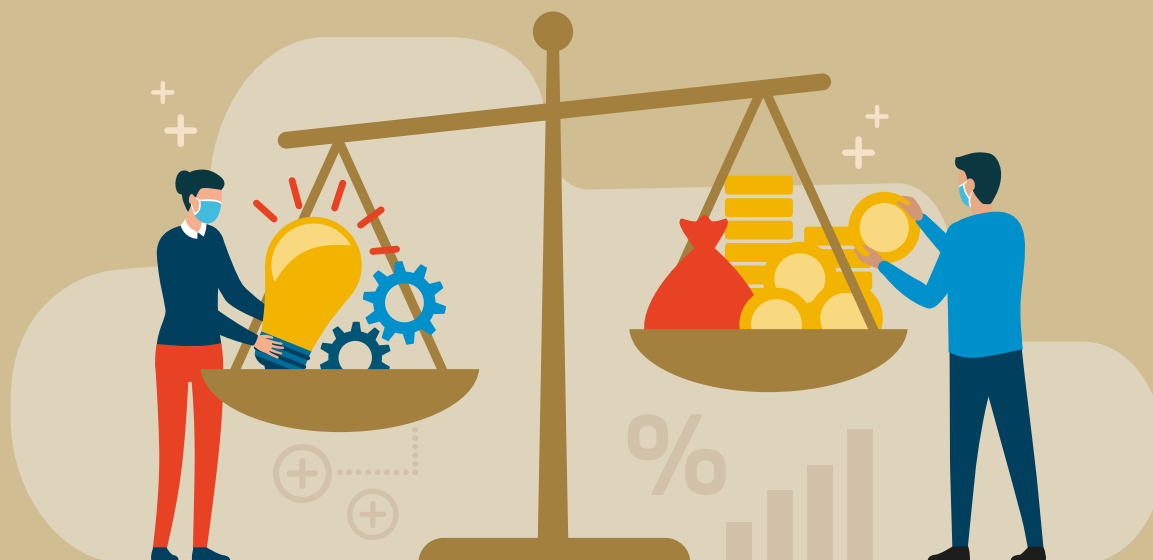


## Innovation in the time of Covid-19



Josh Lerner  
*Harvard Business School*

Nick Bloom  
*Stanford*



## Hi-tech growth in the digital era

Jacques Crémer  
*TNIT Coordinator*

Christophe Bisière & Bruno Jullien  
*Co-directors, TSE Digital Center*

**D**ear friends,  
The whirlwind transformation of human society wrought by the digital age, and now Covid-19, has left policymakers, firms and analysts struggling to keep up. The pandemic in particular has laid bare the urgent need for rigorous research and solid statistics to guide our response to a fast-changing world.

With a special focus on innovation, this issue highlights economists who are stepping up to the challenge. Josh Lerner (Harvard Business School) and regular TNIT News contributor Nick Bloom (Stanford) demonstrate their scientific tools and ingenuity in tracking the storm path of digitization, measuring the spread of AI and emerging technologies through the US economy. In a separate article, Josh builds on his research on venture capital to show how a Covid-19 recession threatens the survival of tech startups and other innovative young firms.

**Wishing you good health and new inspiration**

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# Will venture capital protect innovators from recession?

Josh Lerner<sup>(1)</sup>  
*Harvard Business School*

Josh Lerner is the head of the Entrepreneurial Management Unit and the Jacob H. Schiff Professor of Investment Banking at Harvard Business School. He worked for several years on issues concerning technological innovation and public policy at the Brookings Institution, for a public-private task force in Chicago, and on Capitol Hill.

Much of his research focuses on venture capital and private equity organizations. He also examines policies on innovation and how they impact firm strategies. He co-directs the National Bureau of Economic Research's program on Productivity, Innovation, and Entrepreneurship.

**F**ears that the Covid-19 crisis will strangle innovation have prompted governments including Canada, France, Germany, and the United Kingdom to spend billions on shoring up venture capital firms. This sector appears to be very efficient in stimulating innovative new companies - particularly in the IT industry - but it is once again threatened by recession. Here, I present some of the latest research on this issue and discuss how governments and firms should respond.

