

Digital Capital and Superstar Firms

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Digital Technologies are transforming the competitive landscape

- Capital and investment are shifting toward **digital intangible assets**.

We call this **digital capital**.

- Technological assets are mostly constituted by **complements** to the machines.
- Using online resume data, We measure digital capital value in firms by tracking the workers that build it.
- We find:
 - Digital capital prices vary significantly over time
 - Digital capital quantities are at least **20% of publicly traded firms' assets**
 - A small group of Superstar firms have most of it, and accumulating digital capital predicts productivity.
 - Early evidence on AI-enabled digital capital (AIDC) indicate **high prices, but low quantities on AI**.

Digital capital: Computerization is more than computers

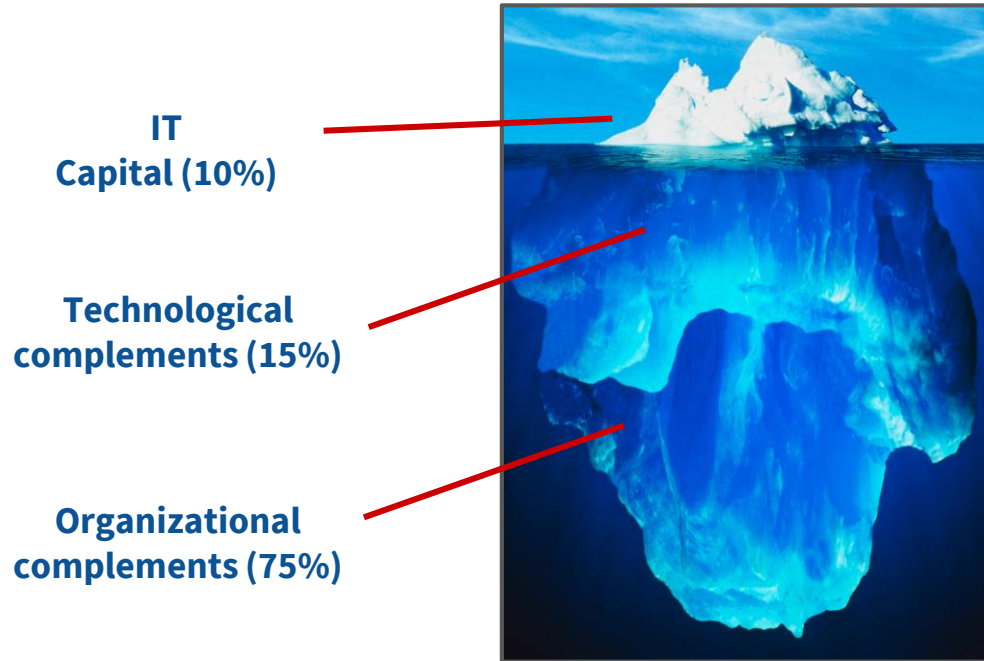
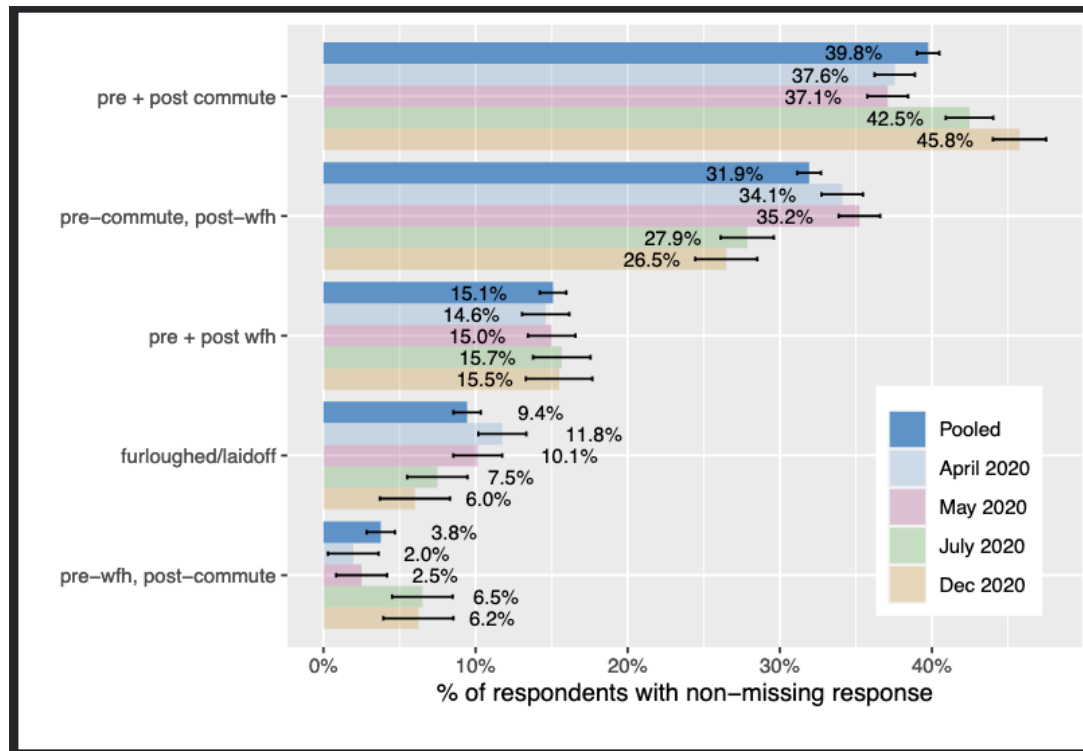


