Week 6: The Funding and Financing of Innovative Activity

Carolyn Stein

Econ 220C: Topics in Industrial Organization

Designing incentives for innovation

- Manso (2010)
- Azoulay, Graff Zivin, and Manso (2011)

How much science should we fund?

- Azoulay et al. (2019)

Motivating innovation

- Standard principal-agent problem trades off pay-for-performance (to induce effort) with flat rate (to mitigate risk aversion)
- This paper recognizes that agents might have choice over what they work on, and that innovative activities might be more risky
- If you want the agent to choose the innovative activity, you have to structure the contract accordingly

Bandit problems

This paper models the choice of whether to innovate as a *bandit problem*

- In bandit problems, the agent is uncertain of the payoffs resulting from some of the actions she might take
- Agents have a choice:
  - They can **exploit** the actions where they know the payoff
  - Or, they can **explore** the actions where they don't know the payoff, and learn. This is how Manso models innovation: exploring unknown actions
- This sets up a tradeoff: exploration reveals information of potentially superior actions, but may also lead to waste if the action is inferior. Exploitation ensures known payoffs, but may prevent the discovery of superior actions

Embedding the bandit problem in a P-A problem

In this paper, we are trying to design a contract to motivate someone *else* to potentially innovate

- A venture capital firm designing incentives for a founder
- A board designing incentives for a CEO at an innovative company

Embed the bandit problem inside a principal-agent model

Start with the bandit problem

Setup:

- Agent lives for 2 periods
- In each period, agent takes an action $i \in \{1, 2\}$
- Each action i has a probability of success (S) equal to p_i and a probability of failure (F) equal to $1 - p_i$
- Action 1 is the "conventional" method, and thus p_1 is known. No learning occurs:

$$E[p_1|F, 1] = E[p_1] = E[p_1|S, 1]$$

- Action 2 is the "innovative" method, and thus p_2 is not known. However, learning can occur:

$$E[p_2|F, 2] < E[p_2] < E[p_2|S, 2]$$

- Assumption: $E[p_2] < p_1 < E[p_2|S, 2]$. Interpret?

Action plan

- Agent chooses an *action plan*: an action for period 1, and an action for period 2 (conditional on the outcome of period 1). Call this $\langle i, j, k \rangle$ where i is period 1 action, j is period 2 action conditional on success, and k is period 2 action conditional on failure
- The action plan should maximize expected payoff (assume agent is risk-neutral):

$$\underbrace{\{E[p_i]S + (1 - E[p_i])F\}}_{\text{period 1}} + \underbrace{E[p_i]\{E[p_j|S, i]S + (1 - E[p_j|S, i])F\}}_{\text{period 2 conditional on S}}$$
$$+ \underbrace{(1 - E[p_i])\{E[p_k|F, i]S + (1 - E[p_k|F, i])F\}}_{\text{period 2 conditional on F}}$$

Exploitation versus exploration

- Action plan $\langle 1, 1, 1 \rangle$ is called exploitation
- Action plan $\langle 2, 2, 1 \rangle$ is called exploration
- These are the two key action plans to consider (why)?
- The payoff from exploration is higher than for exploitation iff:

$$E[p_2] \geq p_1 - \underbrace{\frac{p_1(E[p_2|S,2] - p_1)}{1 + (E[p_2|S,2] - p_1)}}_{\text{information premium}}$$

Embedding this in the principal-agent problem

- Principal hires the agent to perform the task
- Agent incurs private costs $c_1 \geq 0$ if he takes action 1, $c_2 \geq 0$ if he takes action 2, or he can shirk and incur zero costs
- Shirking results in the lowest probability of success: $p_0 < E[p_i]$ for $i = 1, 2$
- Principal cannot observe which action the agent takes
- Can only offer a fully state-contingent contract: $\vec{w} = \langle w_F, w_S, w_{FF}, w_{FS}, w_{SF}, w_{SS} \rangle$

