

Technology M&As and Knowledge Diffusion

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Motivation: Synergy or Hoarding?

Background Examples

- J&J–ALZA (2001): Integrated drug-delivery tech into global distribution
- NVIDIA–Arm (2021): \$40B deal blocked over restricted tech access concerns

Competing Mechanisms

- **Synergy:** Combined firm enhances technology value (e.g., Teece, 1986; Bena & Li, 2014)
- **Hoarding:** Strategic restrictions block diffusion (e.g., Bryan & Hovenkamp, 2020; Akcigit & Ates, 2021, 2023; Cunningham et al., 2021)

Research Questions

- Do tech M&As increase or reduce diffusion of target technology?
- How much do diffusion effects matter for aggregate productivity growth?

Identification: Withdrawn Deals DiD

- **Data:** SDC M&A matched to PatentsView USPTO (1980–2021)
- **Design:** Patent-level DiD tracking non-self forward citations
- **Controls:** 63 withdrawn deals failed for exogenous reasons (e.g., macro shocks) as control group (following Seru, 2014)
- **Matching:** CEM on industry composition, timing, and pre-event citations

Empirical Findings: Acceleration of Diffusion

Tech Acquisition Accelerates Knowledge Diffusion

- Acquired patents experience a **significant surge** in external citations
- Impact: **1.4**× increase (0.41 → ~1.0 scaled citations/year)
- Persistence: Effect remains significant for **5+ years**

Higher Quality Follow-on Innovation

- Average renewal rate of citing patents increases by ~**20%**
- Evidence of a more promising environment for acquired technology

The Bridge: Model of Idea Flows

Disentangle Synergy vs. Hoarding Effects on innovation diffusion:

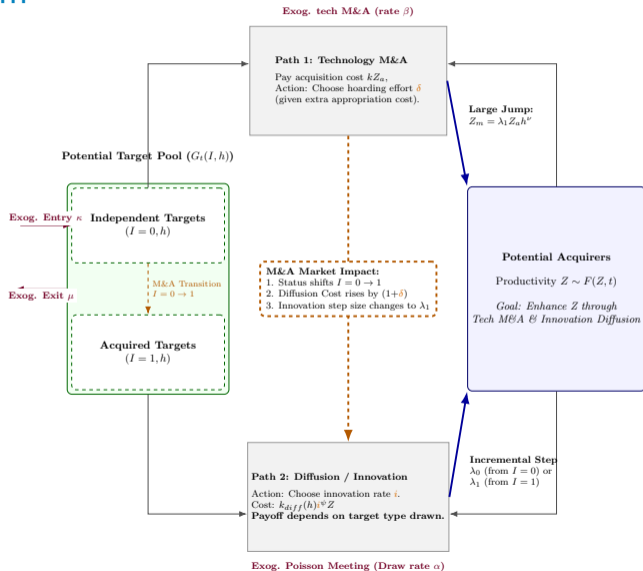
- Identify innovation step size via empirical citation surge:

$$IRR_{10} = \frac{5 \cdot IRR_1 + 5 \cdot IRR_2}{10} = \frac{5 \times 2.41 + 5 \times 1}{10} = 1.705$$

- Approximate hoarding via self-citation rate differences (acquired vs. controls)

Isolate the Diffusion Channel of tech M&As' productivity impact

Model Mechanism



Aggregate Impact on Productivity Growth

Counterfactual Exercises

1. Increase Tech M&A Rate:

- Doubling 2015 tech M&A rate \Rightarrow **+0.05 pp** annual productivity growth
- Diffusion channel accounts for **40%** of this gain

2. Reduce Knowledge Hoarding Cost:

- Enhancing acquirer's appropriation ability **need not reduce** aggregate productivity
- Reason: Higher acquisition value \Rightarrow more innovation based on independent targets

Takeaways

Main Findings

- Tech M&A **catalyzes diffusion** with measurable productivity impact
- **Policy:** Account for positive diffusion effects; balance acquirer incentives against diffusion of acquired innovation

Future Directions

- Richer modeling of acquirer–target dynamics
- Consider competition and market structure heterogeneity

Appendix

Appendix A: Sample Statistics

Table A1: Summary Statistics for M&A Sample

	Full M&A Sample	Tech M&As	Tech Share
<i>Deal Characteristics</i>			
Number of deals	32,917	3,692	11.21%
Total deal value (\$ mi)	–	–	42.76%
Average deal value (\$ mi)	406.21	1,553.08	382.3%
Same-industry deals (%)	48.07	44.66	–
<i>Target Characteristics</i>			
Private targets (%)	75.50	38.60	–
High-tech industry (%)	43.41	61.16	–
<i>Patent Portfolio</i>			
Total patents	5,422	3,689	68.04%
Patents per target (mean)	2.6	4.1	157.69%
Patents per target (median)	1.0	1.5	150%
Citations per patent per year	0.656	0.664	101.22%

Note: Tech M&As defined as acquisitions where target has patents granted within 7 years before deal announcement.

