Three Essays on Dynamic Mechanism Design

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Ouline

Ch1. Non-clairvoyant Dynamic Mechanism Design: Experimental Evidence

- We compare the performance of two non-clairvoyant mechanisms.
- We find that non-clairvoyant mechanisms work as theory predicts.

Ch2. How Sellers Choose Dynamic Mechanism: Information Matters

- We study whether human sellers can choose the correct dynamic mechanism.
- We find that human sellers can find intuition when they gain expeirence.

Ch3. Using (Merit-Based) Default to Reduce Gender Gaps in Contribution of Ideas: Evidence from an Online Experiment

- We explore how default options affect the gender gap of idea contribution.
- We find that random defaults are as effective as merit defaults.

Chapter 1

Non-clairvoyant Dynamic Mechanism Design: Experimental Evidence

Shan Gui and Daniel Houser

Optimal Dynamic Mechanism Design

- To maximize the revenues (payoff), the seller (principle) sets rules of allocations and prices over multi-period as the buyer (agent) receives private information over time.
  - **Repeated selling of perishable goods**
  - Long-term principal-agent relationship
- Dynamic mechanism improves revenues and the efficiency (Baron & Besanko, 1984).

A "Simple" Example

Scenario U

- two-period, single-buyer
- the seller sells one item in each period; zero production cost
- Distribution of Buyer's value: $F_1 = U[0,1] = F_2$, independent draws

What are the best rules of allocation and price?

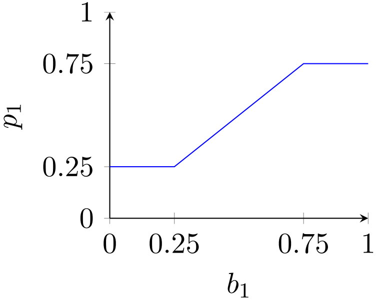
- Dynamic IC: the buyer reports the true value
- Ex-post IR: the buyer gains a non-negative payoff after realization of values

A complicated Answer

Buyer knows the clairvoyant bundle:

$$p_2 = 1 - \sqrt{2p_1 - 0.5}$$

- Buyer makes a bid in Period 1, pays p_1 if $b_1 \geq p_1$
- p_1 is a function of b_1



Clairvoyant mechanism is hard to solve, understand, and implement

Clairvoyant Mechanisms

- Full information design $\Rightarrow$ Future demand (F_2) is used to design the structure

Why not clairvoyant mechanism in real-life?

- Difficult to compute
- Non-intuitive
- Need to share a common belief
- Lack of a general form
- Real revenue is not as expected

Non-Clairvoyance Environment: more practical

Future demand is not accessible at the beginning.

- No needs to share unbiased belief.
- General Form.

F_2 is unknown in Day 1

$v_1 \sim F_1$

$v_2 \sim F_2$?

Non-Clairvoyant Mechanisms: general form

RS: Repeated Static optimal mechanism (Myerson, 1981)

- Rules in two days are independent of each other

  Maximize **intra-period revenue** for each period separately.

  $\Rightarrow \frac{Rev^{RS*}}{Rev^{*}}$ could be arbitrarily small (Papadimitriou et al., 2016)

NC: Non-Clairvoyant optimal dynamic mechanism (Mirrokni et al., 2020)

- Rules in Day 2 depends on bid in day 1

  Best Revenue Guarantee: $\Rightarrow \frac{Rev^{NC*}}{Rev^{*}} \geq \frac{1}{a}$

  Achieve at least $\frac{1}{2}$ revenue produced by optimal clairvoyant mechanism under all scenarios in **two-period single-buyer** case.

Constructing Dynamic Mechanisms

Three Basic Dynamic Mechanism satisfies IC and IR

- F: Free item
- M: get the item if $b \geq r$, pay r
- P: pay upfront fee $s = \min[v_{-1}, \mathbb{E}(v)]$,
  get the item if $b \geq r$, such that $\mathbb{E}[v - r | v \geq r] = s$

NC, RS in a two-period case

- RS: M in Period 1 and Period 2;
- NC: 50% chance of F and 50% chance of M in Period 1;
  ask an upfront fee
  50% chance of P and 50% chance of M in Period 2

When can NC do better than RS?

Relative size of optimal intra- and inter-period revenues is the key.

- Scenario A: Optimal inter - period revenue is larger $\Rightarrow$ NC outperforms.

  $F_1 = F_A = \{v, p(v)\} = \{(2, \frac{1}{2}), (4, \frac{1}{2})\},$ $\qquad \mathbb{E}_A = 3.$

  $F_2 = F_B = \{v, p(v)\} = \{(2, \frac{1}{2}), (4, \frac{1}{4}), (8, \frac{1}{8}), (16, \frac{1}{16}), (32, \frac{1}{16})\},$ $\qquad \mathbb{E}_B = 6.$

$$REV^{RS} = 4,\ REV^{NC} = 4.5\ \uparrow 12.5\%$$

- Scenario B: Optimal intra - period revenue is larger $\Rightarrow$ RS outperforms.

$$F_1 = F_B, F_2 = F_A$$

$$REV^{RS} = 4,\ REV^{NC} = 3.5\ \downarrow 12.5\%$$

Experimental Design $2 * 2$

Two Mechanisms * Two Scenarios

- Non-Clairvoyant Dynamic Mechanism (NC)
- Repeated Static Mechanism (RS)

- Scenario A (S_A)
- Scenario B (S_B)

Non-Clairvoyant Environment

- Participants as the **Buyer** trading with **Robot Seller**, $c = 0$,
- **Two periods**: The buyer can buy one item in each period from the seller
- **Non-clairvoyance** : The distribution of buyer's value (F_t) is common knowledge only in that period
- **Incomplete Information**: Only buyer knows his value for the item in each period, v_t, independent draw.
- **Endowment** $= 50$

Mechanism - Repeated Static (RS)

Period 1

- Seller sets a reserve price r_1 based on the distributional knowledge F_1.
- Buyer learns his value (v_1), makes a bid : b_1
- Buyer can get the item only when $b_1 \geq r_1$ and pay $p_1 = r_1$.

