

Recommendations in High-Stake Settings

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Announcements

- In person lecture on Wednesday! (Weather permitting)

<https://networksmarketscornelltech.github.io/Spring2026/1to100/>

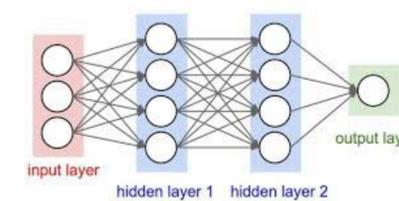
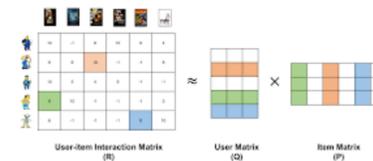
Matching \leftrightarrow Recommenders



Matching systems from Econ-CS

Residency matching, HS matching

- Offline, ~once a year
- Every participant sees + can rank entire relevant other side
- Central Algorithm
 - Given rankings, decides who goes where
 - Stability (equilibrium) desideratum



Recommendation systems from ML

Netflix, Spotify, news, ...

- Real-time
- Millions of participants; can't possibly give full rankings for other side
- Recommender algorithm
 - Estimates user preferences with data
 - ~ naïve suggestions given estimates

Companies have deployed recommenders into platforms for jobs, dating, housing, healthcare
→ How do we incorporate market design ideas into designing recommendation systems?

Market designers have launched stable matching-like systems where humans can't fully rank
← What is the role of noise and ML recommendations in historically "offline" matching systems?

Recommenders: high level agenda

Recommenders are used in online platforms for hiring, dating, healthcare, research dissemination

These settings have desiderata that go beyond preference prediction

- Multi-sided fairness and capacity constraints
- “Mutual” preferences
- Handling strategic behavior for both production and consumption
- Set recommendation and diversity

Opportunity: Tools from market design and economics

Challenge: Take seriously *uncertainty* and *approximation* of machine learning preference prediction

Monoculture in matching markets

Algorithmic monoculture (Kleinberg & Raghavan 2021)

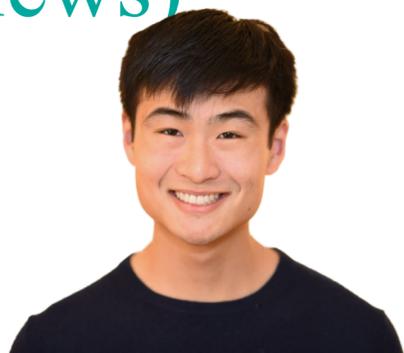
What happens when firms use the same algorithm for decisions?

Applicant has a value v

Firms rank according to $v + \text{noise}$

Monoculture: shared across firms
(e.g., common test scores/algorithm)

Polyculture: Independent across firms
(e.g., independent interviews)



Monoculture in matching markets

The answer from existing literature: monoculture is unequivocally bad

- Firms *can* make worse decisions (compared to independent, “worse” algorithms) [Kleinberg & Raghavan]
- Worse for applicants (increases “systematic exclusion”) [Creel & Hellman; Bommasani et al; Touts et al; Jain et al]

However, this literature ignores two-sided preferences and doesn't have many participants!

Our work: Many firms and many applicants, incorporates applicant preferences

- Fully strengthen KR result: with many firms, “wisdom of the crowds” (when noise is well behaved)
- Monoculture improves *overall* applicant welfare. Individual applicants' preferences vary
- Monoculture more robust to disparities in number of applications

Theoretical tool: Azevedo Leshno continuum model of matching markets





Firm 1

Firm 2

Firm 3

Firm 4

Firm 5

Polyculture



Firm 1

Rejected

Firm 2

Rejected

Firm 3

Accepted

Firm 4

Accepted

Firm 5

Rejected



Firm 1

Firm 2

Firm 3

Firm 4

Firm 5

Polyculture

Monoculture

Rejected

Rejected

Rejected

Rejected

Accepted

Rejected

Accepted

Rejected

Rejected

Rejected

Monoculture

Rejected

Rejected

More systemic exclusion

Rejected

Rejected

Rejected

Monoculture

Rejected

~~More systemic exclusion~~

Rejected

Similar number of people should
get hired overall in equilibrium!

Rejected

(Firms do “yield math”)

Rejected

Rejected

Many Applicants

Many Firms



Need for incorporating
market-level effects
(e.g., stable matching as
calculated by Gale Shapley
algorithm)

Model in one slide

Adapt [Azevedo & Leshno] continuum model for stable matching

- There is a *continuum* of students (uncountably many students)
- Finite number of firms (we will take the limit of number of colleges)
- Students have uniform at random rankings over firms*
- *True preferences* of firms depend on student value v
- Firms *estimated* rankings $v + \text{noise}$, where $\text{noise} \sim D$
- We analyze the stable matching using estimated preferences

