The Two Faces of VC Networks: Performance Premiums and Entry Deterrence

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Stockholm School of Economics

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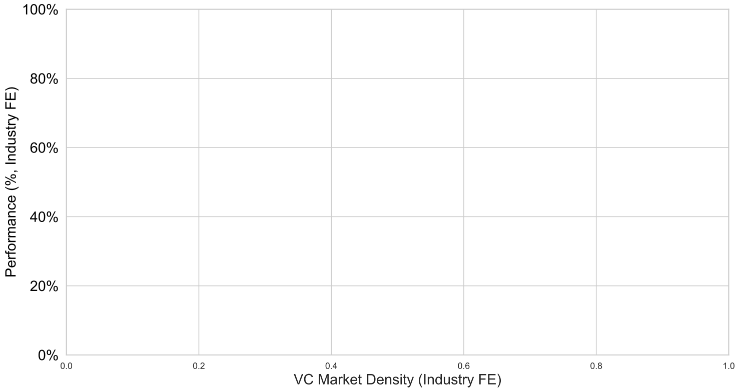
$\rightarrow$ "Performance premium"

Performance Premium

Industry-State Level Evidence (1980 - 2015)



- **Market Density** (x-axis): Fraction of realized network ties among all possible ties

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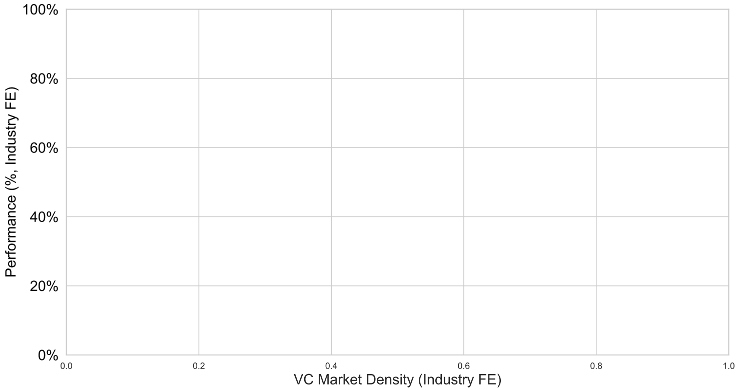

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- **Performance** (y-axis): Fraction of startups that exit (IPO/M&A)

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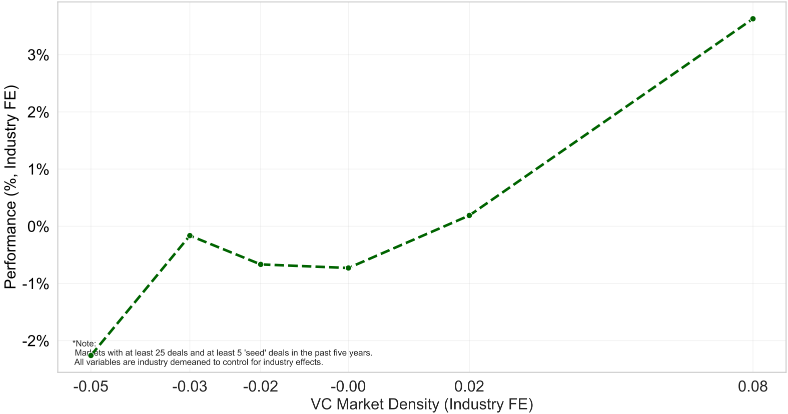

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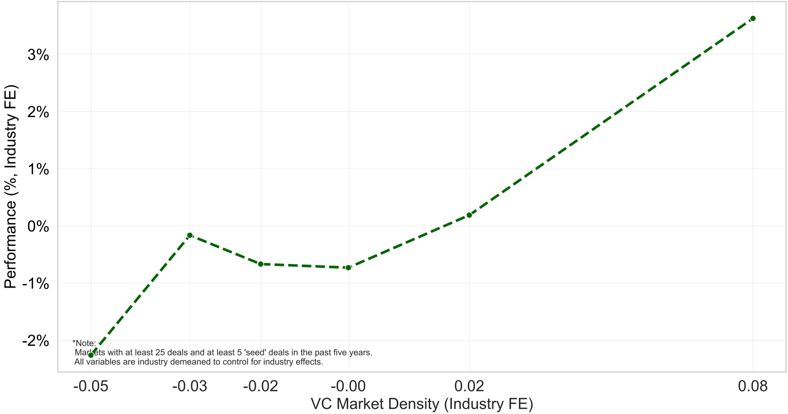

- Exit rate increases with market density. (Value-added/Sorting)

(Sorenson and Stuart, 2001; Stuart and Sorenson, 2007; Hochberg, Ljungqvist, and Lu, 2007)

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- Investment concentration in the market using HHI
  - Share of investment that each company receives in the market.

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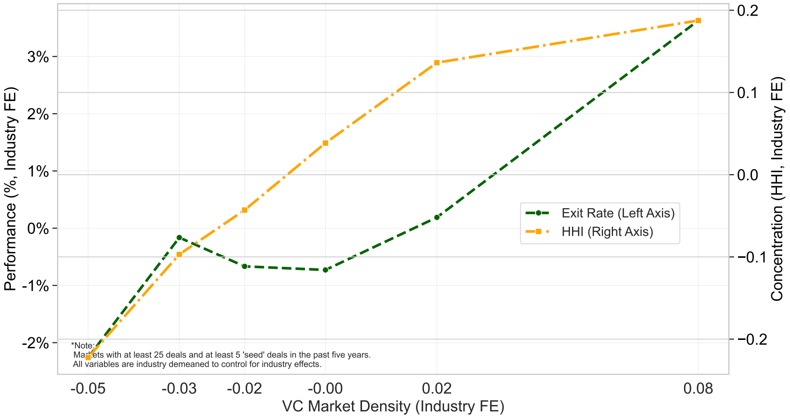

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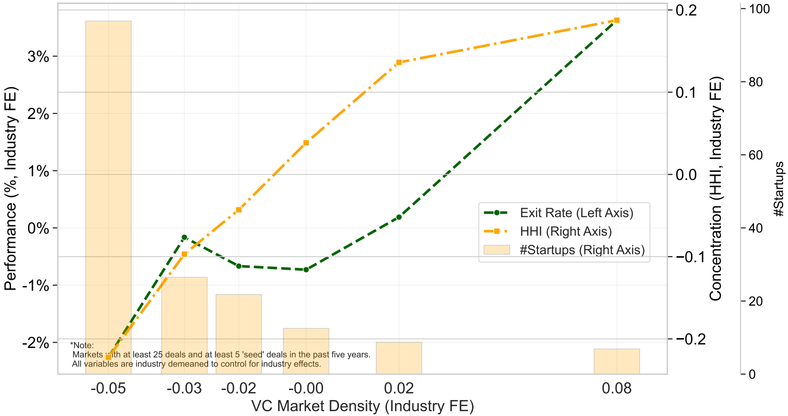

- Investment is more concentrated (HHI, Right axis) within denser markets
- Fewer startups in denser markets.

Seed deals | Company-level | Summary Stats

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    - Denying capital to competing startups. (i.e., financial market deterrence)
    - Due to spillover from one startup to another

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- **Today's Presentation:** Model outline and empirical design

Related Literature and Contributions

VC Performance

Sorting and value-added

Sørensen (2007); Gompers et al. (2010); Kaplan and Schoar (2005); Ewens and Rhodes-Kropf (2015)

Syndication and Networks

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  - Market entry deterrence via networked financial intermediaries.

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  - Quantifies welfare costs of collusion.

Model Overview

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- To explain the performance premium.
- Model features:
    - One-to-many matching market with contract
        - Sorting between startups and VCs.
    - Collusive equilibrium in Syndicated market
        - Entry deterrence through investment rejection.

Setup

Startups

- Set of arriving startups with value v
- Each startup, e, has:

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- c: investment cost

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$$\pi_f^e = x_f \, q_e \, v - c - \beta \, S_f \, \rho_e$$

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Syndicate

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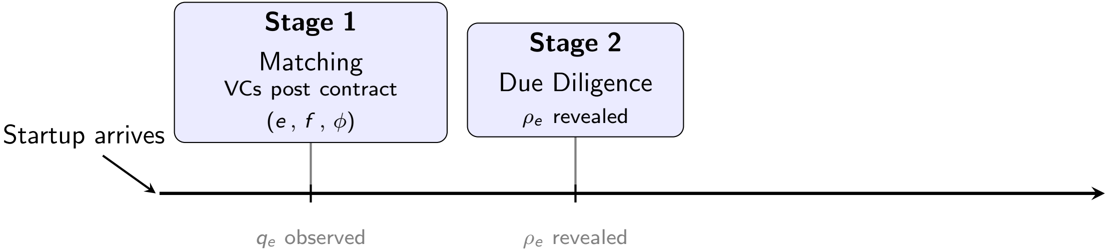

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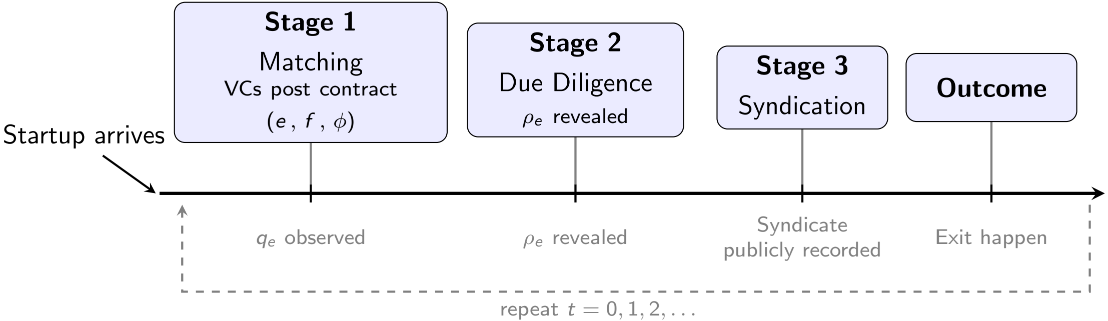

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- Value from matching for each agent:

$$V_e(f) \;=\; \mathbb{E}_H[x_f\, q_e\, v | \phi_f(\rho_e) = 1]$$

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- Higher quality startups match with better-connected VCs
  - Assortative matching on quality and connections
  - Conditional on minimum level of value-added capability

Proposition 1 Details

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$\rightarrow$ **Spillover management** is not enough to deter entry

Definition 1 (Collusive equilibrium)

- Every VC follows the collusive funding rule

$$\phi_f^{\text{coll}}(\rho_e) = \mathbf{1}\{\rho_e \le \bar{\rho}\}$$

(i) **Block every startup with** $\rho_e > \bar{\rho} = \min(\rho^*, \rho_f^*(q_e))$

(ii) **Deviate** and be permanently excluded from Network benefits

Stage Timing | Assumptions | Collusive Threshold ρ^* | Proposition 3 | Punishment Value

Collusive Equilibrium

Exit Rates and Punishment Value

- Blocking raises the **exit probability**:

$$x_f^{\mathrm{coll}}(\bar{\rho}, d) \;=\; x_f(k_f, \mathbf{z}_f) \;+\; \theta\, \mathcal{M}(\bar{\rho}, d)$$

  - $\mathcal{M}(\bar{\rho}, d)$, the **collusion premium**
    - Density-scaled blocked mass $\equiv\; d \cdot \Lambda \int_{\bar{\rho}}^{1} \left[1 - F(q^*(\rho))\right] dH(\rho)$
    - Strictly increasing in d at fixed k_f.