Period 2

- $F_2 \Rightarrow r_2$, $v_2 \Rightarrow b_2$, pays $p_2 = r_2$ if $b_2 \geq r_2$

Myerson's Auction

monopoly price: $r_1 = r_2 = 2$

$r_A = 2 \in \{arg\max_r \ r \cdot P(v_A > r)\}, \quad r_B = 2 \in \{arg\max_r \ r \cdot P(v_B > r)\}$

Mechanism - Non-Clairvoyant Dynamic (NC)

How the dynamic mechanism work?

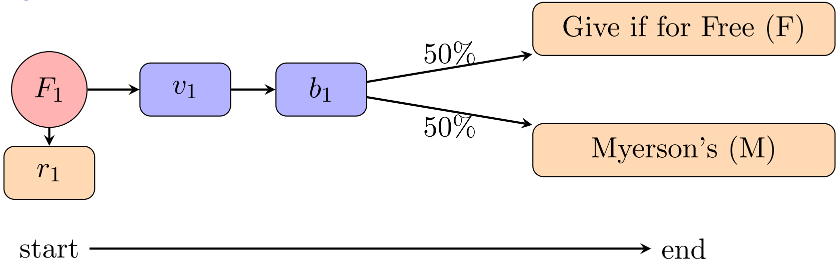
Half chance of free item in period 1

Half chance of upfront fee in period 2

Non-Clairvoyant Mechanism in Period 1

- Seller sets a fixed reserve price r_1 based on the distribution F_1.
- Buyer learns his value (v_1), makes a bid : b_1
- Buyer has 50% chance to get the item for free: $p_1 = 0$;
  Otherwise, buyer can get the item only when $b_1 \geq r_1$ and pay $p_1 = r_1$.

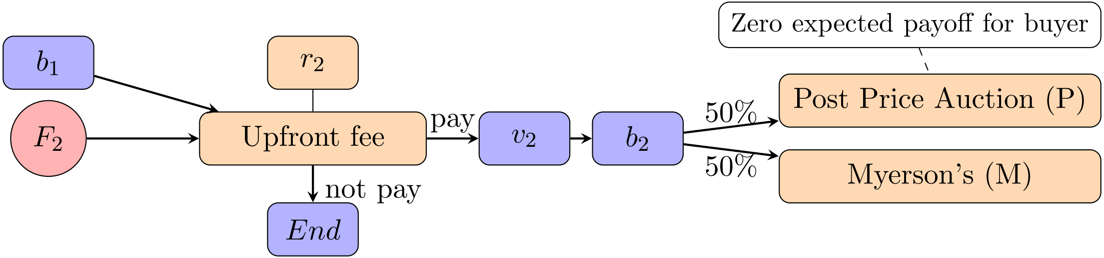
Uniform Combination of Two Auctions



Non-Clairvoyant Mechanism in Period 2

- Seller sets an upfront fee $s_2 = \min(b_1, E(v_2))$.
- Buyer decides pay or leave. If buyer leave ($enter = 0$), game over.
- If buyer pays, ($enter = 1$),
  - Buyer learns his value, v_2, and makes a bid: b_2
  - Buyer has 50% chance to get refund on the upfront fee ($luck = 1$).
  - Seller sets two reserve prices (r_2) based on the $F_2, luck$ for each given m_2, Buyer can get the item only when $b_2 \geq r_2$ and pay $p_2 = r_2$

Uniform Combination of Two Auctions



Hypotheses

Hypothesis 1 - On Revenue Comparison

- In Scenario A (S_A), the non-clairvoyant mechanism (NC) generates greater revenue than the repeated static mechanism (RS);
- In S_B, NC generates less revenue than RS.

Hypothesis 2 - On Individual Rationality

- Some buyers choose not to pay the upfront fee, such that the experimental revenue of the non-clairvoyant mechanism is less than its theoretical prediction.

Hypothesis 3 - On Incentive Compatibility

- Participants' bids are closer to true value under NC than RS.

Experiments

- 256 George Mason Students. September to November 2021.

Treatment	**Scenario A**		**Scenario B**	
	Non-Clairvoyant	**Repeated Static**	**NC**	**RS**
Age	21.6	22.3	21.9	22.7
Gender (Male=1)	0.48	0.44	0.52	0.47
Risk aversion	4.46	4.90	4.55	4.63
Observation	64	64	64	64

Table 1: Summary Statistic

Results

Result 1.

Experimental observations match theoretical predictions.

- In S_A, the non-clairvoyant dynamic mechanism gains more revenue than the repeated static mechanism.
- In S_B, the non-clairvoyant dynamic mechanism gains less revenue than the repeated static mechanism. mechanism.