Lemma and intuition

In polyculture: whether you get hired ~depends on *maximum* score

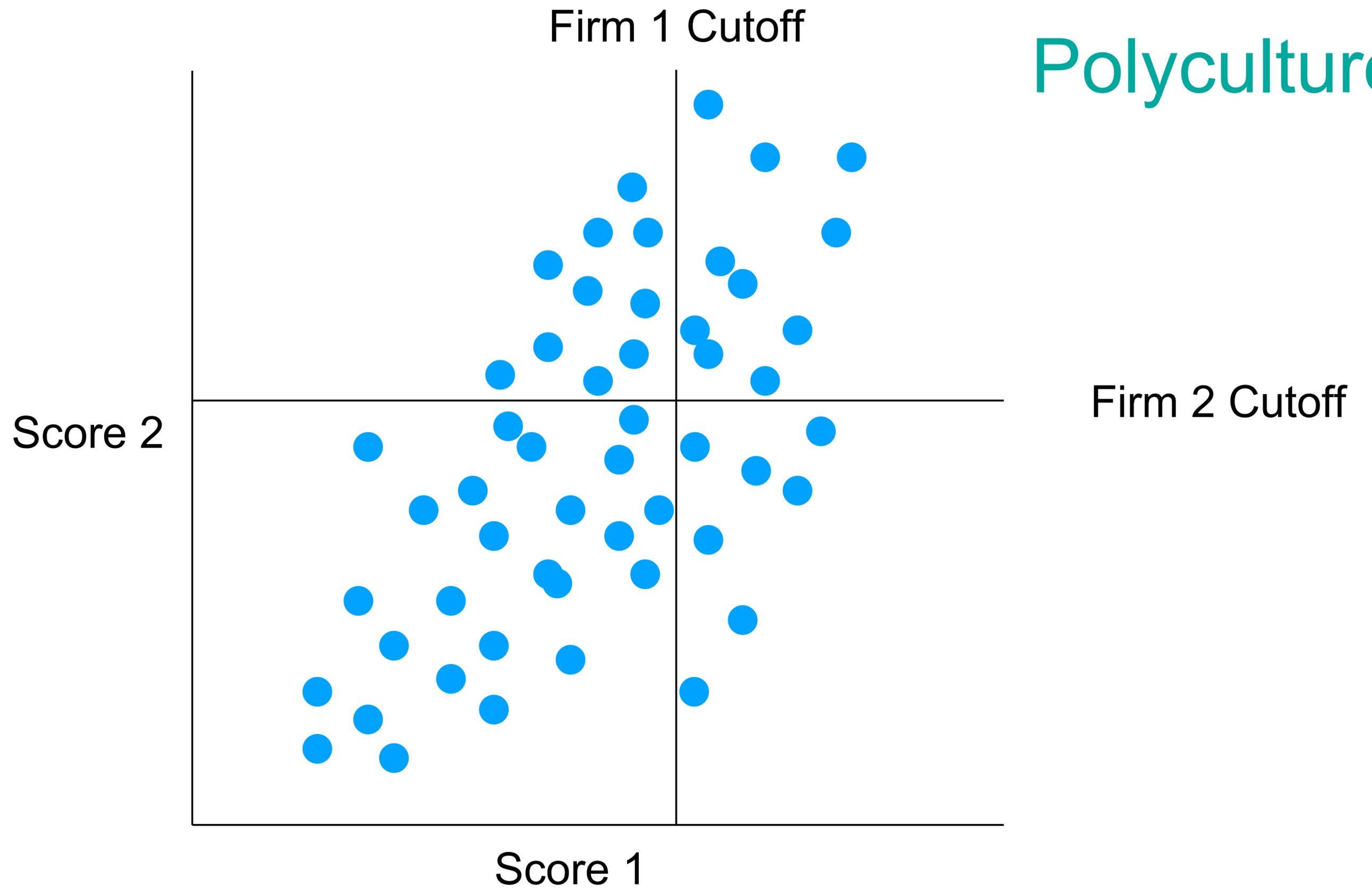
In monoculture, only on a single draw

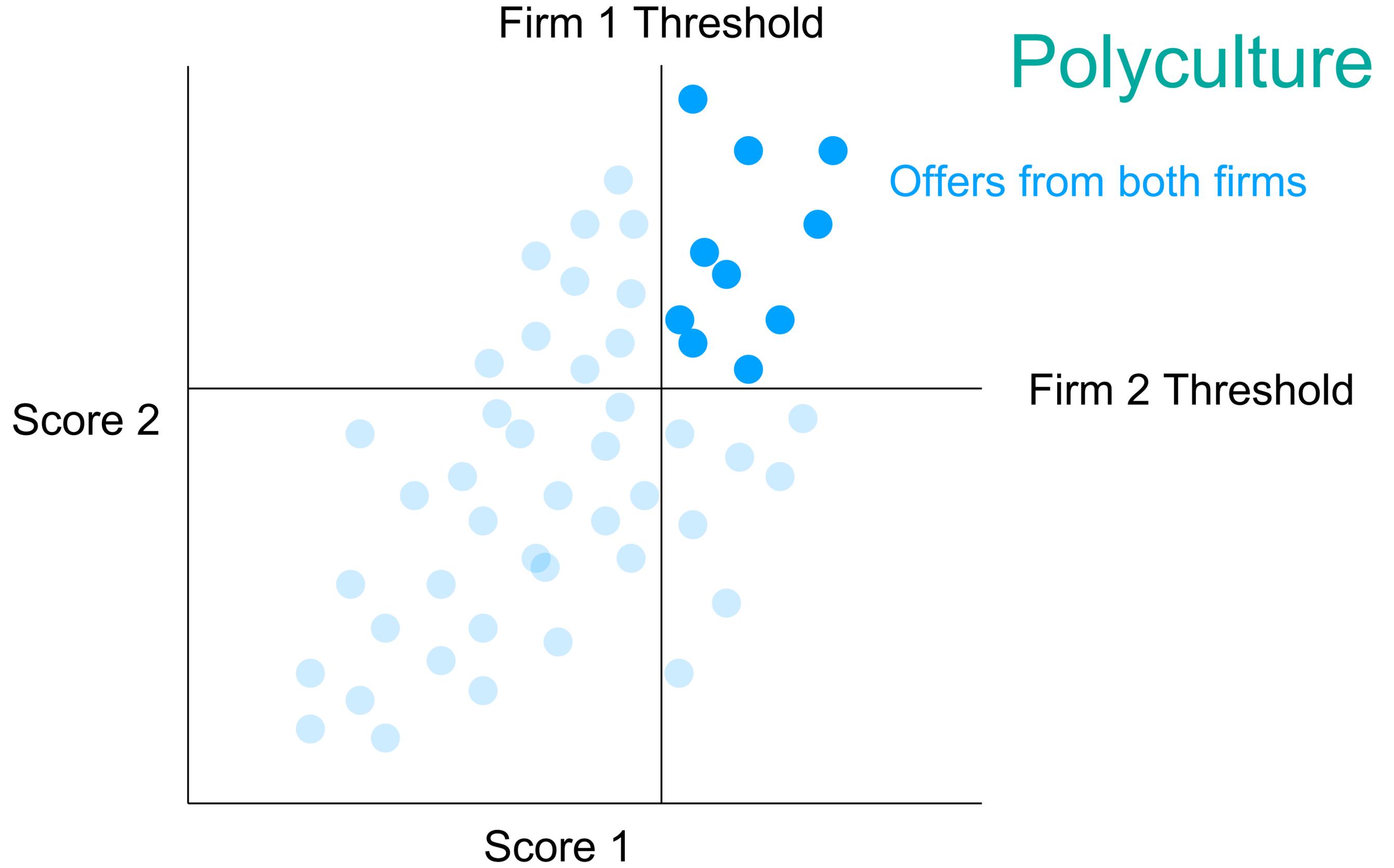
⇒ In polyculture, applicants get “more lottery tickets”

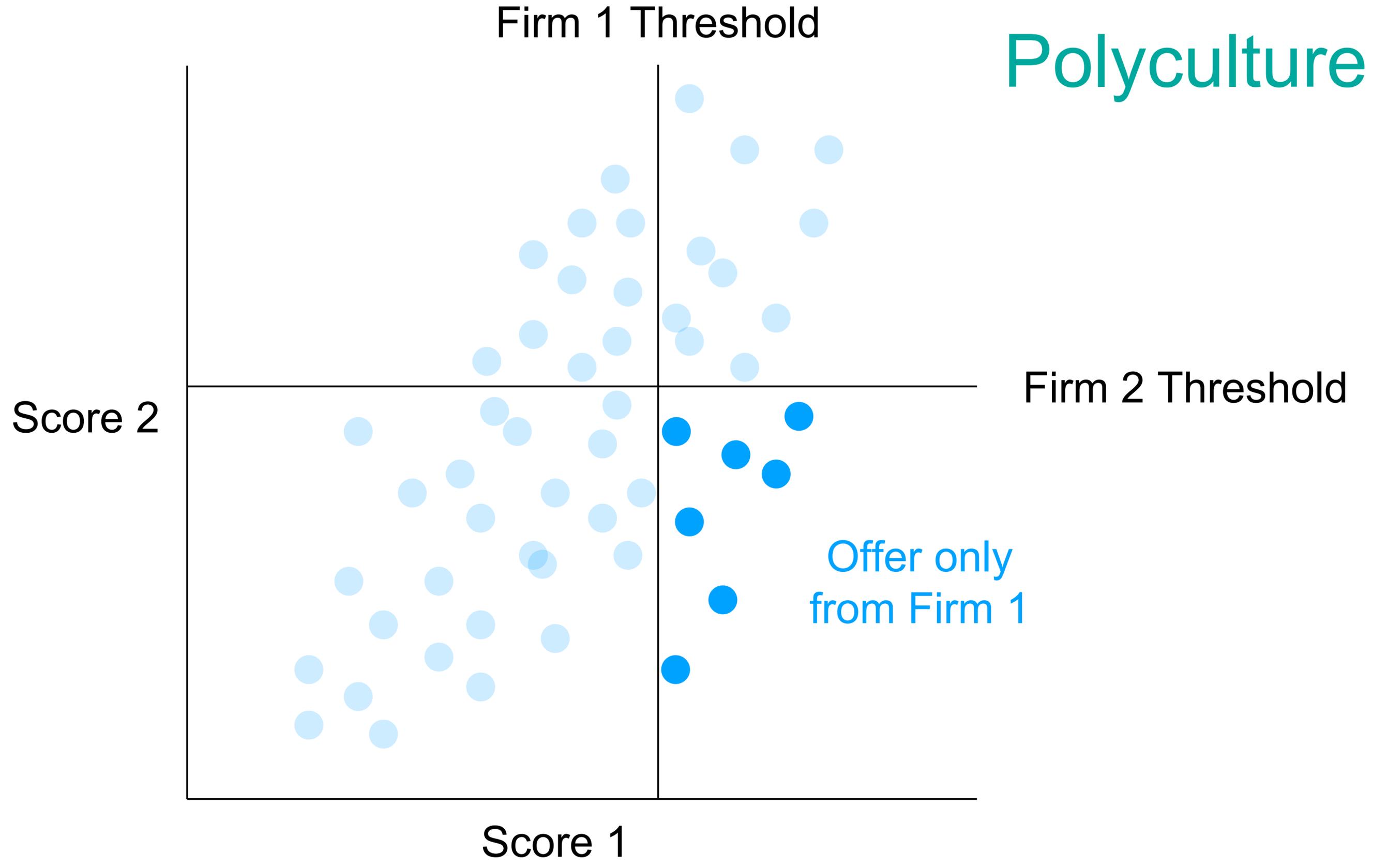
⇒ Thus, firm cutoffs (admission standards) are higher

Proof strategy: reason about **max order statistic** -- what is the distribution of the *max* score that someone receives?

