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COMPLEXITY IN PROCUREMENT DECISION MAKING

A Dissertation in
Business Administration
by
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Abstract

In the first essay, we investigate the effect of observed inventory decisions on firm performance. In particular, our goal is to measure and understand how much profit a newsvendor-type of decision maker stands to lose due to behavioral (intuitive but suboptimal) ordering. The current literature, primarily focused on a newsvendor making decisions in isolation, reports results which imply profit losses of 1-5% when compared to the analytical solution, due to the flatness of the profit curve in the neighborhood of the optimum. In contrast, we show that in a practical situation, when a behavioral inventory decision-maker competes against a management-science-driven competitor, profit losses are orders of magnitude larger. By considering several plausible and simple competitor policies, we demonstrate average profit losses between 22-76%, regardless of policy sophistication or embedded assumptions. Our results send a clear message to business executives and highlight the importance of considering behavioral biases in procurement.

In the second essay, we study the econometric identification of multi-attribute score auctions. Governmental agencies use score procurement auctions to incorporate other attributes beyond price in their purchase decisions. We establish nonparametric identification of bidders’ independent private (pseudo)types for multi-attribute procurement where bids are evaluated using a preannounced quasi-linear-score, calculated on the basis of the submitted levels of the attributes. Hence, it is possible to extend the standard nonparametric method for independent private costs sealed-bid-first-price auctions to multi-attribute score auctions by incorporating the optimal bidding structure.

In the third essay, we analyze bidding behavior in two closely related sealed-bid scenarios: One where the rule to assign the contract is transparently communicated to bidders before they submit their offers (the score auction analyzed in the preceding essay), and another where the assignment rule is only known to the buyer and not to the bidders (what we have called a “multi-dimensional beauty-contest auction”). Our results show substantial losses in terms of social welfare and buyer surplus as a direct effect of transparency loss in this procurement system.

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C44, C91, D03;
C50, D44, L51;
D44, H57, C91, D47.

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behavioral economics; newsvendor; decision biases; inventory competition;
score auctions; structural econometrics; nonparametric identification;
multi-dimensional procurement; market design; information disclosure; social welfare.
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University Park PA, Spring 2015
A mi familia – Osaposa Muñita, Viejito Perro y Roscapumpa
Introduction:
Complexity in Procurement Decision Making

1. An Overview

While the analytical solution to a procurement problem might exist, and even be tractable, the economic decisions involved in the process are far from trivial. For inventory managers making stocking decisions under competition, ignoring or not adequately incorporating decision support information, negatively impacts the firm’s profit performance. For sellers participating in a procurement auction, there is a clear difficulty in formulating an “optimal” bid, especially when price is not the only factor weighing in the assignment criterion. The implications of bad decisions in these complex environments can have a huge impact on the financial health and/or reputation of those actors involved. In this dissertation, I take a close look at specific cases of decisions under complex procurement environments.

Figure 1: Organization of the Dissertation.
A canonical example of a complex procurement decision environment is the so-called *newsvendor problem*. First presented by Edgeworth (1888) as the problem of a bank that needs to stock optimal cash reserves to fulfill random withdrawals from customers, the problem to procure inventory units of a perishable good to satisfy random demand was not solved analytically in its current general form until an *Econometrica* article by Nobel Prize winner Ken Arrow and his coauthors 63 years later (Arrow et al. 1951). The incorporation of a game-theoretical approach to solve the same procurement problem in a competitive environment was not answered until other 37 years later (Parlar 1988), assuming full rationality of both buyers. The newsvendor setting can be extended in further dimensions, making its solution even more complex. However, in the real world, inventory managers regularly face stock procurement problems, and face the prospect of making decisions under complex competitive environments they do not fully understand.

The first chapter of this dissertation is the second part of an ongoing research collaboration with Brent Moritz and Anton Ovchinnikov that started back in 2010. Our first paper together, titled “How to Compete Against a Behavioral Newsvendor” (Ovchinnikov et al. 2015, which I presented as my M.S. thesis at Penn State), was the first piece to study in a laboratory environment whether the commonly observed behavioral regularities presented by the existing literature about isolated newsvendors (i.e., how people solve the problem set forth by Edgeworth 1888 or Arrow et al. 1951) propagated to competitive inventory environments (i.e., the setting of Parlar 1988). We also had attempted to prescribe a way to exploit those regularities systematically. Now, for chapter 1 presented here, we explore the flip side of the problem: Should a behavioral newsvendor, one exhibiting the biases we had observed, try to invest in avoiding them? Is it worth it for a CEO to intervene and prevent procurement managers from following their “gut feeling” when stocking inventory? We measured the behavioral newsvendors’ performance against three plausible, easy-to-execute, management-science-driven policies implemented by computerized competitors. The answer we provide here is unambiguously “yes, it is worth it to intervene”, based on the profits forgone by the behavioral competing newsvendors in the lab.

Auctions are another traditional economic institution used for procurement, involving very complex decisions both on the part of the bid-taker and on the side of the supplier of the good or service being auctioned. The Roman Prætorian Guard, upon the murder of Emperor Pertinax in A.D. 193, conducted one of the earliest known examples of a governmental procurement auction. The new emperor was “hired” using what we would call today an open-
ascending price-only procurement auction mechanism, via a public selection process (offers were communicated publicly by the Guard as they arrived, and suppliers competed in increasing bids to get the contract). Having offered 25,000 sesterces per guardian against the 20,000 offered by his highest competitor Flavius Sulpicianus, Didius Julianus became the winner. In an early example of the “winner’s curse”, the new emperor was executed by order of the Roman Senate a little over two months later. Bad bidding decisions in procurement auctions can lead to quite costly outcomes, as this story attests.\(^1\)

Consider the problem of bidding in procurement auctions that take into consideration multi-dimensional bids (i.e., bids considering price and quality dimensions). In the second and third essays of this dissertation, I study these types of procurement mechanisms, with very different aims in each case. As a starting point, I considered the game-theoretical optimal bid for the case where a publicly-known quasi-linear scoring rule (as used by many governmental agencies to procure goods and services) is used to weight the different dimensions of a bid. Asker and Cantillon (2008) provided an optimal bidding strategy for those mechanisms, and I make use of their result to answer two distinct research questions, which were developed through my interaction with the Directorate of Public Procurement and Contracting of the Chilean Government, better known as ChileCompra.

For chapter 2, I developed an estimation procedure to retrieve the cost structure of a supplier which is implicit in the offered multi-dimensional bid. Specifically, under a set of standard assumptions, if bidders are rational, I established the nonparametric econometric identification of the cost structure. In simple terms, by using multi-dimensional bidding data for score auctions, it is possible to retrieve back non-parametrically the entire distribution of production costs for suppliers, based on the analytical solution of their optimal bids. This result makes it possible to use the standard nonparametric econometrics methods used in auctions also for multi-dimensional bids.

In chapter 3, in joint work with Brent Moritz and Dan Guide, we empirically test the effect in social welfare and buyer’s surplus of transitioning from a sealed-bid transparent scores multi-dimensional auction (as those studied in chapter 3) to a sealed-bid buyer-determined multi-dimensional auction process. In the latter process, offered attribute levels are weighted into a score formula with parametric values only known to the buyer, not to the

\(^1\) For further details on Didius Julianus’s life, see Leaning (1989).
suppliers, who have to choose their price and quality levels under complete disinformation about the buyer’s weighting procedure to rank offers. I developed a careful between-subjects experimental design to make both sealed-bid methods comparable from an outcome perspective. Our key finding is that, for a governmental buyer concerned with their own surplus, or with social welfare, the loss of transparency is immensely costly.

Note that the third chapter repeats in similar fashion many concepts already presented in chapter 2. I wanted each essay of this document to be self-contained, with the possibility to be read in isolation from the rest. As Richard Bellman once commented, “Repetition, however, no matter how dismaying as a social or literary attribute, is no great mathematical sin” (Bellman 1957, p. 12).

This brief editorial overview is my attempt to put all three essays of this dissertation in perspective. All these pieces were written with the goal of understanding better how managers and economic agents make decisions. Complex decisions are sometimes optimal, sometimes biased, and often costly. I doubt we will ever fully understand all the intricacies embedded in human decision mechanisms for any given problem, and procurement issues are not an exception. However, I cannot help to feel, looking back into the pieces that form part of this dissertation, that we have improved our understanding of the problems studied here compared to what we knew five years ago. For that, I am genuinely grateful.

2. References
Chapter 1: 
Behavioral Ordering: Inventory, Competition and Policy*

1. Introduction

Starting with a seminal work by Schweitzer and Cachon (2000), multiple authors have examined human inventory ordering decisions in the context of the newsvendor model, e.g., Bolton and Katok (2008), Ho et al. (2010), Bolton et al. (2012), Becker-Peth et al. (2013), Moritz et al. (2013). A consistent finding of this literature is that human newsvendors are “biased”: they deviate from the optimal order quantities, and in high margin cases, which reflect most practical situations, deviations of 10-20% are not uncommon. For example, subjects in Schweitzer and Cachon (2000) ordered an average of 176 units when the optimum was 225, a 21% deviation. In Bolton et al. (2012), trained graduate students ordered 70 units on average and experienced managers ordered 62 units on average when the optimum was 75, 6% and 17% deviations, respectively. An implication of these findings is that, because the deviations are large and consistent, business executives should do something about them – and many of the prior studies suggest ways to “de-bias” procurement managers.

However, a missing link in this literature is whether business executives should be concerned about these biases at all. As the CEO of florist F (case details below) noted, “I cannot micro-manage all my people: Before I go and intervene, I need to know the impact on the business.” Specifically, because the expected profit in the newsvendor model is rather “flat” around the optimal order quantity under most settings, a 10-20% deviation in order quantity corresponds to only 1-5% loss in profit based on the ordering patterns observed in previous studies², and it may be that executives are reluctant to intervene when the impact on the business is so small.

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² Schweitzer and Cachon (2000), p.414, calculate that, in their high margin condition, ordering the average quantity instead of the critical fractile quantity would yield a profit 5% smaller. Moritz et al. (2013) (through their study 2) report results which imply profit losses of 2.8%. Studying multi-location newsvendors, Ho et al. (2010) show results which would translate into profit loss of 4.8% (decentralized system, uncorrelated demands). Beyond these examples, for the case with a critical fractile of 75% and uniformly distributed demand (as in Schweitzer and Cachon (2000), Bolton et al. (2012) and several other studies), a 10% deviation in order corresponds to a 1%
The goal of this paper is to evaluate the effect of behavioral ordering in terms of profits, and by doing so, emphasize the value of “de-biasing” procurement managers. Specifically, because in practice most firms operate in competitive environments, we measure the “true cost” as a percentage profit loss of a firm at which procurement managers make inventory ordering decisions as compared to a competitor that uses management science to decide on orders. We consider a spectrum of plausible competitor ordering policies and customer behaviors, and demonstrate profit losses of the behavioral firm vis-à-vis the science-driven competitor range from 20 to over 70% – orders of magnitude larger than the current literature implies and likely worth executive attention for many firms.

1.1. Motivation, approach and contributions

We consider two firms, which compete as newsvendors: selling price and purchase costs are identical between firms, and the only decision is how much to order. Consumers first visit their firm of choice, but if it stocked-out then such stranded overflow consumers visit the competitor and attempt to purchase there. At one firm, referred to as h (for human), an individual makes ordering decisions given the information available, but without a sophisticated decision support tool – as do procurement managers in our example case below. At another firm, to which we refer as c (for competitor or computer), inventory ordering decisions are made by an automated system programmed to follow a management-science driven ordering policy.

To illustrate this setup, consider the case of medium-sized online florist F. F’s sales and procurement for 2012 and 2013 are illustrated on Figure 2, which depicts several major demand peaks: just a few days in a year (Valentine’s day, Mother’s day, etc.) correspond to a significant proportion of F’s sales and an even larger proportion of profits (mark-up on flowers often exceeds 300%). F’s product is physically perishable, and because flowers are sourced from growers in Latin America, Africa and East Asia, inventory replenishment within the duration of a single peak is impossible. In other words, around the peaks F operates in a classical high critical ratio newsvendor situation.

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loss in expected profit, and a 20% deviation corresponds to a 4% loss. The loss percentages are nearly identical for the 66.7% critical fractile that we use in this paper.
Procurement at F is done manually. To determine order quantities procurement managers use past sales data, industry trends and their own intuition, but no formal decision support system is in place. This is firm h in our paper.

F’s main competitors are giant multi-billion-dollar online florists such as 1-800-Flowers and ProFlowers. While we have no direct information about how these firms make their ordering decisions, intuitively, the likelihood that they use sophisticated management-science driven techniques is a lot higher. Such a competitor corresponds to firm c in our paper.

Specifically, we considered three ordering policies for the firm c. Because c does not know exactly how h orders our policies cover a spectrum of its plausible beliefs that about the behavior of h.

On one end of the spectrum is the standard Nash Equilibrium policy (NE). This policy corresponds to a case when both c and h are fully rational and implement a newsvendor competition solution as recommended by current literature, e.g., Parlar (1998), Lippman and McCardle (2000). Note that this policy is optimal only if c believes that h is fully rational; c can then predict h’s best response to its order and arrive to the equilibrium.

On the opposite end of the spectrum is a policy under which c makes no assumptions on the rationality of h. This also embeds the case where h is so irrational that there is no point in predicting its behavior at all – an unpredictably irrational policy, which agnostically updates (AU) orders according to observed sales over time. In this case c uncensors its sales data, updates its estimate of demand distribution, and orders accordingly. In contrast to the NE policy, the AU policy does not rely on any beliefs about the rationality or ordering behavior of a competitor, in fact it does not explicitly account for the competitor at all.
A third policy we have called the Predictably Irrational (PI) policy. This policy explicitly acknowledges that the competitor is a human, who is subject to a number of biases identified by the previous research on newsvendor behavior (pull-to-center, demand chasing, etc.) Capitalizing on the knowledge of these biases, c estimates the distribution of the human orders, and optimally responds to it. This approach is inspired by a recent work of Ovchinnikov et al. (2015). PI does not rely on the restrictive assumption of h’s full rationality, but at the same time explicitly acknowledges that the competitor exists; it is therefore somewhat in-between the NE and AU.

Our results show that the losses against the NE competitor (which ignores that it competes with a behaviorally-biased human) averaged 22-29%. The profit losses against the AU competitor (which entirely ignores competition) averaged 26-76%. The losses against the PI competitor (which observes and acts on the decisions of the human retailer) averaged 28-60%. While these percentages differ because the policies vary in performance under different market conditions, the final conclusion is evident: under competition, the actual profit losses—measured as % profit differences between h and c—from behavioral ordering are very large. Our results emphasize the need for executives to carefully reexamine their procurement managers’ ordering biases, because such biases provide science-driven competitors with opportunities to improve profits.

Next we describe the business environment we used to operationalize inventory competition in our experiment. Our experimental procedure is described in Section 3. We present our results in Section 4, further analyses in Sections 5 and 6, and conclude in Section 7.

2. Business Environment

To operationalize inventory competition, we consider the following business environment. Over a series of periods, denoted by $t$, two retailers, indexed by $i \in \{h, c\}$, make simultaneous inventory decisions, $q_{it}$, ahead of learning what their demand will be. While $h$ is a human retailer, $c$ is his or her competitor. The product is perishable, sells at unit price $p$, is purchased at cost $w$, and has zero salvage value at the end of the period. Firm $i$’s demand in period $t$ consists of its initial demand $D_{it}$ (from customers for whom firm $i$ is the firm of choice) and the overflow demand of stranded customers from firm $-i$ if it stocks-out, $\max\{0, D_{-it} - q_{-it}\}$, where $-i$ refers to the firm other than $i$. 
As in most studies of newsvendor ordering behavior, we assume that \( D_{i,t} \sim iid \ U[0, b_{i,t}] \). The definition of \( b_{i,t} \), however, depends critically on customer behavior.

