Mapping Technology Startup Ecosystems

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AI4Law Closing Conference Webinar

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INDUSTRIAL STRATEGY | UK Research and Innovation

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Agenda

Lawtech and Fintech startup ecosystems in London, New York and San Francisco

Knowledge similarity among founders and joiners: impact on venture scaleup

Venture Analytics Initiative (VAI): taxonomy, annotation, webtool

Lawtech and Fintech startups in three locations

What do we learn from these comparisons?

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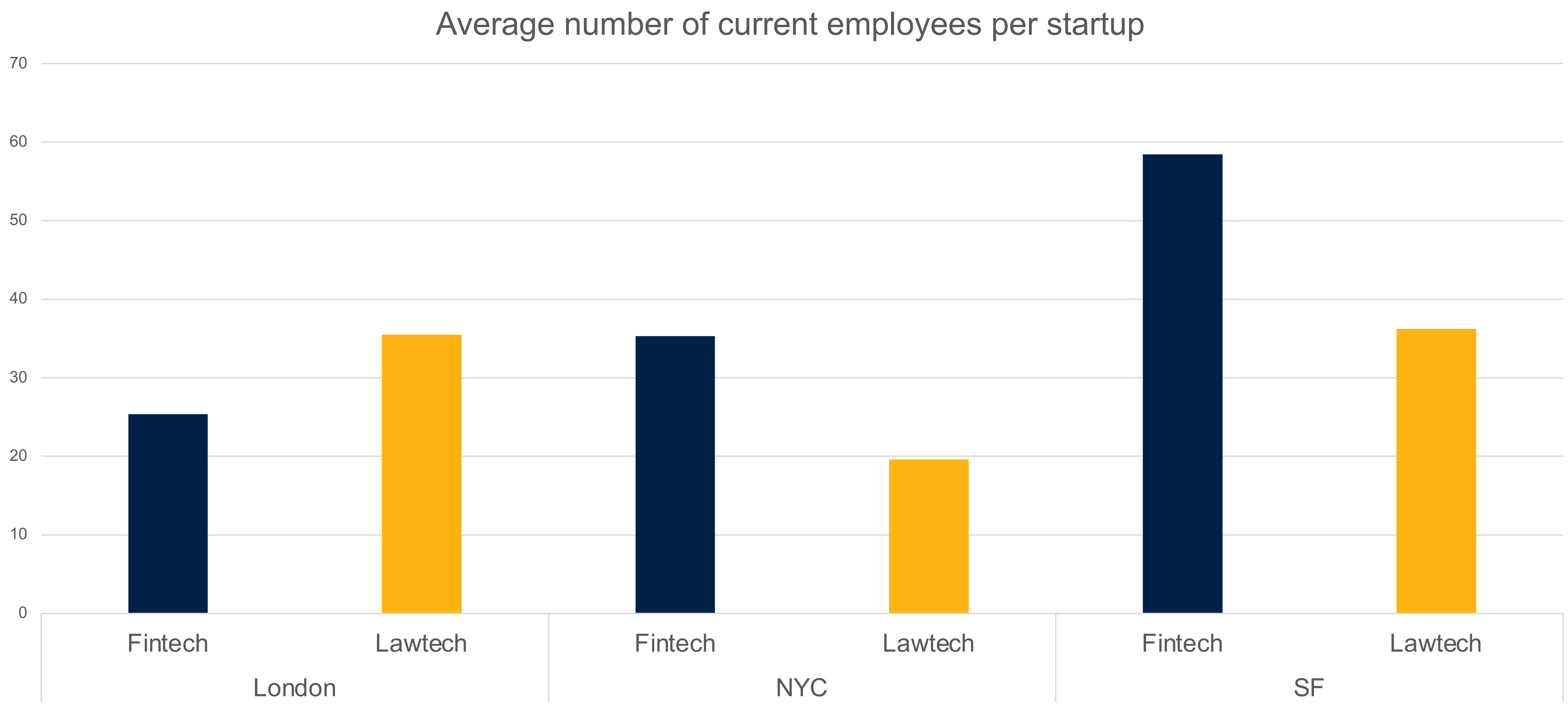
1. Lawtech startup firms are smaller on average than Fintech startups, except in London

Startups are larger in Fintech than in Lawtech, except in London



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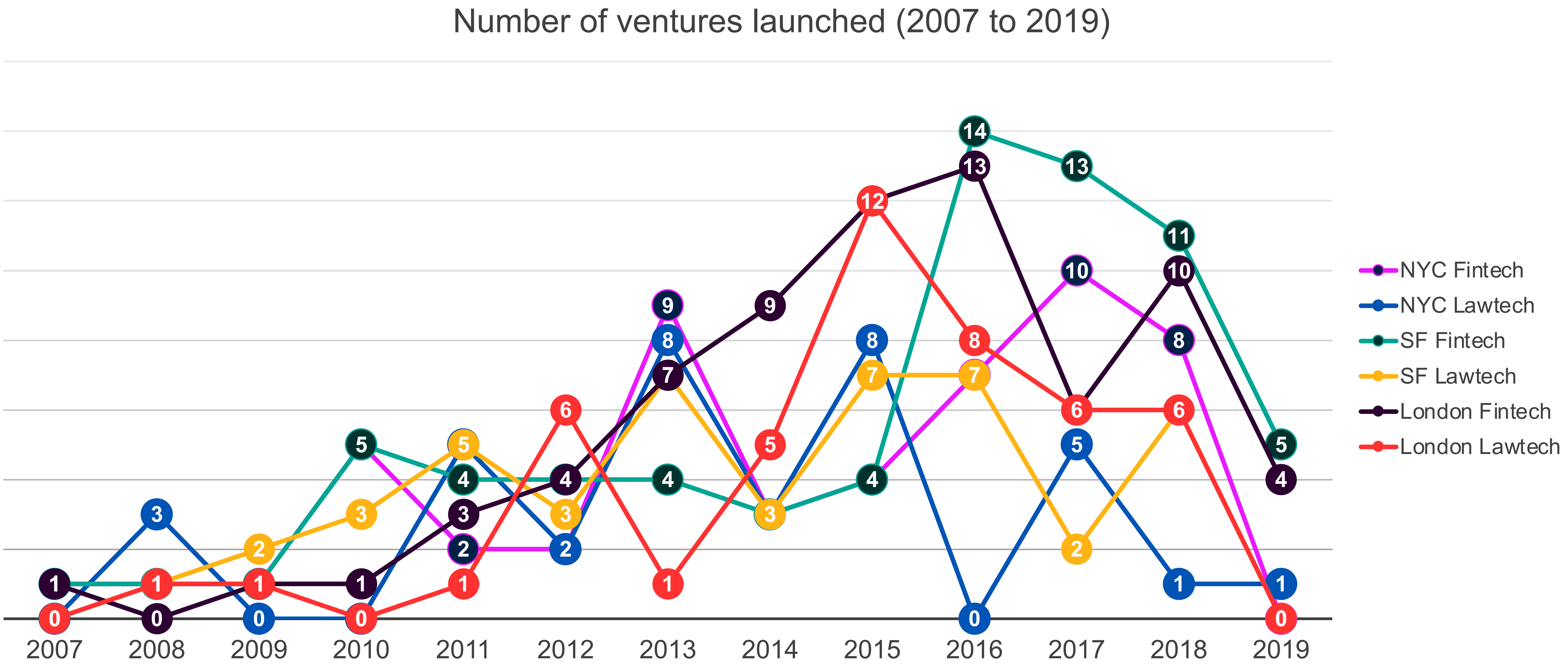
Lawtech startups are not necessarily younger than Fintech startups



