Persuasion, Delegation, and Private Information

Ruqing Xu

September 21, 2023

Motivation

- A principal chooses a technology to make predictions about the best course of action.
- The principal can use the prediction to take an action directly, or pass it to an agent who then takes an action.
- The agent may have private information but also distinct goals.
- How should the principal choose the prediction technology?
- When should the principal pass the prediction and the decision authority to the agent?

Motivation

Child maltreatment screening

The CPS designs an algorithm to output a risk score for child maltreatment reports. If the risk score is above certain thresholds, cases are automatically screened-in. Otherwise, the social worker sees the score and makes the final decision. The social workers under-investigate since it is costly to them. How should the CPS design the algorithm, and when should the case be passed to the worker?

Real life example

Motivation

Child maltreatment screening

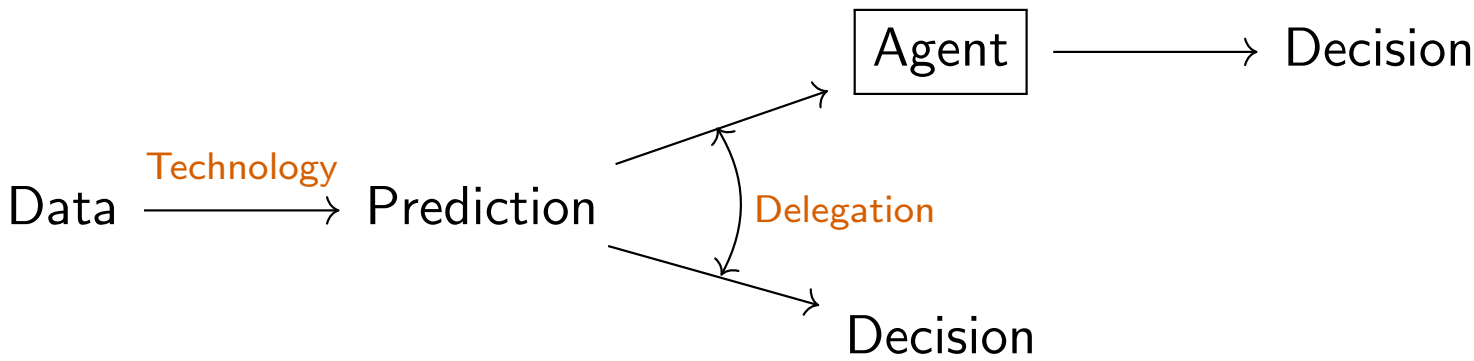
The CPS designs an algorithm to output a risk score for child maltreatment reports. If the risk score is above certain thresholds, cases are automatically screened-in. Otherwise, the social worker sees the score and makes the final decision. The social workers under-investigate since it is costly to them. How should the CPS design the algorithm, and when should the case be passed to the worker?

Real life example

Management consulting

A CEO hires a consultant to inspect the company and produce a report. After receiving the report, the CEO can implement a policy by herself, or pass the report and the decision authority to a manager, who may have private information but also ulterior motives. How detailed the CEO wants the report to be? When should the CEO trust the manager?

Motivation



- Study the joint design of the prediction technology and delegation rule in the presence of a privately informed but biased agent.
- Apply to general contexts where the principal decides both the strength of information and how to use the information.

Preview of results

- Delegation to a more informed but biased agent is valuable iff:
  1. The principal is not too confident with her own prediction such that the agent's private information provides no "surprise;"
  2. The agent is informative enough compared to the degree of preference misalignment between the two players.

- The principal is always more likely to delegate to a more aligned agent, but not necessarily to a more informed one.

- Next steps: characterize the optimal design of information when delegation is an option.

Problem setting

- A principal (she) and an agent (he).
- $\Theta = \{0, 1\}$, binary states. Common prior $\mu = \Pr(\theta = 1)$.
- Public signal S_1 and agent's private signal S_2 are generated by:

Public signal

Signal S_1 \ State Θ	0	1
0	p	$1-p$
1	$1-p$	p

Agent's signal

Signal S_2 \ State Θ	0	1
0	q	$1-q$
1	$1-q$	q

- Assume $p, q > \frac{1}{2}$.
- Principal's interim posterior after observing s_1: $\mu_{s_1} = \Pr(\theta = 1 \mid S_1 = s_1)$.
- Agent's final posterior after observing s_1, s_2: $\mu_{s_1 s_2} = \Pr(\theta = 1 \mid S_1 = s_1, S_2 = s_2)$.

Problem setting

- A principal (she) and an agent (he).
- $\Theta = \{0, 1\}$, binary states. Common prior $\mu = \Pr(\theta = 1)$.
- Public signal S_1 and agent's private signal S_2 are generated by:

Public signal

Signal S_1 \ State Θ	0	1
0	p	$1-p$
1	$1-p$	p

Agent's signal

Signal S_2 \ State Θ	0	1
0	q	$1-q$
1	$1-q$	q

- Assume $p, q > \frac{1}{2}$.
- Principal's interim posterior after observing s_1: $\mu_{s_1} = \Pr(\theta = 1 \mid S_1 = s_1)$.
- Agent's final posterior after observing s_1, s_2: $\mu_{s_1 s_2} = \Pr(\theta = 1 \mid S_1 = s_1, S_2 = s_2)$.

Problem setting

- A principal (she) and an agent (he).
- $\Theta = \{0, 1\}$, binary states. Common prior $\mu = \Pr(\theta = 1)$.
- Public signal S_1 and agent's private signal S_2 are generated by:

Public signal

Signal S_1 \ State Θ	0	1
0	p	$1-p$
1	$1-p$	p

Agent's signal

Signal S_2 \ State Θ	0	1
0	q	$1-q$
1	$1-q$	q

- Assume $p, q > \frac{1}{2}$.
- Principal's interim posterior after observing s_1:
  $\mu_{s_1} = \Pr(\theta = 1 \mid S_1 = s_1)$.
- Agent's final posterior after observing s_1, s_2:
  $\mu_{s_1 s_2} = \Pr(\theta = 1 \mid S_1 = s_1, S_2 = s_2)$.

Problem setting

- Common set of actions $Y = \{0, 1\}$.
- Preferences:

Action Y	State Θ: 0	State Θ: 1
0	r_{00}	r_{01}
1	r_{10}	r_{11}

Principal's payoffs

Action Y	State Θ: 0	State Θ: 1
0	v_{00}	v_{01}
1	v_{10}	v_{11}

Agent's payoffs

- We assume payoffs are such that both players prefer to match the state, and there is no dominating action for either player.

Problem setting

- Common set of actions $Y = \{0, 1\}$.
- Preferences:

Action Y	State Θ: 0	State Θ: 1
0	r_{00}	r_{01}
1	r_{10}	r_{11}

Principal's payoffs

Action Y	State Θ: 0	State Θ: 1
0	v_{00}	v_{01}
1	v_{10}	v_{11}

Agent's payoffs

- We assume payoffs are such that both players prefer to match the state, and there is no dominating action for either player.

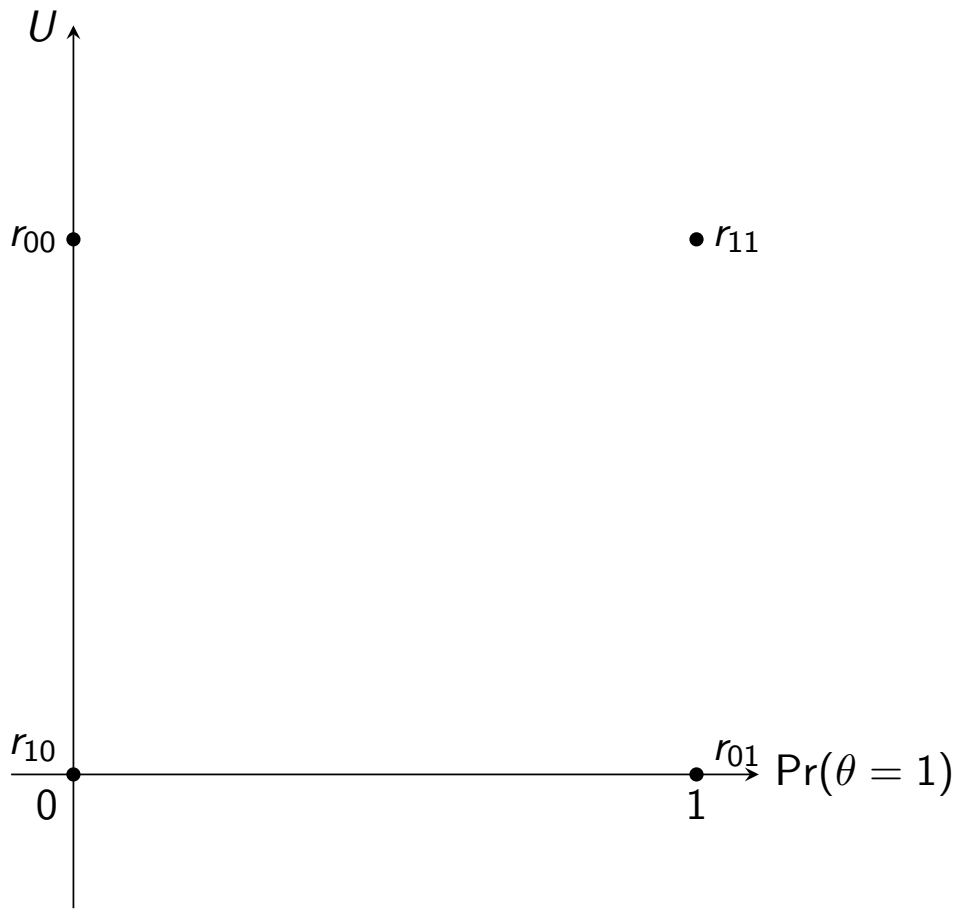
Timing of the model

1. The principal designs the information structure of the public signal. The information structure of both signals are common knowledge.

2. After observing the public signal, the principal decides whether to take an action by herself or to delegate the decision to the agent.