In the case with *loyal consumers*, being stranded in period \( t \) does not affect consumers’ choice of the firm they initially visit in period \( t+1 \). Hence \( b_{i,t} = b_{i,t+1} \equiv b \), a constant.

In the case with *switching consumers*, after being stranded by their firm of choice in period \( t \), only a fraction \( \alpha \) of stranded consumers return to their firm of choice in period \( t+1 \), and the remainder switch and in the next period first visit the other firm. Thus the net change in the initial demand distribution support of firm \( i \) is the difference between the number of customers stranded by firm \(-i\) (who switch from firm \(-i\) to \(i\)) and the number of customers stranded by firm \( i \) (who switch in the opposite direction), multiplied by \( 1 - \alpha \). Note, that this approach to modeling switching consumers does not capture customers’ contemporaneous strategic decisions of which retailer to buy from, but rather, captures *brand loyalty* over time.

Letting \( x_{i,t} \) denote the net change in the initial demand distribution support of firm \( i \), this logic implies that
\[
b_{i,t+1} = b_{i,t} + x_{i,t+1},
\]
where:
\[
x_{i,t+1} = (1 - \alpha) \cdot \left[ \max\{0, D_{i,t} - q_{-i,t}\} - \max\{0, D_{i,t} - q_{i,t}\} \right] = -x_{-i,t+1} \quad \forall t \geq 1, \quad x_{i1} = 0 \tag{1}
\]

Note that this formulation includes the case with loyal customers when setting \( \alpha = 1 \). Observe further that this formulation captures the service level effect (Olivares and Cachon 2009): if the firm strands less customers than the competitor, then its initial demand distribution will see its support increased in the future, and vice versa.

### 2.1. Ordering Behavior and Policies

As mentioned in the introduction, order quantities \( q_{h,t} \) are determined by a procurement manager, who uses his/her intuition and available information about the past sales, demands, leftovers and profits, but not a formal decision support system. In contrast, order quantities \( q_{c,t} \) are determined by an automated system pre-programmed to follow one of the

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\(^3\) While in practice retail demands are often correlated, we have opted for retailer-specific initial demands to be independent realizations for the following reason: In our setting, correlated demands would further complicate retailer \( h \)'s decision problem and may confound the impact of behavioral ordering with uncontrollable mistakes in forecasting the overflow demand, as similar tasks have been demonstrated to be difficult (e.g., Lee and Siemsen 2013). Correlated demands would also provide an additional advantage to a more sophisticated retailer such as \( c \), since it would be able to better forecast the overflow demand from its own sales information. As a result, the differences in financial performance between behavioral and science-driven ordering are likely to be even larger than in the current setting with independent initial demands.
three policies. Figure 3 offers a brief summary of the policies we chose. These policies differ in the way they inform the distribution of total demand observed by firm $c$, which in turn is used to calculate a modified newsvendor-type of critical fractile solution. These policies cover a spectrum of beliefs about the rationality of $h$ and the information available.

<table>
<thead>
<tr>
<th>Policy NE</th>
<th>Policy PI</th>
<th>Policy AU</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Nash Equilibrium</strong></td>
<td><strong>Predictably Irrational</strong></td>
<td><strong>Agnostic Updating</strong></td>
</tr>
<tr>
<td>* $c$ believes $h$ is fully rational, identical and just as informed</td>
<td>* $c$ believes it can forecast the distribution of $h$’s order for period $t+1$ based on the available market information about $c$ and $h$’s past performance.</td>
<td>* $c$ does not believe it can predict what $h$ will do, and makes no assumption on $h$’s behavior</td>
</tr>
<tr>
<td>* $c$ orders the Nash Equilibrium quantity</td>
<td>* $c$ orders according to the best response to such a distribution</td>
<td>* $c$ orders according to the critical fractile from that distribution, disregarding possible competitive response from $h$.</td>
</tr>
<tr>
<td>* this policy is what the current literature on newsvendor competition suggests one should do.</td>
<td>* this type of policy is what the existing experimental literature on inventory competition suggests one should use when facing a behavioral newsvendor.</td>
<td>* a simple-to-implement heuristic that many firms could do in practice</td>
</tr>
</tbody>
</table>

**Figure 3:** Schematic of the three ordering policies for firm $c$.

We first considered a *Nash Equilibrium* policy (NE), which represents the current state of the literature on newsvendor competition, e.g., Parlar (1988) and Lippman and McCardle (1997) and related works. This literature considers a retailer $c$ who assumes that its competitor $h$ is fully rational and informed, and therefore, prescribes $c$ to order the symmetric Nash equilibrium solution for this setting. From an informational standpoint, such a retailer either ignores or does not observe past ordering history of $h$, and is also unable to observe the relative stock-outs, meaning that it assumes $x_{c,t} = 0$ for any period $t$, regardless of the value of $\alpha$. While this informational structure might seem unrealistically limited, it also illustrates the worst scenario for firm $c$, as it plays the best possible response, assuming its competitor, $h$, is equally rational, i.e., best-responds back, while in reality it does not.

The *Predictably Irrational* policy (PI) policy makes extensive use of past information. Under PI, $c$ estimates a behavioral model to predict a distribution for $q_{h,t}$, based on a reaction to prior sales and a reaction to past over and understock realizations, which in turn is used by $c$ to calculate a best-response solution. The parameters for this behavioral model were calibrated using experimental data from Ovchinnikov et al. (2015). Their policy builds on competitors’ past demand realizations and overage/underage levels. However, the behavioral model specification we apply require less information about the competitor, and
specifically only requires sales rather than demand data. The PI policy requires c to have access to stockout indicators and past sales and data for both h and c, which are in practice available to retailers through industry reports, such as AC Nielsen; Besbes and Muharremoglu (2013) also report on the generalized availability of stockout indicators.

Finally, with our Agnostic Updating policy (AU), we offer a non-behavioral perspective for how c can incorporate the decisions of retailer h without any assumptions on h’s behavior. Under such a policy, c observes its own sales data, uncensors them to obtain the distribution of its total demand, $D_{c,t} + \max\{0,D_{h,t} - q_{h,t}\}$, and orders accordingly. That is, c does not need to know the current realizations of demands of either firm; instead, it infers them from its own past sales data, acknowledging that its total demand is indistinguishable between customers coming to c’s store first and those overflowing when h stocks out. This policy starts from a prior distribution of demand, and over time learns from its own sales data about the distribution of total demand which is impacted by h’s behavior. However, AU does not account for a possible competitor response, i.e., effectively disregards competition. A natural question to ask is how good is this policy that disregards competition in a situation when a competitor may respond, and our experiment will also answer this question. Note though, that to the best of our knowledge, policies similar to AU, due to their simplicity, can be potentially used by many firms in practice.

### 2.2. Operationalization of Policies

For a given $q_h$ and $x_{c,t}$, the best response order quantity for retailer c, $q_c^*(q_h)$, satisfies:

$$q_c^*(q_h) = \begin{cases} 
(b + x_{c,t})(1 - \frac{w}{p}) - q_h, & \text{if } 0 \leq q_2 \leq (b + x_{c,t}) \left(1 - \frac{2w}{p}\right) \\
(b + x_{c,t}) \left(1 - \frac{w}{p}\right) + \frac{(b - x_{c,t})^2}{2(b - x_{c,t})}, & \text{if } (b + x_{c,t}) \left(1 - \frac{2w}{p}\right) \leq q_h \leq b - x_{c,t} \\
(b + x_{c,t}) \left(1 - \frac{w}{p}\right), & \text{if } q_h \geq b - x_{c,t}.
\end{cases}$$

(2)

Observe that $q_c^*(q_h)$ in equation (2) is a monotone decreasing policy function convex in $q_h$. With this information, next we describe how each of the three policies is operationalized.

**Operationalization of Policy NE.** Under NE, c believes that h is fully rational and symmetric, and therefore at equilibrium will be placing the same order quantity as c.
Further, since \(c\) and \(h\) face iid demands, the number of customers stranded by \(c\) and \(h\) are stochastically equal, hence, every period \(b_{h,t} = b_{c,t} = b\) (or, equivalently, \(x_{c,t} = 0 \forall t\)). Because \(q^*_c(q_h)\) is decreasing and convex in \(q_h\), by symmetry, \(q^*_h(q_c)\), is increasing and concave in \(q_c\), therefore a unique fixed point \(q^{EQ}\) exists that solves \(q^*_c(q^*_h(q^{EQ})) = q^{EQ}\) which is the equilibrium of this game.

When individual demands \(D_{i,t} \sim \text{DiscreteUniform}[1,100], p = 3, c = 1\) (the parameters we use in the experimental section of the paper), the Nash equilibrium provides an order of \(q^{EQ} = 72\) units. Therefore, under the policy NE, firm \(c\) will order \(q_{c,t} = 72\) units of inventory \(\forall t\), assuming that \(h\) will also order \(q_{h,t} = 72\) \(\forall t\), because that is \(h\)'s best response to \(q_c = 72\).

**Operationalization of Policy PI.** The vast behavioral literature on newsvendor behavior has shown that assuming a symmetric rational behavior from human newsvendors is unrealistic. Consistent with existing behavioral literature, retailer \(c\) can model \(q_h\) as a random variable following a distribution with mean and standard deviation \((\mu, \sigma)\). Thus, the ordering strategy is as follows:

1. Estimate a simple behavioral model for \((\mu, \sigma)\), capturing empirical regularities and biases observed in ordering quantities in past data, in order to predict \(h\)'s behavior.
2. Calculate a best response to that predicted behavior.

We used data from Ovchinnikov et al. (2015) to fit our own empirical model to implement \(c\)'s ordering policy PI. While that paper used demand information directly, we fit a model based on observed sales and an indicator variable for overstocks. This removes their strong assumption that competitor \(c\) knows the actual demand realizations and over/under quantities (i.e., effectively knows the exact order quantity) of \(h\). In practice, competitors may only have information about the competitors’ sales and whether they stocked out or not. Our behavioral model here acknowledges this practical difference, and includes only the information about competitor sales, plus an over/under dummy variable.

Formally, our behavioral model for subject \(j\) in period \(t\) is:

\[
\mu_{j,t} = \beta_0 + \beta_1 Sales_{t-1,j} + \beta_2 OverDummy_{t-1,j}; \quad \sigma_{j,t} = SE
\]  

(3)

Following Ovchinnikov et al. (2015)'s finding that behavioral competitors do not seem to respond to competitors whose ordering pattern is not constant, we implemented a linear best
response model that predicts the moments of the distribution of orders from retailer \( h \), and calculates a best response based on it. While this is not an equilibrium best response model, it is a deterministic heuristic that captures the frequent non-response of human subjects to varying orders by competitor \( c \). Note that we also tested inclusion of other candidate variables, but found them statistically insignificant for most subjects.

The corresponding estimated parameters are displayed on Table 1:

**Table 1**: Behavioral model used to implement policy PI.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Aggregate Model, Random Effects:</th>
<th>Individual Models:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Value of Coefficient (Standard Error)</td>
<td>% of subjects where variable is significant, ( p \leq 0.05 )</td>
</tr>
<tr>
<td>Intercept</td>
<td>48.08** (0.649)</td>
<td>97.0%</td>
</tr>
<tr>
<td>Sales,( t-1 )</td>
<td>0.237** (0.007)</td>
<td>46.1%</td>
</tr>
<tr>
<td>OverDummy,( t-1 )</td>
<td>4.505** (0.319)</td>
<td>23.0%</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.121</td>
<td>( N ) (Groups): 13,035(165)</td>
</tr>
<tr>
<td>( SE )</td>
<td>14.77</td>
<td>Normal (at ( p \leq 0.05 ), using S-K, S-F and S-W) for 77.6% of subjects</td>
</tr>
</tbody>
</table>

From the estimates displayed above we dynamically evaluate \( \mu \) and \( \sigma \) as per (3), and as per the best-response policy implied by (2), estimating \( q_h \) using its predicted mean and standard deviation, we programmed \( c \)'s PI as follows:

\[
\hat{q}_c^*(\mu, \sigma, x_{c,t}) = (b + x_{c,t})(1 - \frac{w}{r}) + \frac{(b-x_{c,t}-\mu)^2}{2(b-x_{c,t})} + \frac{\sigma^2}{2(b-x_{c,t})} \tag{4}
\]

However, if a subject places a constant order \( q_h \) for five consecutive rounds, then PI switches from using the parameters in Table 1 to a deterministic and constant best response \( (\mu_{jt} = q_h, \sigma_{jt} = 0) \) as per equation (2).

**Operationalization of Policy AU.** Under AU, firm \( c \) does not try to predict what \( h \) will do whatsoever. Instead, it uses its own sales data to update its demand distribution and then order a critical fractile from that distribution. Although this approach does not directly account for \( h \)'s behavior (as NE or PI do), \( c \)'s sales history indirectly captures the outcomes of \( h \)'s actions through the overflow demand that \( c \) intercepts when \( h \) stocks out.
Let $F_{c,t}$ denote firm $c$'s prior on its total demand distribution (i.e., its own initial demand plus the overflow demand from $h$ when it stocks out) for period $t$. We assume that $F_{c,t}$ is a discrete distribution with support $[0,2b]$. Given this prior, $c$ will order quantity $q_{c,t}$ according to the standard newsvendor logic, i.e., such that $q_{c,t}$ is the smallest quantity for which $Pr(y_{c,t} \geq q_{c,t}) \geq w/r$ where $y_{c,t}$ is a random variable with distribution $F_{c,t}$. Firm $c$ will then observe sales, $s$, and will use this observation to update $F_{c,t+1}$.

Several recent studies have considered the problem of simultaneously learning about the demand distribution and making optimal ordering decisions based on it. Huh et al. (2011) considered a Kaplan-Meier estimator, Besbes and Muharremoglu (2013) considered expectation-maximization (EM) algorithms, while van Ryzin and McGill (2000) considered a general adaptive learning algorithm. Inspired by these approaches we implemented the following EM-like heuristic:

- If $s < q_{c,t}$ then the demand is uncensored, i.e., the firm knows that demand was equal to $s$. In this case, the firm will decrease the probability of every demand realization by a factor of $1 - \phi$ and add additional probability mass of $\phi$ to the new observation, $s$. That is, if $f_{c,t}(y)$ denotes the probability that demand in round $t$ equals $y$, then in this uncensored demand case:

$$f_{c,t+1}(y) = (1 - \phi) \times f_{c,t}(y) + \phi \times 1_{y=s}$$  \hspace{1cm} (5)$$

Here $\phi \in [0,1]$ is a learning/smoothing constant. A low $\phi$ implies that each new sales observation has little impact on the updated distribution, i.e., the learning is slow; a high $\phi$ implies the opposite.

- If $s = q_{c,t}$ then the demand is censored, i.e., the firm knows that demand was between $q_{c,t}$ and $2b$. In this case, we assume that the firm will similarly decrease the probability mass of every possible demand by $1 - \phi$ and place an equal mass $\phi \frac{2b - q_{c,t}}{q_{c,t}}$ on each of the potentially censored demand realization points. Therefore in the censored demand case:

$$f_{c,t+1}(y) = (1 - \phi) \times f_{c,t}(y) + \phi \frac{2b - q_{c,t}}{q_{c,t}} \times 1_{y \geq q_{c,t}}$$  \hspace{1cm} (6)$$

The difference between our approach and a traditional EM algorithm is that the latter would determine which probability mass to add to every censored demand point in order to
maximize the ex-post likelihood of previous demands being drawn from that distribution. An implicit assumption for an EM would be that the distribution is stationary throughout the observation horizon – an assumption too strong for our case, when the distribution is impacted by possibly irrational (and hence non-stationary) decisions of $h$. Additionally, the lab experimental software we use is not designed to perform a complex optimization every round for every subject, thus making the implementation of a traditional EM algorithm for multiple simultaneous subjects prohibitively complex. In any case, our heuristic provides a very simple and intuitive way to update a distribution based on existing sales data. More crucially, the profit results from the implementation of a full EM algorithm are very similar to the results obtained using our heuristic.

