

Peer Effects on Team Innovation

Evidence from the iGEM Synthetic Biology Competition

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Motivation

We increasingly look to teams as a source of innovation

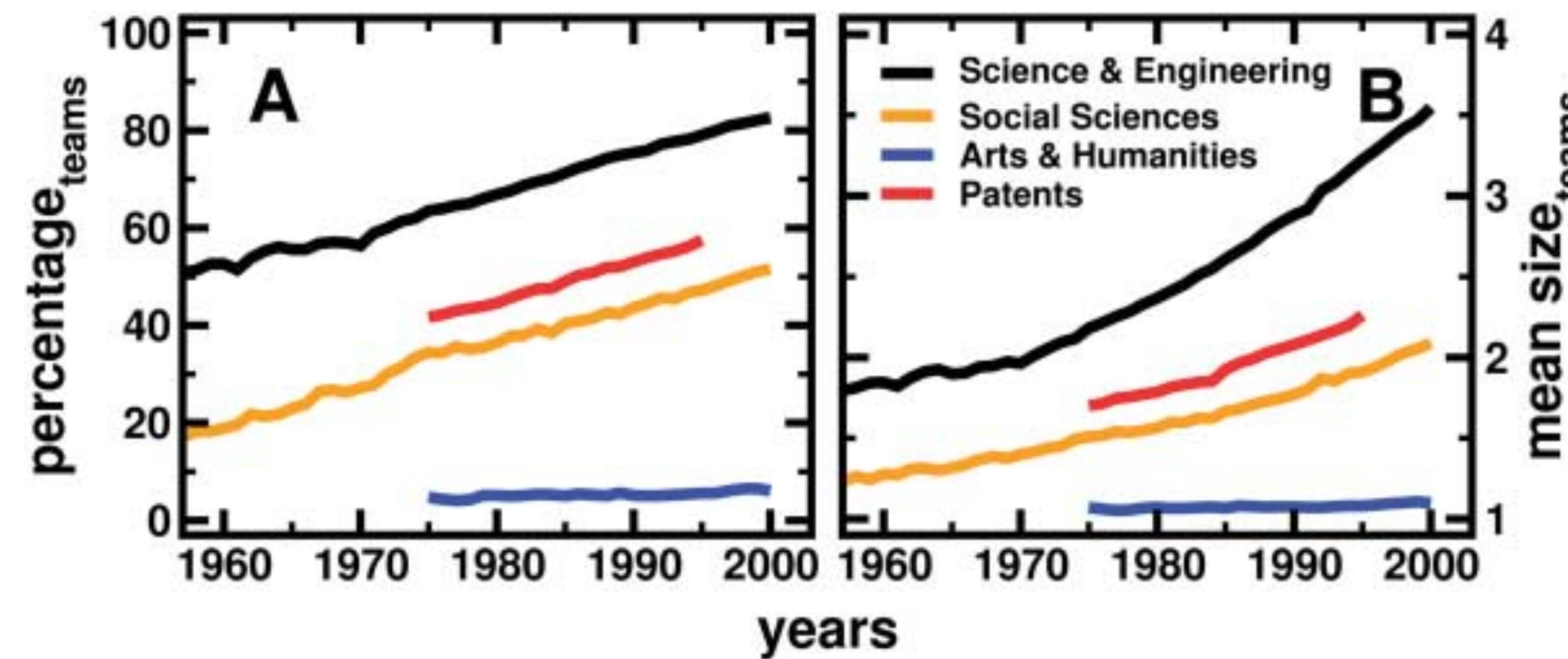


Fig. 1. The growth of teams. These plots present changes over time in the fraction of papers and patents written in teams (**A**) and in mean team size (**B**). Each line represents the arithmetic average taken over all subfields in each year.

