Accept this Paper

Lones Smith Andrea Wilson Mavi Wilson

Wisconsin and Princeton



Best, Brightest and Rejected: Elite Colleges Turn Away Up to 95%

By RICHARD PÉREZ-PEÑA APRIL 8, 2014



Stanford University accepted 5 percent of applicants in the latest admissions season, a new low among elite colleges. Thor Swift for The New York Times

Goal: Is Selectivity Excellence?

Colleges advertise "selectivity"

 U.S. News and World Report college rankings puts 12.5% weight on selectivity

The Princeton Review weights it as one of seven factors

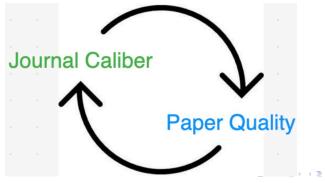
- Should the best colleges have the highest rejection rates?
- Should the best journals have the highest rejection rates?
- Better journals have higher standards, but get better papers. Why should the former effect dominate?

Selectivity Need Not Be Excellence

- Short run shrink your college and your rejection rate rises
- Chade, Lewis, and Smith "Student Portfolios and the College Admissions Problem" (*REStud*, 2014)
 - An elite college 1 and a safety college 2 respectively offer students a fixed high and low payoff
 - A continuum of heterogeneous students each choose to apply to stretch college 1, or safety college 2, or both, or neither; each application costs c > 0
 - Student evaluation is noisy: Colleges choose admission thresholds for random signals generated by students
 - Proposition: If college 2 shrinks its student capacity enough,
 (a) better students need not apply more ambitiously, and
 (b) college 1 has lower admission standards than college 2

Static Game of Incomplete Information

- Step 1 An endogenous pool of journals publicize and commit to standards and "calibers"
- Step 2 As a function of his paper quality, each author submits to a single journal, seeking to maximize caliber \times admission chance
- Step 3 Rational expectations: Acceptance decisions ensure that average acceptance quality equals advertised caliber
 - Similar to Bayesian persuasion's cheap talk with commitment



Benchmark Model: The Author Knows His Paper Quality

Continuum Mass of Heterogenous Authors/Papers

- Each has a unique paper with some quality x
- Density of paper qualities on $[\underline{x}, \infty)$, where $0 < \underline{x} < \infty$

Benchmark Model: The Author Knows His Paper Quality

- Continuum Mass of Heterogenous Authors/Papers
 - Each has a unique paper with some quality x
 - Density of paper qualities on $[\underline{x}, \infty)$, where $0 < \underline{x} < \infty$
- ► No Market Power: Continuum Mass of Journals
 - Journal caliber is the average quality of accepted papers
 - Caliber is in monetary value units: a quality v publication is worth v to the author
 - Free entry and exit of journals of any caliber
 - Knowing his paper quality, author picks a journal to submit to

Benchmark Model: The Author Knows His Paper Quality

Continuum Mass of Heterogenous Authors/Papers

- Each has a unique paper with some quality x
- Density of paper qualities on $[\underline{x}, \infty)$, where $0 < \underline{x} < \infty$

No Market Power: Continuum Mass of Journals

- Journal caliber is the average quality of accepted papers
- Caliber is in monetary value units: a quality v publication is worth v to the author
- Free entry and exit of journals of any caliber
- Knowing his paper quality, author picks a journal to submit to

Submission and Stochastic Evaluation

- Journals see a noisy signal σ of the quality of any submitted paper, and choose whether to accept or reject it
- Evaluation noise has location family: a quality x paper yields a signal realization σ, where σ x has a probability density g.