Finally, to initialize the AU policy, and for simplicity of exposition and implementation in the lab experiment, we assumed that $F_{c,1}$ is calculated conditional on mutually rational best response (as in NE).

To summarize, in contrast to the NE and PI policies, AU makes no assumptions whatsoever on what firm $h$ is doing, how rational it is, what its demand distribution is, how correlated it is to that of the firm $c$, etc. Instead, AU uses a non-parametric algorithm to learn about what the competitor is doing through the firm’s own sales realizations, updates the demand distribution, and places optimal newsvendor orders for that distribution. The AU policy is extremely practical and easy to implement for many firms in practice. But its obvious shortcoming is that it does not explicitly account for the competitor’s response. In any case, if behavior cannot be predicted, then accounting for such a response is not possible, and arguably not necessary.

In conjunction with NE and PI, however, we believe that the three policies we consider nicely cover a spectrum of plausible ordering policies of firms with whom a human newsvendor may be competing. We next turn to assessing how human newsvendors perform against such competitors.

3. Experimental Procedure

Our experimental design consisted of six treatments, varying the loyalty parameter and the competitor’s policy, as discussed below. Subjects were placed in the role of retailer $h$, making decisions simultaneously in two independent, different markets for 80 sequential periods. We did this to facilitate parallelism with earlier studies such as Ovchinnikov et al.
(2015). Initial (“own”) demands for $h$ and $c$ were each independent uniform random variables, but they corresponded to the same percentile in both markets for the same decision maker (therefore were indeed identical whenever the demand supports were the same in both markets). Only one set of 80 independent random realizations of percentiles were drawn for $h$ and $c$, and was used for all sessions of all treatments (“blocking”). Given this parameterization, for $NE$, retailer $c$ orders an equilibrium quantity of 72 for the entire length of the game. $AU$ was implemented with a learning/smoothing constant $\phi = 0.10$. As mentioned above, $PI$ used pre-fitted parameters from Table 1 to implement the linear behavioral model given by (3) and (4). In all treatments demand was discrete uniform, $b_{l,1} = b = 100$, $w = 1$, $p = 3$.

Each pairing of a human retailer $h$ and a preprogrammed competitor $c$ is called a market, and a market is labeled $A$ or $B$. Three treatments considered switching consumers (loyalty parameter $\alpha = 0.5$), while the other three considered loyal consumers, $\alpha = 1$. Loyalty level $\alpha$ is fixed throughout the treatment for both markets. In each treatment, player $h$ has to make inventory decisions against two of the three types of players $c \in \{NE, AU, PI\}$, and the type of $c$ assigned to Market $A$ and the one assigned to Market $B$ remains the same throughout the session. Table 2 describes our 6 treatments under study.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Market A</th>
<th>Market B</th>
<th>Sample size</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>$AU$</td>
<td>$NE$</td>
<td>80 rounds</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>26 subjects</td>
</tr>
<tr>
<td>T2</td>
<td>$AU$</td>
<td>$PI$</td>
<td>80 rounds</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>26 subjects</td>
</tr>
<tr>
<td>T3</td>
<td>$NE$</td>
<td>$PI$</td>
<td>80 rounds</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>26 subjects</td>
</tr>
<tr>
<td>T4</td>
<td>$AU$</td>
<td>$NE$</td>
<td>80 rounds</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>25 subjects</td>
</tr>
<tr>
<td>T5</td>
<td>$AU$</td>
<td>$PI$</td>
<td>80 rounds</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>25 subjects</td>
</tr>
<tr>
<td>T6</td>
<td>$NE$</td>
<td>$PI$</td>
<td>80 rounds</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>25 subjects</td>
</tr>
</tbody>
</table>

Simultaneously subjecting our participants to submit parallel decisions allowed us to perform within-subjects comparisons for each of the three types of $c$’s policies. The fact that decisions were made simultaneously, and not sequentially, allowed us to minimize order effects. To avoid hedging effects, subjects were (truthfully) informed they would be paid for
only one of the two markets in any given period, determined at random, and communicated at the end of the session.

We conducted all experimental sessions at a major public U.S. university, using the subject pool associated with the business school. Participants were randomly assigned to one of the treatments, and subjects read the instructions (available on request). After this, we also read the instructions out loud, and utilized PowerPoint slides and examples. We programmed the experimental interface using the zTree system (Fischbacher 2007). In our sample, subjects did not interact with one another for the length of the session.

The order screen (Appendix A) included information for each of the parallel markets about the wholesale price \( w \) and retail price \( p \), the current demand support levels \( b_{h,t} = 100 + x_{h,t} \) and \( b_{c,t} = 100 + x_{c,t} \), and a graph that included both retailers’ past orders (remember \( x_{h,t} = -x_{c,t} \)). It also included a table that showed all relevant information from past periods (demand, orders, sales, overage, underage, profits, etc.); information about \( c \)’s past decisions was also provided, including \( c \)’s order, and units of \( c \)’s unfilled demand (if any) filled by the participant. After placing the order, each participant saw a results screen that showed the realized demand, overage, underage, and profit. Subjects were compensated in a dollar amount proportional to their total personal experimental earnings (recorded in tokens), plus a $5 participation fee. The average pay was $13, and each subject only participated in one session. Participants were paid in private at the end of the session; cash was the only incentive offered.

4. Experimental Results

We tested two measures of human newsvendors’ performance when competing against the three ordering policies. One is a simple test of means with paired samples, using the average profit of one individual across all \( T = 80 \) periods as the unit of analysis. The other is the percentage profit loss for the \( j^{th} \) retailer \( h \):

\[
\Pi_{j,loss \% | m} = \frac{\bar{\Pi}_{j,c|m} - \bar{\Pi}_{j,h|m}}{\bar{\Pi}_{j,h|m}}
\]  

(7)

Here, the variable \( \Pi_{j,i|m} = (1/T)\Sigma_{t=1}^{T}\Pi_{j,i,t|m} \) denotes the sample average of profits (in tokens) for the \( j^{th} \) subject \( i \in \{h, c\} \) playing in market \( m \in \{A, B\} \) over all \( T = 80 \) periods. Therefore, the percentage profit loss captures how much larger, in % terms, is \( c \)’s mean profit
compared to h’s. Our experimental results are summarized on Figure 4 and Tables 3a-3b. Two observations are immediately evident:

![Average Profits by Treatment](image)

**Figure 4:** Average profits within treatments, between human (h) and computerized (c) competitors under each policy.

**Table 3a:** Average profits and t-tests within treatment, between human (h) and computerized (c) competitors under each policy.

(sample sizes: N = 26 each for T1-3; N = 25 each for T4-6)

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Policy</th>
<th>h</th>
<th>c</th>
<th>Difference</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T1</td>
<td>0.5</td>
<td>AU</td>
<td>67.36</td>
<td>90.39</td>
<td>23.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(12.69)</td>
<td>(13.17)</td>
<td></td>
</tr>
<tr>
<td>T2</td>
<td>0.5</td>
<td>AU</td>
<td>60.27</td>
<td>96.37</td>
<td>36.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(13.35)</td>
<td>(11.83)</td>
<td></td>
</tr>
<tr>
<td>T3</td>
<td>0.5</td>
<td>NE</td>
<td>71.71</td>
<td>89.02</td>
<td>17.31</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(8.02)</td>
<td>(7.70)</td>
<td></td>
</tr>
<tr>
<td>T4</td>
<td>1</td>
<td>AU</td>
<td>71.02</td>
<td>89.29</td>
<td>18.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.26)</td>
<td>(4.45)</td>
<td></td>
</tr>
<tr>
<td>T5</td>
<td>1</td>
<td>AU</td>
<td>70.87</td>
<td>90.29</td>
<td>19.42</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(6.11)</td>
<td>(8.53)</td>
<td></td>
</tr>
<tr>
<td>T6</td>
<td>1</td>
<td>NE</td>
<td>71.56</td>
<td>90.94</td>
<td>19.38</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(6.29)</td>
<td>(6.79)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Policy</th>
<th>h</th>
<th>c</th>
<th>Difference</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market B</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T1</td>
<td>0.5</td>
<td>NE</td>
<td>72.97</td>
<td>87.91</td>
<td>14.93</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(6.22)</td>
<td>(8.32)</td>
<td></td>
</tr>
<tr>
<td>T2</td>
<td>0.5</td>
<td>PI</td>
<td>64.57</td>
<td>95.68</td>
<td>31.11</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(12.17)</td>
<td>(11.00)</td>
<td></td>
</tr>
<tr>
<td>T3</td>
<td>0.5</td>
<td>PI</td>
<td>65.42</td>
<td>93.49</td>
<td>28.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(10.85)</td>
<td>(10.96)</td>
<td></td>
</tr>
<tr>
<td>T4</td>
<td>1</td>
<td>NE</td>
<td>72.12</td>
<td>91.19</td>
<td>19.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.28)</td>
<td>(4.44)</td>
<td></td>
</tr>
<tr>
<td>T5</td>
<td>1</td>
<td>PI</td>
<td>71.67</td>
<td>91.18</td>
<td>19.51</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.74)</td>
<td>(6.66)</td>
<td></td>
</tr>
<tr>
<td>T6</td>
<td>1</td>
<td>PI</td>
<td>70.78</td>
<td>91.69</td>
<td>20.91</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(6.72)</td>
<td>(7.60)</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:**

i. Within each market/treatment pair, **average profits** are presented, with the unit of analysis represented by each jth subject averaged across all 80 periods. Paired samples t-tests of hypotheses related to the difference in profits for (h, c). Standard errors in parentheses.
Table 3b: Percentage profit losses, and \( t \)-tests within treatment, between human (\( h \)) and computerized (\( c \)) competitors under each policy. (sample sizes: \( N = 26 \) each for \( T1-3 \); \( N = 25 \) each for \( T4-6 \))

<table>
<thead>
<tr>
<th>Treatment</th>
<th>( \alpha )</th>
<th>% Profit Loss (( h ) vs ( c ))</th>
<th>Market A</th>
<th>Market B</th>
<th>Difference</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>0.5</td>
<td>AU 42.94%</td>
<td>NE 22.29%</td>
<td>-20.65%</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.49)</td>
<td>(0.23)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T2</td>
<td>0.5</td>
<td>AU 76.52%</td>
<td>PI 59.66%</td>
<td>-16.86%</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.81)</td>
<td>(0.65)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T3</td>
<td>0.5</td>
<td>NE 27.22%</td>
<td>PI 50.73%</td>
<td>23.51%</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.29)</td>
<td>(0.50)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T4</td>
<td>1</td>
<td>AU 26.46%</td>
<td>NE 27.21%</td>
<td>0.76%</td>
<td>0.229</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.13)</td>
<td>(0.14)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T5</td>
<td>1</td>
<td>AU 29.41%</td>
<td>PI 28.24%</td>
<td>-1.17%</td>
<td>0.397</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.25)</td>
<td>(0.17)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T6</td>
<td>1</td>
<td>NE 28.81%</td>
<td>PI 31.72%</td>
<td>2.91%</td>
<td>0.027</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.21)</td>
<td>(0.24)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:

i. The percentage profit loss for \( h \) with respect to \( c \), is defined by (7) for each player, averaged over each market/condition. The p-values are single sided, paired samples \( t \)-tests, representing the hypotheses related to the difference between the profit loss rate between Market A and B. The unit of analysis is represented by each \( j^{th} \) subject (the profit loss rate is already a ratio of averages over time) Standard errors in parentheses.

Observation 1. The losses from behavioral ordering under competition are consistently very large, ranging from 22\% to 77\% across all alternative policies. This occurred with both fully loyal and with switching consumers.

This finding is our main contribution: The profit losses from behavioral ordering are not in the lower single-digit percentages implied by the existing literature for newsvendors who do not face competition (e.g., Schweitzer & Cachon 2000). In contrast, Table 3 shows that the losses from behavioral ordering are orders of magnitude larger – in magnitudes that would be substantial for most business executives to seriously re-examine their firms’ ordering practices.

The reason why we observe such large profit losses (when considering competitive cases), while the current literature (for isolated newsvendors) observes only small losses is as follows: From the current literature we know that individuals in high margin scenarios exhibit systematic under-ordering (pull-to-center bias). The direct loss from this under-ordering is small (no larger than 5\% based on existing studies). But such under-ordering
leads to more stranded consumers who then visit the competitor, providing the additional
demand. If the competitor is following NE policy then it simply captures this additional
demand more often than it projected, thus increasing its profit; the amount of overflow from
the competitor to the human is unchanged. With both PI and AU, the competitor increases
its order quantity above the NE in response to the observed larger and more frequent
overflows from the human newsvendor. Hence, these policies not only capture more of the
overflow from the human, but also decrease the frequency and the amount of demand
overflowing back to the human competitor. Since these three effects build on top of each other,
firm $h$ performs *substantially worse* than firm $c$ under either of the three policies.

**Observation 2.** *The ordering policy AU performs surprisingly well.*

The relative profit loss is statistically indifferent from NE or PI when dealing with loyal
consumers, and substantially higher when dealing with switching consumers. The
performance gap between human inventory ordering and computerized policies is the largest
(76.52% and 42.94%) for ordering policy AU under the presence of switching consumers. In
terms of profit losses for the human competitor, in general we observe that AU generated the
largest profit losses to humans, followed by PI, and then by NE for the switching consumers
case, while the same phenomenon was directionally consistent (though not statistically
significant) for the loyal consumers case.

This is interesting because it provides a validation for a policy similar to what many firms
would readily implement in practice. The reason for its solid response is as follows: While AU
does not explicitly account for the competitive response, human competitors tend not to
respond to the mean competitor order if the orders fluctuate. The distribution updating
procedure in AU reacts to random demand realization and changes to the distribution over
time. Hence, while the actual decision policy in AU is deterministic (as in PI), the underlying
distribution changes, hence AU results in fluctuating orders, allowing firm $c$ to disregard $h$’s
subsequent response, which was a regularity observed by Ovchinnikov et al. (2015).

To expand on this point, we performed some follow-up analyses in the next two sections,
where we cover specifically the effect of consumer loyalty, and dual market design.
5. Consumer Loyalty Effects on Human Performance

In this section, we compare human profits by loyalty level $\alpha$: Since treatments 1-3 mirror 4-6 with the sole difference being the loyalty parameter $\alpha$, we test the effect of consumer loyalty on subjects’ performance. Recall that $\alpha$ shifts the support for the distribution towards the retailer that stocks out less, or less often.

Table 4: Average profits, Percentage profit loss, and $t$-tests between treatments:
Effect of different loyalty levels ($\alpha = 0.5$ vs $\alpha = 1$) on human performance

<table>
<thead>
<tr>
<th>Policy</th>
<th>Treatments</th>
<th>Profits (h only)</th>
<th>% Profit Losses (h vs c)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$a = 0.5$</td>
<td>$a = 1$</td>
</tr>
<tr>
<td>h’s results when</td>
<td></td>
<td>$N = 26$</td>
<td>$N = 25$</td>
</tr>
<tr>
<td>competing against:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>other market against:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AU</td>
<td>NE</td>
<td>67.36</td>
<td>71.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(12.69)</td>
<td>(4.26)</td>
</tr>
<tr>
<td>PI</td>
<td>AU</td>
<td>60.27</td>
<td>70.87</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(13.35)</td>
<td>(6.11)</td>
</tr>
<tr>
<td>h’s results when</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>competing against:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>other market against:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PI</td>
<td>AU</td>
<td>64.57</td>
<td>71.67</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(12.17)</td>
<td>(4.74)</td>
</tr>
<tr>
<td>NE</td>
<td>AU</td>
<td>65.42</td>
<td>70.78</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(10.85)</td>
<td>(6.72)</td>
</tr>
<tr>
<td>h’s results when</td>
<td></td>
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<td></td>
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<tr>
<td>competing against:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>other market against:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NE</td>
<td>AU</td>
<td>72.97</td>
<td>72.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(6.22)</td>
<td>(4.28)</td>
</tr>
<tr>
<td>PI</td>
<td>AU</td>
<td>71.71</td>
<td>71.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(6.22)</td>
<td>(4.28)</td>
</tr>
</tbody>
</table>

Notes:

i. For each market/treatment pair, average profits and percentage profit losses for $h$ are presented, with the unit of analysis represented by each $j$th subject averaged across all 80 periods.

ii. The first column indicates the market under study. The second column indicates the market under study on the parallel dual market taking place at the same time.