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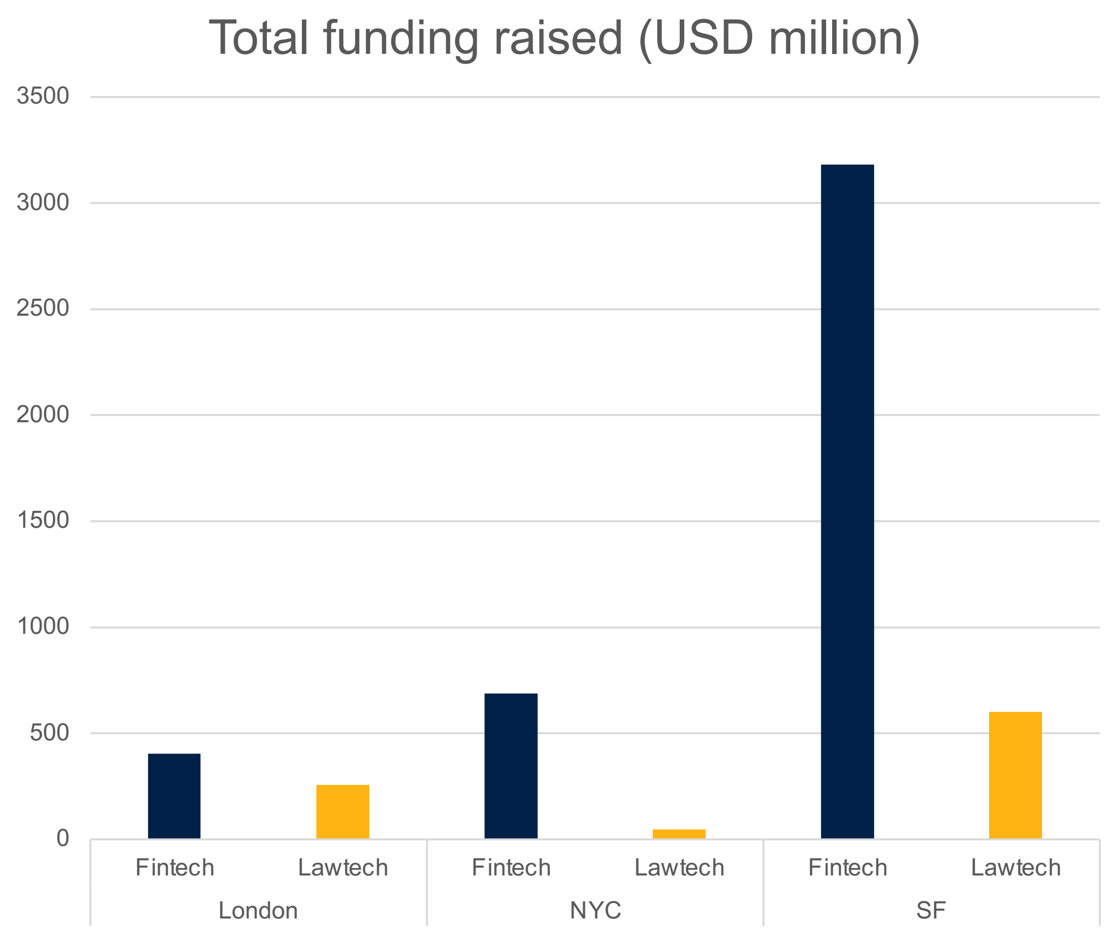
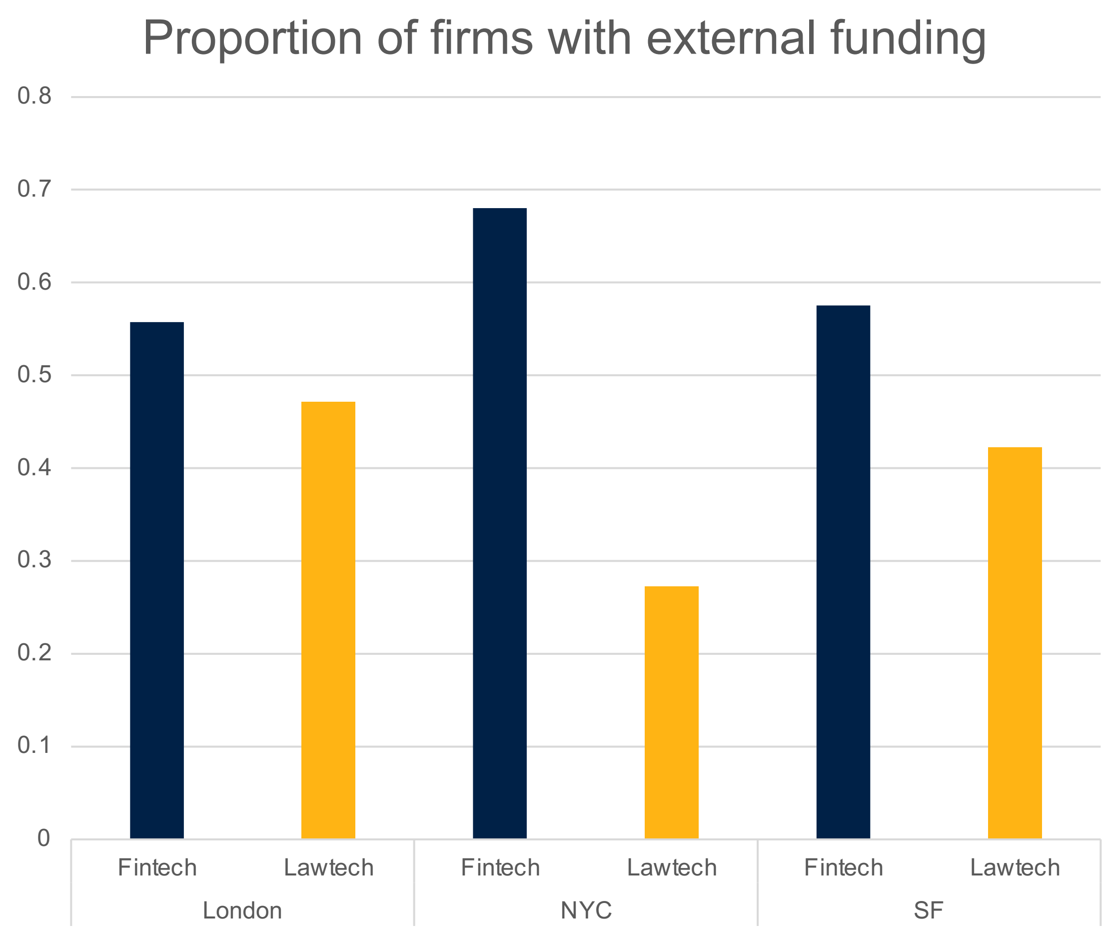
2. A smaller proportion of startups get external funding in Lawtech than in Fintech

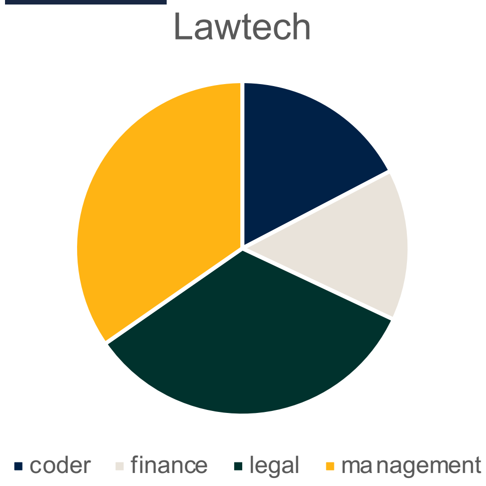
Proportion of startups with external funding is lower in Lawtech than in Fintech in all three locations

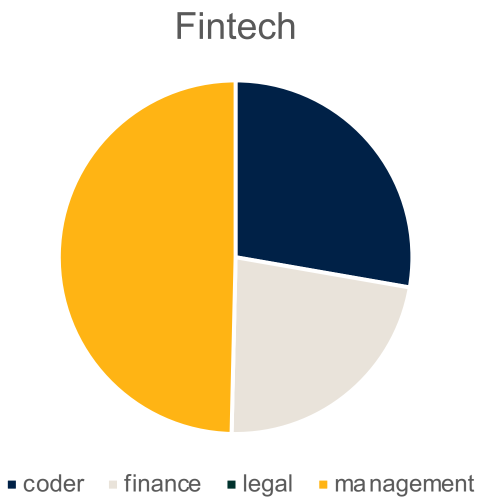




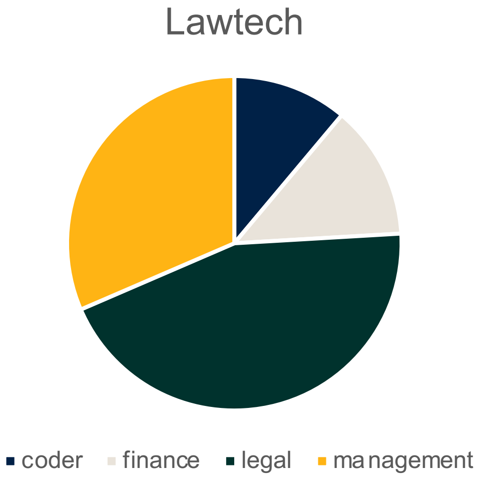
3. **Founders’ knowledge domains**:
San Francisco has a higher proportion of founders with coding skills

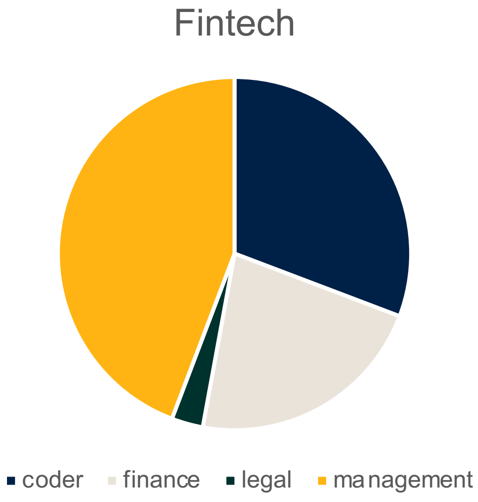
Most Lawtech founders are non-lawyers across all locations