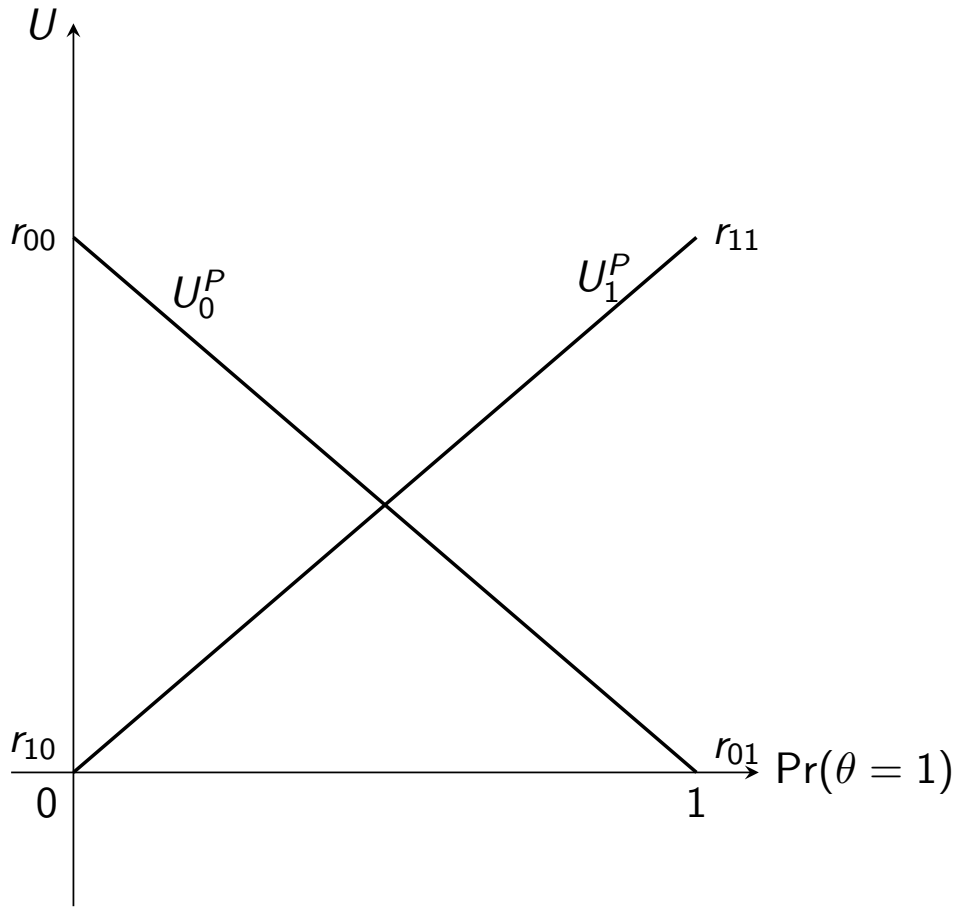
3. If delegated, the agent observes both the public and private signals and takes an action. Otherwise, the principal takes an action.

Payoff functions



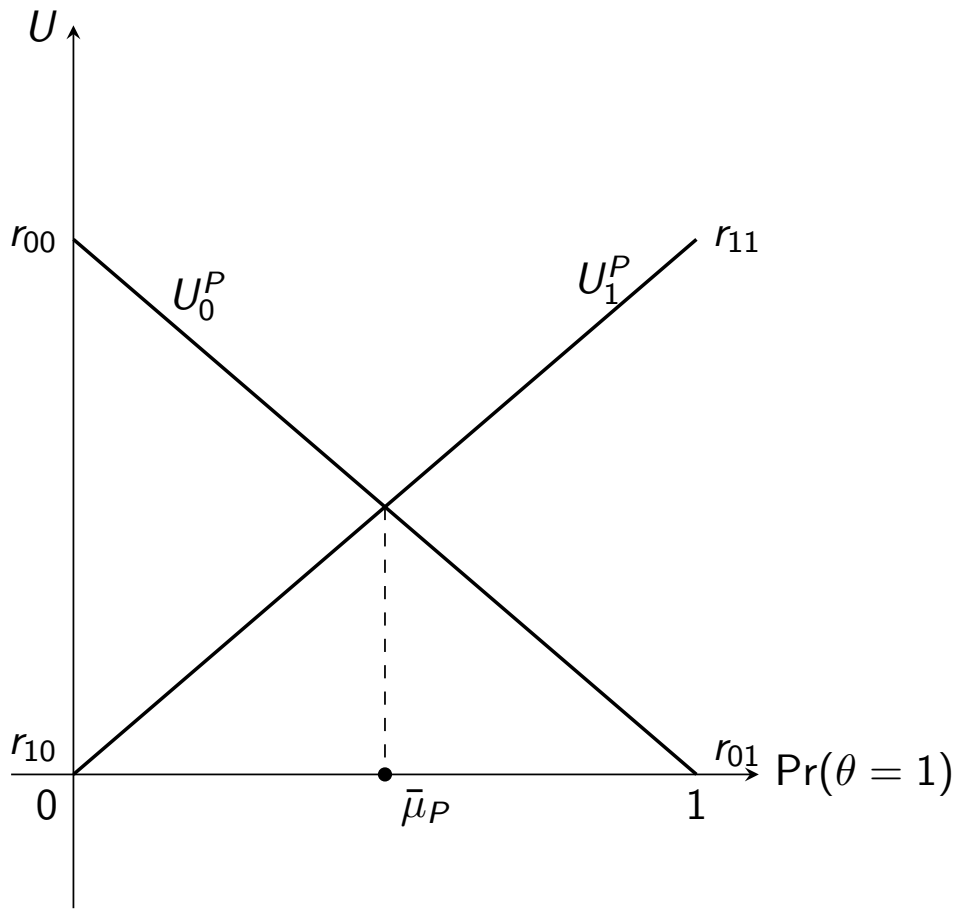
Players' payoffs as functions of the belief

Payoff functions



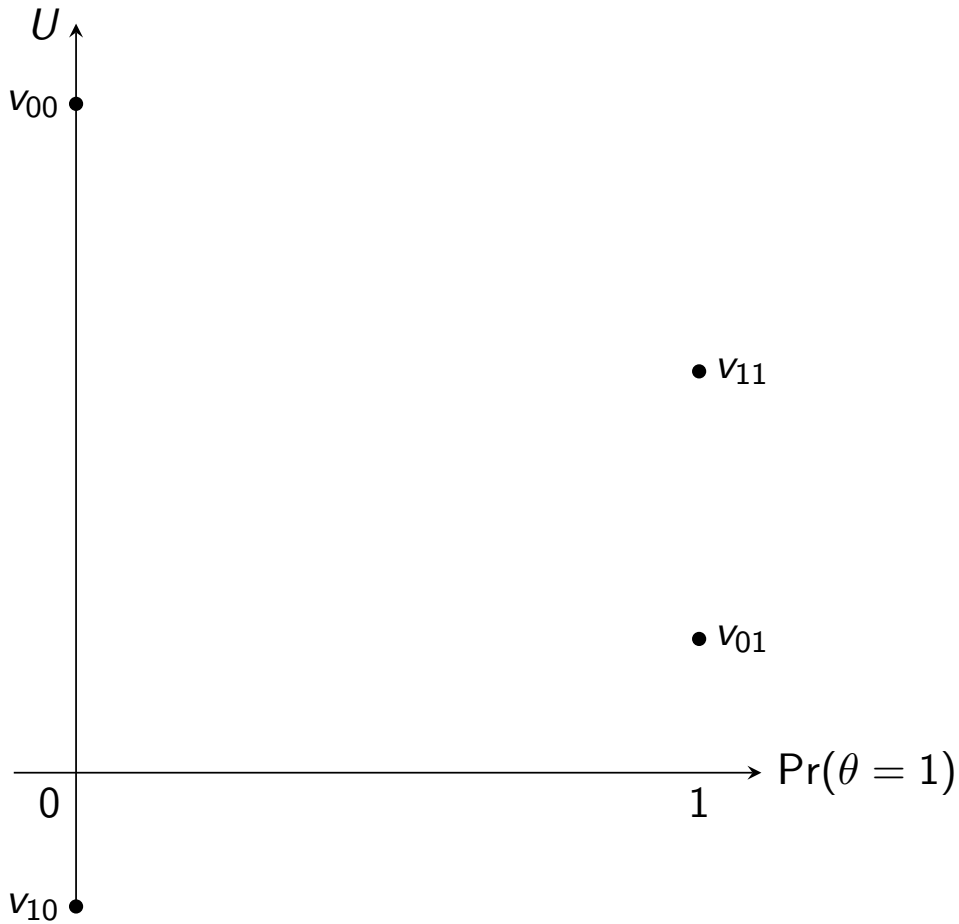
Players' payoffs as functions of the belief

Payoff functions



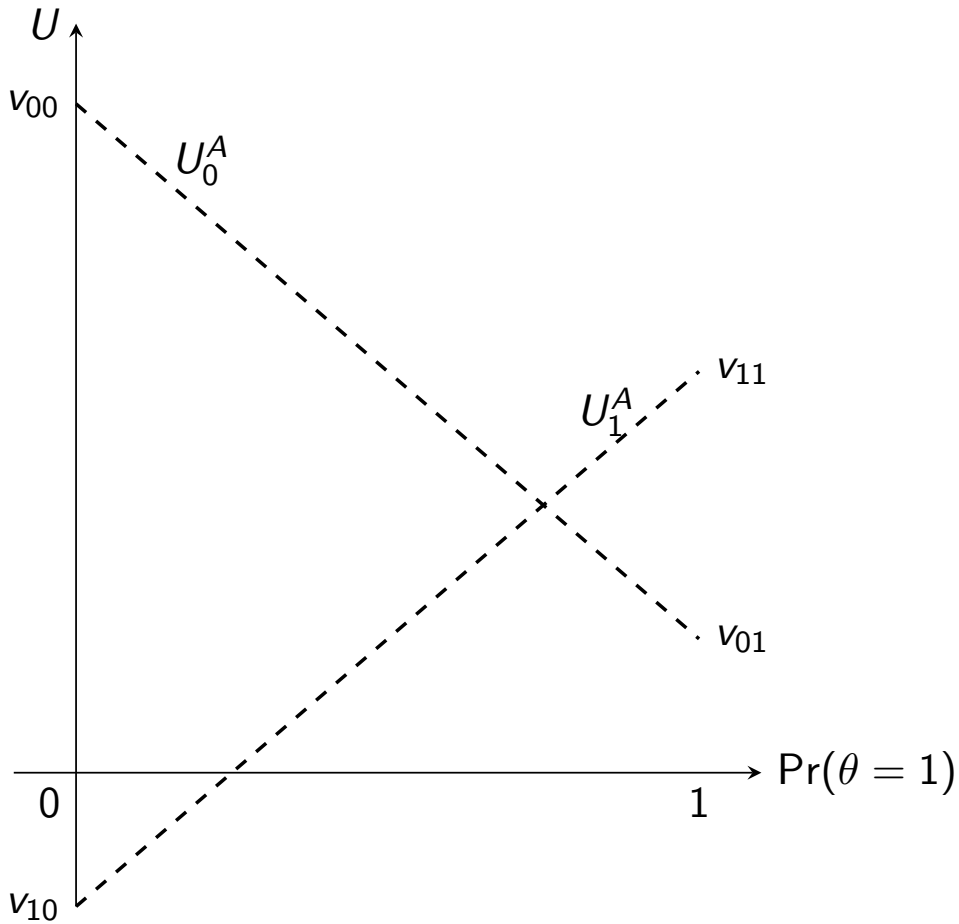
Players' payoffs as functions of the belief

