

# Adverse Selection in Adaptive Settings

Carlos Gonzalez

University of Oxford, Department of Economics

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- ③ Bandits as Policy
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- ⑤ Adaptive Adverse Selection
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## Motivation

- A set of agents have some productivity  $u$  and some reservation value to work  $v$
- Firm wants to maximize profits  $\Pi$  by setting wage  $x$ , but it does not observe  $u_i$ , neither  $v_i$  for any agent  $i$
- Classic literature show foundational results on wage setting when joint distribution  $F_{U,V}$  is known. But this seems rather unreasonable...
- Adaptive characterization of the problems above with imperfect information allow firms to set wages iteratively such that they can learn the underlying distribution while maximizing profits
- BT: What if the policymaker also cared about the welfare of workers?

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# Multi-Armed Bandits

- What is a (multi-armed) bandit?
  - Slot machines example. Exploration vs Exploitation
  - Let's be a bit more rigorous...
- Some important concepts
  - History  $H_t$
  - Policy  $\pi_t : H_t \mapsto A_t$
  - Regret  $R(\pi, \epsilon)$  with  $\epsilon$  the competitor class
- Two kinds of Bandits
  - Stochastic Bandits:  $P_a : a \in \mathcal{A}$ . Learner chooses action  $A_t$
  - Adversarial Bandits: Arbitrary sequences  $\{x_t\}_1^T$ . Learner chooses  $P_t$
  - Differences across  $\mathbb{E}[R]$

# Mutli-armed bandits

- Two main objects of interest in a bandit problem
- An Upper Bound in the Regret of an Algorithm
  - For a given algorithm  $\alpha$ , what is the (order of the) regret of the worst bandit I can give you?
- A Lower Bound in the Regret of the Problem
  - Which is the regret of the algorithm with the lowest Upper Bound among all possible (reasonable) algorithms.
- Usual goal is to obtain sublinear regrets  $R_\pi < \mathcal{O}(T)$

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- Bandits are amazing, but how are they policy relevant?
- Rather than  $T$  periods, think about  $N$  agents. Every period, I select a policy parameter (a wage, a tax rate, a price) and I observe the behaviour of agent  $i$
- If I understand policy parameters as (continuous) arms and rewards as particular realizations (either stochastic, either adversarial) of some unknown distribution (or sequence of rewards), then we are back to normal!
- Three foundational papers to my work
  - [Kleinberg and Leighton, 2003] A monopolist problem
  - [Cesa-Bianchi et al., 2021] A bilateral trade problem
  - [Cesa-Bianchi et al., 2022] A policy parameter problem
- More on their models and results later

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## Classic Problem, Classic Solutions

- [Akerlof, 1978], [Mas-Colell et al., 1995], [Cowell, 2018]
- Consider the following setting
  - $N$  agents, with ability (type)  $u_i \in \mathcal{U}$  and reservation value  $v_i \in \mathcal{V}$ .  $\mathcal{U}, \mathcal{V}$  closed intervals in  $\mathbb{R}^+$
  - Formally, consider a measure space  $(\Omega, \mathcal{F}, \mu)$  and define two rv  $U, V$  such that  $U : \mathcal{F} \mapsto \mathcal{B}(\mathcal{U})$ ,  $V : \mathcal{F} \mapsto \mathcal{B}(\mathcal{V})$ , where  $\mathcal{B}(\cdot)$  is the Borel  $\sigma$ -algebra.
  - You may think of  $F_{U,V}$  as the product measure  $F_U \otimes F_V$  where  $F_Z$  is the induced measure of  $\mu$  on  $\mathcal{Z}$  defined via  $(\mu \circ Z^{-1})(B)$  for every  $B \in \mathcal{B}(\mathcal{U})$
  - $u_i$  and  $v_i$  are simply the  $i$ th realizations of such variables
  - Agent  $i$  observes wage  $x_i$  and makes decision  $J_i = \mathbb{1}(x_i > v_i)$
  - Define  $J^j = \{i : J_i = j\}$