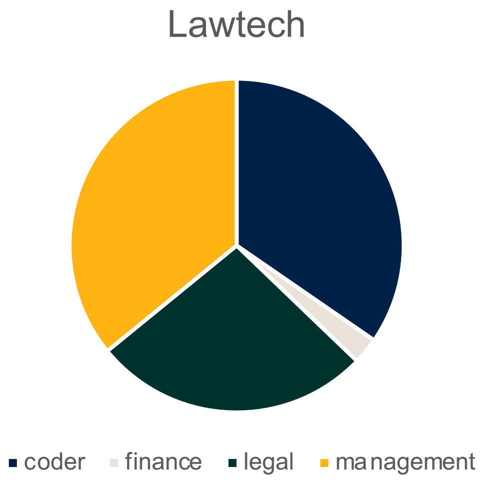


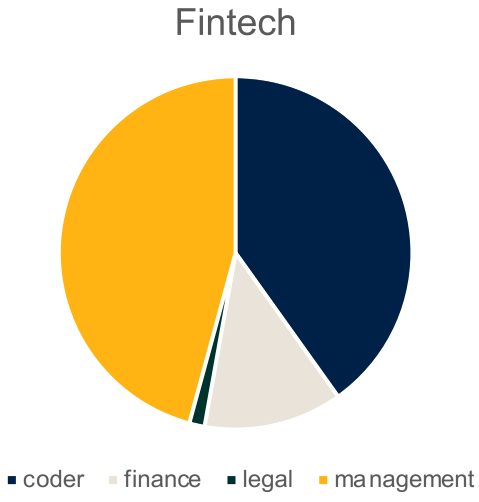
London





New York City

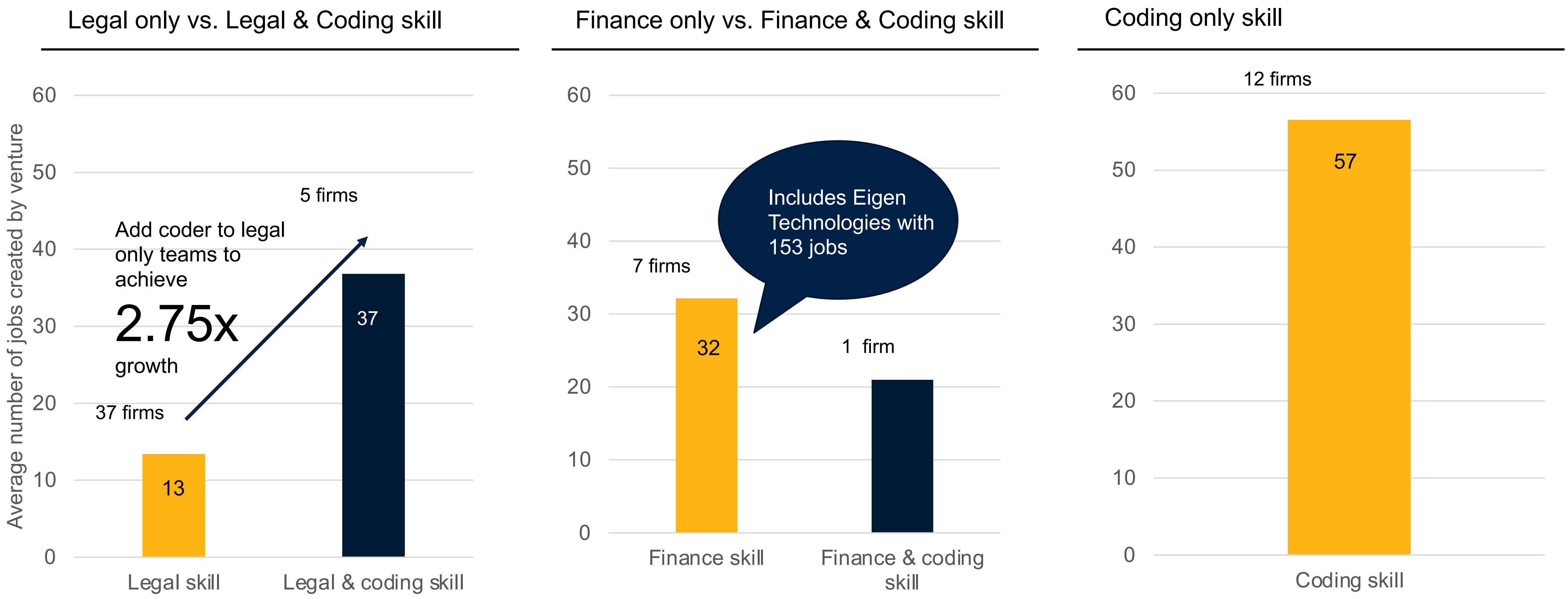




San Francisco Bay Area

4. **Impact of founders' knowledge domains on scaleup:**
Lawyer-only founding teams do not scale up

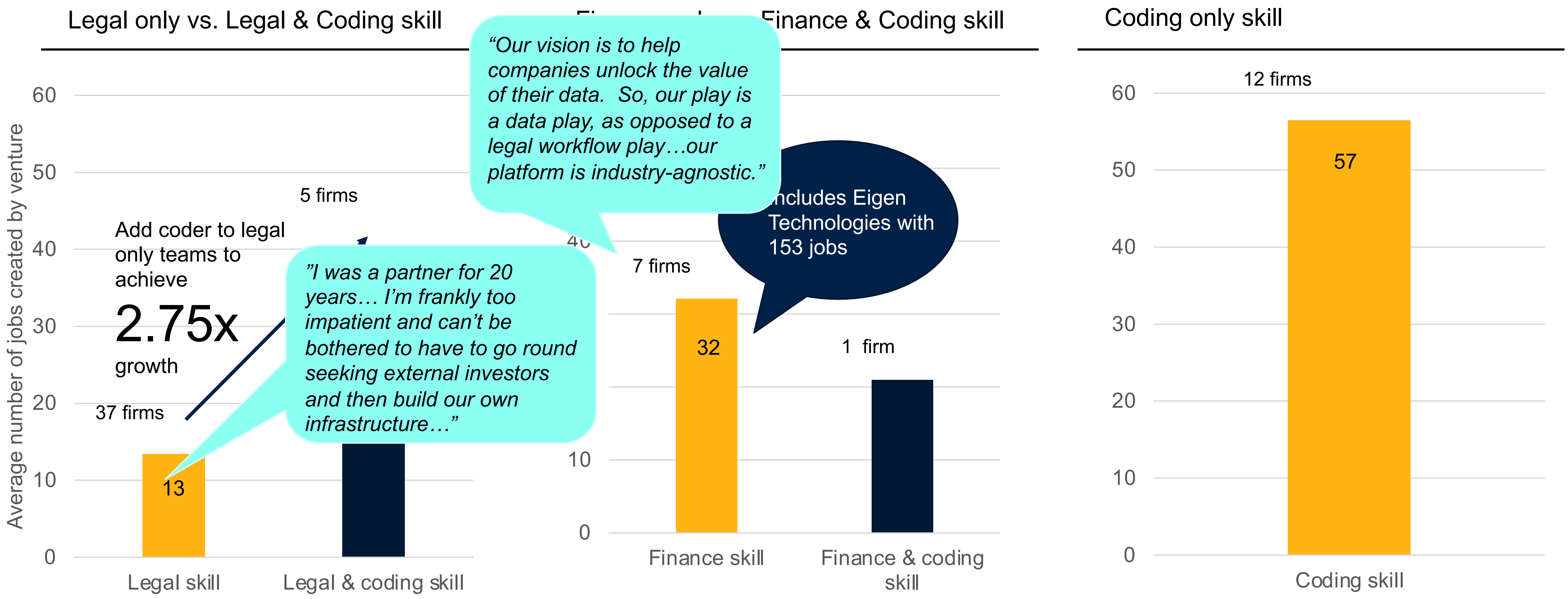
Lawtech firms with lawyer-only teams remain small



Note: Skill determined by categorizing LinkedIn endorsements into legal, finance and coding; each founder assigned to one skill category, based on most frequently endorsed category. Number of jobs created based on current employee counts by venture on LinkedIn.

Lawtech firms with lawyer-only teams remain small

Combing legal and coding skills lead to faster growth, but coder-only teams grow even faster



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Explaining the variation in scale-up success with founders and joiners

Pros and Cons of knowledge similarity

- Novelty creation happens when people come from backgrounds that are sufficiently similar to facilitate communication, but at the same time different enough to provide access to new ideas → optimal **knowledge diversity** (see diagram)

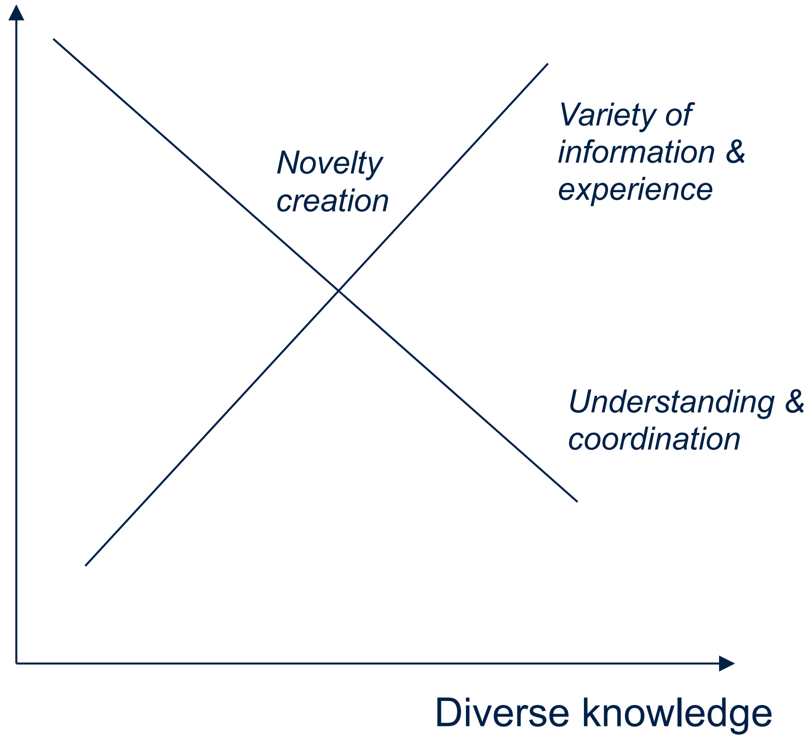
- Benefits of knowledge similarity: faster decision making and execution

- Benefits of knowledge diversity: may draw on a wider variety of information and experiences

- Fintech and Lawtech are sectors in which firms combine knowledge from different domains (finance + tech, law + tech) to generate and capture value

  We leverage different cognitive distances between the knowledge domains to further our understanding

The effect of knowledge diversity



Sample construction

Data	Circumstance	597 Founders	315 Ventures	3,054 Outcomes
Data source	Crunchbase & desk research defines universe of ventures	Crunchbase founder info, LinkedIn education and employment info, Google search	LinkedIn education and employment, info endorsements	LinkedIn employee counts, Burning Glass job ads, Crunchbase fundraising data
Variables	3 Locations (London, NY, SF) 2 Areas of work (Lawtech, Fintech) 12 Years (2009 – 2020)	Serial entrepreneur, Uni ranking, Year of work experience, degree centrality in social network	Age of venture, number of founders in knowledge domain, knowledge-similar employees, network density, knowledge-similar network, knowledge-similar founders	Dependent variables: Jobs created, 10,533 Vacancies posted, 6,210 Fundraising, $ 4.900 M

Examples of ventures in Lawtech & Fintech and London, NY & SF

	London		New York		San Francisco	
Fintech	ZEGO	$52 MM funding	MoneyLion	$227 MM funding	FIGURE	$1,412 MM funding
	GROWTH STREET	$30 MM funding	AlphaSense	$87 MM funding	FUNDBOX	$454 MM funding
Lawtech	ContractPodAi	$55 MM funding	Leverton	$17 MM funding	Legalist	$100 MM funding
	EigenTechnologies	$54 MM funding		$14 MM funding	Qualia	$95 MM funding

Notes: The funding data is from 2020 and may have changed since. Growth Street since went into administration.