Experimental Revenue Comparison - Period 1

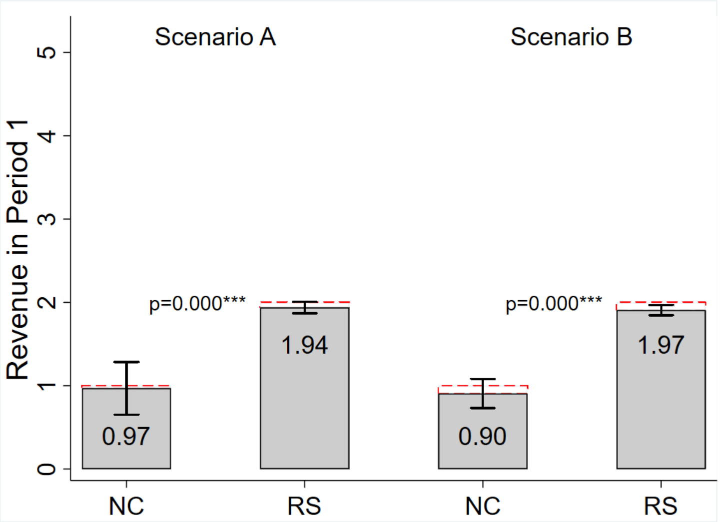


Figure 3: Revenues of Period 1 in each Treatment

Experimental Revenue Comparison - Period 1 & Period 2

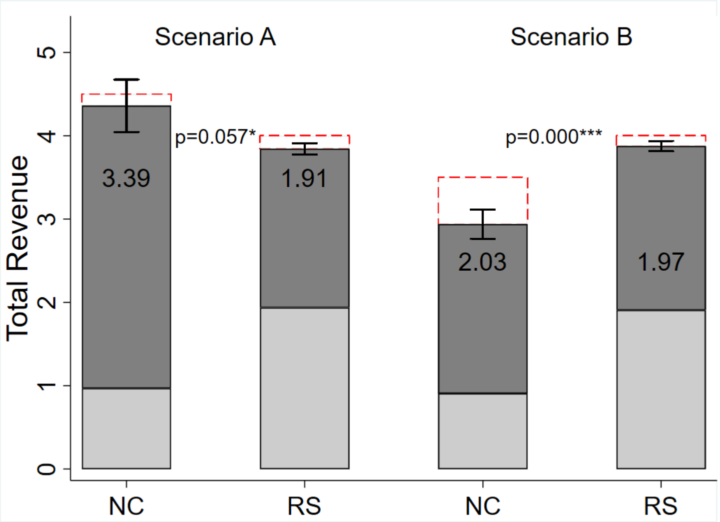


Figure 4: Revenues in each Treatment

Results

Result 2.

Risk aversion deters buyers from participating in the second period in NC.

- In S_A, 4 buyers quit the second period, and the number doubles in S_B.
- Revenue from NC being less than theoretically predicted.

Revenue Loss Decomposition

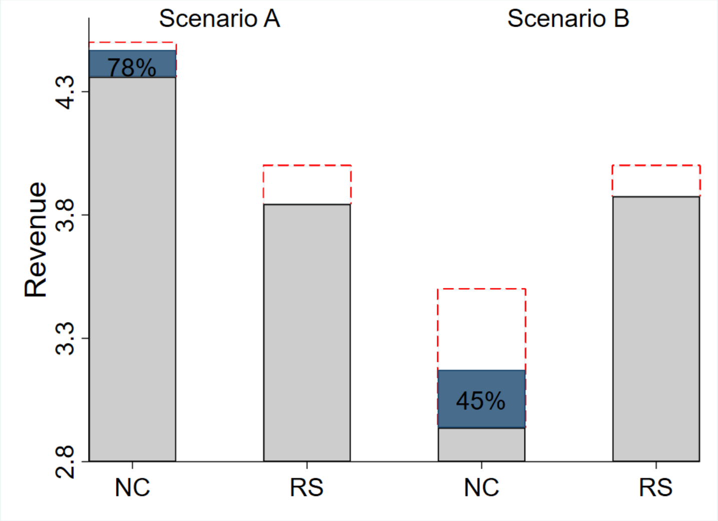


Figure 5: Revenues Increase if all Buyers enter in Period 2.

Why not Pay the Upfront Fee (membership fee)

- “Since I got a profit the first time I didn’t want to go again with my luck”
- “Risk vs Reward...... I got lucky and did not have to pay.”
- “Based on the membership fee. ”
- “didn’t want to take any big risks so I just lowballed my offers and refused to take the membership”
- “i read the instructions carefully. i think the second period isn’t worth losing the points - i had to pay membership fee and could only get the item by bidding higher than the price set by the seller...... honestly, i haven’t been feeling lucky so i’d rather not take my chances. so i tried not to lose money in the first period and just left it as is.”

Risk Aversion Affects Second-period Participation Indirectly

	DV: Enter in Period 2 (=1)	
	(1)	(2)
Scenario A (=1)	0.17^{**}	0.25^{*}
	(0.08)	(0.13)
$notfree_1(=1)$	0.07	0.08
	(0.07)	(0.11)
Scenario A * $notfree_1$	-0.18^{*}	-0.14
	(0.10)	(0.17)
risk aversion	-0.01	-0.03
	(0.01)	(0.02)
$payoff_1$	0.00	0.00
	(0.01)	(0.01)
$upfront_2$	-0.01	-0.03
	(0.03)	(0.05)
Controls		✓

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2: Regression of Participation Choice on Risk attitude.

Results

Result 3.

- Generally overbid.
- Buyers overbid less under Non-Clairvoyant mechanism when the distribution of their valuation has low variance.

Bid-Value Ratio Comparison

Bid/value	**Non-Clairvoyant Dynamic**	**Repeated Static**	(p-value) [1]
F_A (Low variance)	1.264 (0.04)	1.379 (0.04)	**0.060***
F_B (High variance)	1.194 (0.05)	1.251 (0.04)	0.392
(p-value)	0.116	**0.008*****	

Table 3: Bid-Value Ratio Comparison

[1] We report two-sided p-value under t-test.