• Example: Gaussian noise $g(\sigma - x) = \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2\phi^2}(\sigma - x)^2}$

A Robust Assumption on Signal Noise

- ▶ log-concave signal density g (eg. Gaussian, Gamma, uniform)
- \Rightarrow signal cdf G is log-concave (and thus continuous)
- \Rightarrow hazard rate $\frac{g(t)}{1-G(t)}$ is increasing.
- \Rightarrow The density is positive on a connected interval
- \Rightarrow No signal is perfectly revealing
- \blacktriangleright assume this interval has upper bound ∞
 - \Rightarrow every paper has a positive chance at every journal

Equilibrium Analysis

- Journal Motivations
 - Rational Expectations: promised caliber is realized
 - intuitive long-run steady-state with journal reputations
 - Short-run: Fly-by-night (or "predatory") journals reimburse authors for gap between their promised and delivered caliber
 - Journals publicly commit to acceptance standards
 - \Rightarrow Journal v accepts when signal $\sigma \ge \theta(v)$, acceptance threshold

Equilibrium Analysis

- Journal Motivations
 - Rational Expectations: promised caliber is realized
 - intuitive long-run steady-state with journal reputations
 - Short-run: Fly-by-night (or "predatory") journals reimburse authors for gap between their promised and delivered caliber
 - Journals publicly commit to acceptance standards

 \Rightarrow Journal v accepts when signal $\sigma \ge \theta(v)$, acceptance threshold

Author Payoffs

Author's payoff is caliber times acceptance chance

- $\Rightarrow\,$ subsumes dynamic case with resubmission and discounting when the author cares about $(1-\delta)$ times this
- Author of quality x paper who submits to a caliber v journal with threshold θ gets payoff

$$(1 - G(\theta - x)) \cdot v$$

 $\Rightarrow \text{ acceptance threshold } \theta \text{ depends only on caliber } v, \text{ for authors clearly submit to the lowest threshold journal for any caliber } a dependence of the second second$

Authors Play a Separating Equilibrium

Lemma

Every author submits to a journal equal to his caliber.

- Proof Sketch
 - ► Assume pooling occurs ⇒ multiple papers go to same journal
 - ▶ Rational expectations \Rightarrow some paper exceeds journal caliber: $x' > \kappa$
 - \Rightarrow A journal κ' in (κ, x') can enter and skim off x' (log-concavity)

Separating Equilibrium Proof

- By rational expectations, it suffices to preclude pooling equilibria, where a journal v₁ (with threshold θ₁) attracts two or more paper qualities x < v₁ and x' > v₁.
- \Rightarrow Claim: If so, a new journal skim off best papers at v₁
 - ▶ Proof of Claim: Let a new journal promise caliber $v_2 \in (v_1, x')$ and choose a threshold $\theta_2 > \theta_1$ that makes type x' indifferent, so that $[1 - G(\theta_2 - x')]v_2 = [1 - G(\theta_1 - x')]v_1$, then

$$\Rightarrow \frac{1 - G(\theta_2 - x')}{1 - G(\theta_1 - x')} = \frac{v_1}{v_2} \in (0, 1) \qquad (\clubsuit)$$

LHS = 1 at θ₂ = θ₁, and continuously falls to zero as θ₂ ↑ ∞.
By log-concavity of G, the left side of (♣) increases in x', since log(1 - G(θ₂ - x')) - log(1 - G(θ₁ - x')) increases in x'
Papers x'' > x' prefer journal v₂, and papers x'' < x' prefer v₁.
Journal v₂ attracts only quality x'' ≥ x', but promise a caliber v₂ < x', earning profits. Contradiction.

Journal Equilibrium: A Reduced Form Description

A journal equilibrium is a threshold function θ(v) for which it is optimal for every author x ∈ [x,∞) to submit to the same caliber journal v = x

The Worst Journal is not Selective

Lemma

The worst journal has caliber \underline{x} , and accepts all submissions.

- Proof: Since we ruled out pooling in equilibrium, the least caliber journal cannot exceed <u>x</u>
- If the least journal <u>x</u> sometimes rejects, a new journal can enter, always accept, and attract all paper qualities just over <u>x</u> > 0 (making profits)

The Equilibrium First Order Condition

Author optimality, given paper of quality x:

$$\max_{v} \left(1 - G(\theta(v) - x)\right) v$$

The interior FOC is

$$(1 - G(\theta(v) - x)) - g(\theta(v) - x)\theta'(v)v = 0$$

• By rational expectations, this must hold at v = x:

$$\Rightarrow \theta'(v) = \frac{1}{v} \cdot \frac{1 - G(\theta(v) - v)}{g(\theta(v) - v)} \qquad [FOC^*]$$

The SOC holds, given log-concavity

Journal Selectivity is Hump-Shaped

- equilibrium toughness $\tau(v) = \theta(v) v$
- equilibrium rejection rate is $R(v) = G(\tau(v))$.

