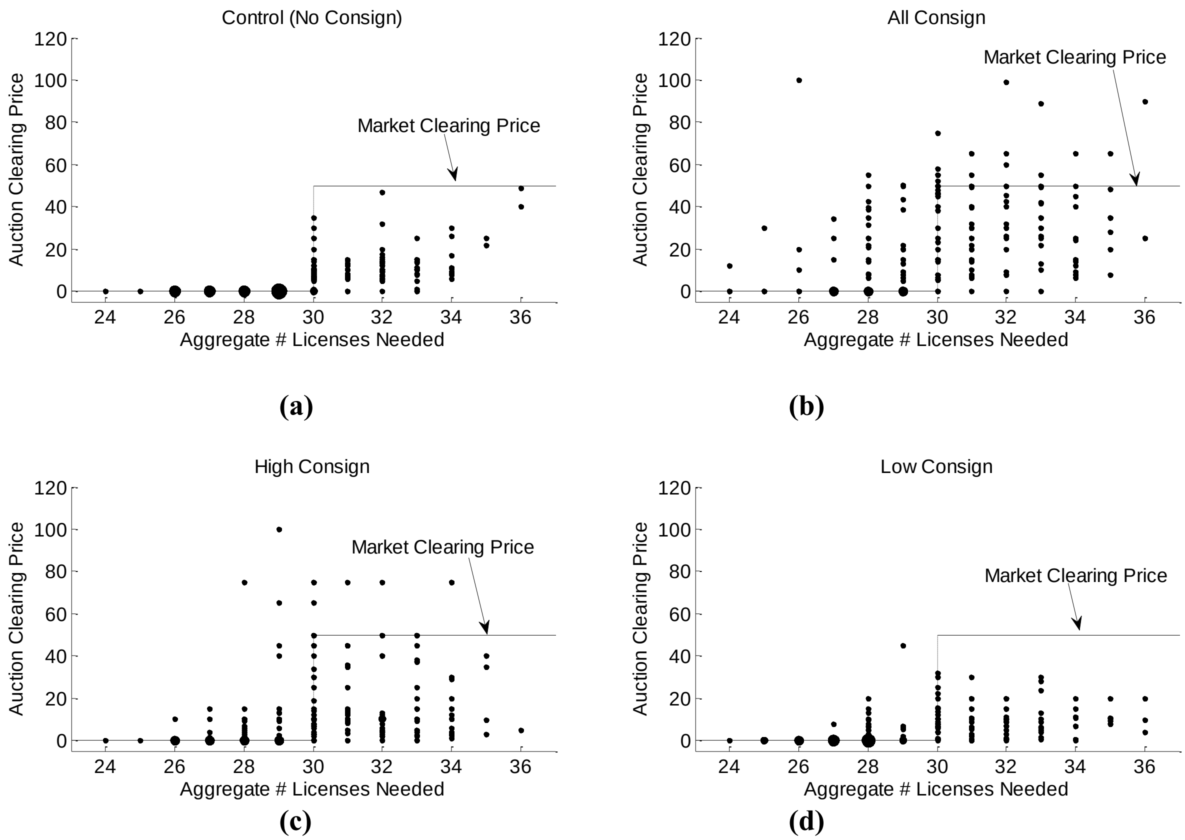


Figure 1a-d: Auction Clearing Prices for Each Treatment
Horizontal line labeled "Market Clearing Price" indicates predicted auction clearing price of $50 in the control group as reference.

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 factor firms) consign permits, consistent with the predictions described 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, as well as medians and standard deviations. Although our point predictions 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—which we discuss in greater detail below. Median values in the All Consign and High Consign treatment paint a much clearer picture of our theory, all at or very near expectations. Finally, net sellers bid higher than net buyers or those with zero net demand.

Table 5. Price Bid Descriptive Statistics

		Not Consigning	Consigning		
Treatment	Type	Net Buyer	Net Buyer	Zero Net Demand	Net Seller
Control (No Consign)	*Low*	\$60.08 \$20.00 \$109.40	-	-	-
	High	\$33.59 \$25.00 \$33.32	-	-	-
Treatment (All Consign)	*Low*	-	\$126.54 \$50.00 \$151.56	\$165.46 \$50.00 \$194.19	\$278.32 \$200.00 \$247.02
	High	-	\$72.14 \$50.00 \$66.31	\$82.21 \$55.00 \$78.06	\$94.67 \$55.00 \$98.01
Treatment (High Consign)	*Low*	\$107.57 \$49.99 \$160.84	-	-	-
	High	-	\$70.73 \$45.00 \$68.54	\$88.92 \$50.00 \$83.98	\$92.97 \$50.00 \$95.82
Treatment (Low Consign)	*Low*	-	\$59.83 \$30.00 \$92.14	\$66.29 \$30.00 \$115.66	\$84.29 \$30.00 \$160.57
	High	\$23.26 \$13.00 \$26.31	-	-	-

Values from top to bottom are mean, median, st. dev. of bid price.

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) for subjects who are consigning permits, and pollution type.[9] The results are shown in Table 6—we include both a cross sectional

[9] 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.

Tobit model and a panel (random effects) model to incorporate dynamics. The regressions confirm 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.