Conclusions

- We find the experimental observations are consistent with theoretical predictions: the optimal Non-Clairvoyant dynamic mechanism outperforms the optimal Repeated Static mechanism when it is predicted to do so.
- Buyers' risk attitudes matter in the success of Non-Clairvoyant mechanism.
- Randomization in non-clairvoyant mechanism leads buyers to overbid less.

Discussion

- How do human sellers choose dynamic mechanisms? $\Rightarrow Ch2$
- How do clairvoyant mechanisms perform in the lab? $\Rightarrow$ new treatment OC
- Another implementation form of NC? $\Rightarrow$ to be finished

The Optimal Clairvoyant Mechanism in S_A

Clairvoyant menu :

$$\{(p_1, p_2)\} = \{(2, 8),\ (4, 2)\}$$

$\Rightarrow$ Cannot discriminate in Period 2: $REV_2^{OC} = 2$

$\Rightarrow$ Extract the whole expected value in Period 1: $REV_1^{OC} = 3$

Check IC and IR $u(b_1)$

- if $v_1 = 2$: $u(2) = 0 + 4 - 4 * \frac{1}{4} * 8 = 2, u(4) = -2 + 4 = 2$
- if $v_1 = 4$: $u(2) = 2 + 2 = 4, u(4) = 0 + 4 = 4$

Implementations of the Optimal Clairvoyant Mechanism in S_A

Free item in Period 1 (Give it for Free)

- Buyer makes a bid in Period 1 (or quit), pays p_1 if $b_1 \geq p_1$
- $p_1 = 0$, give it for free in Period 1

Upfront fee in Period 2 (Posted Price Auction)

- Upfront fee equals to past bid: $s_2 = b_1$, buyer pays or quit
- Buyer makes a bid in Period 2 if enter pays p_2 if $b_2 \geq p_2$

The Optimal Clairvoyant Mechanism in S_B

Clairvoyant menu:

$$\{(p_1, p_2)\} = \{(2, 4),\ (4, 1)\}$$

- Buyer makes a bid in Period 1 (or quit), pays p_1 if $b_1 \geq p_1$
- $p_1 = 2$ or $p_1 = 4$ with equal chance

$\Rightarrow$ Cannot discriminate in Period 2: $REV_2^{OC} = 2$

$\Rightarrow$ Cannot discriminate among $v_1 \geq 4$: $REV_1^{OC} = \frac{1}{2}(2+3) = 2.5$

Check IC and IR $u(b_1)$

- if $v_1 = 2$: $u(2) = 0 + 0 = 0, u(4) = -2 + 2 = 0$
- if $v_1 = 4$: $u(2) = 2 + 0 = 2, u(4) = 0 + 2 = 2$

OC does not do better than NC

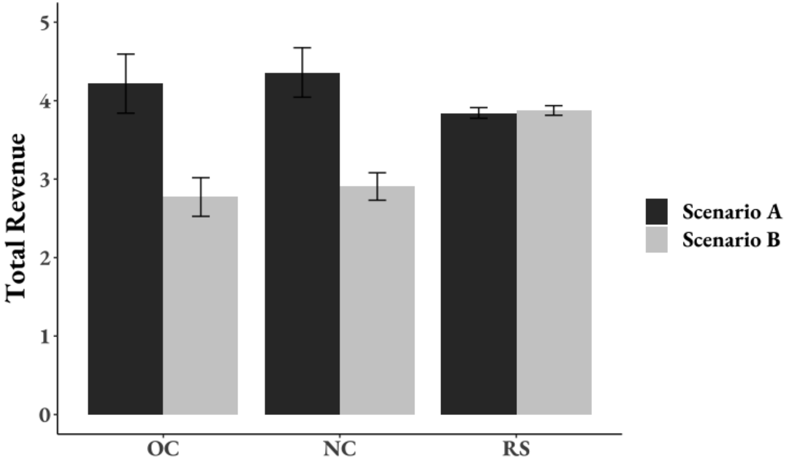
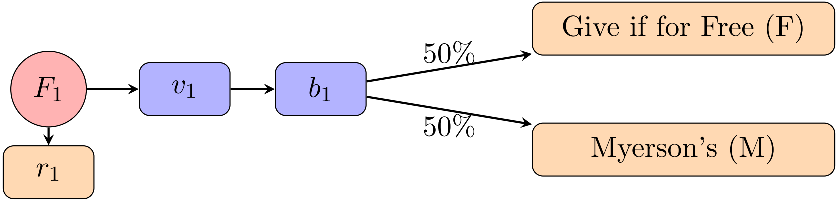


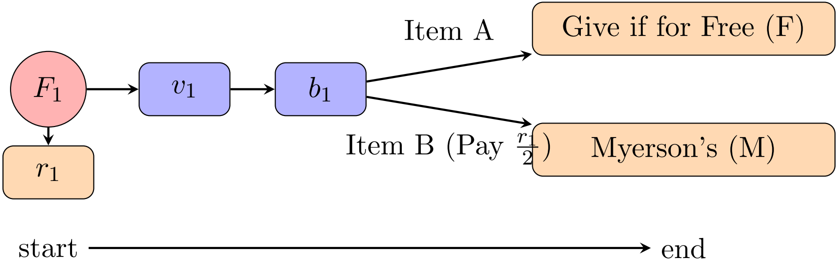
Figure 6: Revenue Comparison

With and without Randomization in Period 1

With Randomization

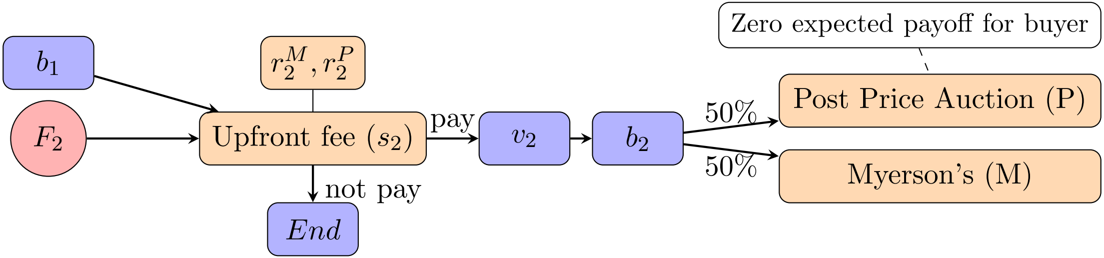


Without Randomization (two small items in Period 1)