Agent payoffs

- For action plan $\langle i, j, k \rangle$ the agent expects payoffs:

$$W(\vec{w}, \langle i, j, k \rangle) = \{E[p_i]w_S + (1 - E[p_i])w_F\} + E[p_i]\{E[p_j|S, i]w_{SS} + (1 - E[p_j|S, i])w_{SF}\}$$
$$+ (1 - E[p_i])\{E[p_k|F, i]w_{FS} + (1 - E[p_k|F, i])w_{FF}\}$$

- And expects costs:

$$C(\langle i, j, k \rangle) = c_i + E[p_i]c_j + (1 - E[p_i])c_k$$

Optimal contract

- The optimal contract $\vec{w}$ that implements $\langle i, j, k \rangle$ minimizes the principal's payments:

$$W(\vec{w}, \langle i, j, k \rangle)$$

- Subject to the IC constraints:

$$W(\vec{w}, \langle i, j, k \rangle) - C(\langle i, j, k \rangle) \geq W(\vec{w}, \langle l, m, n \rangle) - C(\langle l, m, n \rangle)$$

- This is a linear program with 6 unknowns ($\vec{w} = \langle w_F, w_S, w_{FF}, w_{FS}, w_{SF}, w_{SS} \rangle$) and 27 constraints ($3^3$ possible combinations of actions)

Special cases

- If $c_1 = c_2 = 0$ there is no conflict of interest between principal and agent (remember that the agent is risk neutral here). Thus, the agent should just solve the 2-armed bandit problem
- if $c_2 = \infty$, exploration is too costly to ever be worth it. Thus, the agent only chooses between shirking and exploitation, and we collapse to the standard P-A problem

Optimal contract that implements exploitation

What is the optimal contract that implements action plan $\langle 1, 1, 1 \rangle$? I will skip the explicit derivation (see paper) but here is the intuition. Key is to think about which of the (27) constraints will bind:

- The principal must prevent the agent from both shirking and exploring
- If c_2 is high relative to c_1 only the shirking constraint is binding (similar to standard P-A problem). Pay for success (agent is risk-neutral)
- If c_2 is low relative to c_1, need to also prevent the agent from exploring. Pay more for success in the first period

Optimal contract that implements exploitation

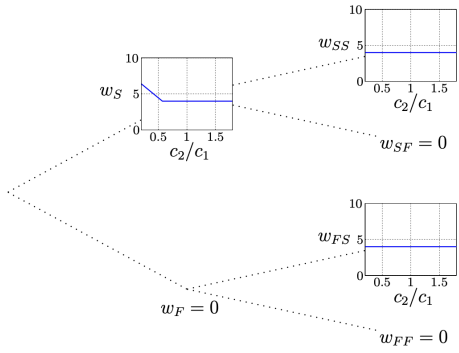


Figure 1. The optimal contract that implements exploitation under the base case parameters. The contract resembles a repetition of standard pay-for-performance contracts. Total pay of the agent depends only on total output, except if c_2/c_1 is small, in which case the agent gets an extra reward for early success to prevent exploration.

Optimal contract that implements exploration

What is the optimal contract that implements action plan $\langle 2, 2, 1 \rangle$? I will skip the explicit derivation (see paper) but here is the intuition. Key is to think about which of the (27) constraints will bind:

- The principal must prevent the agent from both shirking and exploiting
- Do not pay after failure in the second period (this only gives incentive to shirk)
- Do not pay for success in the first period (this gives incentive to exploit)
- If c_2 is low relative to c_1, then we only need to worry about shirking. Pay for repeated success to avoid this (w_{SS})
- If c_2 is high relative to c_1, then we need to structure the contract to also avoid exploiting. This can be done by further increasing (w_{SS}) and/or by explicitly rewarding first period failure (w_F)

Optimal contract that implements exploration

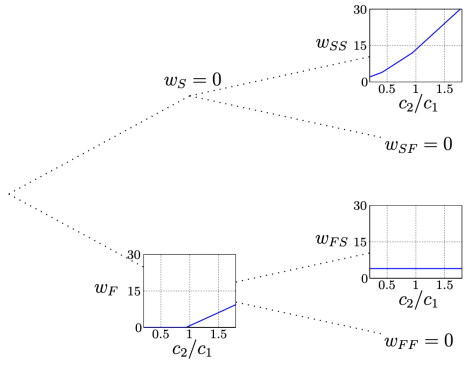


Figure 2. The optimal contract that implements exploration under the base parameters. Under this contract, an agent who succeeds early and fails later has lower total compensation than an agent who fails early and succeeds later or even an agent who fails twice if c_2/c_1 is high.

