Robust Mechanisms Under Common Valuation

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Abstract

We study robust mechanisms to sell a common-value good. We assume that the mechanism designer knows the prior distribution of the buyers' common value but is unsure of the buyers' information structure about the common value. We use linear programming duality to derive mechanisms that guarantee a good revenue among all information structures and all equilibria. Our mechanism maximizes the revenue guarantee when there is one buyer. As the number of buyers tends to infinity, the revenue guarantee of our mechanism converges to the full surplus.

1 Introduction

In this paper we study robust mechanism design for selling a common-value good. A robust mechanism is one that works well under a variety of circumstances, in particular under weak assumptions about participants' information structure. The goal of robust mechanism design is to reduce the "base of common knowledge required to conduct useful analyses of practical problems," as envisioned by Wilson (1987).

The literature on robust mechanism design has so far largely focused on private value settings.[1] Common value is of course important in many real-life markets (particularly

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[1]See Chung and Ely (2007), Brooks (2013), Frankel (2014), Carroll (2015, 2016), Yamashita (2015, 2016), Carrasco, Farinha Luz, Monteiro, and Moreira (2015), Chen and Li (2016), among others; we follow this literature by adopting a max-min approach for robust mechanisms.

financial markets) and has a long tradition in auction theory. Robustness with respect to information structure is especially relevant in a common-value setting, since it is hard in practice to pinpoint exactly what is a signal (or a set of signals) for a participant and to quantify the correlation between the signal and the common value, not to mention specifying the joint distribution of signals for all participants that correctly captures their beliefs and higher order beliefs about the common value.

We are inspired by a recent paper of Bergemann, Brooks, and Morris (2016) which, among other results, shows that in a first price auction of a common value good and for a fixed prior distribution of value, there is a strictly positive lower bound such that for any information/signal structure that is consistent with the prior the equilibrium revenue is always above that lower bound. For example, if there are two buyers who have quasi-linear utility and a uniform $[0, 1]$ prior distribution for the common value, then the first price auction without a reserve price guarantees a minimum revenue of $1/6$ for any information structure consistent with the prior and any equilibrium from the information structure. Clearly, the maximum revenue that any mechanism can possibly achieve in equilibrium is $1/2$ which is the expected common value, so the revenue guarantee of $1/6$ is already 33% of the best case scenario. This is quite an attractive prospect for a ambiguity averse seller (in the sense of Gilboa and Schmeidler (1989)) who has large uncertainty about buyers' information structure and equilibrium play.

The natural followup question is whether we can achieve an even better revenue guarantee with an alternative mechanism. To answer this question we work with a max-min setup, where we first minimize the revenue over the set of information structures and equilibria for a given mechanism, and then maximize the minimized revenue over the set of mechanisms. Bergemann and Morris (2016) give the powerful insight that we can combine information structure and equilibrium into a single entity called *Bayes Correlated Equilibrium*, which is a joint distribution over actions and value subject to obedience and consistency constraints. We note that minimizing revenue over Bayes correlated equilibria for any fixed mechanism is a linear programming problem, and we can equivalently solve the dual of that problem which is a maximization problem over the dual variables of constraints associated with Bayes correlated equilibrium. These dual variables have the interpretation as transition rates for a continuous-time Markov process over discrete states, similar to the transition probabilities in Myerson (1997) as dual variable to complete information correlated equilibrium. Moreover, we can combine the maximization over these dual variables with the maximization over the mechanism design variables, so we have a single maximization problem which is equivalent

to but more tractable than the original max-min problem.

This duality approach yields new mechanisms with better revenue guarantee than the first price auction. We now describe these mechanisms. Suppose there is one common-value good to sell, and $I \geq 1$ buyers with quasi-linear utility. Let the message space for each buyer i be the interval $[0,1]$. We think of a message $z_i \in [0,1]$ as the demand of buyer i. Buyer i gets the good with probability $q_i(z_i, z_{-i})$ (q_i could also be buyer i's quantity of allocation if the good is divisible) and pays $P_i(z_i, z_{-i})$. If $z_1 \geq z_2 \geq \cdots \geq z_n$, then

$$q_i(z_i, z_{-i}) = \sum_{j=i}^{I-1} \frac{z_j - z_{j+1}}{j} + \frac{z_I}{I}, \qquad P_i(z_i, z_{-i}) = X(\exp(z_i/A) - 1), \tag{1}$$

and analogously for any other ordering of $(z_1, z_2, \ldots, z_n)$. That is, the lowest buyer gets $1/I$ of his demand, the second lowest buyers gets that plus $1/(I-1)$ of the difference between his and the lowest demand, and so on. Thus, the total probability/quantity of allocation is equal to the highest demand. Moreover, each buyer's payment depends only on his demand and is independent of his final allocation. In this sense, this mechanism is similar to an all-pay auction. Finally, $A > 0$ and $X > 0$ in Equation (1) are constants that are optimized for the prior distribution of value.

We prove that the mechanism in Equation (1) is optimal when there is one buyer ($I = 1$). In this case we know sharp upper bound on the revenue guarantee. For example, if the prior is the uniform distribution on $[0,1]$, then the designer can guarantee (among all information structures and all equilibria) a revenue of at most $1/4$: fix any mechanism, there is the private-value information structure, and its equilibrium revenue must be less than $1/4$ which is obtained by the private-value optimal mechanism (a posted price of $1/2$). Roesler and Szentes (2016) study the optimal information structure for a buyer when the seller is best responding to this information structure. Roesler and Szentes's optimal information structure gives a subtle upper bound on the seller's revenue guarantee. For example, when the prior is the uniform distribution on $[0,1]$, the seller can guarantee a revenue of at most 0.2036. We prove that the mechanism in Equation (1) exactly guarantees the Roesler-Szentes upper bound for any prior distribution when $I = 1$.[2]

[2]In other words, Roesler and Szentes (2016) characterize for one buyer:

$$\min_{\text{info. structure}} \quad \max_{\text{mechanism, equilibrium}} \quad \text{Revenue}$$

while we characterize:

$$\max_{\text{mechanism}} \quad \min_{\text{info. structure, equilibrium}} \quad \text{Revenue}$$

When there are more than one buyer, the mechanism in Equation (1) still guarantees a good revenue, as we demonstrate in Figure 1 and Figure 2. As the number I of buyers tends to infinity, the revenue guarantee (over all information structures and all equilibria) becomes arbitrarily close to the full surplus (the expectation of the common value). Since the full surplus is an upper bound on the equilibrium revenue of every mechanism, the mechanism in Equation (1) achieves the optimal revenue guarantee as $I \to \infty$. This guarantee in full surplus extraction in the limit is not obtained by the first price auction (as shown in Bergemann, Brooks, and Morris (2016)), the second price auction, or all-pay auction.[3] And unlike the mechanisms of Crémer and McLean (1985, 1988), our mechanism is detail free and extracts the full surplus for all information structures in the limit.

2 Model

Information

The mechanism designer has a single good to sell. Let $\mathcal{I} = \{1, 2, \ldots, I\}$ be a finite set of buyers, $1 \leq I < \infty$. The buyers have a common value $v \in V = \{0, \nu, 2\nu, \ldots, 1\}$ for the good and have quasi-linear utility, where $\nu > 0$ is a constant. Let $p \in \Delta(V)$ be the prior distribution of common value; the prior p is known by the designer as well as by the buyers. (The designer only knows the prior p about the value.) Suppose

$$p(v) = \frac{\rho(v)}{\sum_{v' \in V} \rho(v')} \tag{2}$$

for every $v \in V$, where $\rho : [0, 1] \to [0, \infty)$ is a density function ($\int_0^1 \rho(v)\, dv = 1$). This assumption has bite only when $\nu \to 0$ and implies that p converges to the distribution given by the density ρ as $\nu \to 0$.

