## Selling Impressions: Efficiency vs Competition

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32nd Stony Brook International Conference of Game Theory July 2021

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    - revenue is common ex ante expected value

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- this is our main theoretical result and first main contribution

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- Advertisers values' might well be correlated, but will be independent as long as advertiser / viewer variation is "horizontal", i.e., attributes and preferences are symmetric across viewers and bidders

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  - A model of the market for impressions with two sided information
  - We describe when this model reduces statistically and strategically to our first model and result

## Hour Long Talk

- Main Result
- Market for Impressions
  - Institutional Details
  - Stylized Model of Market for Impressions with Two-Sided Information
  - 3 Statistical and Strategic Analysis

## Part I: Main Result

## Setting for Main Result

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 $\bullet \ \ \text{if} \ F \ \ \text{is a mean preserving spread of} \ G \ \ \text{we write} \ F \prec G$ 



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- neither convex nor concave program



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- just as quantile of any random variable is uniformly distributed, the quantile of second-order statistic of N random variables is distributed according to S for every distribution

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- $F \prec G$  if and only if  $G^{-1} \prec F^{-1}$
- objective is linear in  $G^{-1}$

## Optimal Information Structure

#### Proposition (Optimal Information Structure)

Suppose that F is absolutely continuous, then the unique optimal symmetric information structure is given by:

$$s(v_i) = \begin{cases} v_j & \text{if } q_i(v_i) \le q^* \\ \mathbb{E}[v_j \mid F(v_j) \ge q] & \text{if } q_i(v_i) \ge q^* \end{cases}$$

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- with change of variables, "upper censorship"



## Competition through Information

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- bundles for every bidder all valuations above the threshold  $F^{-1}(q^*)$  into a single mass point
- information rent of the winning bidder is depressed considerably with a corresponding gain in the revenue for the seller

### Intuitive Proof Step 1: Integrate by Parts

• if  $\overline{v} = G^{-1}(1)$  is the upper bound on expected value, by integration by parts, revenue is:

$$\int_0^1 S'(q)G^{-1}(q)dq = \overline{v} - \int_0^1 S(q)dG^{-1}(q)$$

so we have minimization problem

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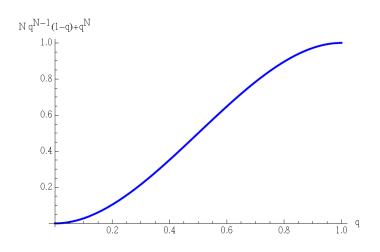
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• HINT: if  $\overline{v} = 1$ ,  $G^{-1}$  is itself a distribution function.

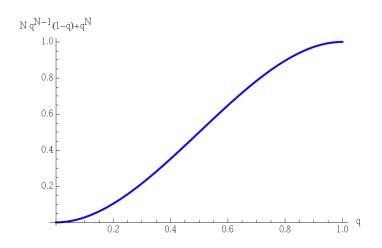
# Step 2: Convexification of Second Order Statistic



• graph of S(q) for N=3



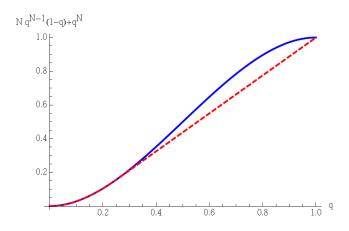
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- ullet unique inflection point for all N

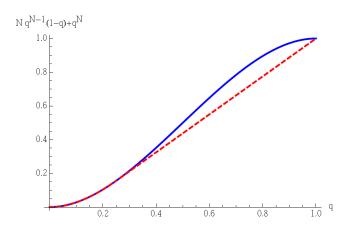


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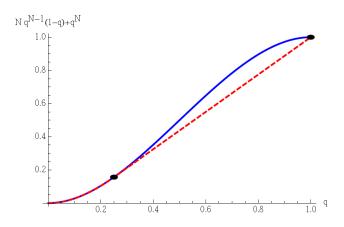