Appendix B: Withdrawn Deal Breakdown

Table A2: Classification of Qualified Withdrawn Deals

Failed Reason	Count	Share	Cumulative
Acquiror issue not related to tech (Unexpected funds issue, negative shocks)	21	33.33%	33.33%
Regulation	18	28.57%	61.90%
Target rejection not related to target tech	11	17.46%	79.37%
Other exogenous reasons (Macro shocks, adverse market conditions)	8	12.70%	92.06%
Competing offers	3	4.76%	96.83%
Management disagreement	2	3.17%	100%
Total	63	100%	

Appendix C: CEM Matching Balance

Patent characteristics do not predict treatment status in the matched sample.

Table A3: Logistic Regression of Treatment Prediction

	Dep. Var: Treatment
	Coefficient (SE)
Originality	-0.655 (0.544)
Breadth	-1.154 (1.053)
New word	0.066 (0.082)
RETech	-0.049 (0.040)
Num claims	-0.005 (0.007)
Observations	1,976

Note: Logistic regression with matched strata FE. Robust SEs in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Appendix D: Full Regression Tables

Significant raw ($>2.5\times$) and scaled ($1.4\times$) citation increase after Tech M&As

Table A4: Diffusion Effects on Non-Self Follow-on Patents

Dep. var: # non-self follow-on	Raw Citations			Scaled Citations		
	(1)	(2)	(3)	(4)	(5)	(6)
D(acquired) \times D(Post)	1.323*** (.298)	1.284*** (.259)	1.162*** (.240)	.884*** (.327)	.891*** (.309)	.822** (.352)
Tech_class F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Patent F.E.	Yes	No	Yes	Yes	No	Yes
Age F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	No	Yes	No	No	Yes
Year \times Strata F.E.	Yes	Yes	No	Yes	Yes	No
Observations	16,492	23,001	16,909	16,492	23,001	16,909

Note: Estimated by Poisson pseudo-maximum likelihood method. Outcome winsorized at 99%. Robust SEs clustered at target firm. Pre-event mean: 0.34 (raw), 0.41 (normalized).

Appendix E: Dynamic Plot

Dynamic results under Poisson regression with binned patents ≥ 5 years old.

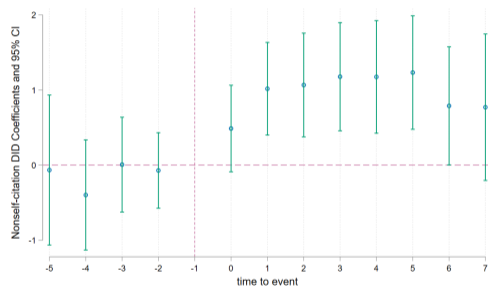


Figure A1: Event study on non-self follow-on patents (CEM matched)

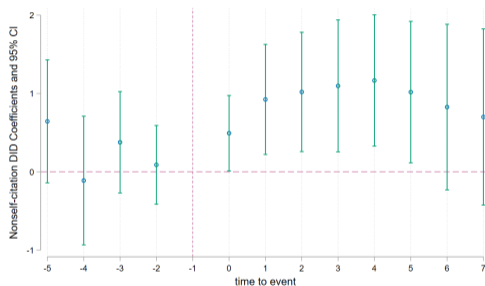


Figure A2: Event study on mean-citation normalized measures (CEM matched)

Appendix F: Quality Increase

A more promising environment for acquired technology.

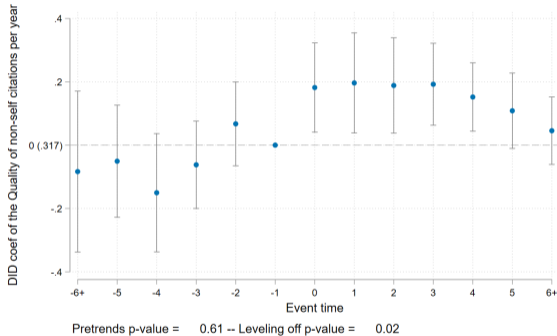


Figure A3: DiD coefficient of citing patents average renewal rate

Appendix G: The Firm's Problem

Firm's Problem (Potential Acquirers)

Firm expected value function satisfies the following HJB equations:

$$rV(Z, t) = \left\{ Z + \alpha \left[\int_h g_0(h, t) \Delta V^{meet-ind} dh + \int_h g_1(h, t) \Delta V^{meet-acq} dh \right] + \beta \int_h \frac{g_0(h, t)}{\text{prob}(h \text{ from ind target})} [\Delta V^{acq}] dh + \frac{\partial V(Z, t)}{\partial t} \right\} \quad (*)$$