Table 4 displays the comparisons by market-in-a-treatment between the two loyalty regimes. In those treatments where subjects competed with a retailer following NE, human profits and profit losses remained statistically the same, irrespective of the loyalty parameter. Since the NE policy always ordered the same quantity (symmetric equilibrium of the NE game), not surprisingly the subjects also seem to anchor at a relatively stable level. This reduced their loss rates to between 20 and 30% (Table 3) and resulted in average profits...
between 71 and 73 tokens. While the loss rates were significant, when faced with a competitor ordering a constant quantity, the profit impact of the demand support shift was insignificant for these NE-related conditions.

In contrast, for treatments where subjects competed against a retailer following either policy that incorporated human behavior (PI or AU), the presence of switching consumers ($\alpha = 0.5$) statistically decreased profits and increased percentage profit losses at levels of significance of 5% or less, except for the case where competition against AU was combined with a competitor following a constant policy (NE) on the parallel dual market. The important observation here is that the combined effect of management-science-driven inventory decision-making and consumer self-selection to the better stocked retailer have a significant impact on human profits and human percentage profit losses. Since in the real world, over time consumers often favor retailers who are less likely to stock-out than their competitors, this indeed makes behavioral ordering even more damaging to the firm, especially in presence of science-driven competitors.

6. Robustness Check: Possible Treatment Effects

Our experimental design, making use of dual markets, allowed us to perform within-subjects comparisons.

As a robustness check, we want to explore how the results in one market are affected by what happens in the other market displayed on the other side of the screen. For example, consider a retailer $h$ who in one market faces a competitor following AU. At the same loyalty level $\alpha$, we explored whether $h$’s profits (and profit losses) differ as a function of whether in the other market the competitor ordered according to NE versus PI.

The results in Table 5 lead us to conclude that, in general, profits and percentage profit losses in a market are statistically unaffected by the competitor’s policy in the other market. This provides an important robustness check for our dual-market design. The one exception is related to the first case, where our human retailers compete against a competitor following policy AU under partial customer loyalty ($\alpha = 0.5$).

The highest profits for humans were observed when competing against NE: As we expected, a constant order of 72 provides an anchoring point to improve $h$’s performance (although, as discussed earlier, it still generates substantial percentage profit losses for subjects, all above 20%), that seems to also have helped decision makers on the parallel market when competing against AU.
Table 5: Average profits, Percentage profit loss, and t-tests between treatments: Comparisons of human performance between different parallel competitive policies. 
(sample sizes: N = 26 each for α = 0.5; N = 25 each for α = 1)

<table>
<thead>
<tr>
<th>h's results when competing against:</th>
<th>Profits (h only)</th>
<th>% Profit Losses (h vs c)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>h competing on the other market against:</td>
<td></td>
</tr>
<tr>
<td>AU α = 0.5</td>
<td>NE  PI t-stat</td>
<td>p-value</td>
</tr>
<tr>
<td></td>
<td>67.36 60.27 2.42</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td>(12.69) (13.35)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>α = 1</td>
<td>71.02 70.87 0.08 0.460</td>
</tr>
<tr>
<td></td>
<td>(4.26) (6.11)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>h competing on the other market against:</td>
<td></td>
</tr>
<tr>
<td></td>
<td>NE  PI t-stat</td>
<td>p-value</td>
</tr>
<tr>
<td></td>
<td>42.94% 76.52% -1.68</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(0.49) (0.81)</td>
<td></td>
</tr>
</tbody>
</table>

|                                    | h competing on the other market against: |                      |
|                                    | NE  PI t-stat   | p-value                 |
|                                    | 26.46% 29.41% -0.27 0.302 |
|                                    | (0.13) (0.25)   |                          |

|                                    | h competing on the other market against: |                      |
|                                    | NE  PI t-stat   | p-value                 |
|                                    | (12.69) (13.35)  |                          |

|                                    | h competing on the other market against: |                      |
|                                    | AU  NE t-stat   | p-value                 |
|                                    | 64.57 65.42 0.30 0.395 |
|                                    | (12.17) (10.85) |                          |
|                                    | α = 1           | 71.67 70.78 0.46 0.297  |
|                                    | (4.74) (6.72)   |                          |
|                                    | h competing on the other market against: |                      |
|                                    | AU  NE t-stat   | p-value                 |
|                                    | 59.66% 50.73% 0.47 0.292 |
|                                    | (0.65) (0.50)   |                          |

|                                    | h competing on the other market against: |                      |
|                                    | AU  NE t-stat   | p-value                 |
|                                    | 28.24% 31.72% -0.30 0.282 |
|                                    | (0.17) (0.24)   |                          |

|                                    | h competing on the other market against: |                      |
|                                    | AU  NE t-stat   | p-value                 |
|                                    | 64.57 65.42 0.30 0.395 |
|                                    | (12.17) (10.85) |                          |
|                                    | α = 1           | 71.67 70.78 0.46 0.297  |
|                                    | (4.74) (6.72)   |                          |
|                                    | h competing on the other market against: |                      |
|                                    | AU  NE t-stat   | p-value                 |
|                                    | 22.29% 27.22% 0.44 0.250 |
|                                    | (0.23) (0.29)   |                          |

|                                    | h competing on the other market against: |                      |
|                                    | AU  NE t-stat   | p-value                 |
|                                    | 27.21% 28.81% 0.14 0.376 |
|                                    | (0.14) (0.21)   |                          |

Notes:

i. For each market/treatment pair, average profits and percentage profit losses for h are presented, with the unit of analysis represented by each jth subject averaged across all 80 periods.

ii. Row information displays the market information for the competitor’s policy, and loyalty value α by treatment. Column information displays what the competitor’s policy looks like on the parallel dual market.

As such, when subjects were given no anchoring indication whatsoever (as in the treatment when the two dual markets were AU and PI, particularly when loyalty was partial), their performance was substantially worse than when the parallel anchoring was provided, in the case of AU in AU-NE. While this situation did not happen in the case of PI (where subjects do not seem to have anchored in the PI-NE treatment quite as much as in the AU-NE case), it still holds true that the largest percentage profit losses (and smallest profits) took place in the AU and PI markets when the two policies were combined and loyalty was only partial. Since in reality, procurement managers likely have not access to salient and
persistent anchors, this provides additional support to the idea that the worst performance scenario of our experiments coincides with the most realistic one.

Figure 5: Percentage Profit Losses differences within treatments from Market A to B, for both customer loyalty levels.

On a relative basis, the gap in performance difference shows that the largest losses are for switching consumers, as shown in Figure 5. We can observe that the difference in performance gaps is largest in treatment T3 (PI vs NE, of 23.51%). Note these are differences-in-differences measures, and do not detract from the fact that $c$’s performance is systematically larger than $h$’s, regardless of the condition.

7. Conclusions

While many studies have examined newsvendor ordering regularities/biases, there is surprisingly little literature investigating whether business executives should even care about these biases. Specifically, the implications of the current literature suggest that the profit losses from behavioral ordering are relatively small and range between 1 and 5%. Such losses are below a threshold worthy of intervention for many executives, for example that of the specialty retailer F presented in our mini-case study.

In this paper we estimated the true cost of behavioral ordering. Motivated by the fact that most firms operate in competitive situations, we compared the profits of two competing firms: one at which a human manager is making procurement decisions, and another that uses a
management science-driven automated inventory policy. We suggested three ordering policies that cover a spectrum of plausible approaches one could use based on the current academic literature and business practice. Using a laboratory experiment, we measured the percentage profit loss of a behavioral firm versus the three policies. We observed profit losses of 22-76% — orders of magnitude larger than the implications of existing literature, and clearly large enough to mandate attention by business executives. The profit losses were consistently large across all the policies we considered, which suggests that effectively regardless of what a competitor is doing (it may even ignore competition whatsoever, as our AU policy does), the behavioral firm stands to lose substantial profits compared to the competitor. This happens because management science-driven competitors have several ways to take advantage of the behaviorally biased inventory manager who “leaves on the table” significant amount of unsatisfied demand and consequently profit.

Our work can be extended in a variety of ways, e.g., by extending it to experienced practitioners, verifying our result using field data where available, or by developing new methods to improve decision making. In any case, we believe that our results offer a fundamental insight into the importance of paying attention to the behavioral biases of the procurement managers. Our work sends a clear message to any CEO who relies on the intuition of procurement managers: For every dollar of net profit made, they are potentially losing out on 20 cents (and potentially, up to over 70 cents!) as compared to their management science-driven competitors.

8. References


Chapter 2: 
Nonparametric Identification of Score Auctions in Multi-attribute 
Procurement*

1. Introduction

Many governmental agencies use multi-attribute mechanisms to purchase, on dimensions such as completion time, service or quality in addition to bid price (e.g., Lewis and Bajari 2011; Bajari et al. 2014; Gupta et al. 2015). A score auction is a multi-attribute procurement mechanism where bidders submit a vector containing levels of attributes in response to a request-for-bids. Bids are ranked using a pre-announced rule transforming that vector into a scalar. The winner is the bidder with the best (highest or lowest, depending on the rule) score.

Previous structural research in multi-attribute score auctions (e.g., Lewis and Bajari 2011) made creative use of additional data and market structure assumptions, to analyze score bids. Unfortunately, such additional data might not be available, and additional assumptions and functional parameterizations might not be appropriate.

Guerre, Perrigne and Vuong (2000) (henceforth, GPV) provided the empirical framework to nonparametrically estimate private values in sealed-bid-first-price auctions from observed price-only bids. The implicit latent bidders’ private pseudotypes (Che 1993, Asker and Cantillon 2008) and corresponding probability densities are nonparametrically identified. Therefore, pseudotype-level GPV-like estimators can be implemented.

2. Definitions

To use existing results (Lemma 1 here, taken from Asker and Cantillon 2008, henceforth AC) on the outcome characterization of a multi-attribute score auction, consider a buyer seeking to procure a good for which there are \( N \) potential suppliers (bidders). The good is

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4 Pseudotypes are assumed to be strictly monotonically related to observed scores (see Theorem 1).
characterized by price $p$, and a contractually-enforceable vector of attributes $Q \in \mathbb{R}^M_+$, $M \geq 1$. The buyer values the good at $V(Q, t) - p$ where $t \in [t_0, t_1]$ captures the buyer’s preferences over $Q$. Bidder $j$’s profit from selling good $(p, Q)$ is $p - C(Z_j, Q)$, with individual production types defined by a vector $Z_j \in \mathbb{R}^K_+$, $K \geq 1$. Thus, social welfare is defined by $V(Q, t) - C(Z_j, Q)$. We need to guarantee that costs are independent across attributes, convex in individual attributes, and that the types can be partially ordered with respect to costs. Hence, we follow AC’s assumptions that functions $V$ and $C$ are twice continuously differentiable, first derivatives are increasing in qualities and types ($V_Q, C_Q, C_{Z_j} > 0$), $V - C$ is bounded, and $(V_{QQ} - C_{QQ})$ is negative semi-definite.

Since social welfare $V - C$ is bounded and strictly concave in $Q$, the social first-best level of attributes for each $j$, $Q^*(Z_j) = \arg\max_Q \{V(Q, t) - C(Z_j, Q)\}$, is well-defined and unique. Preferences are common knowledge. Bidders’ types $Z_j$ are private information. Types are independently distributed according to a publicly-known smooth joint probability function with density $f(.)$, with support on a convex, bounded subset of $\mathbb{R}^K$ with nonempty interior $\Xi_j$.

The scoring rule in the auction is assumed quasi-linear: $S(p, Q) \equiv A(Q) - p$, and represents a continuous preference relation over contract characteristics $(p, Q)$. Quasi-linearity is observed in the practical implementation of scoring mechanisms used by governmental agencies (e.g., Lewis and Bajari 2011; Bajari et al. 2014), so this assumption is not restrictive in practice. We assume the rule is twice continuously differentiable and increasing in $Q$. Further, to ensure participation of all bidders in equilibrium, we follow AC’s assumption that $A(Q) - C(Z, Q)$ is bounded, strictly concave in $Q$ for any $Z$, and such that $\max_Q \{A(Q) - C(Z, Q)\} \geq 0$ for all $Z$.

The outcome of the score auction is a probability of winning, $\xi_i$, and a score to fulfill when bidder wins the contract, $s_i$. While the auction mechanism defining $s_i$ can be flexibly defined—e.g., open-ascending scores, Vickrey auction, sealed-bid-first-score—we focus on the third.

Winning bidder with type $Z_j$ bidding score $s_j$ chooses $(p, Q)$ to maximize profit $p - C(Z_j, Q)$ s.t. $s_j = A(Q) - p$. Adding the constraint in the objective function yields:

\[ \text{Note that this is a less restrictive assumption than } A(Q) \equiv V(Q, t). \text{ For welfare considerations, AC wanted to keep a distinction between implied score preferences and the buyer's actual preferences, but this distinction does not bear an effect in our results, and thus, we keep it here only for completeness, and to give a social welfare interpretation to } Q^*(Z_j). \]
\[
\max_Q \{ A(Q) - C(Z_j, Q) - s_j \} \tag{1}
\]

From observing (1), the optimal \( Q \) does not depend on \( s_j \). Following Che (1993), AC define pseudotype, \( v(Z_j) \), a value function denoting the highest level of observable social surplus bidder \( j \) can generate, given a quasi-linear scoring rule:

\[
v(Z_j) \equiv \max_Q \{ A(Q) - C(Z_j, Q) \} \tag{2}
\]

This expression is well-defined given the pre-announcement of the scoring rule. The set of pseudotypes is a real-valued interval. The pseudotypes’ density inherits the smoothness of \( f(.) \). Expected profit for bidder \( j \) is given by:

\[
\Pi_j = x_j \cdot (v(Z_j) - s_j) \tag{3}
\]

Therefore, \( v(Z_j) \) fully captures bidders’ preferences over outcomes \((x, s)\).

This setting allows AC to completely characterize the set of equilibrium outcomes of the auction, and to evaluate the buyer’s expected payoffs via the distribution of pseudotypes. Hence, pseudotypes are sufficient statistics for this auction mechanism. Define outcome-equivalence as follows: two equilibria are outcome-equivalent if they both lead to the same distribution of outcomes \(((x_1, ..., x_N); (s_1, ..., s_N))\) in the aggregate; they are typewise-outcome-equivalent if they generate the same distribution of outcomes in the aggregate, conditional on types in the (nonempty) interior set \( \Xi_1 \times ... \times \Xi_N \). The following result, from AC, is crucial for the identification result included in the next section:

**Lemma 1** (Asker and Cantillon 2008): *Every equilibrium in a score auction using a quasi-linear-scoring rule is outcome-equivalent, and also typewise-outcome-equivalent, to an equilibrium where buyers are constrained to bid only as a function of their pseudotypes, and vice-versa.*

**Proof**: see Lemmas 1-2 and Theorem 1 from AC. \( \square \)
3. Optimal Bid and Nonparametric Identification

The previous characterization allows us to develop an empirical strategy to treat submitted bids in a multi-attribute score auction. We need to find now the optimal bidding strategy under this setting.

Starting with Che (1993), researchers studying multi-attribute auctions have defined bidders’ pseudotypes—as measures of the worth of winning a contract for bidders capturing their complete cost structure—to derive score auctions equilibria. Lemma 1 demonstrates that, despite of the multidimensional aspect of this framework, we do not discard any relevant equilibria by using pseudotypes: we can concentrate on analyzing pseudotypes to derive optimal bidding behavior without loss of generality.