Image by Ralph Clevenger

- Example: For ERP systems, firms can spend **10 MM for hardware and software** and another **100 MM for reengineering**
- The economics of DC assets should be similar to physical capital:
 - Firms build DC to increase output capacity
 - Market value reflects the net present value of the cash flows DC can generate

Where does remote work end up? Who benefits from the change?



Source: Brynjolfsson, Horton, Ozimek, Rock, Sharma, and Tu Ye (2020)

We measure the growth of digital capital and relate it to current waves of technology investment (AI)

- Digital capital is hard to measure. Basic distinctions, like *price* and *quantity*, remain elusive.
 - Compared with tangible capital, it is less fungible, there are no secondary markets on which to observe prices during exchange
 - Difficult to capitalize on a firm's balance sheet
- We measure the accumulation path of this hidden capital stock over three decades using a new IT investment series along with the insight that the value of a firm's assets reveals quantities (Baily 1981; Hall 2001)
- We then test the relationship between the digital capital stock and modern AI investment

First, hedonic regressions generate a series of IT values for firms

- Hedonic regression generates IT intangible value estimates (BHY 2002)

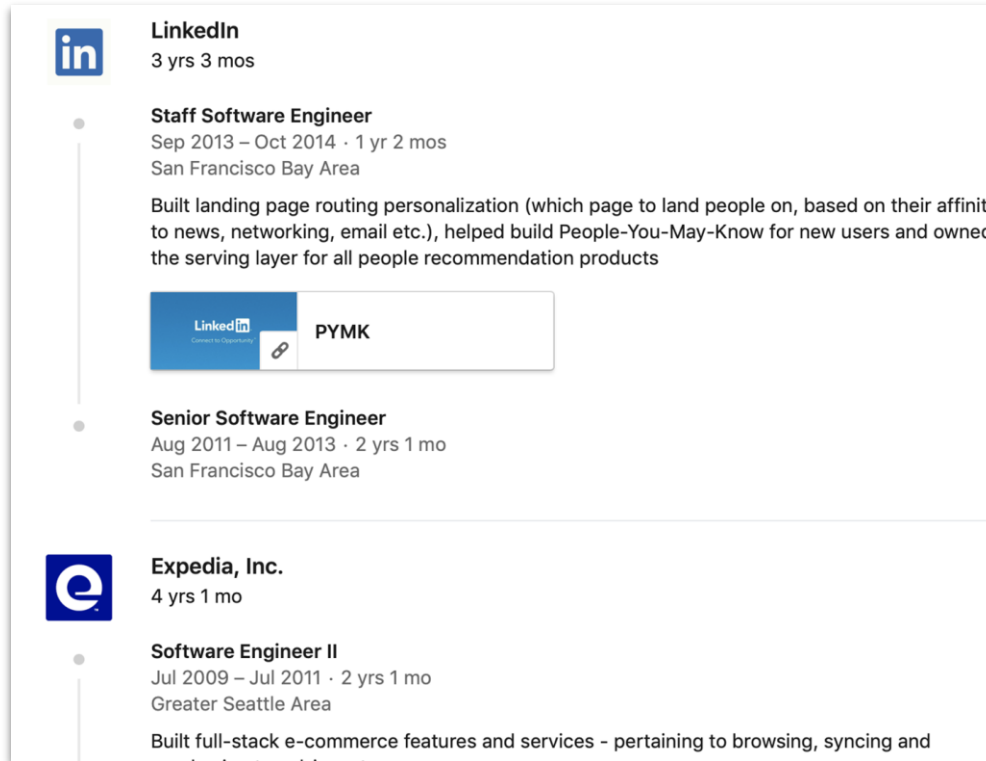
$$MV_{i,t} = \beta_{PPE}PPE_{i,t} + \beta_{OA}OA_{i,t} + \beta_{IT}IT_{i,t} + \epsilon_{i,t}$$

- To compute IT value estimates for the firm-year:
 - Compute regression estimates using a window around each year $t = [-1, +1]$.

$$\hat{V}_i^{IT} = \hat{\beta}_{IT} * IT_i$$

- Has historically been hard to generate IT investment time series ...
- We use measures of IT labor from LinkedIn to measure IT investments
- IT headcounts are **converted to dollars** using *BLS job title wages x firm title counts*

LinkedIn profiles measure the firm's IT investment (IT_{it})




The image shows a LinkedIn profile with two job entries. The first entry is for LinkedIn, where the user worked as a Staff Software Engineer from Sep 2013 to Oct 2014. The description mentions building landing page routing personalization and helping build the PYMK (People-You-May-Know) feature. The second entry is for Expedia, Inc., where the user worked as a Software Engineer II from Jul 2009 to Jul 2011, building full-stack e-commerce features.

