Information Collection and Reporting through Strategic Agents

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Bocconi University

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Quantifying Uncertainty: Stochastic, Adversarial, and Beyond
@ Simons Institute

Economics of Statistics

- Statistics, based on decision theory, does not *explicitly* account for:
  - incentive problems
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  - data **collection**
  - information **reporting**
- Implications for **regulation**

Plan

Data: HARD information

1. Strategic sample selection
   selective disclosure in “hard” data reporting

2. Persuasion bias
   optional stopping in data collection

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Predictions: SOFT information

3. Forecasting contest
   competition for best record

4. Reputational forecasting
   reputation for accurate information

Impact of Sample Selection on Value of Information

Di Tillio-Ottaviani-Sørensen (EMA, 2021)

- Biased researchers in **observational studies**:
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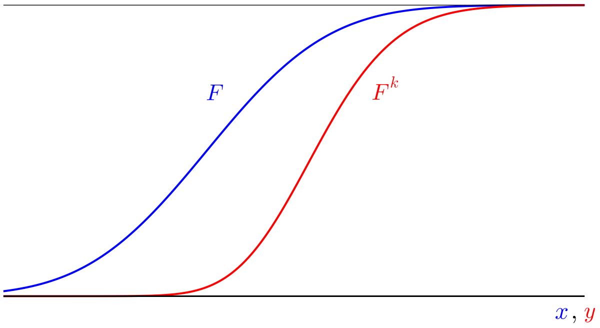
- **How does sample selection affect the value of information?**

Impact of ANTICIPATED Selection

- Compare information value of two experiments:
  - **Random** : $X = \theta + \varepsilon$ with $\varepsilon \sim F$ [BLUE]
  - **Selected** : max of k iid draws: $Y = \theta + \varepsilon_{(k)}$ with $\varepsilon_{(k)} \sim F^k$ [RED]



Cournot (1843) on P-Hacking

"§101 ... A person not knowing how the data were analysed and whom the experimenter told the result of that analysis concerning the system ... but not **how many attempts he made** to achieve that result, is unable to judge with a determined chance of error whether the chances ... are equal or not..."

"... However, **unsuccessful tests usually leave no traces**; **the public only knows the results** which the experimenter thought to be deserving notice. It follows that a person alien to the testing is **absolutely unable** to regulate bets on **whether the result is, or is not attributable to anomalies of chance**."

Illustration: Simple Hypothesis Testing

- Here we illustrate idea for **simple hypothesis testing:**

	θ_L	θ_H
reject	R	R
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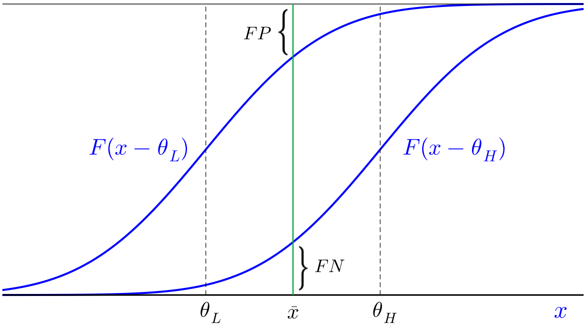
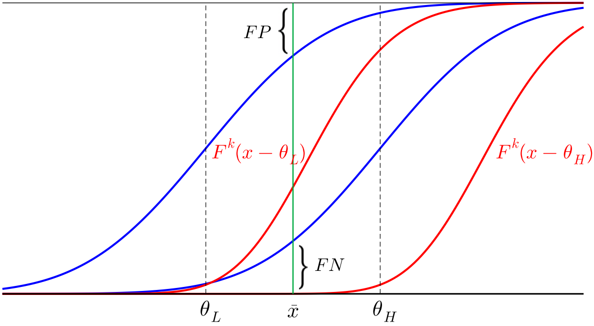
- With a single draw, cutoff rule optimal: accept iff

$$\frac{f(x-\theta_H)}{f(x-\theta_L)} \geq \frac{1-p}{p} \frac{R-\theta_L}{\theta_H - R} \Leftrightarrow x \geq \bar{x}$$