Startups, particularly those backed by venture capital (VC), are an increasingly important channel for early-stage innovation in areas such as artificial intelligence (AI) and cloud computing. In June, AngelList's database of young firms seeking investors ([www.angel.co](http://www.angel.co)) listed 7,900 ventures in response to a search for the keyword "cloud", nearly 5,000 for "intelligence" or "machine learning", and more than 1,200 for "payments".

Successful startups occasionally go public but most end up being acquired by larger firms. As evidenced by the proliferation of corporate venturing programs, tech giants increasingly rely on such acquisitions to develop new ideas, rather than the central research spending which traditionally formed the bulk of R&D expenditure.<sup>(2)</sup>

## Innovation or bust?

The strong relationship between VC and innovation is supported by extensive research<sup>(3)</sup>, and is particularly striking in light of the slowdown in productivity growth across the developed world. But VC is prone to boom-bust cycles. This might seem surprising, because VC firms, like other types of private equity, usually employ a 10-year fund structure and make private, long-term investments which should provide insulation from downturns.

(1) This essay is based on joint work with Sabrina Howell, Ramana Nanda, and Richard Townsend. Harvard Business School's Division of Research provided funding for our work. I have received compensation from advising institutional investors in venture capital funds, venture capital groups, and governments designing policies relevant to venture capital. All errors and omissions are our own.

(2) See Arora, Belenzon, and Sheer (2019); Bloom et al. (2020).

(3) See Akcigit et al. (2019); Bernstein, Giroud, and Townsend (2016); Kortum and Lerner (2000).



**Successful startups occasionally go public but most end up being acquired by larger firms. As evidenced by the proliferation of corporate venturing programs, tech giants increasingly rely on such acquisitions to develop new ideas, rather than central research spending.**

Venture investors are also fond of pointing to successful companies launched in recessions, such as Airbnb, which received its initial funding in 2009. However, studies show that important aspects of VC - such as the volume of investment, company valuations, and exits through IPO or acquisition - are pro-cyclical.<sup>(4)</sup>

In our recent working paper (Howell et al., 2020), we show that VC activity fell precipitously in the US during the initial phases of the Covid-19 crisis. The number of weekly early-stage VC deals declined by nearly 38% in the two months starting March 4, 2020, relative to the previous four months. In contrast, later-stage VC has remained much more robust.

The Covid-19 crisis is not an anomaly in this regard. Examining historical data on VC investment activity, we show that aggregate deal volume, capital

invested, and deal size all decline substantially in recessions. Investors who specialize in early-stage deals are significantly more responsive to business cycles than later-stage investors.

We also examine the impact of recessions on the volume and quality of VC-backed innovation, using data on VC financing matched to the patenting of VC-backed startups from 1976 to 2017.

## Key findings

- **Patents filed by VC-backed startups are of higher quality and greater impact than the average patent.** For instance, 29.4% of the VC-backed patents are in the top 10% of most-cited patents (defined relative to all patents filed in the same month), and 4.7% are in the top 1% of most-cited patents. VC-backed firms are also disproportionately likely to have more original patents, more general patents, and patents more closely related to fundamental science.
- **This pattern is even clearer for AI patents.** Table 1 examines all US patents applied for between 2000 and 2018, and awarded by 2019. It shows that “AI patents” are 2.2 times more likely to be VC-backed. Focusing on the most influential patents (those in the top 1% of citations), AI patents are 2.8 times more likely to be venture-backed. VC-backed non-AI patents are 4.9 times overrepresented in the top 1%, while AI patents are 6.3 times overrepresented.

*Table 1: AI patents have more funding and impact*

AI patents are those with a primary assignment to US Combined Patent Classification subclass G06N. The table presents the share of venture-backed patents among all patents applied for between 2000 and 2018 and awarded by 2019, as well as those in the top 1% of citations relative to those applied for in the same year.