Proposition

- (a) There exists a unique equilibrium.
- (b) The rejection rate is hump-shaped for all small $\underline{x} > 0$.
 - The rejection rate is hump-shaped if $\tau(v)$ is hump-shaped.

Proof of Hump-Shaped Toughness

► Recall equilibrium FOC:

$$\Rightarrow \theta'(v) = \frac{1}{v} \cdot \frac{1 - G(\theta(v) - v)}{g(\theta(v) - v)} \qquad [FOC*]$$

• Let's rewrite equilibrium FOC using τ :

$$\tau'(v) = \frac{1}{v} \cdot \frac{1 - G(\tau(v))}{g(\tau(v))} - 1 \qquad (\bigstar)$$

▶ First, (★) ⇒ $\tau'(\underline{x}) > 0$ for small enough \underline{x}

- ▶ By log-concavity, the reciprocal hazard rate (1 G)/g falls
- So $\tau(v)$ weakly rising implies $\tau'(v)$ strictly falling
- \Rightarrow any critical point is a max: $au'(extsf{v}) = 0 \Rightarrow au''(extsf{v}) < 0$
- But \(\tau(\nu)\) cannot rise forever: For if so, the RHS of (★) tends to -1, contradiction

An Intuition for the Hump-Shape

• Rewrite the equilibrium FOC with θ as independent variable:

$$\frac{v'(\theta)}{v(\theta)} = \frac{g(\theta - v(\theta))}{1 - G(\theta - v(\theta))} \qquad (\bigstar)$$

Aside: The *rate* of increase in the journal caliber matches the (absolute) *rate* of fall of the acceptance rate in toughness:

$$\left[\log v(\theta)\right]' = -\left[\log(1 - G(t))\right]' \Big|_{t=\theta - v(\theta)}$$

Whenever the rejection rate is increasing in θ

 ⇒ equilibrium toughness t(θ) = θ - v(θ) is increasing in θ
 ⇒ Differentiating, 0 < t(θ) = 1 - v'(θ)
 ⇒ If rejection rate always increases: v'(θ)/v(θ) < 1/v(θ) ↓ 0 at high θ

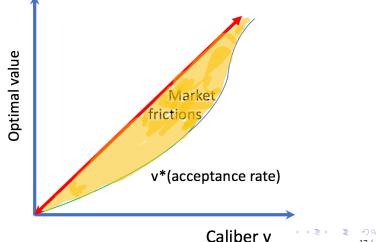
 But an increasing rejection rate G(τ) in θ

 ⇒ increasing g(t)/[1 - G(t)], by log-concavity
 ⇒ monotone increasing v'(θ)/v(θ), by (★)

 So forever increasing rejection rate ⇒ contradiction

Matching Frictions and Caliber

- ▶ The rejection rate is an informational market friction.
- Here, all rejections are mistakes.
- ▶ We plot the expected payoff for each caliber of paper.
- The sorting losses reflect the hump-shaped rejection rates



Solved Exponential Noise Example

• Assume
$$g(t) = \lambda e^{-\lambda t}$$
 and $G(t) = 1 - e^{-\lambda t}$

The equilibrium FOC is

$$\theta'(v) = \frac{1}{v} \cdot \left(\frac{1 - G(\theta(v) - v)}{g(\theta(v) - v)}\right) = \frac{1}{\lambda v} \Rightarrow \theta(v) = \frac{1}{\lambda} \log v + C$$