Payoff functions



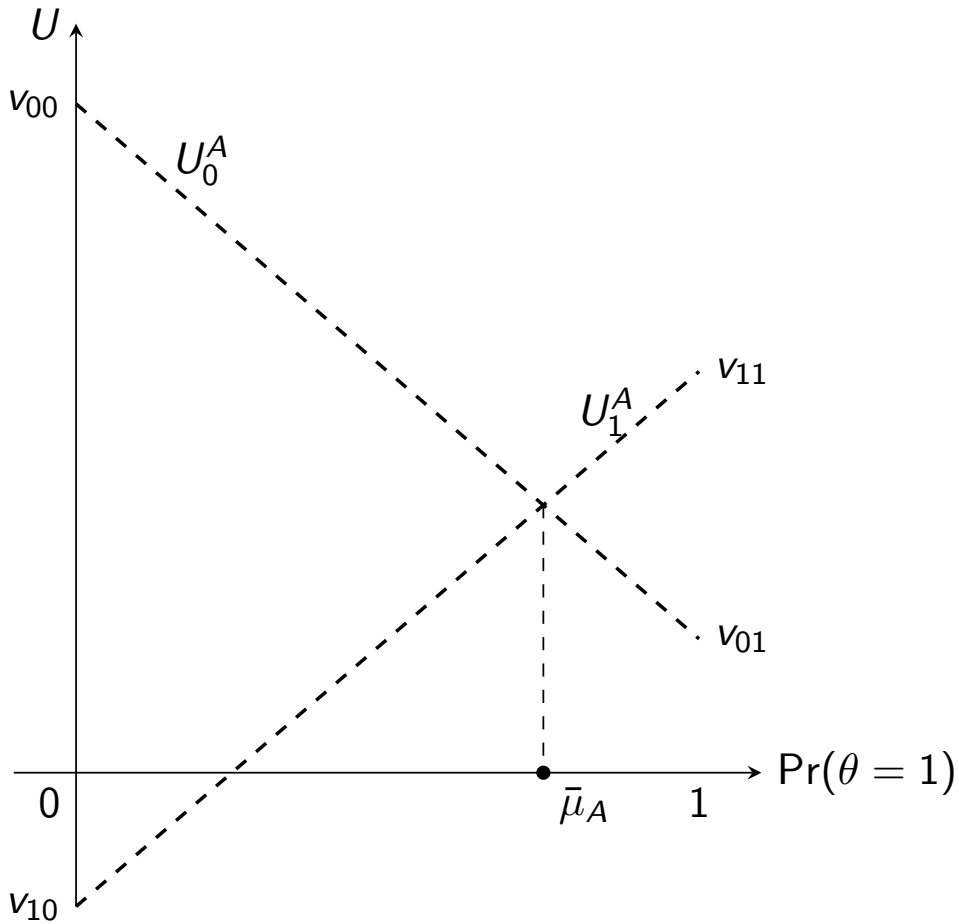
Players' payoffs as functions of the belief

Payoff functions



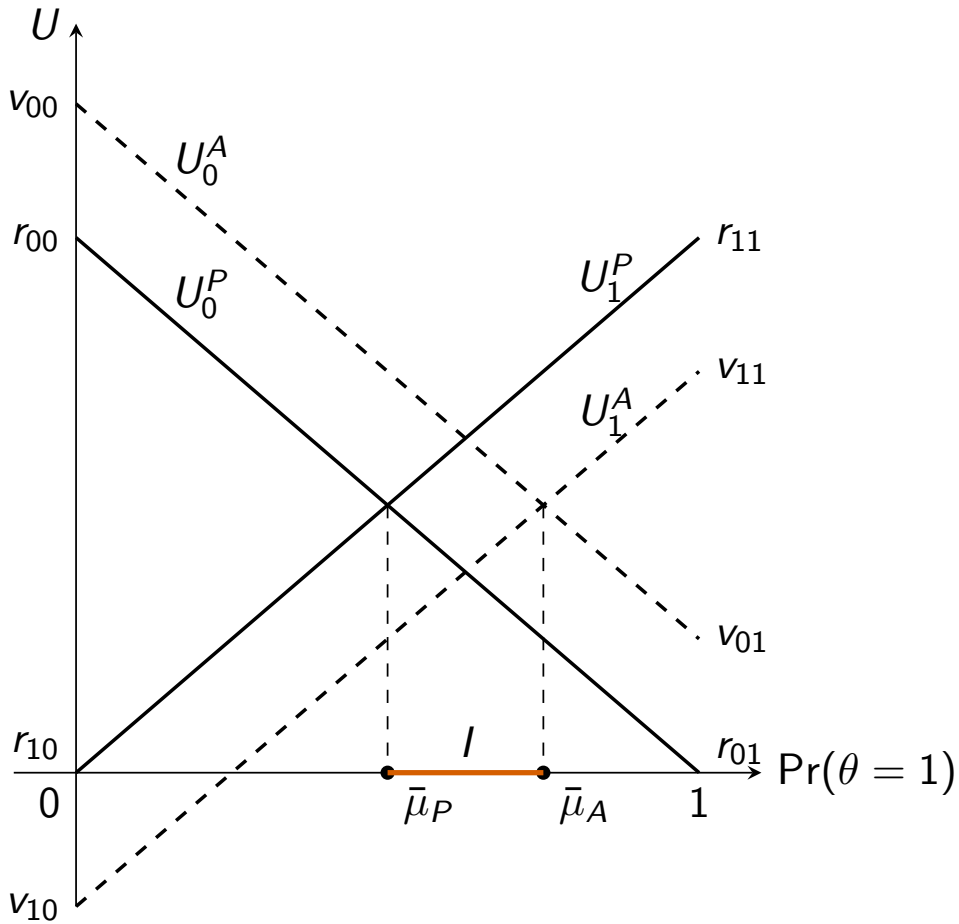
Players' payoffs as functions of the belief

Payoff functions



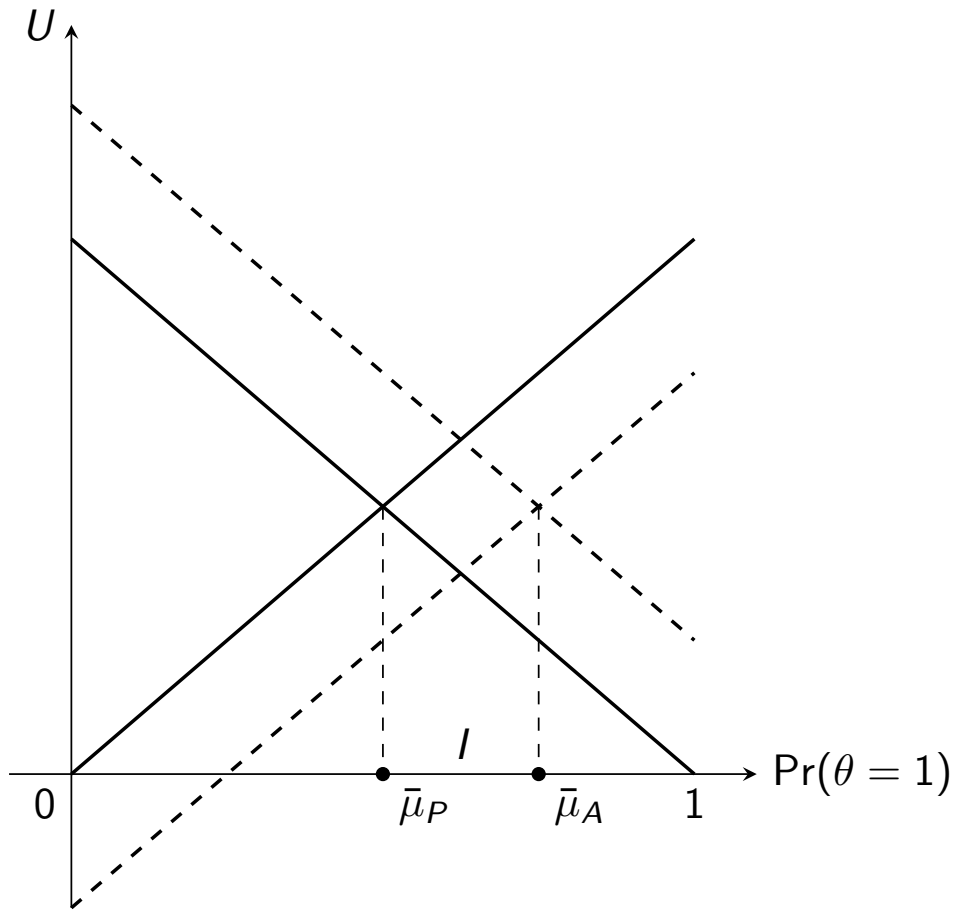
Players' payoffs as functions of the belief

Payoff functions



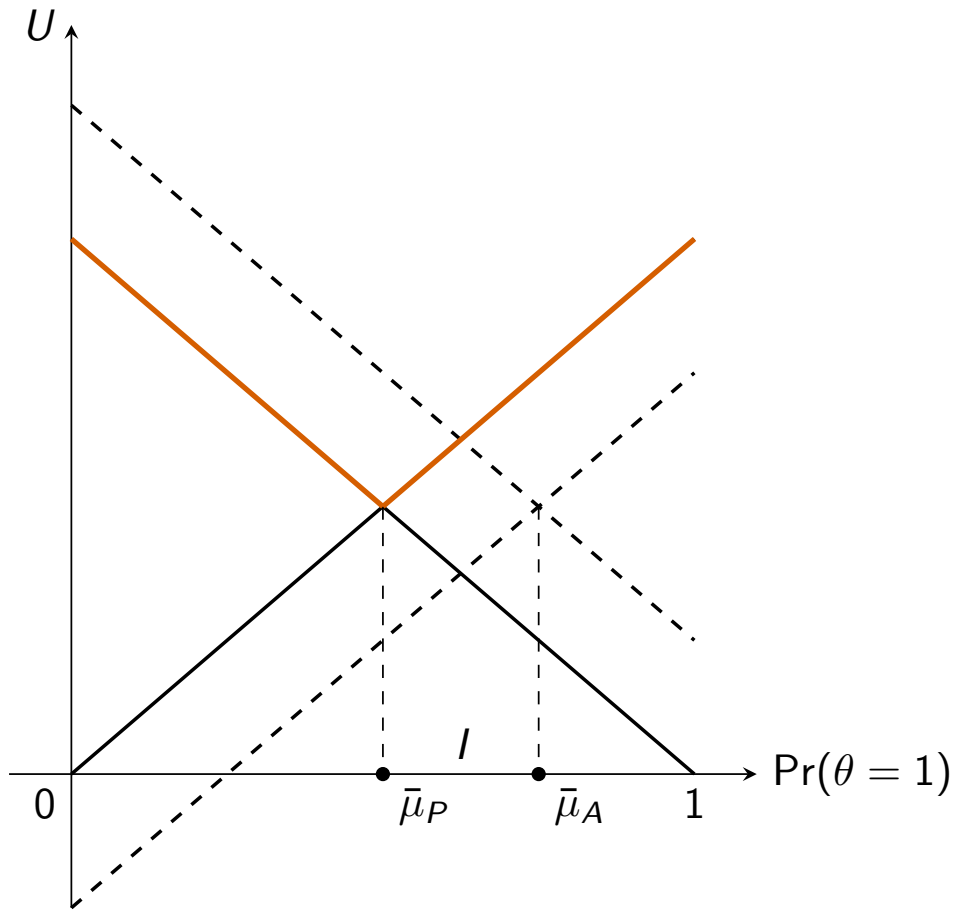
Players' payoffs as functions of the belief