With or without Randomization in Period 2

With Randomization



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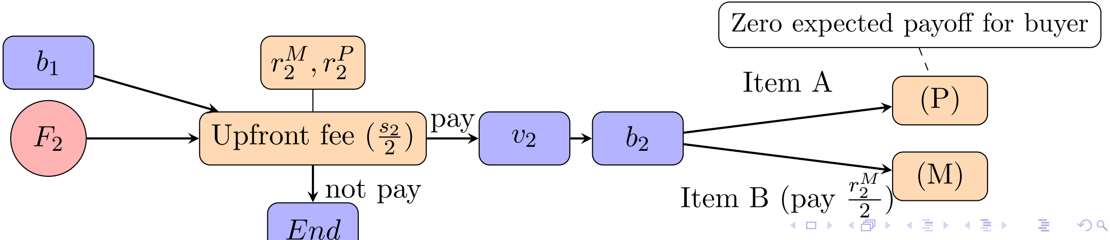


Chapter 2

How Sellers Choose Dynamic Mechanism: Information Matters

Shan Gui and Daniel Houser

Research Question

How do Sellers Decide on Dynamic Mechanisms?

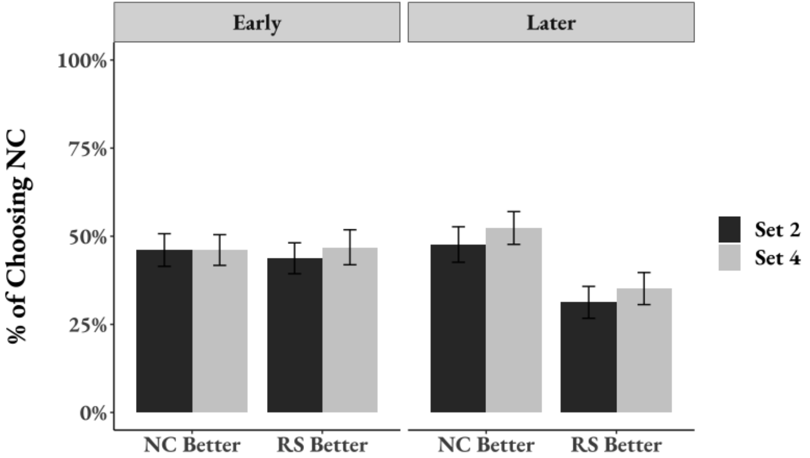
- How do Sellers choose between NC and RS?
- Can Sellers make good decision and improve revenues?

What Information Sellers Use in Deciding on Mechanism?

- **Relative Simplicity**: NC is harder: set more prices.
- **Distributional Knowledge**: NC is optimal for some conditions.
- **Feedback**: NC gets less revenue as Buyers might quit the second period.

Main Result: Sellers choose more correct mechanism in Later stage

Sellers Choose NC Less in RS Better



Chapter 3

Using (Merit-Based) Default to Reduce Gender Gaps in Contribution of Ideas: Evidence from an Online Experiment

Jingnan Chen, Shan Gui, Daniel Houser, and Erte Xiao

Background

Women are under-represented in many domains.

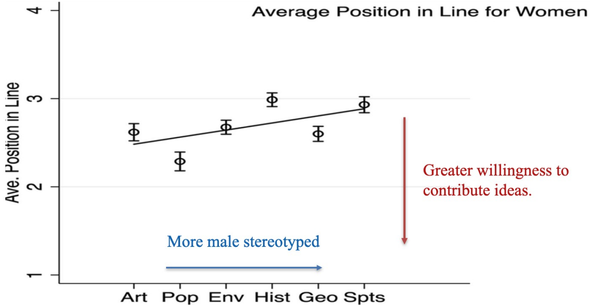
- 44.3% of labor force in S&P 500 companies are women, only 25.1% executive/senior-level managers are female.
- The gender divide is more dramatic in male-stereotyped industries (STEM).

Greater Gender Pay Gap if Women are Under-represented.

Willingness to Contribute and Stereotype

- Gender gap in willingness to contribute ideas is an important factor in explaining the under representation of qualified women. (Babcock and Laschever, 2007; Coffman 2014).