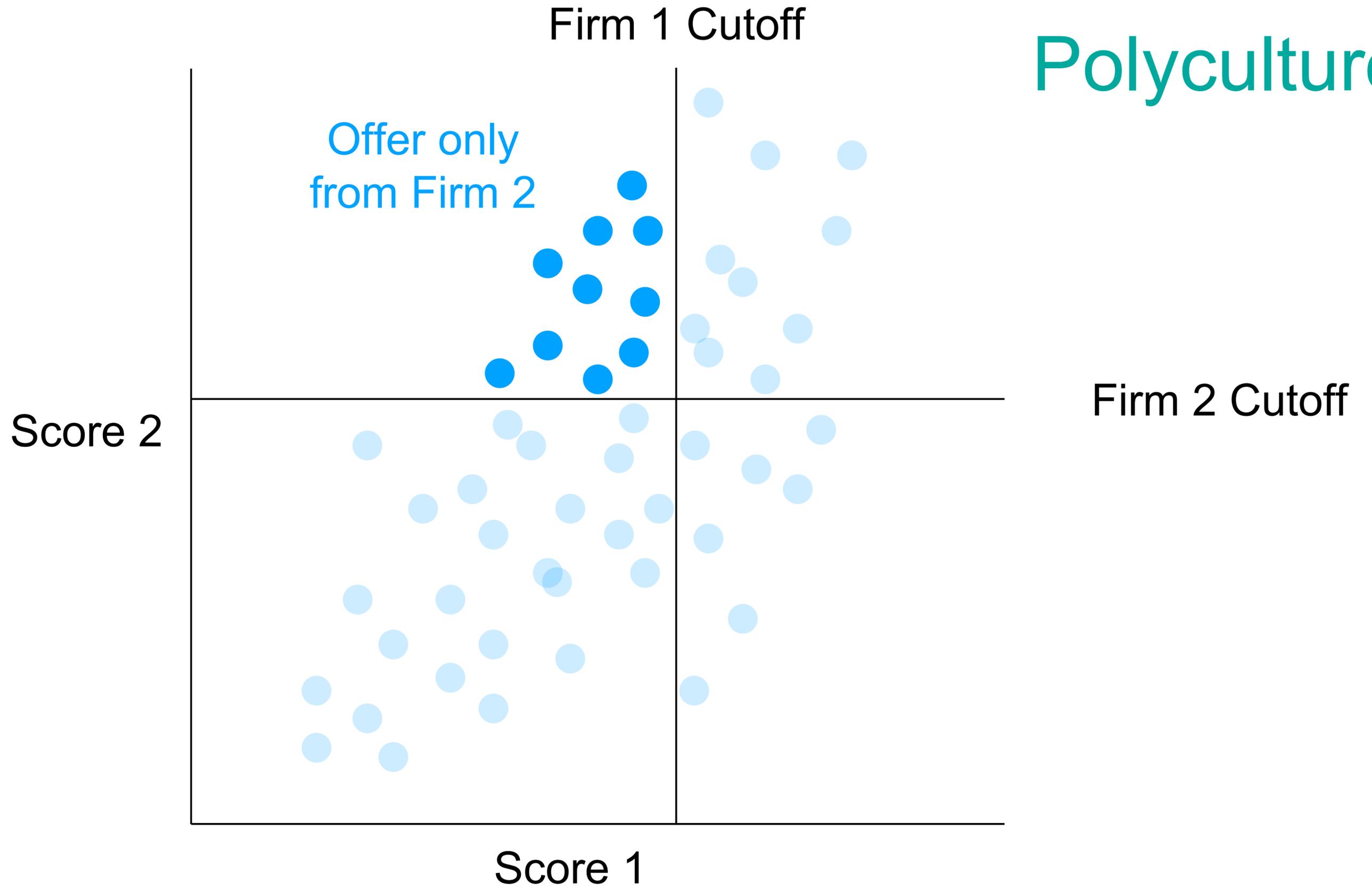
Polyculture



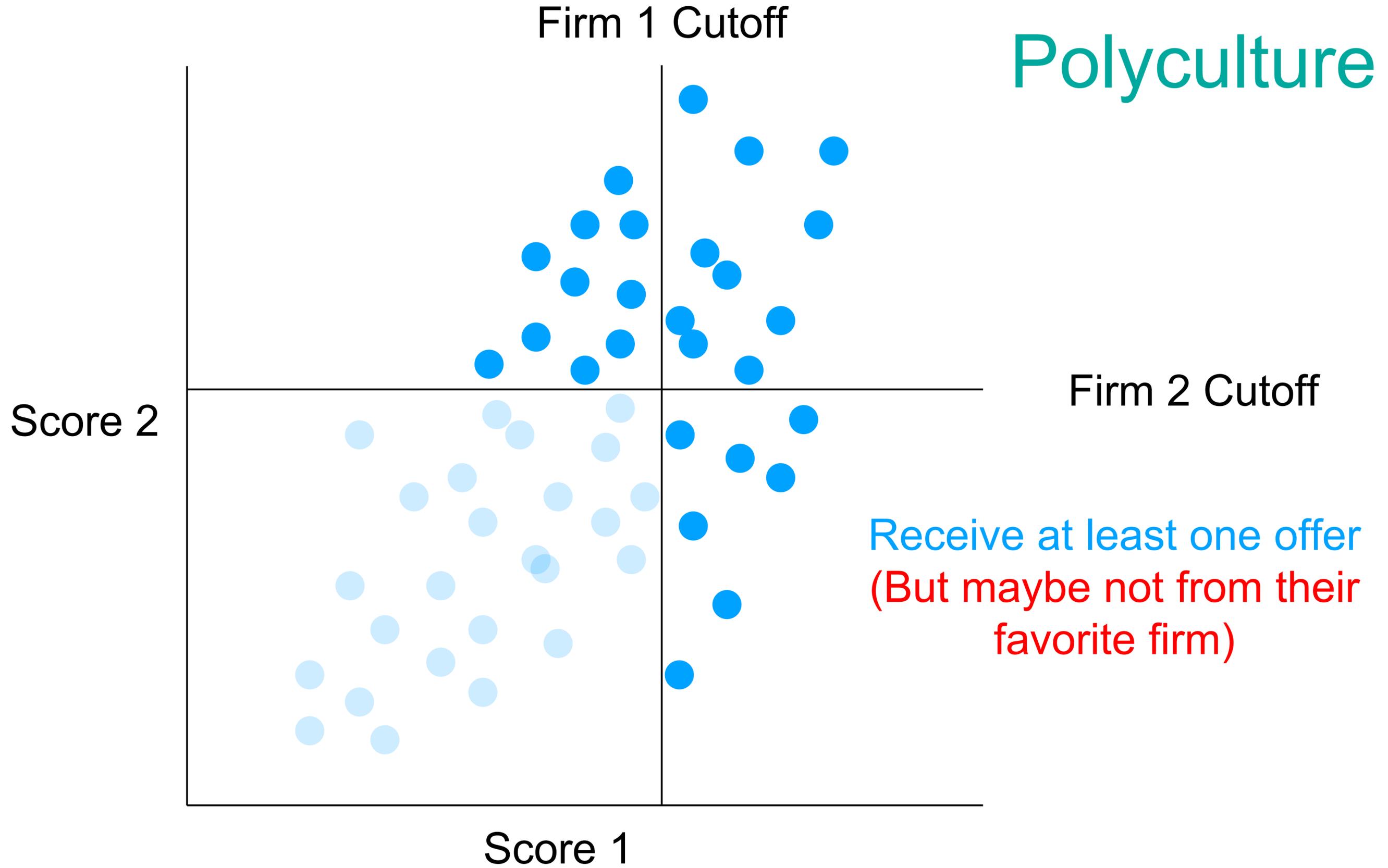


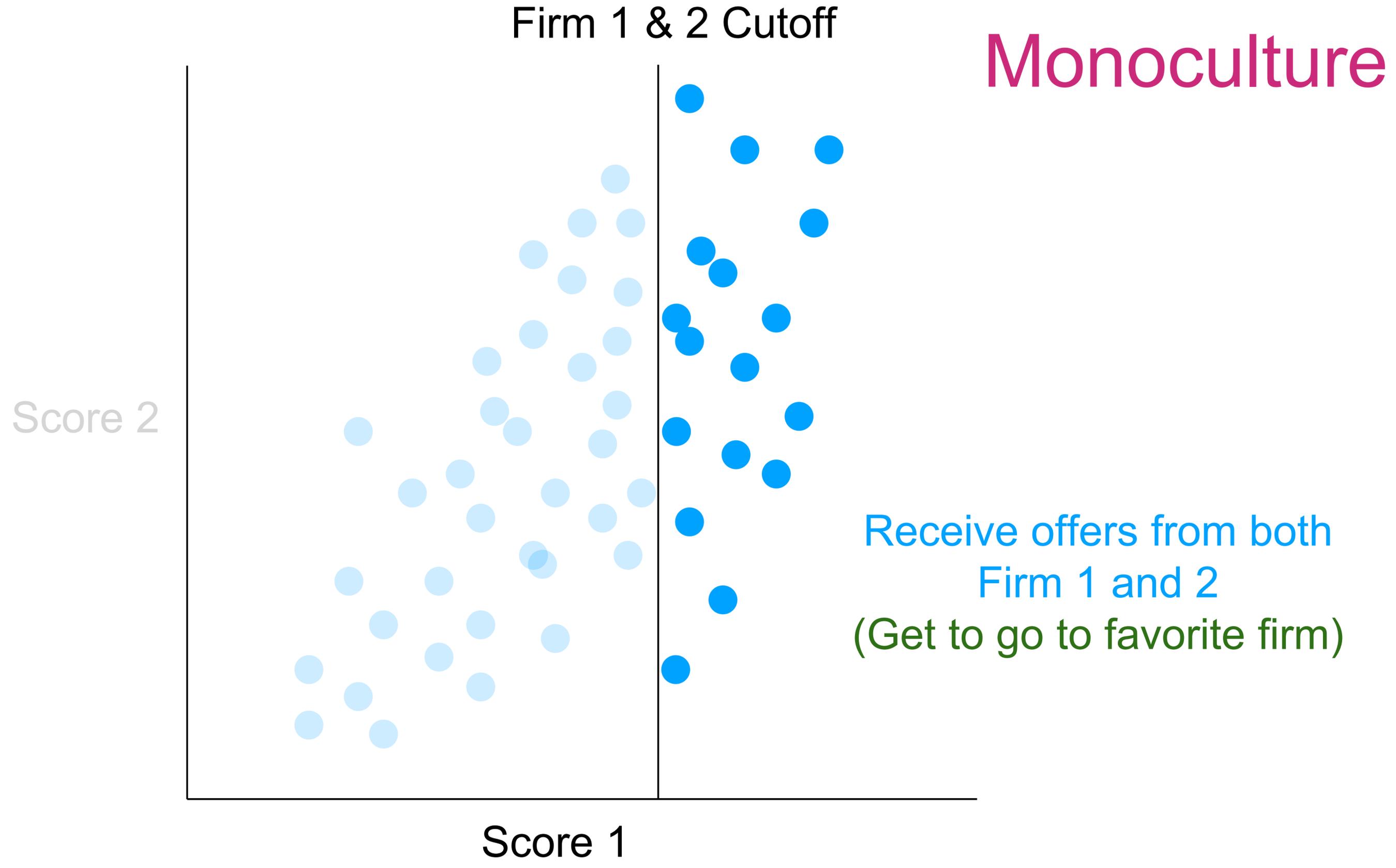


Polyculture



Polyculture





Monoculture