Payoff envelopes



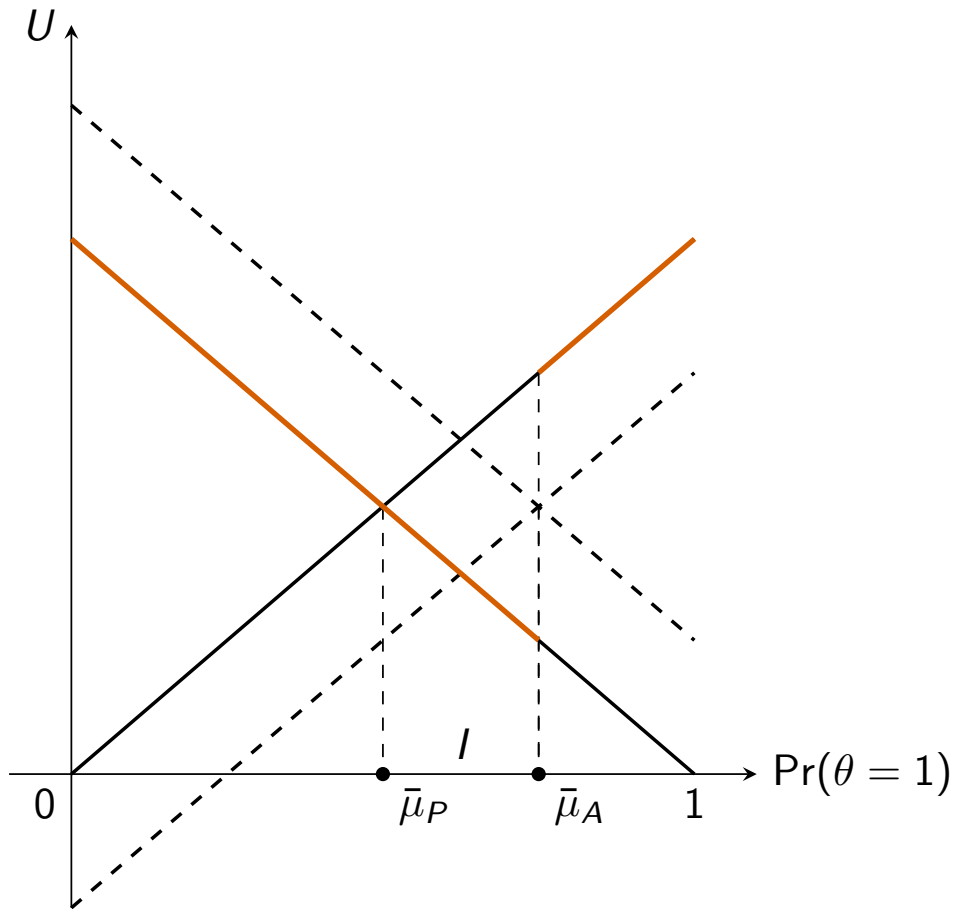
Players' payoffs as functions of the belief

Payoff envelopes



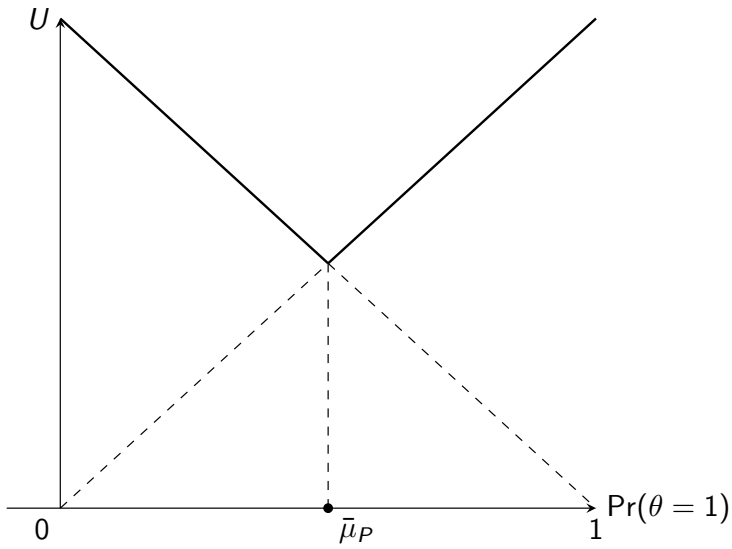
Players' payoffs as functions of the belief

Payoff envelopes

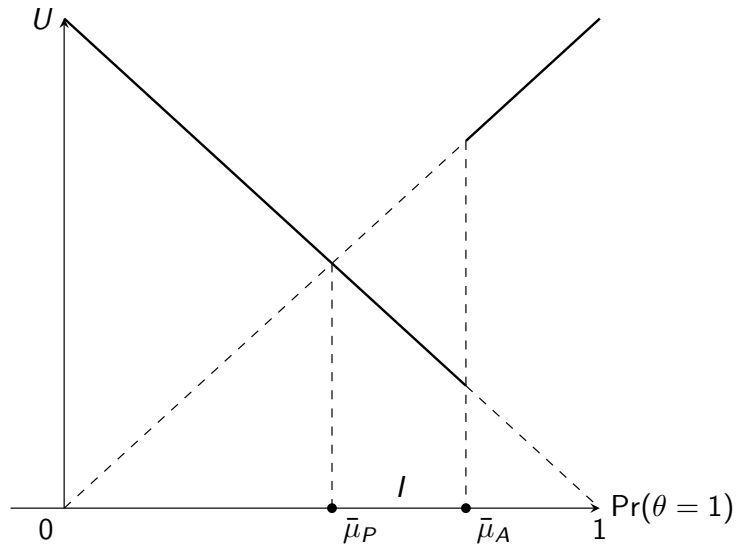


Players' payoffs as functions of the belief

Payoff envelopes



(a) Principal's non-delegation envelope



(b) Principal's delegation envelope

Value of delegation

- When is it strictly valuable for the principal to delegate?