Each buyer i *may* possess some additional information $s_i \in S_i$ about the common value beyond the prior, where S_i is a finite set of signals. We have $\tilde{p} \in \Delta(V \times \prod_{i \in \mathcal{I}} S_i)$ such that

and show it is equal to their min-max value. By equilibrium here we mean a mapping from signals in the information structure to messages in the mechanism, such that there is no incentive to deviate given every realization of the signal.

[3] For a second price auction with a reserve price (potentially zero), suppose there is one informed buyer who knows the common value v, and $I - 1$ uninformed buyers who only knows the expected value $\mathbb{E}[v]$. The following is an equilibrium: the informed buyer truthfully bids v, and all uninformed buyers bid 0. Clearly, this equilibrium does not obtain the full surplus in revenue as $I \to \infty$. From the same information structure, we can also construct equilibrium that does not obtain the full surplus in revenue as $I \to \infty$ for the all-pay auction.

$\text{marg}_V \tilde{p} = p$,[4] so buyer i's information about the common value is informed by $\tilde{p}(\cdot \mid s_i)$. As discussed in the introduction, the information structure $(S_i, \tilde{p})_{i\in\mathcal{I}}$ is *not* known by the designer.

Mechanism

A mechanism is a set of allocation rules $q_i : M \to [0,1]$ and payment rules $P_i : M \to \mathbb{R}$ satisfying $\sum_{i\in\mathcal{I}} q_i(m) \leq 1$, where M_i is the message space of buyer i, and $M = \prod_{i\in\mathcal{I}} M_i$ the space of message profile. A mechanism defines a game in which the buyers simultaneously submit messages and have utility

$$U_i(v, m) = v \cdot q_i(m) - P_i(m). \tag{3}$$

The allocation $q_i(m)$ can be interpreted as the probability of getting the good in the case of an indivisible good, and as the share of the good in the case of a divisible good.

We assume that a mechanism always has an opt-out option for each buyer i: there exists a message $m_i \equiv 0 \in M_i$ such that $q_i(0, m_{-i}) = P_i(0, m_{-i}) = 0$ for every $m_{-i} \in M_{-i}$.

In this paper we focus on *symmetric* mechanism, which satisfies

$$\begin{aligned} q_i(m_i', m_{-i}') &= q_1(m_1 = m_i', m_{-1} = m_{-i}') \equiv q(m_i', m_{-i}') \\ P_i(m_i', m_{-i}') &= P_1(m_1 = m_i', m_{-1} = m_{-i}') \equiv P(m_i', m_{-i}') \end{aligned} \tag{4}$$

for every $i \in \mathcal{I}$ and $m' \in M$. By $m_{-1} = m_{-i}'$ we mean that m_{-1} and m_{-i}' have the same elements but not necessarily the same ordering of elements; for example we may have $m_{-1} = (a, b, c)$ and $m_{-i}' = (c, b, a)$. Intuitively, in a symmetric mechanism every player is treated in the same way. For a symmetric mechanism we abbreviate $q_1(m)$ to $q(m)$ and $P_1(m)$ to $P(m)$.

Equilibrium

Given a mechanism $(q_i, P_i)_{i\in\mathcal{I}}$ and an information structure $(S_i, \tilde{p})_{i\in\mathcal{I}}$, we have a game of incomplete information. A *Bayes Nash Equilibrium* (BNE) of the game is defined by strategy $\sigma_i : S_i \to \Delta(M_i)$ for each buyer i such that for every $s_i \in S_i$, the support of $\sigma_i(s_i)$ is among

[4] Let $\text{marg}_V \tilde{p}$ be the marginal distribution of $\tilde{p}$ over V.

the best responses to others' strategies:

$$\operatorname{supp}\sigma_i(s_i) \subseteq \operatorname*{argmax}_{m_i \in M_i} \sum_{(v,s_{-i})\in V\times S_{-i}} U_i(v,(m_i,\sigma_{-i}(s_{-i})))\tilde{p}(v,s_{-i}\mid s_i). \tag{5}$$

The ex ante distribution $\mu \in \Delta(V\times M)$ generated by any BNE $(\sigma_i)_{i\in\mathcal{I}}$ of any information structure $(S_i,\tilde{p})_{i\in\mathcal{I}}$ satisfies the following two conditions:

$$\sum_{m\in M}\mu(v,m) = p(v), \quad v\in V, \tag{Consistency}$$

$$\sum_{(v,m_{-i})\in V\times M_{-i}} \mu(v,m)\left(U_i(v,(m_i,m_{-i})) - U_i(v,(m_i',m_{-i}))\right) \geq 0, \quad i\in\mathcal{I}, (m_i,m_i')\in M_i\times M_i. \tag{Obedience}$$

A distribution $\mu\in\Delta(V\times M)$ that satisfies the above two conditions is called a *Bayes Correlated Equilibrium* (BCE) of the mechanism $(q_i,P_i)_{i\in\mathcal{I}}$. For any BCE μ, there exists an information structure and a BNE of that information structure that generates μ. See Bergemann and Morris (2016) for more details.

Designer's problem

The mechanism designer wants to solve:

$$\max_{(q_i,P_i)_{i\in\mathcal{I}}} \min_{\mu\in\Delta(V\times M)} \sum_{(v,m)}\sum_i \mu(v,m)P_i(m) \tag{6}$$
$$\text{such that } \mu \text{ is a BCE of } (q_i,P_i)_{i\in\mathcal{I}}.$$

Definition 1. A mechanism *guarantees* a revenue R if every BCE of this mechanism has a revenue larger than or equal to R.

3 Main Results

Our main results is a class of mechanisms that give good revenue guarantee. Consider a symmetric mechanism with k messages besides the opt-out message: $M_i = \{0,1,\ldots,k\}$, for

every buyer $i \in \mathcal{I}$. The allocation $q(m_1, m_{-1})$ is given by:

$$q(0, m_{-1}) = 0, \qquad m_{-1} \in M_{-1}, \tag{7}$$

$$q(m_1 + 1, m_{-1}) - q(m_1, m_{-1}) = \left(\frac{1}{|\operatorname{rank}(m_1, m_{-1})|} \sum_{j \in \operatorname{rank}(m_1, m_{-1})} \frac{1}{j} \right) \cdot \frac{1}{k}, \quad 0 \le m_1 \le k - 1,$$

where $\operatorname{rank}(m_1, m_{-1}) \subseteq \{1, 2, \ldots, I\}$ is the set of ranks (from the top) of m_1 in $(m_1, m_2, \ldots, m_I)$; for example, $\operatorname{rank}(20, 10, 20, 40, 30) = \{3, 4\}$, because $m_1 = 20$ and $m_3 = 20$ are tied for the third and the fourth place in this list; and $\operatorname{rank}(20, 10, 30, 40, 30) = \{4\}$ because in this list $m_1 = 20$ is unambiguously ranked fourth, even though there is a tie for the second and the third rank. We think of a message m_i as the demand of a fraction m_i/k of the good; the allocation in Equation (7) is increasing with the demand at a rate equal to the reciprocal of the demand's rank: a rate of 1 for the highest demand, of $1/2$ for the second highest demand, of $1/3$ for the third highest demand, and so on. Moreover, we break tie in a symmetric way and randomize over all feasible ranks, in the case when $|\operatorname{rank}(m_1, m_{-1})| > 1$. It is easy to check that Equation (7) uniquely defines an allocation function (i.e., the feasibility condition is always satisfied); the total amount of allocation is at most $\max(m_1, m_2, \ldots, m_I)/k$.

