Licensing and Innovation Regimes in Pharmaceutical R&D

Michele Liberatore[1,2] Massimo Riccaboni[1,3]

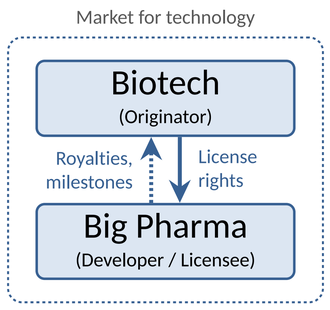
[1]IMT School for Advanced Studies Lucca [2]University of Florence [3]IUSS Pavia

AEA/ASSA Annual Meeting – Washington, DC, January 3–5, 2027 | *JEL: L65, O31, D82, L24, C55*

Scan the code for the full paper

Motivation & Research Questions

Pharma increasingly sources innovation through **markets for technology**: biotech *originators* out-license R&D projects to pharma *developers* (Arora, Fosfuri & Gambardella, 2001).
Originators know more about project quality ⇒ risk of a **lemons market**, where the worst projects are licensed out (Akerlof, 1970; Pisano, 1997).
Mixed evidence: in-licensed drugs succeed more often (27% vs. 16%) (DiMasi et al., 2010), yet biotechs get discounted deals (Nicholson et al., 2005), licensed patents are more often litigated (Palermo et al., 2019) and *rushed* licenses underperform (Hermosilla, 2021).



RQ1: Is there a lemons equilibrium in pharmaceutical licensing markets?

RQ2: Are the effects heterogeneous across innovation regimes (incremental vs. novel projects)?

Contribution: effects are *not stable across innovation regimes*. Precise signals (incremental) ⇒ separating equilibrium, positive selection, return equalization. Noisy signals (novel) ⇒ lemons-type frictions persist.

Model: Licensing & Innovation Types

Projects have latent quality $\theta \in [0,1]$, privately known to the originator, and an observable innovation regime $\tau \in \{I, N\}$: *incremental* (established pathway) or *novel* (frontier biology).
Information precision $\lambda(\tau)$: developers only observe a noisy signal of quality,

$$\hat{\theta} = \theta + \varepsilon, \qquad \varepsilon \sim \mathcal{N}\left(0, \frac{1}{\lambda(\tau)}\right), \qquad \lambda(I) > \lambda(N) > 0.$$

The developer chooses **effort** $e \geq 0$: success (i.e. regulatory market approval) has probability $p(\theta, e) = \theta e$, effort costs $\frac{k}{2}e^2$, and revenue upon success is V.

In-house development (H)

$$\max_e \ \theta e V - \tfrac{k}{2}e^2$$
$$e_H^* = \frac{\theta V}{k}, \qquad \pi_H(\theta) = \frac{\theta^2 V^2}{2k}$$

Licensing (L), royalty rate r

$$e_L^* = \frac{(1-r)\theta V}{k} < e_H^*$$
$$\pi_L(\theta) = \frac{(1-r)^2\theta^2 V^2}{2k} - C_c(\tau)$$
coordination cost $C_c(N) > C_c(I) > 0$

Gains from trade: the licensee's superior regulatory and commercial capabilities imply a higher revenue from licensed projects. The originator licenses iff $U_L(\theta, r) \geq U_H(\theta)$; single crossing yields a quality cutoff $\theta^*(\tau)$.

Competitive equilibrium. As both strategies coexist, neither can dominate on *both* success probability and monetary returns, or competitive bidding would move license prices until risk-adjusted monetary returns equalize. Hence a **trade-off**: no difference, or a success advantage offset by lower monetary returns.

Prop. 1 – Positive selection. Licensed projects have higher success probabilities: with precise signals the cutoff $\theta^*(I)$ sustains a *separating equilibrium*.

Prop. 2 – Return equalization. *Incremental:* $\mathbb{E}[\pi_H(\theta)] = \mathbb{E}[\pi_L(\theta) \mid \theta \geq \theta^*(I)]$: higher success, lower monetary returns. *Novel:* noisy signals limit ex-ante pricing, equalization may **fail** (Gans & Stern, 2003; Arora et al., 2022).