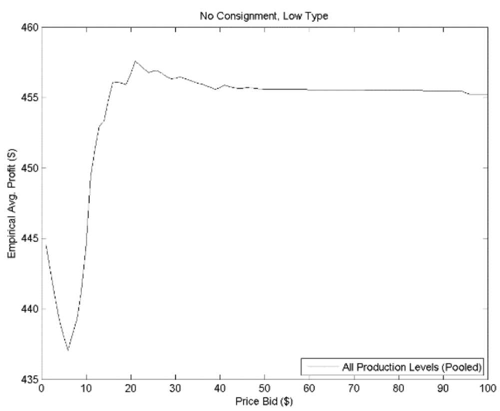
Table 6: Bid Price Regression Analysis

	Tobit	**RE Tobit**
Independent Variable	Coefficient (St. Err.)	Coefficient (St. Err.)
Treatment (All Consign)	82.45***	85.29**
	(27.21)	(25.24)
Treatment (High Consign)	45.59*	46.93*
	(24.46)	(25.16)
Treatment (Low Consign)	-4.59	-2.92
	(17.92)	(25.17)
Net Seller	40.42**	30.57***
	(19.16)	(4.04)
Net Buyer	-16.12	-15.11***
	(11.87)	(3.98)
High Type	-50.39***	-50.65***
	(17.77)	(17.78)
Constant	72.03***	72.17***
	(16.72)	(19.87)
Log Likelihood		-18,920.36
Log Psuedo Likelihood	-20,632.71	
F-statistic	5.80**	
Wald Chi^2		158.02**
McFadden's Pseudo R^2	0.01	
N	3,328	3.328

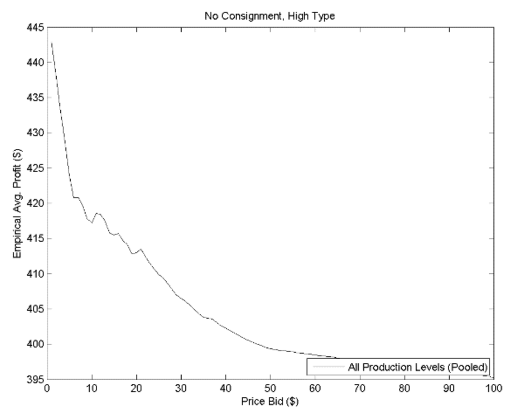
Robust std. errors clustered by subject (excludes panel model). * *p<0.10,* ** *p<0.05,* *** *p<0.01*

To further understand the actual incentives faced by the bidders when choosing their price bids, we perform a Monte Carlo simulation of a hypothetical subject submitting various price bids when paired with three other randomly-selected subjects from our data. For each price level this calculation is done 250 times—each with a new group of three opponents—and the average profit for each price bid is graphed in

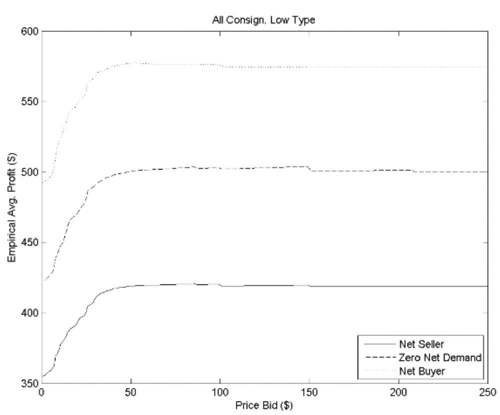
Figure 2.[10] In the No Consignment treatment, we see that the low type's optimal price bid is $21, though any bid of $50 or greater still achieves over 99% of the maximum expected profit. In other words, subjects' incentives are quite flat, and any price bid over $20 appears to be a near-optimal response to the behavior of others. This is because subjects who submit high bids are very unlikely to affect the auction clearing price, so one high bid is just as good as another. A similar outcome arises for both types in the *All Consign* treatment: the apparent over-bidding by subjects is in fact a best response to the actual bids of others.[11]



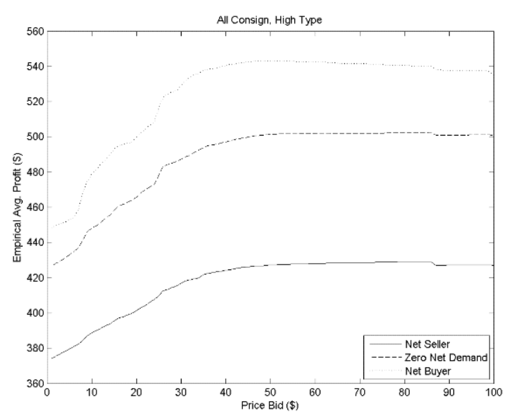
(a) *No Consign*, Low Type



(b) *No Consign,* High Type



(c) *All Consign,* Low Type



(d) *All Consign,* High Type

Figure 2 a-d: Price Bid Monte Carlo Simulation Outputs

[10] We assume the hypothetical subject's quantity bid equals the median quantity bid for his type and production level. Changing this assumption does not appear to change the qualitative features of the resulting graphs. Graphs for the remaining treatments appear in the appendix.

[11] This does not mean that high bids could be part of an equilibrium. If all price bids were above $50 then subjects would prefer to deviate and submit a price bid of $0.