Firm 1 & 2 Cutoff



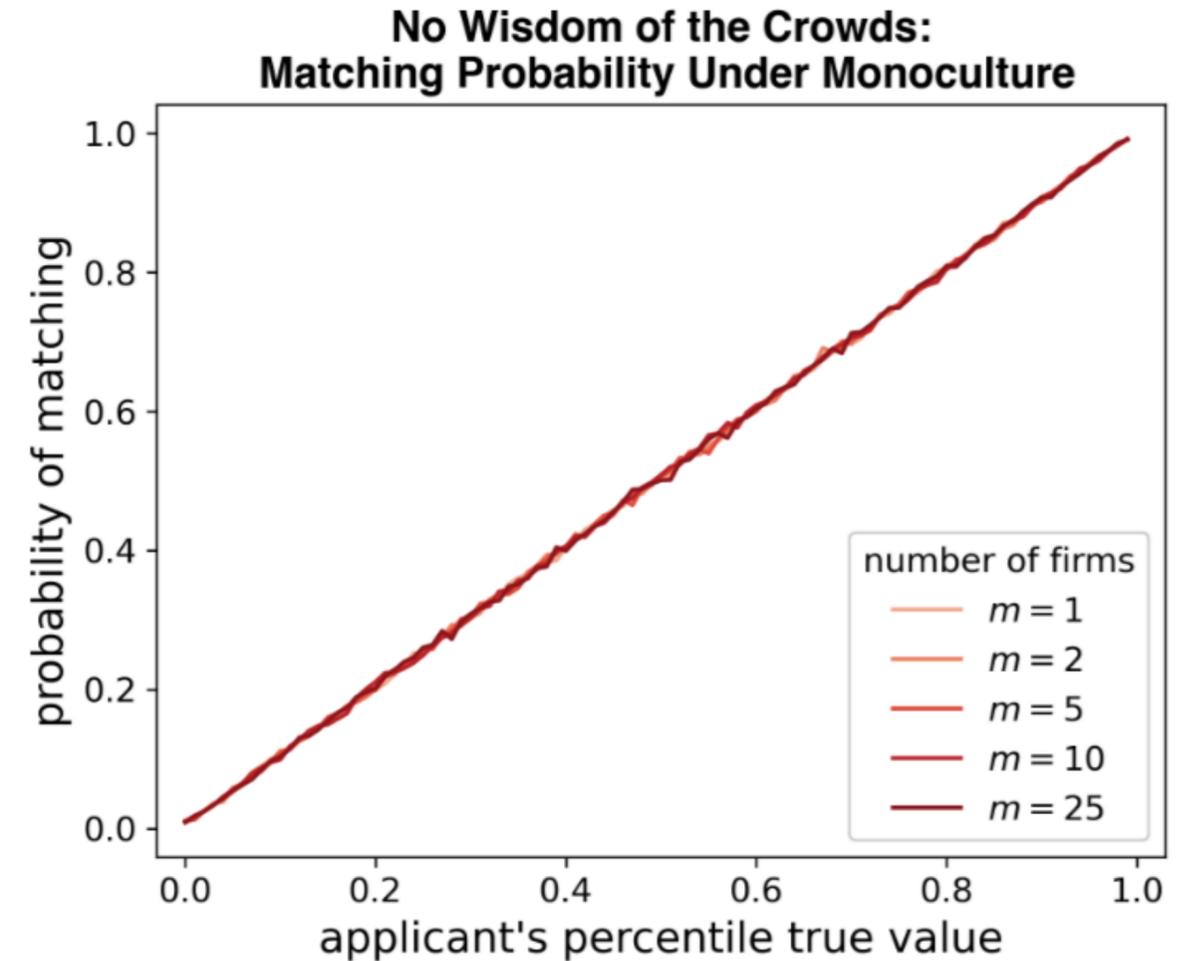
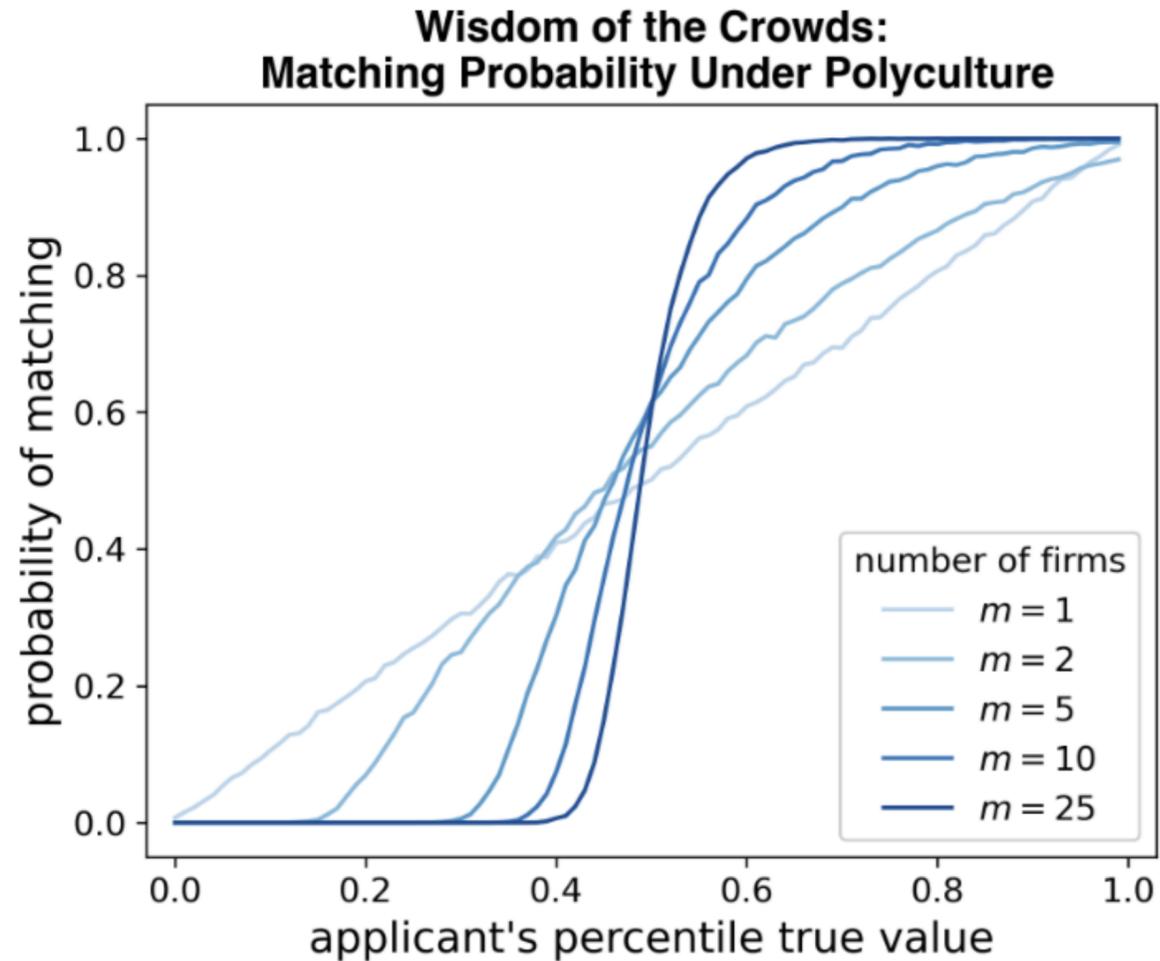
Receive offers from both firm 1 and 2

Score 1

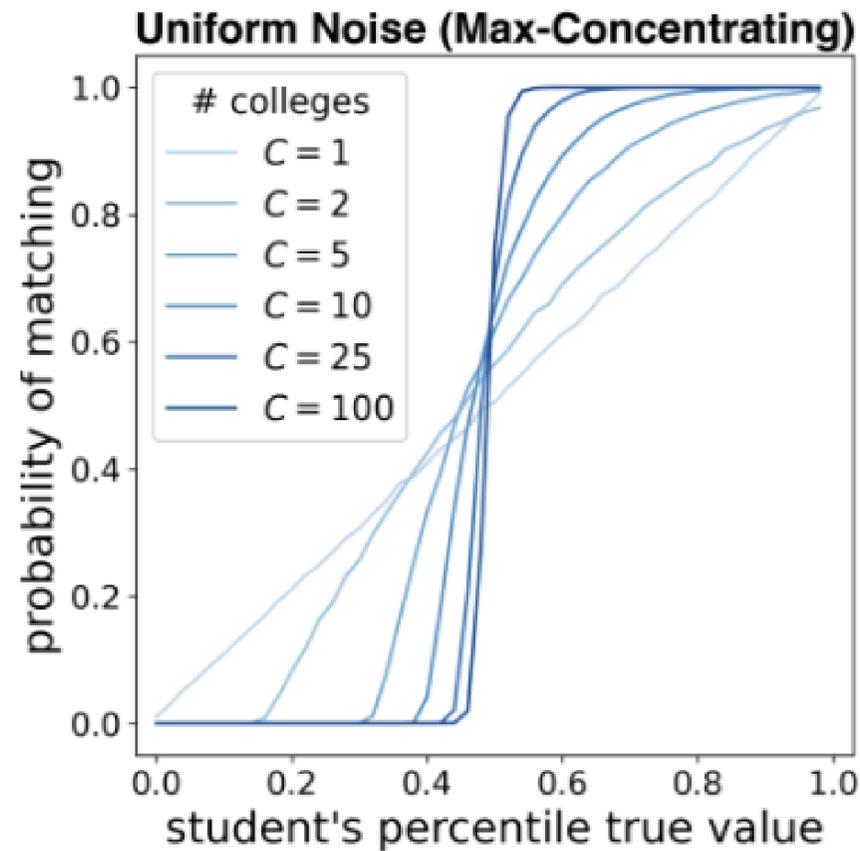