Data & Empirical Strategy

Data	Evaluate Pharma: approved *and* failed projects; 140+ controls X_i
Treatment	$D_{\text{lic},i}$ = 1 if in-licensed before approval, 0 if developed in-house
Outcomes	Y_1 = Market approval (binary) (N = 90,336) Y_2 = Monetary return = lifetime sales − trial costs (N = 13,595)
Proxy for $\lambda(\tau)$	Predicted success probability $\hat{S}_i$ (random forest on pre-treatment features, out-of-sample). Established pathways (generics, follow-on drugs) are well understood and usually approved; first-in-class projects face deep scientific uncertainty and mostly fail ⇒ high $\hat{S}$ = incremental (high λ), low $\hat{S}$ = novel (low λ)

Double Machine Learning (DML) (Chernozhukov et al., 2018)

$$Y_{1i} = \theta_0 + \theta_{\text{lic}} D_{\text{lic},i} + g(X_i) + \varepsilon_i$$
$$Y_{2i} = \theta_0 + \theta_{\text{lic}} D_{\text{lic},i} + \gamma_{\text{lic}}\left(D_{\text{lic},i} \times \tilde{S}_i\right) + g(X_i) + \varepsilon_i$$
$g(\cdot)$ learned by ML, K-fold cross-fitting. Y_2 effect at percentile p of $\hat{S}$: $\theta_{\text{lic}} + \gamma_{\text{lic}}\tilde{S}(p)$, $\tilde{S} = \hat{S} - \bar{S}$

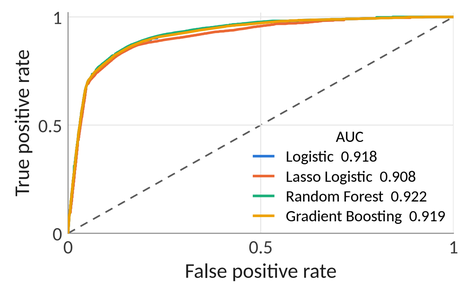
DML-IV (Hermosilla, 2021)

Binary instrument built on *Phase III failures* (P3Fs) in the licensee's pipeline:

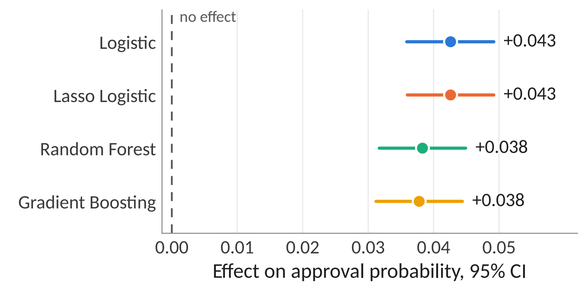
$$Z_i = \begin{cases} 1 & \text{if } i \text{ is in-licensed and its licensee had a P3F in the 365 days before the deal} \\ 0 & \text{otherwise} \end{cases}$$

A P3F suddenly removes a late-stage asset, pushing the licensee to *rush-license* within one year to refill its pipeline, with less time for due diligence. Given X_i and the licensee's predicted P3F risk, failure timing is as-good-as-random ⇒ LATE for *compliers*, i.e. rushed licenses.

Result 1: Positive Selection into Licensing



ROC curves of the Y_1 nuisance learners

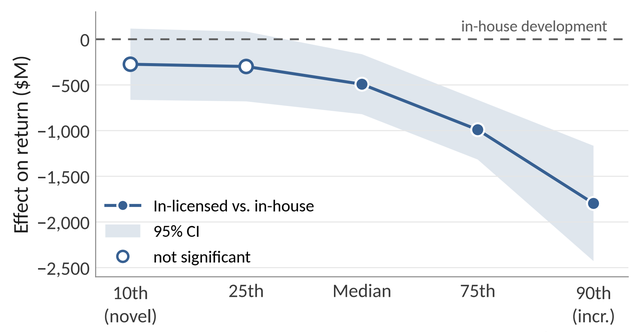


DML estimate of θ_{lic} on Y_1 (95% CI)

- In-licensed projects are **+3.8 to +4.3 pp** more likely to be approved (all $p < 0.001$), i.e. a **+9.6–10.9% relative increase** over the baseline approval rate.
- Stable across learners (nuisance AUC 0.908–0.922).
- Robust to pre-clinical/Phase I deals only (≈ +2 pp).

Consistent with **Prop. 1**: *positive selection* into licensing, not pure adverse selection.

Result 2: Monetary Returns by Innovation Regime



In-licensed vs. in-house development, $M (95% CI). Mean effect in levels.

Percentile of $\hat{S}$	Effect (%)	p
10th (novel)	−0.96	0.174
25th	−1.07	0.121
Median	−1.34**	0.042
75th	−3.02***	<0.001
90th (incr.)	−8.17***	<0.001

Total effect $\hat{\theta}_{\text{lic}} + \hat{\gamma}_{\text{lic}}\tilde{S}(p)$. % effects are on shifted log returns.