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- Entrepreneur's Matching value from collusion is ambiguous
  - Higher exit probability from blocking, $x_f^{\text{coll}} > x_f$
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Collusive Equilibrium

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  - d: market density $\equiv$ fraction of realized ties among all possible ties

Collusive Equilibrium

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  - Funding cutoff $\bar{\rho}$ may be higher or lower than non-collusive cutoff.
- How interconnected the network is helps sustain collusion
  - d: market density $\equiv$ fraction of realized ties among all possible ties
  - d is different from k_f:
    - d is a market-level measure of interconnectedness
    - k_f is an individual VC's degree.

Degree Distribution over Density

Empirical Predictions

Proposition 5

(i) *Exit rates* **increase** *in VC degree* k_f.

Full Prop 5 Identification Welfare

Empirical Predictions

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(ii) *Fewer startups funded in denser markets.*

Full Prop 5 Identification Welfare

Empirical Predictions

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(ii) *Fewer startups funded in denser markets.*

(iii) *Mean* $\hat{\rho}_e$ *of funded deals is* **lower** *in dense markets*

Full Prop 5 Identification Welfare

Empirical Predictions

Proposition 5

(i) *Exit rates* **increase** *in VC degree k_f.*

(ii) *Fewer startups funded in denser markets.*

(iii) *Mean $\hat{\rho}_e$ of funded deals is* **lower** *in dense markets*

(iv) *Mean $\hat{\rho}_e$ of funded deals is lower for high-S_f VCs*

Full Prop 5 Identification Welfare

Data and Measurement

- SDC Platinum / PitchBook — Only Funded startups!
  - VC funding rounds in the US, 1980–2015
  - Firm/Fund level characteristics, including deal value, syndicate size, etc.
  - Company/Founder characteristics, including industry, location, etc.

Firm-level Fund-level Industry-level State-level Company-level Market-level Syndication Market Density

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  - Patent (and trademark) similarity Warg (2023) Additional - Paine (2026)

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- VC market exposure (S_f):
  - Portfolio score from patent (and trademark) similarity data. (Warg, 2023)
  - Aggregated at VC-market-year level

Estimation

- Functional form assumptions:

$$x_f(k_f, \mathbf{z}_f) = \alpha_v k_f + \mathbf{z}_f' \gamma$$

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$$x_f(k_f, \mathbf{z}_f) = \alpha_v k_f + \mathbf{z}_f' \gamma\,, \qquad q_e = \mathbf{x}_e' \beta_q + \varepsilon_e$$

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- **Parameters:**

$$\Theta = (\alpha_v,\ \beta,\ \theta,\ c)$$

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α_v: Network value-added

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β: Spillover penalty

θ: Collusion strength

c: Investment cost

Estimation

- Functional form assumptions:

$$x_f(k_f, \mathbf{z}_f) = \alpha_v k_f + \mathbf{z}_f' \gamma\,, \quad q_e = \mathbf{x}_e' \beta_q + \varepsilon_e\,, \quad \mathcal{M} = V_e(f) + \Pi_f(e) + \xi_{ef}$$

- **Parameters:**

$$\Theta = (\alpha_v,\ \beta,\ \theta,\ c)$$

α_v: Network value-added

β: Spillover penalty

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c: Investment cost

- **Estimator:** SMM
  - match complementarities ξ_{ef} absorbed by fixed effects

$$\hat{\Theta} = \arg\min_{\Theta} \left[\mathbf{m}^{\text{data}} - \mathbf{m}^{\text{sim}}(\Theta)\right]' W \left[\mathbf{m}^{\text{data}} - \mathbf{m}^{\text{sim}}(\Theta)\right]$$

Identification

Variation	Moment	Identifies
Panel A: Structural Parameters (SMM)		
Exit rate slope on k_f, sparse markets	$\mathbb{E}[\Delta \text{Exit}/\Delta k \mid d \approx 0, \mathbf{z}_f]$	α_v

- Sorting has been included in the estimation.

Degree Distribution | Panel B + Calibrated → | Empirical Predictions

Identification

Variation	Moment	Identifies
Panel A: Structural Parameters (SMM)		
Exit rate slope on k_f, sparse markets	$\mathbb{E}[\Delta\text{Exit}/\Delta k \mid d \approx 0, \mathbf{z}_f]$	α_v
$\hat{\rho}_e$ slope on S_f, sparse markets	$\mathbb{E}[\Delta\hat{\rho}_e/\Delta S \mid d \approx 0]$	β

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Degree Distribution Panel B + Calibrated → Empirical Predictions

Identification

Variation	Moment	Identifies
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$\hat{\rho}_e$ slope on S_f, sparse markets	$\mathbb{E}[\Delta\hat{\rho}_e/\Delta S \mid d \approx 0]$	β
$\hat{\rho}_e$ gap: dense vs. sparse	$\mathbb{E}[\hat{\rho} \mid d \approx 1] - \mathbb{E}[\hat{\rho} \mid d \approx 0]$	θ

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$\hat{\rho}_e$ gap: dense vs. sparse	$\mathbb{E}[\hat{\rho} \mid d \approx 1] - \mathbb{E}[\hat{\rho} \mid d \approx 0]$	θ
Exit rate, solo unconstrained deals	$\mathbb{E}[\text{Exit} \mid S \approx 0, \hat{\rho} \approx 0, s_e = 1, d \approx 0]$	c

- Sorting has been included in the estimation.

Degree Distribution | Panel B + Calibrated → | Empirical Predictions

Next Steps

- Match startups to patents (and trademarks)
- Measurement of $\hat{\rho}_e$ and S_f
- Implement the SMM estimator
- Results:
  - Decomposition of the performance premium
  - Counterfactuals

Thank you!

References I

Cestone, Giacinta, and Lucy White. 2003. "Anticompetitive financial contracting: The design of financial claims." *The Journal of finance*, 58(5): 2109–2141.

Cetorelli, Nicola, and Philip E Strahan. 2006. "Finance as a barrier to entry: Bank competition and industry structure in local US markets." *The journal of Finance*, 61(1): 437–461.

Choo, Eugene, and Aloysius Siow. 2006. "Who Marries Whom and Why." *Journal of Political Economy*, 114(1): 175–201.

Cunningham, Colleen, Florian Ederer, and Song Ma. 2021. "Killer acquisitions." *Journal of political economy*, 129(3): 649–702.

Eldar, Ofer, and Jillian Grennan. 2024. "Common venture capital investors and startup growth." *The Review of Financial Studies*, 37(2): 549–590.

Ewens, Michael, and Matthew Rhodes-Kropf. 2015. "Is a VC partnership greater than the sum of its partners?" *The Journal of Finance*, 70(3): 1081–1113.

Fried, Jesse M, and Mira Ganor. 2006. "Agency costs of venture capitalist control in startups." *NYUL rev.*, 81: 967.

Fulghieri, Paolo, and Merih Sevilir. 2009. "Size and focus of a venture capitalist's portfolio." *The Review of Financial Studies*, 22(11): 4643–4680.

Giannetti, Mariassunta, and Farzad Saidi. 2019. "Shock propagation and banking structure." *The Review of Financial Studies*, 32(7): 2499–2540.

References II

Gompers, Paul, Anna Kovner, Josh Lerner, and David Scharfstein. 2010. "Performance persistence in entrepreneurship." *Journal of financial economics*, 96(1): 18–32.

González-Uribe, Juanita. 2020. "Exchanges of innovation resources inside venture capital portfolios." *Journal of Financial Economics*, 135(1): 144–168.

Hatfield, John William, and Paul R Milgrom. 2005. "Matching with contracts." *American Economic Review*, 95(4): 913–935.

Hatfield, John William, Scott Duke Kominers, and Richard Lowery. 2025. "Collusion in brokered markets." *The Journal of Finance*, 80(3): 1417–1462.

Hellmann, Thomas. 2002. "A theory of strategic venture investing." *Journal of financial economics*, 64(2): 285–314.

Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu. 2007. "Whom You Know Matters: Venture Capital Networks and Investment Performance." *Journal of Finance*, 62(1): 251–301.

Hochberg, Yael V, Alexander Ljungqvist, and Yang Lu. 2010. "Networking as a barrier to entry and the competitive supply of venture capital." *The Journal of Finance*, 65(3): 829–859.

Kaplan, Steven N, and Antoinette Schoar. 2005. "Private equity performance: Returns, persistence, and capital flows." *The journal of finance*, 60(4): 1791–1823.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. "Technological innovation, resource allocation, and growth." *The quarterly journal of economics*, 132(2): 665–712.

References III

Lindsey, Laura. 2008. "Blurring firm boundaries: The role of venture capital in strategic alliances." *The Journal of Finance*, 63(3): 1137–1168.

Li, Xuelin, Tong Liu, and Lucian A Taylor. 2023. "Common ownership and innovation efficiency." *Journal of financial economics*, 147(3): 475–497.

Mayer, Colin. 1988. "New issues in corporate finance." *European Economic Review*, 32(5): 1167–1183.

Paine, Fiona. 2026. "The Startup Valley of Death and Measuring Innovation." *Available at SSRN 5521639*.

Petersen, Mitchell A, and Raghuram G Rajan. 1995. "The effect of credit market competition on lending relationships." *The Quarterly Journal of Economics*, 110(2): 407–443.

Pichler, Pegaret, and William Wilhelm. 2001. "A theory of the syndicate: Form follows function." *The Journal of Finance*, 56(6): 2237–2264.

Pollman, Elizabeth. 2019. "Startup governance." *U. Pa. L. Rev.*, 168: 155.

Saidi, Farzad, and Daniel Streitz. 2021. "Bank concentration and product market competition." *The Review of Financial Studies*, 34(10): 4999–5035.

Sørensen, Morten. 2007. "How smart is smart money? A two-sided matching model of venture capital." *The Journal of Finance*, 62(6): 2725–2762.