- ► Boundary condition: Sure acceptance at journal $\underline{x} \Rightarrow \theta(\underline{x}) = \underline{x}$ and $C = \underline{x} - \frac{1}{\lambda} \log \underline{x}$
- \Rightarrow Journal threshold $\theta(v) = \underline{x} + \frac{1}{\lambda} \log \frac{v}{\underline{x}}$.
- \Rightarrow Rejection rate

$$R(v) = G(\theta(v) - v) = 1 - e^{-\lambda(\theta(v) - v)} = 1 - \frac{X}{e} e^{\lambda(v - \underline{x})}$$

Solved Exponential Noise Example Grows Noisier

- Case 1: Precise signals: $\lambda > 1/\underline{x}$
 - corner solution $\theta(v) = v$, and zero rejection chance in equilibrium for all qualities.
- Case 2: Noisy signals: $\lambda < 1/\underline{x}$
 - A hump shape emerges



How Evaluation Noise Impacts Rejection Rates

- Old school: mean preserving spread. Not strong enough.
- Dispersion measures how "spread out" a distribution is
- ▶ G_2 is more dispersed than G_1 $\Leftrightarrow G_2^{-1}(b) - G_2^{-1}(a) \ge G_1^{-1}(b) - G_1^{-1}(a)$ for any b > a $\Leftrightarrow g_2(G_2^{-1}(a)) < g_1(G_1^{-1}(a))$ for any $a \in (0, 1)$, with a density
- So the difference between any two quantiles (or percentiles) is higher under the more disperse distribution

Proposition (Increasing Rejection Rates)

The rejection rate rises and peaks later if the evaluation noise G grows more disperse

Rejection Rate Rises in Evaluation Noise Dispersion

► The equilibrium FOC* is

$$\theta'(v) = \frac{1 - G(\theta(v) - v)}{vg(\theta(v) - v)} = \frac{1 - G(\tau(v))}{vg(\tau(v))}$$

• The rejection rate $R(v) = G(\tau(v))$ has slope

$$R'(v) = g(\tau(v))\tau'(v) = g(\tau(v))[\theta'(v) - 1]$$

$$\Rightarrow R'(v) = \frac{1 - R(v)}{v} - g(G^{-1}(R(v)) \quad (\bigstar)$$

 More Dispersion \Rightarrow Higher Rejection Rates

Assume density g₂ is more disperse than g₁

Let rejection rates R₁, R₂ satisfy

$$R'_{i}(v) = \frac{1 - R_{i}(v)}{v} - g_{i}(G_{i}^{-1}(R(v))) \qquad (\bigstar)$$

• Claim: $R_1(v) = R_2(v) \Rightarrow R'_2 > R'_1$

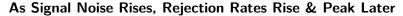
- Apply (\bigstar) and $g_2(G_2^{-1}(x)) < g_1(G_1^{-1}(x)) \ \forall x$
- \Rightarrow $R_2(v)$ can only upcross through $R_1(v)$
- \Rightarrow Since $R^1(\underline{x}) = R^2(\underline{x}) = 0$, there is no no crossing

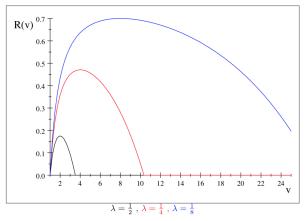
More Dispersion \Rightarrow Later Peak Rejection Rate

- Andrea show that $R'_1 = R'_2 \ge 0 \Rightarrow R''_2 > R''_1$
- \Rightarrow The peak of R_2 is right of the peak of R_1 .
- But Andrea also claim she is not rejected:



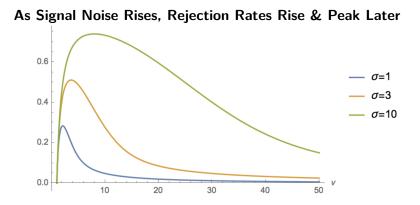
Increasing Dispersion with Exponential Noise





The plots assume a worst paper $\underline{x} = 1$.

Gaussian Noise



<ロト < 部 > < 言 > < 言 > 言 の < C 25 / 48

What if Authors Do Not Know Paper Quality?