	Non-AI Patents	AI Patents	Ratio, AI/Non-AI
% VC Backed	2.22%	4.95%	2.23
% VC Backed and in Top 1% of Citations	0.11%	0.31%	2.82
Over representation in Top 1%	4.95x	6.26x	
Number	3,799,824	5,870	

- **VC-backed innovation is even more pro-cyclical than the broader economy.** Relative to all other patent filings within a technology class, the number and quality of patents applied for by VC-backed firms is positively correlated with the amount of VC investment in startups in a given month. Recessions are associated with low levels and quality of innovation, even after controlling for the lower amount of VC finance available.

(4) See Kaplan and Schoar (2005); Gompers et al. (2008); Robinson and Sensoy (2016).

- **As with deal size, our innovation results are driven by startups financed by venture groups specialized in early-stage investment.** In some specifications, there are few differences in the volume of innovation across the business cycle for startups backed by late-stage investors.<sup>(5)</sup>
- **The impact of recession on innovation stems from the types of firms receiving VC financing and a change in the nature of innovation within these firms during the business cycle.** Our results appear to be driven by startups that raised their most recent VC round either during the recession, or long before. For startups that raised their most recent round during the six months before the recession started (i.e., the boom period), there is no relative decline in innovation quality.

## How should governments respond?

Concern for venture-backed innovation in the wake of the Covid-19 crisis<sup>(6)</sup> led the UK Treasury to introduce the Future Fund in April 2020 to provide a lifeline to unprofitable tech firms unable to gain access to other relief financing schemes. Our research suggests that such policies should be carefully targeted to favor innovators rather than corporate lobbyists.

One key to success for government programs is to provide smaller amounts of capital to young firms. Policies often gravitate to providing larger sums even though capital shortfalls during busts are often in the early stages of financing, as highlighted above. The largest US government-funded program to help new ventures, the two-phase Small Business Innovation Research (SBIR) program, offers a useful illustration. While its Phase I awards made up only 20% of the \$2.8 billion total awards for fiscal year 2017, these initial grants produced essentially all the program's positive benefits.<sup>(7)</sup> Our research points to the problems that arise when companies capture a disproportionate number of awards.<sup>(8)</sup> "SBIR mills" often have staffs of active, wily lobbyists in Washington that focus only on identifying opportunities for subsidy applications. Such firms commercialize far fewer projects than those that receive just one SBIR grant.

## Companies must uphold commitments

Corporations are playing an increasingly important role in the venture market, whether by supporting companies or seeding funds. A critical driver of success is *the need for staying power*. The commitment that an institutional investor, such as a pension fund or an endowment, makes to a traditional venture fund is binding: even if the limited partner contributes a small amount of the total capital promised at the time of closing, there is an expectation that the total amount promised will be provided. Even during the depths of the global financial crisis, it was rare for investors to walk away from these commitments.

In contrast, companies have been too fickle in their commitment to "corporate venturing" initiatives for funding startups. Many programs begun during venture booms are abandoned in downturns.<sup>(9)</sup> It is almost a corporate ritual for a new senior officer - a replacement CEO, chief financial officer, or R&D head - to discard the pet projects of their predecessor. This lack of commitment has important consequences: Employees are less likely to join a corporate venturing group they fund; entrepreneurs are reluctant to accept their funds; independent venture funds are hesitant to syndicate investments with these groups; and corporate-funded startups find collaborations harder to arrange. In each case, the threat that the corporate venture initiative will be abandoned deters the involvement of others and reduces its effectiveness in boosting innovation.

“  
**Concern for venture-backed innovation in the wake of the Covid-19 crisis led the UK Treasury to introduce the Future Fund to help unprofitable tech firms unable to gain access to other relief financing schemes. Such policies should be targeted to favor innovators rather than corporate lobbyists.**

(5) The fact that late-stage VC appears to be more insulated from the public markets is consistent with Bernstein, Lerner, and Mezzanotti (2019), who find that investment at private equity-funded companies was less sensitive to the 2008 financial crisis.

(6) For instance, leading British venture capitalists and entrepreneurs recently argued that absent targeted government aid, "companies of the future such as ours... will be put at risk" See <https://www.scribd.com/document/455681169/Letter-to-the-Chancellor>

(7) See Howell (2017).

(8) See Howell (2017); Lerner (1999).