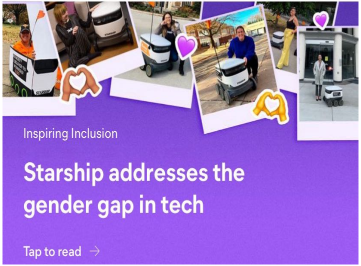
- Stereotype affects women's willingness to contribute. (Coffman 2014; Chen and Houser 2019)



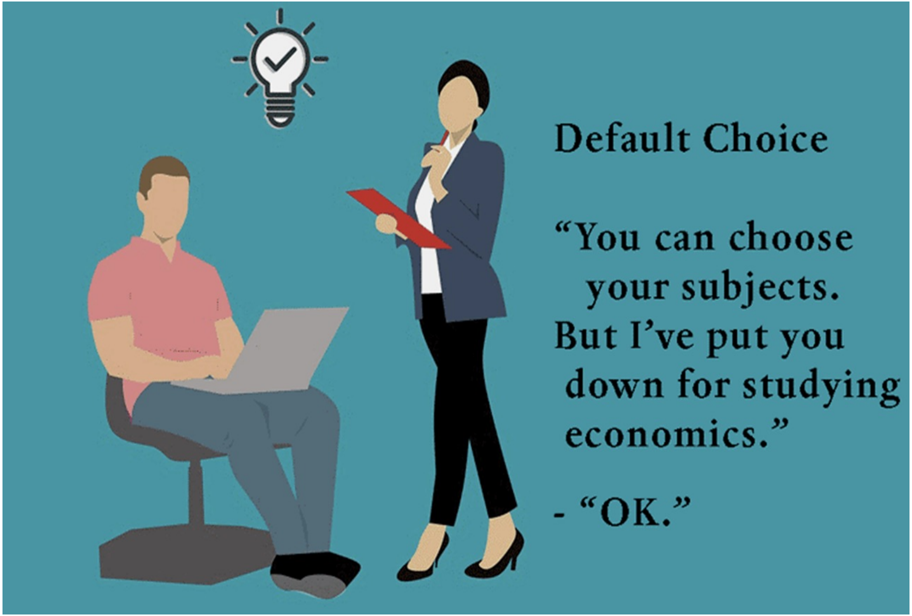
Motivation

How to reduce the gender gap in contribution of ideas?

- Increasing pressure to adopt diversity programs – Lack of evidence
- Training programs – Limited effect
- Instructive mechanisms such as quotas – Questionable in their effectiveness



What else can we try to encourage women to contribute more to a group?


Default Choice
"You can choose your subjects. But I've put you down for studying economics."
- "OK."

Default Effect

- People generally **stay with** the pre-selected choice significantly more frequently.
- Widely used technique in environment, consumer, and healthrelated domains.
- Erkal et al. (2022): opt-out mechanism mitigates the gender gap in participating leadership selection.

Merit-based or Random-assigned?

- Individuals react differently toward merit and luck.
- More willingness to redistribute, steal, lie, and bargain in luck-based mechanisms. (Cappelen et al., 2007; Gravert, 2013; Kajackaite, 2018 ;Cherry et al., 2002)

Merit Defaults on Contributing Ideas

Only high-qualified individuals are defaulted to contribute.

Enhancing the default effect

- Stay with pre-selected options more when deserving the positions.

Building confidences

- Being defaulted indicates high ability $\Rightarrow$ mitigates stereotype effect.

Promoting the right leader

- Defaults matched with performances.

Research Questions

- Can default options promote greater willingness to contribute ideas?
- Whether merit-default is more effective? What is the mechanism behind it?
- Can the default option mitigate the stereotype effect on the contribution of ideas?

Experimental Task

Three parts with a questionnaire (Coffman (2014) and Chen and Houser (2019))

- Part A – 30 MCQs from 6 categories with varying gender stereotype. Individual task.
- Part B – New 30 MCQs with willingness to contribute elicitation. Group task in pairs.
- Part C – Confidence elicitation for questions answered in Part B. Individual task.

Experimental Task - Part A

Part A - Question 1 of 30

DIS: Finish the lyrics from Aladdin: "I'm like a shooting star, I've ____" My answer is:

- ◯ Come to shine
- ◯ Come so far
- ◯ Danced across the sky
- ◯ Got a whole new world
- ◯ Lived the night sky

Next

Experimental Task - Part A

Part A - Question 1 of 30

DIS: Finish the lyrics from Aladdin: "I'm like a shooting star, I've ____" My answer is:

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- ◯ Come so far
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- ◯ Lived the night sky

Next

Experimental Task - Part B

Part B - Question 10 of 30

SPORTS&GAMES: Which of these NHL teams is from New Jersey? My guess is:

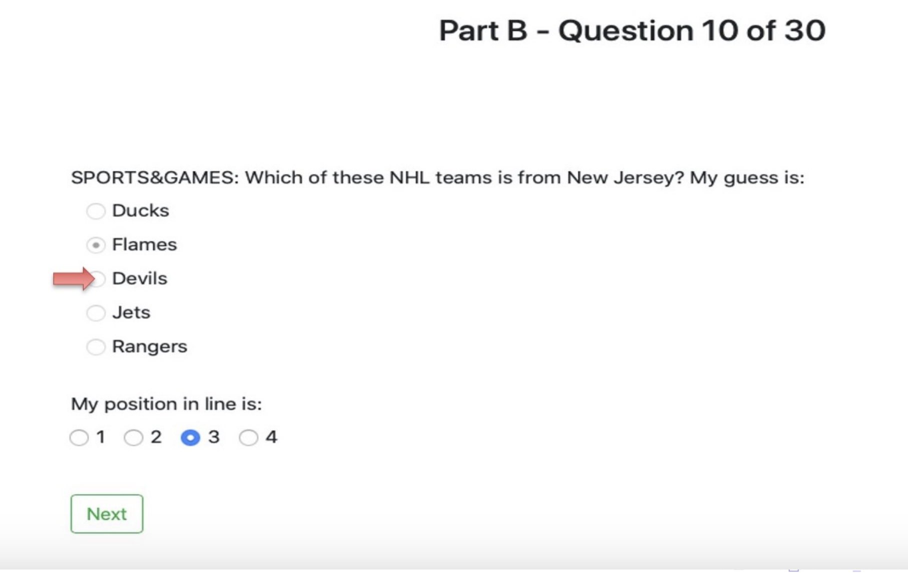
- Ducks
- Flames
- Devils
- Jets
- Rangers