Figure 2 shows that high types in the *No Consign* treatment have a fairly strong incentive to bid \$0. Doing so drops the expected clearing price because the lowest bidder often sets the clearing price, but also exposes the bidder to possible non-compliance penalties due to rationing. High types need to buy many permits (because none are consigned to them), so for them the benefit of reducing the clearing price far outweighs the cost of a couple of non-compliance penalties.[12] Thus, we see the lowest price bids from high type subjects in the two treatments where they are not consigned any permits (*No Consign* and *Low Consign* only).

4.3 Quantity Bids

Our prediction is that, in the *All Consign* treatment, net sellers have pressure to overbid their true quantity demand and net buyers have pressure to underbid their true quantity demand. But it is only the high types that can act on this pressure, since low types who misrepresent their true demand become zero net demanders and the incentive to misrepresent disappears.

We show the average, median and standard deviation of the amount by which quantity bids exceed permit requirements (*i.e.*, pollution output) in Table 7. In the *All Consign* treatment we see a general tendency to overbid quantities, and that high type net buyers overbid less and high type net sellers overbid more. Thus, we see evidence that high types respond to the over- and underbidding incentives, as predicted by theory.

Looking at the median data from Table 7 reveals that most quantity bids are truthful, meaning they exactly equal the number of permits needed. In the control (*No Consign*) treatment, 97.2% of quantity bids are truthful, so mean overbidding levels are essentially zero for both pollution types. In the *All Consign* treatment 78.4% of quantity bids are truthful, so the pattern of over- and underbidding is driven by a

[12] Of course, all high types bidding \$0 would not be an equilibrium, for the bidder could raise their price bid to \$1 and greatly reduce the risk of being assessed non-compliance penalties.

minority of subjects. The percentage of quantity overbids in the *High Consign* and *Low Consign* treatments are similar at 16.3% and 16.7%, respectively.

Table 7: Quantity Overbidding Descriptive Statistics

		Not Consigning	**Consigning**		
Treatment	Type	Net Buyer	Net Buyer	Zero Net Demand	Net Seller
Control (No Consign)	*Low*	0.02 0.00 0.26	-	-	-
	High	-0.01 0.00 0.39	-	-	-
Treatment (All Consign)	*Low*	-	0.11 0.00 0.79	0.54 0.00 2.81	0.27 0.00 1.08
	High	-	0.52 0.00 1.68	0.94 0.00 2.81	1.22 0.00 3.71
Treatment (High Consign)	*Low*	1.81 0.00 5.31	-	-	-
	High	-	0.24 0.00 2.17	0.27 0.00 1.22	0.63 0.00 2.30
Treatment (Low Consign)	*Low*	-	0.16 0.00 0.58	0.35 0.00 1.56	0.62 0.00 2.01
	High	0.44 0.00 1.83	-	-	-

Values from top to bottom are mean, median, st. dev. of overbidding (quantity bid minus permits needed).

We confirm these insights with regression analysis of bid quantities on permits needed, treatments, and bidder types. We use cluster-robust standard errors, clustering by subject[13] for our cross-sectional model, and we similarly include a random effects Tobit panel model to incorporate any dynamic effects. The results appear in Table 8. The coefficient on permits needed is slightly greater than one, indicating the

[13] For each of our subject-level regressions (i.e., those with the dependent variable of bid price, bid quantity and profit) we also performed the same regressions with robust standard errors clustered at the session level. The results were not qualitatively different from the models with subject-level clustering.

general tendency to overbid in the control treatment. The treatment variables are all significantly positive as well, indicating an even higher general tendency to overbid quantities.

The interactions of pollution types with production types (for example, *High Type * Net Buyer*) further confirm the theoretical prediction: high type net buyers underbid and high type net sellers overbid. These are significant when random effects are included. We also see some tendency for low type net buyers to underbid, even though in theory they should not be able to gain from this strategy. Overall, however, we do find that bidders respond to incentives to manipulate the clearing price via manipulations in their quantity bids.

Table 8: Bid Quantity Regression Analysis

	Tobit	**RE Tobit**
Independent Variable	Coefficient (St. Err.)	Coefficient (St. Err.)
Permits Needed	1.09***	1.06***
	(0.06)	(0.36)
Treatment (All Consign)	0.86***	0.64
	(0.33)	(0.42)
Treatment (High Consign)	1.14**	1.09***
	(0.58)	(0.42)
Treatment (Low Consign)	0.65***	0.46
	(0.18)	(0.42)
High Type	-1.15	-0.70
	(0.71)	(0.49)
Low Type	-0.29	-0.17
	(0.22)	(0.39)
*High Type * Net Buyer*	-0.62*	-0.43**
	(0.37)	(0.17)
*High Type * Next Seller*	0.31	0.40**
	(0.32)	(0.18)
*Low Type * Net Buyer*	-0.90**	-0.34**
	(0.36)	(0.17)
*Low Type * Net Seller*	-0.38	0.10
	(0.27)	(0.17)
Log Likelihood		-7,041.01
Log Psuedo Likelihood	-7,758.48	
F-statistic	5,563.80***	
Wald Chi^2		4,620.31***
N	3,328	3,328

Robust std. errors clustered by subject (excludes panel model). * *p<0.10,* ** *p<0.05,* *** *p<0.01*

4.4 Permit Allocation Inefficiency

Quantity manipulation should lead to permit allocation inefficiencies. Bidders who 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 her 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. Mathematically, the resulting measure is min{unused permits, penalties paid}. 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.