LinkedIn
3 yrs 3 mos

Staff Software Engineer
Sep 2013 – Oct 2014 · 1 yr 2 mos
San Francisco Bay Area

Built landing page routing personalization (which page to land people on, based on their affinity to news, networking, email etc.), helped build People-You-May-Know for new users and owned the serving layer for all people recommendation products



Senior Software Engineer
Aug 2011 – Aug 2013 · 2 yrs 1 mo
San Francisco Bay Area

Expedia, Inc.
4 yrs 1 mo

Software Engineer II
Jul 2009 – Jul 2011 · 2 yrs 1 mo
Greater Seattle Area

Built full-stack e-commerce features and services - pertaining to browsing, syncing and

Sampling considerations with data from online professional networks

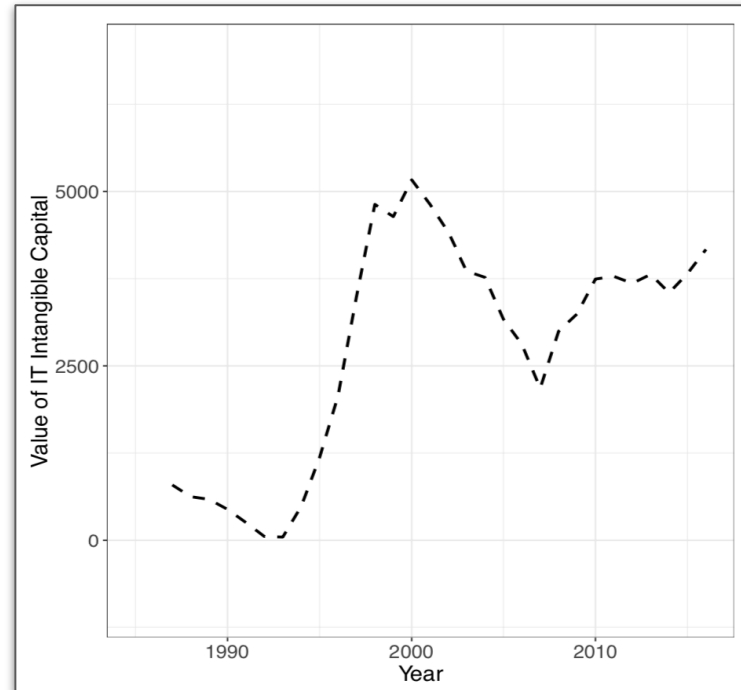
- **Challenges** with the use of online professional network data
 - Uneven sampling across firms, industries, regions, etc. (mitigated by sample size)
 - Biases in employee characteristics, job hoppers, favors white-collar, technical work
 - Missing data on interesting characteristics such as college or degree obtained
 - Potential falsification of some resume data
- **Opportunities**
 - IT workers are very well represented in these data
 - Combines information on occupations, skills, and employers
 - Arguably a better indicator than IT hardware, new ITIC can be deployed on old machines
 - Granular data on technical skills allows further investigation of **technology class** (e.g. AI, cybersecurity, networks, web development)
- Enables construction of a **fairly comprehensive and consistent** firm-level IT time-series when compared with possible alternative approaches

Estimates from hedonic regression on market value

	1987-1998			1987-2016		
	DV: Market Value					
	OLS	OLS	OLS	OLS	FE	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
PPE	1.758*** (0.184)	1.576*** (0.160)	1.724*** (0.174)	1.472*** (0.231)	1.272*** (0.211)	1.474*** (0.226)
Other assets	0.982*** (0.200)	1.055*** (0.188)	0.921*** (0.192)	1.319*** (0.213)	1.328*** (0.259)	1.351*** (0.217)
IT capital	8.300 (13.173)		-3.000 (12.492)			
IT labor		3.771** (1.639)	4.371* (2.592)	8.786*** (2.391)	10.381*** (3.803)	
IT wage bill						11.737*** (3.443)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	No
Industry FE	Yes	Yes	Yes	Yes	No	Yes
Observations	1,604	3,017	1,603	8,521	8,521	5,540
R ²	0.731	0.774	0.734	0.826	0.902	0.823