- find largest convex function below the original one
- ullet problem reduces to finding q such that:

$$S(q) + S'(q)(1-q) = S(1) = 1$$

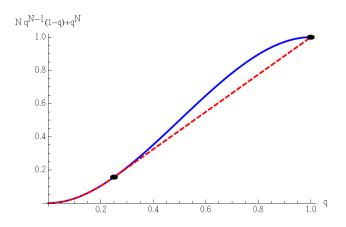


### End Points of Affine Segment



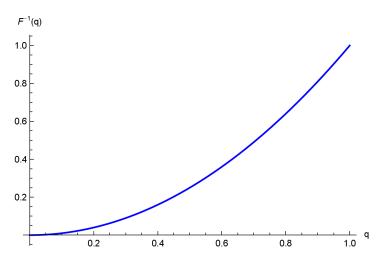
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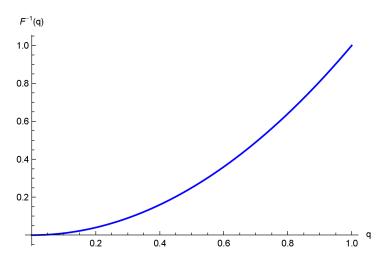
- ullet we take the mass of  $F^{-1}$  to the extremes of the affine segment
- the mass at each extreme must keep the expected mean of quantile constant

## Step 3: Back to Value Distribution



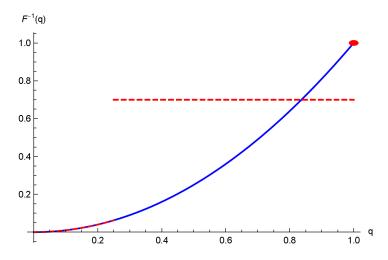
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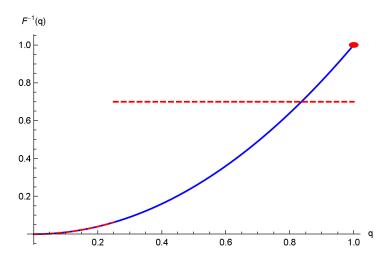
- map back to value distribution of bidder i
- we draw the quantile function for  $F\left(v\right)=\sqrt{v}$

### From Quantile to Convexified Quantile



• the mass is moved to the end points

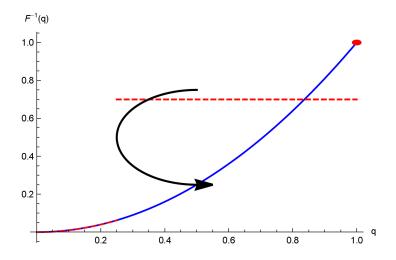
## From Quantile to Convexified Quantile



- the mass is moved to the end points
- while keeping expectation of quantile constant

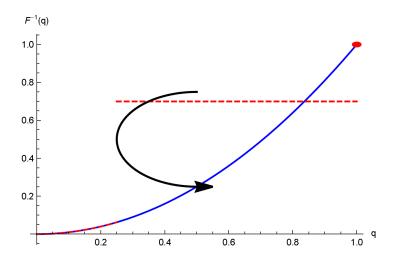


#### From Convex Quantile to Convex Distribution



• we have been working with the quantile function

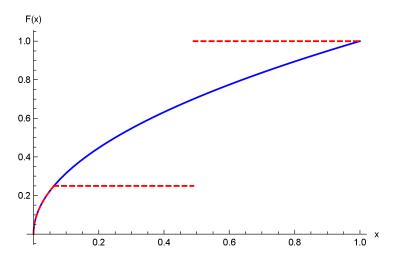
#### From Convex Quantile to Convex Distribution



- we have been working with the quantile function
- to recover the distribution we rotate

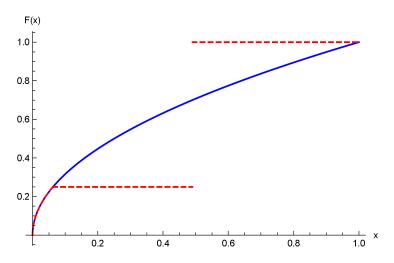


#### From Convex Distribution to Information Structure



ullet we now have the distribution Q

#### From Convex Distribution to Information Structure



- ullet we now have the distribution Q
- there is one step in distribution of expected value



#### Verification

 this is an example of a problem of characterizing extreme points of monotone functions subject to majorization constraints (Kleiner et al. 2021)

#### Proposition (Kleiner et al. Proposition 2)

Let  $G^{-1}$  be such that for some countable collection of intervals  $\{[\underline{x}_i, \bar{x}_i) \mid i \in I\}$ ,

$$G^{-1}(q) = \begin{cases} F^{-1}(q) & q \notin \bigcup_{i \in I} [\underline{x}_i, \bar{x}_i) \\ \frac{\int_{\underline{x}_i}^{\overline{x}_i} F^{-1}(t) dt}{\overline{x}_i - \underline{x}_i} & q \in [\underline{x}_i, \bar{x}_i) \end{cases}$$

If conv S is affine on  $[x_i, x_i)$  for each  $i \in I$  and if  $\operatorname{conv} S = S$  otherwise, then G solves the maximization problem. Moreover, if F is strictly increasing the converse holds.