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 our control group that does not utilize consignment.

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

	Not Consigning	**Consigning**		
Treatment	Net Buyer NCPs	Net Buyer NCPs	Zero Net Demand NCPs	Net Seller NCPs
Treatment (All Consign)	-	$82.92	$50.00	$33.59
Treatment (High Consign)	$45.12	$76.92	$51.47	$15.91
Treatment (Low Consign)	$73.04	$33.33	$30.00	$3.03

Above, we made 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, production type and pollution type, clustering by individual (again, table omitted for simplicity). We find that all treatments are positive and statistically different from the *No Consign* treatment with the *All Consign* treatment resulting in the highest NCPs (all *p*-values less than 0.01). We find that high emissions bidders pay significantly higher NCPs (p-value <0.001) and net sellers pay substantially lower NCPs than net buyers (p-values <0.01).

4.5 Profit

We also find that the inefficiency from the quantity bid distortions under consignment is injurious to subject-level profit. In Figure 3 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.

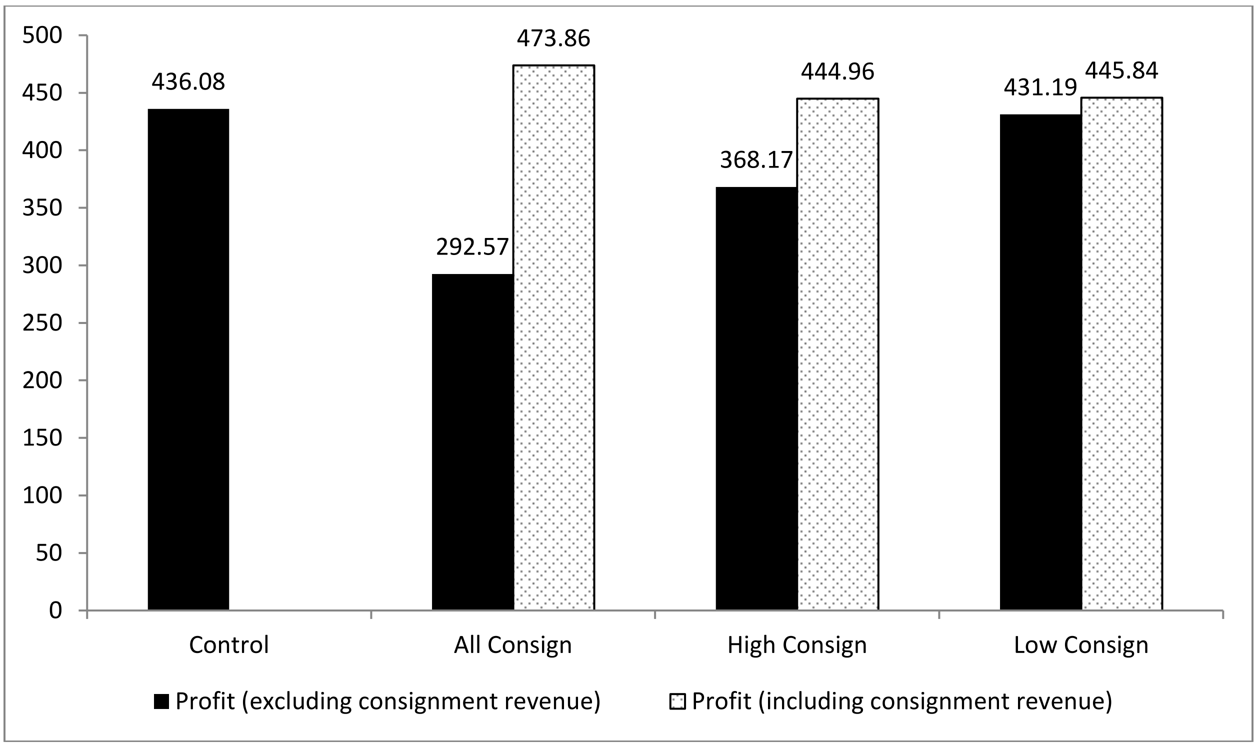


Figure 3. Average Subject Profit by Treatment

In the control group, the mean profit is approximately \$436. It is \$293 in the *All Consign* treatment, excluding consignment revenue. 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 some 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.[14]

Table 10. Average Profits (Excluding Consignment Revenue)

	Not Consigning	**Consigning**		
Treatment	Net Buyer	Net Buyer	Zero Net Demand	Net Seller
Control (No Consign)	$436.08	-	-	-
Treatment (All Consign)	-	$305.05	$297.03	$274.79
Treatment (High Consign)	$405.32	$357.49	$320.78	$313.90
Treatment (Low Consign)	$404.32	$543.40	$463.27	$376.37

Table 11. Average Profits (Including Consignment Revenue)

	Not Consigning	**Consigning**		
Treatment	Net Buyer	Net Buyer	Zero Net Demand	Net Seller
Control (No Consign)	$436.08	-	-	-
Treatment (All Consign)	-	$534.19	$479.58	$404.00
Treatment (High Consign)	$405.32	$540.23	$490.66	$414.12
Treatment (Low Consign)	$404.32	$579.78	$489.87	$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 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.