Stylized fact 1 : Knowledge-similar founding teams create more jobs and post more job vacancies

	Startups with knowledge-similar founding teams		Startups without knowledge-similar founding teams		Absolute difference of means
	Mean	S.D.	Mean	S.D.	
Panel A: Job creation per year					
Location					
London	5.79	6.17	5.34	8.01	0.45
New York	6.08	9.31	4.23	6.26	1.85
San Francisco	12.22	19.57	5.99	13.83	6.23
Area of work					
Legaltech	7.87	10.46	4.22	11.75	3.65
Fintech	8.65	7.87	5.98	4.22	2.67
Combined	8.31	13.57	5.25	10.05	3.06
Observations	60		255		
Panel B: Job postings per year					
Location					
London	3.48	4.42	3.50	5.85	0.02
New York	4.94	5.31	1.96	2.10	2.98
San Francisco	12.17	18.99	7.21	8.87	4.96
Area of work					
Legaltech	6.54	16.06	2.16	4.08	4.39
Fintech	7.87	9.13	5.33	7.37	2.54
Combined	7.18	12.96	4.36	6.66	2.82
Observations	58		246		

Startups with knowledge similarity in founding teams create more jobs and post more job vacancies per year. The number of legal founders, however, decreases the speed of scale-up.

Model	(1)	(2)	(3)	(4)
	Job creation		Job postings	
Level of analysis	Venture	Founder	Venture	Founder
Key variables				
Knowledge-similar founding team	0.4878***	0.4364***	0.3390***	0.3153**
	(0.1648)	(0.1593)	(0.1297)	(0.1248)
Venture-level control variables				
Number of coder founders	0.0323**	0.0318**	0.0183*	0.0158
	(0.0153)	(0.0146)	(0.0099)	(0.0112)
Number of manager founders	0.0476***	0.0410***	0.0229***	0.0239***
	(0.0111)	(0.0096)	(0.0066)	(0.0068)
Number of finance founders	0.0403*	0.0477**	0.0255**	0.0305**
	(0.0219)	(0.0227)	(0.0126)	(0.0146)
Number of legal founders	-0.0350*	-0.0320	-0.0222**	-0.0265***
	(0.0205)	(0.0213)	(0.0089)	(0.0088)
Age	0.1555***	0.1355***	0.0806***	0.1095***
	(0.0316)	(0.0321)	(0.0234)	(0.0258)
Founder-level control variables				
Years of experience		0.0135**		-0.0019
		(0.0062)		(0.0041)
University ranking		0.1813		0.1283
		(0.1549)		(0.1031)
Serial entrepreneur		0.3070		0.2478
		(0.2118)		(0.1598)
Area of work fixed effect	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R^2	0.2671	0.2807	0.1600	0.1945
No. of firms	315	315	304	304
Observations	1651	3054	1336	2449

Startups with knowledge similar founders create 48% more jobs than startups without knowledge similar founders.

Startups with knowledge similarity in founding teams create more jobs and post more job vacancies per year. The number of legal founders, however, decreases the speed of scale-up.

Model	(1)	(2)	(3)	(4)
	Job creation		Job postings	
Level of analysis	Venture	Founder	Venture	Founder
Key variables				
Knowledge-similar founding team	0.4878*		0.3390***	0.3153**
	(0.164		(0.1297)	(0.1248)
Venture-level control variables				
Number of coder founders	0.0323		0.0183*	0.0158
	(0.015		(0.0099)	(0.0112)
Number of manager founders	0.0476*		0.0229***	0.0239***
	(0.011		(0.0066)	(0.0068)
Number of finance founders	0.040		0.0255**	0.0305**
	(0.0219)	(0.0227)	(0.0126)	(0.0146)
Number of legal founders	-0.0350*	-0.0320	-0.0222**	-0.0265***
	(0.0205)	(0.0213)	(0.0089)	(0.0088)
Age	0.1555***	0.1355***	0.0806***	0.1095***
	(0.0316)	(0.0321)	(0.0234)	(0.0258)
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No. of firms	315	315	304	304
Observations	1651	3054	1336	2449

Startups with knowledge similar founders create 34% more vacancies than startups without knowledge similar founders.

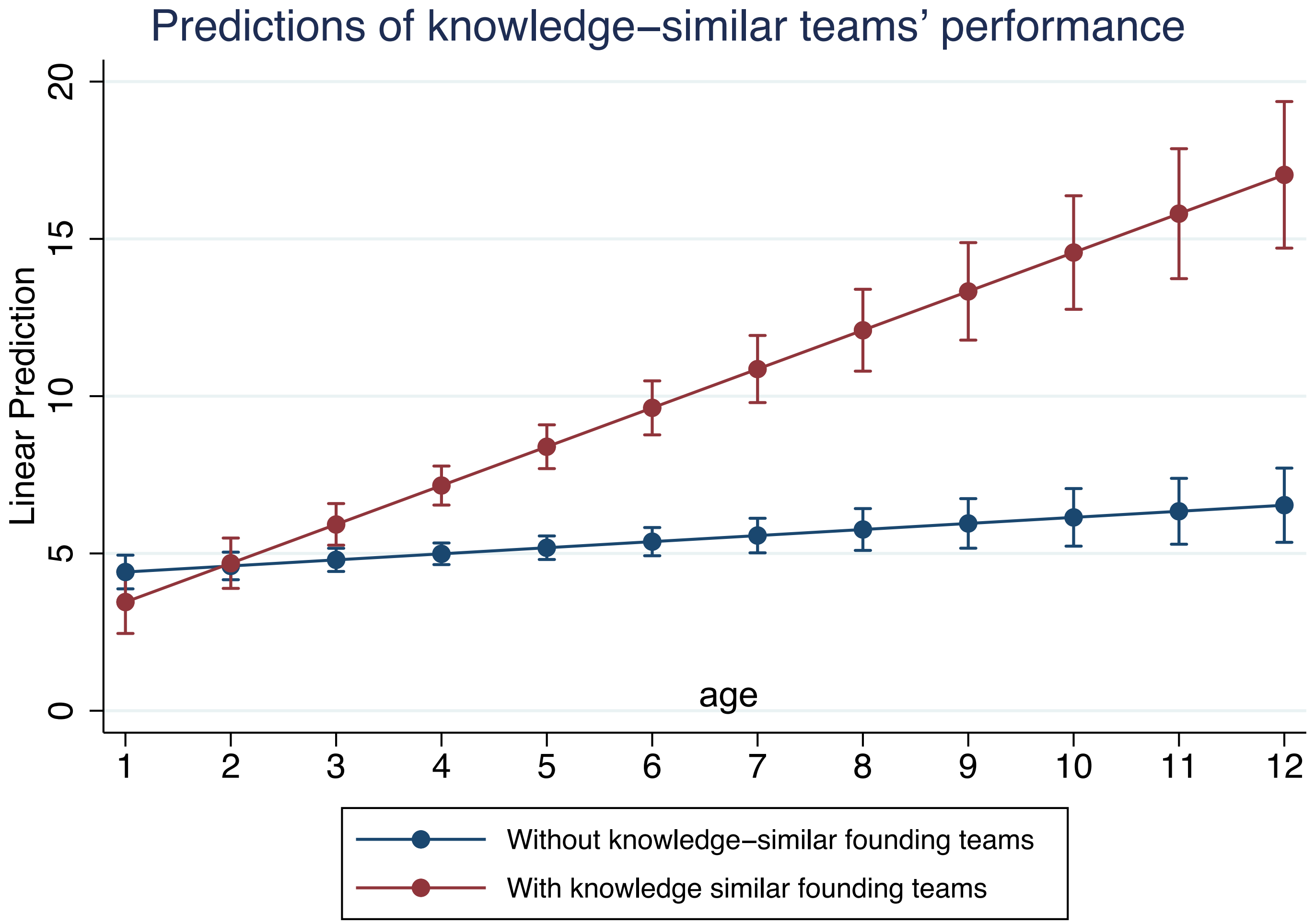
Startups with knowledge-similar teams do not scale-up faster within the first three years of venture. In nascent ecosystems, knowledge similar teams underperform, consistent with novelty creation in diverse teams.

Model	(1)	(2)	(3)	(4)
Corresponding hypothesis	H1b	H1c	H1b	H1c
	Job creation		Job postings	
Level of analysis	Founder	Founder	Founder	Founder
Knowledge-similar founding team	0.7541***	0.4787***	0.6934***	0.3266**
	(0.2297)	(0.1558)	(0.2569)	(0.1260)
Young venture	0.0699		-0.0166	
	(0.1022)		(0.1534)	
Young venture x knowledge-similar founding team	-0.5572***		-0.5927**	
	(0.1952)		(0.2456)	
Nascent ecosystem		-0.4501**		0.1681
		(0.2139)		(0.1289)
Nascent ecosystem x knowledge-similar founding team		-2.2038***		-0.9067**
		(0.4536)		(0.4022)
Venture-level control variables	Yes	Yes	Yes	Yes
Founder-level control variables	Yes	Yes	Yes	Yes
Area of work fixed effect	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R^2	0.2878	0.2589	0.2094	0.1831
No. of firms	315	315	304	304
Observations	3054	3054	2449	2449

Young ventures benefit less from knowledge-similar founding team.

Outperformance of knowledge similar teams varies over age

In first years of venture, diversity in founding teams trumps similarity.