Wuchty et al. 2007, Science

Their success is important... but failure is the most common result

Across science
and technology,
academia and industry
Edmonson, 2012

Learning to successfully innovate

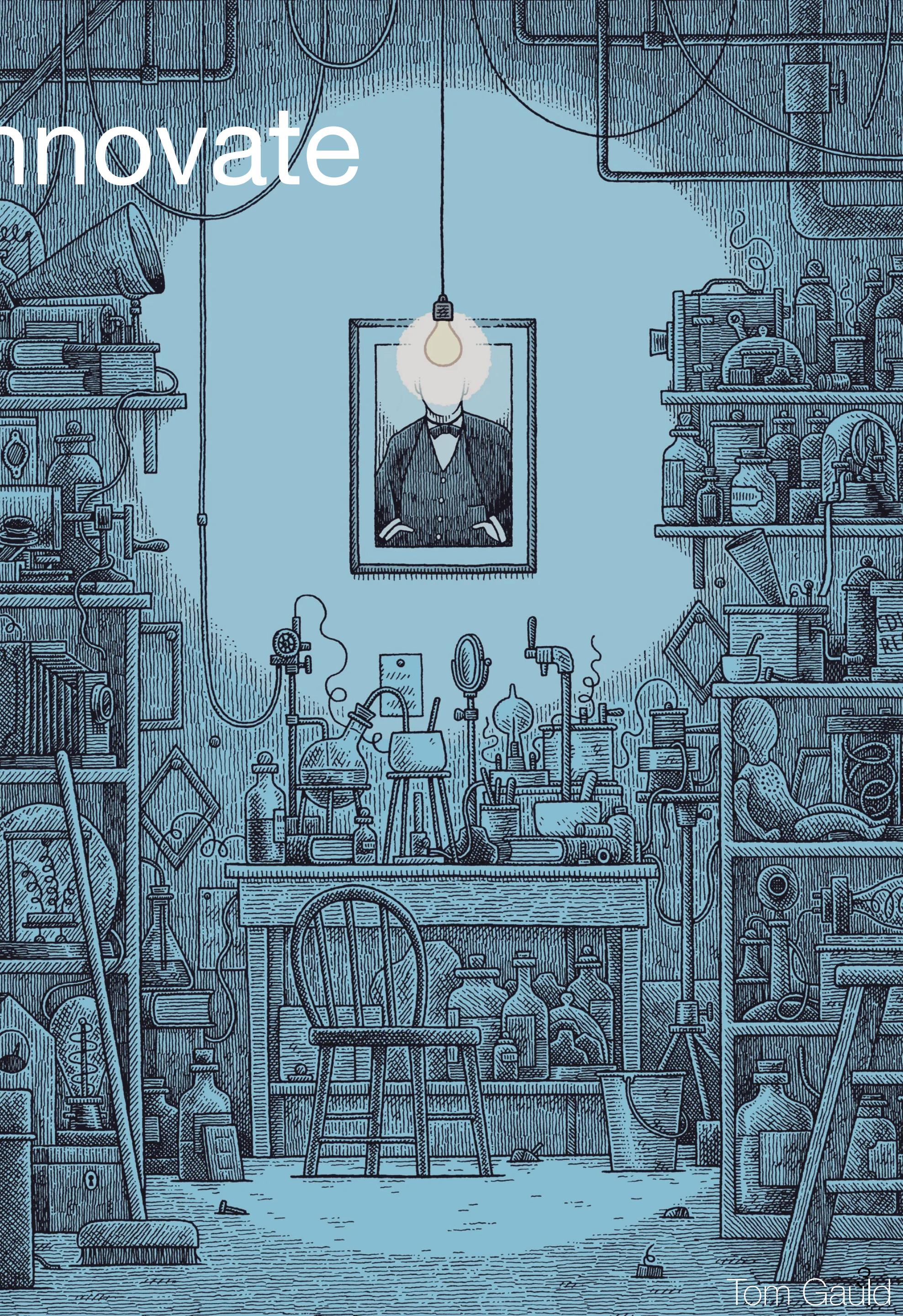
One story... Persistence through repeated failure is the path to success

- But ability to persist and learn depends on access to resources
- Many environments exhibit self-reinforcing inequality

Merton 1968, Science; Perc et al.

2014, J Royal Society Interface

If attempts are costly, early failures are likely to exhaust resources before they find success.



Social Learning Circumvents Direct Experience

Another story... you get by with the help of your friends.

Social interactions allow information to flow between actors Podolny,
2001

Teams may learn from more quickly from peers because they typically provide access to more extensive and diverse experience by observing/interacting with peers Bandura, 1977

Who should teams ask for help?