Value of delegation

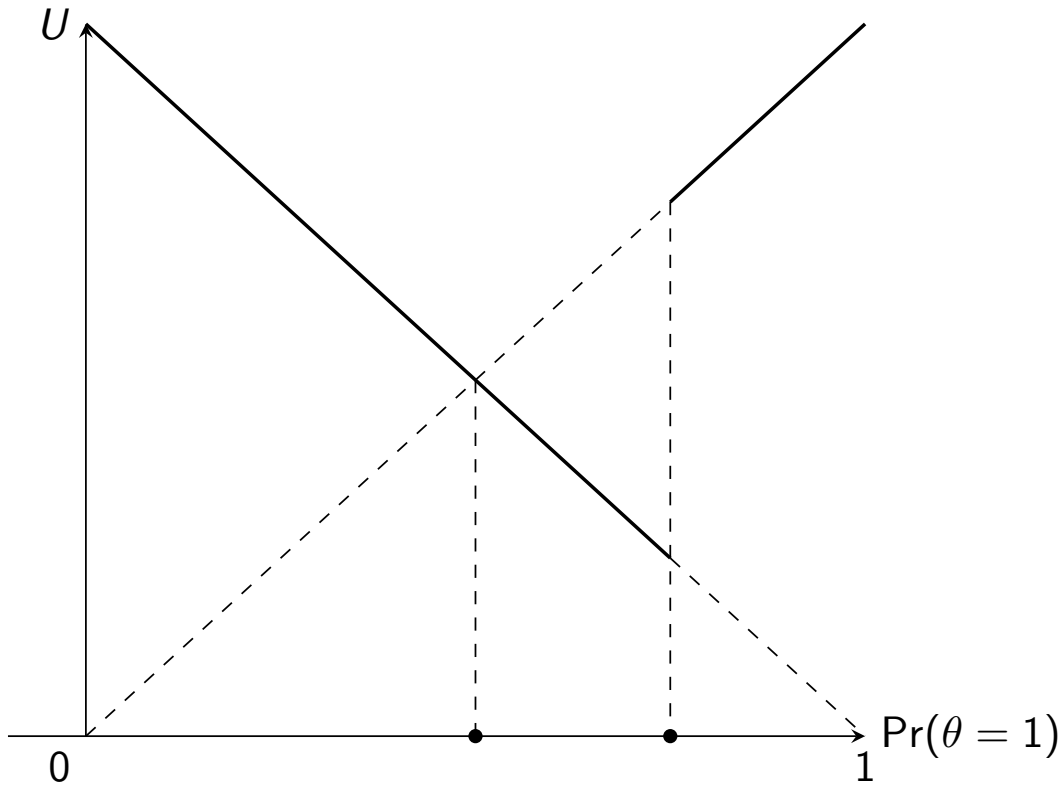


Figure: Delegation is strictly valuable

Value of delegation

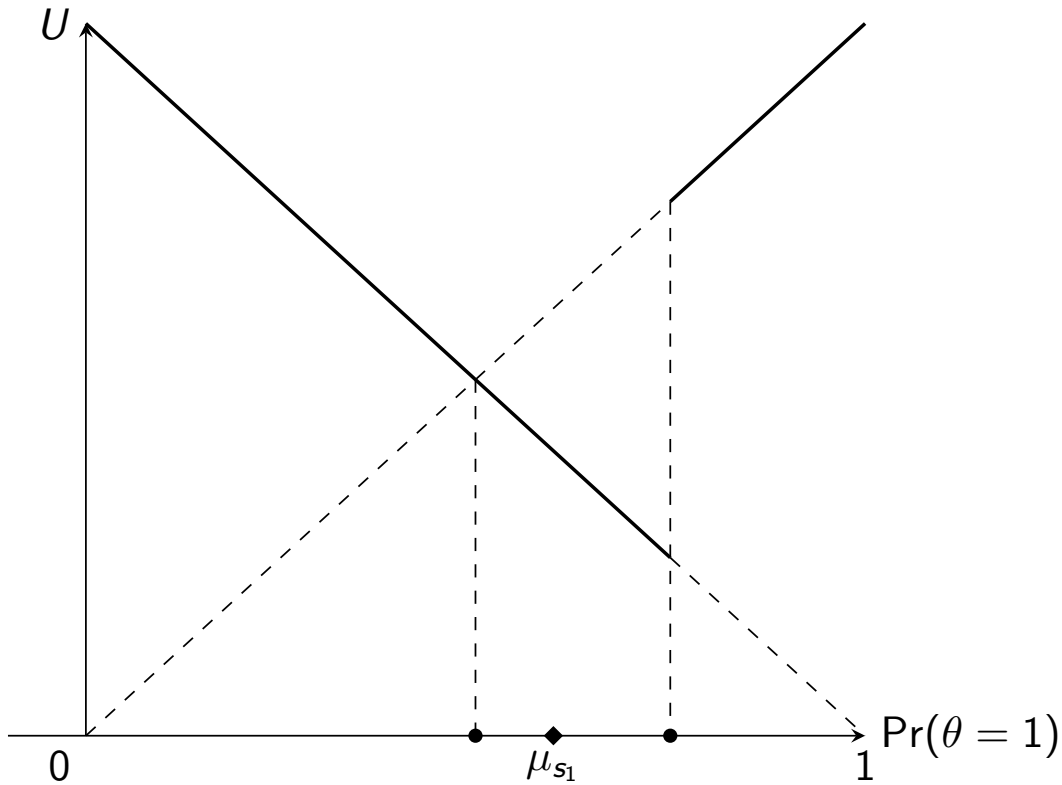


Figure: Delegation is strictly valuable

Value of delegation

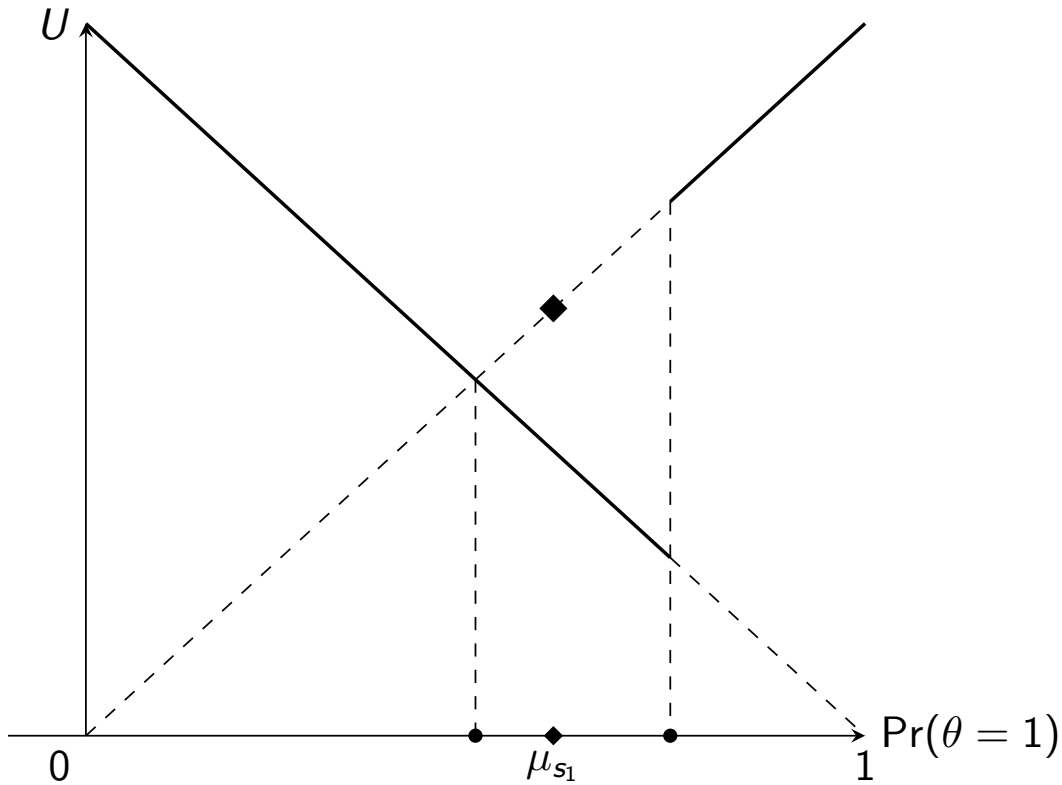


Figure: Delegation is strictly valuable

Value of delegation

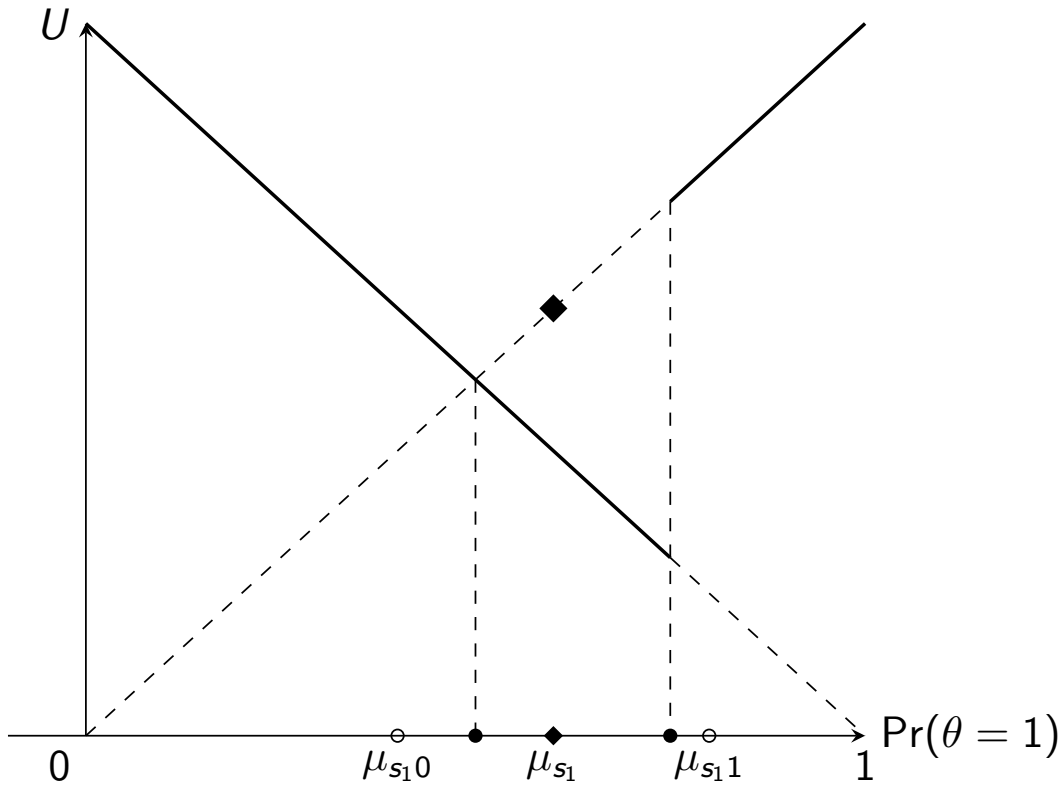


Figure: Delegation is strictly valuable

Value of delegation

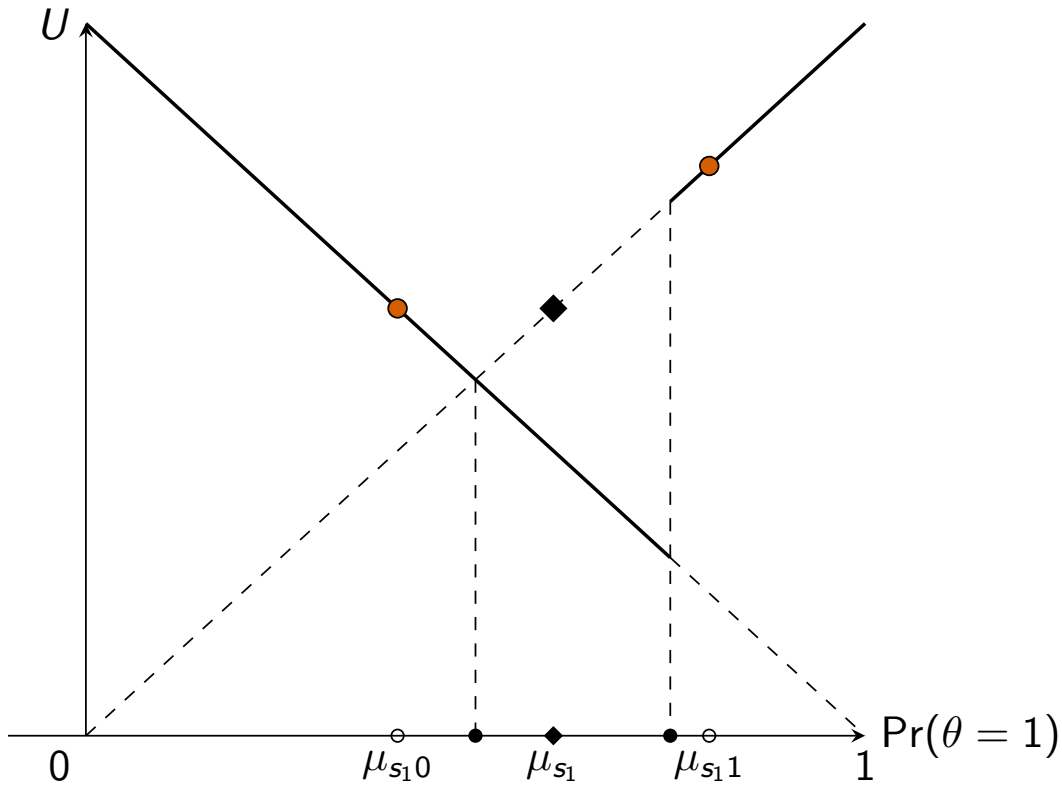


Figure: Delegation is strictly valuable

Value of delegation

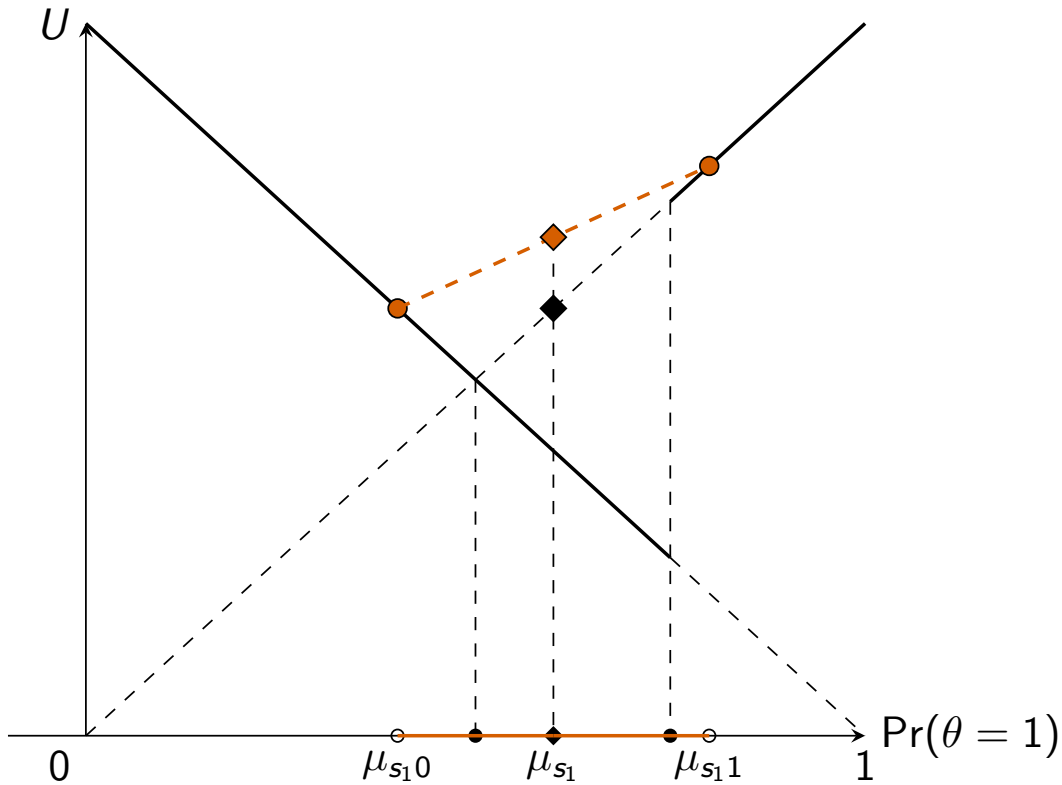


Figure: Delegation is strictly valuable

Value of delegation

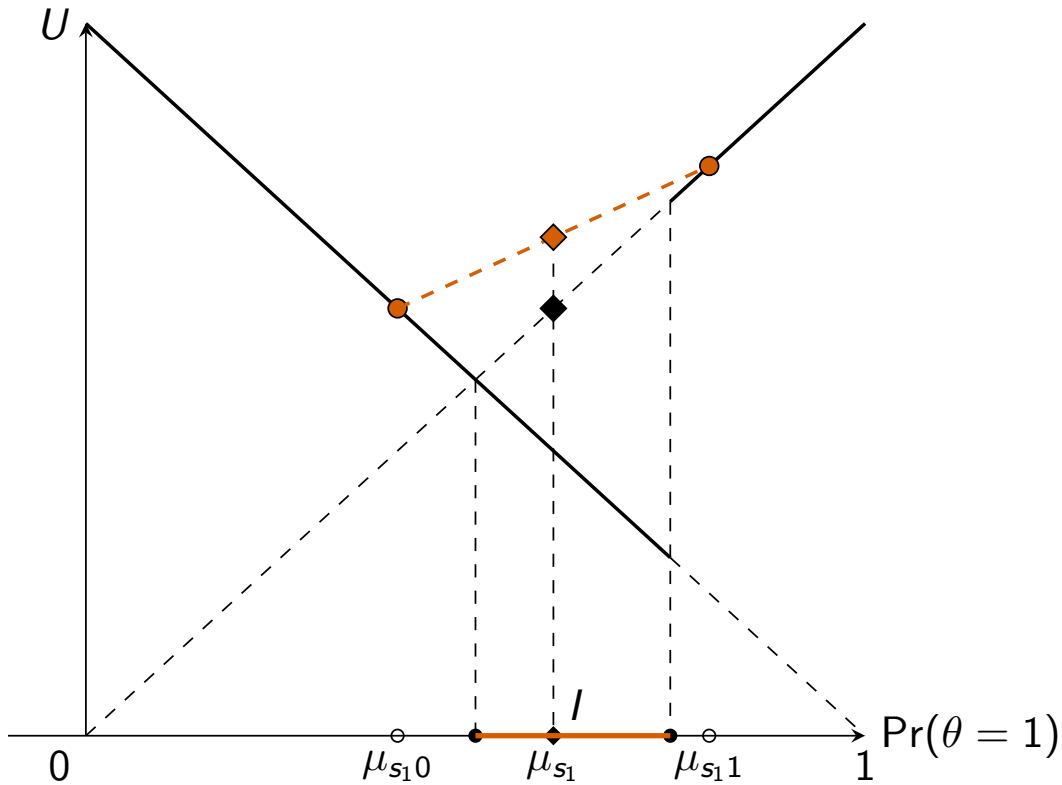


Figure: Delegation is strictly valuable

Other cases

Value of delegation

Proposition 1

Given a realized signal s_1 and the principal's interim posterior μ_{s_1}, delegation is strictly valuable to the principal if and only if the agent's final posteriors $\mu_{s_1 0}$ and $\mu_{s_1 1}$ lie on the opposing sides of the disagreement interval. In other words,