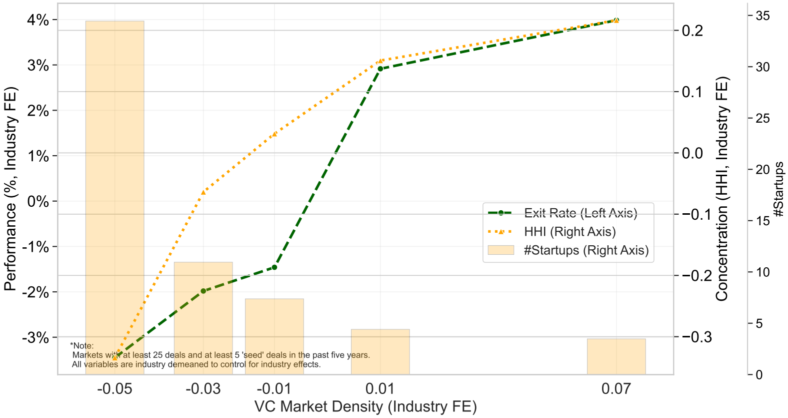
Sorenson, Olav, and Toby E Stuart. 2001. "Syndication networks and the spatial distribution of venture capital investments." *American journal of sociology*, 106(6): 1546–1588.

Stuart, Toby E, and Olav Sorenson. 2007. "Strategic networks and entrepreneurial ventures." *Strategic Entrepreneurship Journal*, 1(3-4): 211–227.

Warg, Katarina. 2023. "The acquisition option and startup innovations." Working paper.

Market Level Evidence (1980-2015)

Seed Deals

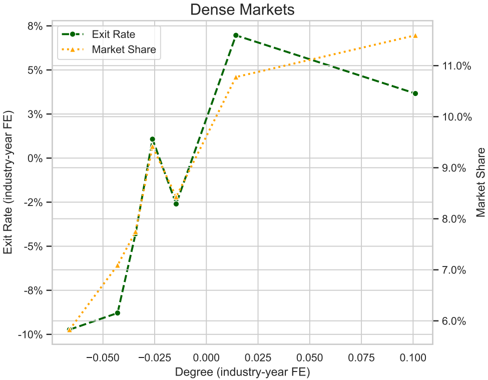


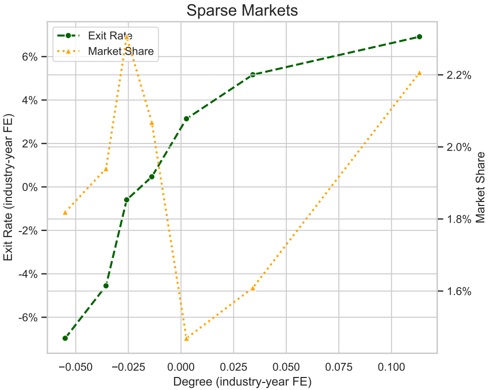
Back

Company Level Evidence (1980-2015)

Seed Deals

- Company-level





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Summary Statistics

Average of Markets in different Density Bins

	Bin 1	Bin 2	Bin 3	Bin 4	Bin 5
Market Density	2.46%	4.50%	6.54%	9.17%	14.94%
Exit Rate	46.54%	49.25%	52.97%	53.05%	55.74%
HHI VC Seed	22.39%	39.69%	47.82%	53.11%	63.69%
HHI VC Overall	9.95%	16.24%	19.61%	24.78%	25.52%
HHI Company Seed	33.30%	61.32%	71.94%	85.91%	92.15%
HHI Company Overall	16.86%	29.79%	34.87%	47.49%	53.32%
Average Round Number	3.23	3.26	3.37	3.42	3.45
# VC Firms	116	45	33	20	15
# Startups	85	25	16	9	6
Market Size	$917.51M	$222.28M	$111.63M	$75.59M	$39.84M

Back

Michael Arrington

TechCrunch co-founder

Yesterday I was tipped off about a "secret meeting" between a group of "Super Angels" being held at Bin 38, a restaurant and bar in San Francisco. "Do not come, you will not be welcome," I was told.

Back

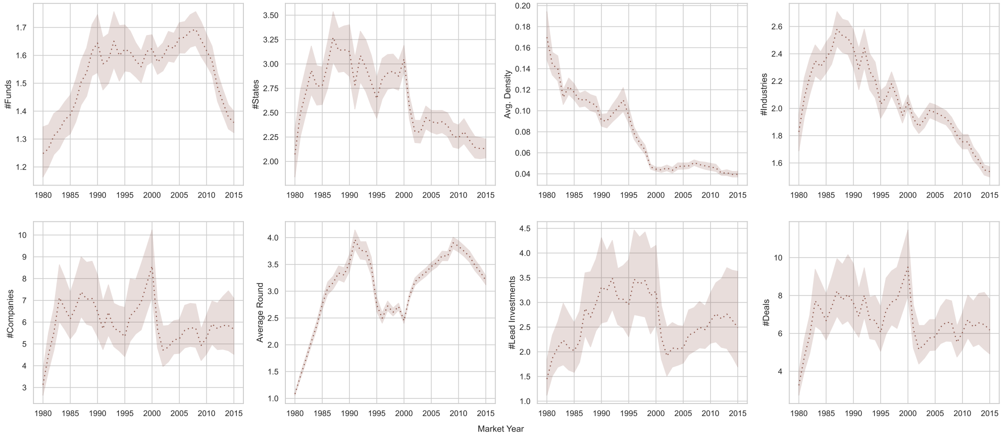
Two Worlds of Venture

Geri Kirilova (she/her)
@geri_kirilova

Seeing all these tweets about how everyone's raising at $30M pre-product, while at least 25% of the founders I'm meeting have been fighting for months to put together $500k. There have always been two worlds of venture but the disconnect has never been starker

9:52 PM · Mar 20, 2021 · Twitter for Android

Firm Level Trends (1980-2015)



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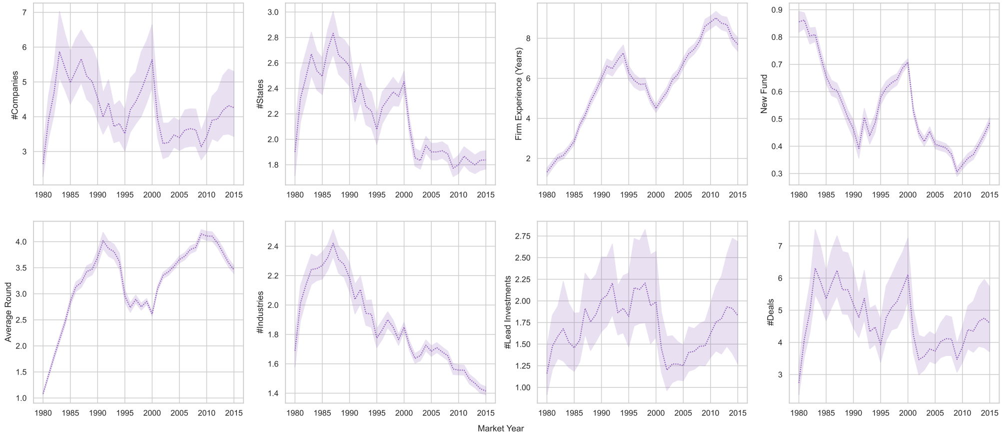
Fund Level Trends (1980-2015)



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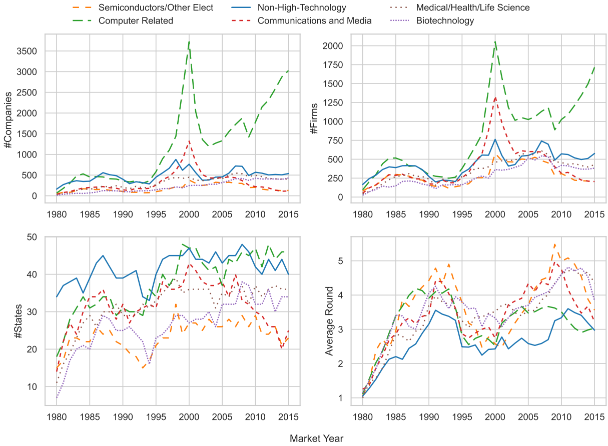
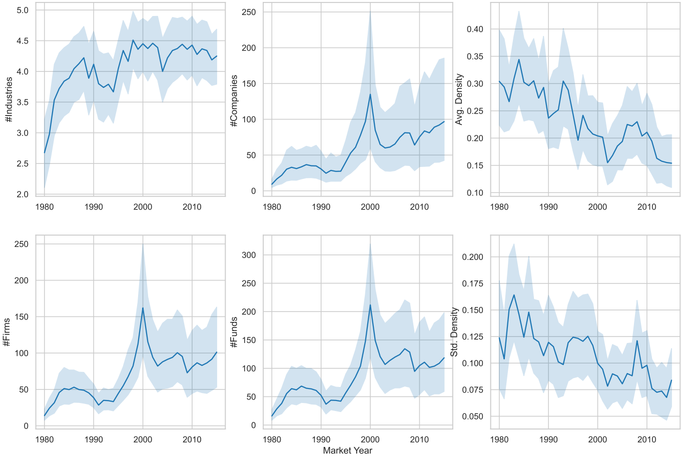
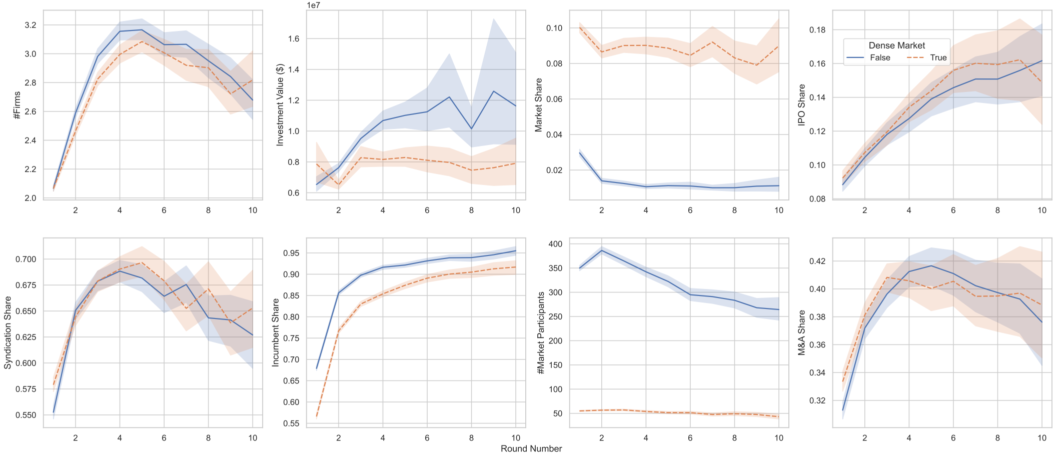
Industry Level Trends (1980-2015)



