Economic impacts of AI-augmented R&D

arXiv:2212.08198

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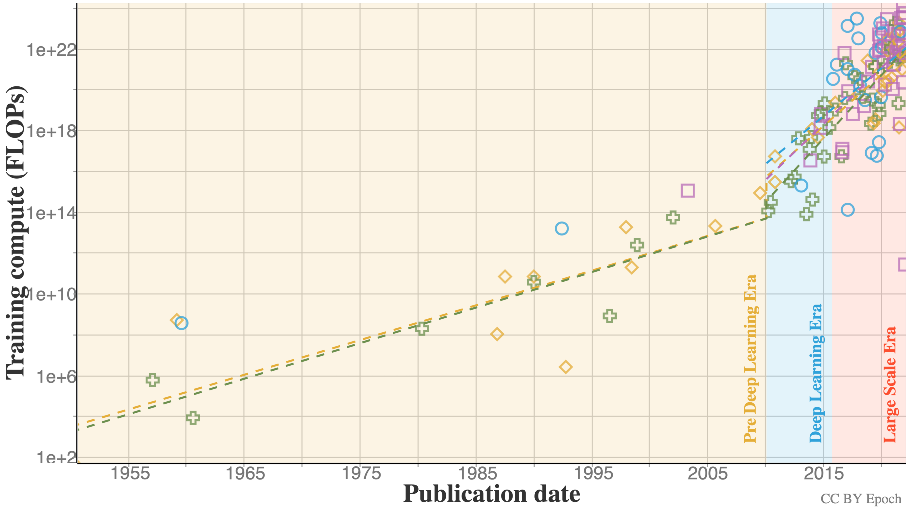
Motivation



Sevialla, Heim, Ho, Besiroglu, Hobbhahn, and Villalobos, 2022

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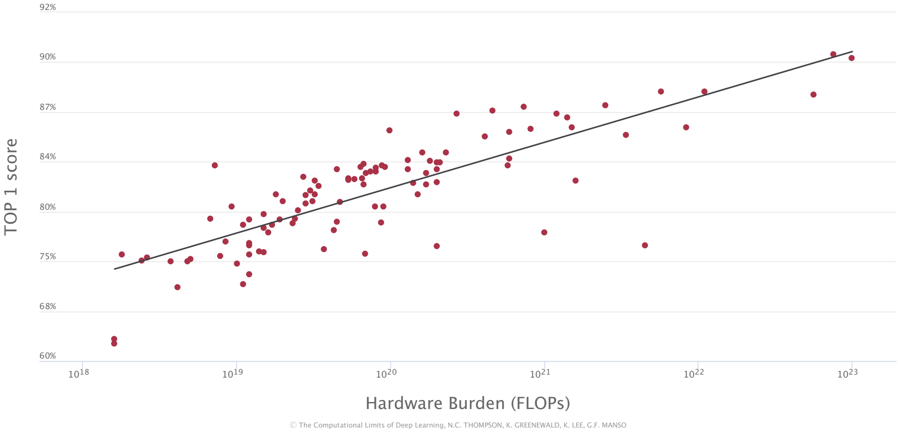
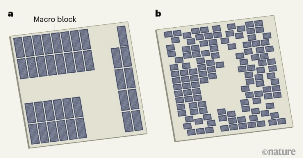
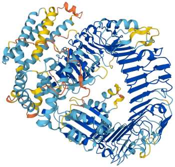


Thompson, Greenewald, Lee, and Manso, 2020

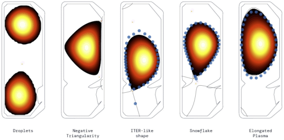
Motivation: AI's inroad into science and technology



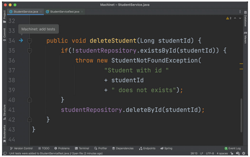
(a) Reinforcement learning for chip floorplanning (Mirhoseini et al. 2021)



(b) AlphaFold (Jumper et al. 2021)



(c) Controlling the nuclear fusion plasma in a tokamak (Degrave et al. 2022)



(d) GitHub CoPilot

How might AI change productivity and growth?