Random Experiment



Selected Experiment



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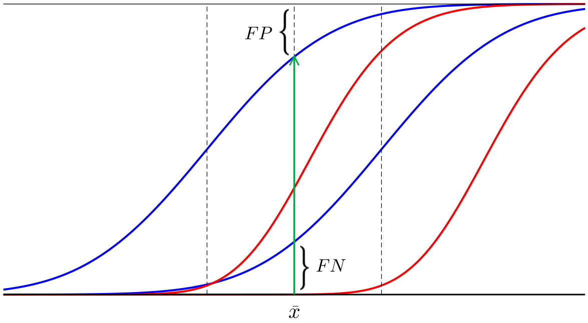

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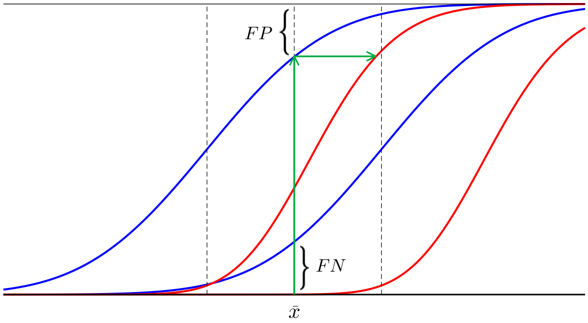
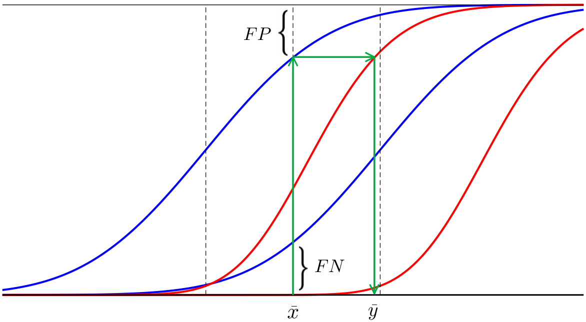


Random v. Selected

$$\underbrace{1 - F^k(\bar{y} - \theta_L) = 1 - F(\bar{x} - \theta_L)}_{\text{Using cutoff } \bar{y} \text{ in } Y \text{ that matches False Positives}} \quad \Rightarrow \bar{y} = (F^k)^{-1} F(\bar{x} - \theta_L) + \theta_L$$



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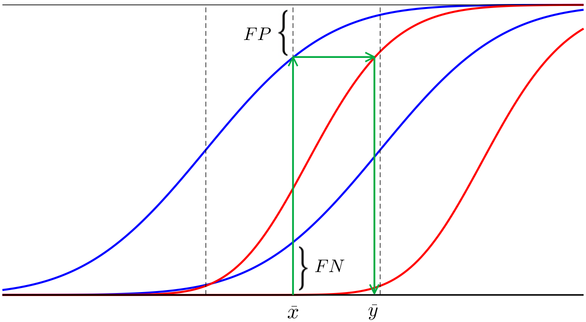

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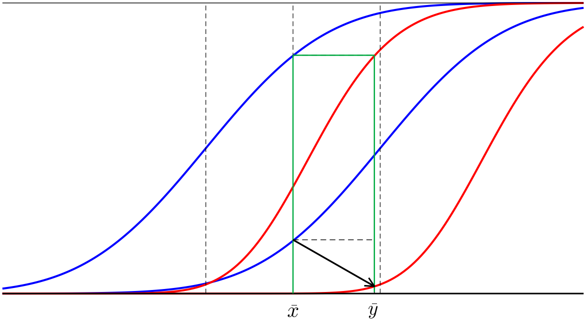

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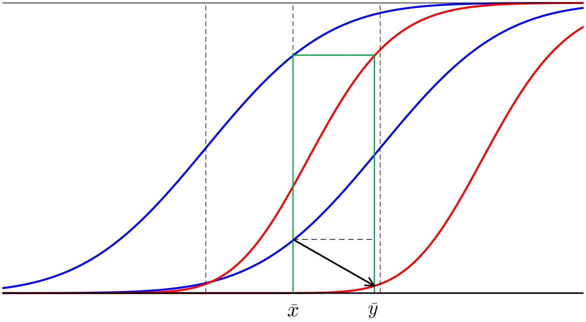

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$\Leftrightarrow F^k$ is **less dispersed** than F ie $(F^k)^{-1}(q) - F^{-1}(q) \searrow q$

Dispersion of Selected Experiment

When is F^k steeper than F at same quantile?