The payment of our mechanism is:

$$P(m_1, m_{-1}) = X \left(\left(1 + \frac{1}{a} \right)^{m_1} - 1 \right), \tag{8}$$

where $X > 0$ and $a > 0$ are constants that are optimized for a given prior distribution p. That is, the payment of every buyer depends only on his message and is independent of his final allocation.

As $k \to \infty$, the mechanism from Equations (7) and (8) converges to (1), where we reparametrize $m_i \in \{0, 1, \ldots, k\}$ to $z_i \equiv m_i/k \in [0, 1]$.

When there is a single buyer ($I = 1$), the mechanism from Equations (7) and (8) becomes:

$$q(m_1) = m_1/k, \qquad P(m_1) = X \left(\left(1 + \frac{1}{a} \right)^{m_1} - 1 \right), \qquad m_1 \in \{0, 1, \ldots, k\}, \tag{9}$$

since $\operatorname{rank}(m_1) = \{1\}$ by definition. In fact, this mechanism achieves the optimal revenue guarantee when $I = 1$:

Theorem 1. *Suppose there is one buyer. There exist constants $A > 0$ and $X > 0$ such that the mechanism from Equations (7) and (8) with $a = A \cdot k$ and the given X achieves the*

optimal revenue guarantee (i.e., solution to Problem (6)) as $k \to \infty$ and $\nu \to 0$.

That is, for any $\epsilon > 0$, there exists $\bar{\nu}$ and $\bar{k}$ such that for any $\nu \leq \bar{\nu}$ and $k \geq \bar{k}$, the mechanism from from Equations (7) and (8) with $a = A \cdot k$ and the given X guarantees a revenue within ϵ of the best possible given by Problem (6).

We compute the optimal revenue guarantee of Theorem 1 for various prior distributions in Figure 2 (page 16).

Our second result states the mechanism from Equations (7) and (8) can guarantee the full surplus (the expected common value) as the number of buyers tends to infinity. In this sense the mechanism is asymptotically optimal.

Theorem 2. *Let $a = \frac{k}{\log(I)}$ and $X = \frac{1}{2I\log(I)}$. The mechanism from Equations (7) and (8) guarantees a revenue of $\sum_v v \cdot p(v)$ as $k \to \infty$ and $I \to \infty$.*

That is, for any $\epsilon > 0$, there exists $\bar{I}$ and $\bar{k}$ such that for any $I \geq \bar{I}$ and $k \geq \bar{k}$, the mechanism from Equations (7) and (8) with $a = \frac{k}{\log(I)}$ and $X = \frac{1}{2I\log(I)}$ guarantees a revenue within ϵ of $\sum_v v \cdot p(v)$. In Figure 1 (page 13) we plot the revenue guarantee as a function of I for the uniform prior distribution.

The values of a and X in Theorem 2 depend only on the support of the prior (which is $[0, 1]$) and is independent of the other details of the prior. Thus, the convergence of the mechanism's revenue guarantee to the full surplus holds for every prior with support on $[0, 1]$.

4 Duality Approach to Robust Mechanism

For a given mechanism $(q_i, P_i)_{i\in\mathcal{I}}$, the BCE that minimizes revenue is found by the following primal problem:

$$\min_{\mu} \sum_{(v,m)} \sum_{i} P_i(m)\mu(v, m) \tag{10}$$

subject to:

$$\sum_{(v,m_{-i})} (U_i(v, m) - U_i(v, (m_i', m_{-i})))\mu(v, m) \geq 0, \quad i \in \mathcal{I}, (m_i, m_i') \in M_i \times M_i,$$

$$\sum_{m} \mu(v, m) = p(v), \quad v \in V,$$

$$\mu(v, m) \geq 0, \quad v \in V, m \in M,$$

where U_i is the payoff function defined by Equation (3). For notational brevity, we omit the set of which a summation variable belongs when it is obvious; for example, summing over m means summing over $m \in M$.

The dual problem to Problem (10) is:

$$\max_{(\alpha_i,\gamma)_{i\in\mathcal{I}}} \sum_v p(v)\gamma(v) \tag{11}$$

subject to:

$$\gamma(v) + \sum_i \sum_{m_i'} (U_i(v,m) - U_i(v,(m_i',m_{-i})))\alpha_i(m_i' \mid m_i) \le \sum_i P_i(m), \quad v \in V, m \in M,$$

$$\alpha_i(m_i' \mid m_i) \ge 0, \quad i \in \mathcal{I}, (m_i, m_i') \in M_i \times M_i,$$

where $\alpha_i(m_i' \mid m_i)$ is the dual variable for the obedience constraint of not playing m_i' when "recommended" to play m_i in (10), and $\gamma(v)$ is the dual variable for the consistency constraint of $\sum_m \mu(v,m) = p(v)$.

Mechanism designer's problem in (6) can be written as:

$$\max_{(P_i,q_i,\alpha_i,\gamma)_{i\in\mathcal{I}}} \sum_v p(v)\gamma(v) \tag{12}$$

subject to:

$$\gamma(v) \le \sum_i P_i(m) + \sum_i \sum_{m_i'} (v(q_i(m_i',m_{-i}) - q_i(m)) - P_i(m_i',m_{-i}) + P_i(m))\alpha_i(m_i' \mid m_i), \quad v \in V, m \in M,$$

$$q_i(m) \ge 0, \quad \sum_{i'} q_{i'}(m) \le 1, \quad q_i(0,m_{-i}) = P_i(0,m_{-i}) = 0, \qquad i \in \mathcal{I}, m \in M$$

$$\alpha_i(m_i' \mid m_i) \ge 0, \qquad (m_i, m_i') \in M_i \times M_i, i \in \mathcal{I},$$

where we label the opt-out message as $0 \in M_i$.

The advantage of problem (12) over the equivalent problem (6) is that we work with a maximization problem instead of a max-min problem. Moreover, we work with $(\alpha_i)_{i\in\mathcal{I}}$, where each α_i has $|M_i \times M_i|$ dimensions, instead of μ which has $|V \times \prod_{i\in\mathcal{I}} M_i|$ dimensions; the reduction in dimensions is significant if $|V|$ is large. Lastly, if we find a tuple $(\alpha_i, q_i, P_i)_{i\in\mathcal{I}}$ that satisfies the constraints of Problem (12), then the value of (12) under such $(\alpha_i, q_i, P_i)_{i\in\mathcal{I}}$ is by definition a lower bound on the optimal revenue guarantee. On the other hand, finding a feasible tuple $(\mu, q_i, P_i)_{i\in\mathcal{I}}$ for Problem (6) (i.e., μ is a BCE of $(q_i, P_i)_{i\in\mathcal{I}}$) does not yield by itself any conclusion about the revenue guarantee, since there may exist another BCE μ' of

$(q_i, P_i)_{i\in\mathcal{I}}$ with a lower revenue than μ.

Problem (12) is a bilinear programming problem: fixing the mechanism $(P_i, q_i)_{i\in\mathcal{I}}$ the maximization problem over $(\alpha_i, \gamma)_{i\in\mathcal{I}}$ is linear; and fixing the dual variables $(\alpha_i)_{i\in\mathcal{I}}$ the maximization problem over $(P_i, q_i, \gamma)_{i\in\mathcal{I}}$ is also linear.

Problem (12) be summarized as:

$$\max_{(q_i,P_i,\alpha_i)_{i\in\mathcal{I}}} \sum_v p(v) \cdot \min_m \mathrm{Rev}(v, m), \tag{13}$$

subject to the feasibility constraints, where

$$\mathrm{Rev}(v, m) \equiv \sum_i \left(P_i(m) + \sum_{m_i'} (U_i(v, m_i', m_{-i}) - U_i(v, m))\alpha_i(m_i' \mid m_i) \right). \tag{14}$$

Since $U_i(v, m)$ is a linear function of v, so is $\mathrm{Rev}(v, m)$ for any fixed m. Intuitively, $\alpha_i(m_i' \mid m_i)$ is buyer i's rate of deviation from message m_i to m_i', and $\mathrm{Rev}(v, m)$ is the revenue generated by the message profile m, *corrected* by the incentive to deviate from m given value v and rates of deviation $(\alpha_i)_{i\in\mathcal{I}}$.