- Authors may be unsure of their paper's quality just as a student may not know how good he is (e.g. Ramanujan)
- In this case, our one-shot model would not recur every period, but learning would occur.
- Our results should still inform what happens in the stage game, but it is a hard learning exercise.

General Model: Authors Do Not Know Their Paper Quality

- ▶ Journals see a noisy signal σ of the quality x of any submitted paper, where σx has a density $g(\sigma x)$.
- Each author sees a noisy signal ψ of his paper quality x, where ψx has a density $h(\psi x)$.

General Model: Authors Do Not Know Their Paper Quality

- ► Journals see a noisy signal σ of the quality x of any submitted paper, where σx has a density $g(\sigma x)$.
- Each author sees a noisy signal ψ of his paper quality x, where ψx has a density $h(\psi x)$.
- Until now, the paper quality distribution was irrelevant for the conclusion, for neither authors nor journals needed Bayes rule
- Quality density f is log-concave on support $[\underline{x}, \infty)$ (say $\underline{x}=1$)
- A journal equilibrium is an application strategy and acceptance threshold obeying author optimality and rational expectations
- Rational expectations trickier: Each journal's caliber equals the expected average quality of papers it accepts
- As before, authors don't mix and no one pools in equilibrium
 - Higher author types ψ are more ambitious: $V(\psi)$ is increasing
 - Better journals v set higher standards: $\theta(v)$ is increasing
 - both maps $V(\psi)$ and $\theta(v)$ are differentiable
 - ▶ Note: Since V > 0, we instead find the inverse $\psi(v)$ of $V(\psi)$

General Journal Equilibrium

- $\theta(v)$ is the equilibrium threshold of journal v (with $\theta'(v) > 0$)
- Author type $\psi(v)$ submits to journal v (with $\psi'(v) > 0$)
- ► The *density of accepted paper qualities x* by journal *v* is:

$$\alpha_{v}(x) \propto f(x)h(\psi(v) - x)(1 - G(\theta(v) - x))$$

The rational expectations (RE) condition is now more involved because journals publish a continuum of qualities:

$$\mathsf{RE} \qquad \mathsf{v} = \int_{\underline{x}}^{\infty} x \alpha_{\mathsf{v}}(x) dx$$

• A *journal equilibrium* (ψ, θ) obeys (RE) and author optimality:

FOC*
$$\frac{1}{\nu\theta'(\nu)} = \int_{\underline{x}}^{\infty} \frac{g(\theta(\nu) - x)}{1 - G(\theta(\nu) - x)} \alpha_{\nu}(x) dx$$

This is the analogue of our earlier equilibrium FOC:

$$\theta'(v) = \frac{1}{v} \cdot \frac{1 - G(\theta(v) - v)}{g(\theta(v) - v)}$$

Equilibrium Rejection Rate

• The density of submitted paper qualities x at journal θ

$$\zeta_{v}(x) \propto f(x)h(\psi(v)-x)$$

The equilibrium rejection rate is then

$$R(v) = \int_{\underline{x}}^{\infty} \zeta_{v}(x) G(\theta(v) - x) dx$$

- Higher-caliber journals
 - reject more often, with higher thresholds $(\theta \uparrow)$
 - get submissions from stochastically better papers $(\psi\uparrow)$
- The rejection rate is hump-shaped if first "direct effect" dominates at low qualities, and second "paper selection effect" at high qualities

Journal Equilibrium Equations, Reformulated

- equilibrium toughness $\tau(v) \equiv \theta(v) v$ is again the excess of the journal threshold over its caliber
- author's equilibrium sheepishness $\xi(v) \equiv \psi(v) v$ is the excess of the author's type over journal caliber he submits to
- Caliber-quality gap $z \equiv v x$
- We can reformulate the accepted density in terms of sheepishness and toughness:

$$\begin{aligned} \alpha_{v}(v-z) &\propto f(x)h(\psi(v)-x)(1-G(\theta(v)-x))\\ &\propto f(v-z)h(\xi(v)+z)(1-G(\tau(v)+z)) \end{aligned}$$