Key takeaways

Contracts that want to encourage innovation should:

- Delay compensation
- Not reward short-term success
- Possibly reward short-term failure!
- The path of performance matters ($w_S + w_{SF} < w_F + w_{FS}$)
- Extension of the model: sharing feedback (information on performance that only that only the principal has) encourages innovation

Designing incentives for innovation

- Manso (2010)
- Azoulay, Graff Zivin, and Manso (2011)

How much science should we fund?

- Azoulay et al. (2019)

Incentives and creativity: evidence from life science

This paper is an empirical test of Manso (2010). Key idea is that there are two types of funding for academic life sciences:

- NIH grants
  - Short award cycles: 3 years
  - Limited feedback
  - Must commit to project
- Howard Hughes Medical Investigator (HHMI) awards
  - Long award cycles: 5 years with first renewal (almost) guaranteed
  - Provide high quality feedback to awardees
  - "People not projects" approach allows for easy pivoting

Which funding scheme leads to more exploration?

Challenge I: HHMI selection is non-random

HHMI is a very prestigious program and selection is inherently non-random. In fact, HHMI is *looking for* scientists whom they expect to do creative work

- Authors wanted to get a list of runners-up, but were unable to do so
- Instead, construct a control group of similar scientists using early career prize winners (Pew, Searle, Beckman, Packard, Rita Allen)
- Still, scientists in the HHMI and non-HHMI groups don't look well-balanced on important covariates
- Authors use a propensity score weighting approach, using covariates to predict selection into HHMI
- Also used an individual FE approach, though note that selection here likely occurs based on trends not just levels

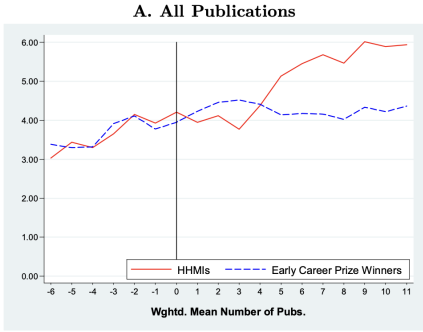
Challenge II: measuring creativity

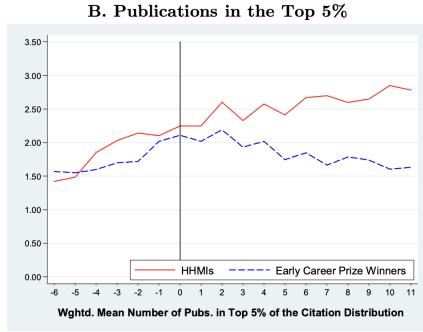
Measuring creativity or risk taking is difficult. One idea: creative projects should be higher variance

- Authors count the number of papers that make it into the top X percentile of the citation distribution as a measure of "big hits."
  - Since older papers have more time to accrue citations, these percentiles are publication-year specific
- Creative and risky work may also lead to more "flops" so they also count papers that fall in the bottom vintage-specific quartile
- Also measure "hits" and "flops" relative to individual past performance
- Alternatively, use MeSH keywords to directly measure the research content

HHMI appointment is correlated (causes?) more papers and more hits

Control scientists are weighted by inverse probability of treatment





Notes: The dashed blue and solid red lines in the above plots correspond to the average yearly number of articles for early career prize winners and HHMIs, respectively. The averages for the control scientists are weighted by each researcher's inverse probability of treatment, where the weights are computed using fitted values of the logit specification. Panel A displays our results for total publications (regardless of impact), whereas Panel B restricts the outcome data to "hits" (publications that fall in the top five percentiles of the vintage-specific article-level distribution of citations).