(9) Gompers and Lerner (2000).

## KEY TAKEAWAYS

- ➔ VC is linked to high-quality and high-impact innovation. But VC-backed innovation is particularly vulnerable to boom-bust cycles.
- ➔ Policymakers will get more “bang for their buck” by streamlining VC funding programs, focusing on early-stage financing for new firms.
- ➔ “Corporate venturing” companies need to stick to their commitments to supporting startups: staying power is key to success.

## FURTHER READING

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# How to track the advance of AI



(1) This essay is based on our joint work with Tarek A. Hassan, Aakash Kalyani, and Ahmed Tahoun (Bloom et al., 2020). Funding for this research was provided by Harvard Business School's Division of Research, the Institute for New Economic Thinking, London Business School's RAMD Fund, and TNIT. Lerner has received compensation from advising institutional investors in venture capital funds, venture capital groups, and governments designing policies relevant to venture capital.



While the increase in references to AI among firms in our sample begins in the early 2010s, exponential growth does not start until 2015. By 2019, almost 20% of firms are reported as exposed to AI using this measure.

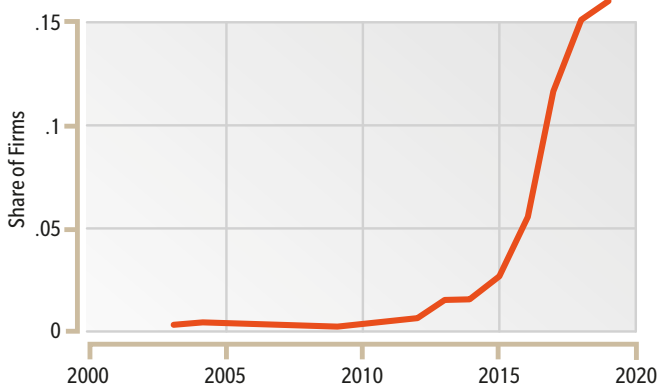


**W**hen did the digital age begin? Where has it had the greatest impact? To answer such questions, we have developed powerful new economic methods for measuring the spread of new technologies. Here, we provide a brief overview of the tools inside our ‘black box’ and demonstrate their effectiveness with a focus on the evolution of artificial intelligence in the US economy.

“You can see the computer age everywhere but in the productivity statistics,” quipped economist Robert Solow in 1987. Digitization has since accelerated, dramatically transforming how we work, shop, and spend our free time. But measuring these changes can be problematic. For instance, government schemes for classifying industry can become quickly outdated. It is also much harder to calculate the impact of an entirely new technology than that of improvements to an existing one.

To identify the evolution of a recent and influential technology such as artificial intelligence (AI), we associate it with business-relevant keywords in patents, earnings calls and job postings. This allows us to assess when companies shift their focus to new technologies, when and where they do new hiring, and how the technology evolves. Our analysis allows us to provide a wide variety of insights, including the location and types of jobs created by emerging technologies.<sup>(2)</sup>

Figure 1: AI-exposed firms



Notes: The picture plots (year by year) the share of firms (red line) which mention AI-related keywords in earnings calls.

## The evolution of AI: Key findings

- Figure 1 shows the growth of the exposure to AI among the publicly traded firms in our sample. While the increase in references to AI begins in the early 2010s, exponential growth does not start until 2015. By 2019, almost 20% of firms are reported as exposed to AI using this measure.



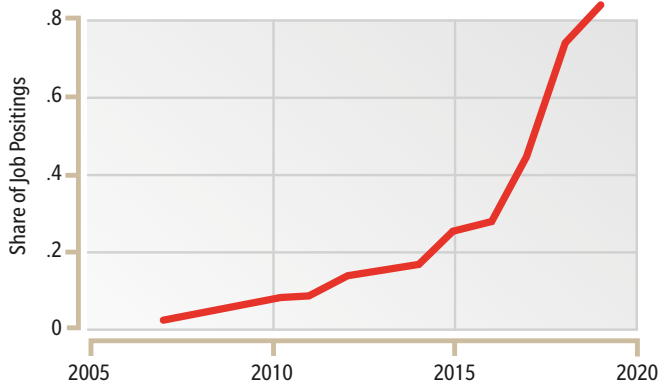
Digitization has dramatically transformed how we work, shop, and spend our free time. But measuring these changes can be problematic. For instance, it is much harder to calculate the impact of an entirely new technology than that of improvements to an existing one.