- $\Delta V^{meet-ind} = \max_{i_{ind}} \left[i_{ind} (V(\lambda_0 Z, t) - V(Z, t)) - k_{diff}(h) i_{ind}^\psi Z \right]$
- $\Delta V^{meet-acq} = \max_{i_{acq}} \left[(i_{acq} V(\lambda_1 Z, t) - V(Z, t)) - (1 + \tilde{\delta}) k_{diff}(h) i_{acq}^\psi Z \right]$
- $\Delta V^{acq} = \max_{\delta} \{ \delta [V(\lambda_1 Z h^\nu, t) - V(Z, t)] - l_{imp}(\delta) Z \} + V(\lambda_1 Z h^\nu, t) - V(Z, t) - kZ$

Appendix H: Model Fit (Non-Targeted Moments)

Model provides reasonable fit to long-run US growth and citation patterns (1980–2015).

Table A5: Model Validation Against Non-Targeted Moments

Non-Targeted Moments	Model	Data
TFP growth rate	0.75%	1.1%
Annual external citations for independent targets (range)	1.2	0.2–1.4
Annual external-citing patents for potential acquirers (range)	8	4–12
Acquired intangibles amortization intensity (range)	0.17%	0.13%–0.57%

Appendix I: Counterfactual on Knowledge Hoarding

Post-merger knowledge hoarding may not harm aggregate growth.

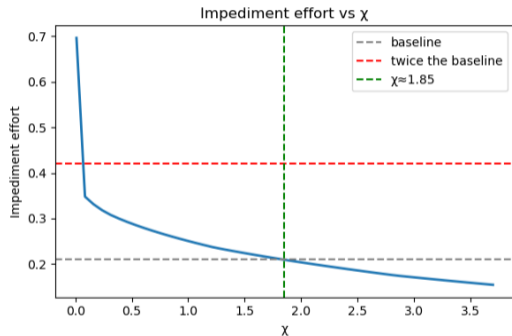


Figure A4: Impediment effort vs. χ

Table A6: Hoarding Counterfactual

Case	Diffusion	TFP Growth
Baseline	1.21	0.7217%
Double hoarding effort	1.21	0.7218%

- Diffusion growth: 0.02% \rightarrow 0.018% (**-10%**)
- Offset by higher innovation on independent targets

Appendix J: Counterfactual on Tech M&A Rate

Diffusion channel plays a measurable role in productivity growth.

Table A7: Counterfactual Analysis: Varying Tech M&A Rates

Scenario	M&A Rate (β)	Growth Rate (γ)	Diffusion
Low M&A Rate (half)	0.00065	0.70%	1.20
Baseline	0.0013	0.72%	1.21
High M&A Rate (double)	0.0026	0.77%	1.22

Key Result (High M&A Rate):

- Diffusion growth: 0.02% \rightarrow 0.04% (contributes **40%** of total increase)

Appendix K: Diffusion to Young Firms

Citations from young US assignees (though fewer in number) also increase after acquisition.

Table A8: Diffusion Effect from US Young Assignees

Dep. var: # non-self follow-on patents	Poisson		OLS	
	(1)	(2)	(3)	(4)
D(acquired)·D(Post)	1.449** (.621)	1.161*** (.386)	.028* (.015)	.027* (.014)
Tech_class F.E.	Yes	Yes	Yes	Yes
Patent F.E.	Yes	No	Yes	No
Age F.E.	Yes	Yes	Yes	Yes
Year×Strata F.E.	Yes	Yes	Yes	Yes
Observations	2,927	14,757	23,841	23,841

Note: Outcome winsorized at 99%. Robust SEs clustered at target firm. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Appendix L: Within-Industry Effects

Within-industry effects and potential defensive strategy by patenting acquirers.

Table A9: Diffusion Effect Conditional on Patenting Acquirer

Dep. var: # non-self follow-on patents	Within-industry citations		All citations	
	(1)	(2)	(3)	(4)
D(acquired)·D(Post)	.725* (.408)	.763** (.380)	.773* (.409)	.816** (.371)
Tech_class F.E.	Yes	Yes	Yes	Yes
Patent F.E.	Yes	No	Yes	No
Age F.E.	Yes	Yes	Yes	Yes
Year×Strata F.E.	Yes	Yes	Yes	Yes
Observations	8,306	10,703	8,439	10,718

Note: Estimated by Poisson pseudo-maximum likelihood method. D(acquired) = 1 for treated patents. D(Post) = 1 after acquisition year. Outcome winsorized at 99%. Robust SEs clustered at target firm. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.