The gap continuously widens between ventures with and without knowledge-similar founding team.

Note: The figure uses 80% confidence bands.

Startups with knowledge-similar teams do not scale-up faster within the first three years of venture. In nascent ecosystems, knowledge similar teams underperform, consistent with novelty creation in diverse teams.

Model	(1)	(2)	(3)	(4)
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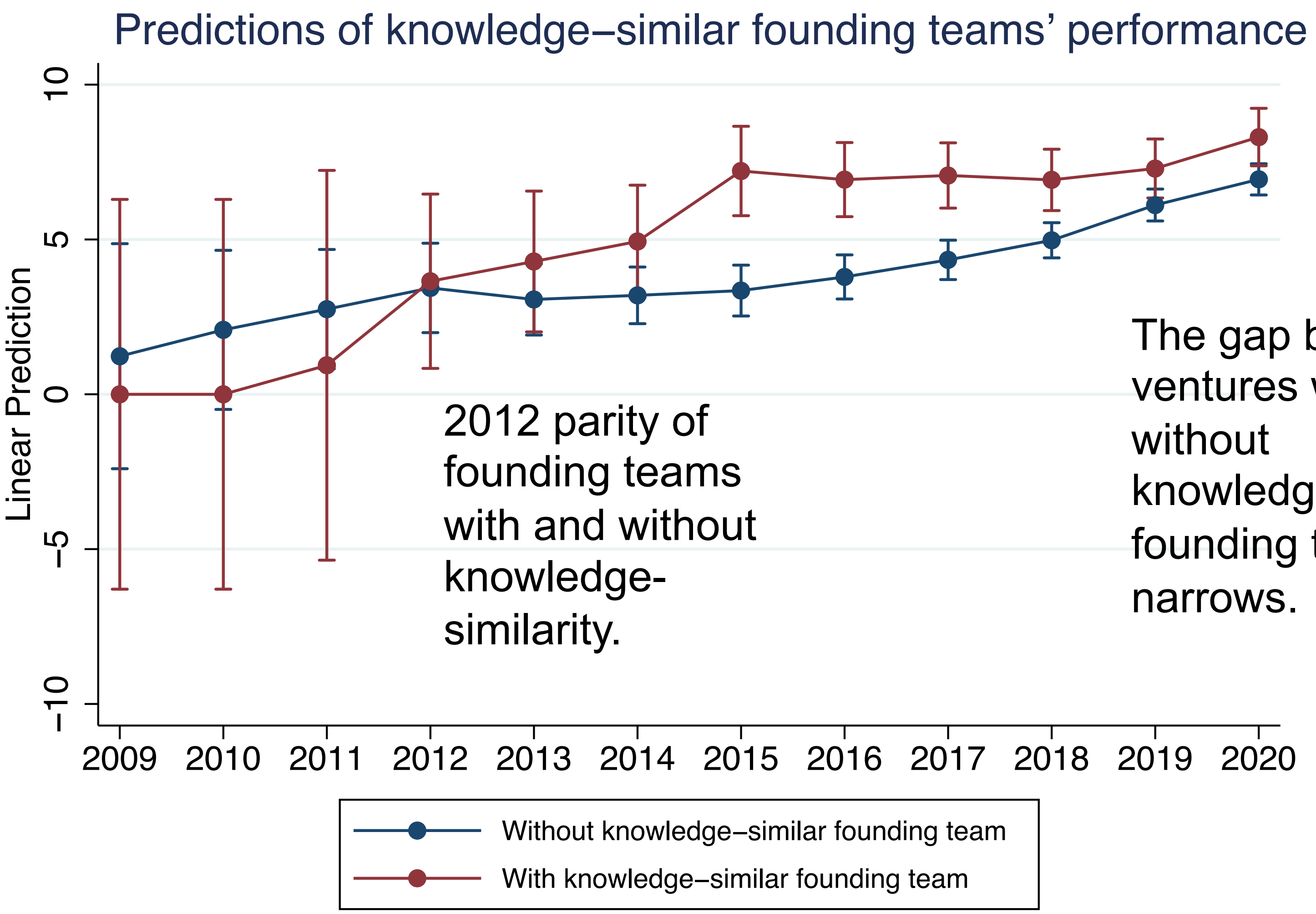
Venture-level control variables	Yes	Yes		Yes
Founder-level control variables	Yes	Yes		Yes
Area of work fixed effect	Yes	Yes		Yes
Location fixed effect	Yes	Yes		Yes
Year fixed effect	Yes	Yes		Yes
R^2	0.2878	0.2589	0.2094	0.1831
No. of firms	315	315	304	304
Observations	3054	3054	2449	2449

Ventures in nascent ecosystems benefit less from knowledge-similar founding team.

Outperformance of knowledge-similar teams varies over years

In first years of ecosystem, diversity in founding teams trumps similarity; but huge variation in performance.



2012 parity of founding teams with and without knowledge-similarity.

The gap between ventures with and without knowledge-similar founding team narrows.

Note: The figure uses 80% confidence bands.

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Startups with knowledge-similar teams raise the initial funding rounds faster. For a Series A, investors prefer to fund serial entrepreneurs.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Corresponding hypothesis	H1	H1	H1	H1	H1	H1
	Raised over $100k		Raised over $1MM		Raised Series A	
Level of analysis	Venture	Founder	Venture	Founder	Venture	Founder
Key variables						
Knowledge-similar founding teams	0.4578**	0.3312*	0.4498**	0.1700	0.2147	-0.0688
	(0.1952)	(0.1948)	(0.2198)	(0.2244)	(0.3383)	(0.3520)
Venture-level control variables						
Number of coder founders	0.0087	0.0066	0.0133	-0.0026	0.0557***	0.0321
	(0.0142)	(0.0151)	(0.0159)	(0.0191)	(0.0172)	(0.0200)
Number of manager founders	-0.0062	-0.0059	0.0098	0.0054	0.0537***	0.0384**
	(0.0120)	(0.0103)	(0.0129)	(0.0119)	(0.0172)	(0.0182)
Number of finance founders	0.0346	0.0439*	0.0463**	0.0416*	0.0594*	0.0407
	(0.0231)	(0.0257)	(0.0217)	(0.0249)	(0.0304)	(0.0338)
Number of legal founders	-0.0146	-0.0065	-0.0792*	-0.0794*	-0.0810	-0.0897
	(0.0310)	(0.0297)	(0.0428)	(0.0424)	(0.0615)	(0.0650)
Founder-level control variables						
Years of experience		-0.0211**		-0.0151		-0.0016
		(0.0092)		(0.0098)		(0.0125)
University ranking		0.0093		0.3114*		0.4014
		(0.1626)		(0.1855)		(0.2672)
Serial entrepreneur		0.2873		0.4590		0.7966**
		(0.2773)		(0.3099)		(0.3368)
Area of work fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Spells	315	605	315	605	315	605
Events	155	337	119	268	58	136
Censored	160	268	196	337	257	469
Log-likelihood	-806.79	-1949.21	-609.60	-1538.98	-288.88	-768.01
Wald χ^2 (8)	27.09	24.48	34.59	27.20	40.88	33.02

Knowledge-similar founders have higher hazard of raising at least $100k.

49%

38%

18%

Startups with knowledge-similar teams raise the initial funding rounds faster. For a Series A, investors prefer to fund serial entrepreneurs.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Corresponding hypothesis	H1	H1	H1	H1	H1	H1
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Number of manager founders	-0.0062	-0.0059	0.0098	0.0054	0.0537***	0.0384**
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Number of legal founders	-0.0146	-0.0065	-0.0792*	-0.0794*	-0.0810	-0.0897
	(0.0310)	(0.0297)	(0.0428)	[illegible]	(0.0615)	(0.0650)
Founder-level control variables						
Years of experience		-0.0211**		[illegible]		-0.0016
		(0.0092)		[illegible]		(0.0125)
University ranking		0.0093		[illegible]		0.4014
		(0.1626)		[illegible]		(0.2672)
Serial entrepreneur		0.2873		[illegible]		0.7966**
		(0.2773)		[illegible]		(0.3368)
Area of work fixed effect	Yes	Yes	Yes	[illegible]	Yes	Yes
Location fixed effect	Yes	Yes	Yes	[illegible]	Yes	Yes
Spells	315	605	315	605	315	605
Events	155	337	119	268	58	136
Censored	160	268	196	337	257	469
Log-likelihood	-806.79	-1949.21	-609.60	-1538.98	-288.88	-768.01
Wald χ^2 (8)	27.09	24.48	34.59	27.20	40.88	33.02

49%

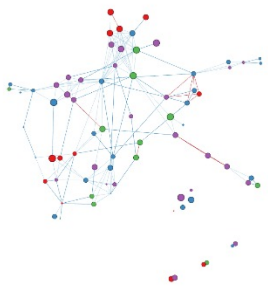
38%

18%

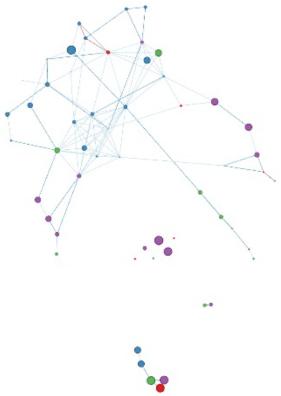
To raise a Series A it's helpful to be a Serial Entrepreneur.