Results suggest more risk-taking in general

In addition to more hits, we see more flops, new topics, bigger pivots

Effects of HHMI Appointment on Citation Impact (N=417 scientists)

Bechmark	Achievement Metric	"Naïve" X-Sect.	ATE	ATT	DD	SDD
Universal Article-level Citation Distribution	All Pubs	0.419** (0.076)	0.235** (0.078)	0.227* (0.088)	0.178* (0.072)	0.333** (0.109)
	Top 25%	0.514** (0.079)	0.297** (0.085)	0.305** (0.087)	0.212** (0.074)	0.268* (0.114)
	Top 5%	0.733** (0.093)	0.482** (0.111)	0.510** (0.102)	0.293** (0.108)	0.439** (0.161)
	Top 1%	0.964** (0.133)	0.663** (0.138)	0.817** (0.133)	0.363* (0.148)	0.678** (0.240)
	Bttm. 25%	0.181 (0.128)	0.094 (0.131)	0.154 (0.135)	0.187 (0.292)	0.155 (0.887)
Relative to Self Citation Impact Pre-Appointment	Number of 'Hits'	0.401** (0.125)	0.299* (0.128)	0.356** (0.128)		
	Number of 'Flops'	0.341* (0.146)	0.272* (0.121)	0.317† (0.162)		

Takeaways

- Results are striking, if not conclusive
  - Small sample (possible to do a larger version today!)
  - P-score matching is not bulletproof
- Yet, on the question of "what is the optimal mechanism to fund science" this is some of the only evidence we have!
- This is a very hot policy question right now, and this paper has been influential
  - Lots of discussion that the NIH is too risk-averse
  - Introduction of MIRA program at NIH
  - Introduction of ARPA-H

Designing incentives for innovation

- Manso (2010)
- Azoulay, Graff Zivin, and Manso (2011)

How much science should we fund?

- Azoulay et al. (2019)

Spillovers and returns from public R&D

If we want to know if we are funding to little (or too much) science, a critical question is: "what is the social return on the marginal dollar spent on science funding?" The question is challenging for several reasons:

- Measuring returns is difficult because positive spillovers are difficult to track through time and space
- Selection is likely an issue: government may fund projects that are most likely to generate spillovers. Ideal experiment would randomly vary the amount of funding in different areas
- Publicly funded research may crowd out other types of funding (private-sector research)

Azoulay, Graff Zivin, Li, and Sampat (2019)

- The authors study the effect of marginal NIH funding on patents. Patents may not be the only margin of spillover, so their estimates can be interpreted as a lower bound
- Use data on underlying application scores (of both accepted and rejected applications) and institutional knowledge of the NIH funding scheme to construct an instrument for funding amounts

Measuring spillovers

For every NIH grant, the authors...

- Find all the publications that cite the grant as a source of funding. This is the "publicly funded research"
- Find all the private-sector patents that cite the "publicly funded research." Note that if a patent is linked back to N NIH grants, each grant gets credit for $1/N$ of the patents (conservative). On average, patents cite 13 NIH grants so there is a lot of credit sharing
- Define a variable $Patents_{\tilde{dst}}$ as the total number of patents to disease d in study section s in year t

How the NIH funds projects I

- The NIH budgets funding at the Institute or Center (IC) level
  - Examples: National Cancer Institute, National Heart, Lung, and Blood Institute.
  - There are 27 of these ICs
- However, applications are evaluated at the study section level
  - Example: Cellular Signaling and Regulatory Systems
  - Multiple ICs fall within a single study section
  - There are 180 study sections
  - Each section assigns proposals a score and a rank ("science rank")

How the NIH funds projects I

Cell Signaling Study Section

Grant ID	*Science Rank*	*Disease*	*Raw Score*
G1	1	Cancer	1.0
G2	2	Cancer	1.1
G3	3	Cancer	1.2
G4	4	Cancer	1.3
G5	5	Cancer	1.4
G6	6	Other	1.6
G7	7	Cancer	1.7
G8	8	Cancer	2.4
G9	9	Other	2.5
G10	10	Other	2.8
G11	11	Other	2.9
G12	12	Cancer	3.2
G13	13	Other	3.4
G14	14	Cancer	3.6
G15	15	Other	3.7