For empirical purposes, the previous observation is both good news and not-quite-as-good news. It is good news as the problem of optimal bidding is now simplified from analyzing observed bid vectors \((p, Q) \in \mathbb{R}^{M+1}\) and their corresponding private cost types \(Z_j \in \mathbb{R}^K\), to focusing instead on observed submitted scores \(S(p, Q) \in \mathbb{R}\) and their respective private pseudotypes \(v(Z_j) \in \mathbb{R}\), collapsing the optimality analysis into one dimension. It is not-quite-as-good news because now that the analysis focuses on the one-dimensional space, it is impossible to econometrically identify specific components of bidding vectors and/or the private cost types from \((p, Q)\), without making many additional assumptions. What is lost in terms of detail is gained in terms of simplicity.

Since the distribution of pseudotypes provides a complete description of the auction optimal outcome, we can use its empirical representation to characterize the auction. Let \(b(\cdot) \equiv b(\cdot, X_p, N_j)\) be a monotone function mapping pseudotypes \(v_j = v(Z_j)\) onto observable scores \(s_j = S(p_j, Q_j)\) in equilibrium\(^6\). As notation, \(s_j = b(v_j)\). Here, \(X_p(v_j) \equiv X_p(v(Z_j)) = F(Z_j)\) is the cumulative distribution of private types defined in the space of pseudotypes, \(X_S(s_j)\) is the distribution of scores induced by the respective pseudotypes, and \(x(\cdot) = X'(\cdot)\) denotes corresponding densities in both cases.

Generalizing the original single-attribute analysis of optimal bidding for first-price-sealed-bids of Riley and Samuelson (1981) to the sealed-bid-first-score case in multi-attribute score auctions, the symmetric Bayesian-Nash equilibrium (SBNE) score satisfies differential-equation (4):

---

\(^6\) Whereas \(N\) denoted number of bidders, \(N_j\) denotes number of bidders in the auction where \(j\) is participating.
\[
1 = (v_j - b(v_j))(N_j - 1) \frac{x_v(v_j)}{x_v(v_j)} \frac{1}{b'(v_j)}
\] (4)

Assuming a score-bidding strategy that is monotone in the pseudotypes for every possible score in equilibrium, then \(X_S(s_j) = \Pr(S \leq s_j) = \Pr(v_j \leq b^{-1}(s_j)) = X_v(b^{-1}(s_j)) = X_v(v_j)\). Thus, with the change of variables \(x_S(s_j) = x_v(v_j)/b'(v_j)\) we establish:

**Theorem 1 (Pseudotype identification):** In a sealed-bid-first-score multi-attribute auction where the buyer uses a quasi-linear-scoring rule, assuming i.i.d. private multi-dimensional types and risk neutrality, private pseudotypes in equilibrium can be uniquely expressed as a strictly monotone, differentiable function of observed equilibrium scoring bids as in (5).

\[
v_j = \xi(s_j, X_S, N_j) \equiv s_j + \frac{x_S(v_j)}{x_S(s_j)} \frac{1}{(N_j - 1)}
\] (5)

**Proof:** We show that the general GPV conditions (C1 and C2 below) hold in the score auction environment. Since \(Z_j\) are drawn from a compact-support distribution, the pseudotype value function (2) is well-defined, given the function it maximizes is assumed bounded, and from concavity in \(Q\), is bounded below (by 0) for any \(Z\). Therefore, the support of the distribution of pseudotypes is a bounded real subset.

Condition C1 requires the joint distribution of bids in an auction to be equal to the product of marginal distributions of bids in that auction. In our case, bids are the resulting scores: \(s_j = b(v_j, X_v, N_j)\) maps pseudotypes \(v_j = u(Z_j)\) onto submitted scores \(s_j = S(p_j, Q_j)\), given that pseudotypes \(v_j\) are i.i.d. (bidders are assumed ex-ante equal). When restricted to strictly monotone, continuously-differentiable SBNE strategies, then scores \(s_j\) are also i.i.d., meaning GPV’s condition C1 follows. The converse can also be established: Take the cdf \(X_S(.)\) of scores with bounded support \([s_0, s_1]\) as established before. Thus, scores approach the lower bound of the support, \(\lim_{s_j \to s_0} \xi(s_j, X_S, N_j) = s_0\), which results from (i) \(s_0\) finite (\(\geq 0\), (ii) \(\lim_{s_j \to s_0} \log X_S(s_j) = -\infty\), and (iii) \(\frac{d\log X_S(s_j)}{ds_j} \Rightarrow \lim_{s_j \to s_0} \frac{x_S(s_j)}{X_S(s_j)} = +\infty\).

Similarly, in the multi-attribute setting, condition C2 requires \(\xi(., X_S, N_j)\) in (5) to be strictly increasing on \([s_0, s_1]\), and its inverse differentiable on \([v_0, v_1]\)
\[ \xi(s_j, X_s, N_j), \xi(s_1, X_s, N_j) \]. Consider the strictly monotone, differentiable, SBNE defined by (4) on support \([v_O, v_1]\). Let \(X_s(\cdot)\) be the distribution of observed optimal bids, defined by \(X_s(s_j) = X_s(b^{-1}(s_j, X_v, N_j)), \forall s_j \in [s_O, s_1] \equiv [b(v_O, X_v, N_j), b(v_1, X_v, N_j)]\). Now, \(b(\cdot, X_v, N_j)\) needs to solve differential equation (4). Since (5) follows from (4), then \(b(v_j, X_v, N_j)\) satisfies \(\xi(b(v_j, X_v, N_j), X_s, N_j)\) for all scores in the support. Given \(b(\cdot)\) was assumed strictly increasing on \([s_O, s_1]\) and differentiable on the support of pseudotypes, C2 holds. Conversely, starting from C2, define a measure \(X_v(\xi^{-1}(\cdot, X_s, N_j))\); it is a valid distribution because \(\xi(\cdot, X_s, N_j)\) is strictly increasing from C2, and support of \(X_v(\xi^{-1}(\cdot, X_s, N_j))\) is \([v_O, v_1]\). Out of differentiability of \(\xi^{-1}\) and absolute continuity of \(X_s\), then \(X_v\) is absolutely continuous. Consequently, \(X_v\) is a valid probability measure on \([v_O, v_1]\). The fact this distribution of independent private pseudotypes \(X_v\) can rationalize \(X_s\) in a sealed-bid-first-score auction with non-binding reservation price is implied from the second part of Theorem 1 in GPV. Therefore, identification of left-hand-side of (5) is established.

This identification result, obtained under assumptions analogous to GPV’s, is driven by AC’s sufficient statistic result. Analogous to the sealed-bid-first-price environment, the difference between a bidder’s pseudotype and submitted score is the optimal amount of “score shading” (bidding margin) as a best response to the other bidders’ strategies. As GPV noted, the main desirable characteristic of expressions similar to (5), is that the right-hand-side is nonparametrically identified, and estimable directly from data on observed scores and number of bidders, yielding an estimate of the (latent) left-hand-side pseudotypes.

When attributes generate disutility to the buyer, the scoring rule is defined as a reverse auction, i.e., the contract is awarded to the lowest score submitted. In those cases, all previous results will carry over, with slight modifications, e.g., expression (12) is rewritten as:

\[
\begin{align*}
  u_j &= \xi(s_j, X_s, N) \equiv s_j - \left( \frac{1 - X_s(s_j)}{X_s(s_j)} \right) \frac{1}{(N-1)} \\
  \end{align*}
\]  

(6)

With our extension to the multi-dimensional score auction environment when the assignment rule uses a sealed-bid-first-score mechanism, we can implement a GPV-like two-step estimator. The context parallels the structure of a traditional sealed-bid-first-price
environment, ensuring that this estimation procedure will inherit the characteristics of the original method.

4. Conclusion

In a score auction procurement mechanism, under standard assumptions, bidders’ pseudotypes (as sufficient statistics of the private characteristics of each attribute) are nonparametrically identified. The additional assumptions of pre-announced, quasi-linear-scoring rules and the independent private values paradigm are not restrictive and apply to many governmental purchases in practice.

While for some analyses, identification of individual cost components is crucial (and for which additional structural assumptions would be required), pseudotype level analyses allow policy-makers and researchers to describe costs via observed bidding behavior. For example, Quiroga and Moritz (2015) use GPV-like estimators to compare implicit pseudotypes on equivalent multi-attribute auctions using either quasi-linear-scores or price-only bids. Therefore, by using estimated pseudotypes and their distributions, one can conduct the same type of analyses GPV’s procedure made possible for price-only environments.

5. References


Chapter 3: 
Complexity and Transparency in Sealed-bid 
Procurement Auctions with Multi-dimensional Bids* 

1. Introduction 

Governmental agencies use sealed-bid multi-dimensional mechanisms to purchase goods and hire services, considering both price and quality dimensions such as time to completion and type of materials. Che (1993) was the first to characterize the US Department of Defense’s (DoD) multi-dimensional sealed-bid auctions to procure weapon systems from an optimal mechanism design perspective. The DoD, using an elaborate scoring system that evaluated suppliers’ bids weighing price in combination with many other key performance/quality metrics, generated a competitive source selection process that Che’s model helped to popularize. Since then, other governmental agencies also started using these types of mechanisms for procurement. Several studies (e.g., Snir and Gupta 2011, Lewis and Bajari 2011, Bajari et al. 2014, Gupta et al. 2015) document how state departments of transportation in the US use scoring rules to rank multi-dimensional bids to assign contracts. These are often called “A+B bidding auctions”, where A is a price bid, and B is acceleration time to deliver the contracted product or service, but which can incorporate other performance metrics.

We designed a laboratory experiment to study multi-dimensional (A+B) sealed-bid mechanisms. We compare two scenarios: First, a sealed-bid transparent scores auction (TS); and second, what we have called a sealed-bid multi-dimensional beauty-contest auction (MDBC). In the TS auction, suppliers know both their production cost and the evaluation rule used by the buyer to rank their bids before they submit them (Che 1993, extended by Asker and Cantillon 2008; henceforth AC). The MDBC auction, on the other hand, is the exact same environment as the previous scenario, but concealing the evaluation rule used by

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the buyer to evaluate suppliers when they make their offers. We use the name “beauty-contest auction” for this mechanism, because suppliers try to choose levels of quality and price to maximize their expected utility given their “guess” on the buyer’s subjective preference for quality. Figure 6 displays the difference between the two scenarios.

![Figure 6: Sealed-bid mechanisms under comparison.](image)

In order to isolate the effect of transparency loss, in our research design we have provided suppliers with perfect information on their own private cost structures –what in auction theory is called the independent private values paradigm. This conceptually prevents the possibility of suppliers falling prey to a “winner’s curse”, where they might end up winning an auction for a lower value than the actual worth of the contract.

In the same spirit, we also assume perfect commitment: A bidder who wins an auction event will automatically supply the same price and quality levels offered, and the buyer will pay that amount for the good. In reality, risks of default and hold-up exist, and Bajari et al. (2014) provide ample evidence of its effects in governmental procurement. However, that additional layer of complexity is a different transparency-related issue than the one we study here.

In sum, our work allows us to better understand how costly it is for a central planner acting as a buyer to conceal information on how they assign multi-dimensional, quality-dependent contracts, as opposed to using a transparent rule.

2. Motivation, Approach and Contributions

Similar to the US governmental examples discussed earlier, the Chilean government also uses multi-dimensional score auctions, incorporating price and one or more measures of
quality, to procure goods and services for the public sector. Chile has centralized all governmental purchases through a procurement agency, ChileCompra, that regulates all public sector auctions and framework agreements (Gur et al. 2013, Corvalán 2013, Reyes 2015). ChileCompra organizationally depends of the Ministry of Finance, operates under supervision of the president, and its director is appointed through an open public hiring process. Over 850 governmental offices use ChileCompra’s electronic procurement platform to purchase and contract goods and services from over 100,000 pre-qualified suppliers and vendors; transactions overseen by ChileCompra every year amount to approximately 3.5% of Chile’s annual GDP. When it was created in 2003, one of the explicit goals for ChileCompra was to increase transparency in governmental acquisitions while generating instances for savings and efficiency due to supplier competition. The communication of transparency and fairness in contract assignments has been one of ChileCompra’s historical institutional concerns since its foundation.

One of the coauthors of the present work had seven group meetings with the chief manager and two analysts of the research department at ChileCompra between 2011 and 2013. The purpose of each of those meetings was to better understand the way that ChileCompra conducts their auctions, as well as what were the specific concerns they had about the way the agency operates. In particular, while substantial efforts have been made by ChileCompra to be transparent in their assignments, communicating criteria, revealing information, and avoiding not only corruption but the perception of corruption, their main question was whether there was an economic and social value in procuring in this transparent fashion, as opposed to a more discrestional manner. In the words of the chief manager: “We want to know what the price of transparency is. What is the cost associated to make scores and bids transparent in our procurement processes? By concealing this information, does our buyer’s surplus become worse or better?” In sum, their question was whether it was worthwhile or not to make all these efforts to conduct these auctions transparently.

In order to address their question, it became crucial that any empirical study we conducted would not tamper with the existing environment, in the understanding that commitment to the rules, information disclosure, and enforceability were all desirable market traits that could not be sacrificed. This ruled out the use of field experiments to make comparisons.
In terms of analytical modeling, prior research has used mechanism design and game theory tools to analyze different mechanisms, providing useful theoretical insights when bids are either fully-transparent (e.g., Che 1993, Asker and Cantillon 2008), open-progressing (e.g., Chen-Ritzo et al. 2005), or single-dimensional (e.g., Kostamis et al. 2009). However, for a large number of the auctions conducted by ChileCompra (sealed-bid, first-score, multi-dimensional), there is no pure-strategies equilibrium solution for a score-auction format concealing information about the assignment rule and/or the metric for quality and restricts feedback to bid levels only, instead of actual scores.

Therefore, we decided that the cleanest way to contrast both mechanisms was through the use of an incentive-compatible controlled laboratory experiment.

In our work, analogously to the governmental procurement auctions we described, we compare experimentally the bidding behavior of suppliers in sealed-bid auctions with multi-dimensional decisions with and without disclosure of the quality-weighted scoring rule as explained previously by Figure 6.

Our work is the first to analyze multi-dimensional procurement bidding decisions using sealed-bid first-scores, comparing transparent to concealed scoring rules in a laboratory setting. Existing experimental work has provided insights for related, but fundamentally different, mechanisms. Chen-Ritzo et al. (2005) studied multi-dimensional bidding in open score auctions with a scoring rule that, while not explicitly announced, could be inferred from the feedback generated by the dynamic of open-progressing bidding. Fugger et al. (2014) studied multi-attribute assignments in open-progressing procurement auctions with price-only bids, in what transforms the quality dimension into a problem of bidding with an additive exogenous disturbance term. Engelbrecht-Wiggans et al. (2007) tested experimentally second-price vs. price-and-quality procurement auctions using sealed-bids, but in their setting, the quality dimension was assumed exogenous, random and observable for the bidder and the buyer (but not by any other competing bidder), making bid decisions effectively single-dimensional. Haruvy and Katok (2013) allowed for both sealed and open bidding and public concealment/disclosure of bids, but quality-levels remained exogenously determined by the buyer. Aside from Chen-Ritzo et al. (2005), only our work allows for bidder-determined quality levels as opposed to exogenous buyer-determined preferences for bidders. In our context, the ability to make non-price bidding decisions (such as acceleration in completion time, number of dedicated service employees, or any other quality dimension of interest) is essential.
In general, we refer to all the “+B” components of an A+B bid as quality. Quality, as understood here, consists of any utility-generating non-price attributes a buyer obtains from a product offered by a supplier, which are verifiable, measurable and contractible/enforceable by the buyer, and therefore, can be used to rank bids and assign contracts.

In order to understand the notion of quality that can be incorporated into an auction by a buyer, we find it useful to refer to the taxonomy on performance measures offered by Ketokivi and Schroeder (2004). They identify three possible types of measures that can be used to quantify what we refer to as quality attributes: operationally-defined measures, perceptual measures, and quasi-perceptual measures.