IT labor series in the regression framework generates a thirty year **panel** of estimated digital capital values

$$\hat{V}_i^{IT} = \hat{\beta}_{IT} * IT_i$$



Second, recovering quantities from values

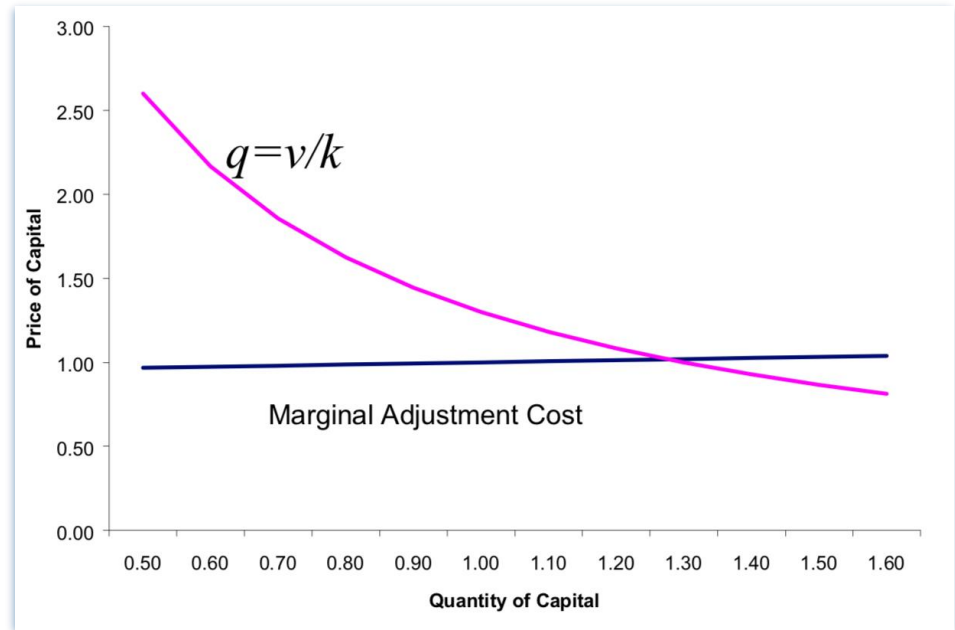
Market value is price x quantity

$$V_t/k_t = p_t$$

Constraints on internal capital adjustment

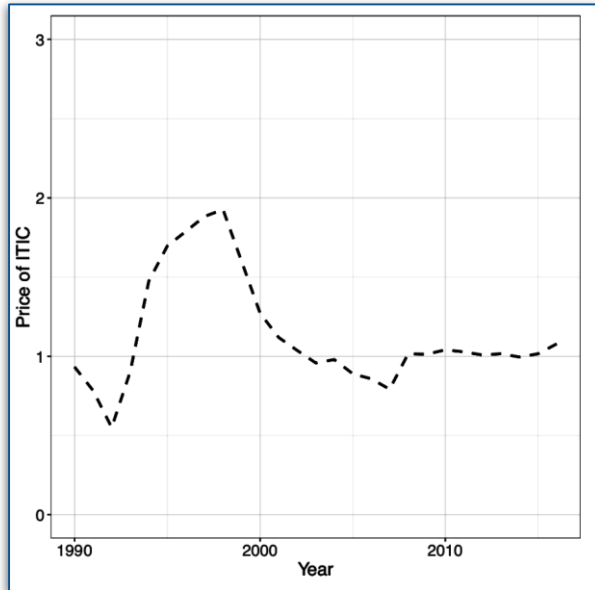
$$p_t = \alpha_t^k \frac{k_t - k_{t-1}}{k_{t-1}} + 1$$

Fixing α and k_0 yield two equations and two unknowns that can be solved recursively to produce changes in prices and quantities.

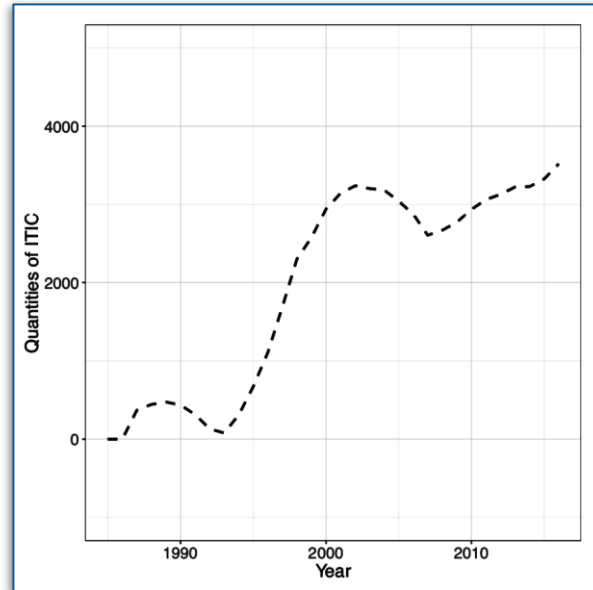


Hall (2001)