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# Competitive Equilibrium

- Consider now two classic problems in Adverse Selection
- **Problem 1: Competitive Equilibrium**
  - Competitive market with 2 firms (wlog) where the policy planner wants to maximize welfare  $S^{\text{CE}}$  defined via

$$S^{\text{CE}} = \int_{u,v} [Jx + (1 - J)v] dF_{u,v} \quad (1)$$

- Profits don't show up because in equilibrium they are driven down to zero through Bertrand-like competition

# Competitive Equilibrium under Full Information

- Under full-information (i.e.  $u_i \in H_i$ ) solution is given by  $x_i = u_i$  (and  $J^1 = \{i : x_i \geq v_i\}$ ).
- This result can be characterized under Competitive Equilibrium (CE) and Perfect Bayesian Equilibrium (PBE)
- Observe that social welfare (1) is maximized. Thus equilibrium is socially optimal  $x_i = x_i^*$ ,  $J^1 = J^{1*}$ .

# Competitive Equilibrium under Partial Information

- But life is not always as beautiful...
- Imagine only  $F_{u,v} \in H_i$  for all  $i$
- CE and PBE solutions to this game are characterized via

$$x = u : \{\mathbb{E}[u] = \mathbb{E}[u_i \mid i : v_i < x_i]\} \quad (2)$$

- (In most cases) the set of solutions is not empty
- Observe that there is no room for price discrimination under partial information
- Is any of these equilibria socially optimal? (In most cases) absolutely NOT!

# Market Unraveling and Adverse Selection under CE

- Consider  $v = r(u)$  with  $r(\cdot)$  strictly increasing AND  $r(u_i) < u_i$  for all  $i$
- Under partial information ( $r(\cdot)$  known,  $F_{u,v}$  known) the market may (completely) unravel driven by Adverse Selection considerations
- Example?



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- **Problem 2: Monopolistic Competition**

- 1 monopolistic firm maximizes profits ( $\Pi$ ) such that

$$\Pi = \int_{\mathcal{U}, \mathcal{V}} [J(u_i - x_i)] dF_{U, V} \quad (3)$$

- A social welfare  $S^{\text{MC}}$  can be defined as

$$S^{\text{MC}} = \int_{\mathcal{U}, \mathcal{V}} J((u_i - x_i) + \lambda(x_i - v_i)) dF_{U, V} \quad (4)$$

- With  $\lambda < 1$

# Monopolistic Equilibrium under Full Information

- Under full-information (i.e.  $u_i \in H_i$ ) solution is given by  $x_i = \mathbb{1}(u_i \geq v_i)v_i$  (and  $J^1 = \{i : u_i \geq v_i\}$ ).
- Workers' revenue is driven down to 0
- For  $\lambda < 1$ , social welfare is maximized (although, possibly, as policymakers we are not very happy with this result).

# Monopolistic Equilibrium under Partial Information

- Define Partial Information like in the Competitive Equilibrium case
- Solution to this game is characterized via

$$x^{\text{MC}} = \arg \max_x \mathbb{E}_v [J(v)(\mathbb{E}_u[u | v] - x + \lambda(x - v))] \quad (5)$$

- An object not as fancy as the one in equation (2), but well-defined

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## Contributions of the Paper

- I derive **adaptive analogs** of the models above
- **Scope:** For the first time, I characterize models which focus on maximizing consumer surplus (not firm's revenue). Lack of Incentive Compatibility constraints pose new challenges in adaptive frameworks.
- **Asymmetric feedback:** Feedback is dependent to agent's actions. There are extra returns to exploration in a particular exploitation instance.
- **Target Distribution Structure:** I model concrete bounds for structurally dependent  $u, v$ . Of particular interest is the dependence structure  $v_i \leq u_i$  for all  $i$ .