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- Theorem (general sample size n): *Fixing sample size n, **as pre-sample size k increases,** experiment becomes **more** (less) **informative** in every monotone problem **if reverse hazard rate RHR** $f(x|\theta)/F(x|\theta)$ **is log-supermodular** (log-submodular, w/ support unbounded above)*

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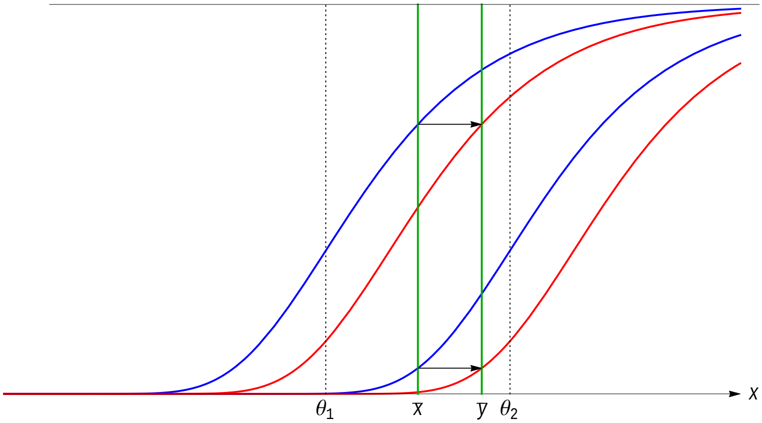
  - **Harmful** selection: logconvex RHR $\frac{f(x)}{F(x)}$ (e.g., Exponential)

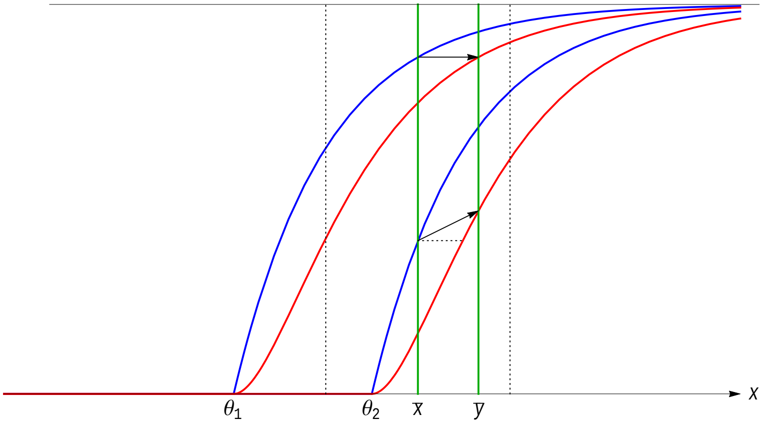
NEUTRAL Selection: Loglinear $f\,/\,F$

Gumbel noise: $F(\varepsilon) = e^{-e^{-\varepsilon}}$



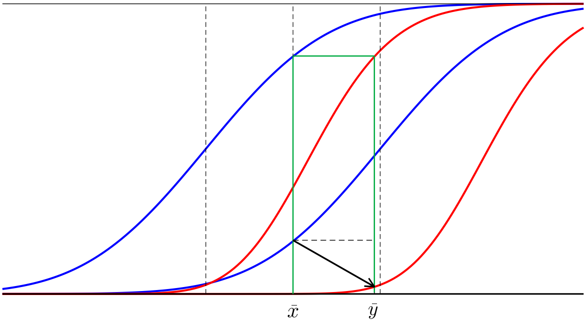
HARMFUL Selection: f LESS Logconcave than F

Exponential noise: $F(\varepsilon) = 1 - e^{-\varepsilon}$



BENEFICIAL Selection: *f* MORE Logconcave than *F*

Normal noise: $\varepsilon \sim \mathcal{N}$



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2. **Wald persuasion games** with costly information collection
   - optional stopping in data collection

Research and the Approval Process

Henry-Ottaviani (AER, 2019)

- Informer benefits from **approval** of drug with uncertain efficacy
  - Evaluator = FDA regulator

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- Evaluator has **coarse instruments** for regulation
  - approve/reject, ask for additional evidence [impose liability]

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TWO players:

1. **Informer *i***

a. directly **controls information** acquisition & pays info cost

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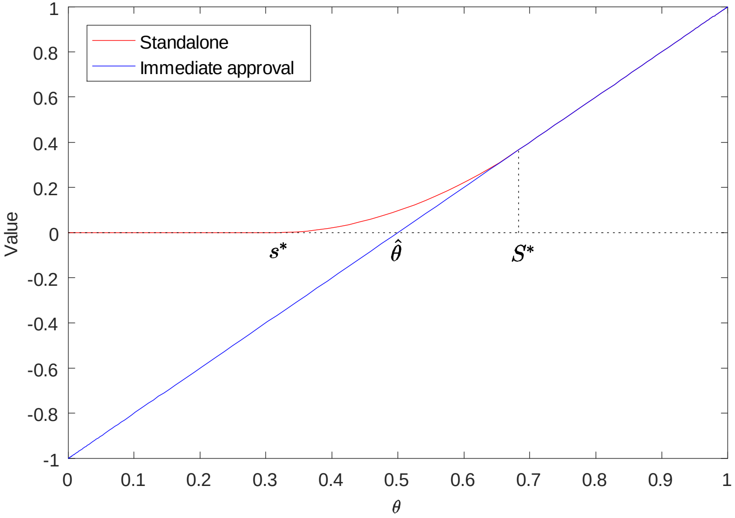
Wald's **social planner** w

a. controls **all decisions** (rejection/approval) & info acquisition

b. obtains **total payoff** $v_w = \theta_e + v_i$ (evaluator+informer) & pays info cost

Wald Welfare Benchmark: Value Function



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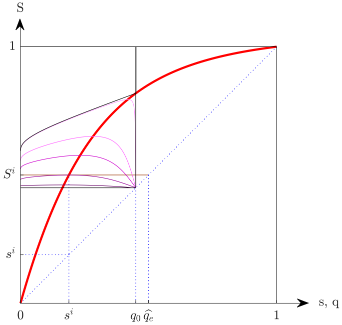
  3. **Evaluator** e **Commitment**: $\max_S u_e|_{s=b_i(S)}$

1. Informer Authority Game

Informer Best Reply [RED]



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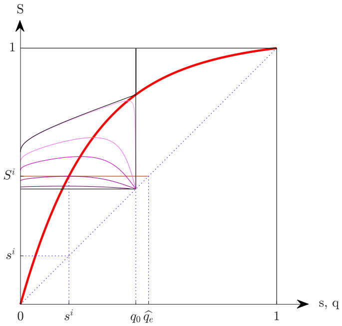

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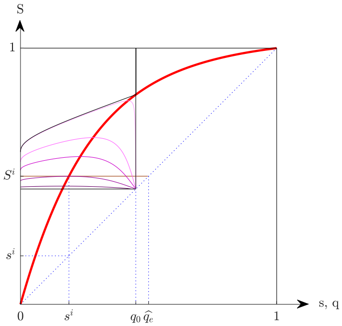

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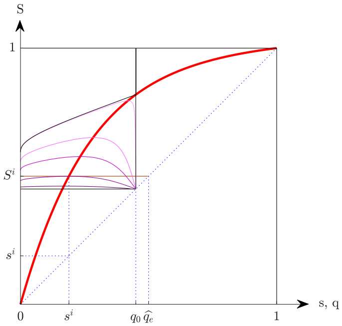

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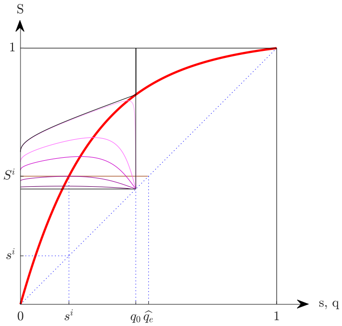
- TOP: Informer stops as soon as evaluator persuaded: $S^i = \hat{q}_e = \frac{-\theta_e^L}{\theta_e^H - \theta_e^L}$

1. Informer Authority Game

Informer Best Reply [RED]



- i's best reply RED $s = b_i(S)$ **given** S [s on horizontal axis]
  - locus of horizontal tangencies of iso-payoff curves PINK
  - $b_i(S) \nearrow S$: LOSS OF CONTROL
- i expects e to adopt for $q \geq S$ [S on vertical axis]
- TOP: Informer stops as soon as evaluator persuaded: $S^i = \hat{q}_e = \frac{-\theta_e^L}{\theta_e^H - \theta_e^L}$
- BOTTOM: Informer withdraws when pessimistic enough: $s^i = b_i(\hat{q}_e)$

Sequential Foundation of Bayesian Persuasion

- Comparison to Kamenica-Gentzkow's (2011) commitment solution?