$$\mu_{s_1 0} < \bar{\mu}_P, \bar{\mu}_A < \mu_{s_1 1}.$$

Value of delegation

Proposition 1

Given a realized signal s_1 and the principal's interim posterior μ_{s_1}, delegation is strictly valuable to the principal if and only if the agent's final posteriors $\mu_{s_1 0}$ and $\mu_{s_1 1}$ lie on the opposing sides of the disagreement interval. In other words,

$$\mu_{s_1 0} < \bar{\mu}_P, \bar{\mu}_A < \mu_{s_1 1}.$$

Corollary

Given a realized signal s_1 and the principal's interim posterior μ_{s_1}, a necessary condition for delegation to be strictly valuable is the following:

$$L := \mu_{s_1 1} - \mu_{s_1 0} > |\bar{\mu}_P - \bar{\mu}_A|,$$

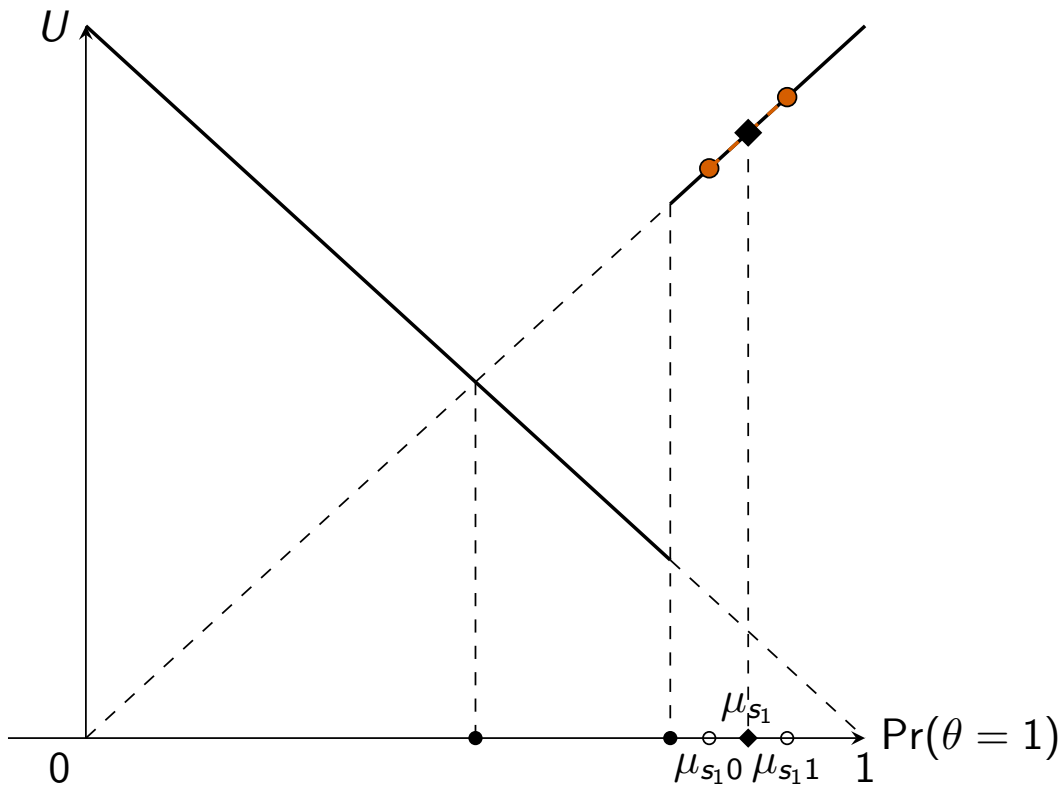
that is, the agent's signal must move the agent's final posteriors more than the length of the disagreement interval.

Comparative Statics

How does the principal's delegation decision change as the parameters of the model change?

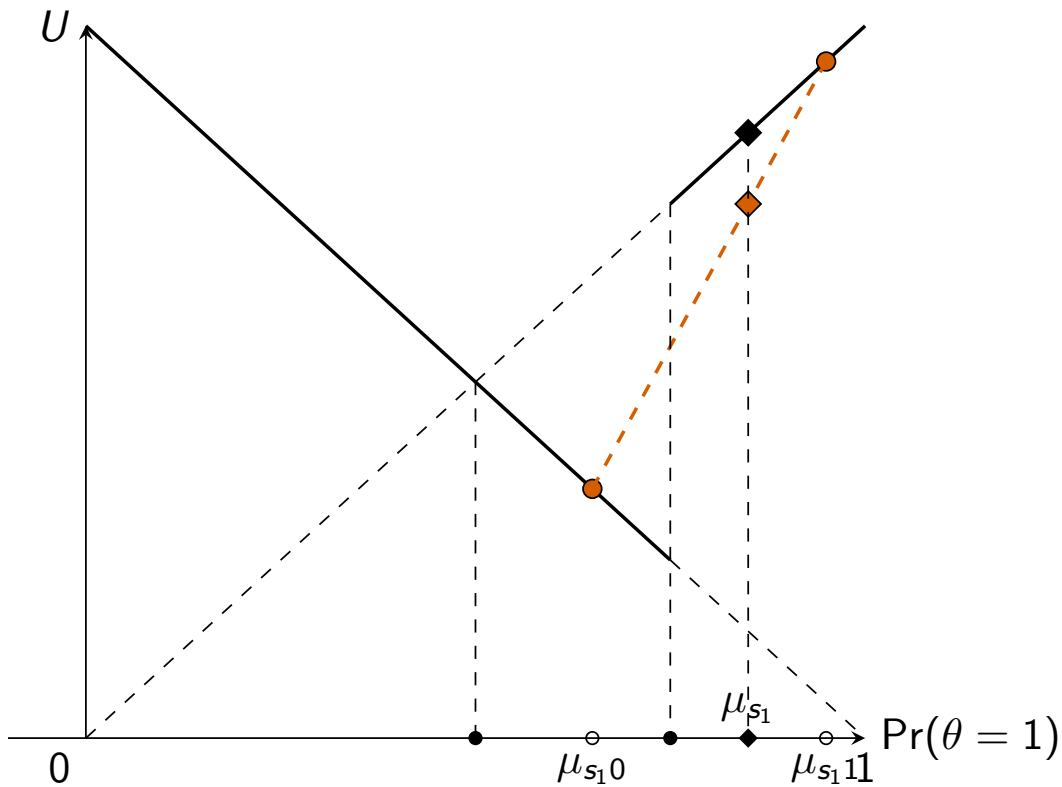
- What if the agent becomes more informative?
- What if the agent becomes more aligned?