#### What is the Critical Quantile?

#### Proposition (Critical Quantile)

The quantile  $q^*(N) \in [0,1)$  that determines the optimal information structure is 0 if N=2, is increasing in N and approaches 1 as  $N \to \infty$ ; for  $N \ge 3$ , it is implicitly defined as the solution of:

$$S'(q)(1-q) = 1 - S(q)$$

ullet this is an  $N{
m th}$  degree polynomial in q

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  - expected gain in approximately:

 $\underbrace{\frac{1-S\left(q\right)}{1-q}}^{\text{prob high payment}} \times \underbrace{\frac{\text{increase in payment}}{\varepsilon\left[\overline{v}-\underline{v}\right]}}^{\text{increase in payment}}$ 

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expected loss is approximately

$$\overbrace{\varepsilon S'\left(q\right)}^{\text{prob low payment}} \times \overbrace{\overline{v}-\underline{v}}^{\text{decrease in payment}}$$

## Critical Quantiles

N	$q^*(N)$
2	0
3	0.25
4	0.46
5	0.58
10	0.81
100	0.98

## Part II: Market for Impressions

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 An advertiser's preference tells them nothing about their or others' valuation of the object (without knowing the attribute)

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• as  $J \to \infty$ , can induce any distribution of values F



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- Preferences and attributes are realized, preferences are reported to the advertiser, signals and bids are realized and the impression is allocated to the highest bidder at the second highest price

#### **Auto-Bidding**

#### Proposition (Truthful Reporting)

Advertisers have an incentive to truthfully report their preferences in the auto-bidding mechanism.

 Corollary: With those commitment powers, publisher's problem reduces to our main result

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- however, there is an information structure where seller pools high and low values and reveals values in between, which attains close to first best



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# Literature II: Mechanics of Bidding in the Market for Impressions

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- a key incentive to pool premium impressions while allowing information about non-premium impressions

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- power law tails
  - gain from pooling is strictly positive even as  $N\to\infty$  and  $q^*\to 1$



#### Large Markets

- large number of (possible) bidders is arguably the prevailing condition in digital advertising how does information respond to random participation of bidders
- revenue performance of auction with optimal information structure when the actual number of participating bidders grows large.

#### Random Number of Bidder

- ullet with probability p, valuation is equal zero
- with probability 1 p, valuation is distributed with F
- limit as  $N \to \infty$  and  $p \to 1$  while expected number of bidders with positive values constant at:

$$\lambda \triangleq N(1-p)$$

 $\bullet$  critical number  $\rho$  of expected bidders

$$\rho \triangleq N(1 - q^*) \tag{1}$$

• as  $N \to \infty$ , (1) converges in terms of  $\rho$ :

$$\rho^2 e^{-\rho} = 1 - e^{-\rho} - \rho e^{-\rho} \Leftrightarrow \rho \approx 1.793$$



## Equilibrium Information

#### Proposition

As  $N \to \infty, p \to 1$ , the optimal information structure is:

- If  $\lambda \leq \rho$ , then bidders observe binary signals and expected value is either 0 or  $\mathbb{E}[v_i]\lambda/\rho$ .
- ② If  $\lambda > \rho$ , bidder  $v_i$  with  $F(v_i) \leq (\lambda \rho)/\lambda$  learns value, and bidder  $v_i \in [F^{-1}((\lambda \rho)/\lambda), 1]$  is bundled.
  - bundle zero values with positive values ("broad search")
  - increase number of bidders even at cost of decreasing expected valuations
  - with sufficently many bidders, we have pooling of high-valuation bidders



## Large Number of Bidders with Heavy Tails

- Arnosti, Beck and Milgrom (2016) argued heavy tails distribution prevail in digital advertising.
- ullet F has regularly varying tails with index  $\alpha$ , if

$$\lim_{t \to \infty} \frac{1 - F(kt)}{1 - F(t)} = k^{\alpha},$$

- we assume  $\alpha < 0$ , and with  $\alpha < -1$ , we guarantee finite mean
- for example Pareto distribution satisfies this assumption

## Revenue Comparison with Heavy Tails

• expected revenue in second price auction with complete disclosure of information,  $R_c$ :

$$R_c \triangleq \mathbb{E}[v_{(2)}].$$

• compare revenue of optimal information structure, R with revenue of complete disclosure,  $R_c$  for large N

#### Proposition (Revenue Ratio with Many Bidders )

As  $N \to \infty$ , there exists  $z \in (1, \infty)$  s.th.:

$$\lim_{N\to\infty}\frac{R}{R_c}=z.$$

Furthermore, in the limit  $\alpha \to -1$ ,  $z \to \infty$ .