Problem (12) is bounded above by $\sum_v v \cdot p(v)$, as the following lemma shows:

Lemma 1. *For every $v \in V$, we have:*

$$\min_m \mathrm{Rev}(v, m) \leq v. \tag{15}$$

Proof. Fix an arbitrary $v \in V$. Consider the problem:

$$\begin{aligned} &\max_{\gamma,(\alpha_i)_{i\in\mathcal{I}}} \ \gamma \\ &\text{subject to:} \\ &\gamma + \sum_i \sum_{m_i'} (U_i(v, m) - U_i(v, (m_i', m_{-i})))\alpha_i(m_i' \mid m_i) \leq \sum_i P_i(m), \quad m \in M, \\ &\alpha_i(m_i' \mid m_i) \geq 0, \quad i \in \mathcal{I}, (m_i, m_i') \in M_i \times M_i. \end{aligned} \tag{16}$$

The dual to the above problem is:

$$\min_{\mu} \sum_{m} \mu(m) \sum_{i} P_i(m) \tag{17}$$

subject to:

$$\sum_{m_{-i}} \mu(m)(U_i(v,m) - U_i(v,(m_i', m_{-i}))) \geq 0, \quad i \in \mathcal{I}, (m_i, m_i') \in M_i \times M_i,$$

$$\sum_{m} \mu(m) = 1,$$

$$\mu(m) \geq 0, \quad m \in M,$$

which is minimizing the revenue over *complete-information* correlated equilibria μ (for the fixed v). For any μ satisfying the constraints, we have $\sum_{m_{-i}} \mu(m) U_i(v,m) = \sum_{m_{-i}} \mu(m)(vq_i(m) - P_i(m)) \geq 0$ for every $i \in \mathcal{I}$ and $m_i \in M_i$ because of the presence of the opt-out message $0 \in M_i$. Therefore, $\sum_m \mu(m) \sum_i (vq_i(m) - P_i(m)) \geq 0$, and $\sum_m \mu(m) \sum_i P_i(m) \leq \sum_m \mu(m) \sum_i vq_i(m) \leq v$. Thus the optimal solution of (16) is bounded above by v. □

4.1 A Lower Bound

We work with symmetric mechanism $q(m) \equiv q_1(m)$ and $P(m) \equiv P_1(m)$ (cf. Equation (4)) and symmetric $\alpha(m_i' \mid m_i) \equiv \alpha_i(m_i' \mid m_i)$.

Instead of directly solving Problem (13), we make some educated guess on (q_i, P_i, α_i) to get a lower bound on the maximum value of Problem (13). Suppose $M_i = \{0, 1, \ldots, k\}$ for every buyer $i \in \mathcal{I}$, where $q(0, m_{-1}) = 0 = P(0, m_{-1})$ for every $m_{-1} \in M_{-1}$.

We focus on

$$\alpha(j' \mid j) = \begin{cases} a & j' = j+1 \\ 0 & j' \neq j+1 \end{cases}, \quad (j, j') \in \{0, 1, \ldots, k\}^2. \tag{18}$$

Condition (18) says that the local obedience constraint in BCE is binding: by the complementarity slackness condition, if the above α is dual to a BCE μ, then a buyer must be indifferent between messages j and $j+1$ if he is "recommended" to submit j in the BCE μ.

Condition (18) implies that there are two kinds of messages: the "interior" message $j \in \{0, 1, \ldots, k-1\}$, and the "boundary" message $j = k$. Thus there are $I+1$ kinds of message profiles $m \in M = \{0, 1, \ldots, k\}^I$, depending on the number of boundary messages

in m. For $0 \leq n \leq I$, define the class of message profiles:

$$M(n) = \{m \in M : |\{i \in \mathcal{I} : m_i = k\}| = n\}. \tag{19}$$

The sets $M(n)$, $0 \leq n \leq I$, form a partition of M. Our second assumption is that

$$\text{Rev}(v, m) = \text{Rev}(v, m') \; \forall v \in V, \qquad \text{if } m \text{ and } m' \text{ belong to the same } M(n). \tag{20}$$

Condition (20) attemps to make $\text{Rev}(v, m)$ over m as redundant as possible, to minimize the number of items inside the min operator in Equation (13).

We now go to the mechanism defined by Equations (7) and (8). Clearly, if there are n boundary messages in a message profile m, then the rest (the interior messages) have ranks among $\{n+1, n+2, \ldots, I\}$, and by Equation (7) we have:

$$\sum_{i:m_i<k} q(m_i + 1, m_{-i}) - q(m_i, m_{-i}) = \frac{1}{k} \sum_{j=n+1}^{I} \frac{1}{j}. \tag{21}$$

Moreover, for an interior m_i we have:

$$P(m_i, m_{-i}) - a(P(m_i + 1, m_{-i}) - P(m_i, m_{-i})) = -X \tag{22}$$

by Equation (8).[5] Therefore, under Condition (18) we have:

$$\text{Rev}(v, m) = \frac{a\,v}{k} \sum_{j=n+1}^{I} \frac{1}{j} + nX((1 + 1/a)^k - 1) - (I - n)X, \quad \text{if } m \in M(n). \tag{23}$$

Thus, Condition (20) is satisfied, and we have the following lower bound on the maximum value of Problem (13):

$$\Pi_I^* \equiv \max_{k \geq 1,\, a \geq 0,\, X} \left(\sum_v \min_{0 \leq n \leq I} \left(\frac{a\,v}{k} \sum_{j=n+1}^{I} \frac{1}{j} + nX((1 + 1/a)^k - 1) - (I - n)X \right) \cdot p(v) \right). \tag{24}$$

Proposition 1. *The mechanism given by Equations (7) and (8) guarantees a revenue of* Π_I^*

[5] In fact, Equation (8) is the solution to the difference equation

$$P(m_i, m_{-i}) - a(P(m_i + 1, m_{-i}) - P(m_i, m_{-i})) = -X$$

for $m_i \in \{0, 1, \ldots, k-1\}$, with the initial condition of $P(0, m_{-i}) = 0$.

defined in (24).

Proof. The proof is given by the construction above. □

We prove Theorem 1 and Theorem 2 by analyzing Π_1^* and $\lim_{I\to\infty}\Pi_I^*$ in Appendix A. In Figure 1 we plot Π_I^* for uniform prior distribution, as $\nu \to 0$.