(2) See Bloom et al. (2020).



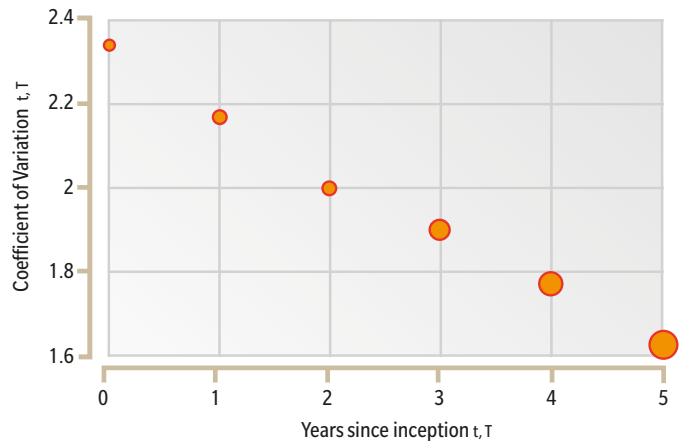
- **Figure 2** shows the share of all job postings associated with AI. Again, we see a precipitous rise in the mid-2010s.
- **Figure 3** examines how variation across regions changes over time for AI. We measure the degree to which each urban area is over or underrepresented by job postings associated with AI, relative to the overall distribution. The analysis reveals a sharp pattern: there is a sharp decline in the concentration of jobs over time. Put another way, the distribution of new hiring over time becomes more evenly spread out.

Figure 2: AI-exposed job postings



Notes: The picture plots (year by year) the share of job postings (red line) which mention AI-related keywords.

Figure 3: Spatial variation of AI job postings



Notes: The coefficient of variation measured is that of the normalized share of technology jobs for AI-exposed job postings across urban areas from 2015–2019 against the years since start of the technology. This allows us to control for the fact that, for instance, Los Angeles will have a large share of job postings of nearly every type, and that different technologies may be implemented at very different scales at a given point in time.

- **Table 2** shows the job titles most associated with AI, as well as the number of postings for each job title (or set of titles). Unsurprisingly, the major job classes most exposed to AI include computer science, computer hardware, and data science positions. We also see that AI has a profound effect on some smaller occupational categories, such as astronomers, life scientists, and social science researchers.

Table 2: AI occupations

SOC Name	Total Jobs	Exposed Jobs	% Exposed
Computer and Information Research Scientists	233,763	134,467	57.52
Astronomers	11,905	637	5.35
Computer Hardware Engineers	100,329	5,151	5.13
Computer Science Teachers, Postsecondary	36,470	1,699	4.66
Statisticians	214,471	9,260	4.32
Life Scientists, All Other	29,543	1,058	3.58
Database Administrators	1,271,844	42,990	3.38
Operations Research Analysts	983,408	32,446	3.30
Social Science Research Assistants	56,496	1,761	3.12
Software Developers, Applications	8,330,098	250,711	3.01

Notes: The table lists top AI occupations (in column 1) by percentage of job postings (in column 4) exposed to AI. The table only shows occupations with at least 10,000 job postings on Burning Glass between 2007 and 2019.



To identify the evolution of AI, we associate it with business-relevant keywords in patents, earnings calls and job postings. This allows us to assess when companies shift to new technologies, when and where they do new hiring, and how the technology evolves



## Words of change

We are able to empirically track this rapid march of AI (and other new technologies) by pinpointing the presence of relevant keywords in several contexts. Patents provide an attractive starting point as they are by definition novel, and must describe their technology and its applications. We only consider patent awards by the US Patent and Trademark Office, which receives important filings for discoveries around the world.