**Operationally-defined measures** are quality metrics which are objectively quantifiable; in governmental auctions, common examples include the acceleration time to fulfill a contract with respect to a maximal acceptable deadline, and the number of employees assigned as staff to cover a point of service during peak time. In our context, these are objective, reliable and verifiable by both bidders and buyers, making their contractibility and enforceability possible. These are the least problematic for the buyer and suppliers to communicate and assess. However, buyers often consider other attributes that generate positive utility that include perceptual components in their measure.

**Perceptual** and **Quasi-perceptual measures** include any metrics that are subjectively quantified by the buyer. While purely perceptual measures are based on impressions and experiences, quasi-perceptual measures also have an underlying operational component embedded in them. A concrete example of a measure with perceptual components that has been considered in auctions by ChileCompra is the quality attribute called “supplier experience”, that reduces scores for inexperienced, non-incumbent suppliers: Previous
experience and incumbency can both be measured in objective scales, but usually when a supplier’s performance is evaluated, a relative measure of the disutility generated by sourcing from a non-incumbent supplier respect to other non-incumbents becomes a perceptual measure. In general, the consideration of quality attributes with perceptual components in governmental procurement auctions is problematic, due to the impression of impropriety that they generate in a process for which one of the goals is precisely transparency.

Critical to our problem is the effect of the presence of perceptual components in quality measures from a modeling perspective. When a perceptual measure in a sealed-bid multi-dimensional bidding auction does not provide a universally understandable metric for the attribute it quantifies, the use of perceptual or quasi-perceptual measures is equivalent to the sealed-bid multi-dimensional beauty-contest auction we study here.

As an example, consider sealed bids \( (p,q) \) on price and quality, and set a scoring rule to rank bids: \( S(p,q) = a q - p \), with \( a > 0 \) known only to the buyer and unknown to the bidders. All that a bidder knows in this case is that \( S \) is increasing in \( q \) and decreasing in \( p \). If the scoring rule was instead \( S(p,q) = a w(q) - p \), with \( a > 0 \) common knowledge to buyer and all suppliers, but with \( w(.) \) unknown to the supplier except for \( w'(.) > 0 \), then both scoring rules are analogous in terms of their lack of transparency. The former case is what we called a sealed-bid multi-dimensional beauty-contest, whereas the latter case is an instance of a quality attribute quantified as a perceptual measure, even if the scoring weight for quality is known.

4. Environment

Consider a buyer that seeks to procure an indivisible good (or service) for which there are \( N \) potential suppliers or bidders. Bidders, indexed by \( j \), know the number of competitors they face, \( N - 1 \), before placing a bid. The good is characterized by its price, \( p \), and quality attributes \( Q \equiv (q_i)_{i=1}^k \) that can be contractually enforced. The buyer values the good according to quasi-linear preferences:

\[
\Pi_B(p,Q) = V(Q) - p = \Sigma_{i=1}^k u_i(q_i) - p
\]
where $u_i > 0$ are attribute-related constants, and the functions $w_i(q_i)$ are assumed twice continuously differentiable, concave, and increasing in the $i$-th attribute. Hence, the buyer has increasing preferences in each quality dimension. Bidder $j$’s profit from selling good $(p, Q)$ —i.e., conditional on winning the contract— consists in the quoted price $p$ minus the production cost $C$:

$$\Pi_j(Z_j, p, Q) = p - C(Z_j, Q)$$

(2)

where $Z_j = (z_{ij})_{i=1}^k$ is a vector of random variables representing bidder $j$’s production efficiency types.

In order to model the cost function $C(Z_j, Q)$, we follow an empirical strategy conceptually analogous to Lewis and Bajari (2011) (henceforth, LB) to model supplier’s production costs in A+B highway construction auctions in California. The one quality dimension considered in their study was the acceleration time to fulfill a contracted construction or repair work. Their single-dimensional quality analysis is generalizable to $k \geq 1$ quality dimensions. As LB did, we structured supplier cost as the sum of a quality-independent baseline cost and a quality-dependent cost structure:

$$C(Z_j, Q) = F + \sum_{i=1}^k \frac{q_i}{(1+\alpha)z_{ij}}$$

(3)

We assumed the baseline cost parameter $F \geq 0$ to be a deterministic, non-sunk, fixed cost incurred only if the auction is won and the good is sold; it is identical and known by all bidders. This baseline cost is to be interpreted as the cost of completing a project at the minimal acceptable quality level\(^7\). We made this baseline cost common to all bidders when they win an auction. We imposed this assumption because we wanted to avoid ex-ante asymmetry among bidders, with bidder favoritism being a different issue to what we aim to address here.

As for the quality-dependent portion of the cost structure, this specification yields a marginal cost (i.e., supply) function for quality dimension $i$ given by $C_{q_i}(Z_j, Q) = q_i^\alpha / z_{ij}$, which

\(^7\) For LB, since their quality dimension is acceleration (completion time savings) baseline cost is interpreted as completing the project on the original design engineer’s schedule.
implies a constant elasticity of supply for quality, $1/\alpha$. This flexible specification allows for a convex ($\alpha > 1$), concave ($\alpha < 1$) or linear ($\alpha = 1$) marginal cost for quality. While LB estimated $1/\alpha$ to be around 0.3 for California highway contractors, different industries and markets will have different elasticities for quality. In the product quality literature in operations management, for instance, total cost has been usually assumed quadratic in quality (e.g., Karmarkar and Pitbladdo 1997, Karaer et al. 2015). This implies in our context an elasticity of supply for quality equal to one, which provides considerable computational advantages without sacrificing the real world characteristics of the problem. Hence, we parameterized that elasticity to $1/\alpha = 1$ throughout this paper.

Social welfare, the sum of buyer and suppliers benefits, becomes $V(Q) - C(Z_j, Q)$. For simplicity, we have assumed costs to be independent across attributes, $V - C$ to be bounded, and $(V_{QQ} - C_{QQ})$ to be negative semi-definite. These mild regularity assumptions, based on existing literature (see AC), and satisfied by the experimental design presented in the next section, guarantee that social welfare $V - C$ is bounded and strictly concave in $Q$, and, hence, $Q^*(Z_j) = \arg\max_Q\{V(Q) - C(Z_j, Q)\}$, the social first best level of quality attributes achievable by each $j$, is well defined and unique. Bidder’s preferences are common knowledge, but bidders’ types $Z_j$ are private information: each bidder knows the realization of their own efficiency type, and knows the distributions from which each of their competitors’ types are (independently) drawn. This is an important assumption: If bidders know their own cost realization, it is rationally impossible for any of them to bid below cost, precluding the possibility of the phenomenon known as winner’s curse. We explicitly preclude that possibility with this independent private values (costs) structure, because otherwise, it would add an additional level of complexity to the bidders’ decisions.

We also assume that efficiency types are random variables defined on a strictly positive closed and bounded support:

$$z_{ij} \in [\beta^L_i, \beta^U_i], \quad 0 < \beta^L_i < \beta^U_i$$ (4)

In this context, we analyze two sealed-bid scenarios. The first scenario is a transparent score auction, where the assignment criterion is communicated to all suppliers before the start of the sealed-bid first-score auction. We compare it then to a second scenario identical
to the first except for the fact that suppliers do not know the weights given by the buyer to each attribute before submitting their bids.

**Scenario 1: Sealed-bid Transparent Scores Auction** (TS). A score auction is a multi-attribute auction where bids \((p, Q)\) are evaluated according to a pre-specified scoring rule, \(S(p, Q)\), to which the buyer commits (and communicates) before the auction takes place. Che (1993) introduced this mechanism and first characterized its equilibrium solution. AC offered a didactic and general characterization of its optimal bids and outcomes.

We assume the scoring rule in the auction is a linear function, i.e.: \(S(p, Q) \equiv A(Q) - p = A'Q - p\). Linearity has been observed in the practical implementation of scoring mechanisms used by governmental agencies (e.g., Lewis and Bajari 2011; Bajari et al. 2014; Snir and Gupta 2011), so this assumption is not restrictive in practice.

In principle, it is not clear whether this rule is used as a translation of the buyer’s preferences, because of its simplicity, or for other considerations. Some studies (e.g., Kersten 2014) have questioned how well scoring rules which are monotone in the individual dimensions of the bids, reflect actual preferences for quality. In spite of those potential concerns, we assume that the quality portion of the rule is a measure of the buyer’s preferences for quality: For every possible value of \(Q\), \(V(Q) \equiv A'Q\). This is a reasonable assumption in practice. The data analyzed by LB comprised many A+B bidding auctions that considered price and completion time for highway infrastructure repairs. In those cases, the score weights given to completion times were calculated by expert engineers on behalf of the California Department of Transportation as measures of the social daily cost of closure to the public for the piece of infrastructure that needed to be repaired. This preference structure also satisfies the assumptions on boundedness and strict concavity of \(V - C\) presented as part of the model environment presented before. Thus, while ensuring participation of all bidders in equilibrium, \(A'Q - C(Z, Q)\) is effectively bounded, strictly concave in \(Q\) for all \(Z\), and such that \(\max_Q [A'Q - C(Z, Q)] \geq 0\) for all \(Z\).

The outcome of the score auction is a probability of winning, \(x_j\), and a score to fulfill when the bidder wins the contract, \(s_j\). A winning bidder of type \(Z_j\) with score \(s_j\) will choose \((p, Q)\) to maximize profit \(p - C(Z_j, Q)\) subject to \(s_j = A'Q - p\). Substituting the constraint in the objective function yields:
\[
\max_Q \{ A'Q - C(Z_j, Q) - s_j \} \quad (5)
\]

From observing (5), the optimal \( Q \) does not depend on \( s_j \). Following AC and others in the multi-attribute auctions literature, we define a value function called \textit{pseudo-type}, \( v(Z_j) \), the maximum social welfare a bidder of type \( Z_j \) can generate given the scoring rule:

\[
v(Z_j) \equiv \max_Q \{ A'Q - C(Z_j, Q) \} = \max_Q \left\{ \sum_{i=1}^{k} \left( a_i q_i - \frac{q_i^2}{x_{zij}} \right) - F \right\} \quad (6)
\]

The quality choice that maximizes (5) is the same that maximizes (6). Solving for the optimal \( Q \) yields an optimal quality-dimension bid and a corresponding pseudo-type.

\[
q_i^* = a_i z_{ij} \quad (7)
\]

\[
v(Z_j) = \frac{1}{2} \left( \sum_{i=1}^{k} a_i^2 z_{ij} \right) - F \quad (8)
\]

Expected profit for bidder \( j \) is given by:

\[
\text{E} \Pi_j = x_j \cdot (v(Z_j) - s_j) \quad (9)
\]

The above expression is mathematically equivalent to a sealed-bid first-price auction with pseudo-types functioning as private valuations, and scores taking the role of prices. Therefore, bidders’ preferences over outcomes \( (x_j, s_j) \) are fully captured by \( v(Z_j) \). Indeed, as AC show, pseudo-types are \textit{sufficient statistics} for this auction mechanism: Once we have the distribution of pseudo-types, we have a complete characterization of the score auction and its outcome.

Given our assumption on the support of efficiency types in expression (4) and the optimal quality bidding described above, the distribution of pseudo-types is defined in the support given by expression (10):

\[
v_j \equiv v(Z_j) \in \left[ \frac{1}{2} \left( \sum_{i=1}^{k} a_i^2 \beta_i^l \right) - F, \frac{1}{2} \left( \sum_{i=1}^{k} a_i^2 \beta_i^U \right) - F \right] \quad (10)
\]
Next, we solve for the optimal price portion of the bid. Let \( b(.) \) be a monotone bidding function mapping pseudo-types \( u_j = v(Z_j) \) onto submitted scores \( s_j = S(p_j, Q_j) \) in equilibrium. Generalizing Riley and Samuelson (1981), the symmetric Bayesian-Nash equilibrium (SBNE) score bid \( b(u_j) \) will satisfy differential equation (11) at optimality:

\[
1 = (v_j - b(u_j))(N - 1) \frac{x_{uv}(v_j)}{x_{uv}(v_j)} \frac{1}{b'(u_j)}
\]  

(11)

This differential equation fully characterizes the optimal bid strategy function, \( b(u_j) \). As can be appreciated, this will depend on the resulting distribution of pseudo-types induced by the bidders’ efficiency types, as well as the number of bidders.

In our characterization of this scenario, we have specified a particular case of the sealed-bid transparent scores model that incorporates a cost structure for quality analogous to the total quality cost structure described by LB, which in turn allows to identify optimal bids not only at the pseudo-type and score level (given by (11)), but also at the individual quality attributes level (given by (7)), and consequently, by difference, at the price level. Whereas the experimental work by Engelbrecht-Wiggans et al. (2007) considered price and quality in sealed-bid procurement auctions, our setting allows us to enrich their single-dimensional decision scenarios that considered supplier’s quality to be fully exogenous, to a multi-dimensional decision setting that better describes the governmental procurement environment that concerns us.

Naturally, solving for this differential equation is a complex task, even in the case where the closed-form analytical solution policy is relatively straightforward to compute (we test in the laboratory one such instance as shown in the next two sections), and even under the assumption that bidders know their own cost structure (i.e., under the private values paradigm). In particular, bidding behavior will differ from the SBNE score bid defined above by chosen quality levels, price levels, and optimal score levels. Consequently, we expect to observe lower bidder profit levels than predicted. Note that, in order to use a uniform language, whenever we observe deviations in behavior that translate into more aggressive bids (i.e., with smaller bidder profit margins) than suggested by the SBNE predictions will be called overbidding, and deviations that translate into less aggressive bids will be called underbidding.
**Scenario 2: Multi-dimensional Beauty-contest Auction** (MDBC). For this scenario, consider the case where the transparent scoring rule is forfeited in favor of a hidden rule. In practice, we implement the same rule as the preceding sealed-bid score auction scenario 1, where bidders submit sealed bids for prices and quality levels, and the winner is determined according to this rule. The only difference is that the weights used to implement the scoring rule are now undisclosed to the bidders.

As discussed in section 2, a mathematically equivalent way to conceal the scoring rule arises from not communicating clearly the metric upon which the quality characteristics will be scaled or measured – using what in the language of Ketokivi and Schroeder (2004) would be classified as (quasi-)perceptual measures of performance. In this case, bidders still make bidding decisions on prices as well as (their controllable driver to the buyer’s perception of) quality. However, even in cases when they are provided the weights given by the scoring rule, they are not informed about how the magnitude of increments in the latter dimensions affect their scores, and their subsequent likelihood of winning.

We use the name *multi-dimensional beauty-contest* for this mechanism, because suppliers choose for their sealed bids the levels of quality and price which maximize their expected utility given their guess on the buyer's subjective preference for quality. Considering that the buyer is a governmental agency whose interest is also to maximize welfare at a society level (making society's preferences their own), in a sense, suppliers are trying to “guess”/estimate on those social welfare terms at large. The name “beauty-contest” is inspired by the comment made by Lord Keynes regarding beauty pageants: Any judge whose performance is evaluated on the quality of his/her own choice for the contest, needs to choose a winner not based on his or her own beauty preferences, but on what his or her own perception of what the general public would consider the most desirable beauty features. Unlike beauty-contests in the traditional game theoretical sense (i.e., a “majority rule”, where decision makers try to guess as close as possible to \(x\%) of the average decision maker’s guess), for the mechanism described here, decisions of suppliers do not have any power to influence the value of the buyer’s preference for quality, at least for that particular auction event. This makes the beliefs formation process for a supplier impossible to determine without additional simplifying assumptions.

Starting with Chen-Ritzo et al. (2005), existing studies have derived bidding strategies for open-progressing MDBC-like mechanism environments, where the buyer’s preference for quality is implicitly revealed via the relative ranking displayed through the auction’s
progress. The open-progressing environment, more common in industrial procurement auctions than in governmental purchasing events, is the key driver of their analytical results.

In contrast, for the sealed-bid case we study here, the equilibrium bid is undetermined without assuming a prior (belief structure) on the buyer’s concealed preferences, or without reducing the dimensionality of the problem. For instance, similar sealed-bid multi-attribute mechanisms were considered by Kostamis et al. (2006, 2009). In that study, quality is not a decision variable for suppliers, but the buyer’s private information about a supplier’s desirability. That model is a tool of mechanism selection for pre-determined supplier discrimination, while here each supplier can still affect their own desirability to the buyer through their own quality-level decisions, i.e., quality is endogenously determined.