Stylized fact 2: Founders' social ties is the densest in San Francisco; each ecosystem has founders with a variety of knowledge domains

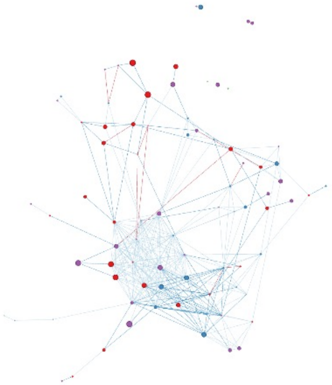
Lawtech London



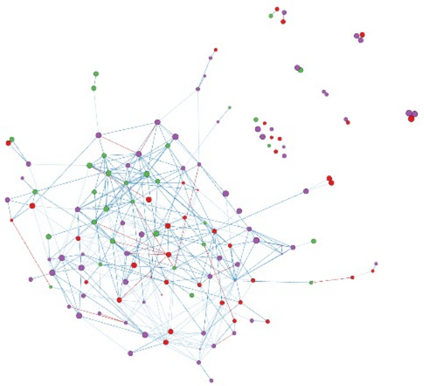
Lawtech NY



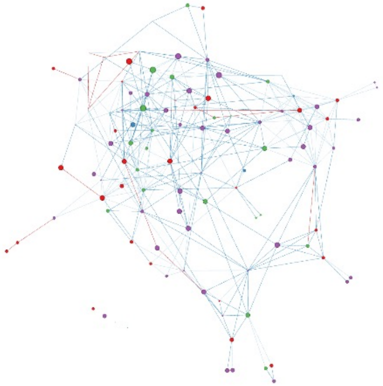
Lawtech SF



Fintech London



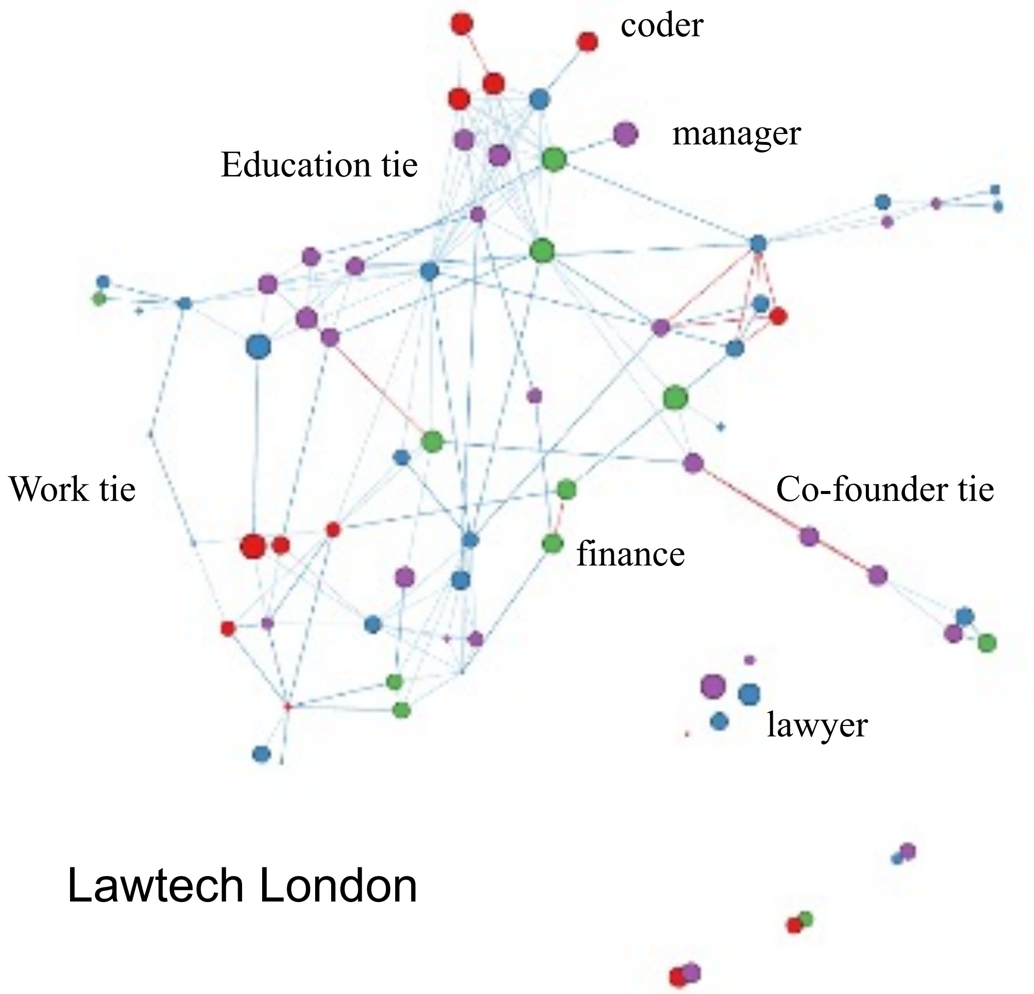
Fintech NY

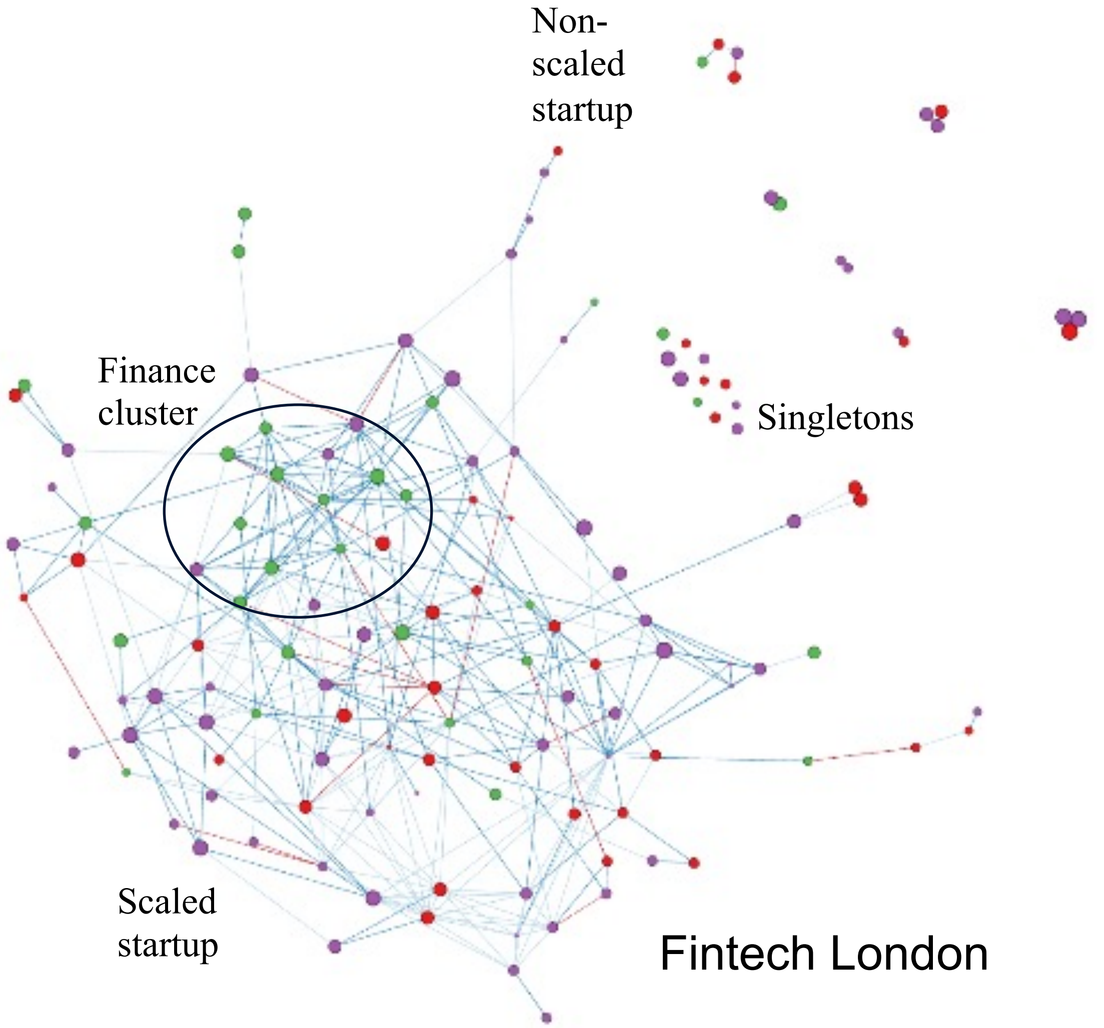


Fintech SF

Notes: dot size indicates venture size by employees. Color codes: Dots for founders (red = coder; blue = lawyer; green = financier; purple = manager; Lines for social ties (red = co-founder ties; dark blue = employment ties; light blue = education ties).