# Adaptive Monopolistic Competition

- I start by characterizing a version of Adaptive Monopolistic Competition
- **Key Idea:** Create a model for equation (4) where  $F_{U,V}$  remains unknown in  $i = 0$
- This model remains novel, as introduces feedback asymmetries, which remain unexplored in the literature.
- Consider the following

$$S_i^{\text{MC}} = \mathbb{1}(x_i > v_i) \left( (u_i - x_i) + \lambda(x_i - v_i) \right) \quad (6)$$

# Adaptive Monopolistic Competition

- **Timeline:** Agent  $i$  arrives, firm offers wage  $x_i$  based on  $H_i$ . Worker observes  $x_i$  and plays  $J_i = \mathbb{1}(x_i > v_i)$ .
- If  $J_i = 1$ , agent  $i$  works. Firm observes productivity  $u_i$  and welfare gains are realized.
- Crucially, productivity  $u_i$  (and consequently  $S_i$ ) is only observed if  $J_i = 1$ . This introduces feedback asymmetry into the problem
- Optimal policy in this context is given by its known distribution analog. Regret is defined accordingly



## Comparison with [Cesa-Bianchi et al., 2021]

- We may rewrite equation (6) following [Cesa-Bianchi et al., 2022] as

$$G_i^v(x_i) \int_x^\infty G_i^u(x') dx' + \lambda \int_0^x G_i^v(x') dx' \quad (7)$$

- Where we used that there is no loss in replacing  $(u_i - x_i)$  by  $\max(u_i - x_i, 0)$
- And we have defined where  $G_i^v(x_i) = \mathbb{1}(x_i \geq v_i)$  and  $G_i^u(x_i) = \mathbb{1}(x_i \leq u_i)$ . Moreover, we use the fact that  $\mathbb{1}(x_i > v_i)(x_i - v_i) = \max(x_i - v_i, 0) = \int_0^x G_i^v(x') dx'$  and  $\max(u_i - x_i, 0) = \int_x^\infty G_i^u(x') dx'$

## Comparison with [Cesa-Bianchi et al., 2021]

- This expression is rather similar to the one in [Cesa-Bianchi et al., 2022]

$$x_i G_i(x_i) + \lambda \int_x^1 G_i(x) dx \quad (8)$$

- And [Cesa-Bianchi et al., 2021]

$$G_i^b(x_i) \int_0^x G_i^s(x) dx + G_i^s(x_i) \int_x^1 G_i^b(x) dx \quad (9)$$

## Comparison with [Cesa-Bianchi et al., 2021]

- In terms of Information requirements, our problem is more similar to the one by [Cesa-Bianchi et al., 2021]
- In particular, it requires global information for both the welfare and the gradient
- [Cesa-Bianchi et al., 2021] establishes optimal upper bounds for algorithms of  $\mathcal{O}(N^{\frac{1}{2}})$  in the stochastic case when full feedback is recovered
- And of  $\mathcal{O}(N)$  when only partial information  $G_i$  is revealed after each iteration. They also get  $\mathcal{O}(N^{\frac{2}{3}})$  bounds in the partial information setting but under strong additional assumptions
- In the adversarial case, they get bounds  $\mathcal{O}(N)$  in all cases

## Comparison with [Cesa-Bianchi et al., 2021]

- **Conjecture:** The non-zero measure of the event "full-information" gives some hope for sublinear regret in the stochastic case
- **Conjecture:** I have little hope for sublinear regret in the adversarial case

## Adaptive Competitive Equilibrium

- **Key Idea:** Create a model for equation (1) where  $F_{U,V}$  remains unknown in  $i = 0$
- **Challenge 1:** Reproduce competition in an adaptive setting is very difficult. Firm should have an idea of the wage setting mechanism of the other firm.
- **Challenge 2:** Cannot introduce constraints in expectation, given that the probability distribution is unknown to the learner in first place
- **Solution?** Introduce a penalization mechanism for firm profits and losses
- **Key idea:** This penalization **CANNOT** be symmetric, otherwise there will exist incentives to subsidize workers via firm losses

## Naive Model Goes Wrong...

$$S_i = \max(x_i, v_i) + \lambda \mathbb{1}(x_i > v_i)(u_i - x_i) \quad (10)$$

- The policymaker finds profitable to subsidize the worker via losses for  $\lambda < 1$
- Setting  $\lambda > 1$  is not helping us neither  $\implies \mathbb{E}[\Pi] > 0$
- We need to "disproportionately" penalize loses, while fostering worker's welfare. This is rather tricky