Journal Equilibrium Equations, Reformulated

- equilibrium toughness $\tau(v) \equiv \theta(v) v$ is again the excess of the journal threshold over its caliber
- author's equilibrium sheepishness $\xi(v) \equiv \psi(v) v$ is the excess of the author's type over journal caliber he submits to
- Caliber-quality gap $z \equiv v x$
- We can reformulate the accepted density in terms of sheepishness and toughness:

$$\begin{aligned} \alpha_{\nu}(\nu-z) &\propto f(x)h(\psi(\nu)-x)(1-G(\theta(\nu)-x))\\ &\propto f(\nu-z)h(\xi(\nu)+z)(1-G(\tau(\nu)+z)) \end{aligned}$$

• Equilibrium equations (recalling that paper quality $x \ge x = 1$)

RE 0 =
$$\int_{-\infty}^{\nu-1} \alpha_{\nu}(\nu-z)zdz$$

FOC* $\frac{1}{\nu(\tau'(\nu)+1)}$ = $\int_{-\infty}^{\nu-1} \alpha_{\nu}(\nu-z)\frac{g(\tau(\nu)+z)}{1-G(\tau(\nu)+z)}dz$

RE requires a zero average accepted caliber-quality gap

Goals

- 1. Equilibrium toughness $\tau(v) \equiv \theta(v) v$ is hump-shaped in journal caliber (as before)
- 2. Hump-shaped toughness \Rightarrow hump-shaped rejection rate

Quasiconcave Toughness

► Say that a density µ is *decreasingly log-concave* if:

$$(\log\mu)'' \le 0 \le (\log\mu)'''$$

Met by many typical log-concave distributions, eg Gaussian, exponential, uniform, Chi-squared, extreme value

Lemma

Assume densities f and h are decreasingly log-concave. Then equilibrium toughness is hump-shaped if author noise is not too dispersed, and otherwise toughness is increasing. Comparative Statics Under Uncertainty Primer

- ► A function φ(x, y) is LSPM (log-supermodular) if log φ is supermodular in (x, y) — ditto LSBM for log-submodular
- $\blacktriangleright\,$ If ϕ and γ are LSPM / LSBM, then so too is the product $\phi\gamma$
- If a density γ is log-concave, then
 - Prekopa Theorem: Its cdf Γ and survivor 1Γ are log-concave
 - the kernel $\phi(v, x) = \gamma(v x)$ is LSPM in (v, x)
 - the kernel $\phi(v, x) = \gamma(v + x)$ is LSBM in (v, x)
- ► Karlin and Rubin (1956): The expectation $\int \phi(v, x)u(x)dx$ of an increasing function u(x) with respect to a LSPM / LSBM kernel $\phi(v, x)$ is increasing / decreasing in v.

Proof:

$$\int [\phi(v_2, x) - \phi(v_1, x)] u(x) dx = \int \left(\frac{\phi(v_2, x)}{\phi(v_1, x)} - 1\right) u(x) \phi(v_1, x) dx$$

▶ by Tchebyshev's inequality, this is positive if u(x) and $\left(\frac{\phi(v_2,x)}{\phi(v_1,x)} - 1\right)$ are comonotone, negative if reverse comonotone

Toughness Proof Sketch: A Failed Attempt

$$\mathsf{FOC}^*: \frac{1}{\nu(\tau'(\nu)+1)} \equiv \int_{-\infty}^{\nu-1} \alpha_{\nu}(\nu-z) \frac{g(\tau(\nu)+z)}{1-G(\tau(\nu)+z)} dz$$

- Equilibrium toughness is quasiconcave if any critical point is a maximum (sufficient condition)
- \Rightarrow it *suffices* that au'(v) falls at a critical point au'(v) = 0
- \Rightarrow it suffices that $v(\tau'(v) + 1)$ falls at a critical point $\tau'(v) = 0$
- \Rightarrow it suffices that the RHS of FOC* increases in v
- This is guaranteed if $\alpha_v(v-z)$ is LSPM in (v, z), since hazard rate increases in z by log-concavity of g, when $\tau'(v) = 0$
- But in that case, ∫ α_ν(ν − z)zdz ↑ in ν, violating RE (zero average accepted paper quality-caliber gap). Contradiction.