1. Recently unsuccessful peers Argote 2021, Management Sci

- Lessons about success may prompt perfunctory imitation
- Learn from lessons about peer failures and find successful strategies by narrowing the search space

2. Recently successful peers Rendell et al., 2010, Science

- Imitate or adapt strategies that have recently lead to peer success

3. Doesn't matter, nor affect success Lerner and Malmendier, 2013, Rev. Financial. Stud.

- May simply help deter the unprepared without effecting success conditional on entry

This study

1. Which peers should teams interact with to increase odds od successful innovation?
2. How should we design interventions to deliver such benefits?

Data

Sample: ~1,600 team-years in iGEM synthetic biology competition

DV: *Successful Innovation* is earning a gold medal in the competition

Treatment: Interacting with at least 3 teams in the current year that earned gold in the previous year

Identification Strategy

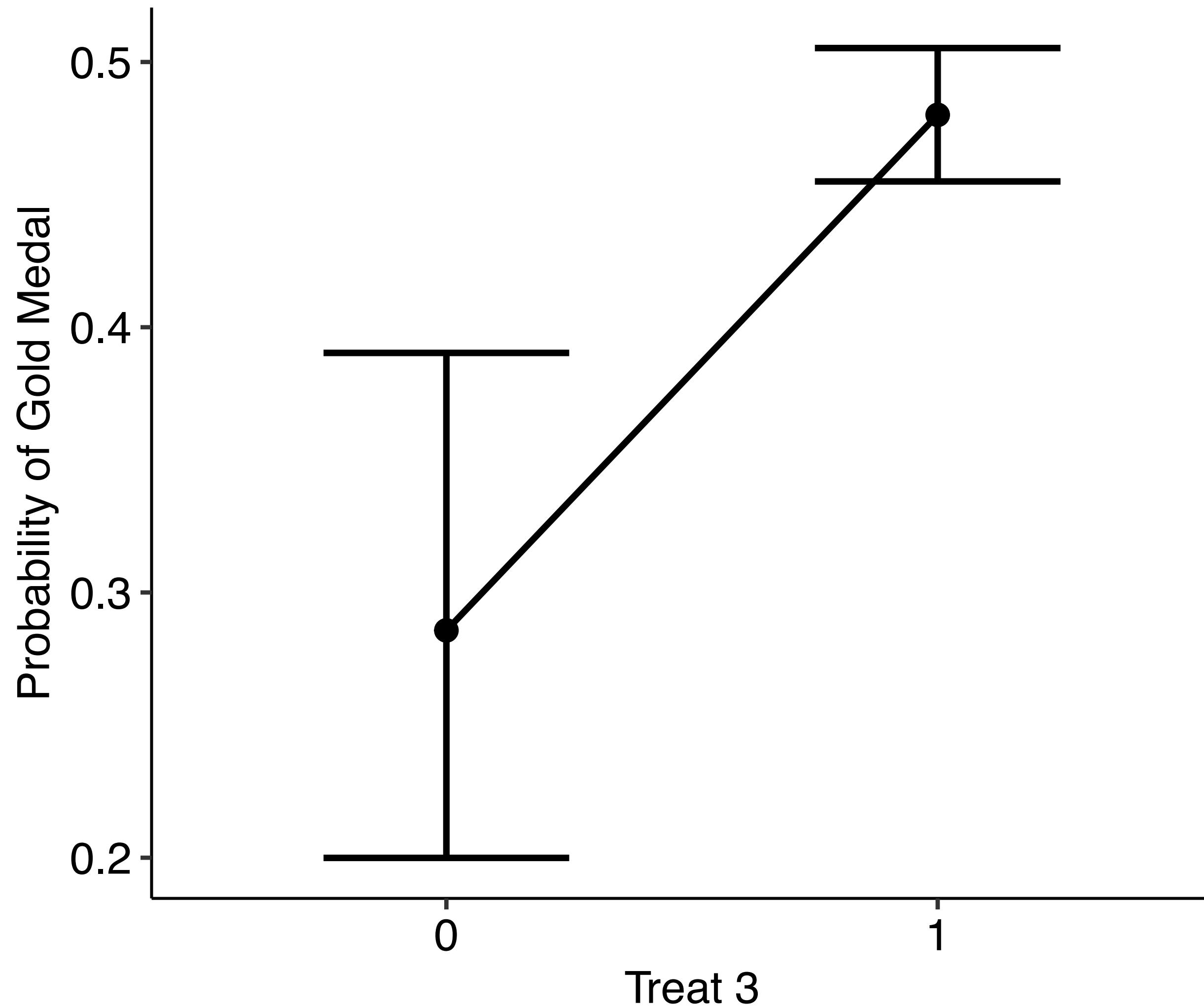
Networks form endogenously and decisions about who to interact with are non-independent
Rubin and Rosenbaum, 1983, Biometrika; Eckles and Bakshy, 2020, JASA, propensity scores can produce peer effect estimates from observational data that are indistinguishable from a randomized experiment.