[14] The mean revenue from permit sales in the *No Consign* treatment—revenue that would be received by the government or regulator—was $202.08.

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.

Table 12. Regression of Profit

	Tobit	**RE Tobit**
Independent Variable	Coefficient (St. Err.)	Coefficient (St. Err.)
Treatment (All Consign)	-139.67***	-135.79***
	(16.19)	(13.78)
Treatment (High Consign)	-66.52***	-64.52***
	(13.30)	(13.30)
Treatment (Low Consign)	-1.97	-4.83***
	(7.61)	(13.34)
Net Seller	-43.11***	-36.21***
	(13.98)	(7.36)
Net Buyer	29.87***	38.23***
	(14.93)	(7.27)
High Type	-78.98***	-73.13***
	(9.25)	(9.30)
Constant	475.57***	472.65***
	(7.05)	(10.39)
Log Likelihood		-20,2221.60
Log Psuedo Likelihood	-21,400.93	
F-statistic	67.04***	
Wald Chi^2		291.97***
McFadden's Pseudo R^2	0.02	
N	3,328	3,328

Robust std. errors clustered by subject (excludes panel model). * *p<0.10,* ** *p<0.05,* *** *p<0.01*

We provide additional insight into these results with regression analysis of subject-level profit, provided in Table 12. We utilize Tobit models and regress profit (excluding consignment revenue for comparison) on our treatment dummies, production type and pollution type. The cross-sectional model 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 (reference variable). Each treatment dummy is significant at the p<0.01 level, except the treatment in which only the low type subjects consign in the cross-sectional model. The results also provide robust evidence that net sellers receive significantly lower profit, and net buyers receive significantly larger profit, than zero net demand bidders. Furthermore, the results indicate that high pollution types incur significantly less profit than low types.

5. Conclusions

This paper has provided an experimental analysis of the use of the consignment mechanism in Coasian auctions. The results showed that the consignment mechanism results in significantly higher auction-clearing prices and permit misallocation compared with the standard uniform-price auction without consignment. 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, inefficiency or misallocation can potentially result in systemic efficiency loss, misallocation, misinformed abatement behavior and/or misinformed regulatory decisions. The debate surrounding the efficient design of carbon auctions has immediate importance in both the U.S. and internationally. In light of the European Union's directive for all member states to move toward auction-based allocation, and in light of the gradual adoption of regional carbon markets in the U.S., understanding pitfalls of auction design can inform future policy adoption and implementation.

Our findings have significant implications for electric distribution utilities that receive a pre-auction endowment of permits to consign. The argument among utilities, and the California regulator (CARB) is that revenue from the sale of consigned emissions permits will offset cost increases that pass through in the wholesale price of power. However, our findings provide evidence that the overbidding incentive inherent to the consignment auction might actually reduce firm profits. 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 mechanism may be deleterious to profit because it is likely to inflate the cost of compliance.

These results also have important policy implications for the regulator. While it is the regulator's aim to effectively balance the social cost of pollution with any economic impacts to households and businesses (who bear the ultimate expense of cleanup), our findings would suggest that the regulator may not be able to balance the two with a simple revenue adjustment like a consignment mechanism. Though, the finding that balancing these major considerations is not as simple as an auction mechanism should not be surprising to readers.

The problem of inefficient auction price may be more expansive in scope than misallocation alone. In auction-allocated carbon markets, the auction price plays a critical and systemic role in providing a price signal to producers and regulators, particularly long-term decision-makers and those setting cost pass-thru. Given that energy firms, in particular, have a planning horizon that exceeds a decade in many cases, the current carbon auction price can send a long-term production and abatement signal with long-lasting macroeconomic implications. This has been long understood in the broader 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). Auction prices distorted by consignment bidding can thus have longer term consequences.

There are two factors that we do not model in our analysis that may serve to mitigate some of this. The first is that we do not model banking. Banking is the ability of firms to store unused 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 firms can simply store those excess permits for future use. On the other hand, banking can also facilitate hoarding of permits, which is supported by Dormady's (2014) experimental results. To the degree that banking mitigates some of this inefficiency, it would be in the longer term, not necessarily providing any net relief for firms and consumers in the here and now.

The second mitigating factor is ex-post trading—the 'trade' in cap-and-trade. While our analysis does not incorporate post auction transfers, strategic overbidding can be balanced in post auction transactions bilaterally among firms. Though Dormady and Englander (2016) identify substantial transaction costs in this process. From a public policy standpoint, it would be more favorable to avoid using secondary market trading to correct auction misallocation, 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.

Moreover, simply because secondary market trading exists and can mitigate some of the adverse consequences of poorly constructed auction designs—or auctions designed with alternative policy considerations in mind—that is no excuse to wash one's hands of inefficiencies in the auction itself. Corrections for inefficient auction allocations are neither costless to firms nor 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, inflated auction prices arising from strategic overbidding can substantially affect system-wide price signals and exchange benchmarks, as well as derivatives markets, and regulatory cases.

References

Arimura, T.H., 2002. An empirical study of the SO2 allowance market: effects of PUC regulations. Journal of Environmental Economics and Management 44(2), 271--289.

Ausubel, L., 2004. An efficient ascending-bid auction for multiple objects. American Economic Review 94(5), 1452--1475.