Cutoff goes down to preserve # accepted

Theorem 1: Wisdom of crowds

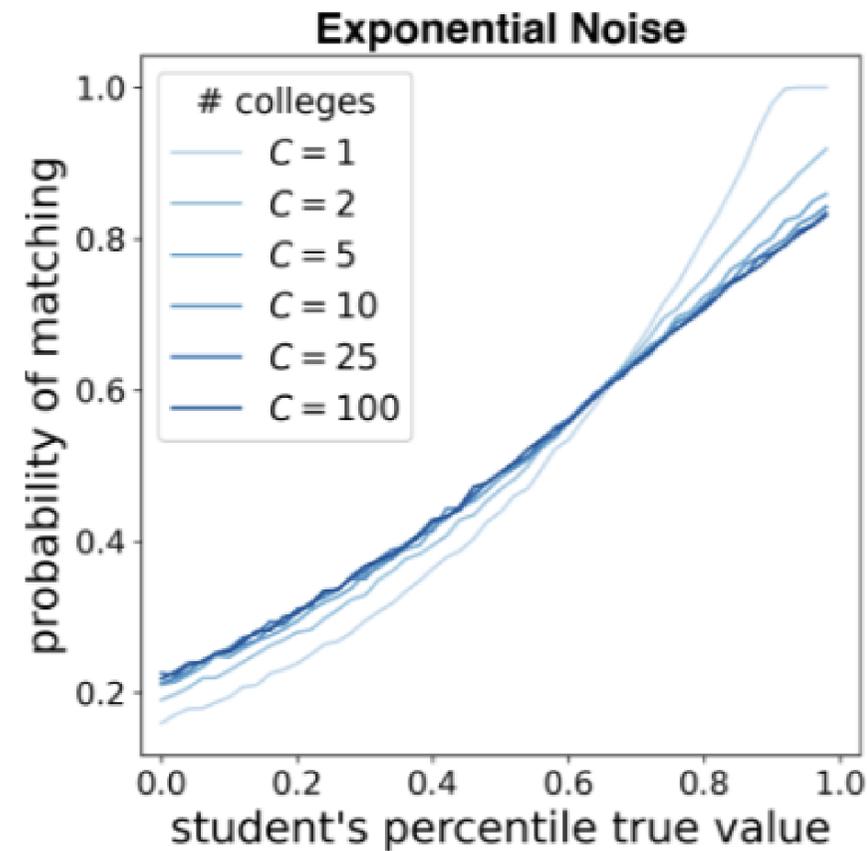
Under polyculture in large markets,*
firms “hire the right applicants,” but not under monoculture