Marginal Structural Model w/three stages

1. Fit Exponential Random Graph Model to observed network in each team-year
2. Construct Inverse probability of treatment weights (IPTW)
 1. Draw graphs with replacement from ERGM by simulation
 2. Calculate propensity scores for and aggregate into IPTW
3. Estimate peer effect by weighted logit

Successful peers drive performance improvement

Truncated IPTW-Logit



Large magnitude effect

1.8x increase in probability of gold

1/3 as valuable as a team themselves earning a gold in the previous year

Contradicts prevailing wisdom in organizational learning

Double-robust estimation suggests

Upper bound on true peer effect is about 1.97x

Assuming all unobserved heterogeneity is time-invariant

How can we deliver these benefits?

Everyone knows networks are important. But changing them is hard.

One, previously unexplored, issue is **structure**:

Any time we create new ties we change local structure

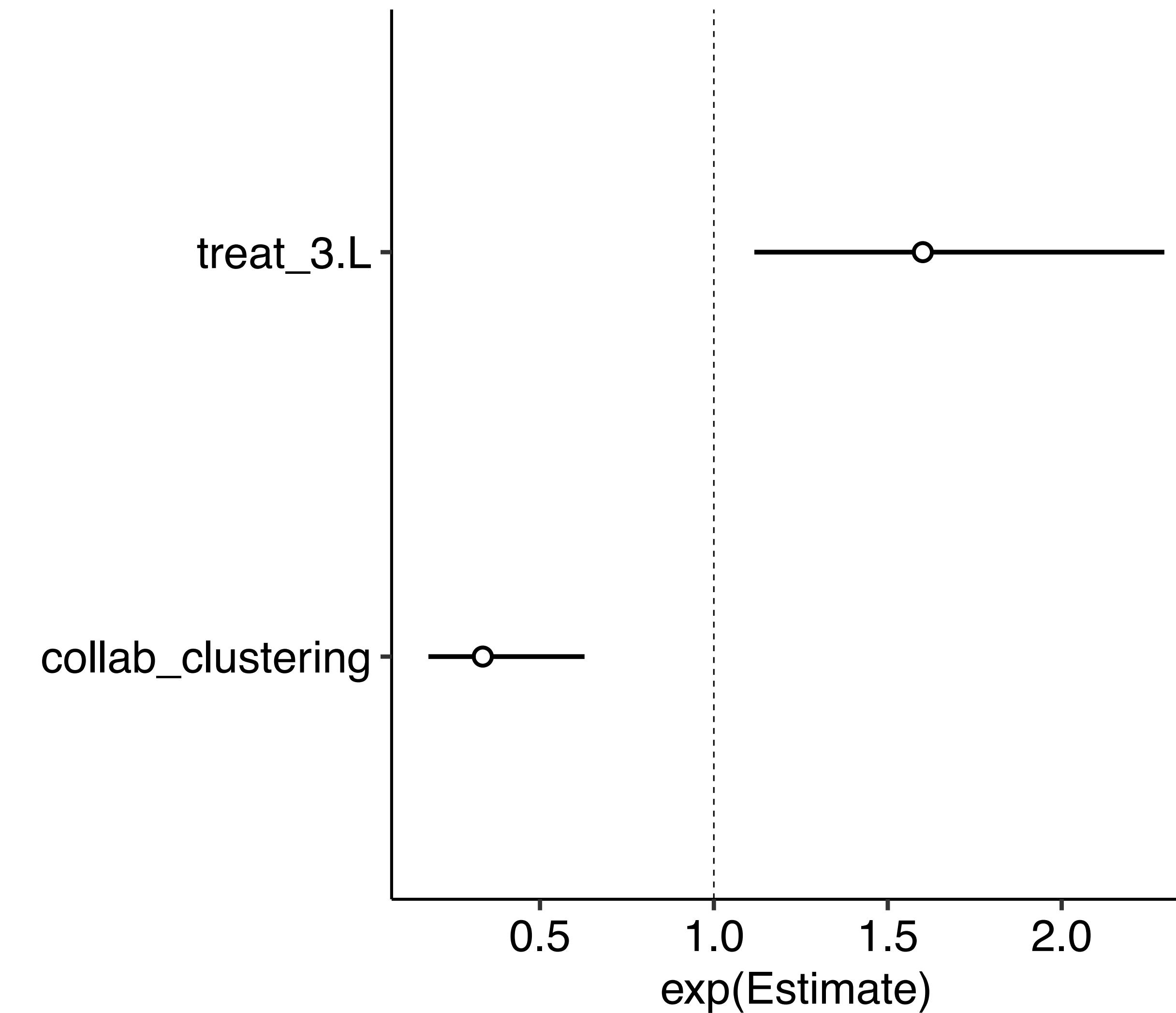
Both individuals and local structure affect performance