My position in line is:

1 2 3 4

Next

Experimental Task - Part B



Part B - Question 10 of 30

SPORTS&GAMES: Which of these NHL teams is from New Jersey? My guess is:

- Ducks
- Flames
- Devils
- Jets
- Rangers

My position in line is:

1 2 3 4

Next

Experimental Task - Part C

Part C - Question 25 of 30

KARD: Who has Khloe Kardashian been married to? My guess was:

- (•) Lamar Odom
- ( ) French Montana
- ( ) Jonathan Cheban
- ( ) Kanye West
- ( ) Kobe Bryant

I think the chance of my answer being right is ____ %. The randomly-drawn robot should answer for me if its accuracy is greater than that.

I think the chance of my other group member's answer being right is ____ %. The randomly-drawn robot should answer for me if its accuracy is greater than that.

Next

Experimental Task - Part C

Part C - Question 25 of 30

KARD: Who has Khloe Kardashian been married to? My guess was:

- (•) Lamar Odom
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I think the chance of my other group member's answer being right is ____ %. The randomly-drawn robot should answer for me if its accuracy is greater than that.

Next

Four Treatments

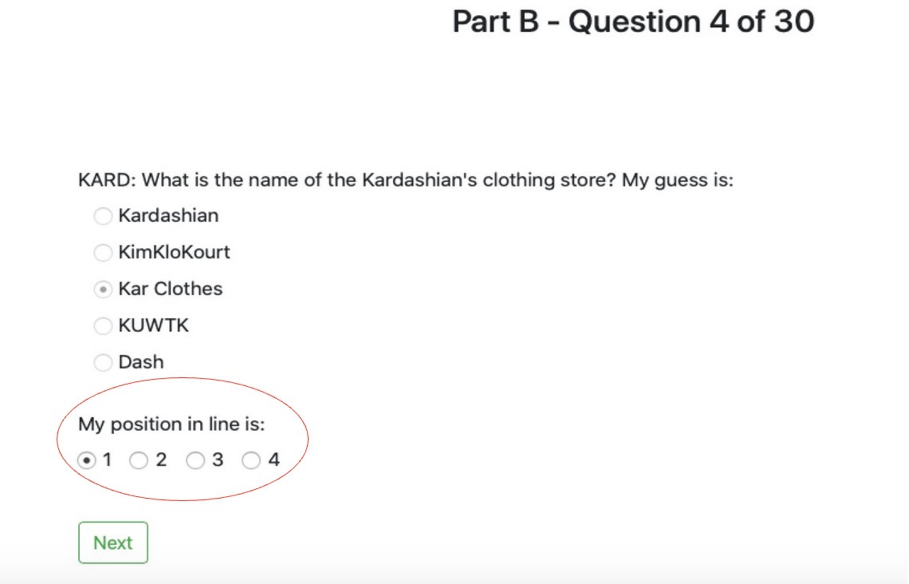
Treatment differs only in Part B

- Control – No default or feedback
- Merit default

  Default to 1 for all five questions if performs better (or equal) in that category

  Default to 4 otherwise
- Random default (No feedback)
- Random default (Feedback)

Treatments with Defaults



Treatments with Feedback

Part A Performance Feedback

Category	Best Performer
Art & Literature	Your group member
Cars	Your group member
Disney movies	You
Kardashians	Your group member
Sports	Your group member
Videogames	Your group member

Experimental Procedure

- Online experiment, July – Aug, 2023.
- Carried out on Prolific.
- 804 subjects. 52% female, average age 35.
- One-to-one matching. The first wave (402 subjects) experienced no defaults or feedback (pooled into Control in data analysis[2]).

[2] T-test and ANOVA are used for this paper.

Result 1. Pure Default Effect (Control VS. RD_NF)

R0. Gender gap and gender stereotypes exist in Control.

- Gender gap: women choose position 1 less than men (28.82% vs. 35.86%).
- Stereotype effect: women choose position 1 less than men in women-dominated categories (26.81% vs. 48.48%).

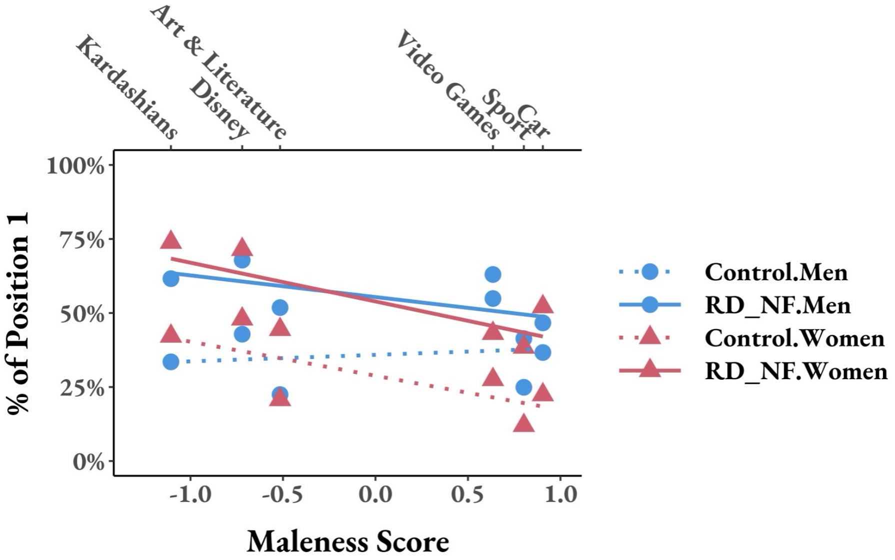
R1. (Random-) Default option mitigates the gender gap.