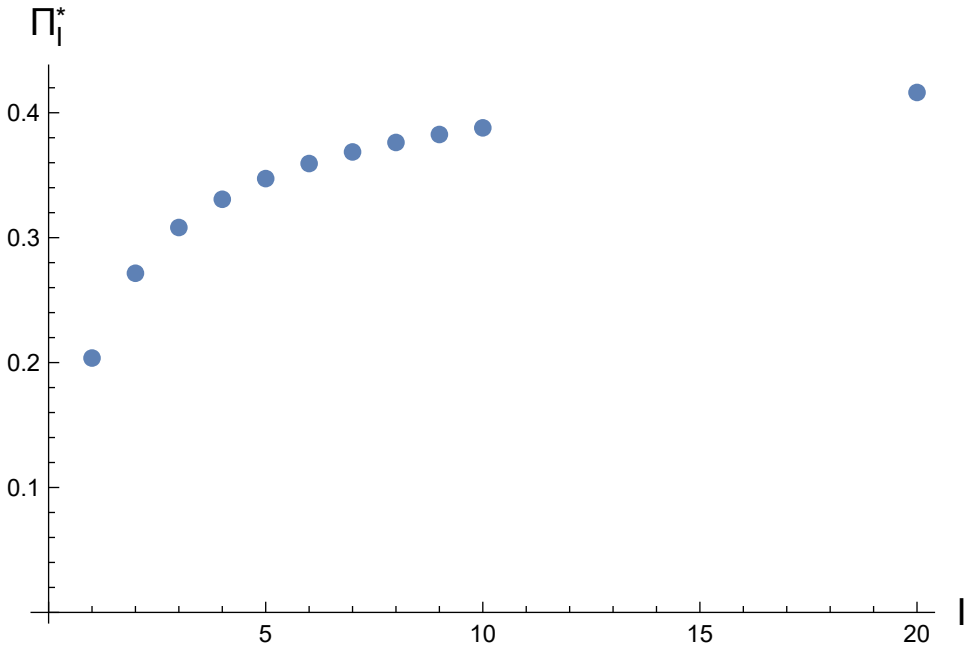


Figure 1: Π_I^* for uniform $[0,1]$ prior distribution.

5 A Refinement when $I = 2$

In this section we study Conditions (18) and (20) in details for the case of two buyers and derive a mechanism with slightly better revenue guarantee than that of Proposition 1.

We consider a symmetric mechanism with two buyers and $k+1$ messages: $M_1 = M_2 = \{0, 1, \ldots, k\}$. Our usual assumption on the mechanism is:

$$q(0,j) = 0 = P(0,j), \quad q(j,l) \geq 0, \quad q(j,l) + q(l,j) \leq 1, \quad (j,l) \in \{0,1,\ldots,k\}^2. \tag{25}$$

Conditions (18) and (20) hold under $I = 2$ if and only if

$$\begin{aligned} 2q(1,0) &= q(j+1,l) - q(j,l) + q(l+1,j) - q(l,j), \quad (j,l) \in \{0,1,\ldots,k-1\}^2, \\ q(1,k) &= q(j+1,k) - q(j,k), \quad j \in \{0,1,\ldots,k-1\}, \end{aligned} \tag{26}$$

and

$$\begin{aligned} -2aP(1,0) &= P(j,l) + P(l,j) - a(P(j+1,l) - P(j,l)) - a(P(l+1,j) - P(l,j)), \\ &\qquad\qquad (j,l) \in \{0,1,\ldots,k-1\}^2, \\ P(k,0) - aP(1,k) &= P(j,k) + P(k,j) - a(P(j+1,k) - P(j,k)), \quad j \in \{0,1,\ldots,k-1\}. \end{aligned} \tag{27}$$

It is without loss to assume that the feasibility constraint $q(j,k) + q(k,j) \leq 1$ binds for every j (if not, we can increase $q(k,j)$, which strictly increases $\text{Rev}(v,(k-1,j))$, without decreasing any other $\text{Rev}(v,m)$ or violating any feasibility constraint):

$$q(j,k) + q(k,j) = 1, \quad j \in \{0,1,\ldots,k\}. \tag{28}$$

Lemma 2. *For any allocation q that satisfies Conditions (26) and (28), we have $q(1,0) = (3k+1)/(4k^2)$ and $q(1,k) = 1/(2k)$.*

Lemma 3. *For any payment P that satisfies Condition (27), we have:*

$$P(k,k) = \left((1+1/a)^k - 1\right)^2 aP(1,0) + \left((1+1/a)^k - 1\right)(aP(1,k) - P(k,0)). \tag{29}$$

Define,

$$Y_0 \equiv 2aP(1,0), \qquad Y_1 \equiv -P(k,0) + aP(1,k), \tag{30}$$

i.e., $-Y_0$ is equal to the first line of (27), and $-Y_1$ is equal to the second line of (27).

Lemma 2 and Lemma 3 lead us unambiguously to the following problem:

$$\Pi_2^{\#} \equiv \max_{k \geq 1,\, a \geq 0,\, Y_0,\, Y_1} \sum_v \min\left(\frac{3k+1}{2k^2}av - Y_0,\ \frac{av}{2k} - Y_1,\ Y_0\left((1+1/a)^k - 1\right)^2 + 2Y_1\left((1+1/a)^k - 1\right)\right) p(v). \tag{31}$$

Comparing $\Pi_2^{\#}$ above with Π_2^* in Equation (24), the main difference is that in $\Pi_2^{\#}$ there are two variables Y_0 and Y_1, instead of a single variable X in Π_2^*. In fact, Π_2^* is a special case of $\Pi_2^{\#}$ with $Y_0 = 2X$ and $Y_1 = X - X((1+1/a)^k - 1)$. Thus, we must have $\Pi_2^{\#} \geq \Pi_2^*$.

Proposition 2. *Suppose there are two buyers. There exists a symmetric mechanism that guarantees a revenue of* $\Pi_2^{\#}$ *defined in* (31).

We now specify the mechanism for Proposition 2. Consider the following allocation rule:

$$q(0,l) = 0, \qquad l \in \{0,1,\ldots,k\}, \tag{32}$$

$$q(j+1,l) - q(j,l) = \begin{cases} (2k+1)/(4k^2) & j < l \\ (3k+1)/(4k^2) & j = l \\ (4k+1)/(4k^2) & j > l \end{cases}, \qquad (j,l) \in \{0,1,\ldots,k-1\}^2, \tag{33}$$

$$q(j+1,k) - q(j,k) = 1/(2k), \qquad j \in \{0,1,\ldots,k-1\}.$$

It is easy to check that the above allocation rule satisfies the feasibility constraint, and Conditions (26) and (28). As $k \to \infty$, the above allocation rule becomes identical to that in Equation (7).

Given any values of Y_0 and Y_1, we can choose the following solution to Equation (27):

$$P(j,l) - a(P(j+1,l) - P(j,l)) = \begin{cases} -Y_0/2 & 0 \le l < k, \\ -Y_1 - P(k,j) & l = k, \end{cases}, \quad j \in \{0,1,\ldots,k-1\}, \tag{34}$$

which is equivalent to (see footnote 5):

$$P(j,l) = \begin{cases} ((1+1/a)^j - 1)\,\frac{Y_0}{2} & 0 \le l < k \\ ((1+1/a)^j - 1)\left(Y_1 + \left((1+1/a)^k - 1\right)\frac{Y_0}{2}\right) & l = k \end{cases}, \qquad (j,l) \in \{0,1,\ldots,k\}^2. \tag{35}$$

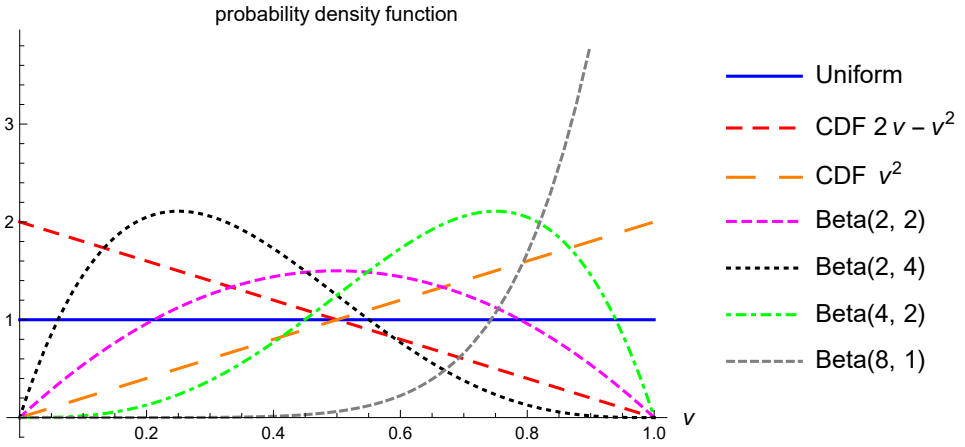
The above payment rule is identical to the one in Equation (8), except when the other player submits the message k.