Successful peers provide *effective strategies*

Different local structures provides different stocks of *inputs*

Structural costs can outweigh peer benefits

Truncated IPTW-Logit



As clustering increases, inputs become more homogeneous and it becomes harder to produce new ideas

Granovetter, 1973, AJS; Uzzi and Spiro, 2005, AJS

Negative structural effect more than outweighs positive peer effect when local clustering coefficient is greater than about 0.89

This trap is hard to avoid even if you know to

Teams more likely to ask and *receive help* from peers with low average path length to them. Long-range ties are both *rare* and *valuable* Park et al. 2018, Science; Jahani et al. 2022, OSF

Successful peers may not want to share their strategies to maintain competitive advantage Park

Compliance with interventions is hard on both sides to motivate
Funk and Park, 2020, SocArxiv; Hasan and Koning, 2019, SMJ

Some thoughts on intervention design

May need to solve this asymmetrically:

Focal teams can be taught how to network... who and how to reach out to peers (dimitriadis and koning, 2022)

Peer teams can be motivated to help by (1) direct brokerage by central institutions (e.g. NIH in biomedical research); or by (2) strong incentives

What have we learned?

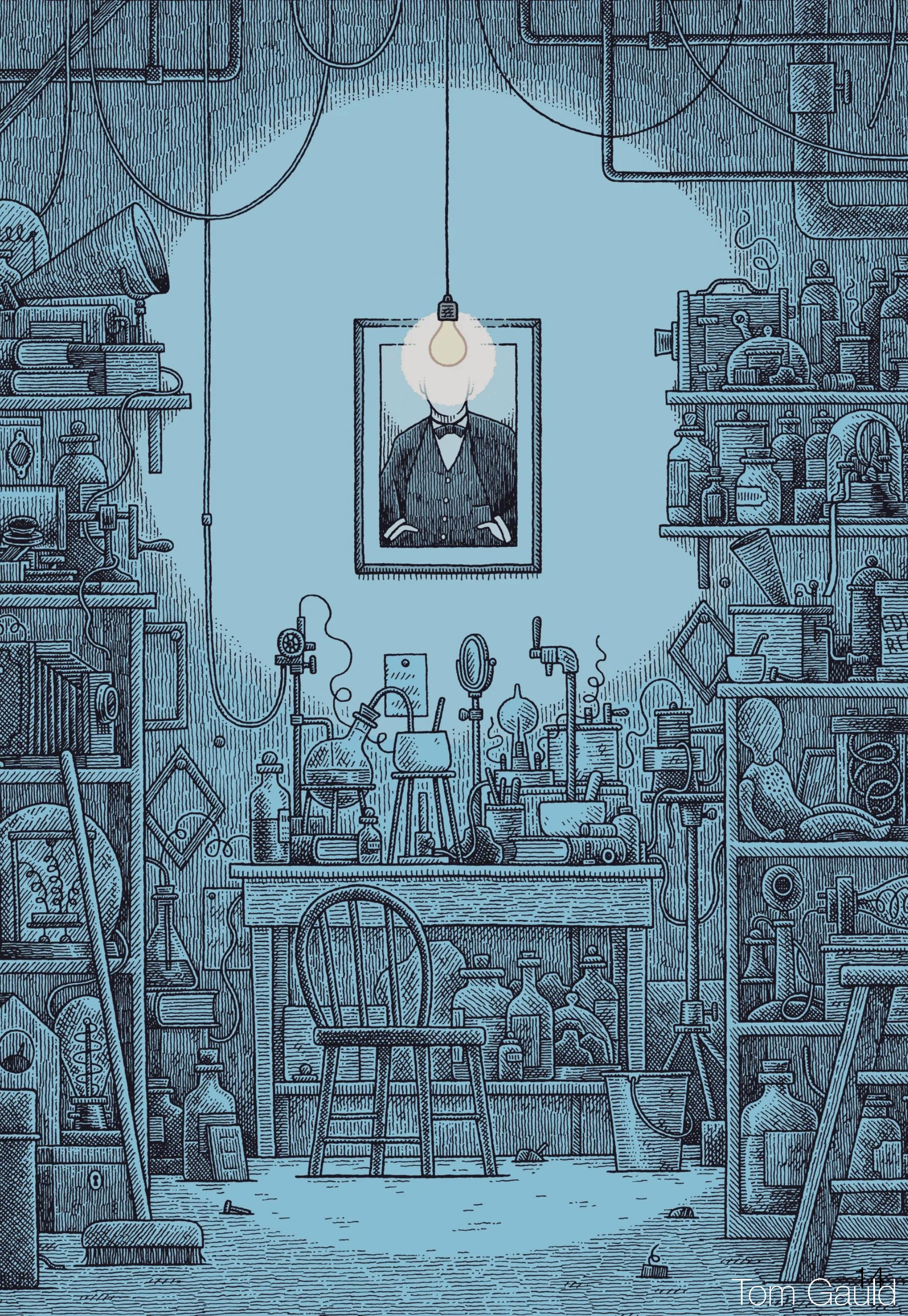
Teams should target socially distant, successful teams to increase rate of successful innovation

Teams more likely to ask *and* receive help from peers at short average path lengths in their network... But increase in local clustering can more than outweigh benefits of successful peers

Teams should try to form long-range ties but are unlikely to do so even if they know they should.

This is hard to do even if you know to do it

1. Direct brokerage by institutional actors
2. Indirect incentives
3. Ideally, field experiments



Contributions

1. Resolve uncertainty about peer effects
 1. Who to seek out?
 2. Content v.s. quality