- Default Effect: Both men and women choose position 1 more in RD_NF than in Control.

  $\Rightarrow$ No Gender gap: In RD_NF, women do not choose position 1 less than men (52.99% vs. 55.54%, $p = .67$).

  $\Rightarrow$ Stereotype effect exists: In RD_NF, women still choose position 1 less than men in men-dominated categories (44.02% vs. 62.24%, $p < 0.01$).

Result 1. Pure Default Effect



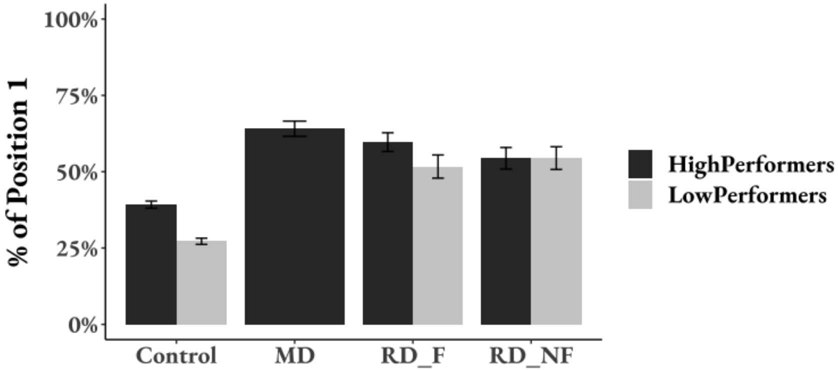
Result 2. No Merit Effect (Merit vs. RD_F, RD_NF)

R2. The merit default does not enhance the default effect

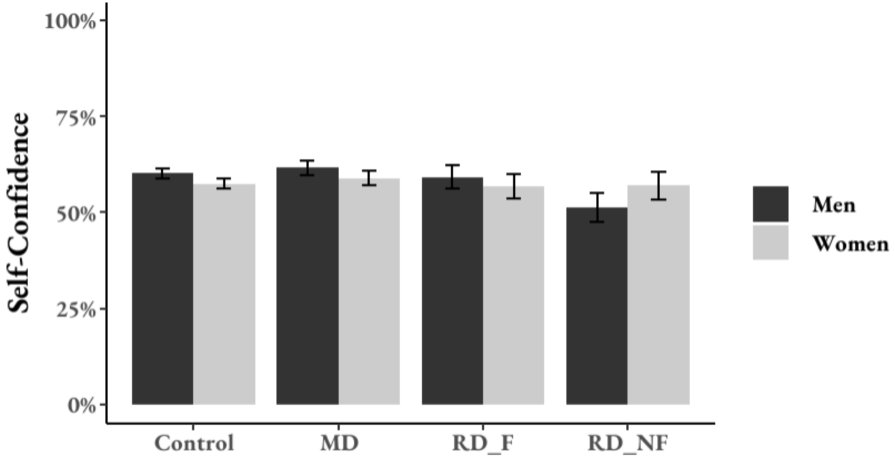
High performers: subjects in wave 2 who answer questions correctly in Part A more than or equal to their partner.

- No Merit-information effect: High performers in MD and RD_F are not more willing to contribute ideas, as compared with RD_NF (64.07% vs. 59.68% vs. 54.41%).
- No Merit-legitimacy effect: High performers in MD are not more willing to contribute ideas, as compared with RD_F.

Result 2. No Merit Effect



R3. Defaults do not affect self-confidence



Conclusion and Discussion

Default option is effective in changing people's willingness to contribute.

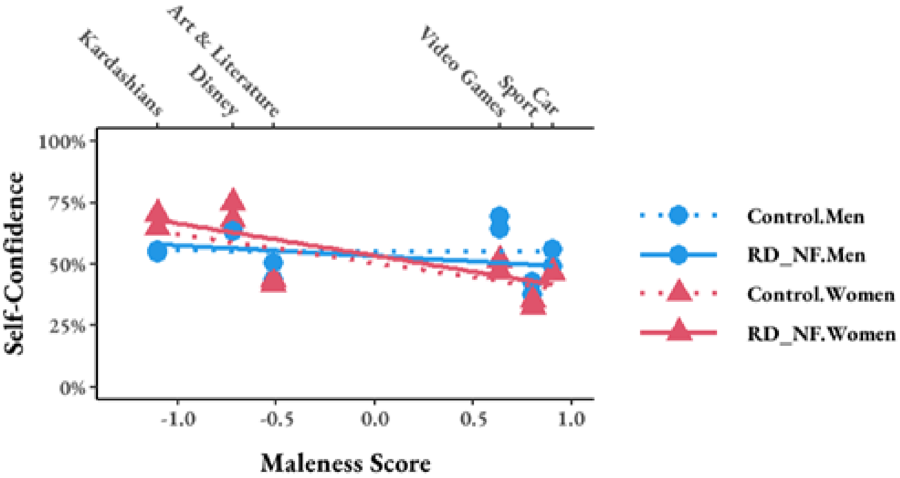
- Both random default and merit default mitigates the gender gap.
- However, the default option is ineffective in correcting the stereotype bias in the willingness to contribute.

How to mitigate the stereotype effect?

- If gender stereotype is a norm such that women should not play an active role in contributing ideas in a group, then default effects might show up in the long run.

Thank you!

R3. Defaults do not affect self-confidence



R3. Defaults do not affect self-confidence