Ausubel, L., Cramton, P., 2002. Demand reduction and inefficiency in multi-unit auctions (Working Paper). Retrieved from University of Maryland: http://www.cramton.umd.edu/papers1995-1999/98wp-demand-reduction.pdf

Averch, H., Johnson, L.L., 1962. Behavior of the firm under regulatory constraint. American Economic Review 52(5), 1052--1069.

Burtraw, D., Sekar, S., 2014. Two worldviews on carbon revenues. Journal of Environmental Studies and Sciences 4(1), 110—120.

Cason, T.N., Plott, C.R. 1996. EPA's new emissions trading mechanism: A laboratory evaluation. Journal of Environmental Economics and Management 30(2), 133--160.

Cramton, P., Kerr, S., 2002. Tradeable carbon permit auctions: How and why to auction not grandfather. Energy Policy 30(4), 333--345.

Dales, J., 1968. Pollution, Property and Prices. University Press, Toronto.

Dewees, D.N., 2008. Pollution and the price of power. The Energy Journal 29(2), 81--100.

Dormady, N., 2013. Market power in cap-and-trade auctions: A Monte Carlo approach. Energy Policy 62, 788--797.

Dormady, N., 2014. Carbon auctions, energy markets and market power: An experimental analysis. Energy Economics 44, 468--482.

Dormady, N. Englander, A.G., 2016. Carbon allowances and the demand for offsets: A comprehensive assessment of imperfect substitutes. Journal of Public Policy 36(1), 139--167.

Ellerman, A.D., Schmalensee, R., Bailey, E.M., Joskow, P.L., Montero, J.P., 2000. Markets for clean air: The U.S. Acid Rain Program. Cambridge University Press.

Fischbacher, U., 2007. Z-TREE: Zurich Toolbox for Ready-made Economic Experiments. Experimental Economics 10(2), 171--178.

Franciosi, R.R, Isaac, R.M., Pingry, D.E., Reynolds, S.S., 1993. An experimental investigation of the Hahn-Noll revenue neutral auction for emissions licenses. Journal of Environmental Economics and Management 24(1), 1--24.

Hahn, R.W., 1984. Market power and transferable property rights. Quarterly Journal of Economics 99, 763--765.

Hahn, R.W., Noll, R.G., 1983. Barriers to implementing tradable air pollution permits: Problems of regulatory interactions. Yale Journal on Regulation 1, 63--91.

Joskow, P.L., Kahn, E., 2002. A quantitative analysis of pricing behavior in California's wholesale electricity market during summer 2000: The final word. The Energy Journal 23(4), 1--35.

Klemperer, P., 2004. Auctions: Theory and practice. Princeton University Press.

Krishna, V., 2000. Auction Theory, 2nd Ed. Elsevier Press, Oxford.

Ledyard, J.O., Szakaly-Moore, K., 1994. Designing organizations for trading pollution rights. Journal of Economic Behavior and Organization 25(2), 167--196.

List, J. A., Lucking-Reiley, D., 2000. Demand reduction in multi-unit auctions: evidence from a sports card field experiment. American Economic Review 90(4), 961--972.

Malik, A.S., 2002. Further results on permit markets with market power and cheating. Journal of Environmental Economics and Management 44(3), 371--390.

Milgrom, P., 2004. Putting Auction Theory to Work. Cambridge University Press.

Misiolek, W.S., Elder, H.W., 1989. Exclusionary manipulation of markets for pollution rights. Journal of Environmental Economics and Management 16(2), 156--166.

Montgomery, W., 1972. Markets in licenses and efficient pollution control programs. Journal of Economic Theory 5(3), 395--418.

Regional Greenhouse Gas Initiative, Inc. 2014. Market Monitor Report for Auction 24. Potomac Economics. Retrieved from: http://www.rggi.org/docs/Auctions/24/Auction_24_Market_Monitor_Report.pdf

Newbery, D. 2016. Towards a green energy economy? The EU Energy Union's transition to a low-carbon zero subsidy electricity system–Lessons from the UK's Electricity Market Reform. Applied Energy 179, 1321-1330.

Ringquist, E., 1998, A question of justice: equity in environmental litigation. The Journal of Politics, 60(4), pp. 1,148-65.

Stevens, B., Rose, A., 2002. A dynamic analysis of the marketable permits approach to global warming policy: A comparison of spatial and temporal flexibility. Journal of Environmental Economics and Management 44(1), 45--69.

Tietenberg, T.H., 2006. Emissions Trading: Principles and Practice. Resources for the Future, Washington, D.C.

Van Egteren, H., Weber, M., 1996. Marketable permits, market power, and cheating. Journal of Environmental Economics and Management 30(2), 161--173.

Webber, R.J., 1997. Making more from less: strategic demand reduction in the FCC spectrum auctions. Journal of Economics & Management Strategy 6(3), 529--548.

Appendix. (Intended for Online Supplement)

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

	Auction Clearing Price		
Treatment	Overall Average	% Periods With Price = 0	Avg. Price When Price > 0
Control (No Consign)	\$7.69 (9.25)	39.2%	\$12.66 (8.83)
Treatment (All Consign)	\$21.08 (20.87)	22.8%	\$27.31 (19.85)
Treatment (High Consign Only)	\$17.51 (23.46)	21.6%	\$22.33 (24.38)
Treatment (Low Consign Only)	\$6.36 (7.31)	30.9%	\$9.19 (7.15)

Note: Standard deviations in parentheses.