 3. Intervention design
2. Novel identification strategy
 1. New use for ERGMs that avoids their negatives for medium sized networks

Future work: content v.s. quality

Little focus on heterogeneous content in studies of peer effects (or networks in general Erikson, 2013, Sociological Theory)

Do interactions with successful teams differ in content? Or is it just higher quality advice?

We have text in which each team describes the content of each interaction (Similar to Dimitriadis and Koning 2020, Management Sci)

Cornell, Purdue, and UMichigan

Cornell iGEM, Purdue iGEM, and UMichigan iGEM mentored our team.

- Cornell: During the summer, we videochatted with Cornell iGEM. They mentored us by sharing their systems regarding team organization and the competition timeline, and they also answered our questions on specific aspects of iGEM like collaboration and human practices research. Some of their recommendations, like their system for logging their work during the summer and a tool they use to find meeting times that work for everyone, were quite helpful to us.
- Purdue: We Skyped with the Purdue team early in the summer to learn more about how their team structured work and responsibilities because we had similarly-sized teams. They were able to help us determine a rough timeline for the iGEM season and evaluate our progress. We were able to visit them late in the summer to observe a typical day for the team and even got to sit in on a meeting with their advisors.
- UMichigan: Three of our members travelled to Ann Arbor for our first meetup with an iGEM team. The Michigan team gave us a tour of their laboratory and workspace, took us to dinner where we had a meaningful Q&A with both the students and their advisor, and allowed us to sit in on a proper team meeting. This meetup provided an outline for functional and effective team discussion and planning, as well as answering our questions about iGEM lab work and the Giant Jamboree.