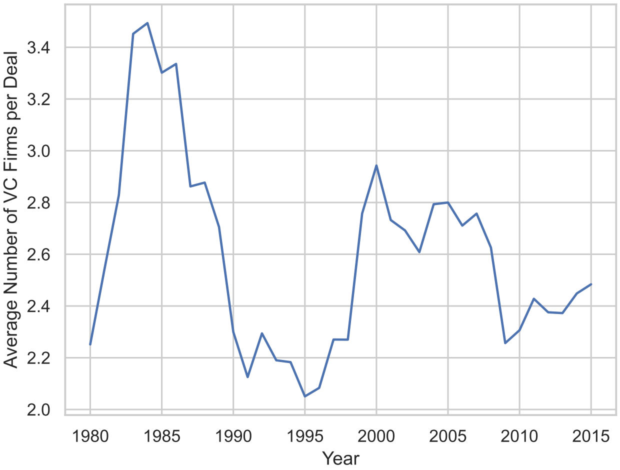
State Level Trends (1980-2015)



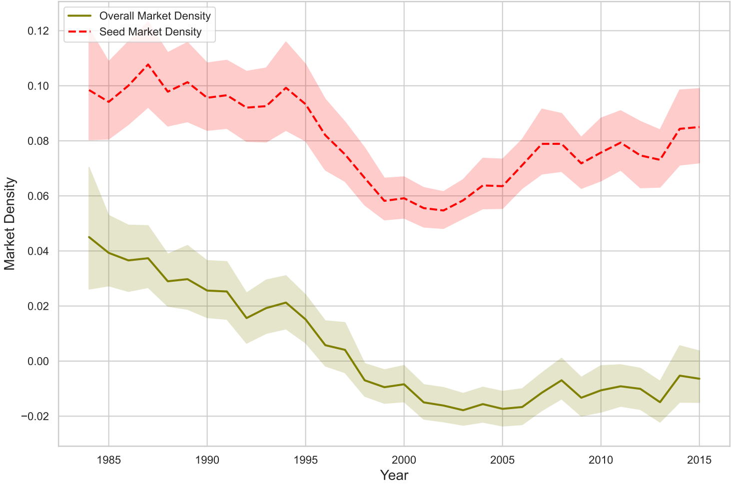
Company Level by Dense Market (1980-2015)



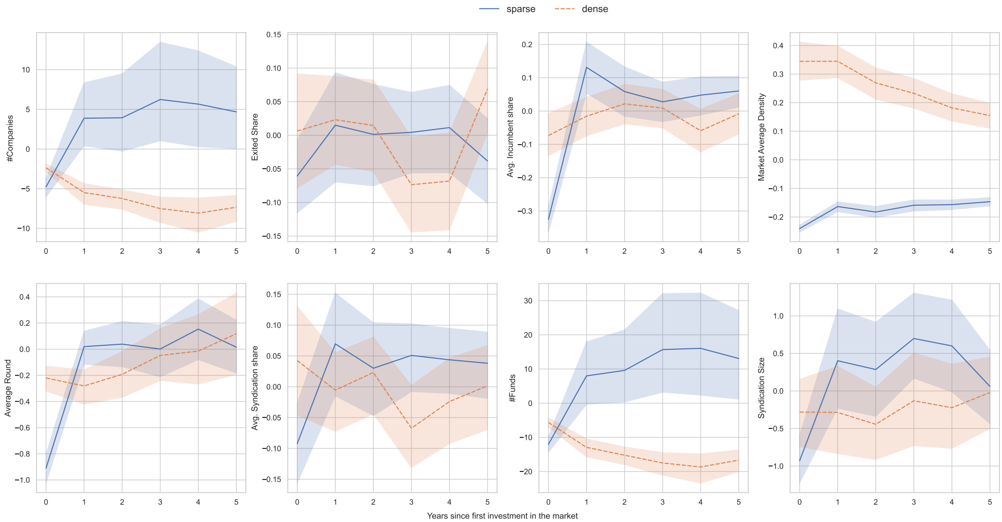
Average Number of Firms per Deal (1980-2015)



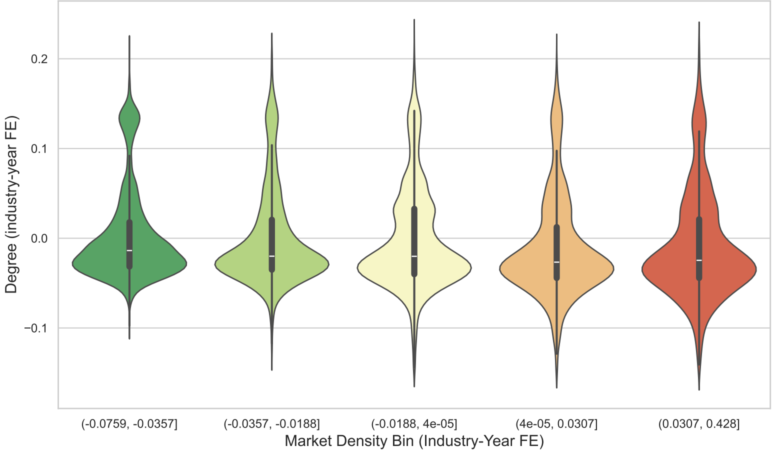
Market Density over Time (1980-2015)



Market Level Trends (1980-2015)



Degree Distribution over Density



VC Payoffs under Syndication

- Investment cost c split equally: each member pays c/s_e
- Exit proceeds split equally: each member receives $1/s_e$ share

- **Lead VC** f payoff:

$$\pi_f^e = \frac{x_f\, q_e\, v - c}{s_e} - \beta\, S_f\, \rho_e, \qquad x_f = x_0 + \alpha_v\, k_f + \boldsymbol{\gamma}'\mathbf{z}_f$$

- **Co-investor** g payoff:

$$\pi_g^{\text{co}}(e, s_e) = \frac{x_f\, q_e\, v - c}{s_e} - \beta\, S_g\, \rho_e, \qquad x_g = x_0 + \alpha_v\, k_g + \boldsymbol{\gamma}'\mathbf{z}_g$$

- Co-investor g accepts iff $\pi_g^{\text{co}} \geq 0$:

$$\frac{x_f\, q_e\, v - c}{s_e} \geq \beta\, S_g\, \rho_e$$

High-exposure co-investors **self-select out** of high-overlap deals

Optimal Syndicate Size I

- Adding a co-investor **dilutes** the lead VC:

$$\frac{\partial \pi_f}{\partial s_e} = -\frac{x_f\, q_e\, v - c}{s_e^2} < 0$$

Syndication is not cost-driven

- Adding a co-investor **strengthens enforcement**: g observes the deal and can punish future deviations. The full enforcement value of co-investor g has **three channels** (value-added loss, collusion-probability loss, matching quality loss):

$$\Pi_g = \frac{\delta}{1-\delta}\left[x_0\, v\,\left(\alpha_v\, k_g + \theta\, \mathcal{M}(\bar{\rho}, d)\right) + \Delta W_g^{\mathrm{match}}\right]$$

Total syndicate enforcement value: $V^{\mathrm{enf}}(s, d) = \sum_{j=1}^{s-1} \Pi_{g_j}$

Optimal Syndicate Size II

- Lead VC invites eligible neighbors in *decreasing order of degree*:

$$s_e^* = \arg\max_s \left[V^{\mathrm{enf}}(s,d) - \frac{x_f\, q_e\, v - c}{s} \right]$$

- **Lemma**: s_e^* is unique — objective is single-peaked (concave enforcement benefit, convex dilution relief), constrained by a shrinking eligible set as $\rho_e \uparrow$
- Two empirical patterns:
  - **Syndicate thinning**: eligible set $\mathcal{E}_e$ shrinks as $\rho_e \uparrow$ — high-exposure neighbors self-select out of high-overlap deals
  - **Size-density gradient**: s_e^* weakly increasing in d — more neighbors and higher Π_g (strictly so when marginal co-investor has $k_g > 0$)
- **Recursive structure**: Π_g depends only on primitives, *not* on $\bar{\rho} \Rightarrow s_e^*$ is determined before the collusive threshold; no circularity

Back

Contract Execution: Self-Enforcing Cutoff

- ρ_e is revealed during due diligence. The VC **executes** the committed rule ϕ_f — no separate decision is made:

$$\phi_f(\rho_e) = \mathbf{1}\{\rho_e \leq \rho_f^*(q_e)\} \iff q_e \geq \tilde{q} + \frac{\beta \, S_f \, \rho_e}{x_f \, v} \equiv q_f^*(\rho_e)$$

- **Comparative statics** (all by direct differentiation):
  - $\partial q_f^* / \partial \rho_e > 0$: higher overlap $\Rightarrow$ stricter quality bar
  - $\partial q_f^* / \partial k_f < 0$: higher-degree VC willing to fund higher-overlap deals
  - $\partial q_f^* / \partial S_f > 0$: more exposed VC applies stricter quality floor
- Some other VC g with $k_g > k_f$ or $S_g < S_f$ will fund what VC f refuses
- **Spillover management alone cannot deter rivals**

Derivation | Full Comp. Statics | Back

Matching Stage: Details

- **Self-enforcing commitment**: the committed rule ϕ_f coincides with the VC's post-match incentive, so no renegotiation occurs on the equilibrium path
- **Acceptance probability** $H(\rho_f^*(q_e))$:
  - Higher k_f raises x_f and widens ρ_f^* (good for startup)
  - Higher S_f narrows ρ_f^* (bad for startup)
  - Whether entrepreneurs prefer higher-degree VCs depends on $\lambda \equiv \partial S_f / \partial k_f$ — **an empirical question**
- **No blocking pair**: $V_e(g) > V_e(f(e))$ *and* g prefers e over a current deal in its portfolio
- **Supermodularity** of $\mathcal{M}(k_f, S_f, q_e, \mathbf{x}_e, \mathbf{z}_f)$ in (k_f, q_e):
  - $\xi_{ef} = \mathbf{x}_e' \Gamma \mathbf{z}_f$ is additively separable: cross-partial is zero, so assortativity condition is unchanged
  - Sufficient condition: $\lambda \leq 0$ (denser VCs carry weakly smaller market exposure)
  - If $\lambda > 0$: assortativity verified at the structural estimates — an over-identifying restriction

Back

Proposition 1 (Assortative matching)

Under A1 and homogeneous capacity $\bar{n}$, a stable allocation exists. It is **positively assortative** *in (k_f, q_e) whenever*

$$\frac{\partial^2 \mathcal{M}}{\partial k_f \, \partial q_e} > 0,$$

where $\mathcal{M}(k_f, S_f, q_e, \mathbf{x}_e, \mathbf{z}_f) = V_e(f) + \Pi_f(e) + \xi_{ef}$ is the joint contract surplus. The complementarity term $\xi_{ef} = \mathbf{x}_e' \Gamma \mathbf{z}_f$ is additively separable and does not affect this cross-partial. A sufficient condition is $\lambda \equiv \partial S_f / \partial k_f \leq 0$.