Output (Solow–Swan):

$$\underbrace{Y}_{\text{Output}} = \underbrace{A^{\theta}}_{\text{Stock of ideas}} \times \underbrace{K^{\beta}}_{\text{Capital}} \times \underbrace{L^{\gamma}}_{\text{Labor}}$$

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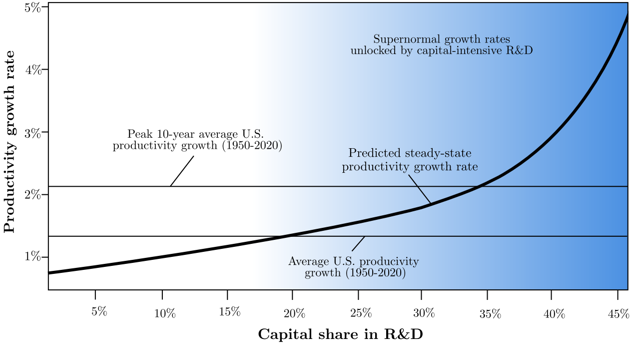
Building on Howitt and Aghion 1998; Howitt 1999, we introduce capital into idea-production:

$$\dot{A} = L^{\gamma} \times K^{\beta} \times A^{\theta}$$

What does theory predict?

Steady-state productivity is increasing in the capital-share of R&D



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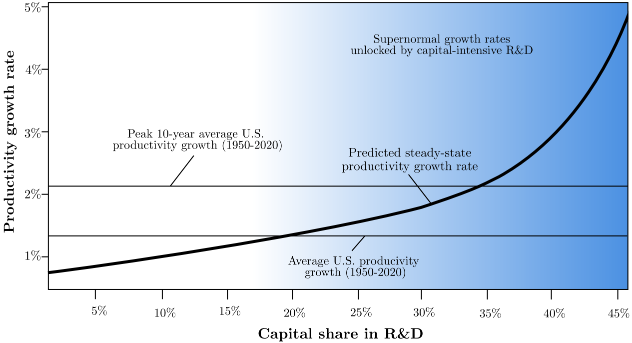
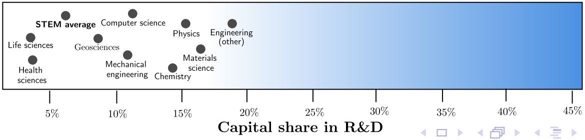


U.S. R&D is highly labor-intensive



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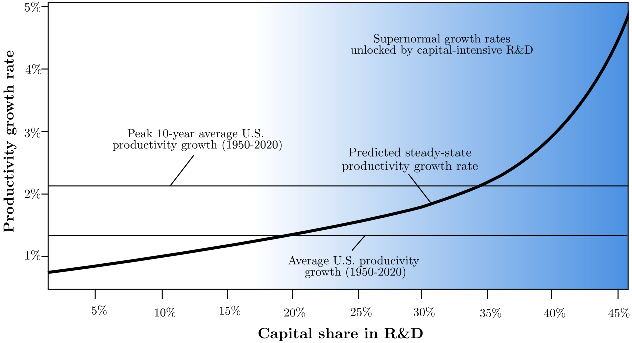
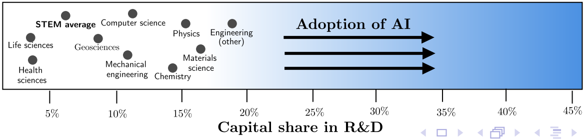


The adoption of AI might change this



Background: Machine Learning

- In classical statistical learning theory, there generally is a trade-off between bias and variance
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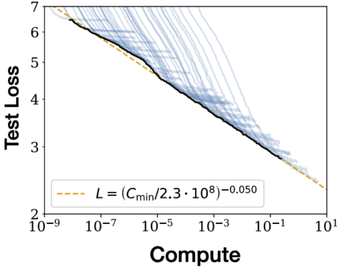
- Scaling laws indicate predictable and regular returns to compute



Scaling laws from Kaplan et al. 2020

Our data

We want estimate the ‘idea production function’ for deep learning

- $\sim$ 150 computer vision from papers published between 2012 and 2022
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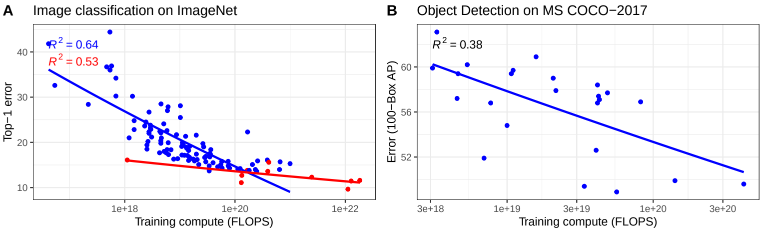