Most founders are connected through work or educational ties





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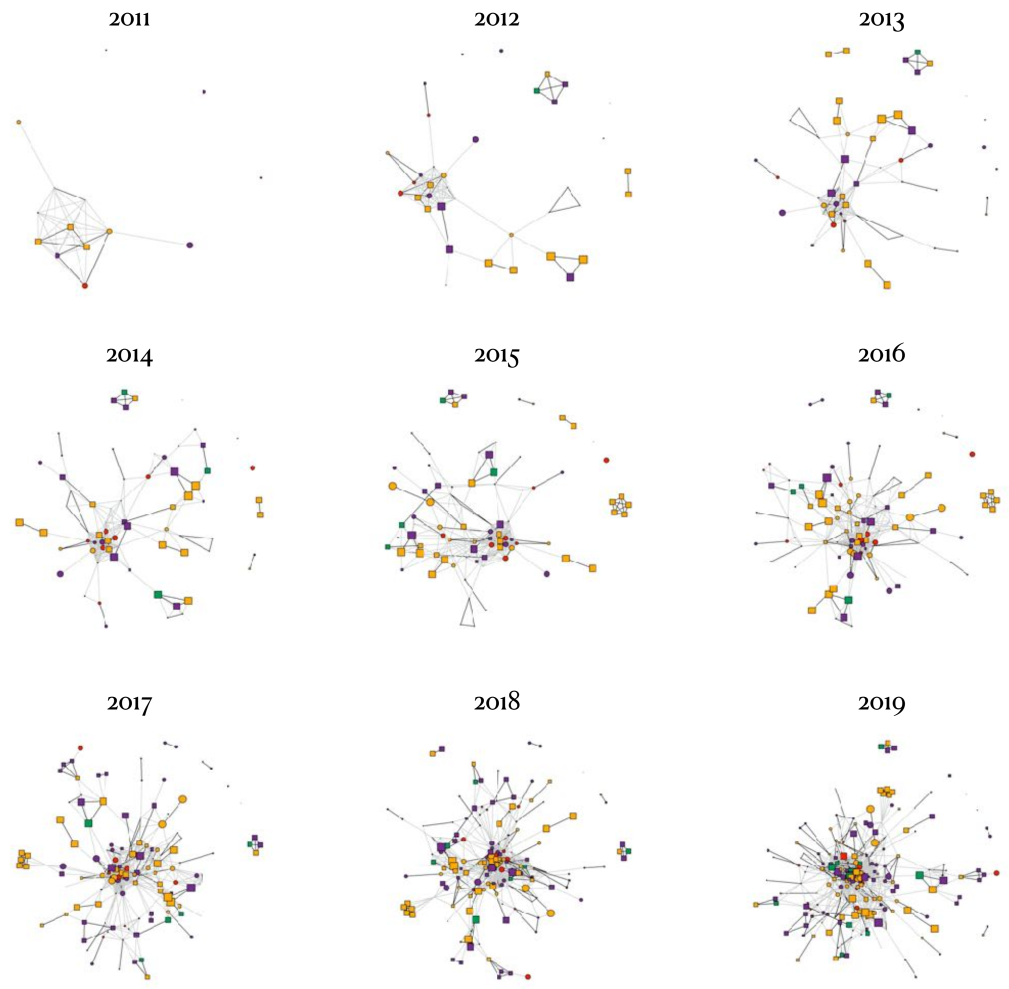
Lines for social ties (red = co-founder ties; dark blue = employment ties; light blue = education ties).

Most founders are connected through work or educational ties

Notes: dot size indicates venture size by employees. Color codes: Dots for founders (red = coder; blue = lawyer; green = financier; purple = manager; Lines for social ties (red = co-founder ties; dark blue = employment ties; light blue = education ties).

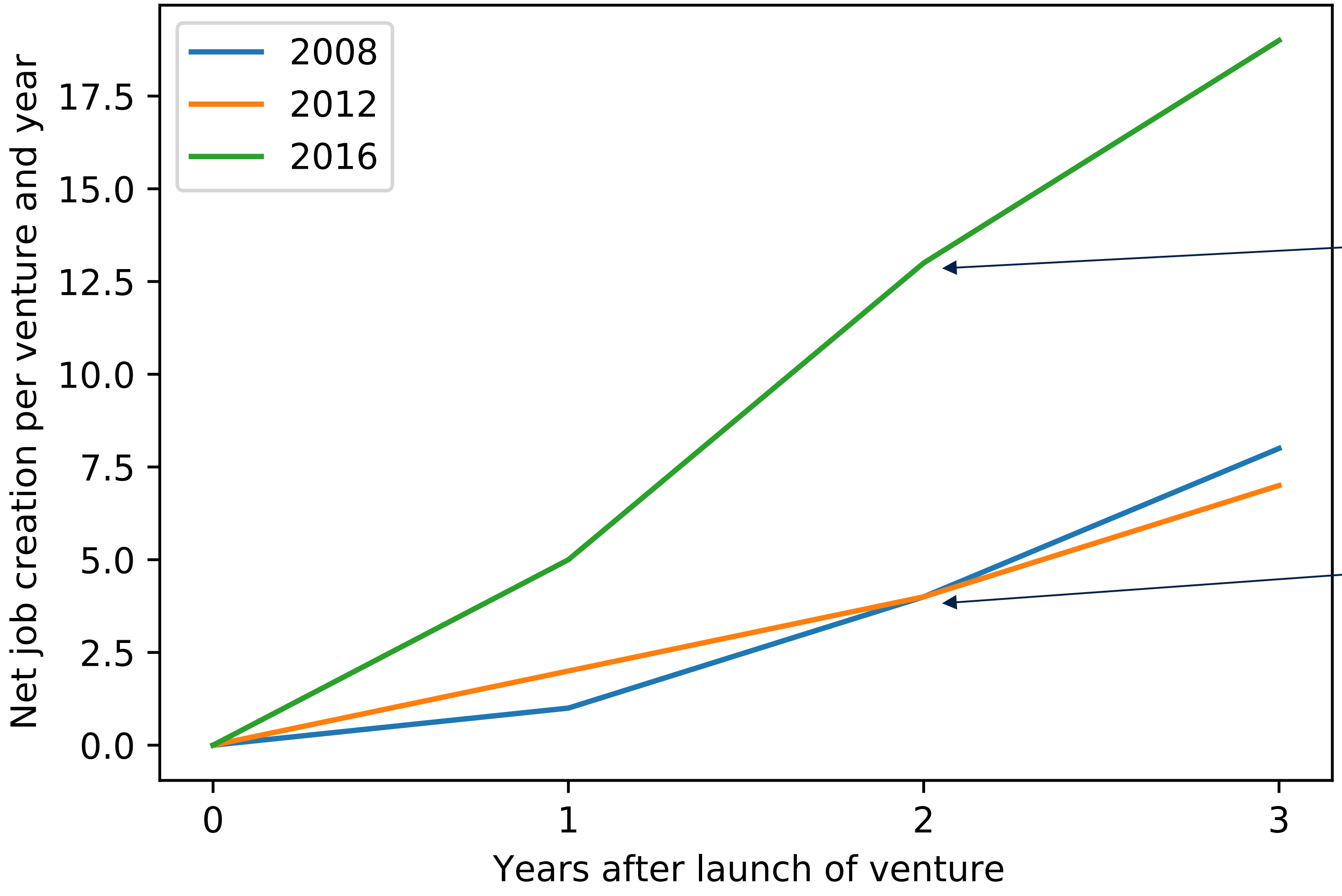
Founder tie networks grew substantially over past decade



San Francisco 2011 to 2019

Notes: the color coding of nodes has changed from previous slides.

Net job creation over the first three years accelerated with maturity of ecosystems



After 2 years, 2016 vintage startups created ~13 jobs per venture

After 2 years, 2008 and 2012 vintage startups created ~3 jobs per venture

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Social networks contribute to scale-up, and highly connected founders scale faster. Both education and employment ties are helpful. Founders benefit from knowledge-similarity within their social network.

A higher degree centrality is helpful for scale-up

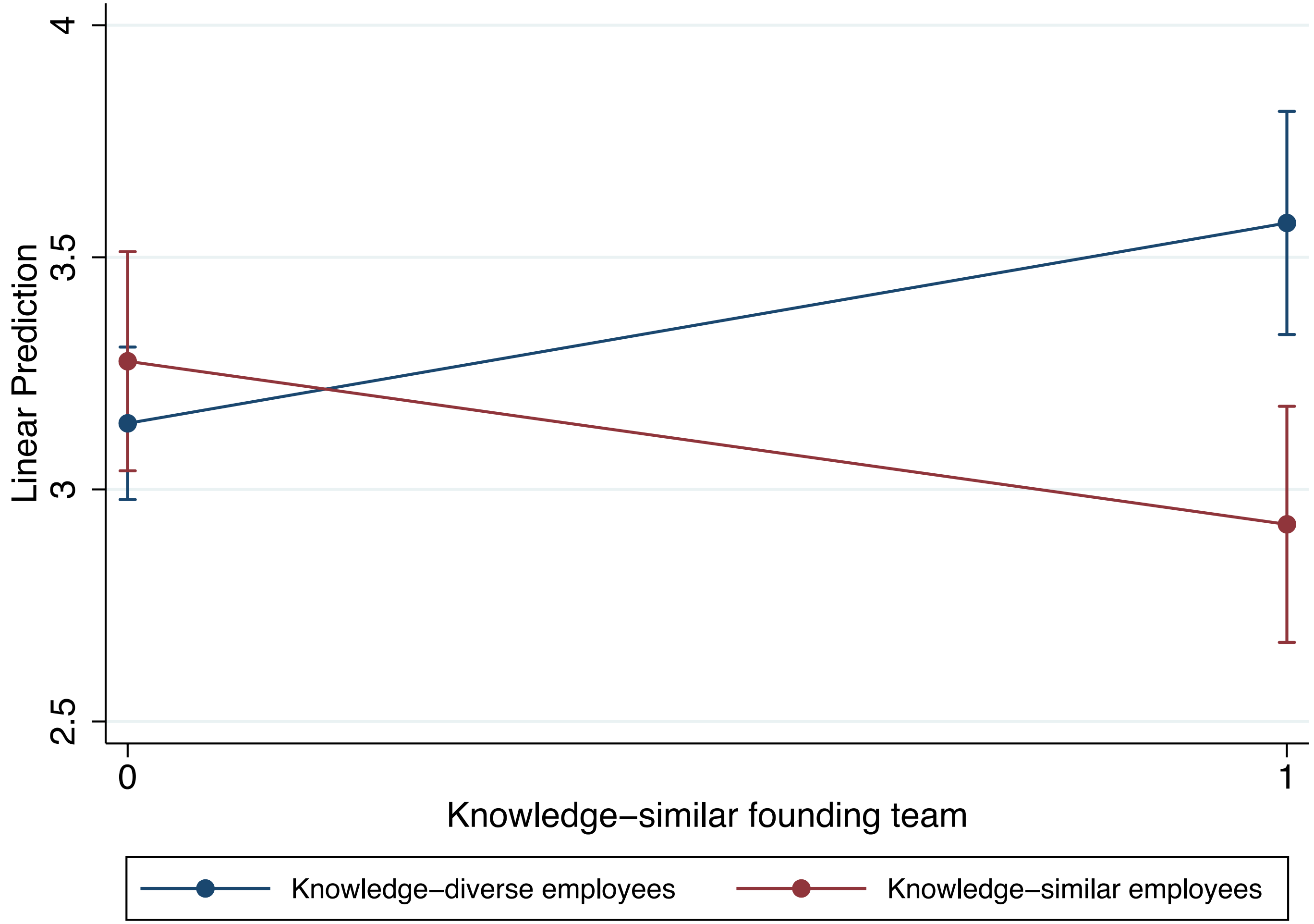
Model	(1)	(2)	(3)
Corresponding hypothesis	H2a &H2c	H2c & H2d	H2c & H2d
Level of analysis	Founder	Founder	Founder
Knowledge-similar founding team	0.4588***	0.4542***	0.4407**
	(0.1546)	(0.1554)	(0.2219)
Founder degree centrality	0.1695***		0.1595***
	(0.0560)		(0.0604)
Founder degree centrality (education)		0.1400***	
		(0.0536)	
Founder degree centrality (employment)		0.1162**	
		(0.0511)	
Founder between centrality	0.0167	-0.0886	-0.1590
	(0.2201)	(0.2365)	(0.2393)
Knowledges-similar networks (relative)	0.2075*	0.1920	0.2974**
	(0.1200)	(0.1185)	(0.1378)
Knowledge-similar networks (absolute)	0.0019	-0.0137	-0.0274
	(0.1096)	(0.1101)	(0.1265)
Founder degree centrality x Knowledge-similar founding teams			0.0259
			(0.1479)
Founder between centrality x Knowledge-similar founding teams			0.8909
			(0.5828)
Knowledges-similar networks (relative) x Knowledge-similar founding teams			-0.3289
			(0.2847)
Knowledge-similar networks (absolute) x Knowledge-similar founding teams			0.1112
			(0.2489)
Venture-level control variables	Yes	Yes	Yes
Founder-level control variables	Yes	Yes	Yes
Area of work fixed effect	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
R^2	0.2943	0.2968	0.2980
Number firms	315	315	315
Observations	3,054	3,054	3,054