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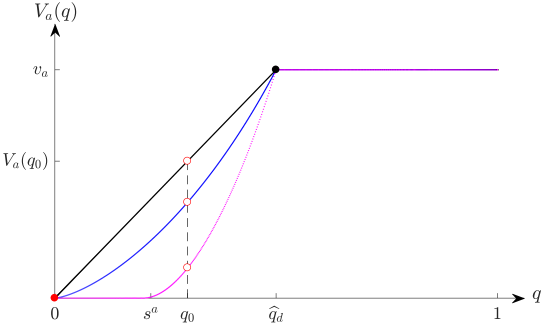
- *We recover KG without info frictions if (1) c* $\rightarrow 0$ *& (2) r* $\rightarrow 0$, so:
  - KG solution becomes **sequentially optimal** without commitment



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- EQUILIBRIUM: **Stationary Markov Perfect Equilibrium** solving
  - *i* controls withdrawal standard: $s^N = b_i\left(S^N\right)$ RED
  - *e* controls adoption standard: $S^N = B_e\left(s^N\right)$ BLUE

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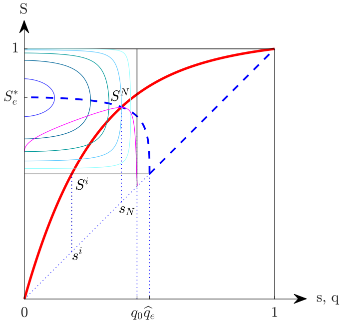

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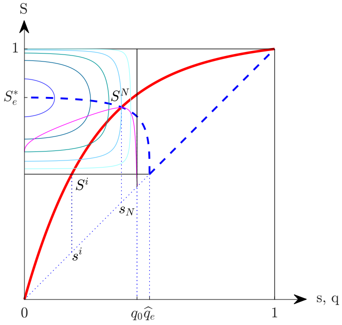

- *e* sets more stringent approval standard: $S^N > S^i$

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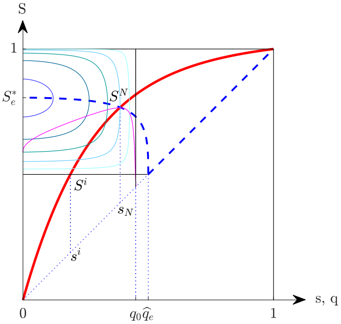
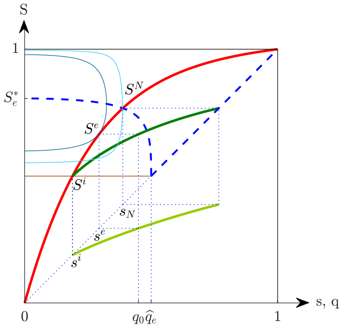


- *e* sets more stringent approval standard: $S^N > S^i$
- *i* withdraws earlier: $s^N > s^i$

3. Evaluator Commitment Solution



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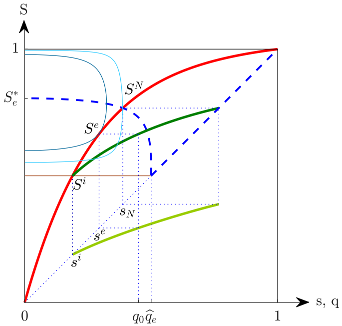

- Evaluator commits ex ante to approval when belief reaches S^e
  - approve iff $q \geq S^e$
- Stackelberg tangency with e's BLUE iso-payoffs
- Evaluator **benefits** to be more lenient $S^e < S^N$
  - commits to free-ride less to encourage more info collection
- Compared to Nash, FALSE POSITIVES ↑ & FALSE NEGATIVES ↓

Plan

Data: HARD information

1. Hypothesis testing with **selected data**
   - anticipated selection benefits/harms if data has thinner/thicker tail than Gumbel
2. **Wald persuasion games** with costly information collection
   - equilibrium persuasion: bias from optional stopping
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Predictions: SOFT information

1. Forecasting **contest**
   - excessive differentiation
2. **Reputational** forecasting
   - conformism with naive audience
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Honest Forecasting: Benchmark Statistical Model