- **Existence** via Hatfield-Milgrom generalized Gale-Shapley algorithm: contracts are substitutes for every VC $\Rightarrow$ stable allocation exists and is generically unique
- **Key boundary condition**: at the funding margin $\rho_e = \rho_f^*$, the VC is exactly indifferent $\Rightarrow$ the boundary term in $\partial \mathcal{M} / \partial q_e$ vanishes, making the cross-partial tractable
- **Sufficient condition** $\lambda \leq 0$: denser VCs carry weakly smaller market exposure $\Rightarrow$ $H(\rho_f^*)$ strictly increasing in k_f $\Rightarrow$ supermodularity holds for any $\alpha_v > 0$

- **When** $\lambda > 0$: there exists an explicit finite bound $\bar{\alpha}_v(\lambda, S_f, q_e)$ such that assortativity holds for all f and $q_e \geq \tilde{q}$ whenever $\alpha_v > \bar{\alpha}_v$. This is verified ex post by evaluating the supermodularity condition at $(\hat{\alpha}_v, \hat{\lambda})$, providing an over-identifying restriction

- **Empirical content**: $\hat{\lambda}$ estimated from VC market exposure S_f regressed on degree; determines which case applies

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Proposition: Stage-Game Equilibrium I

Proposition 2 (Stage-game equilibrium)

Under A1 and homogeneous capacity $\bar{n}$, the stage game has a unique subgame-perfect equilibrium in threshold strategies:

(i) *Assortative stable allocation (Proposition 1)*

(ii) *Each VC f funds iff $q_e \geq q_f^*(\rho_e)$; committed rule ϕ_f coincides with post-match incentive — no renegotiation*

(iii) *Syndicate composition follows $s_e^* = \arg\max_s \Phi(s)$ (Lemma 1)*

(iv) *Portfolio management alone cannot deter all profitable high-overlap startups*

- Part (iv) is the key bridge to the repeated game: heterogeneity in (k_f, S_f) guarantees some VC always finds it profitable to fund a high-overlap startup unilaterally
- The proof is constructive: for any startup with $\rho_e > \rho_f^*(q_e)$ for some lead VC f, a VC g with $k_g > k_f$ or $S_g < S_f$ satisfies $q_g^*(\rho_e) < q_f^*(\rho_e)$, so g would profitably fund it

Proposition: Stage-Game Equilibrium II

- This means pure portfolio management — the stage game alone — cannot block all profitable rivals; network coordination (Mechanism III) is required

Back to Matching Repeated Game

Proposition: Existence of the Collusive Equilibrium I

Proposition 3 (Collusive equilibrium existence)

Under A1, A3 (contraction), A4 ($\delta < 1/(1 + x_0)$), and A5 (α_v dominance), a collusive equilibrium (Def. 1) exists with:

(i) *Unique threshold $\bar{\rho} \in (0, 1)$ from the fixed-point equation*

(ii) $x_f^{\mathrm{coll}}(\bar{\rho}, d) > x_f$ *for all f; acceptance distribution truncated at $H(\bar{\rho})$ for high-quality startups*

(iii) *Credible punishment: threshold $\underline{k}$ exists s.t. all g with $k_g \geq \underline{k}$ prefer exclusion*

(iv) *Renegotiation-proof: contagion punishment makes bilateral renegotiation unprofitable for all g with $k_g \geq \underline{k}$*

- **Part (i) — interiority**: at $\bar{\rho} = 0$, RHS $> 0 =$ LHS (viable market condition $x_0 v > c$); at $\bar{\rho} = 1$, LHS grows large enough $\Rightarrow$ crossing at interior $\bar{\rho}^* \in (0, 1)$
- **Part (ii) — two collusion effects on H**: the exit-rate upgrade $\theta\, \mathcal{M}(\bar{\rho}, d)$ raises x_f^{coll} above the competitive x_f; the acceptance probability collapses from $H(\rho_f^*(q_e))$ to $H(\bar{\rho})$ for all high-quality startups with $\rho_f^*(q_e) > \bar{\rho}$
- **Part (iii) — punishment threshold**: $\underline{k} = \left(\bar{\pi}^{\mathrm{co}}/\delta - x_0 v\, \theta\, \mathcal{M}\right) / (\alpha_v x_0 v)$; finite and strictly below $k_{\max}$ in any dense market

Proposition: Existence of the Collusive Equilibrium II

- **Subgame-perfection**: on-path play follows the stage-game equilibrium (Proposition 2) subject to $\rho_e \leq \bar{\rho}$; off-path punishment and contagion are individually rational at every history

Back to Collusion

Derivation of the Funding Cutoff

- After the match is formed and ρ_e is revealed, lead VC f compares startup e to the *marginal startup at the participation threshold* e': same overlap $\rho_{e'} = \rho_e$, quality $q_{e'} = \tilde{q}$
- VC f prefers startup e over e' iff:

$$\frac{x_f\, q_e\, v - c}{s_e} - \beta\, S_f\, \rho_e \geq \frac{x_f\, \tilde{q}\, v - c}{s_e} - \beta\, S_f\, \rho_e$$

- Spillover terms $\beta\, S_f\, \rho_e$ cancel (S_f is a VC characteristic, same on both sides). Syndicate size s_e cancels (same $\rho_e \Rightarrow$ same optimal syndicate at the margin). Rearranging:

$$q_e \geq \tilde{q} + \frac{\beta\, S_f\, \rho_e}{x_f\, v} \equiv q_f^*(\rho_e), \qquad x_f = x_0 + \alpha_v\, k_f + \boldsymbol{\gamma}' \mathbf{z}_f$$

- **Key implications**:
  - Cutoff is *invariant to syndicate size* s_e — equal splitting cancels
  - Cutoff depends on α_v through x_f — once matched, funding reflects exit-rate ability
  - S_f enters as a VC-level constant: two startups with the same overlap facing the same VC get the same quality hurdle

Funding Cutoff: Comparative Statics

- Equilibrium funding cutoff:

$$q_f^*(\rho_e) \;=\; \tilde{q} + \frac{\beta\, S_f\, \rho_e}{x_f\, v}, \qquad x_f = x_0 + \alpha_v\, k_f + \boldsymbol{\gamma}'\mathbf{z}_f$$

- Comparative statics :
  (i) $\partial q_f^* / \partial \rho_e = \beta\, S_f \,/\, (x_f\, v) \geq 0$, *strictly* when $S_f > 0$
  (ii) $\partial q_f^* / \partial k_f = -\beta\, S_f\, \rho_e\, \alpha_v \,/\, (x_f^2\, v) \leq 0$, *strictly* when $\alpha_v > 0$, $S_f > 0$, and $\rho_e > 0$
  (iii) $\partial q_f^* / \partial S_f = \beta\, \rho_e \,/\, (x_f\, v) \geq 0$, *strictly* when $\rho_e > 0$
- Part (ii): cutoff signed by α_v — once matched, funding depends on exit-rate ability
- **Pure complements ($\rho_e = 0$)**: overlap penalty vanishes; $q_f^* = \tilde{q}$ for all VCs — degree-invariant cutoff
- **Participation threshold**: NPV floor $\underline{q} = c/(x_0 v)$ is the lower bound; capacity constraint $\Lambda\left[1 - F(\tilde{q})\right] = N\bar{n}$ pins $\tilde{q} \geq \underline{q}$
  - $\tilde{q} = \underline{q}$: capacity slack, all NPV-positive deals funded
  - $\tilde{q} > \underline{q}$: capacity scarce, VCs ration to top-quality arrivals

Punishment Strategy and Compliance

Compliance incentive constraint for every VC g (evaluated at $q_e = 1$, $s_e^* = 1$):

$$\underbrace{\big(x_0 + \alpha_v k_g + \boldsymbol{\gamma}'\mathbf{z}_g + \theta\,\mathcal{M}(\bar{\rho}, d)\big)v - c}_{\text{gross deviation gain}} \leq \underbrace{\beta\, S_g\, \bar{\rho}}_{\text{market-exposure harm}} + \underbrace{\frac{\delta}{1-\delta}\left[x_0\, v\, (\alpha_v\, k_g + \theta\,\mathcal{M}(\bar{\rho}, d)) + \Delta W_g^{\text{match}}\right]}_{\text{punishment value } \delta\Pi_g}$$

- Deviation gain uses $x_g^{\text{coll}} = x_0 + \alpha_v k_g + \boldsymbol{\gamma}'\mathbf{z}_g + \theta\,\mathcal{M}(\bar{\rho}, d)$: deviator funds startup *while coalition still active*
- Punishment loses only $\alpha_v k_g$ (network component): $\boldsymbol{\gamma}'\mathbf{z}_g$ (fund size, sequence) persists after exclusion
- **Three punishment channels**: value-added loss, collusion-probability loss, and matching quality loss $\Delta W_g^{\text{match}}$ (drops to bottom of startup queue)
- **Co-investor credibility**: g prefers exclusion iff $\Pi_g \geq \pi_g^{\text{co,outside}}$; holds for $k_g \geq \underline{k}$
- **Renegotiation-proof**: contagion — any (f^*, g) resuming co-investment triggers punishment against g

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Punishment Value: Three Channels

- After exclusion from all future syndicates, deviator f^* suffers three per-period payoff losses, discounted at rate δ:

$$\Pi_{f^*} = \frac{\delta}{1-\delta}\Big[\underbrace{\alpha_v\, k_{f^*}\, x_0\, v}_{\text{(1) value-added loss}} + \underbrace{\theta\, \mathcal{M}(\bar{\rho}, d)\, x_0\, v}_{\text{(2) collusion-probability loss}} + \underbrace{\Delta W^{\mathrm{match}}_{f^*}}_{\text{(3) matching quality loss}} \Big]$$

- **(1) Value-added loss.** Exclusion collapses f^*'s effective degree to zero, removing the *network* component $\alpha_v k_{f^*}$ of the exit rate. Observable VC characteristics $\gamma' \mathbf{z}_{f^*}$ (fund size, sequence) are not network-mediated and **persist** after exclusion. Per-period payoff loss: $\alpha_v k_{f^*} \cdot x_0 v$
- **(2) Collusion-probability loss.** f^*'s portfolio reverts to the competitive exit rate x_{f^*}, forfeiting the exit-probability upgrade $\theta\, \mathcal{M}(\bar{\rho}, d)$ sustained by the coalition. Per-period loss: $\theta\, \mathcal{M}(\bar{\rho}, d) \cdot x_0 v$
- **(3) Matching quality loss.** Under positive assortative matching, f^*'s degree was the basis for attracting high-quality startups. After exclusion, f^* drops to the bottom of every startup's preference ranking and is left with startups near the participation floor $\tilde{q}$:

$$\Delta W^{\mathrm{match}}_{f^*} \equiv \int_{Q_{f^*}} x_0\, q_e\, v\, \mathrm{d}F(q_e) - x_0\, \tilde{q}\, v\, \bar{n} \geq 0$$

Strictly positive whenever assortativity holds; strictly increasing in k_{f^*}: better-networked VCs attract higher-quality portfolios and therefore fall further upon exclusion

Maintained Assumptions I

Assumption 1 (A1 — Independence of startup attributes)

$q_e \perp \rho_e$: quality and competitive overlap are independently distributed. $\mathbb{E}[\rho_e] \equiv \mu_\rho$ is the same constant for every VC–startup pair, regardless of degree or market exposure. Role: ensures overlap does not affect which startup is matched to which VC, so matching is driven by (k_f, S_f, q_e) alone. Testable: $\hat{\rho}_e^{\text{pat}}$ uncorrelated with VC degree and the entrepreneur quality index $\mathbf{x}_e'\hat{\beta}_q$ within market-year cells.