Tumor Physiology Study Section

Grant ID	*Science Rank*	*Disease*	*Raw Score*
G16	1	Other	1.1
G17	2	Other	1.2
G18	3	Other	1.3
G19	4	Other	1.4
G20	5	Other	1.5
G21	6	Cancer	1.6
G22	7	Cancer	2.1
G23	8	Other	2.2
G24	9	Cancer	2.3
G25	10	Cancer	2.8
G26	11	Other	2.9
G27	12	Other	3.1
G28	13	Other	3.3
G29	14	Cancer	3.5
G30	15	Cancer	3.6
G31	16	Cancer	3.7

How the NIH funds projects II

- Projects are then sent back from the study sections to their respective ICs
- They are ordered by their science ranks, creating a "rank of ranks"
- Projects are funded sequentially, up to the budgeted limit within the IC

How the NIH funds projects II

Cancer Institute (NCI)

Grant ID	*Rank of Ranks*	*Science Rank*	*Study Section*	*Raw Score*	*Funding Granted*
G1	1	1	Cell	1.0	$2M
G2	2	2	Cell	1.1	$2M
G3	3	3	Cell	1.2	$2M
G4	4	4	Cell	1.3	$2M
G5	5	5	Cell	1.4	$2M
G21	6	6	Tumor	1.6	$2M
G7	7	7	Cell	1.7	$2M
G22	8	7	Tumor	2.1	$2M
G8	9	8	Cell	2.4	$2M
G24	10	9	Tumor	2.3	
G25	11	10	Tumor	2.8	
G12	12	12	Cell	3.2	
G29	13	14	Tumor	3.5	
G14	14	14	Cell	3.6	
G30	15	15	Tumor	3.6	
G31	16	16	Tumor	3.7	

How the NIH funds projects II

- Projects are then sent back from the study sections to their respective ICs
- They are ordered by their science ranks, creating a "rank of ranks"
- Projects are funded sequentially, up to the budgeted limit within the IC

Instrument for funding at the DST level

- Focusing on projects ± 5 of the payline, the authors argue that these are of similar quality (in fact, projects with higher science scores can have lower rank-of-rank scores)
- And yet, within this band, there is variation in how much funding each DST gets
- Call this the "windfall" and use this to instrument for total DST funding

Instrument for funding at the DST level

Cancer Institute (NCI)

Grant ID	*Rank of Ranks*	*Science Rank*	*Study Section*	*Raw Score*	*Funding Granted*
G1	1	1	Cell	1.0	$2M
G2	2	2	Cell	1.1	$2M
G3	3	3	Cell	1.2	$2M
G4	4	4	Cell	1.3	$2M
G5	5	5	Cell	1.4	$2M
G21	6	6	Tumor	1.6	$2M
G7	7	7	Cell	1.7	$2M
G22	8	7	Tumor	2.1	$2M
G8	9	8	Cell	2.4	$2M
G24	10	9	Tumor	2.3	
G25	11	10	Tumor	2.8	
G12	12	12	Cell	3.2	
G29	13	14	Tumor	3.5	
G14	14	14	Cell	3.6	
G30	15	15	Tumor	3.6	
G31	16	16	Tumor	3.7	

Comparison of Outcomes: Cancer-Cell Signaling vs. Cancer-Tumor Physiology

	Cancer CS	**Cancer TP**
All applications		
# of Apps	9	7
Mean Raw Score	1.88	2.8
Mean Science Rank	6.22	11
Total DST Funding	$14M	$4M
In 5-grant window		
# of Apps in Window	5	5
Mean Raw Score	2.46	2.46
Mean Science Rank	9.2	9.2
Windfall DST Funding	$6M	$4M

Empirical strategy

Key regression:

$$Patents_{\tilde{dst}} = \alpha_0 + \alpha_1 Funding_{dst} + \Lambda(\#Applications_{dst}) + \Phi(ScoreControls_{dst})$$
$$+\delta_{ds} + \gamma_{dt} + \nu_{st} + \varepsilon_{dst}$$

where *Funding* is instrumented with windfall amounts (the amount of DST funding that comes from the window around the payline)