Early joiners help knowledge-similar founders to access the diverse ideas and skill-sets to scale ventures. Diversity of employees contributes to fast scale-up.

Model	(1)	(2)	(3)	(4)
Corresponding hypothesis	H3a	H3a	H3b	H3b
Level of analysis	Venture	Founder	Venture	Founder
Knowledge-similar founding teams	0.3403**	0.3253**	-0.2723	-0.3125
	(0.1492)	(0.1432)	(0.2612)	(0.2613)
Absolute knowledge-similar employees	0.0533	0.0975	-0.2019	-0.1337
	(0.1690)	(0.1970)	(0.1775)	(0.2256)
Absolute knowledge-similar employees x knowledge-similar founding teams			1.0031***	0.7830**
			(0.3629)	(0.3597)
Relative knowledge-similar employees	-0.2887*		-0.2714*	-0.3872**
	(0.1434		(0.1600)	(0.1944)
Relative knowledge-similar employees x knowledge-similar founding teams			-0.2986	-0.0823
			(0.3052)	(0.3099)
Venture-level control variables	Yes		Yes	Yes
Founder-level control variables	No	Yes	No	Yes
Area of work fixed effect	Yes	Yes	Yes	Yes
Location fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R^2	0.4103	0.4336	0.4184	0.4411
Number firms	315	315	315	315
Observations	1651	3054	1651	3054

Absolute knowledge-similar employees can moderate and mediate the effect of knowledge-similar founding teams.

Knowledge-diverse employees and knowledge-similar founders with highest net job creation



Note: The figure uses 80% confidence bands.

Venture Analytics Initiative (VAI)

Aims and objectives of VAI

- Problems identified
  - Existing classifications of tech startups in databases are incomplete or inaccurate
  - Decisions made by ecosystem stakeholders – founders, investors, policymakers -- are based on incomplete data
  - Gut feel may lead to bias, undermining diversity, equality and inclusion

- How to solve this market failure?
  - Develop a taxonomy that satisfies multiple stakeholders' purposes
    - **Founders:** which client base is underserved?
    - **Investors:** how to identify investment targets faster (which venture characteristics best predict scale-up potential?)
    - **Policy-makers:** which technology area or skill area require policy support?
  - Use publicly available data and private data (in a privacy-preserving way) to classify ventures

- Nine-dimensional taxonomy, with applications in Lawtech, Fintech, HealthTech, and PropTech

Building an automatic technology venture classifier

Scrape text from company webpages and structure information from pitch decks

Annotate sentences according to taxonomy

Apply classification engine to universe of startups

- Daily scrapes of 40k webpages of startups.
- Process and structure pitch deck data for ventures currently seeking funding.
- Integrate the pitch deck data in a privacy preserving way.
- Split the web page text corpus into sentences. Use sentences as the unit of classification.

- Manually annotate for the OVET categories.
- Use the Oxford Sentence Annotators, with its integrated machine learning models to accelerate annotation process.
- Achieve cost-efficient annotation process using integration into Amazon Mturk, to crowdsource annotations.

- Use annotations to automatically classify startups into OVET categories.
- Dynamically update classifications based on new available information.
- Make the classifications available to the public within an open-source, open-access web tool.

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The taxonomy for the Lawtech sector with its categories. Some OVET dimensions require third-party data, such as from LinkedIn.

Areas of legal work

Managing the business
- People & resources
- Finance & operations
- Clients

Managing & performing
- Knowledge
- Matters
- Risks
- Rights management

Performing
- Documents & contracts
- Transactions (including M&A)
- Litigation

Funding cycle
- Funding raised
- Types of funding raised
- Present fundraising stage
- Time measures
- Revenue measures
- Secondary markets
- Type of exit

Geographical footprint

Headquarter & other locations

Employees

Founder and funders

Founder characteristics
- Age of founder at launch
- Gender
- Has children
- Is immigrant

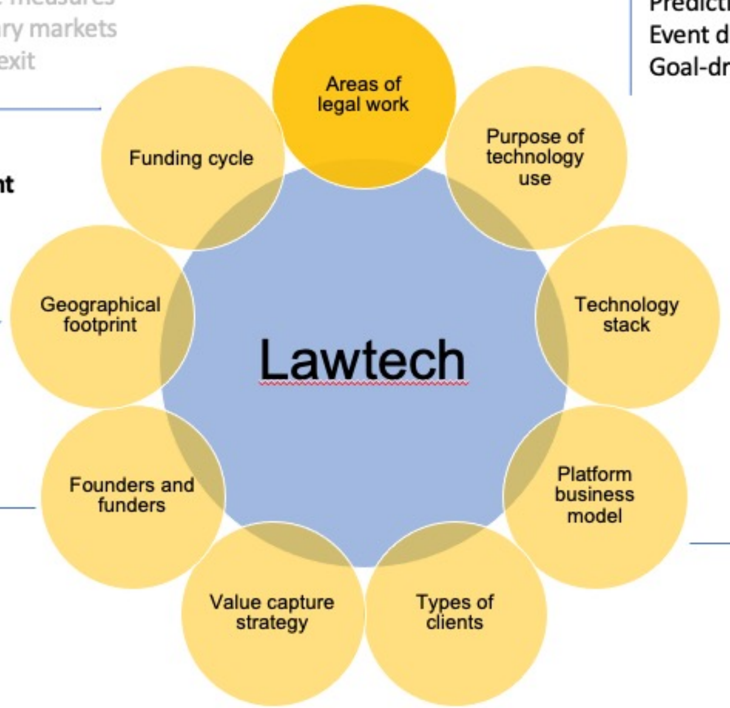
Founder experience
- Founder knowledge domains
- Founder education and employment
- Founder social networks

Serial entrepreneur

Founder family ties
- Parental occupation of founder
- Relatives as investors

Founder strength
- Product development capabilities
- B2B sales capabilities

Investors
- Funder identity
- Funder social networks
- Total funds of existing funders
- Has international funder



Purpose of technology use
- Personalisation and customisation
- Privacy protection
- Recognition
- Generation
- Forecasting
- Prediction
- Event detection
- Goal-driven optimisation

Technology stack

Applications
- Services
- APIs

Tools
- Orchestration and pipelines
- Monitoring
- Code management
- Data management
- Languages and frameworks

Workload enablers
- Middleware
- Virtualisation
- Scaling infrastructure
- Databases
- Runtime/OS

Hardware
- Processors
- Networking
- Storage
- Sensors

Value capture strategy
- Commission
- Contingent Payment
- Licensing
- One-time Purchase
- Subscription
- Time-based pricing
- Usage-based pricing
- Patent granted or applied

Types of clients
- In-house legal teams
- Governments & courts
- Individuals & households
- Law firms, chambers and ALSPs
- Non-legal

Platform business model

Facilitating transactions

Innovation platform
- Providing standards & interfaces
- Using standards & interfaces

Note: Grayed out categories require additional third-party data.

Summary and next steps

Lawtech vs Fintech

Lawtech startups are **smaller** on average than fintech startups

Smaller proportion of lawtech startups get **external funding** than fintech startups

Ventures with **lawyer founders** scale more slowly

Founders' knowledge domains vary by location: in lawtech ecosystems, 44% of founders are lawyer-founders in NYC, 33% in London, and 26% in SF

Knowledge domains of founders and early joiners

Knowledge-diversity in founding teams important in early stages of ecosystems

Knowledge-similarities in founding teams help scaleup and obtain funding

Dense social ties of founders facilitate scaleup

Early joiners' knowledge domains complement founders' knowledge domains and help ventures access diverse skills

Venture Analytics Initiative (VAI)

Oxford Venture Ecosystem Taxonomy (OVET) being finalized

Plan to start with UK ventures based on startup population identified by Beauhurst

Plan to launch a webtool in summer 2022

IF YOU'RE INTERESTED IN GETTING INVOLVED, PLEASE CONTACT US AT:

VAI@sbs.ox.ac.uk

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