Content vs. quality

1. Multi-label classification of interaction contexts into topics
2. Test if distribution of interactions over topics for interactions with successful/unsuccessful peers are equal

Provides asymmetric test of content/quality question.

- If topics are the same, peer effect likely because successful peers either have higher quality information or transfer it more effectively.
- If topics are different, it's likely topics matter but exact test hard

Thank you!

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Endogenous Division of Labor and Innovation

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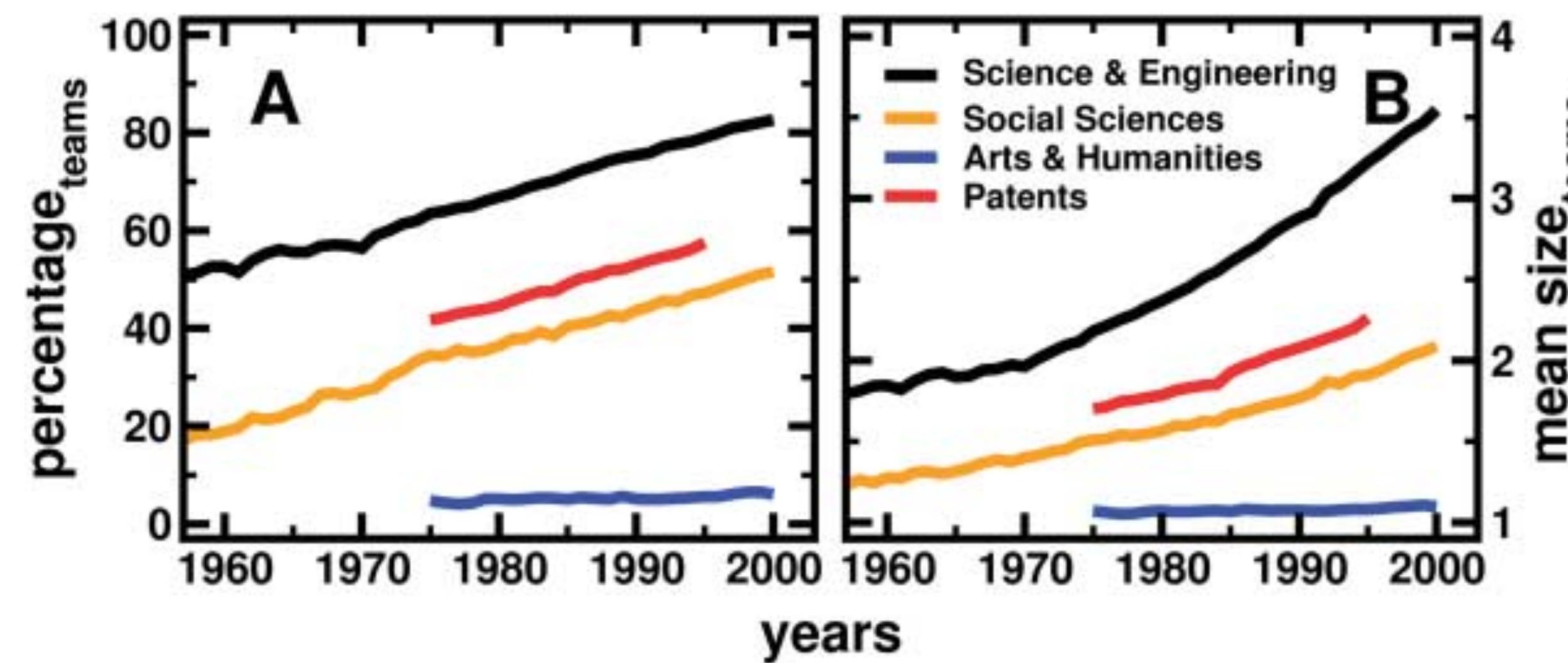


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Wuchty et al. 2007

How should we select their members and structure their work?