#### Revenue Gains

- gains from optimal information structure do not vanish
- ullet when the distribution has fat tails, or lpha < 0

$$\mathbb{E}[v_{(1)}] - \mathbb{E}[v_{(2)}] \to \infty, \text{ as } N \to \infty.$$

- optimal information structure thickens the market at the tail of the distribution
- thus provide a revenue improvement even as the numbers of bidders becomes arbitrarily large

# Honesty and Obedience

#### Eliciting Advertisers' Preferences

- examine advertisers' incentives to truthfully report their preferences
- a reporting strategy for bidder *i* is denoted by:

$$\widetilde{y}_i: \{-1,1\}^J \to \Delta \{-1,1\}^J.$$

• given reported preferences, the seller discloses to the bidder a signal  $s(\widetilde{v}_i)$ , where

$$\widetilde{v}_i \triangleq u(\frac{1}{\sqrt{J}} \sum_{j=1}^{J} \widetilde{y}_{ij}(y_{ij}) x_j)$$

 since preferences and attributes are symmetrically distributed, a sufficient statistic for the bidder's strategy is the fraction of preferences truthfully reported:

$$t_i \triangleq \sum_{i=1}^{J} \frac{\widetilde{y}_i y_i}{J}$$

# Critical Reporting Strategies

 with preferences and attributes symmetrically distributed, a sufficient statistic is:

$$t_i \triangleq \sum_{j=1}^{J} \frac{\widetilde{y}_i y_i}{J}$$

- in other words, for any reporting strategy  $\widetilde{y}_i, \widetilde{y}'_i$  satisfying  $t_i = t'_i$ , the induced distribution of expected valuations will be the same:  $\widehat{G}_i = \widehat{G}'_i$
- if t=1 then preferences have been correctly reported; if t=0 then half of all preference components have been misreported; if t=-1 then every preference component has been incorrectly reported

#### Honesty and Informativeness

 following lemma establishes that the only relevant incentive constraints are those induced by reporting the exact opposite preference

#### Lemma (Informativeness of Signals)

Let s be the optimal information structure. For every  $t \in [0,1)$ , the generated signal is less informative than the signal generated when reporting truthfully. For every  $t \in (-1,0]$ , the generated signal is less informative than the signal generated when reporting the exact opposite preference (i.e., t=-1).

## Truthful Reporting Under Auto Bidding

• informative lemma helps to establish:

#### Proposition (Honesty)

Under auto bidding and the optimal information structure, it is a dominant strategy for the advertiser to report his preference truthfully.

- misreporting leads to automated bids different from the expected value given limited information
- truthtelling guarantees that bid always equals expected value

#### Manual Bidding

- ullet truthtelling is not an equilibrium for every  $N,\ u$
- $\bullet$  there is a class of information structures balancing revenue-maximization and incentive compatibility with large N
- consider the two-sided pooling structure:

$$s(v_i) = \begin{cases} \mathbb{E}[v_j \mid F(v_j) \le 1 - q] & \text{if } F(v_j) \le 1 - q^* \\ v_j & \text{if } 1 - q^* \le F(v_j) \le q^* \\ \mathbb{E}[v_j \mid F(v_j) \ge q] & \text{if } F(v_j) \ge q^* \end{cases}$$

 above information structure adds pooling at the bottom to pooling at the top

# Truthful Reporting Under Manual Bidding

#### Proposition (Honesty and Obedience)

Under manual bidding, it is a dominant strategy for the advertiser to report his preference truthfully in the two-sided pooling structure.

#### Proposition (Approximate Optimality)

Under the two-sided pooling information structure the revenue converges to the one under the optimal information structure when the number of bidders grows large:

$$\lim_{N \to \infty} (\mathbb{E}[w_{(2)}] - R) = 0.$$

ullet revenue under two-sided pooling is given by  $w_{(2)}$ 



#### Discussion and Conclusion

- correlated values and adverse selection
- vertical differentation of attributes
- auction format
- reserve price and optimal auction
- asymmetric information structure