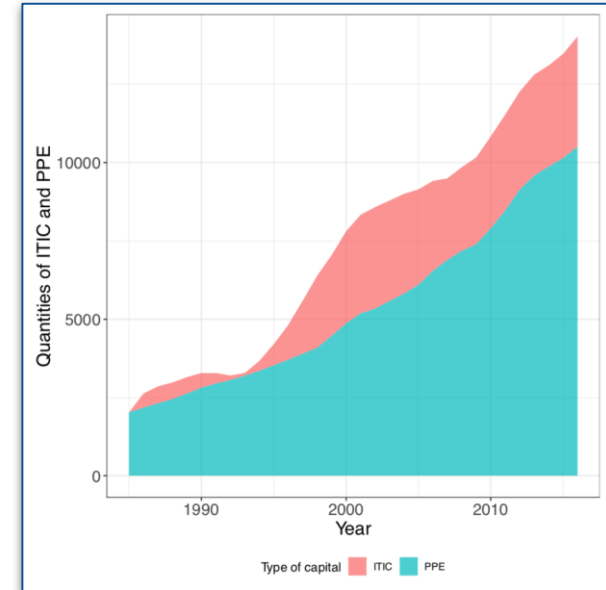
Prices and quantities of DC (charts are sample averages*)



Prices

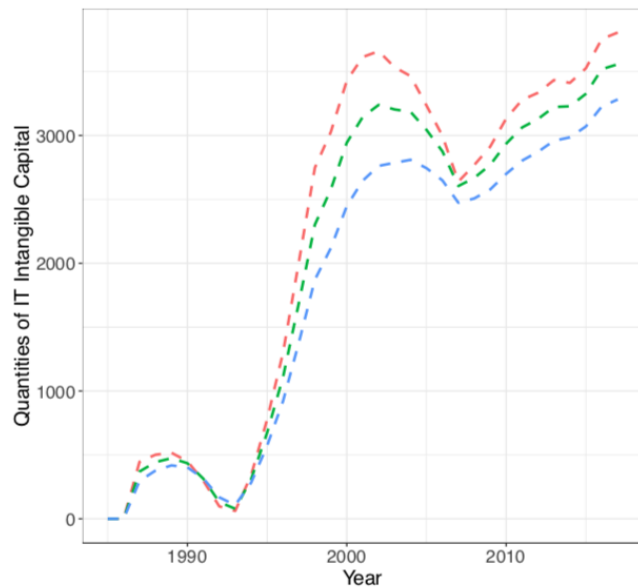


Quantities



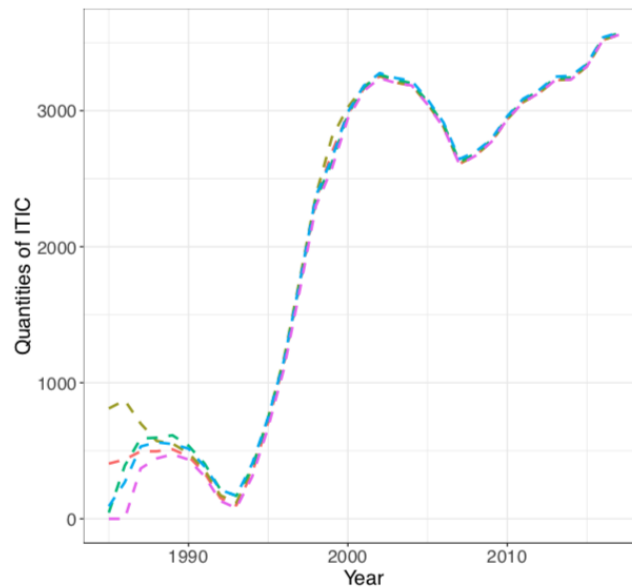
Quantities v PPE

Computed values are fairly robust to perturbing parameter values (α and k_0)



α — =1.5 — =3.0 — =6.0

Adjustment costs (α)



Initial ITIC — No init — PPE 20% — PPE 40% — Random, 1990 — Random, 1995

Starting capital (k_0)