In scenario 2, bidders only learn what the winning price and quality levels were after the auction, and who the winner was, but are completely uninformed in terms of what was the actual score implied by that winning bid. The difference in mechanism performance between scenario 2 and scenario 1 is our metric for the cost of transparency loss. To measure social welfare, since price is a transfer variable, we can subtract the winner’s costs from the buyer’s quality preference in every auction. Social welfare is, thus, similar to the pseudo-type defined in (6), with the difference that the pseudo-type maximizes social welfare, whereas the actual winner’s quality bid will most likely not yield that maximum. Thus, we can test the following research hypothesis:

**HYPOTHESIS 1:** In the (sealed-bid) multi-dimensional beauty-contest auction (scenario 2), we expect to observe lower buyer’s surplus and social welfare per auction, when compared to the sealed-bid transparent scores auction (scenario 1).

5. **Empirical Procedure and Design**

For our experiments, we consider two treatments, each representing one of the two auction scenarios described in our modeling environment. The streams of parameters and random production efficiency factors are the same for all treatments (although the efficiency factors are re-drawn after every period, every auction will have the same $N$ draws within a given round). Half of the participants is assigned to each treatment. We use a between-subjects design.
Subjects are matched in groups of \( N = 4 \) bidders for 40 rounds. Subjects do not know the identity of the bidder against whom they are competing, as they are rematched in every round to different competitors in the room. Subjects are not allowed to participate in more than one session or more than one treatment. They are compensated according to their performance in terms of profits.

**Experimental parameterization.** As discussed earlier, submitting a multi-dimensional bid is a complex task, even when the scoring rule is known. In our experiments we consider bi-dimensional bids, in price \( p \) and one quality dimension \( q \), meaning that all \( i \)-indices can be dropped. We also consider the efficiency type \( z_j \) to be uniformly distributed between \( \beta^L = 10 \) and \( \beta^U = 90 \), elasticity of supply for quality \( 1/\alpha \) to be equal to unity, and the baseline cost \( F \) to be equal to 500. We also fixed the parameter measuring preference for quality to \( a = 10 \). The goal with this set of parameters was to provide bidders a simple enough numerical setup that still captured the real-world features of the problem.

For the TS auction, with this parameterization, the bid constituting an SBNE in pure strategies (in terms of quality \( q^*_j \) and price \( p^*_j \)) reduces to expression (12) below:

\[
q^*_j = az_j = 10z_j \\
v_j = \frac{1}{2}a^2z_j - F = 50z_j - 500 \sim U[0, 4000] \\
s^*_j = b(v_j) = \frac{v_j (N - 1)}{N} = 37.5z_j - 375 \\
\Rightarrow p^*_j = aq^*_j - s^*_j = 62.5z_j + 375
\]

Here, (12) is a relatively simple closed-form expression. In terms of scores, optimal bidding shading suggests that the SBNE scoring bid for the TS case with these parameters should be \((N - 1)/N = 75\% \) of the bidder’s pseudo-type \( v_j \).

Remember that for the MDBC auction, an expression analogous to (12) is not well defined, because bidders are fully uninformed of the value of the quality weight parameter \( a \), which is, by mechanism definition, private information of the buyer.

Also, keep in mind we have defined the \( a \) parameter as **both** a measure of the true preference of the buyer with respect to quality and the weight used by the buyer in determining the winner of the auction, regardless of whether this value is communicated (TS
auction) or not (MDBC auction). As such, the winning score bid is also the buyer’s surplus in both treatments. Therefore, for welfare comparisons, we maintained parallelism by keeping everything the same in both auctions aside from revealing or concealing the numerical value of the quality weight parameter, and we kept that parameter constant throughout the experiment.

Protocol. Each subject was compensated in proportion to their total earnings for all 40 rounds, plus a $5 participation fee. $JT_S = 24$ subjects participated in the transparent scores (TS) treatment session, and other $JM_DBC = 24$ participated in the multi-dimensional beauty-contest (MDBC) treatment session. The average pay was $13.48, and each subject only participated in one session. Payment took place in private at the end of the session; cash was the only incentive offered. All sessions were conducted at a major public U.S. research university, using the subject pool associated with the business school. Subjects privately read the printed instructions (see Appendix B). After this, the experimenter read the same instructions out loud and presented screen captures as examples. 10 minutes were used for reading instructions and answering questions, and 80 minutes were used for the actual task.

We programmed the experimental interface using the zTree system (Fischbacher 2007). The bidding screen (see Appendix B) included the realization of efficiency type $z_j$ as well as the parameters for fixed cost $F = 500$ and weight $a = 10$ (the latter only displayed during the TS treatment). It also included a table that showed all relevant information from past periods (own offered price and quality, winning price and quality, profits, etc.). The cost function and scoring function equations were provided in the printed instructions and the bidding screen.

Because the decision task is computationally involved, we provided subjects with a simulator that calculated costs and earnings using the efficiency type and the choices of price and quality as inputs. This simulator precluded bidders from making mistakes related to submitting bids that generated negative supplier profits. We did not provide calculations for the actual scores in the TS treatments, to avoid giving bidders in that case an special advantage over MDBC participants aside from knowing the value of $a$. After all four bidders in an auction submitted their offers, each saw a results screen showing if they had won or not, their own offered price and quality, the auction’s winning price and quality, their profits, and a table with their past history of play. Subjects did not know the identity of their
competitors in any round, and were aware they were rematched every round with different people in the room.

6. Results

In this section, we measure differences in both bidding behavior and mechanism performance. We compared the outcomes of the TS and the MDBC auctions, and also compared the outcomes of the TS auction with its SBNE predictions.

**Bidding behavior.** Tables 6 and 7 offer a summary of bidding behavior and outcomes per subject. While the main goal of this subsection is to verify deviations of the TS auction from the theoretical predictions, we have summarized both mechanisms/treatments, for each of the 48 participants, averaged over all 40 auctions. The variables presented are number of wins ($\#w$), qualities ($q$), prices ($p$), scores ($s$), profits ($\Pi$) and private types ($z$), with upper bars denoting averages over all 40 periods and the asterisks indicating predicted behavior, measured as the decisions that a decision-maker would have made if pre-programmed to make SBNE decisions knowing its own efficiency type $\hat{z}_j$ and the scoring rule.

For Table 7, note that the predicted averages do not correspond to the MDBC mechanism, but to the TS case, and are included here only as a reference point, given that participants would have needed the actual scoring rule to be able to realize those predicted decisions were optimal. Note also that both sets of predicted behaviors in each of the treatments do not perfectly coincide, because, in order to control that every round and every auction had the same four random realizations (crucial for the welfare analyses that will follow later), and that at the same time, people would be randomly rematched every period. For every person, the stream of realizations depended on which “role” they had in the auction (i.e., what order statistic in terms of efficiency types they had been assigned to in every period), and that role assignment was fully randomized during the session.

We contrast the bidding outcomes for the two treatments using the data from Tables 6 and 7 together. Using Mann-Whitney’s unmatched samples tests, we find that average quality levels ($z_{M-W} = -0.753, p = 45.17\%$) and equivalent scores ($z_{M-W} = 1.278, p = 20.11\%$) are not statistically different in the two treatments, while average prices ($z_{M-W} = -2.062, p = 3.92\%$) and profits ($z_{M-W} = -2.165, p = 3.04\%$) were higher in the MDBC
condition. The higher average profits per bidder were driven by the higher price bids in general observed in MD BC8.

In TS, as expected, we observe deviations from the predicted SBNE outcomes. Observed average bidder profit is lower than predicted, but not significantly (Wilcoxon signed-rank test, $z_W = 0.857, p = 39.14\%$). Underbidding is observed, and statistically significant in terms of lower average scores ($z_W = 4.286, p < 0.01\%$), and higher average prices ($z_W = -3.629, p = 0.03\%$). Lower-than-predicted average quality bids were observed as well, but they were statistically insignificant ($z_W = 0.171, p = 86.39\%$).

Table 6: Average bidder behavior and outcome (actual vs. predicted), Sealed-bid Transparent Scores. (Unit of analysis: $J_{TS} = 24$ bidders, each averaged over 40 auctions)

<table>
<thead>
<tr>
<th>$j$</th>
<th>$#w_j$</th>
<th>$\bar{q}_j$</th>
<th>$\bar{p}_j$</th>
<th>$\bar{\pi}_j$</th>
<th>$\bar{\pi}_j$</th>
<th>$\bar{\pi}_j$</th>
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<tr>
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<td>237.6</td>
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<td></td>
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<tr>
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<td>4504.7</td>
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<td>188.4</td>
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<td></td>
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Mean: 478.9 4416.3 372.9 173.4
SD: 133.5 988.2 841.2 114.2

8 Tables 6 and 7 show that five subjects in the TS treatment and one in the MDBC treatment obtained an average profit smaller than two standard deviations below the theoretical prediction. However, their omission from the sample would not change qualitatively these results.
Table 7: Average bidder behavior and outcome (actual vs. TS predicted), Multi-dimensional Beauty-contest.

(Unit of analysis: $J_{MDBC} = 24$ bidders, each averaged over 40 auctions)

<table>
<thead>
<tr>
<th>Actual subjects behavior</th>
<th>Predicted behavior for TS</th>
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<tr>
<td>$j$</td>
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<tr>
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<tr>
<td>Mean</td>
<td>509.1</td>
</tr>
<tr>
<td>SD</td>
<td>113.1</td>
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</table>

These results indicate a lower level of competitiveness than the SBNE predicted for the TS scenario. This outcome has some degree of parallelism in the implicit collusion outcome observed in the price-and-quality open-progressing auction studied by Fugger et al (2014). In their case, the buyer had a private random signal for quality for each supplier, unknown to all suppliers, including the bearer of the signal, which leads to a steep increase in prices due to the uncertainty in the quality component assigned by the buyer, similarly to our case here. In their case, however, collusion was characterized by a pegging-to-the-reserve-price behavior (what they identified as implicit collusion), which in our case is not observed due to the fact
Table 8: Average auction performance per treatment.
(Unit of analysis: $T = 40$ rounds, each averaged over 6 parallel auctions per treatment)

<table>
<thead>
<tr>
<th>Avg. by auction</th>
<th>Buyer's surplus</th>
<th>Winner profit</th>
<th>Social welfare</th>
<th>Quality</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>1842.65</td>
<td>693.74</td>
<td>2536.39</td>
<td>657.38</td>
<td>4731.14</td>
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<tr>
<td><strong>Std. Deviation</strong></td>
<td>484.24</td>
<td>253.64</td>
<td>564.29</td>
<td>145.55</td>
<td>1084.11</td>
</tr>
<tr>
<td><strong>Min</strong></td>
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<td>1305.08</td>
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<td><strong>Max</strong></td>
<td>2658.33</td>
<td>1499.42</td>
<td>3709.59</td>
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<table>
<thead>
<tr>
<th>Avg. by auction</th>
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<th>Winner profit</th>
<th>Social welfare</th>
<th>Quality</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
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<td>459.84</td>
<td>2584.83</td>
<td>666.66</td>
<td>4541.64</td>
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<tr>
<td><strong>Std. Deviation</strong></td>
<td>350.19</td>
<td>191.90</td>
<td>492.34</td>
<td>93.38</td>
<td>583.64</td>
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<td><strong>Min</strong></td>
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<td><strong>Max</strong></td>
<td>2854.50</td>
<td>951.50</td>
<td>3806.00</td>
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<td>5757.50</td>
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<table>
<thead>
<tr>
<th>Avg. by auction</th>
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<th>Winner profit</th>
<th>Social welfare</th>
<th>Quality</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>1614.65</td>
<td>229.98</td>
<td>1844.62</td>
<td>509.06</td>
<td>4915.47</td>
</tr>
<tr>
<td><strong>Std. Deviation</strong></td>
<td>526.29</td>
<td>51.62</td>
<td>529.00</td>
<td>105.46</td>
<td>642.33</td>
</tr>
<tr>
<td><strong>Min</strong></td>
<td>383.33</td>
<td>124.75</td>
<td>579.53</td>
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<td>3364.58</td>
</tr>
<tr>
<td><strong>Max</strong></td>
<td>2376.83</td>
<td>351.86</td>
<td>2612.05</td>
<td>703.38</td>
<td>6010.96</td>
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<table>
<thead>
<tr>
<th>Avg. by auction</th>
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<th>Winner profit</th>
<th>Social welfare</th>
<th>Quality</th>
<th>Price</th>
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</thead>
<tbody>
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<td><strong>Mean</strong></td>
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<td>193.88</td>
<td>1683.44</td>
<td>497.22</td>
<td>3482.61</td>
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<td>249.94</td>
<td>2565.69</td>
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</table>

<table>
<thead>
<tr>
<th>Avg. by auction</th>
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<th>Winner profit</th>
<th>Social welfare</th>
<th>Quality</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>2091.97</td>
<td>697.32</td>
<td>2789.29</td>
<td>657.86</td>
<td>4486.61</td>
</tr>
<tr>
<td><strong>Std. Deviation</strong></td>
<td>497.66</td>
<td>165.89</td>
<td>663.55</td>
<td>132.71</td>
<td>829.43</td>
</tr>
<tr>
<td><strong>Min</strong></td>
<td>713.25</td>
<td>237.75</td>
<td>951.00</td>
<td>290.20</td>
<td>2188.75</td>
</tr>
<tr>
<td><strong>Max</strong></td>
<td>2973.75</td>
<td>991.25</td>
<td>3965.00</td>
<td>893.00</td>
<td>5956.25</td>
</tr>
</tbody>
</table>

Notes:
i. The lower section “Theoretical Pred. (Expected winner)” refers to the performance of the winners if all bidders had played according to the SBNE strategy and had known the scoring rule.

ii. The sections corresponding to “Pred. for Winner” summarize the predicted performance that the actual winners would have achieved if they had played the SBNE transparent score strategy and had won, regardless of whether they were the predicted winners or not.
Figure 8: Cumulative Distributions for Mechanism performance metrics.
(□: Theoretical benchmark for TS; ▲: Actual TS; ○: Actual MDBC)
that bidders in our experiments still had control over their quality portion of the score through their own quality decisions, since they were informed that scores were increasing in quality in both of our treatments.

**Mechanism performance and welfare.** Now we move our attention to the mechanism performance in both treatments. This is the key comparison of this paper. We kept the same type realizations fixed by auction (round), so we can average the outcomes of each of our six observations per auction for each treatment. Those averages are reported in Table 8.

The results of Table 8 show the average groups results per each of the 40 auctions. We also observed 58.75% of efficient assignments in the TS treatment and 60.83% in the MDBC treatment using each individual auction round as the unit of analysis. This means that in approximately 2 out of 5 auctions we observed winners who should not have won. That inefficiency in the actual assignment drives the difference in Table 8 between the panels devoted to Pred. for Winner (which consists of the expected-profit-maximizing performance for the winner, regardless of whether said winner was the true expected winner or not) and the Theoretical Pred. (Expected Winner) panel (devoted to the expected-profit-maximizing measures for the predicted winner in the TS case, who would have been the efficient supplier). 9

Buyer’s surplus in the TS auctions was significantly larger (Wilcoxon signed-rank test \( z_W = 3.844, p = 0.01 \)) than in the MDBC auctions. Winner’s profits were also larger \((z_W = 5.511, p < 0.01)\), whereas Social welfare, measured as the sum the two, was consequently larger as well \((z_W = 5.484, p < 0.01)\). Winning quality was significantly higher in the TS case than in the MDBC scenario \((z_W = 5.390, p < 0.01)\), while winning prices were directionally lower but not statistically different \((z_W = -1.116, p = 26.46\%\)).