Figure 2 shows the revenue guarantees Π_2^* and $\Pi_2^{\#}$ for various prior distributions[6] as $\nu \to 0$ and compares them with first price auction with reserve price and two buyers. We choose the reserve price that maximizes the revenue guarantee in first price auction (Section B.5 in Bergemann, Brooks, and Morris (2016)). We see that Π_2^* and $\Pi_2^{\#}$ are generally close, though $\Pi^{\#}$ is slightly but noticeably better than Π_2^* when the distribution is heavily

[6]Distribution Beta(b,c) has a p.d.f. of $v^{b-1}(1-v)^{c-1} \cdot \frac{\Gamma(c)\Gamma(d)}{\Gamma(c+d)}$ for $v \in [0,1]$. Beta$(1,1)$ is of course the uniform distribution.

concentrated among high values. In these examples $\Pi_2^{\#}$ is always better than the optimal revenue guarantee from first price auction with reserve price. In Figure 2 we also include the optimal revenue guarantees from the mechanism in Theorem 1 with one buyer.

Figure 2: Revenue guarantees from Proposition 1 (Π_2^*), Proposition 2 ($\Pi_2^{\#}$), first price auction with optimal reserve price (Bergemann, Brooks, and Morris, 2016), and one buyer mechanism in Theorem 1 (Π_1^*).



Prior distribution	Mean	$\Pi_2^{\#}$	Π_2^*	FPA w/ optimal reserve	Π_1^*
Uniform	0.5	0.273	0.272	0.177	0.204
CDF $2v - v^2$	0.3333	0.166	0.166	0.102	0.120
CDF v^2	0.6667	0.437	0.431	0.346	0.341
Beta$(2, 2)$	0.5	0.302	0.301	0.230	0.229
Beta$(2, 4)$	0.3333	0.188	0.188	0.139	0.140
Beta$(4, 2)$	0.6667	0.475	0.463	0.414	0.381
Beta$(8, 1)$	0.8889	0.751	0.710	0.716	0.652

Appendix

A Proofs

A.1 Proof of Theorem 1

In the case of one buyer, Problem (24) simplifies to:

$$\Pi_1^* \equiv \max_{k\geq 1,\, a\geq 0,\, X} \sum_v \min\left(\frac{a\,v}{k} - X,\; X\left(\left(1+\frac{1}{a}\right)^k - 1\right)\right) p(v), \tag{36}$$

Set $a = A \cdot k$. As $\nu \to 0$ and $k \to \infty$, we have

$$\sum_v \min(av/k, X(1+1/a)^k)\, p(v) - X \longrightarrow \int_0^1 \min(Av, X\exp(1/A))\, \rho(v)dv - X = \Pi. \tag{37}$$

We maximize Π over A and X. Suppose $\frac{X\exp(1/A)}{A} \in [0,1]$, the first order condition is:

$$\begin{aligned} \frac{\partial \Pi}{\partial X} &= \int_{\frac{X\exp(1/A)}{A}}^1 \exp(1/A)\,\rho(v)\,dv - 1 = 0, \\ \frac{\partial \Pi}{\partial A} &= \int_0^{\frac{X\exp(1/A)}{A}} v\,\rho(v)\,dv - \int_{\frac{X\exp(1/A)}{A}}^1 \frac{X\exp(1/A)}{A^2}\,\rho(v)\,dv = 0. \end{aligned} \tag{38}$$

Suppose the above first order condition holds. We then have $\Pi = X/A$.

Before proving the existence of A and X that satisfy (38), we first discuss the result in Roesler and Szentes (2016). Roesler and Szentes (2016) study the optimal information structure for the buyer given the seller is best responding to this information structure. Such information structure has the following cumulative distribution function of signals:

$$G_\pi^B(s) = \begin{cases} 1 & s \geq B \\ 1 - \pi/s & s \in [\pi, B) \\ 0 & s < \pi \end{cases}, \tag{39}$$

where $s \in [0,1]$ is an unbiased signal of the buyer for his value ($\mathbb{E}[v \mid s] = s$), $0 < \pi \leq B$ are two free parameters, and there is an atom of size π/B at $s = B$. If the buyer has this distribution of unbiased signals (and observes the realization of the signal), then the seller

is clearly indifferent between every posted price in $[\pi, B]$ and has an optimal revenue of π.

Suppose the value v is distributed according to ρ. Then $G_\pi^B(s)$ is a distribution of unbiased signal of v if and only if ρ is a mean-preserving spread of $G_\pi^B(s)$, which holds if and only if

$$\int_0^1 s\, dG_\pi^B(s) = \int_0^1 v\, \rho(v)\, dv, \text{ and } \int_0^s G_\pi^B(s')\, ds' \leq \int_{s'=0}^{s} \int_{v=0}^{s'} \rho(v)\, dv\, ds' \text{ for every } s \in [0,1], \tag{40}$$

i.e., G_π^B has the same mean as ρ and second-order stochastically dominates ρ.

Roesler and Szentes (2016) prove that the best information structure for the buyer is $G_{\pi^*}^{B^*}$, where π^* is the smallest π such that Condition (40) holds for some B (such B must be unique; let B^* be the one corresponding to π^*). For example, if ρ is the uniform $[0,1]$ distribution, then $\pi^* = 0.203632$ and $B^* = 0.872814$. We note that if the buyer has information structure $G_{\pi^*}^{B^*}$, then in any mechanism and any equilibrium of the mechanism the seller's revenue is at most π^*, since the best mechanism for the seller given a fixed information structure is a posted price mechanism, and any posted price in $[\pi^*, B^*]$ generates a revenue of π^* by construction. (The order of quantifiers is important though: if the seller commits to a posted price mechanism, then his revenue guarantee is strictly less than π^*.) Thus whatever mechanism the seller uses, his revenue guarantee is bounded above by π^*.

We now relate Roesler and Szentes (2016) to Equation (38), which simultaneously proves the existence of X and A that satisfy (38) and that X/A is the optimal revenue guarantee. The requirement that G_π^B has the same mean as p is equivalent to:

$$\int_0^1 v\, \rho(v)\, dv = \int_0^1 s\, dG_\pi^B(s) = B - \int_\pi^B G_\pi^B(s)\, ds = \pi + \int_\pi^B \pi/s\, ds = \pi + \pi \log B - \pi \log \pi, \tag{41}$$

i.e.,

$$\log(B) = \frac{\int_0^1 v\, \rho(v)\, dv - \pi + \pi \log \pi}{\pi}. \tag{42}$$

Clearly, $B \geq \pi$ if and only if $\pi \leq \int_0^1 v\, \rho(v)\, dv$.

The requirement that G_π^B second-order stochastic dominates p is equivalent to:

$$\int_\pi^s (1 - \pi/s')\, ds' = s - \pi - \pi \log s + \pi \log \pi \leq \int_{s'=0}^{s} \int_{v=0}^{s'} \rho(v)\, dv\, ds', \tag{43}$$

for every $s \in [\pi, B]$.

Define

$$F(s,\pi) \equiv \int_{s'=0}^{s} \int_{v=0}^{s'} \rho(v)\, dv\, ds' - (s - \pi - \pi \log s + \pi \log \pi). \tag{44}$$

Let π^* be the minimum π such that $\min_{s\in[\pi,B]} F(s,\pi) \geq 0$, and let B^* be the corresponding B from (42). Let s^* be an arbitrary selection from $\operatorname{argmin}_{s\in[\pi^*,B^*]} F(s,\pi^*)$.