Searching the patent for tech-related keywords, we focus on two-word combinations because they are less ambiguous than single words. For example, words like “autopilot” or “cloud” can have a variety of colloquial meanings, but “autonomous vehicle” and “cloud computing” are much less ambiguous.<sup>(3)</sup> After collecting about 17 million of these “bigrams”, we remove “non-technical” pairs that feature in everyday discussion.

## Let’s talk business

We also uncover vital clues about the advance of AI by analyzing the words that companies use to discuss their operations. We concentrate on the earnings call transcripts of publicly listed firms, in which management executives present their financial results and respond to questions from investment analysts.

From a list of the 500 “technical” bigrams that most commonly appear in these conference calls, we select those that we believe clearly reflect specific technological advances that have changed the way businesses operate. For example, “rapid prototyping” and “additive manufacturing” are associated with 3D printing, while “solar cell” and “solar module” are linked to solar power.

To address our concern that the vocabulary used by executives might not appear in patent awards, we introduce a natural language processing algorithm. It uses the context (neighboring words) for each bigram to suggest “proximate” other bigrams. These are added to our selection if, in our reading, they clearly describe the technology in question.

We conduct a human audit for each bigram in which a team member reviews 100 randomly sampled excerpts from the earnings calls. This process helps us to ensure that our selection of keywords correctly captures firms’ exposure to a given technology.

## Where are the jobs?

The final piece of the puzzle is job postings. By providing information about the job description, location and number of new positions that firms are looking to fill, these open another important window for observing the spread of AI and other emerging technologies.

Using “spider bots”, the analytics software company Burning Glass aggregates online job postings into a machine readable, de-duplicated database.<sup>(4)</sup> For each job, Burning Glass provided us with the geo-coded location and Standard Occupational Classification (SOC).<sup>(5)</sup> We also obtained the raw unprocessed text of the job postings.

Combining these data with our keyword shortlist, we are able to measure the exposure of occupations, firms, and geographies to a given technology. In particular, we create a measure which reflects, in a given urban area, both the diffusion of the technology and the overall level of hiring.<sup>(6)</sup>

(3) We follow the methodology of papers undertaking textual analyses of patents and earnings calls, such as Kelly et al. (2018) and Hassan et al. (2019).

(4) See Hershbein and Kahn (2018).

(5) The SOC is a US government system of classifying occupations.

(6) The Normalized Share of Technology Jobs for every core-based

statistical area (CBSA), technology  $T$ , and year  $t$  can be written as:  $Normalized\ share_{cbsa,t,T} = \frac{share\ jobs\ exposed_{cbsa,t,T}}{share\ jobs\ exposed_{t,T}}$



**Unsurprisingly, the major job classes most exposed to AI include computer science, computer hardware, and data science positions. We also see that AI has a profound effect on some smaller occupational categories, such as astronomers, life scientists, and social science researchers**

## Final thoughts

Together with information on patenting and news stories, our systematic approach provides a rich sense of the diffusion of new technologies, both separately and across technologies. To understand the impact of digitization, we need innovative methods. This essay has given a brief overview of some of the cutting-edge techniques we have developed, exploiting some of the information technologies that are reshaping the 21<sup>st</sup> century. We look forward to describing the consequences of these innovations in future essays.

### KEY TAKEAWAYS

- ➔ We track the evolution of AI and other new technologies by linking them with keywords from patents, earnings calls and job postings. This methodology allows us to investigate when companies embrace new technologies, when and where they do new hiring, and the types of jobs created.
- ➔ We show exponential growth in references to AI from 2015. By 2019, almost 20% of firms are exposed to AI. Similarly, the share of job postings associated with AI begins a precipitous rise in the mid-2010s.
- ➔ Job classes most exposed to AI include computer science, computer hardware, and data science positions. AI has also had a profound effect on some smaller occupational categories, such as astronomers, life scientists, and social science researchers.
- ➔ Looking at variation across regions, we find that new hiring for AI jobs has become much more evenly spread out over time.

### FURTHER READING

- **Nicholas Bloom, Tarek A. Hassan, Aakash Kalyani, Josh Lerner and Ahmed Tahoun (2020)**, “The geography of new technologies”, *Unpublished working paper*.
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