Assumption 2 (A2 — Stationarity of post-exclusion matching)

After deviator f^* is excluded, the matching equilibrium of surviving VCs converges to a fixed distribution within one period; f^*'s deal flow converges to startups near the participation floor $\tilde{q}$. Role: makes the matching quality loss $\Delta W_{f^*}^{\text{match}}$ tractable. Direction of loss is robust to convergence speed; magnitude verified in the estimation section.

Assumption 3 (A3 — Contraction of the blocking feedback)

Maintained Assumptions II

$\theta \, \Lambda \, h(\bar{\rho}) \, [1 - F(q^*(\bar{\rho}))] \cdot \left(1 - \frac{\delta x_0}{1-\delta}\right) v < \beta \, S_{g^*}$ for all $\bar{\rho} \in [0,1]$. Role: the marginal deterrence force (market-exposure penalty) dominates the marginal feedback from blocking — guarantees a unique fixed-point $\bar{\rho}^*$. Plausible: θ is a second-order effect; βS_{g^*} is a first-order direct cost. Parameter restriction maintained throughout.

Assumption 4 (A4 — Discount-rate bound)

$\delta < 1/(1 + x_0)$. Role: ensures the value-added punishment channel $(\delta \alpha_v x_0 v/(1-\delta))$ outweighs the value-added deviation gain $(\alpha_v v)$, making the net fixed-point shift positive in k_{g^*}. Not restrictive: $x_0 = 0.15$ gives $\delta < 0.87$. Relation to HKL: plays the same role as $\delta \geq \frac{1}{2}$ in Hatfield, Kominers, and Lowery (2025) — ensuring the future is valuable enough to deter deviation. No closed-form δ threshold arises here because the $\theta \mathcal{M}$ feedback prevents the proportionality cancellation that yields the clean HKL condition. Details

Assumption 5 (A5 — Parametric compliance restriction)

Maintained Assumptions III

$\alpha_v\, v\,(1 - \frac{\delta x_0}{1-\delta}) > \frac{\delta\, \omega}{1-\delta}$, *where* $\omega \equiv \partial \Delta W^{\text{match}}_{g^*} / \partial k_{g^*} > 0$ *is the marginal matching quality loss. Role: ensures the value-added channel in the deviation gain dominates the matching quality loss increment in the punishment, so* $\partial \bar{\rho} / \partial k_{g^*} > 0$. *Parameter restriction maintained throughout; verification in estimation section.*

Assumption 6 (A6 — HHI dominance of entry deterrence)

$\Delta N_f / N_f < \Delta D / D$ *for every incumbent VC* f *with* $N_f > 0$, *where* $\Delta N_f \leq 0$ *and* $\Delta D < 0$ *are the reductions in deal counts caused by tightening* $\bar{\rho}(d)$. *Role: ensures each incumbent's market share* $\sigma_f = N_f / D$ *rises strictly when blocking increases, so HHI rises through the entry-deterrence channel. Sufficient condition: blocked deals are spread across at least two VCs (guaranteed when* $N \geq 2$ *and the blocked startups span multiple portfolios).*

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Repeated Game and Collusion I

- The stage game infinitely repeated, $t = 0, 1, 2, \ldots$
- **Public history**: Funded deals and syndicate compositions through $t - 1$
- Collusion adds a **coalition-level blocking threshold** $\bar{\rho} \in [0, 1]$ on top of individual funding rules. The **collusive contract** becomes:

$$\phi_f^{\text{coll}}(\rho_e) \; = \; \mathbf{1}\Big\{\rho_e \leq \min\big(\bar{\rho}, \; \rho_f^*(q_e)\big)\Big\}$$

  - $\rho_e \leq \bar{\rho}$: startup funded under competitive cutoff $q_f^*(\rho_e)$
  - $\rho_e > \bar{\rho}$: startup **blocked by the coalition**, regardless of quality
- **Collusion also changes the matching stage**
  - Acceptance probability becomes $H(\min(\bar{\rho}, \rho_f^*(q_e)))$
- **Two forces** deter deviation:
  1. **Portfolio harm**: funding a rival hurts own incumbents directly
  2. **Network exclusion**: neighbors permanently cut off the deviator

The Collusive Threshold $\bar{\rho}$ I

- Bind the CIC at the *weakest-link VC* g^* at the *highest-quality* blocked startup ($q_e = 1$):

$$\beta\, S_{g^*}\; \bar{\rho} \;=\; x_g^{\text{coll}}(\bar{\rho}, d)v - c - \Pi_{g^*}(\bar{\rho}, d)$$

Derivation

  - LHS: market-exposure deterrence force
  - RHS: net deviation incentive = gross gain − punishment (value-added, collusion-probability, *and matching quality loss*)

- This is a **fixed-point equation** in $\bar{\rho}$ — solved numerically
  - RHS increasing in $\bar{\rho}$ (via $\theta\,\mathcal{M}$, which rises as lower limit $\bar{\rho}$ falls); LHS linear
  - Unique solution under **A2**: $\theta\,\Lambda\,h(\bar{\rho})\,[1 - F(q^*(\bar{\rho}))] \cdot (1 - \frac{\delta x_0}{1-\delta})v < \beta\, S_{g^*}$

- Two deterrence forces both expand $\bar{\rho}$:
  - $\uparrow S_{g^*}$: more exposed VC bears greater market-exposure harm from deviating
  - $\uparrow k_{g^*}$: higher-degree VC loses more from exclusion ($\Pi_{g^*} \uparrow$); requires **A3+A4**

The Collusive Threshold $\bar{\rho}$ II

- $\bar{\rho}$ is **strictly increasing in market density** d Proposition 4 Back
  - Direct channel: $\mathcal{M}(\bar{\rho}, d) = d \cdot \Lambda \int_{\bar{\rho}}^{1} [\cdots] \, dH(\rho)$, so $\partial \mathcal{M}/\partial d > 0$ *at fixed* $k_f \Rightarrow \partial R/\partial d > 0$ in the fixed-point condition
  - Operates independently of average degree: two markets with the same k distribution but different d sustain different $\bar{\rho}$

Derivation of $\bar{\rho}$

- **Step 1 — Binding quality**: deviation gain increasing in q_e; deterrence forces independent of $q_e \Rightarrow$ constraint *hardest* at $q_e = 1$
- **Step 2 — Cancel s_e^***: set $s_e^* = 1$ (solo deviation — worst case); substitute $x_g^{\text{coll}} = x_0 + \alpha_v k_g + \boldsymbol{\gamma}'\mathbf{z}_g + \theta\,\mathcal{M}(\bar{\rho}, d)$ and Π_g; bind at equality:

$$\big(x_0+\alpha_v k_g+\boldsymbol{\gamma}'\mathbf{z}_g+\theta\,\mathcal{M}(\bar{\rho},d)\big)v-c \;=\; \beta\,S_g\,\bar{\rho}+\frac{\delta}{1-\delta}\big[x_0\,v\,(\alpha_v k_g+\theta\,\mathcal{M}(\bar{\rho},d))+\Delta W_g^{\text{match}}\big]$$

- **Step 3 — Fixed point**: isolate $\bar{\rho}$ at binding VC g^*:

$$\beta\,S_{g^*}\,\bar{\rho} \;=\; \underbrace{\big(x_0+\alpha_v k_{g^*}+\boldsymbol{\gamma}'\mathbf{z}_{g^*}+\theta\,\mathcal{M}(\bar{\rho},d)\big)v-c-\frac{\delta}{1-\delta}\big[x_0 v(\alpha_v k_{g^*}+\theta\,\mathcal{M}(\bar{\rho},d))+\Delta W_{g^*}^{\text{match}}\big]}_{R(\bar{\rho};\,S_{g^*},\,k_{g^*},\,d)}$$

  - Punishment loses only $\alpha_v k_{g^*}$: $\boldsymbol{\gamma}'\mathbf{z}_{g^*}$ persists after exclusion
  - $\mathcal{M}(\bar{\rho},d) = d\cdot\Lambda\int_{\bar{\rho}}^{1}[1-F(q^*(\rho))]\,dH(\rho)$; $\partial\mathcal{M}/\partial\bar{\rho}<0$ (RHS increasing in $\bar{\rho}$); $\partial\mathcal{M}/\partial d>0$ at fixed k_{g^*} (direct density effect)
  - $R(\bar{\rho};\cdot)$ increasing in $\bar{\rho}$ via $\theta\,\mathcal{M}$ but at a *slower rate* than LHS (Assumption A2: $\theta\,\Lambda\,h(\bar{\rho})[1-F(q^*(\bar{\rho}))]\cdot(1-\frac{\delta x_0}{1-\delta})v<\beta\bar{S}_{g^*}$) $\Rightarrow$ unique fixed point; solved numerically

Empirical Predictions: Full Proposition 5

Proposition 5 (Identifying restrictions and market concentration)

(i) *Exit rates are* **strictly increasing** *in VC degree k_f, for all startups and all overlap levels.*

(ii) *The* **market-wide coalition funding probability** *is strictly decreasing in ρ_e. For $\rho_e \leq \bar{\rho}$ the decline is continuous with slope independent of d. At $\rho_e = \bar{\rho}(d)$ the probability* **drops discontinuously** *to zero and this threshold shifts left as $d \uparrow$. No individual VC's rule ϕ_f is discontinuous; the drop is a coalition-level effect.*

(iii) *Mean syndicate size $\mathbb{E}[s_e^*]$ is weakly increasing in d, strictly so whenever the marginal co-investor's degree is positive.*

(iv) *The post-match funding rate $H(\rho_f^*(q_e))$ is strictly decreasing in S_f conditional on q_e. Since rejections are unobserved, the observable implication is that the* **overlap distribution of funded deals shifts left** *for higher-S_f VCs conditional on quality.*

(v) *Market concentration $\mathrm{HHI}(d)$ is strictly increasing in d under the supermodularity condition and Assumption A6, decomposing additively into a sorting component (assortative deal-flow skewness) and an entry-deterrence component (D falls proportionally more than any N_f). No single mechanism generates all five patterns jointly.*

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Proposition: Collusive Threshold Increases in Density I

Proposition 4 (Collusive threshold)

Under Assumptions A2 (contraction), A3 ($\delta < 1/(1+x_0)$), and A4 (α_v dominance), the equilibrium overlap threshold $\bar{\rho}$ is strictly increasing in S_{g^*}, k_{g^*}, and market density d.