Incremental: higher success **offset by lower monetary returns** ⇒ competitive equilibrium (Prop. 2).

Novel: higher success, **no return penalty** ⇒ lemons-type frictions persist.

Result 3: Causal Check with DML-IV

Success probability (Y_1)

Panel A: LATE estimate

Outcome	$\hat{\theta}^{IV}_{\text{lic}}$	SE	p	95% CI
Succ. prob.	+0.025	0.018	0.167	[−.011, .061]

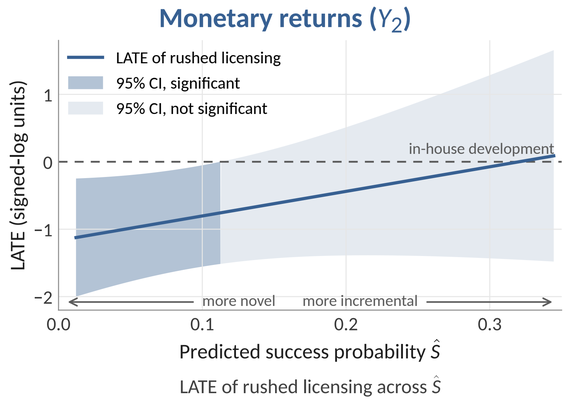
Panel B: First stage

	$\hat{\pi}$	SE	p	95% CI
P3F → Lic.	0.650***	0.012	<.001	[.626, .674]

Panel C: Nuisance performance

	AUC(Y)	AUC(D)
RF (5-fold)	0.899	0.842

Monetary returns (Y_2)



LATE of rushed licensing across $\hat{S}$

Rushed licenses are **not positively selected**: compressed due diligence removes the +3.8–4.3 pp advantage.

Large, significant losses for **novel** projects (−0.36 SD at the 10th pct.), fading to zero for **incremental** ones.

Conclusions & Takeaways

Summary of Estimated Effects

	DML (full population)		DML-IV (rushed licenses)	
	Succ. prob.	Mon. return	Succ. prob.	Mon. return
Incremental	↑***	↓***	=	=
Novel	↑***	=	=	↓**
Equil. (incr.)	Neither strategy dominates		Neither strategy dominates	
Equil. (novel)	Licensing weakly dominates		In-house weakly dominates	

Key takeaway: no aggregate lemons market, but market performance depends systematically on *information precision* and the *innovation regime*: **competitive equilibrium** for incremental projects, **lemons-type frictions** at the novel frontier, confirmed causally by the DML-IV, which uses P3Fs as a source of exogenous variation in firms' licensing propensity.

Policy: standardized disclosure and milestone-based contracts could improve the ex-ante pricing of novel projects, provided they do not discourage novelty (Tyagi et al., 2025).

Contact

Michele Liberatore
PhD Student, IMT School for Advanced Studies Lucca & University of Florence
Email: michele.liberatore@imtlucca.it

Questions and comments are very welcome by email!

References

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *QJE*, 84(3).

Arora, A., Belenzon, S., & Suh, J. (2022). Science and the market for technology. *Management Science*, 68(10).

Arora, A., Fosfuri, A., & Gambardella, A. (2001). Markets for technology and their implications for corporate strategy. *Industrial and Corporate Change*, 10(2).

Chernozhukov, V., et al. (2018). Double/debiased machine learning for treatment and structural parameters. *Econometrics Journal*, 21(1).

DiMasi, J. A., Feldman, L., Seckler, A., & Wilson, A. (2010). Trends in risks associated with new drug development. *Clinical Pharmacology & Therapeutics*, 87(3).

Gans, J. S., & Stern, S. (2003). The product market and the market for "ideas". *Research Policy*, 32(2).

Hermosilla, M. (2021). Rushed innovation: Evidence from drug licensing. *Management Science*, 67(1).

Nicholson, S., Danzon, P. M., & McCulloch, J. (2005). Biotech-pharmaceutical alliances as a signal of asset and firm quality. *Journal of Business*, 78(4).

Palermo, V., Higgins, M. J., & Ceccagnoli, M. (2019). How reliable is the market for technology? *Review of Economics and Statistics*, 101(1).

Pisano, G. P. (1997). R&D performance, collaborative arrangements, and the market for know-how: A test of the "lemons" hypothesis in biotechnology. HBS Working Paper 97-105.

Tyagi, H., Hermosilla, M., & Shah, R. (2025). Does transparency hinder technological novelty? *Manufacturing & Service Operations Management*, 27(5).