Table A2. Auction Clearing Price Regression (all periods)

	Auction Clearing Price
Independent Variable	Coefficient (St. Err.)
Treatment (All Consign)	17.95** (6.51)
Treatment (High Consign)	13.91* (8.40)
Treatment (Low Consign)	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

Robust std. errors clustered by session. * *p<0.10*, ** *p<0.05*, *** *p<0.01*

Table A3. Price Bid Descriptive Statistics (all periods)

		Not Consigning	**Consigning**		
Treatment	Type	Net Buyer	Net Buyer	Zero Net Demand	Net Seller
Control (No Consign)	*Low*	\$75.49 \$25.00 \$136.57	-	-	-
	High	\$40.88 \$27.00 \$48.99	-	-	-
Treatment (All Consign)	*Low*	-	\$100.22 \$50.00 \$129.00	\$135.60 \$50.00 \$167.88	\$228.39 \$99.00 \$235.48
	High	-	\$65.18 \$40.00 \$65.93	\$70.51 \$40.00 \$77.81	\$83.89 \$40.00 \$99.03
Treatment (High Consign)	*Low*	\$106.72 \$49.99 \$158.59	-	-	-
	High	-	\$75.21 \$42.00 \$76.59	\$83.66 \$50.00 \$85.53	\$89.82 \$50.00 \$98.08
Treatment (Low Consign)	*Low*	-	\$66.15 \$20.00 \$108.30	\$72.47 \$20.00 \$130.88	\$74.83 \$22.00 \$149.24
	High	\$24.39 \$13.50 \$27.06	-	-	-

Values from top to bottom are mean, median, standard deviation of bid price.

Table A4: Bid Price Regression Analysis (all periods)

Independent Variable	Tobit Coefficient (St. Err.)	RE Tobit Coefficient (St. Err.)
Treatment (All Consign)	48.78**	51.23**
	(24.86)	(23.89)
Treatment (High Consign)	33.49	34.68
	(25.56)	(23.85)
Treatment (Low Consign)	-14.31	-12.97
	(19.89)	(23.85)
Net Seller	31.99*	26.46***
	(16.39)	(3.15)
Net Buyer	-10.71	-12.71***
	(11.64)	(3.11)
High Type	-46.25***	-46.29***
	(16.93)	(16.85)
Constant	81.17***	81.23***
	(19.20)	(18.84)
Log Likelihood		-37,460.37
Log Psuedo Likelihood	-40,417.65	
F-statistic	5.63***	
Wald Chi^2		177.98***
McFadden's Pseudo R^2	0.01	
N	6,528	6,528

Robust std. errors clustered by subject (excludes panel model). * *p<0.10,* ** *p<0.05,* *** *p<0.01*

Table A5: Quantity Overbidding Descriptive Statistics (all periods)

		Not Consigning	**Consigning**		
Treatment	Type	Net Buyer	Net Buyer	Zero Net Demand	Net Seller
Control (No Consign)	*Low*	0.13 0.00 1.53	-	-	-
	High	0.12 0.00 1.06	-	-	-
Treatment (All Consign)	*Low*	-	0.47 0.00 2.19	0.57 0.00 2.31	0.85 0.00 3.01
	High	-	0.69 0.00 2.10	1.45 0.00 3.58	1.20 0.00 3.70
Treatment (High Consign)	*Low*	1.98 0.00 5.22	-	-	-
	High	-	0.15 0.00 2.30	0.42 0.00 2.06	0.61 0.00 2.31
Treatment (Low Consign)	*Low*	-	0.37 0.00 1.31	0.58 0.00 1.83	0.63 0.00 1.74
	High	0.55 0.00 2.09	-	-	-

Values from top to bottom are mean, median, st. dev. of overbidding (quantity bid minus permits needed).

Table A6: Bid Quantity Regression Analysis (all periods)

Independent Variable	Tobit Coefficient (St. Err.)	RE Tobit Coefficient (St. Err.)
Permits Needed	1.03***	1.02***
	(0.26)	(0.30)
Treatment (All Consign)	1.07***	0.81*
	(0.33)	(0.42)
Treatment (High Consign)	1.20**	1.14***
	(0.58)	(0.42)
Treatment (Low Consign)	0.60***	0.39
	(0.21)	(0.42)
High Type	-0.31	-0.14
	(0.37)	(0.45)
Low Type	0.14	0.11
	(0.13)	(0.37)
*High Type * Net Buyer*	-0.74**	-0.52***
	(0.31)	(0.14)
*High Type * Next Seller*	-0.13	0.01
	(0.30)	(0.15)
*Low Type * Net Buyer*	-0.72**	-0.11
	(0.31)	(0.14)
*Low Type * Net Seller*	-0.34	0.24*
	(0.30)	(0.14)
Log Likelihood		-14,633.74
Log Psuedo Likelihood	-15,849.07	
F-statistic	2,904.53***	
Wald Chi^2		5,280.83***
N	6,528	6,528

Robust std. errors clustered by subject (excludes panel model). * *p<0.10,* ** *p<0.05,* *** *p<0.01*