- **Monotonicity in S_{g^*}:** larger market exposure raises LHS only $\Rightarrow$ fixed point shifts up

$$\frac{d\bar{\rho}}{dS_{g^*}} = \bar{\rho}\,\beta \,/\, (\beta S_{g^*} - \partial R/\partial\bar{\rho}) > 0$$

- **Monotonicity in k_{g^*}** (under A3 and A4): implicit differentiation gives

$$\frac{\partial R}{\partial k_{g^*}} = \alpha_v v\left(1 - \frac{\delta x_0}{1-\delta}\right) - \frac{\delta\omega}{1-\delta} > 0$$

  where $\omega = \partial \Delta W^{\text{match}}_{g^*}/\partial k_{g^*} > 0$ is the marginal matching quality loss. A3 makes the first term positive; A4 requires it to exceed $\delta\omega/(1-\delta)$. The matching loss *tightens* the coalition but adds an additional punishment channel that reinforces compliance

Proposition: Collusive Threshold Increases in Density II

- **Monotonicity in** d (direct channel, at fixed k_{g^*}): since $\mathcal{M}(\bar{\rho}, d) = d \cdot \Lambda \int_{\bar{\rho}}^{1} [\cdots]\, dH(\rho)$,

$$\frac{\partial R}{\partial d} = \theta \Lambda \int_{\bar{\rho}}^{1} \left[1 - F(q^*(\rho))\right] dH(\rho) \cdot v \left(1 - \frac{\delta x_0}{1-\delta}\right) > 0$$

so by the IFT: $\frac{d\bar{\rho}}{dd} = \frac{\partial R/\partial d}{\beta S_{g^*} - \partial R/\partial \bar{\rho}} > 0$. Holds independently of k_{g^*}.

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Welfare: Four Channels

- Network affects welfare through four channels:

$$\Delta W(d) = W_I(d) + W_{II}(d) + B(d) - L(d) - \mu(d)$$

- W_I: Sorting gain: assortative vs. random assignment
- W_{II}: Value-added gain: higher exit rates from network ties
- B: Collusion-enabled investments
- L: Forgone surplus of blocked startups
- μ: Consumer surplus loss from incumbents' market power

- All five components **strictly increasing in** d

Back $\mu(d)$ $L(d)$ $B(d)$ W_{II} W_I

Welfare: Sorting $W_I(d)$

- **Sorting** — gain from routing high-q_e startups to high-x_f VCs:

$$W_I(d) = \underbrace{\sum_f \int_{Q_f} x_f \, q_e \, v \, \mathrm{d}F(q_e)}_{\text{assortative surplus}} - \underbrace{\sum_f x_f \, \bar{q} \, v \, \bar{n}}_{\text{random-assignment surplus}}$$

$$= \alpha_v v \, \bar{n} \sum_f k_f(\bar{q}_f - \bar{q}) \geq 0$$

- Mechanism: $x_f q_e v$ is **supermodular** in (k_f, q_e) — pairing high-q_e startups with high-x_f VCs raises total surplus relative to random assignment
- $W_I = \alpha_v v \bar{n} \sum_f k_f(\bar{q}_f - \bar{q})$: positive because under assortativity, high-degree VCs have $\bar{q}_f > \bar{q}$ and low-degree VCs have $\bar{q}_f < \bar{q}$, and the positive deviations are weighted by higher k_f
- Strictly increasing in d via two channels: higher average degree (more weight) and stronger assortativity (wider $|\bar{q}_f - \bar{q}|$ gaps)
- No separate parameter: sorting is an endogenous equilibrium outcome driven by $\alpha_v > 0$

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Welfare: Value-Added $W_{II}(d)$

- **Value-added** — surplus gain from $\alpha_v > 0$ vs. $\alpha_v = 0$, holding $\boldsymbol{\gamma}'\mathbf{z}_f$ fixed across counterfactuals:

  $$W_{II}(d) = \sum_f \int_{Q_f} \alpha_v \, k_f \, q_e \, v \, \mathrm{d}F(q_e) \;\geq\; 0$$

  Strictly increasing in d: higher d raises average degree, expanding value-added per deal. The term $\boldsymbol{\gamma}'\mathbf{z}_f$ enters both counterfactuals (1) and (2) symmetrically and cancels in the difference, so W_{II} isolates the *pure network* value-added
- Both W_I and W_{II} governed by α_v; W_I is the reallocation gain, W_{II} is the direct exit-rate gain
- W_{II} computed in counterfactual (3) with collusion *off* — no double-counting

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Welfare: Blocked Startups $L(d)$

- Forgone surplus from startups blocked by the coalition:

$$L(d) = \Lambda \int_{\bar{\rho}(d)}^{1} \int_{c/(x^{\mathrm{coll}}_{\max}(\bar{\rho},d)\, v)}^{1} \left(x^{\mathrm{coll}}_{\max}(\bar{\rho}, d)\, q\, v - c\right) \mathrm{d}F(q)\, \mathrm{d}H(\rho)$$

  where $x^{\mathrm{coll}}_{\max}(\bar{\rho}, d) = x_0 + \alpha_v\, k_{\max} + \boldsymbol{\gamma}' \mathbf{z}_{\max} + \theta\, \mathcal{M}(\bar{\rho}, d)$ — the best-networked VC's collusive exit rate

- Uses the *collusive* exit rate: a blocked startup *would have been* funded under the collusive regime, where fewer rivals raise exit probability

- $\partial L / \partial d > 0$: both $\bar{\rho}(d)$ (lower outer limit) and $\theta\, \mathcal{M}(\bar{\rho}(d), d)$ (integrand) strictly increase in d

Back

Welfare: Collusion-Enabled Investment $B(d)$

- Collusion lowers the funding bar for low-overlap startups via higher exit probability $x_f^{\mathrm{coll}}(\bar{\rho}, d) > x_f$:

$$B(d) = \Lambda \int_0^{\bar{\rho}(d)} \sum_{f \in \mathcal{F}} \int_{q_f^{\mathrm{coll}}(\rho,d)}^{q_f^*(\rho)} \left(x_f^{\mathrm{coll}}(\bar{\rho}, d)\, q\, v - c\right) \mathrm{d}F(q)\, \mathrm{d}H(\rho) \;\geq\; 0$$

- $x_f^{\mathrm{coll}}(\bar{\rho}, d) = x_0 + \alpha_v k_f + \gamma' \mathbf{z}_f + \theta\, \mathcal{M}(\bar{\rho}, d)$: blocking reduces rival count by $\mathcal{M}(\bar{\rho}, d)$; each blocked rival raises exit probability by θ; $\theta\, \mathcal{M}$ strictly increasing in d
- Three forces expand $B(d)$ as d increases:
  - x_f^{coll} rises via $\theta\, \mathcal{M}(\bar{\rho}, d)$ — startups worth more under collusion
  - $q_f^{\mathrm{coll}}(\rho, d)$ falls — funding bar for low-overlap startups drops
  - $\bar{\rho}(d)$ widens — more deals fall in the low-overlap region

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Welfare: Product Market Wedge $\mu(d)$

- Blocking rivals gives incumbents market power — consumers pay higher prices:

$$\mu(d) = \gamma \bar{\rho}(d)$$

- $\gamma \geq 0$ is the consumer surplus pass-through from reduced competition
  - Calibrated from product market price-cost margins in the IO literature
  - **Not estimated** — reported under $\gamma = 0$ and $\gamma = 1$ as bounds
  - Preferred estimate at calibrated γ
- $\mu(d)$ strictly increasing in d since $\bar{\rho}(d)$ strictly increasing in d
  - Denser markets block more entrants $\Rightarrow$ incumbents face less competition $\Rightarrow$ larger consumer surplus loss

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Startup Quality Measurement I

- Latent quality q_e linked to observables via the measurement equation:

$$q_e = \mathbf{x}_e'\boldsymbol{\beta}_q + \varepsilon_e, \qquad \varepsilon_e \perp \mathbf{x}_e$$

  $\boldsymbol{\beta}_q$ estimated jointly with Θ

- **Primary components of $\mathbf{x}_e$** — entrepreneur characteristics observable before the match:
  - Prior successful exit (IPO or acquisition) by any founding team member
  - Serial entrepreneur indicator (prior VC-backed startup)
  - Number of prior startups founded by team members
  - Years of prior industry experience (where available)

- **Firm-level attributes** (full sample): funding stage (seed/early/late), industry sector, geographic location, founding year

Startup Quality Measurement II

- **Coverage**: founder characteristics available in *PitchBook*; coverage improves for post-2000 deals and later-stage investments; results validated on subsample with full founder data

- **Pre-money valuation** (secondary, $\approx 68\%$ coverage): used as overidentifying restriction — conditional on $\mathbf{x}_e$, residual valuation variation should be orthogonal to k_f and d

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Measuring ρ_e — Robustness

Paine (2026)

- **Robustness measure** $\hat{\rho}_e^{\text{web}}$: TF-BIDF cosine similarity constructed from startup website text; all main results verified under this measure

- **Construction**:
  (i) **Text extraction**: scrape startup home page from the Wayback Machine one year after founding; remove stop words, pronouns, and company-specific identifiers; re-pull if blank or fewer than five informative words ($\approx 82\%$ coverage)
  (ii) **TF-BIDF similarity**: for each startup e funded by VC f, compute cosine similarity between e's website text and each active portfolio company $p \in \mathcal{P}_{f,t}$, using a backward-looking four-year IDF window
  (iii) **Aggregation**: $\hat{\rho}_e^{\text{web}} = \max_{p \in \mathcal{P}_{f,t}} \text{sim}^{\text{web}}(e, p)$, normalized to $[0, 1]$ within market-year

- **Limitation relative to primary**: coverage depends on website availability; no legal-entity matching required but text quality varies; used as independent validation of $\hat{\rho}_e^{\text{pat}}$

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Measuring ρ_e — Primary Measure

Warg (2023)

- **Primary measure** $\hat{\rho}_e^{\text{pat}}$: patent and trademark similarity between startup e and VC f's incumbent portfolio

- **Construction**:
  (i) **Text corpus**: combine patent claim language (technology space) and trademark goods-and-services descriptions (commercial space) for each firm
  (ii) **Cosine similarity**: pairwise TF-IDF cosine similarity between startup e and each active portfolio company $p \in \mathcal{P}_{f,t}$, restricted to the top-k most similar incumbents
  (iii) **Aggregation**: $\hat{\rho}_e^{\text{pat}} = \max_{p \in \mathcal{P}_{f,t}} \text{sim}^{\text{pat}}(e, p)$, normalized to $[0, 1]$ within market-year

- **Startup-to-patent matching**: startup names matched to USPTO assignee names via exact and fuzzy string matching (Kogan et al., 2017); high coverage expected for startups with at least one filing by round date; missing values verified uncorrelated with d and k_f

- **Why maximum**: the VC's incentive to block is governed by the *most threatened* incumbent, not the portfolio average

Identification (cont.)