Compute usage and performance
With extra training data (red), without (blue)

Human capital

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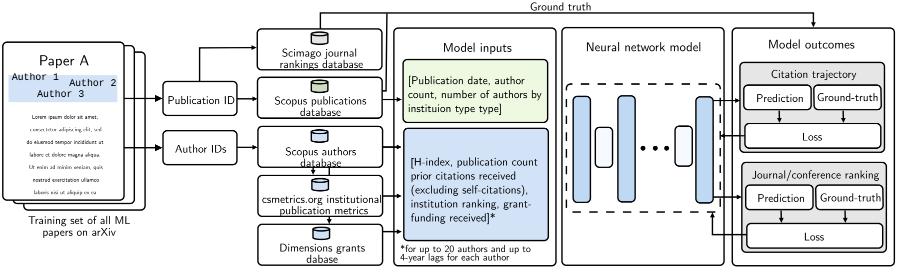
Our training setup



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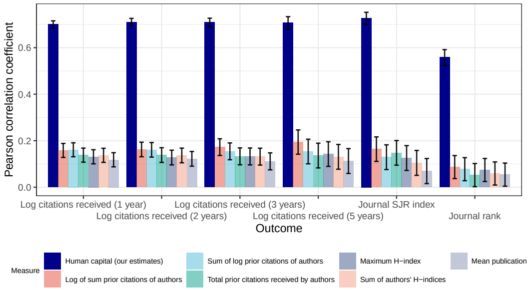
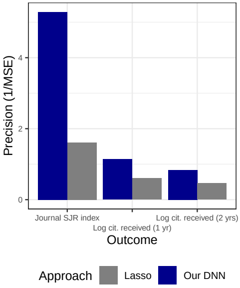


(g) Our human capital estimates predicts key outcomes much better than commonly used indicators



(h) Our estimates surpass individual lasso regs on test-set

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More generally, we consider CES production:

$$\dot{A} = \left[\gamma L^{\frac{\sigma-1}{\sigma}} + \beta K^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \times A^{\theta}$$

In a competitive R&D sector, we derive the optimal capital share:

$$\underbrace{f}_{\text{Capital share in R\&D}} = \frac{\beta K^{\frac{\sigma-1}{\sigma}}}{\beta K^{\frac{\sigma-1}{\sigma}} + \gamma L^{\frac{\sigma-1}{\sigma}}}.$$

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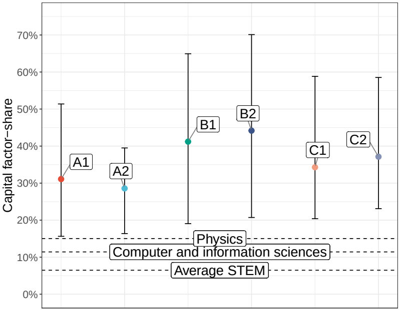
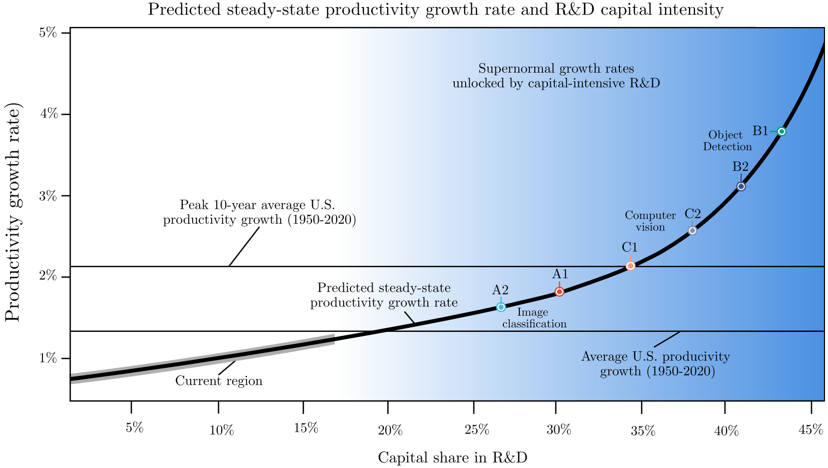
R&D capital shares for AI are high:



Capital shares for deep learning in computer vision

What do our results imply?



Widespread adoption of deep learning could raise productivity growth to between 2% and 2.5% merely by changing factor shares

Thanks!

Feedback would be much appreciated. Get in touch at tamay@mit.edu

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