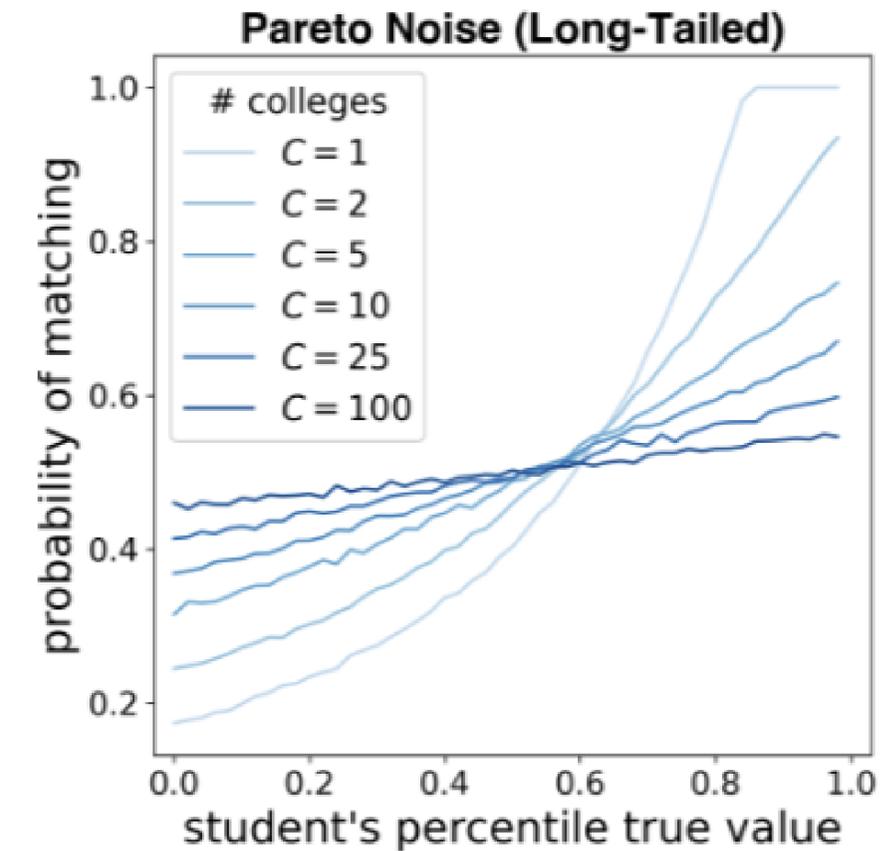
But is only true with “max concentrating” noise



(a) Noise Attenuation as $C \rightarrow \infty$
(Wisdom of Crowds)

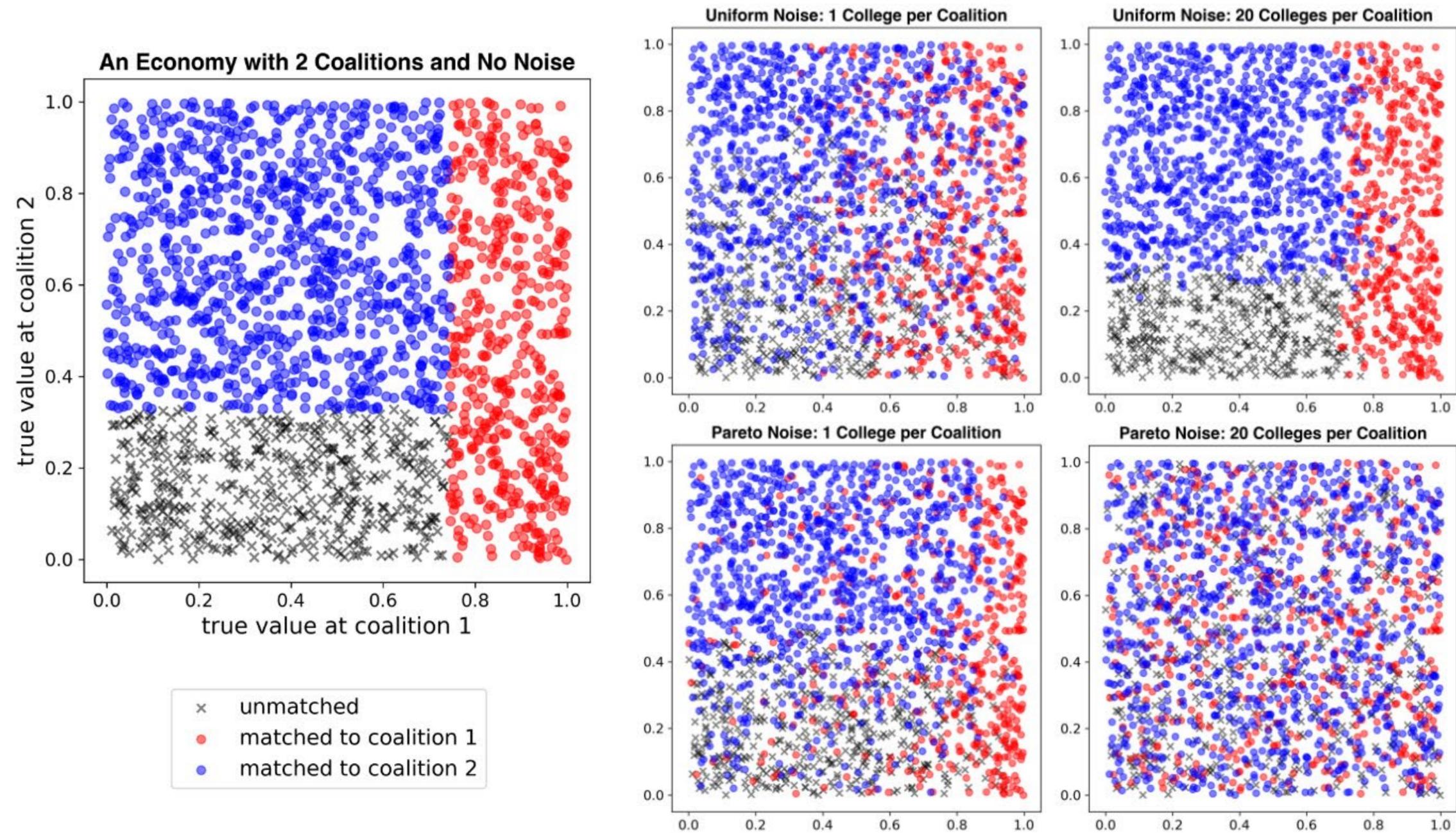


(b) Noise Stays \approx Same



(c) Noise Amplification as $C \rightarrow \infty$
(Foolishness of Crowds)