For $\pi \leq \int_0^1 v\,\rho(v)\,dv$, B (defined by Equation (42)) decreases as π increases. Moreover, $\frac{\partial F}{\partial \pi}(s,\pi) > 0$ for every $s > \pi$. Thus, $\min_{s\in[\pi,B]} F(s,\pi)$ is a continuously increasing function of π. So we must have $F(s^*,\pi^*) = 0$.

If $B^* < 1$, we must have $F(B^*,\pi^*) > 0$, for otherwise we would have $\int_0^1 G_{\pi^*}^{B^*}(s)\,ds > \int_{s=0}^1 \int_{v=0}^s \rho(v)\,dv\,ds$, which would contradict the fact that $G_{\pi^*}^{B^*}$ has the same mean as p. If $B^* = 1$, then we have $\frac{\partial F}{\partial s}(B^*,\pi^*) = \frac{\pi^*}{B^*} > 0$. In any case $B^* \neq s^*$. Since $F(\pi^*,\pi^*) > 0$, we also have $\pi^* \neq s^*$. Thus we must have $\frac{\partial F}{\partial s}(s^*,\pi^*) = 0$.

Therefore, we have (the first line is $\frac{\partial F}{\partial s}(s^*,\pi^*) = 0$, and the second line is $F(s^*,\pi^*) = 0$):

$$\int_{v=0}^{s^*} \rho(v)\,dv - 1 + \pi^*/s^* = 0, \tag{45}$$
$$\int_{s=0}^{s^*} \int_{v=0}^{s} \rho(v)\,dv\,ds - (s^* - \pi^* - \pi^* \log s^* + \pi^* \log \pi^*) = -\int_0^{s^*} v\,\rho(v)\,dv + \pi^* \log s^* - \pi^* \log \pi^* = 0,$$

where in the second equality of the second line we use integration by parts and substitute in the first line. Clearly, there exist unique $A > 0$ and $X > 0$ such that $s^* = X\exp(1/A)/A$ and $\pi^* = X/A$. Then the above equations become:

$$\int_{\frac{X\exp(1/A)}{A}}^{1} \rho(v)\,dv = \exp(-1/A), \qquad \int_0^{\frac{X\exp(1/A)}{A}} v\,\rho(v)\,dv - \frac{X}{A^2} = 0,$$

which is clearly equivalent to Equation (38).

Therefore, for any $\epsilon > 0$, when k is sufficiently large and ν sufficiently small, we have $\Pi_1^* \geq \pi^* - \epsilon$. When ν is sufficiently small, the revenue guarantee must be smaller than $\pi^* + \epsilon$ by the Roesler-Szentes construction. This concludes the proof.

A.2 Proof of Theorem 2

For each $0 \leq n \leq I$, define

$$\mathrm{Rev}_n(v) = \frac{a\,v}{k} \sum_{j=n+1}^{I} \frac{1}{j} + nX((1+1/a)^k - 1) - (I-n)X, \tag{46}$$

which is $\mathrm{Rev}(v, m)$ for any $m \in M(n)$. Let

$$v(n) = \frac{(n+1)kX}{a}(1+1/a)^k, \tag{47}$$

By construction, we have $\mathrm{Rev}_n(v(n)) = \mathrm{Rev}_{n+1}(v(n))$ for each $0 \le n \le I-1$. Set $v(-1) = 0$ and $v(n) = \infty$. Clearly, if $X > 0$, then $\mathrm{Rev}_n(v) = \min_{0 \le n' \le I} \mathrm{Rev}_{n'}(v)$ if and only if $v \in [v(n-1), v(n)]$.

Set $A = 1/\log(I)$, $X = 1/(2I\log(I))$ and $a = Ak$. We have $\lim_{k\to\infty}(1+1/a)^k = I$, $\lim_{k\to\infty} v(1) = 1$. Thus,

$$\begin{aligned}\lim_{k\to\infty} \sum_{v\in V} p(v) \min_{0\le n\le I} \mathrm{Rev}_n(v) = &\sum_{v\in V} p(v) \left(\frac{v}{\log(I)} \sum_{j=1}^{I} \frac{1}{j} - \frac{1}{2\log(I)} \right) \\ &+ \sum_{v > v(0), v\in V} p(v) \left(\frac{v}{\log(I)} \sum_{j=2}^{I} \frac{1}{j} - \frac{1}{\log(I)} \right)\end{aligned} \tag{48}$$

Clearly, the above equation converges to $\sum_v v \cdot p(v)$ as $I \to \infty$.

A.3 Proofs for Section 5

Proof of Lemma 2. By (28) we have $q(k,k) = 1/2$. By the second line of (26) this implies that $q(j,k) = j/(2k)$ and $q(k,j) = 1 - j/(2k)$, $j = 0, 1, \ldots, k$. Then we have

$$k - \frac{(k-1)k}{4k} = \sum_{j=0}^{k-1} q(k,j) = \sum_{j=0}^{k-1}\sum_{l=0}^{k-1} q(l+1,j) - q(l,j) = k^2 q(1,0) \tag{49}$$

where the last equality follows from the first line of (27). Thus, $q(1,0) = (3k+1)/(4k^2)$.

□

Proof of Lemma 3. Fix an arbitrary P that satisfies Condition (27).

From the second line of (27) ($\mathrm{Rev}(v,(j-1,k)) = \mathrm{Rev}(v,(j,k))$), we have

$$P(j+1,k) - P(j,k) = (1+1/a)(P(j,k) - P(j-1,k)) + (P(k,j) - P(k,j-1))/a, \tag{50}$$

for $j = 1, 2, \ldots, k-1$. Equation (50) implies that

$$P(j+1,k) - P(j,k) = (1+1/a)^j P(1,k) + \sum_{j'=1}^{j} (1+1/a)^{j-j'} (P(k,j') - P(k,j'-1))/a, \quad (51)$$

and as a consequence, for any $j = 0, 1, \ldots, k$:

$$P(j,k) = a((1+1/a)^j - 1)P(1,k) + \sum_{j'=1}^{j-1} ((1+1/a)^{j-j'} - 1)(P(k,j') - P(k,j'-1)). \quad (52)$$

We claim that

$$\begin{aligned} X(l) &\equiv \sum_{j=1}^{l-1} (1+1/a)^{l-j} (P(l,j) - P(l,j-1)) \\ &= P(l,l-1) + a((1+1/a)^l - 1)^2 P(1,0) - (1+1/a)^l P(l,0), \end{aligned} \quad (53)$$

for every $l = 1, 2, \ldots, k$. Equation (53) for $l = k$ and Equation (52) together imply Equation (29), which proves the lemma.

Clearly, (53) is true for $l = 1$. Suppose (53) is true for $l = \kappa < k$ as an induction hypothesis; we prove that this implies (53) is true for $l = \kappa + 1$.