Some trends

In firms

Increasing willingness to give workers the right to organize themselves Lee and Edmondson, 2017

In academe

Shifts towards bureaucratic organization Walsh and Lee, 2015.

But bureaucracy often emerges from more collegial negotiation amongst members Vertesi, 2020; Lazega, 2020

Both trends violate a classic assumption (from Weber) that the division of labor is exogenous to the members that fill its roles.

Autonomy may lead to more effective organization by increasing worker motivation Bartling, 2014 and improving task allocation under some conditions Raveendran et al. 2022

Recent studies on the topic assume that workers express their autonomy with the best interests of the team in mind, seeking optimal task allocations based on their skills and the work to be done.

This seems unlikely.

This study

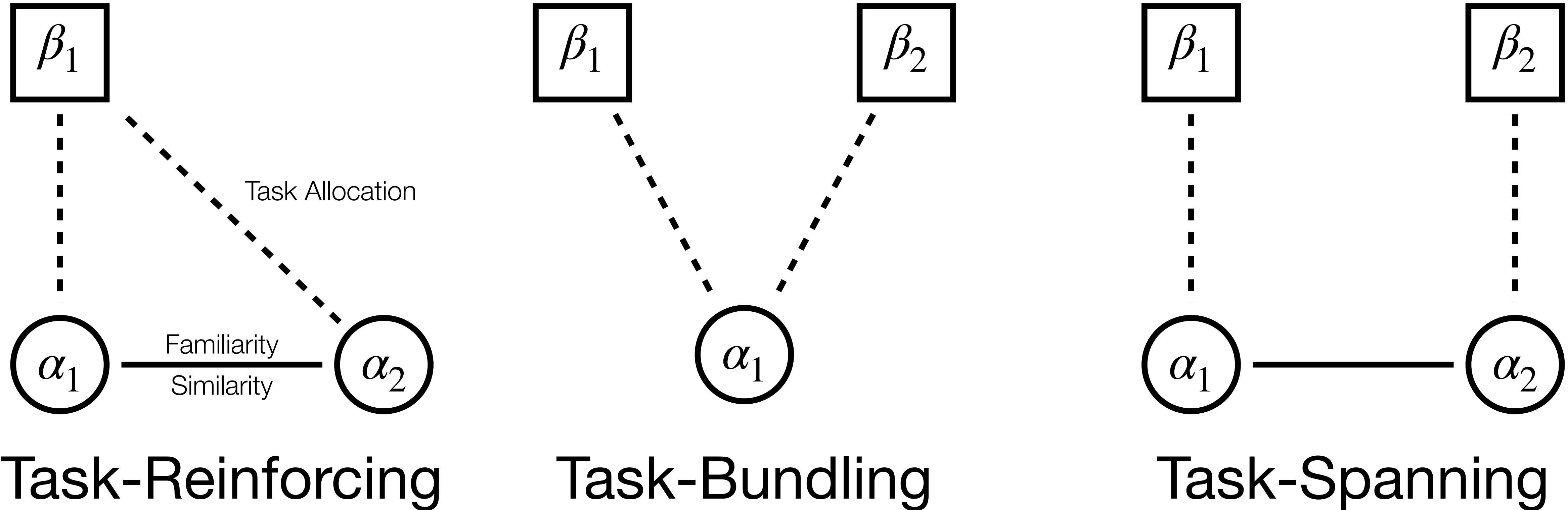
1. How does the interpersonal composition of a team affect the way its members divide their labor

When workers are socially familiar or similar are they more likely to seek task allocations that let them work together?

2. Does a team rich in familiar/similar members find more effective divisions of labor than a team with sparser interpersonal priors?

1. Net effect
2. Heterogeneity across tasks, outcomes

Subgraphs in the division of labor



*Caused by task environment, team composition
Cause variation in performance*

2022 iGEM TIES Questionnaire

1. Skills (self-efficacy, experience)
2. Preferences
3. Familiarity (duration, closeness)
4. Similarity (education, demographics)

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