Comparative Statics



Delegation payoff at a small q

Comparative Statics

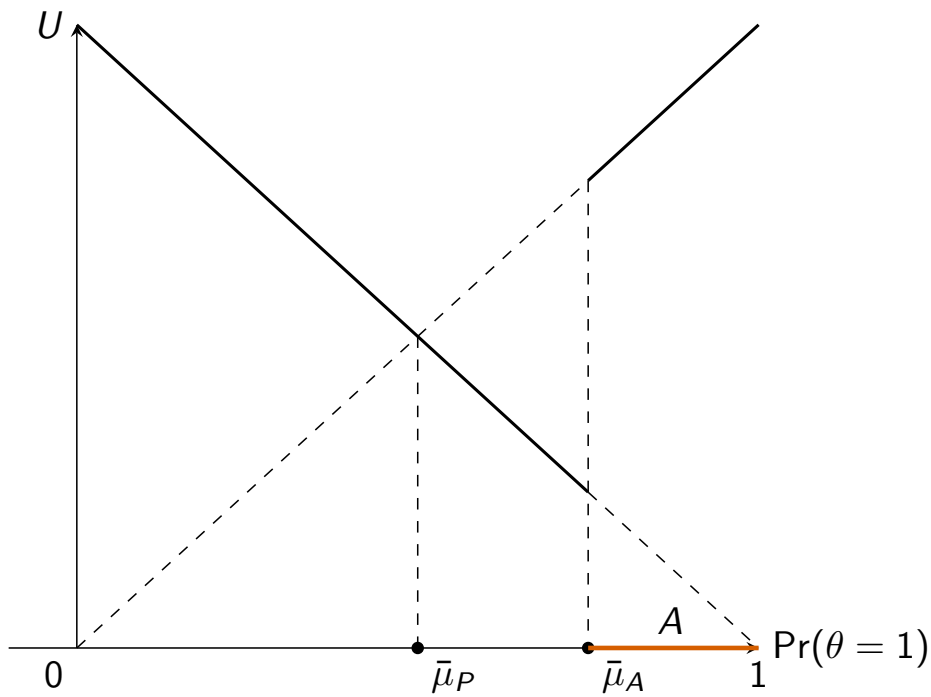


Delegation payoff at a median q

Comparative Statics

Proposition 2

When the principal's interim posterior lies in the agent's interval (A), an increase in q could let the principal change from indifference to no-delegation. When the principal's interim posterior lies in anywhere else, an increase in q always changes the delegation decision in the positive direction.



Literature

Economics:

- Optimal delegation: the principal specifies a set of actions from which the agent can choose. (Holmström, 1978; Holmstrom, 1980; Alonso and Matouschek, 2008; Amador and Bagwell, 2013)
- Bayesian persuasion: the principal designs the information structure of a publicly observable signal. (Kamenica and Gentzkow, 2011)
- Contribution: we consider the joint design of optimal persuasion and delegation mechanisms.

Computer Science:

- Design decision-aid algorithms in the presence of a misaligned agent. (Xu and Dean, 2023; McLaughlin and Spiess, 2023)
- Human-machine complementarity: when it is valuable to have "human-in-the-loop?" (Rastogi et al., 2022; Donahue et al., 2022)
- Contribution: we provide an economic framework to think about these long-standing problems and derive theoretical insights.

Next steps

1. Impose reasonable restrictions on the set of feasible public signals.
2. Solve the optimal information design in the presence of delegation.
3. Generalize the model to multiple/continuous actions (states).
4. Allow "partial delegation" – delegate a subset of actions.

Simulations

References I

Alonso, R. and Matouschek, N. (2008). Optimal Delegation. *The Review of Economic Studies*, 75(1):259–293. Publisher: [Oxford University Press, Review of Economic Studies, Ltd.].

Amador, M. and Bagwell, K. (2013). The theory of optimal delegation with an application to tariff caps. *Econometrica*, 81(4):1541–1599.

Donahue, K., Chouldechova, A., and Kenthapadi, K. (2022). Human-Algorithm Collaboration: Achieving Complementarity and Avoiding Unfairness. arXiv:2202.08821 [cs].

Holmstrom, B. (1980). On the theory of delegation. Technical report, Discussion Paper.

Holmström, B. R. (1978). *On Incentives and Control in Organizations*. Stanford University.

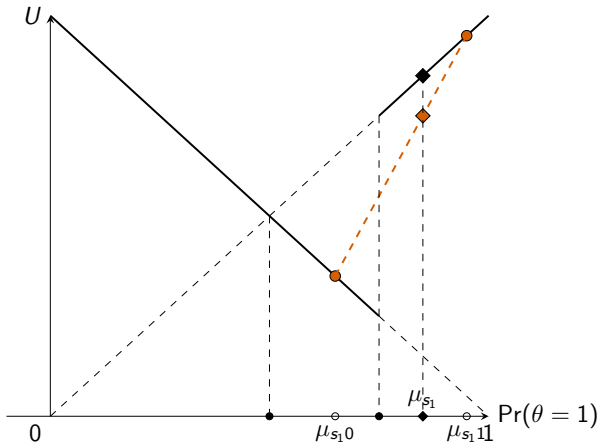
Kamenica, E. and Gentzkow, M. (2011). Bayesian Persuasion. *American Economic Review*, 101(6):2590–2615.

McLaughlin, B. and Spiess, J. (2023). Algorithmic Assistance with Recommendation-Dependent Preferences. In *Proceedings of the 24th ACM Conference on Economics and Computation*, EC '23, page 991, New York, NY, USA. Association for Computing Machinery.

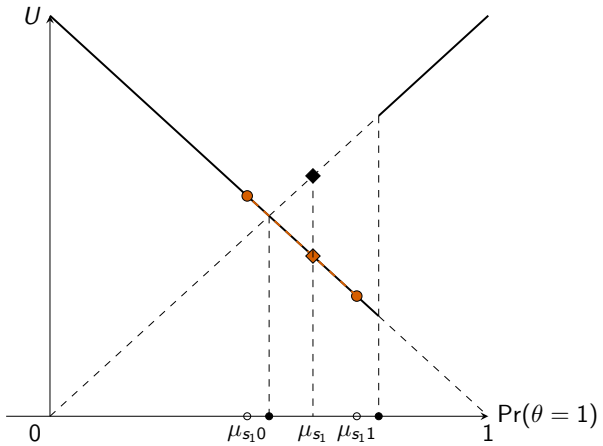
Rastogi, C., Leqi, L., Holstein, K., and Heidari, H. (2022). A Unifying Framework for Combining Complementary Strengths of Humans and ML toward Better Predictive Decision-Making. arXiv:2204.10806 [cs].

Xu, R. and Dean, S. (2023). Decision-aid or Controller? Steering Human Decision Makers with Algorithms. arXiv:2303.13712 [cs].