From $\mathrm{Rev}(v, (\kappa, j-1)) = \mathrm{Rev}(v, (\kappa, j))$ we have:

$$\begin{aligned} & P(\kappa+1,j) - P(\kappa+1,j-1) \quad (54) \\ =& (1+1/a)(P(\kappa,j) - P(\kappa,j-1)) + (1+1/a)(P(j,\kappa) - P(j-1,\kappa)) \\ & - (P(j+1,\kappa) - P(j,\kappa)), \end{aligned}$$

summing the above equation across $j = 1, 2, \ldots, \kappa - 1$ gives:

$$\begin{aligned}
&\sum_{j=1}^{\kappa-1}(1+1/a)^{\kappa+1-j}(P(\kappa+1,j)-P(\kappa+1,j-1)) \qquad (55)\\
=&\sum_{j=1}^{\kappa-1}(1+1/a)^{\kappa+2-j}(P(\kappa,j)-P(\kappa,j-1))+\sum_{j=1}^{\kappa-1}(1+1/a)^{\kappa+2-j}(P(j,\kappa)-P(j-1,\kappa))\\
&-\sum_{j=1}^{\kappa-1}(1+1/a)^{\kappa+1-j}(P(j+1,\kappa)-P(j,\kappa))\\
=&\sum_{j=1}^{\kappa-1}(1+1/a)^{\kappa+2-j}(P(\kappa,j)-P(\kappa,j-1))+(1+1/a)^{\kappa+1}P(1,\kappa)-(1+1/a)^2(P(\kappa,\kappa)-P(\kappa-1,\kappa)).
\end{aligned}$$

That is,

$$\begin{aligned}
&X(\kappa+1) \qquad (56)\\
=&\sum_{j=1}^{\kappa-1}(1+1/a)^{\kappa+2-j}(P(\kappa,j)-P(\kappa,j-1))+(1+1/a)^{\kappa+1}P(1,\kappa)\\
&-(1+1/a)^2(P(\kappa,\kappa)-P(\kappa-1,\kappa))+(1+1/a)(P(\kappa+1,\kappa)-P(\kappa+1,\kappa-1))\\
=&(1+1/a)^2[P(\kappa,\kappa-1)+a((1+1/a)^\kappa-1)^2P(1,0)-(1+1/a)^\kappa P(\kappa,0)]+(1+1/a)^{\kappa+1}P(1,\kappa)\\
&-(1+1/a)^2(P(\kappa,\kappa)-P(\kappa-1,\kappa))+(1+1/a)(P(\kappa+1,\kappa)-P(\kappa+1,\kappa-1)),
\end{aligned}$$

where in the last equality we have used the induction hypothesis (53) for $l = \kappa$.

From $\mathrm{Rev}(v,(\kappa,0)) = \mathrm{Rev}(v,(1,0))$ we have $(1+1/a)P(\kappa,0) - P(1,\kappa) = P(\kappa+1,0) - 2P(1,0)$. Therefore, the previous equation is equivalent to:

$$\begin{aligned}
&X(\kappa+1) \qquad (57)\\
=&(1+1/a)^2P(\kappa,\kappa-1)+a(1+1/a)^2((1+1/a)^\kappa-1)^2P(1,0)-(1+1/a)^{\kappa+1}(P(\kappa+1,0)-2P(1,0))\\
&-(1+1/a)^2(P(\kappa,\kappa)-P(\kappa-1,\kappa))+(1+1/a)(P(\kappa+1,\kappa)-P(\kappa+1,\kappa-1))\\
=&(1+1/a)^2P(\kappa,\kappa-1)+[a(1+1/a)^2((1+1/a)^\kappa-1)^2+2(1+1/a)^{\kappa+1}]P(1,0)-(1+1/a)^{\kappa+1}P(\kappa+1,0)\\
&-(1+1/a)^2(P(\kappa,\kappa)-P(\kappa-1,\kappa))+(1+1/a)(P(\kappa+1,\kappa)-P(\kappa+1,\kappa-1))
\end{aligned}$$

From $\mathrm{Rev}(v,(\kappa,\kappa)) = \mathrm{Rev}(v,(1,0))$ we have $(1+1/a)P(\kappa,\kappa) - P(\kappa+1,\kappa) = -P(1,0)$.

Therefore, the previous equation is equivalent to:

$$\begin{aligned} & X(\kappa+1) \\ =& (1+1/a)^2 P(\kappa,\kappa-1) + [a(1+1/a)^2((1+1/a)^\kappa-1)^2 + 2(1+1/a)^{\kappa+1} + (1+1/a)]P(1,0) \\ & - (1+1/a)^{\kappa+1}P(\kappa+1,0) + (1+1/a)^2 P(\kappa-1,\kappa) - (1+1/a)P(\kappa+1,\kappa-1). \end{aligned} \tag{58}$$

From $\mathrm{Rev}(v,(\kappa-1,\kappa)) = \mathrm{Rev}(v,(1,0))$ we have $(1+1/a)P(\kappa,\kappa-1)+(1+1/a)P(\kappa-1,\kappa)-P(\kappa+1,\kappa-1) = P(\kappa,\kappa) - 2P(1,0)$, Therefore, the previous equation is equivalent to:

$$\begin{aligned} & X(\kappa+1) \\ =& [a(1+1/a)^2((1+1/a)^\kappa-1)^2 + 2(1+1/a)^{\kappa+1} - (1+1/a)]P(1,0) \\ & - (1+1/a)^{\kappa+1}P(\kappa+1,0) + (1+1/a)P(\kappa,\kappa). \end{aligned} \tag{59}$$

Finally, using $(1+1/a)P(\kappa,\kappa) - P(\kappa+1,\kappa) = -P(1,0)$ again we get:

$$\begin{aligned} & X(\kappa+1) \\ =& [a(1+1/a)^2((1+1/a)^\kappa-1)^2 + 2(1+1/a)^{\kappa+1} - (1+1/a) - 1]P(1,0) \\ & - (1+1/a)^{\kappa+1}P(\kappa+1,0) + P(\kappa+1,\kappa). \end{aligned} \tag{60}$$

Since $a(1+1/a)^2((1+1/a)^\kappa-1)^2 + 2(1+1/a)^{\kappa+1} - (1+1/a) - 1 = a((1+1/a)^{\kappa+1}-1)^2$, this proves (53) when $l = \kappa+1$. □

References

Bergemann, D., B. Brooks, and S. Morris (2016): "First Price Auctions with General Information Structures: Implications for Bidding and Revenue," Working paper.

Bergemann, D. and S. Morris (2016): "Bayes Correlated Equilibrium and The Comparison of Information Structures in Games," *Theoretical Economics*.

Brooks, B. (2013): "Surveying and Selling: Belief and Surplus Extraction in Auctions," Working paper.

Carrasco, V., V. Farinha Luz, P. Monteiro, and H. Moreira (2015): "Robust Selling Mechanisms," Working paper.

Carroll, G. (2015): "Robustness and Linear Contracts," *American Economic Review*, 105, 536–63.

——— (2016): "Informationally Robust Trade Under Adverse Selection," Working paper.

Chen, Y.-C. and J. Li (2016): "Revisiting the Foundations of Dominant-Strategy Mechanisms," Working paper.

Chung, K.-S. and J. C. Ely (2007): "Foundations of Dominant-Strategy Mechanisms," *The Review of Economic Studies*, 74, 447–476.

Crémer, J. and R. P. McLean (1985): "Full Extraction of the Surplus in Bayesian and Dominant Strategy Auctions," *Econometrica*, 53, 345–361.

——— (1988): "Optimal Selling Strategies under Uncertainty for a Discriminating Monopolist when Demands are Interdependent," *Econometrica*, 56, 1247–1257.

Frankel, A. (2014): "Aligned Delegation," *American Economic Review*, 104, 66–83.

Gilboa, I. and D. Schmeidler (1989): "Maxmin Expected Utility with Non-unique Prior," *Journal of Mathematical Economics*, 18, 141–153.

Myerson, R. B. (1997): "Dual Reduction and Elementary Games," *Games and Economic Behavior*, 21, 183–202.

Roesler, A.-K. and B. Szentes (2016): "Buyer-Optimal Learning and Monopoly Pricing," Working paper.

Wilson, R. (1987): "Game-Theoretic Analyses of Trading Processes," in *Advances in Economic Theory: Fifth World Congress*, ed. by T. Bewley, Cambridge University Press, 33–70.

Yamashita, T. (2015): "Implementation in Weakly Undominated Strategies: Optimality of Second-Price Auction and Posted-Price Mechanism," *The Review of Economic Studies*, 82, 1223–1246.

——— (2016): "Revenue Guarantee in Auction with Common Prior," Working paper.