AI and intangible capital: LinkedIn skills describe AI investment

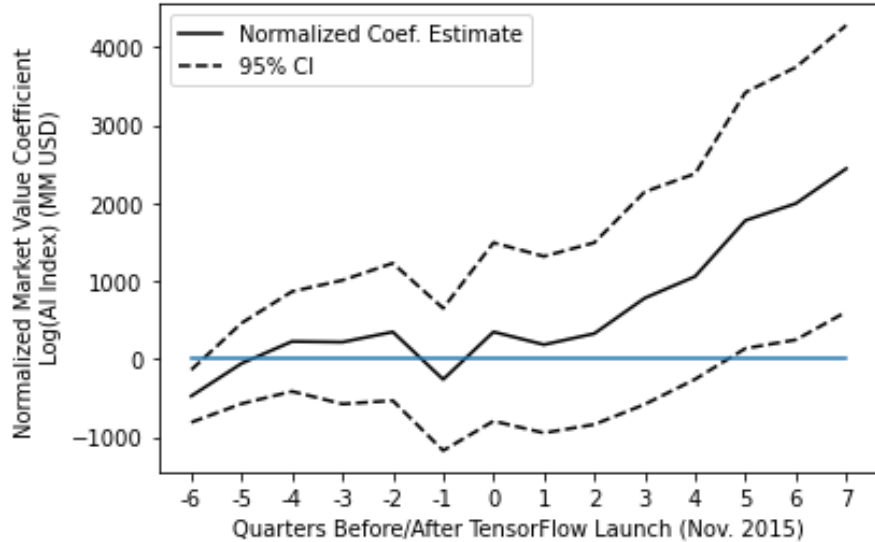


Figure notes: This chart illustrates average AI skills per 1000 employees for a balanced panel of publicly traded US firms in 2017. Industries are categorized as 2-Digit NAICS codes. The Information (NAICS 51) and Professional, Scientific, and Technical Services (NAICS 54) industries have the highest concentration of AI skills. Industries with fewer than 10 firms are omitted.

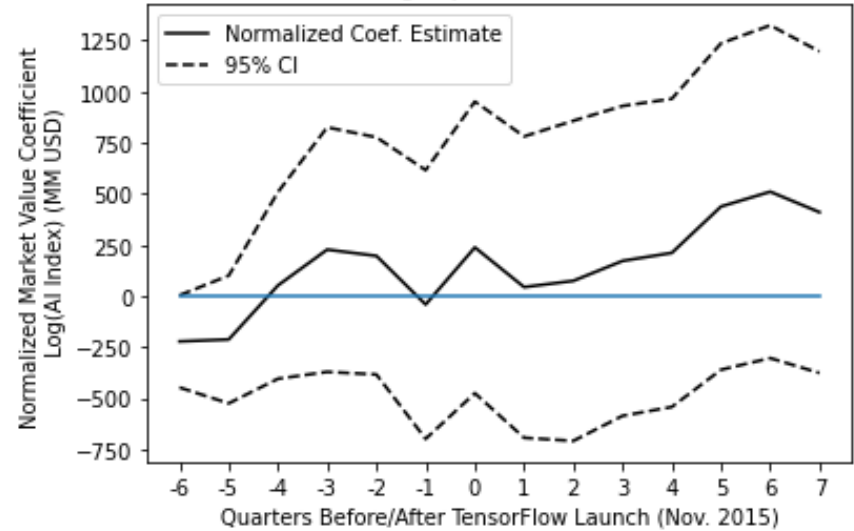
Source: Rock (2019)