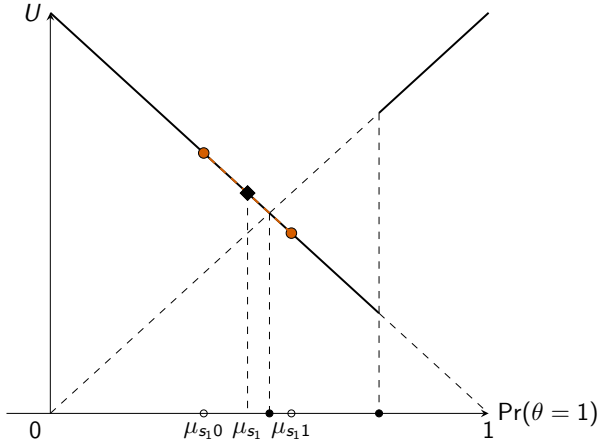
Appendix: Value of delegation



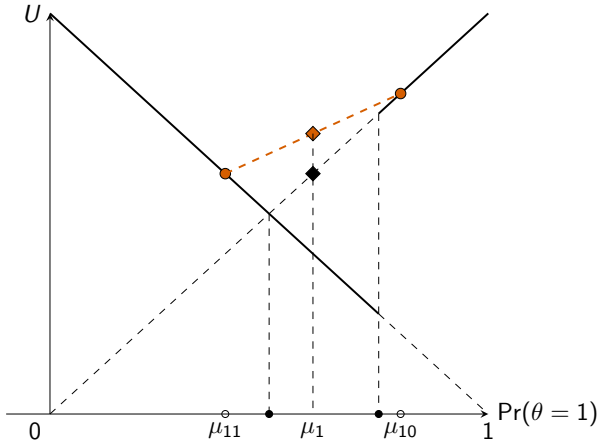
(d) Delegation is not valuable



(e) Delegation is not valuable



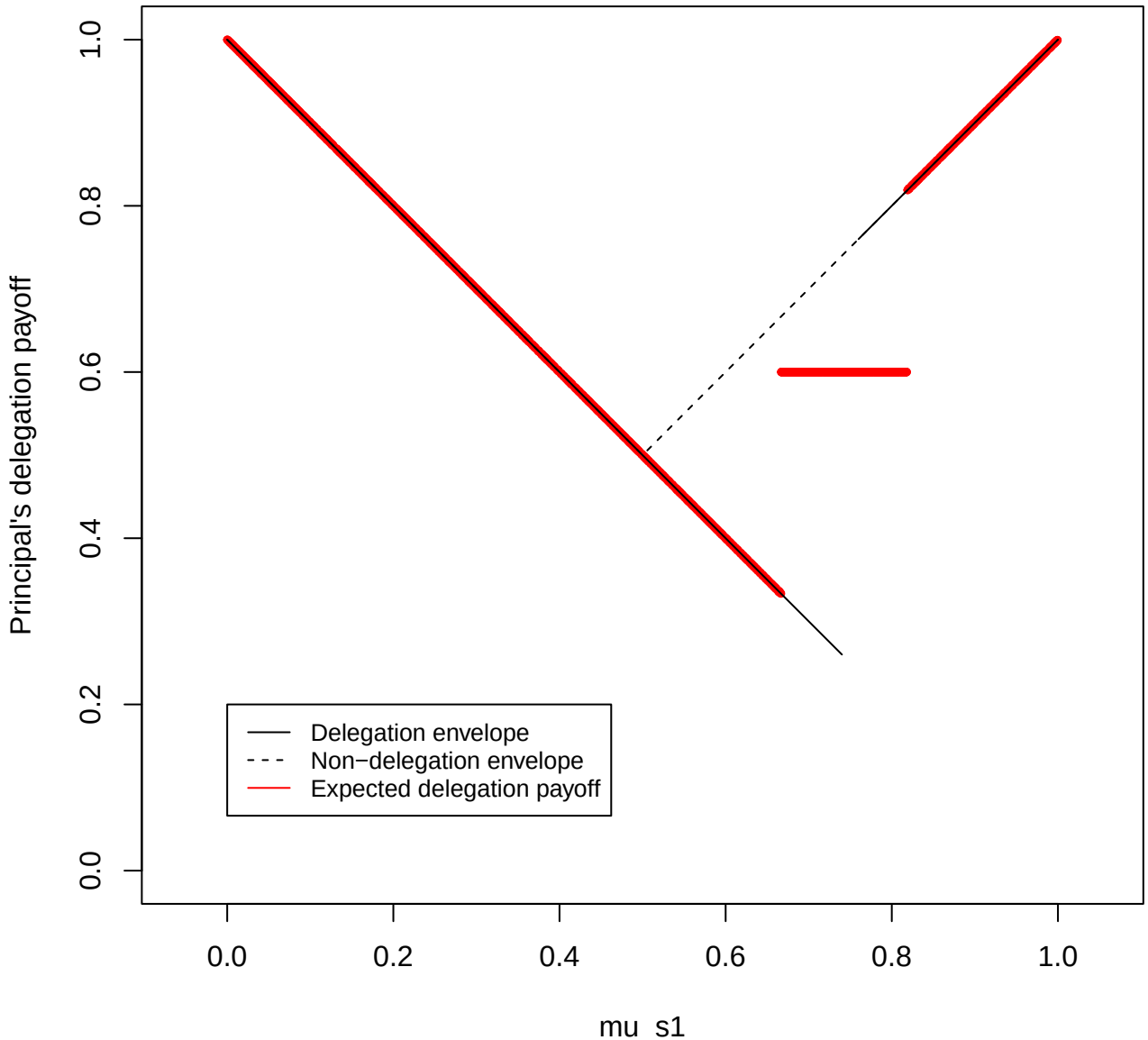
(f) Delegation is indifferent



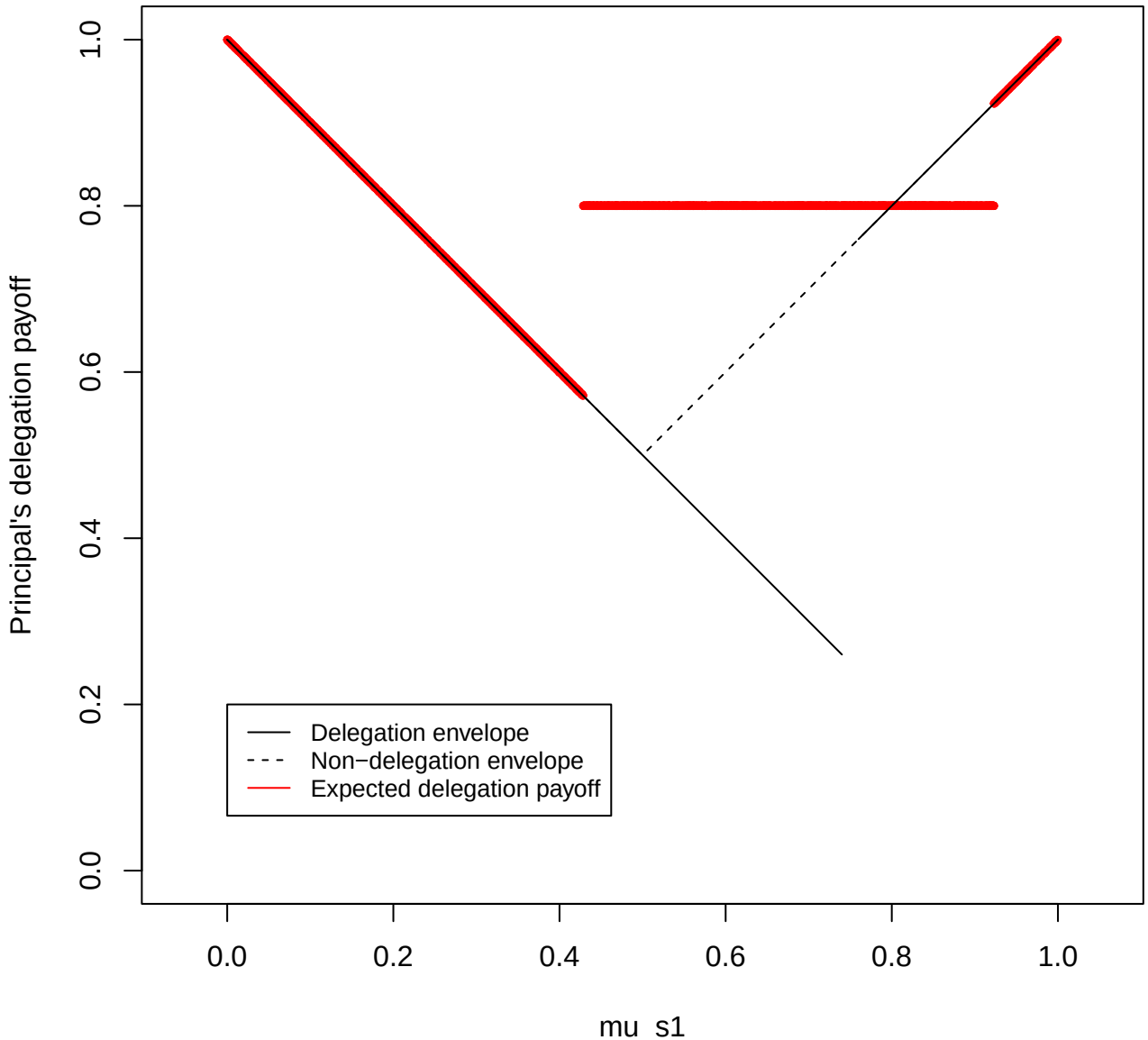
(g) Delegation is strictly valuable

Return

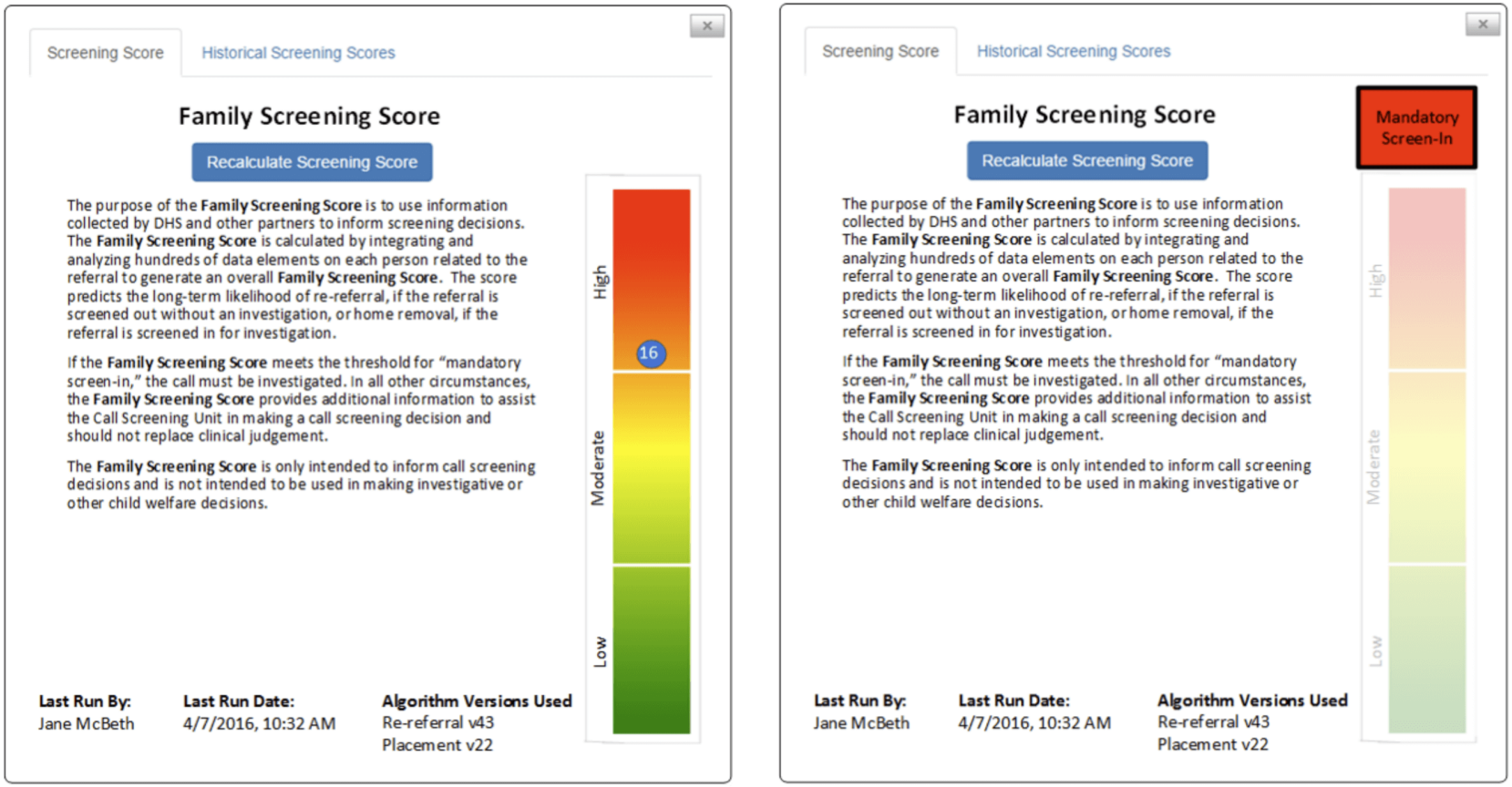
Appendix: Simulation



Appendix: Simulation



Example: Allegheny Family Screening Tool (AFST)



The AFST interface

Return