Getting Over the Hump for Hump-Shaped Toughness

Recall the density of accepted paper qualities

$$\alpha_{v}(v-z) \propto f(v-z)h(\xi(v)+z)(1-G(\tau(v)+z))$$

First factor: f(v-z) is LSPM in (v, z)
Middle factor: h(ξ(v) + z) is LSBM in (ξ(v), z)
Last factor: (1 - G(τ(v) + z)) is LSBM in (τ(v), v), by Prekopa
So α_v(v - z) would be LSPM in (v, z) if
ξ(v) is decreasing, and
τ'(v) = 0 (namely, a critical point)
But we just showed α_v(v - z) is not LSPM at a critical point
ξ(v) must be increasing ⇒ h(ξ(v) + z) is LSBM
α_v(v - z) is a product of a LSPM and a LSBM function

Decreasingly Log-concave to the Rescue

The density of accepted paper qualities

$$\alpha_{v}(v-z) \propto f(v-z)h(\xi(v)+z)(1-G(\tau(v)+z))$$

has cdf
$$A_{\nu}(x)$$
, i.e. $A'_{\nu}(x) = \alpha_{\nu}(x)$

Insight (\bigstar)

If f and h are decreasingly log-concave, then the cdf difference $A_{v_1}(v_1 - z) - A_{v_2}(v_2 - z)$ is upcrossing in z (though 0) for $v_2 > v_1$, and so is the slope $-\frac{d}{dv}A_v(v-z)$.

Comparative Statics Under Uncertainty Primer, Part II

Fact (The Folk Single Crossing Property for Integrals) Let a(x) be an upcrossing function with $\int a(x)dx = 0$. Then $\int a(x)b(x)dx \ge 0$ (or ≤ 0) if b(x) is increasing (or decreasing). Proof.

• Let a(x) be upcrossing say at x_0 , and b(x) increasing

$$\implies \int a(x)b(x)dx = \int_{-\infty}^{x_0} \underbrace{a(x)}_{- \leq b(x_0)} \underbrace{b(x)}_{- \leq b(x_0)} dx + \int_{x_0}^{\infty} \underbrace{a(x)}_{\geq 0} \underbrace{b(x)}_{\geq b(x_0)} dx$$
$$\geq b(x_0) \int a(x)dx = 0$$

ヘロト ヘ回ト ヘヨト ヘヨト

Toughness is Quasiconcave: Easy Case

► If the journal hazard rate r(x) := g(x)/(1 - G(x)) is convex (eg Gaussian), then toughness is quasiconcave

Integrate RE by parts and then differentiate in v:

$$0 = \frac{d}{dv} \int_{-\infty}^{v-1} \alpha_v (v-z) z dz = \int_{-\infty}^{v-1} -\frac{d}{dv} A_v (v-z) dz \quad (1)$$

• Integrate FOC* by parts, & differentiate in v when $\tau'(v) = 0$:

$$\frac{d}{dv}\frac{1}{v(\tau'(v)+1)} = \int_{-\infty}^{v-1} -\frac{d}{dv}A_v(v-z)r'(\tau(v)+z)dz \quad (2)$$

•
$$-\frac{d}{dy}A_v(v-z)$$
 is upcrossing by Insight (\bigstar),

- $-\frac{d}{dv}A_v(v-z)$ integrates to zero by (1)
- The FOC derivative (2) is positive, by the folk SCP, since r' is increasing by convexity

• Hence,
$$\tau'(v) = 0 \Rightarrow v(\tau'(v) + 1)$$
 is falling $\Rightarrow \tau''(v) < 0$