First stage and placebo checks

	Dependent variable: Total DST Funding		
	Past Windfall	Current Windfall	Future Windfall
	(1)	(2)	(3)
Windfall Funding	0.067	1.251^{***}	0.085
	(0.243)	*(0.232)*	*(0.205)*
R^2	0.927	0.921	0.927
Observations	9,326	14,085	9,326

Note: This table presents alternative first stages using past and future windfall funding. Current windfall funding is the total amount of funding for awarded DST grants within 25 grants of an Institute specific award cutoff in the same year T. Future windfall is this same amount, but defined for DS,T+1. Past windfall funding is similarly defined, for DS,T-1. Controls include disease-science and disease-year fixed effects, linear science-year time trends, as well as fixed effects for the number of applicants to a DST, the number of applicants within a 25-grant radius window around the IC payline, as well as cubics in the average raw and rank scores of applications in the funding window. The outcome variables are fractional patent counts.

Standard errors in parentheses, clustered at the disease/science level ($^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$).

2SLS results

An additional $10 million in NIH funding leads to 2 to 2.5 additional patents. Since the average NIH grant is $1.6 million, this is 1 patent for every 2-3 grants

	First Stage		**Citation Linked**	
	DST Funding (× $10 mln.)		Mean=12.82; SD=19.17	
			OLS	IV
	(1)		(2)	(3)
Windfall Funding (×$10 mln.)	1.251*** *(0.194)*	DST Funding (×$10 mln.) Mean=4.06;	2.478*** *(0.658)*	2.002* *(1.106)*
		Elasticity	0.785	0.634
Cragg-Donald Wald F-stat	478			
Kleibergen-Paap Wald F-stat	37.51			
Observations	14,085		14,085	14,085
Year FEs	Incl.		Incl.	Incl.
Disease × Science FEs	Incl.		Incl.	Incl.
Disease × Year FEs	Incl.		Incl.	Incl.
Science × Year Linear Trends	Incl.		Incl.	Incl.
Application Controls	Incl.		Incl.	Incl.

Testing for crowd-out

- If NIH funding simply replaces research funding that would have occurred anyway, then the total number of DST patents should not change, even if the number of DST patents linked to NIH grants increases
- Create a new outcome: total number of DST patents. But without NIH funding, how do you categorize the DST? Authors look for patents that cite papers that are similar to papers funded by a particular DST
- If there is full crowd-out, the coefficient on *Funding* should be 0

Crowd-out results

Results not consistent with crowd-out...coefficient is in fact larger

	First Stage		Citation Linked		Total Related	
	DST Funding (× $10 mln.)		Mean=12.82; SD=19.17		Mean=24.8; SD=28.0	
			OLS	IV	OLS	IV
	(1)		(2)	(3)	(4)	(5)
Windfall Funding (×$10 mln.)	1.251*** *(0.194)*	DST Funding (×$10 mln.) Mean=4.06;	2.478*** *(0.658)*	2.002* *(1.106)*	3.615*** *(0.817)*	2.329** *(1.159)*
		Elasticity	0.785	0.634	0.592	0.381
Cragg-Donald Wald F-stat	478					
Kleibergen-Paap Wald F-stat	37.51					
Observations	14,085		14,085	14,085	14,085	14,085
Year FEs	Incl.		Incl.	Incl.	Incl.	Incl.
Disease × Science FEs	Incl.		Incl.	Incl.	Incl.	Incl.
Disease × Year FEs	Incl.		Incl.	Incl.	Incl.	Incl.
Science × Year Linear Trends	Incl.		Incl.	Incl.	Incl.	Incl.
Application Controls	Incl.		Incl.	Incl.	Incl.	Incl.

Back-of-the-envelope returns

- What is the dollar value of a patent? Very unclear
- But maybe less unclear for patents on marketed drugs?
- If the authors restrict to patents for marketed drugs and assign a PDV of \$3.5 billion to each drug, they find that an additional \$10 million in NIH funding leads to \$14.7 million in patent value (nearly 50% return)