The effects of making AI Talent more abundant

Event Study: AI Index Market Value Coefficient Trends

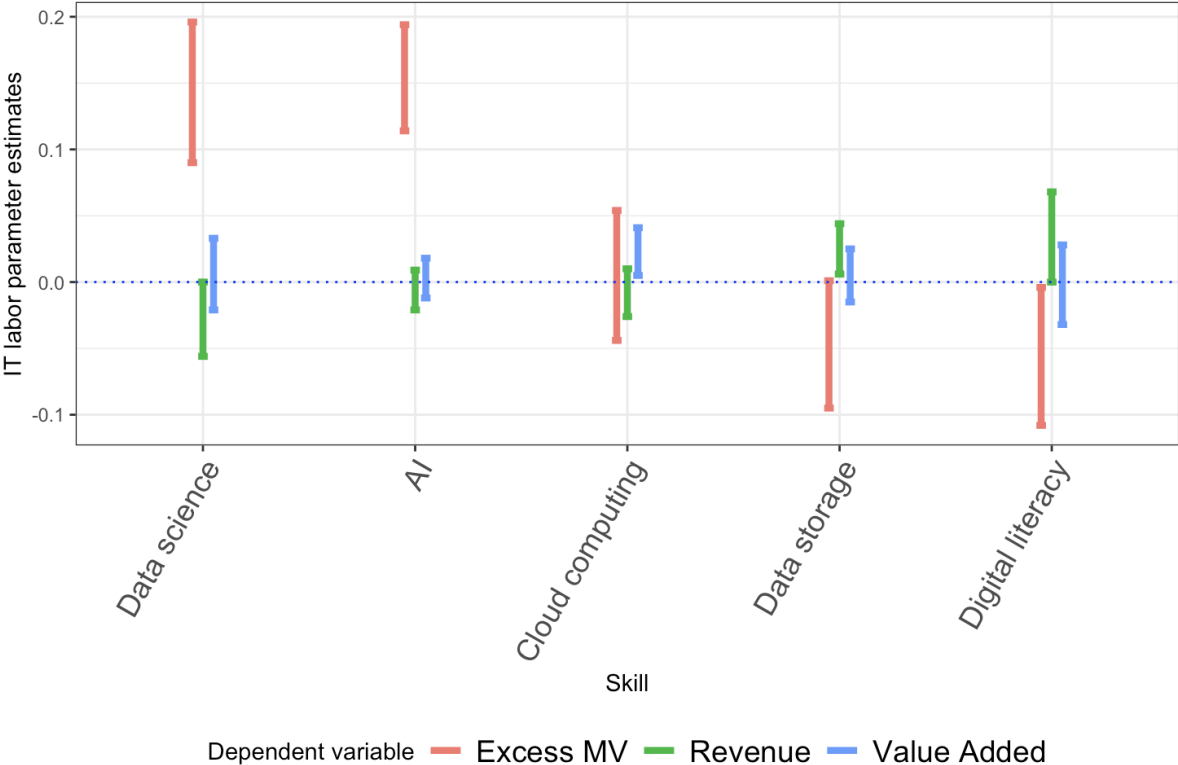


Event Study: AI Index Market Value Coefficient Trends
Excluding Top Quintile of AI Firms

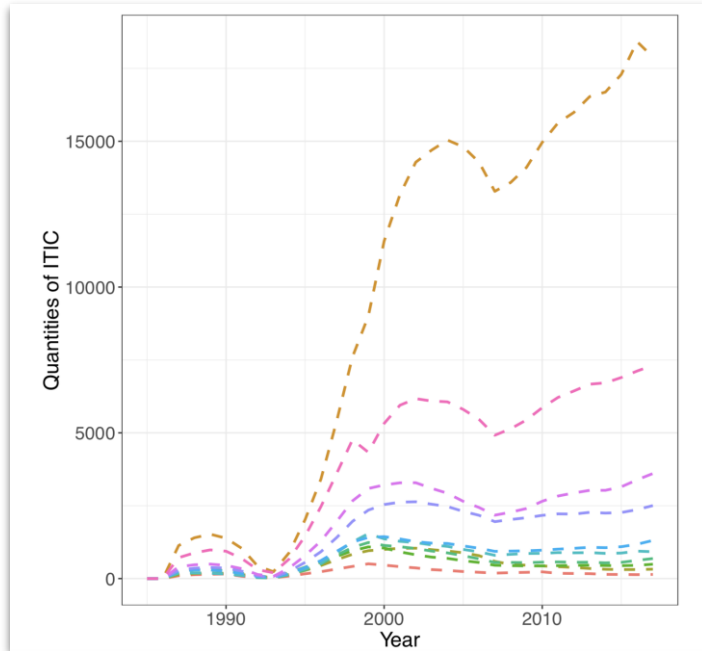


Source: Rock (2019)

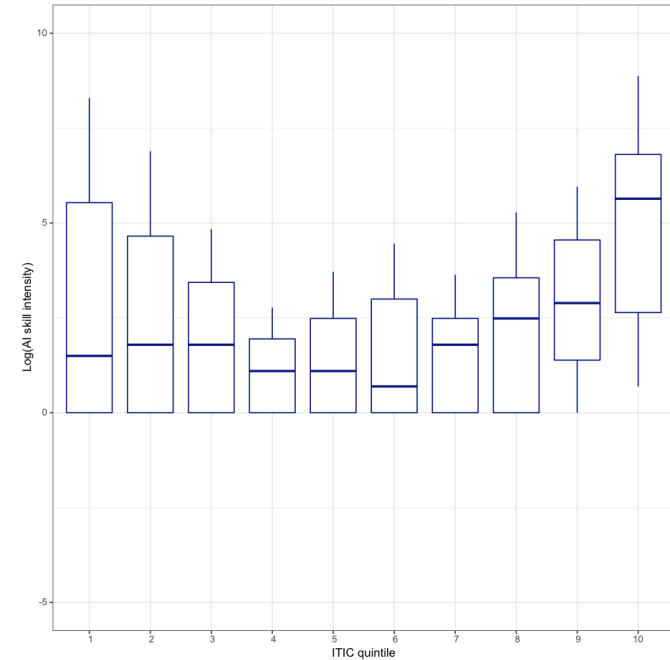
Data Science and AI are driving new market value



Digital capital concentrated in top 20% of firms by market value ... and AI skills are concentrating in high DC firms



Digital capital by market value decile



AI skills by DC decile

AI skill intensity predicted by lagged ITIC quantities

	<i>Log(AI)</i>	<i>Log(AI)</i>	<i>Log(AI)</i>	<i>Log(AI)</i>
Log(DC stock)	.065** (.015)	.060** (.015)	.077** (.017)	.098** (.018)
Log(DC price)	219.57 (121.78)	205.58 (127.19)	-70.21 (107.42)	137.7 (115.31)
	1 yr lag of stock	2 yr lag of stock	3 yr lag of stock	4 yr lag of stock
Controls	Size Year Industry	Size Year Industry	Size Year Industry	Size Year Industry

- **AI prices** should be high because the capital base is low and investment rates are high
- For AI, we would expect to see high prices but not early stage productivity or contributions to digital capital stock
- **Older** data technologies should have equilibrated prices and a stronger effect on productivity
- Remote work?