Can extend more generally



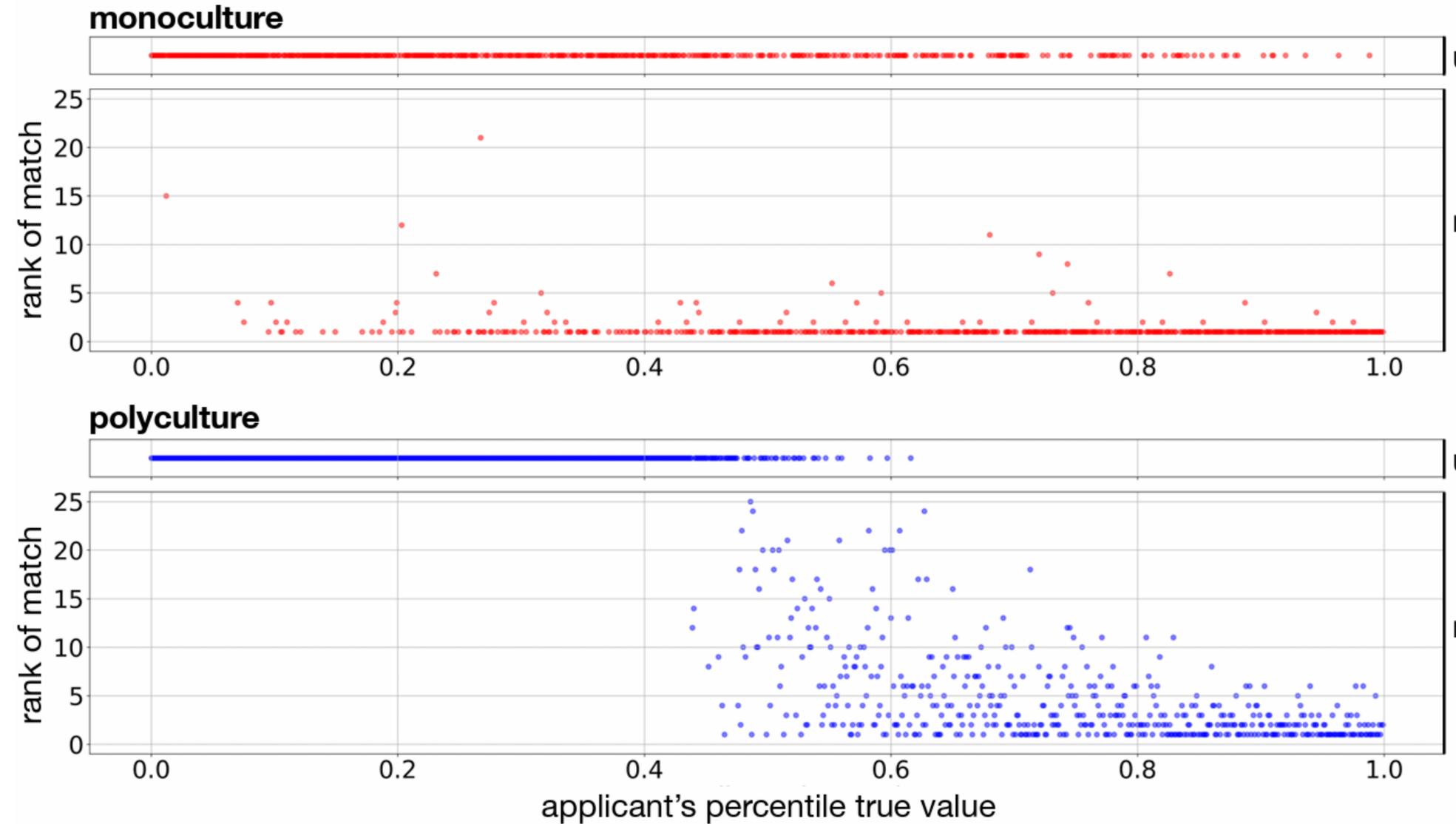
Theorem 2: Applicant welfare

Overall applicant welfare *higher* under monoculture!

By assumption, *same number of applicants receive a match*

But, conditional on matching, more likely to match with favorite firm!

Welfare also depends on true applicant value

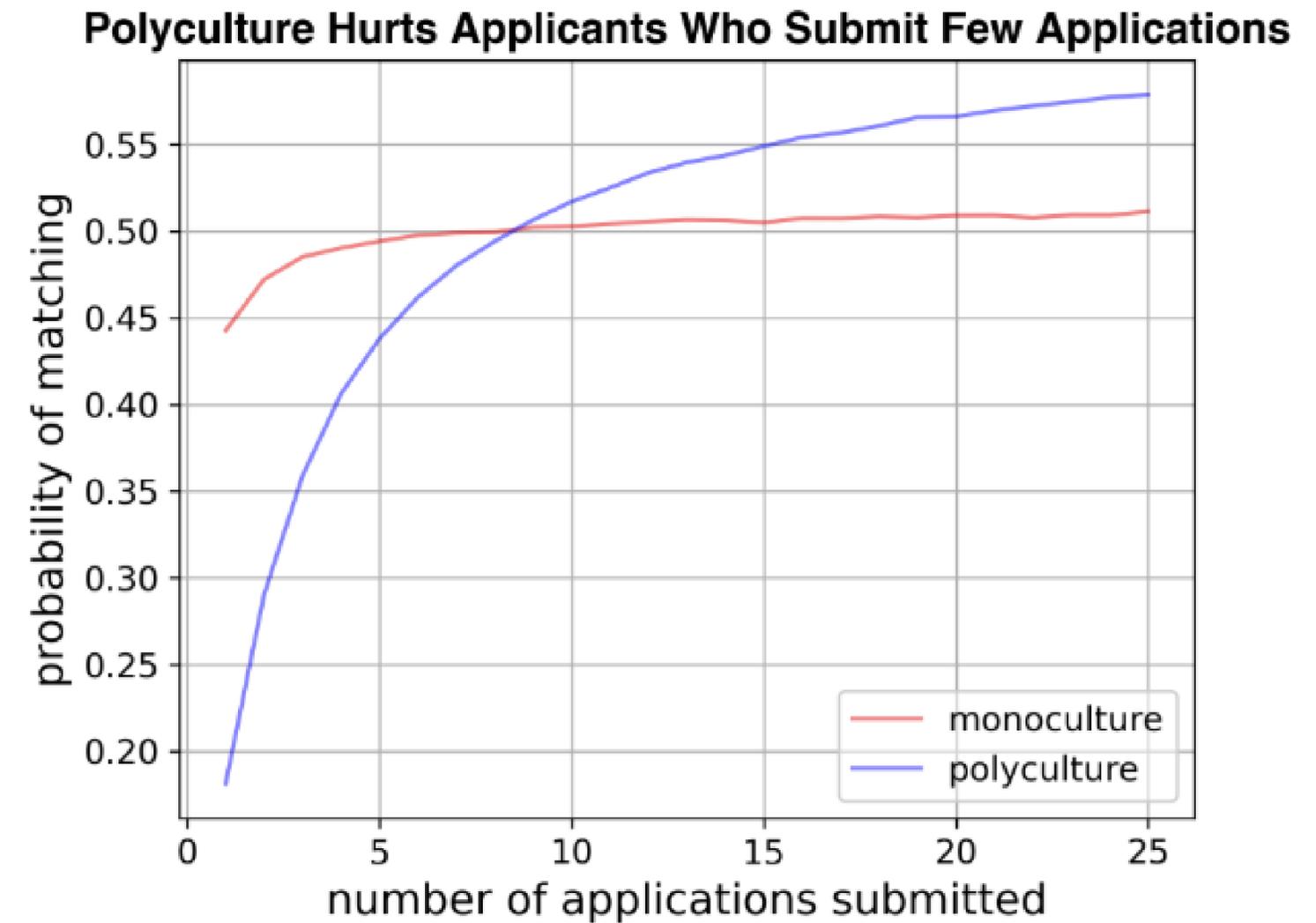


Theorem 3: Disparities

In practice, some people submit many more applications than others

Monoculture is more robust to these disparities!