- Unknown state with prior $x \sim N\left(\mu, \frac{1}{v}\right)$
- Single forecaster with private signal s about state x
- Honest forecaster (naive statistician) minimizes forecast error

$$\min_{m} E\left[(m-x)^2 | s\right]$$

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- Best statistical forecast is posterior expectation

$$m = E\left[x|s\right]$$

  - Forecasts are orthogonal to the forecast error
  - Forecasts are dispersed, but less than the state

Forecasting Contest

Ottaviani-Sørensen (2006, J of Financial Economics)

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4. Forecaster whose forecast is closest to the state wins

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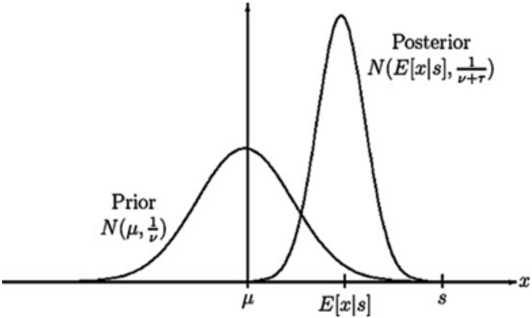

- At the posterior expectation

$$m_i = E\left[x|s_i\right]$$

a small deviation away from the prior mean μ results in

  - a second-order loss due to lower chance of winning, but
  - a first-order gain due to reduced competition

Excessive Differentiation in Forecasting Contest

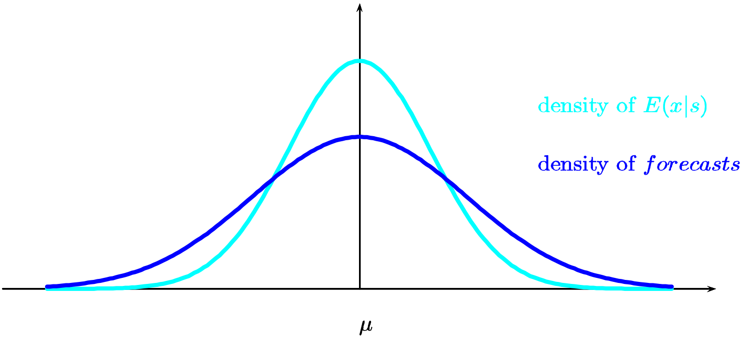

Figure: Equilibrium forecasts are more variable than posterior expectation

Reputational Cheap Talk

Ottaviani-Sørensen (2006, RAND J Economics)

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- Objective of forecaster is to obtain **favorable evaluation** $E\left[t|m,x\right]$
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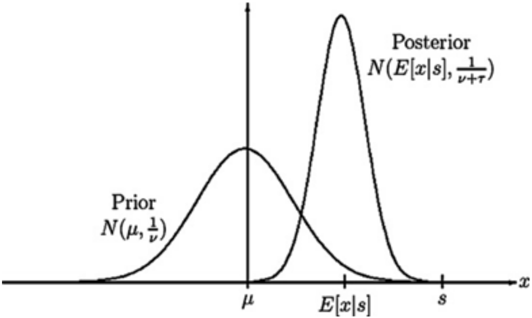
  - **Is honest** $m=E\left[x|s\right]$ **an equilibrium?**

Misreporting Incentives



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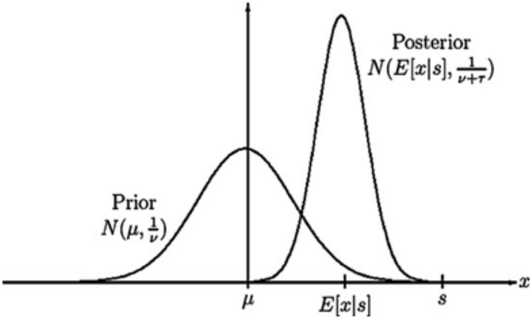

- If evaluator (naïvely) expects honest forecasting $m = E[x|s]$
  - Will forecaster want to report honestly?
- With location signal, forecaster has **incentive to lie** reporting

$$E[x|\hat{s} = E[x|s]],$$

Reputational Cheap Talk Equilibrium

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- Equilibrium communication is coarse (as in Crawford and Sobel, 1982)
  - Forecasters with signals in an interval send identical message
  - Loss of forecast accuracy!
- E.g., there exists a two-message equilibrium:
  - Report whether s is above or below prior mean $E[x]$

Forecasting Summary

- Concern for accuracy leads to:
  - excessive conformity if the market is naïve
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- Competition for best accuracy record leads to excessive differentiation

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