## Adaptive Competitive Equilibrium

$$S_i = \max(x_i, v_i) + \mathbb{1}(x_i > v_i) [\lambda_1 \mathbb{1}(x_i \leq u_i)(u_i - x_i) + \lambda_2 \mathbb{1}(x_i > u_i)(x_i - u_i)] \quad (11)$$

$$S_i = \max(x_i, v_i) + \mathbb{1}(x_i > v_i) [\lambda_1 \mathbb{1} \max(u_i - x_i, 0) + \lambda_2 \max(x_i - u_i, 0)] \quad (12)$$

$$S_i \sim \max(x_i - v_i, 0) + \mathbb{1}(x_i > v_i) [\lambda_1 \mathbb{1} \max(u_i - x_i, 0) + \lambda_2 \max(x_i - u_i, 0)] \quad (13)$$

- Weights  $\lambda_1 < 1$  and  $\lambda_2 < -1$  ensure dislike for profits and losses

## Did We Get It Right?

- Under full information equation (13) is maximized by setting  $x_i = u_i$  with induced  $J^1 = \{i : x_i = u_i \geq v_i\}$ . Just like in equation (1) (classic result)
- However, under partial information our results will be in general different from Akerlof's  $x_i = \mathbb{E}[u_i | i : x_i \geq v_i]$ . Why? We broke asymmetry!



## Does It Really Matter?

Consider two increasing sequences  $\{\lambda_{1n}\}_1^N, \{\lambda_{2n}\}_1^N$  such that  $\{\lambda_{1n}\}_1^N \rightarrow 1, \{\lambda_{2n}\}_1^N \rightarrow -1$ .  $x_i$  is not well defined as the limit of the optimization problem BUT

**Claim:** For any  $\epsilon > 0 \exists$  an  $n \in \mathbb{N}$  such that  $x_i - \mathbb{E}[u_i | x_i < v_i] < \epsilon$  where  $x_i = \arg \max_x S_i(x, \lambda_{1n}, \lambda_{2n})$

**Corollary:** In general our problem characterizes a different equilibrium (a slightly more complicated object) than the one in Akerlof's static unknown distribution **BUT** we can get our solution as close as we want to his result.

# Adaptive Competitive Equilibrium

- We may write equation (13) in integral form such that

$$S_i = \int_x^\infty G_i^v(x') dx' + (1 - G_i^v(x_i)) \left( \lambda_1 \int_0^x G_i^u(x') dx' + \lambda_2 \int_x^\infty (1 - G_i^v(x')) dx' \right) \quad (14)$$

# Adaptive Competitive Equilibrium

- Comments wrt [Cesa-Bianchi et al., 2021] remain valid
- **Conjecture:** Similar? I guess?

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## Conclusion

- Bandits are a very powerful tool for public policy design!
- This paper introduces analogs for Monopolistic and Competitive Equilibrium in adaptive settings which can be of relevance in many settings
- This paper introduces the concept of feedback asymmetry within the adaptive public policy literature
- This paper introduces competitive mechanisms within adaptive public policy literature. Results are not perfect, but not too bad!
- Previous results give me hope for sublinear regret bounds in the problems above

*Thanks!*

[Akerlof, 1978] Akerlof, G. A. (1978).

The market for “lemons” : Quality uncertainty and the market mechanism.

In *Uncertainty in economics*, pages 235–251. Elsevier.

[Cesa-Bianchi et al., 2021] Cesa-Bianchi, N., Cesari, T. R., Colomboni, R., Fusco, F., and Leonardi, S. (2021).

A regret analysis of bilateral trade.

In *Proceedings of the 22nd ACM Conference on Economics and Computation*, pages 289–309.

[Cesa-Bianchi et al., 2022] Cesa-Bianchi, N., Colomboni, R., and Kasy, M. (2022).

Adaptive maximization of social welfare.

[Cowell, 2018] Cowell, F. (2018).

*Microeconomics: principles and analysis.*

Oxford University Press.

[Kleinberg and Leighton, 2003] Kleinberg, R. and Leighton, T. (2003).

The value of knowing a demand curve: Bounds on regret for online posted-price auctions.

*In 44th Annual IEEE Symposium on Foundations of Computer Science, 2003. Proceedings.*, pages 594–605. IEEE.

[Mas-Colell et al., 1995] Mas-Colell, A., Whinston, M. D., Green, J. R., et al. (1995).

*Microeconomic theory*, volume 1.

Oxford university press New York.