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

	Not Consigning	Consigning		
Treatment	Net Buyer NCPs	Net Buyer NCPs	Zero Net Demand NCPs	Net Seller NCPs
Treatment (All Consign)	-	\$96.68	\$58.77	\$48.46
Treatment (High Consign)	\$47.62	\$100.00	\$83.65	\$71.87
Treatment (Low Consign)	\$70.59	\$39.80	\$30.33	\$21.76

Table A8. Average Profits (Excluding Consignment Revenue) (all periods)

	Not Consigning	Consigning		
Treatment	Net Buyer	Net Buyer	Zero Net Demand	Net Seller
Control (No Consign)	$426.62	-	-	-
Treatment (All Consign)	-	$335.43	$318.57	$270.23
Treatment (High Consign)	$382.18	$324.69	$389.01	$280.22
Treatment (Low Consign)	$393.88	$536.70	$453.38	$369.91

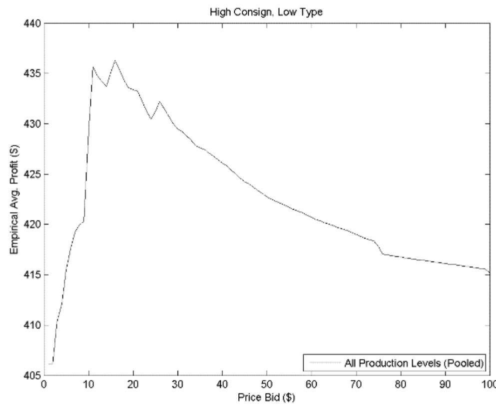
Table A9. Average Profits (Including Consignment Revenue) (all periods)

	Not Consigning	Consigning		
Treatment	Net Buyer	Net Buyer	Zero Net Demand	Net Seller
Control (No Consign)	$426.62	-	-	-
Treatment (All Consign)	-	$530.06	$473.45	$393.47
Treatment (High Consign)	$382.18	$531.64	$479.37	$401.03
Treatment (Low Consign)	$393.88	$574.53	$484.83	$396.20

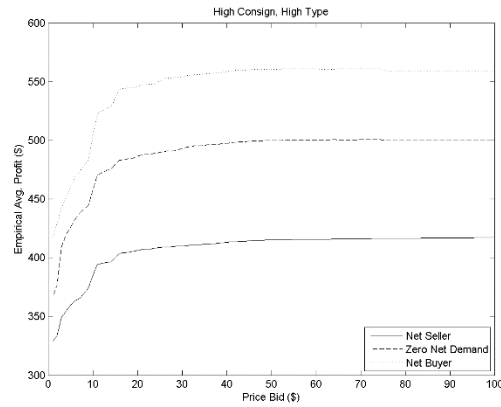
Table A10. Regression of Profit (all periods)

Independent Variable	Tobit Coefficient (St. Err.)	RE Tobit Coefficient (St. Err.)
Treatment (All Consign)	-111.86***	-108.33***
	(41.17)	(12.88)
Treatment (High Consign)	-83.89	-72.54***
	(54.19)	(12.61)
Treatment (Low Consign)	0.25	-2.04
	(11.16)	(12.62)
Net Seller	-54.23*	-48.01***
	(29.03)	(5.32)
Net Buyer	33.71	39.58***
	(25.87)	(5.25)
High Type	-81.22***	-78.14***
	(12.52)	(8.86)
Constant	467.23***	465.67***
	(10.96)	(9.90)
Log Likelihood		-39,595.99
Log Psuedo Likelihood	-42,563.93	
F-statistic	159.35***	
Wald Chi^2		449.21***
McFadden's Pseudo R^2	0.01	
N	6,528	6,528

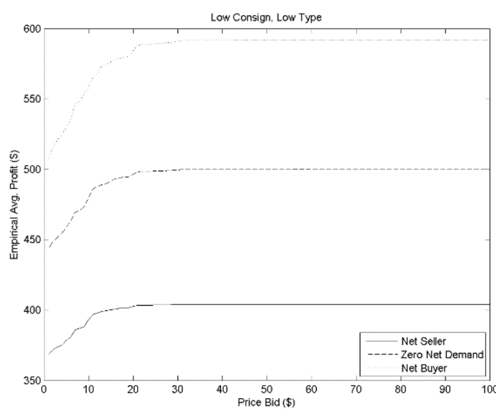
Robust std. errors clustered by subject (excludes panel model). * *p<0.10,* ** *p<0.05,* *** *p<0.01*



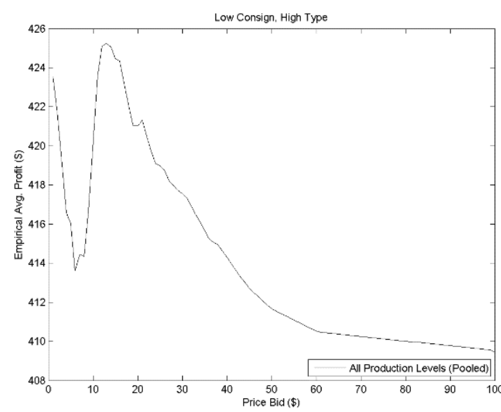
(a) *High Consign,* Low Type



(b) *High Consign,* High Type



(c) *Low Consign*, Low Type



(d) *Low Consign*, High Type

Figure A1 a-d: Price Bid Monte Carlo Simulation Outputs