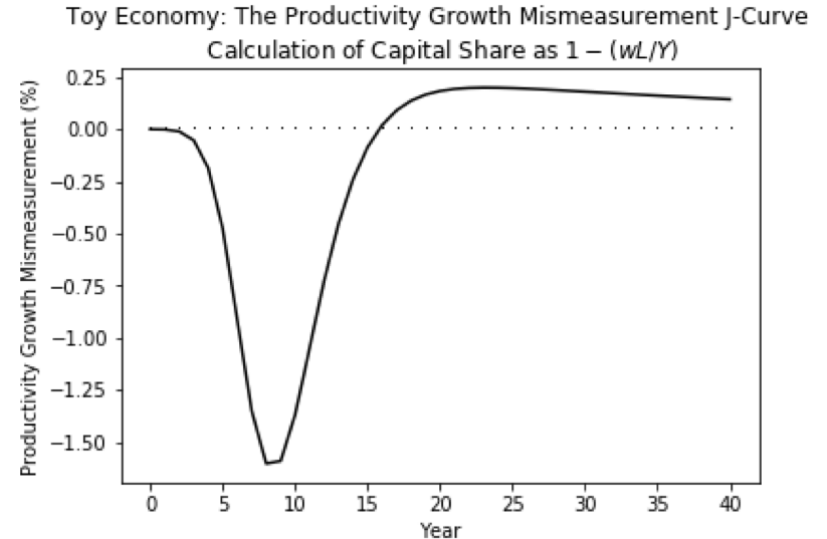
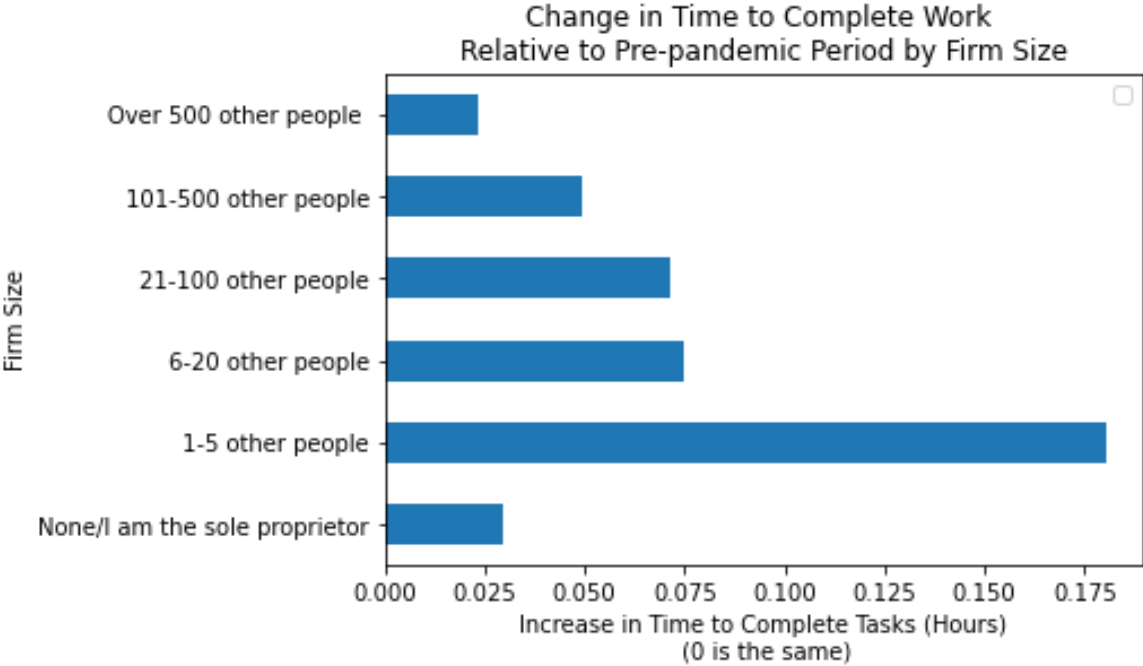


Figure from Brynjolfsson, Rock, and Syverson (2021)

Returning to remote work: Larger firms appear more productive (preliminary)



Source: Brynjolfsson et al. (2021) Gallup Survey

Summary of key findings

We use a **new IT labor series** to measure how quantities of IT-related intangible capital have been building in firms over the last three decades.

Using this firm-level panel, we document:

1. Significant concentration in the **top 20% of firms**, by market value.
2. We separate digital capital quantities from prices.
3. These digital capital-”rich” firms are building AI capabilities.
4. AI is correlated with market value, but the intangible capital driving revenue has **yet to be built**.
5. Preliminary evidence is consistent with a **progression of investments in intangible capital** (around networks, data, etc.) supporting modern AI investments.
6. Some preliminary evidence that **remote work** taps into this digital capital and may support larger companies to a greater extent