38 / 48

Toughness is Quasiconcave: Hard Case

For most log-concave distributions g, the hazard rate r is convex-then-concave



≣ •∕ ९ (२ 39 / 48

Equilibrium Rejection Rates

With known author types, hump-shaped toughness was necessary and sufficient for a hump-shaped rejection curve, via

$$R(v) \equiv G(\tau(v))$$

For our unknown-types case, hump-shaped toughness is necessary (but not sufficient) for hump-shaped rejection rates:

$$1 - R(v) = \frac{\int f(v-z)h(\xi(v)+z)(1 - G(\tau(v)+z)dz)}{\int f(v-z)h(\xi(v)+z)dz}$$

• We show that rising toughness \Rightarrow rising rejection rates

Equilibrium Rejection Rates

For our unknown-types case, hump-shaped toughness is a necessary (but not sufficient) condition for a hump-shaped equilibrium rejection rate:

$$\frac{1}{1-R(v)} = \int_{-\infty}^{v-1} \alpha_v(v-z) \left(\frac{1}{1-G(\tau(v)+z)}\right) dz$$

Now, 1/(1-G(\(\tau(v)+z)\)) is convex in *z*, by log-concavity of *G* Mimicking earlier integration by parts analysis:

•
$$(1 - R(v))^{-1}$$
 increases in v when $\tau'(v) = 0$

- ► The derivative in v is $\int -\frac{d}{dv}A_v(v-z)\cdot \frac{d}{dz}\left(\frac{1}{1-G(\tau(v)+z)}\right) dz$: the first term is upcrossing and integrates to zero, and the second increases by convexity
- clearly, it is also increasing in $\tau(v)$

► Increasing toughness ⇒ increasing rejection rate

Hump-Shaped Rejection Rates

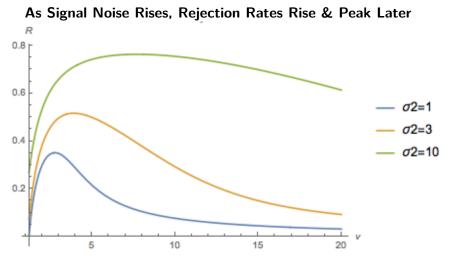
Mavi's Ruff Result

If the author signal is sufficiently less noisy than the journal signal, then the rejection rate R(v) is hump-shaped; otherwise, it is everywhere increasing.

Mavi's Second Ruff Result

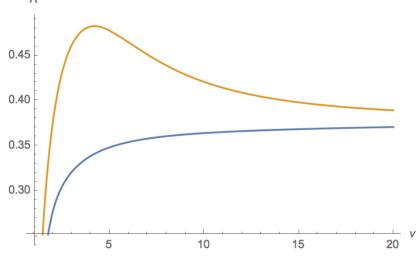
The rejection rate rises — and its peak shifts out — as the journal or author signal noise increases.

Gaussian Noise



Assume an improper uniform prior f, standard normal author signal distribution, and journal signal as above.

Humps Emerge with More Precise Author Information



▶ paper prior $f = \Gamma[2, 1]$, author signal $h = \Gamma[2, 1]$

► Blue journal signal $g = \Gamma[2, 1]$, orange $g = \Gamma[2, 2]$

Mavi's Sheep



Journal Rejection Rates

Hamermesh (2008), "How to Publish in a Top Journal"

- QJE 4%, JPE 5%, AER 7%, APSR 8%, JoLE 8%
- Econometrica 9%, EER 9%
- ▶ Journal of Human Resources 10%, Economica 11%
- RAND 11%, REStat 12%, Economics Letters 17%
- Canadian Journal of Economics 18%
- Industrial and Labor Relations Review 18%
- Journal of Monetary Economics 20%

Stanford University	CA	5%
Harvard University	MA	5
Columbia University	NY	6
Yale University	СТ	6
Princeton University	NJ	7
California Institute of Technology	CA	8
Massachusetts Institute of Technology	MA	8
University of Chicago	IL	8
Brown University	RI	9
University of Pennsylvania	PA	9