Variation	Moment	Identifies
Panel B: Absorbed by Fixed Effects		
Industry-stage interactions in SMM moments	FE absorb $\xi_{ef} = \mathbf{x}_e' \Gamma \mathbf{z}_f$; Γ not estimated	α_v, γ unaffected
Panel C: Calibrated / Endogenous		
Fund capacity	Median fund portfolio count	$\bar{n}$
Discount factor	Annual VC fund horizon	$\delta = 0.90$
Collusive threshold	Fixed-point at each (Θ, d)	$\bar{\rho}(d; \Theta)$

← Panel A | Why ξ_{ef} safe | Empirical Predictions

Why Matching Is One-Dimensional Despite (q_e, ρ_e) I

- Each startup has **two characteristics**: quality q_e (publicly observable before matching) and competitive overlap ρ_e (private, revealed post-match during due diligence)

- **Timing collapses matching to one dimension**: because ρ_e is unobserved at matching and $\mathbb{E}[\rho_e] = \mu_\rho$ is constant across all VC–startup pairs (Assumption A1), expected payoffs at the matching stage depend only on (k_f, S_f, q_e). Startups rank VCs by

$$V_e(f) \;=\; x_f\, q_e\, v \cdot H(\rho_f^*(q_e)),$$

  in which ρ_e has been integrated out. The match is formed on q_e; the contract ϕ_f commits the VC's response to ρ_e once revealed

- **Why the contract structure is necessary**: without a committed funding rule embedded in the contract, a startup matched to a high-S_f VC faces post-match rejection risk not priced into the match — creating a blocking pair. The Hatfield–Milgrom (2005) contract resolves this directly

Why Matching Is One-Dimensional Despite (q_e, ρ_e) II

- **Welfare consequence**: sorting (W_I) is indexed by q_e; the collusion gate on ρ_e generates B, L, and μ. The two characteristics contribute to distinct, non-overlapping welfare channels — no double-counting

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The Exit Rate x_f: Identification of α_v

- **Structural specification**:

$$x_f \;=\; x_0 + \alpha_v\, k_f + \boldsymbol{\gamma}'\mathbf{z}_f\,,$$

where $\mathbf{z}_f$ collects fund sequence number, committed capital, and vintage year

- **Theory is unchanged**: all assortative-matching and collusion results require only that x_f enters joint surplus supermodularly in (k_f, q_e). The cross-partial $\partial^2\mathcal{M}/\partial k_f\,\partial q_e$ depends on α_v alone; $\boldsymbol{\gamma}'\mathbf{z}_f$ is additive in k_f and q_e independently, so its cross-partial is zero

- **Punishment**: exclusion removes $\alpha_v k_{f*}$ (network ties gone) but *not* $\boldsymbol{\gamma}'\mathbf{z}_{f*}$ (fund characteristics persist). So the punishment value Π_{f*} correctly contains only $\alpha_v k_{f*}$

- **Identification of α_v**: identified from the residual exit-rate slope on k_f after partialling out $\mathbf{z}_f$ in the moment conditions. In sparse markets ($d \approx 0$), $\bar{\rho}(d) \approx 1$ so $\theta\mathcal{M} \approx 0$, and the exit-rate moment cleanly separates α_v from θ. Consistent with Hochberg, Ljungqvist, and Lu (2007) showing degree retains its effect after controlling for experience and fund size

- **Identification of $\boldsymbol{\gamma}$**: from the cross-section of exit rates on $\mathbf{z}_f$ within sparse markets after absorbing k_f; SDC Platinum and PitchBook provide fund sequence, AUM, and vintage for all sample VCs

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Why ξ_{ef} Does Not Contaminate α_v or γ I

- The joint surplus contains the match complementarity $\xi_{ef} = \mathbf{x}_e' \Gamma \mathbf{z}_f$, which captures surplus from aligning startup sector with VC industry focus. Left uncontrolled, it could bias the exit-rate moments that identify α_v and γ
- **Additive separability is the key**:

$$\mathcal{M}(k_f, S_f, q_e, \mathbf{x}_e, \mathbf{z}_f) = \underbrace{x_f q_e v \cdot H(\rho_f^*) + \int_0^{\rho_f^*} \pi_f \, dH}_{\text{structural surplus: depends on } k_f,\, q_e,\, S_f} + \underbrace{\mathbf{x}_e' \Gamma \mathbf{z}_f}_{\xi_{ef}}$$

Because ξ_{ef} is *additively separable*, two things follow immediately:

1. ξ_{ef} **drops out of the cross-partial** $\partial^2 \mathcal{M} / \partial k_f \, \partial q_e$ — assortativity is governed by α_v alone; Γ does not affect sorting

Why ξ_{ef} Does Not Contaminate α_v or γ II

2. ξ_{ef} **does not appear in the exit-rate equation** $x_f = x_0 + \alpha_v k_f + \gamma' \mathbf{z}_f$ — the sparse-market exit-rate moments that identify α_v and γ are orthogonal to ξ_{ef} by construction

- **Implementation**: industry × stage interaction fixed effects included directly in the SMM moment conditions absorb ξ_{ef} nonparametrically via within-cell demeaning — no inversion step required. This is consistent with the transferable-utility matching literature (Choo and Siow, 2006), where additive separability of match heterogeneity implies cell FE absorb it without loss of identification of the structural surplus parameters
- **Conclusion**: Γ is not estimated. $\hat{\alpha}_v$ and $\hat{\gamma}$ are not biased by unobserved characteristic complementarities

Back to Estimation | Complementarity ξ_{ef}

Startup Quality Measurement and Match Complementarity I

- **Latent quality** q_e is linked to observable startup characteristics via the measurement equation:

$$q_e \;=\; \mathbf{x}_e'\boldsymbol{\beta}_q + \varepsilon_e, \qquad \varepsilon_e \perp \mathbf{x}_e,$$

  where $\mathbf{x}_e$ includes entrepreneur prior exits, serial founder indicator, prior startup count, and industry experience (primary); plus funding stage, sector, and geography (firm-level, full sample). $\boldsymbol{\beta}_q$ is estimated jointly with Θ

- **Match-specific complementarity**: the joint surplus is extended to

$$\mathcal{M}(k_f, S_f, q_e, \mathbf{x}_e, \mathbf{z}_f) \;=\; x_f q_e v \cdot H(\rho_f^*(q_e)) + \int_0^{\rho_f^*} \pi_f \, dH + \underbrace{\mathbf{x}_e'\Gamma\mathbf{z}_f}_{\xi_{ef}},$$

  where ξ_{ef} captures surplus from characteristic alignment (e.g. fintech startup matched to fintech-specialist VC). The term is **additively separable**, so $\partial^2\xi_{ef}/\partial k_f\,\partial q_e = 0$ and Proposition 1 is unaffected

Startup Quality Measurement and Match Complementarity II

- **Why ξ_{ef} does not enter the collusion mechanism**: both ϕ_f and ϕ_f^{coll} operate on realized ρ_e *after* the match forms. The complementarity ξ_{ef} is priced in at the matching stage and shared between parties; it does not alter the VC's post-match incentive or the compliance constraint

- **Why ξ_{ef} does not contaminate α_v or γ**: additive separability has two consequences. First, ξ_{ef} drops out of the cross-partial $\partial^2\mathcal{M}/\partial k_f\,\partial q_e$, so assortativity is unaffected. Second, ξ_{ef} does not appear in the exit-rate equation $x_f = x_0 + \alpha_v k_f + \boldsymbol{\gamma}'\mathbf{z}_f$, so the sparse-market exit-rate moments that identify α_v and $\boldsymbol{\gamma}$ are orthogonal to ξ_{ef} by construction. Industry-stage interaction fixed effects in the SMM moment conditions absorb ξ_{ef} nonparametrically; Γ is not estimated

Back to Payoffs | Back to Estimation | Back to Matching

The Discount Factor δ: Role and Connection to HKL

- δ scales the punishment value for every co-investor:

$$\Pi_g = \frac{\delta}{1-\delta}\left[x_0 v\big(\alpha_v k_g + \theta\mathcal{M}(\bar{\rho}, d)\big) + \Delta W_g^{\text{match}}\right]$$

  Higher δ tightens $\bar{\rho}$: $\partial\bar{\rho}/\partial\delta > 0$

- **Connection to Hatfield, Kominers, and Lowery (2025)**: Assumption A4 ($\delta < 1/(1+x_0)$, implying $\delta > \frac{1}{2}$) plays the same role as their $\delta \geq \frac{1}{2}$ — ensuring the future is valuable enough to deter deviation

- **Why no closed-form δ threshold here**: in HKL, deviation gain and continuation value are proportional to the same market-share factor, so they cancel, yielding a clean condition purely in δ. Here the gain involves $x_g^{\text{coll}} = x_0 + \alpha_v k_g + \gamma' \mathbf{z}_g + \theta\mathcal{M}(\bar{\rho}, d)$, which feeds back through $\bar{\rho}$ — preventing that cancellation. Assumption A4 imposes the necessary bound in terms of primitives (x_0, δ) instead

- **Why δ is calibrated, not estimated**: δ is not separately identified from (α_v, θ) in the compliance constraint — raising δ has the same qualitative effect on $\bar{\rho}$ as raising α_v or θ. Estimating δ would inflate standard errors without providing additional moment restrictions. We set $\delta = 0.90$ (annual, consistent with VC fund horizons) and verify robustness at $\delta \in \{0.85, 0.90, 0.95\}$

Assumptions Estimation