Why? Polyculture gives *some* people “more lottery tickets”

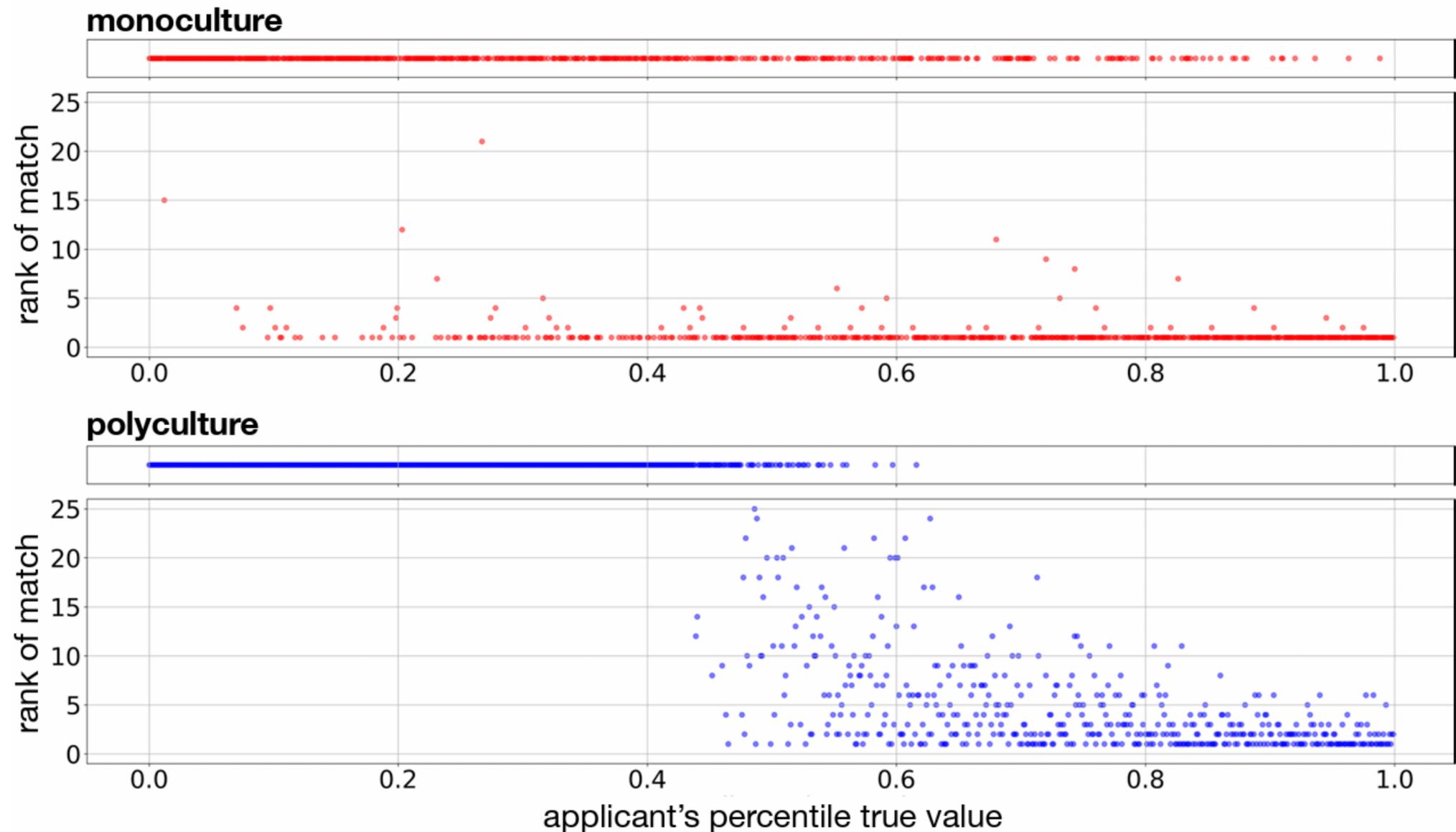


Polyculture

- High firm efficiency (welfare)
- Benefits highest-quality applicants
- Lower “variance” outcomes

Monoculture

- Higher overall applicant welfare
- Benefits lower-quality applicants
- “Fairer” under disparities
- Systematize bias*



Correlated Errors in LLMs

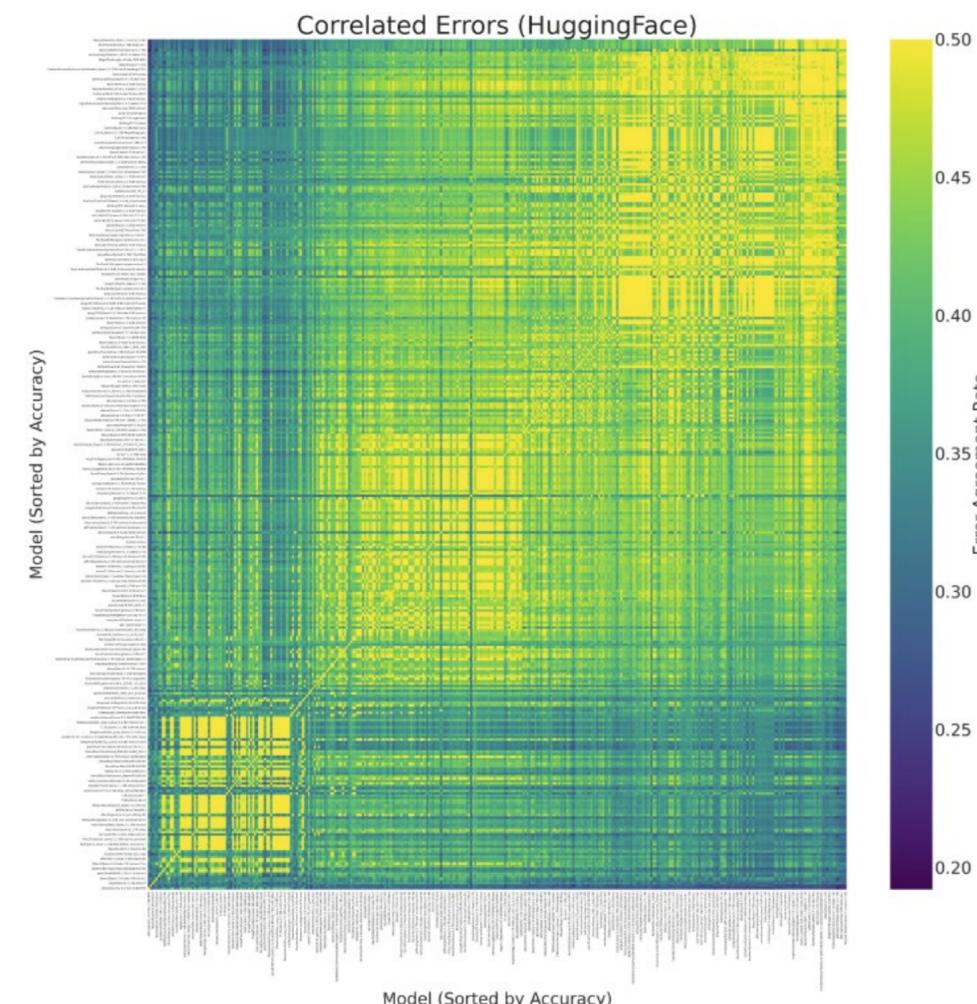
Are LLMs correlated (even conditional given ground truth)?

- Models by same companies
- Larger models

Yes!



Elliot Kim, Avi Garg, Kenny Peng and **NG**, ICML 2025



(a) HuggingFace

Table 1. Agreement on Errors

	HUGGINGFACE	HELM	RESUMES
Intercept	0.398** (0.001)	0.602** (0.001)	0.653** (0.007)
Same Company	0.066** (0.003)	0.022** (0.005)	0.021 (0.012)
Same Architecture	0.076** (0.001)		
Acc. 1	0.014** (0.000)	0.055** (0.001)	0.015** (0.006)
Acc. 2	0.013** (0.000)	0.054** (0.001)	0.028** (0.006)
Acc. 1: Acc. 2	0.023** (0.000)	0.026** (0.001)	0.043** (0.005)
# models	349	71	20
# responses/model	12,032	14,042	1,800
R^2	0.340	0.613	0.415

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