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9 In specific, for the TS case, we observe (Wilcoxon signed-rank test results available upon request) that the difference between the predicted social welfare and the actual social welfare is driven by inefficiency in the assignment of the contract rather than suboptimal bidding behavior by the actual winner, whereas the difference in buyer’s surplus is driven by suboptimal bidding behavior of the actual winner rather than the inefficiency in the assignment to a different winner than the predicted best supplier; for the winner’s profit, we observe that the deviation from optimality and the inefficiency in assignment both have an statistically significant effect. Since buyer’s surplus is equivalent to the score offered by the winner in the auction, this smaller-than-predicted surplus is equivalent to the score underbidding result we encountered in the previous subsection.
Since our metrics are random variables, we also compared whether the distributions of all three main performance metrics differ or not. Figure 8 shows plots of cumulative distributions between the theoretical prediction for the TS auction (□), the empirically observed TS auction (▲), and the empirically observed MDBC auction (○). We observe that, in our experiments, TS first-order stochastically dominated MDBC in both buyer’s surplus and social welfare, while we do not observe such dominance in the winner’s profit. All are first-order stochastically dominated by the TS theoretical prediction.

Combining both sets of results, we can make some important conclusions. We observe that for the buyer, especially one such as a governmental agency who cares about both their auction surplus as well as social welfare, not disclosing the scoring rule was highly detrimental. This result is the main contribution of this paper. We were able to assess that concealing the scoring rule in a multi-dimensional sealed-bid first score procurement auction significantly lowers social welfare, buyer’s surplus, and winning supplier’s profits. Transparency loss, as ChileCompra’s executives inquired, creates a tremendously negative social impact, making the non-transparent auction a strictly worse mechanism in the multi-dimensional sealed-bid first-offer context under study here.

7. Discussion and Conclusions

In this study we compared the performance of two similar multi-dimensional sealed-bid procurement auction mechanisms, one considering transparent rules, and another concealing said rules. As we verified with our experiment, the effect of transparency loss, even in the case of the simple uncertainty of the size of the rule coefficient, is statistically significant and substantial in magnitude.

The policy implication is that any social or political pressures towards relaxing the transparency requirements by ChileCompra can lead to the destruction of the institutional advances achieved by the agency in the past 13 years. At least based on our laboratory results, we recommend in favor of transparency rules and against non-transparent assignment criteria. Our advice is, whenever a scoring rule is used, that (a) the weights for each of the attributes are communicated, and that (b) the measurement scale for attributes are clearly explained, specified and measurable. This is important, because communicating a scoring rule without clearly providing a universal measuring scale for the quality attributes being evaluated is analogous, in terms of lack of transparency, to concealing the weights
constituting the scoring rule. **Our results provide clear evidence of the pervasiveness of these non-transparent practices.**

A particularly important, but non-trivial extension to our research, would arise from changing the auction valuation paradigm from independent private values to common values. In the common values framework, bidders only receive a signal that is correlated with their (common and unknown) cost structure realization, not the cost realization itself. That opens the door to the presence of the winner’s curse, through lack of information for a bidder about her/his own true cost structure until after winning the contract. Note that this should increase the detrimental effects we found on social welfare due to the lack of transparency, since winner’s profits would now be expected to be reduced, while buyer’s surplus would also need to be adjusted downwards due to the need to allow for supplier default in the case of negative profits.

8. References


Appendices

Appendix A: Experimental Materials for Chapter 1

The instructions that follow were distributed to the participants and reviewed in a presentation before each session. For some conditions, these instructions were modified to reflect differences in experimental conditions, including possible changing demand support.

**Participant Instructions (example)**

You are about to participate in an experiment in the economics of decision-making. If you follow these instructions carefully and make good decisions, you will earn money that will be paid to you in cash at the end of the session. If you have a question at any time, please raise your hand and the experimenter will answer it. We ask that you not talk with one another for the duration of the experiment.

The experiment consists of 80 periods. The unit of exchange in all the transactions is called token. At the end of the session, your earnings in tokens will be converted to US dollars at a pre-specified rate, and paid to you in cash.

In this experiment, you will be in the role of a retailer in two separate markets. In each market you will be matched with a different computerized competitor.

**Overview of the Game**

Your task will be to decide how many units of inventory to order before you know what the customer demand will be. This decision is called Your Order. In both markets, each unit you order costs you 1 token, and you make money by selling units for 3 tokens. Unsold units are worth nothing to you. The following describes the demand in each market, the primary Selling Season and secondary sales in the Post-Season.

You will participate in two markets, Market A and Market B. In each market, you will be matched with a computerized competitor for 80 rounds. Each computerized competitor has been pre-programmed to place orders. Customer demand for you and the computerized competitor will be randomly distributed between 1 and 100 units, with each number of units in that range being equally likely. In each market, you and your competitor will have different demands. If your demand is high or low, it will have no effect on the computerized competitor’s demand number being high or low.

Each period starts with the Selling Season, in which you and the computerized competitor simultaneously place your respective Orders, without knowing your respective Demands. The outcomes of each period are determined as follows:

If your Order is equal to or greater than your Demand then:

- **Your Profit** = 3 × Demand (Revenue) − 1 × Order (Cost)
- **Sales** = Demand
- **Extra Units** = Order − Demand
- **Unfilled Demand** = 0

For example, if you order 100 units and the demand is 50 units then:

- **Your Profit** = 3 × 50 − 1 × 100 = 50
- **Sales** = 50
- **Extra Units** = 100 − 50 = 50 units
- **Unfilled Demand** = 0 units

If your Order is less than your Demand then:

- **Your Profit** = 3 × Order (Revenue) − 1 × Order (Cost)
- **Sales** = Order
Extra Units = 0
Unfilled Demand = Demand – Order
For example, if you order 10 units and the demand is 50 units then:
Your Profit = 3 × 10 – 1 × 10 = 20
Sales = 10
Extra Units = 0 units
Unfilled Demand = 50 – 10 = 40 units

There is also an opportunity for Post-Season Sales:
If you have Extra Units and the computerized competitor has Unfilled Demand then the computerized competitor’s additional Post-Season Revenue will be 0, but you will make additional Post-Season Revenue = 3 × Your Post-Season Sales. Your Post-Season Sales are determined as follows:

If your Extra Units is equal to or greater than the computerized competitor’s Unfilled Demand then:
Your Post-Season Sales = The Computerized Competitor’s Unfilled Demand

If your Extra Units is less than the computerized competitor’s Unfilled Demand then:
Your Post-Season Sales = Your Extra Units

For example, if during the selling season you ordered 80 and the computerized competitor ordered 55, your Demand was 40 and computerized competitor’s Demand was 100 then:
Your have Extra Units of 80–40 = 40.
The computerized competitor has Unfilled Demand of 100–55 = 45.
Your Post-Season Sales are 40 and your Post-Season Revenue = 3 × 40 = 120.
The computerized competitor’s Post-Season Revenue is 0.

Suppose the computerized competitor ordered 85 instead of 55 (all other numbers are the same). Then:
You have Extra Units of 80 – 40 = 40.
The computerized competitor has Unfilled Demand of 100-85 = 15.
Your Post-Season Sales are 15 and your Post-Season Revenue = 3 × 15 = 45.
The computerized competitor’s Post-Season Revenue is 0.

If you have Unfilled Demand and the computerized competitor has Extra Units then your Post-Season Revenue will be 0, but the computerized competitor will make Post-Season Revenue as described above.

If you and the computerized competitor either both have Unfilled Demand or both have Extra Units, then both of you will have the Post-Season Revenue of 0.

In each period, you will place orders for Market A and for Market B on the same screen. Computerized competitors in the two markets are programmed to place orders that may differ. After you place your orders for each market, you will see a screen that provides the results of the period, including:

Selling Season Results: your Order, customer Demand, Sales, Extra Units, Unfilled Demand.
Post-Season Results: the computerized competitor’s Unfilled Demand, your Post-Season Sales
Profit Results: Selling Season Revenue, Post-Season Revenue, Your Cost, Your Profit.

Additional Information you will see
You will always have access to information from all previous periods, including your order, demand, extra units, unfilled demand, and profit. You will also see a chart that tracks your own and your competitors’ past orders in Market A and B.
How You Will Be Paid

At the end of each period, the computer will determine at random whether you are paid your profit from Market A or from Market B (imagine that a fair coin is tossed every period). In other words, you will be paid for only one of the two markets in any given period.

At the end of the session your earnings from the 80 periods in the chosen market will be converted to US dollars at the rate of 650 tokens per $1. This amount in addition to the $5 participation fee will be paid to you in cash. All earnings are confidential.

Quiz

Please answer the following questions to make sure you understand the instructions.

1. Player X ordered 60 units. Demand was 40 units:
   Sales = __________________
   Extra Units = __________________
   Unfilled Demand = __________________
   X's Selling Season Profit = __________________

2. Player Y ordered 20 units. Demand was 90 units:
   Sales = __________________
   Extra Units = __________________
   Unfilled Demand = __________________
   Y's Selling Season Profit = __________________

3. Suppose Players X and Y are matched together in Part B. What is their Post-Season outcome?
   Player X Post-Season Sales = __________________
   Player X Post-Season Revenue = __________________
   Player Y Post-Season Sales = __________________
   Player Y Post-Season Revenue = __________________

4. Suppose your Extra Units are 0, your Unfilled Demand is 10 and the computerized competitor's Extra Units are 20.
   What is Your Post-Season Revenue? __________________
   What is the computerized competitor's Post-Season Revenue? __________________
Computer interface screenshots
This example is for treatment T3: NE-PI, with $\alpha = 1$; all others were similar

**Order Entry Screen:**

**Results Screen:**
Appendix B: Experimental Materials for Chapter 3

The instructions that follow were distributed to the participants and reviewed in a presentation before each session. Instructions for both conditions (TS vs. MDBC auction) were identical, except for one paragraph regarding the definition of “Buyer Quality Weighting” which varied from one treatment to the other as indicated below.

Participant Instructions

You are about to participate in an experiment in the economics of decision-making. If you follow these instructions carefully and make good decisions, you will earn money that will be paid to you in cash at the end of the session. If you have a question at any time, please raise your hand and the experimenter will come to your station and answer it. We ask that you not talk with one another for the duration of the experiment.

Government agencies or companies often ask suppliers to participate in a Procurement Auction by submitting a bid to supply equipment or construct a building, a bridge or a highway. These bids are often at a combination of price, quality and possibly other factors.

In this experiment, you will be in the role of a Supplier (Bidder) who participates in 40 Procurement Auctions, competing against three (3) human competitors (there are 4 suppliers in total). Your competitors are determined through a random match with other individuals in the room. You will be matched with different people in each round.

The session consists of 40 separate auction rounds, and you will submit a bid in each round. The unit of exchange in all the transactions is called experimental currency units (ECUs). At the end of the session, your earnings in ECUs will be converted to US dollars at a pre-specified rate, and paid to you in cash.

How you earn money

Each bid you make consists of (A) a money price you request in ECUs (“Your Price”), and (B) a quality level (“Your Chosen Quality”). The buyer has established a scoring rule to compare bids submitted by each supplier.

Supplier Score increases with Chosen Quality, and decreases with Price:

\[ \text{Supplier Score} = (\text{Buyer Quality Weighting} \times \text{Your Chosen Quality}) - \text{Your Price} \]

“Buyer Quality Weighting” represents the evaluation the buyer makes about the quality level offered by any supplier. It is a positive constant, known and common to all bidders. (TS only)

“Buyer Quality Weighting” represents the evaluation the buyer makes about the quality level offered by any supplier. It is a positive constant, unknown and common to all bidders. Only the Buyer knows their Quality Weighting and the Supplier Score. (MDBC only)

The highest score among all four competitors wins the contract (Any ties in supplier scores are broken at random). You earn money each time you win a contract at a good price and appropriate quality. If you win the contract:

\[ \text{Your Earnings} = \text{Your Price} - \text{Your Cost} \]

If you don’t win the contract, your profit, your earnings and your cost will be 0 regardless of your bid.

Only if you win the contract, you incur a production cost (“Your Cost”) to produce the good at Your Chosen Quality. This cost varies based on Your Efficiency and Fixed Costs:
Your Cost = \left(0.5 \times \frac{(Your \ Chosen \ Quality)^2}{Your \ Efficiency}\right) + Fixed \ Costs

You will see Your Efficiency before deciding how much to bid, but not the efficiency of any other competitor. For each bidder, the higher the efficiency, the cheaper it is to offer the chosen quality level. Your Efficiency will change from round to round; it is independent from your competitors' efficiencies, and is unrelated to your efficiency in any other auctions. Your Efficiency is a random number within the range $[10, 90]$, with all values in that range being equally likely.

Fixed Costs are the same and are known for all bidders before each auction, but are only incurred by the winner.

For each auction, enter a number for Your Price and another for Your Chosen Quality in the boxes on your computer screen, and then click the “Make Offer” button. For price decisions you can choose any number between 0 and above. For quality levels, you can choose any number from 0 and above. Your decisions can have up to two decimals.

With the above information, you will be able to calculate Your Cost and Your Earnings in each round in case you win. Our software has an embedded simulator you can use for this. Each bidder knows only their own cost, but not the cost of any other bidder.

Note: If a supplier bids his/her Price below his/her Cost, and wins the auction, he/she loses money. Therefore, carefully choose your price and quality. Hint: Use the Simulator tool for this purpose.

**Information you will see at the end of each auction**

At the end of each auction you will see the following information:
- Your own efficiency and bid (price and quality) in this auction.
- Your Cost (which will only be different from 0 if you win).
- The winning bid (price and quality).
- Your earnings from the auction.

You will also have access to this information for all past auctions.

**How you will be paid**

At the end of the session you will see the final screen summarizing your earnings for the session. This screen will calculate your net profits from the 40 auctions, convert them to US dollars at the rate of 1,100 ECU per $1, and add them to your $5 participation fee.

Please use this information to fill out your check-out form and wait quietly until the experimenter calls you to come to the front of the room and be paid your earnings in private and in cash. After you have been paid, you may leave the laboratory.
Computer interface screenshots
This example is for the MDBC treatment; the TS case was virtually identical (the term “UNKNOWN” was replaced by the number “10”).

**Bidding Entry Screen:**

![Bidding Entry Screen](image)

**Results Screen:**

![Results Screen](image)
Vitae
Bernardo F. Quiroga Gómez

Bernardo Francisco Quiroga Gómez was born in Arica, Chile, in May 1982. He grew up in Santiago, Chile, with his parents Carmencita Gómez Peña and Bernardo Quiroga Figueroa, and his brother Francisco Javier Quiroga Gómez. He graduated from the Pontifical Catholic University of Chile with a Licentiate degree in Economics and Management Sciences, a título profesional (professional degree) in Commercial Engineering with a concentration in Economics, a Specialist’s Diploma in Applied Macroeconomics, and a Magister (Master’s) degree in Economics with a concentration in Public Policy. Quiroga completed his doctoral studies at the Pennsylvania State University in 2015, affiliated with the Laboratory for Economics, Management and Auctions. En route towards his doctorate, he also received from Penn State two Master’s degrees, one in Economics and another in Business Administration.

His current research is devoted to economic decision making in procurement, auctions and inventory. Quiroga uses laboratory experiments, econometrics and applied game theory to analyze human behavior. In other research, his work includes financial performance of public family-controlled firms, and hedonic valuation measures of attributes of durable goods. His paper “Family Ownership and Firm Performance: Evidence from Public Companies in Chile,” co-authored with Jon Martínez and Bernhard Stöhr and published by Family Business Review, has been cited over 150 times according to Google Scholar.

Before joining Penn State, Quiroga worked as a faculty member at the Pontifical Catholic University of Chile and the University of the Andes, both in Santiago, Chile, where he taught Statistics, Econometrics, Managerial Decision Making, Data Analysis, Microeconomics, and Optimization Methods, at the graduate (MBA, M.Sc.) and undergraduate levels. He also taught the Business Analytics undergraduate core course for Supply Chain Management majors at Penn State.

Starting the second semester of 2015, Quiroga will be an Assistant Professor in the College of Business and Behavioral Science at Clemson University in South Carolina.