Discussion: AI in R&D by Ben Jones

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Intro

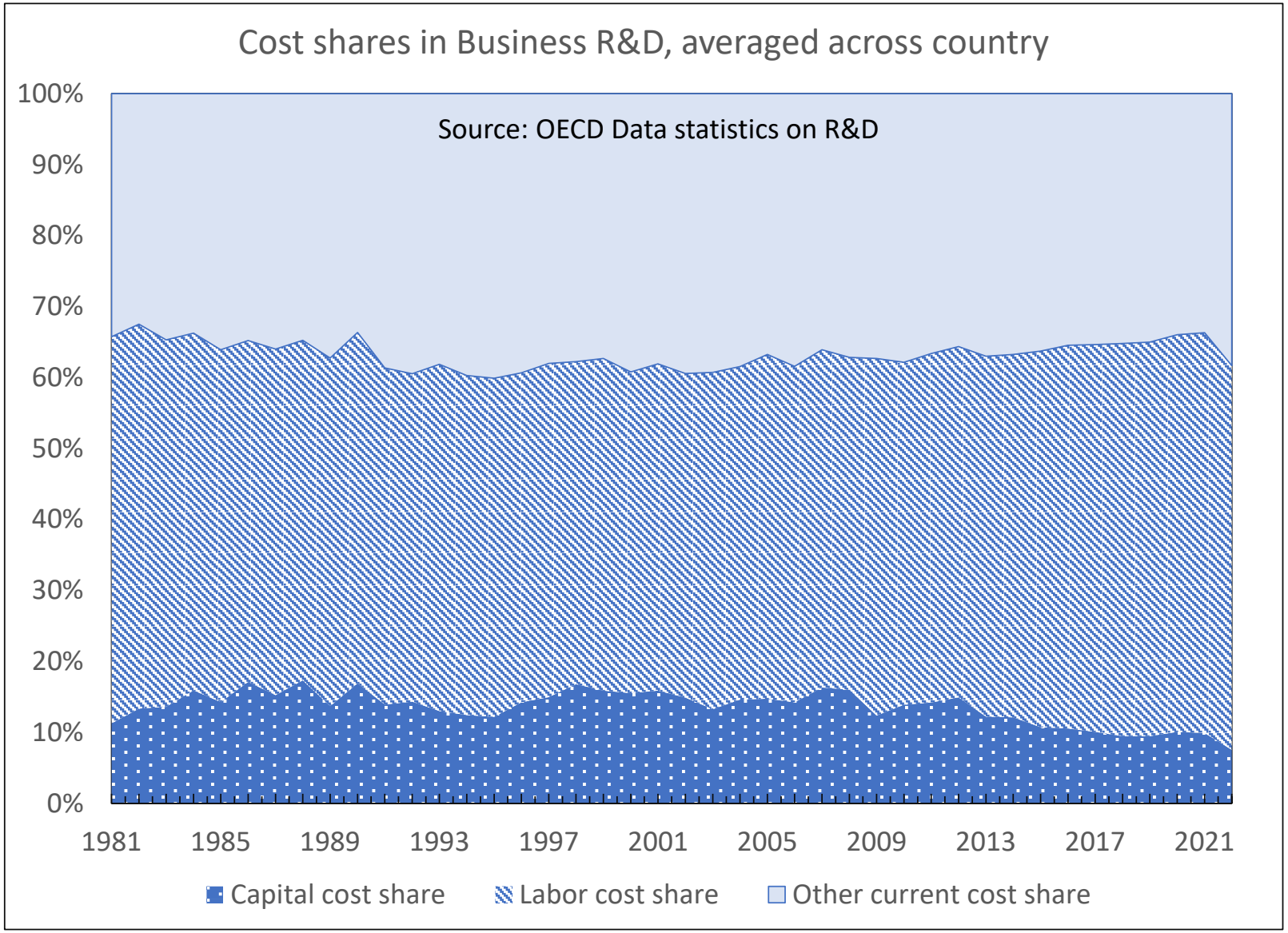
- Very interesting paper, enjoyed reading and thinking about the subject
- Core Question: How will AI affect the productivity of research and development?
- Jones' Approach - A very elegant task-based model of the R&D process, with a focus on three measures that determine AI's impact on R&D:
  - Share of tasks AI can handle (γ_t)
  - Efficiency of AI in tasks (M_t)
  - Bottlenecks in the innovation process (θ)

Discussion outline

1. My puzzle with model:
   - M_t and γ_t are not parameters; they are jointly determined from the primitives of machine productivity m_t and cost μ_t (as well as labor productivity and cost)
   - Ok for static analysis of one-time growth rate increase, I think.
2. Reconciling the model with the data: what is the machine share?
3. Case study: evolution of research in particle physics in response to increases in computing power and other innovations.

Reconciling the model with the data (1)

- Paper uses a capital cost share in R&D of one-third (33%) to proxy for the machine (software and AI) share.
- The Evidence:
  - OECD Data: Average across countries show the capital share is well below 33% and has been declining.
  - U.S. Data (2021): The capital share in R&D is even lower, around 8%.
- Conclusion: A more appropriate capital share for the model's computations would be approximately 10%.


Cost shares in Business R&D, averaged across country
Source: OECD Data statistics on R&D
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1981
1985
1989
1993
1997
2001
2005
2009
2013
2017
2021
Capital cost share
Labor cost share
Other current cost share

Composition of Business R&D spending in the US - 2021	
	Share
Total capital cost, of which	**8.25%**
Other IP products (purchased)	0.89%
Land & buildings	0.91%
Machinery	3.07%
Software	2.54%
Other	0.84%
Total current cost, of which	**91.75%**
Labor costs	61.71%
External R&D personnel	4.20%
Current cost NEC	15.94%
Materials purchased	6.53%
Services purchased	3.36%
Total	**100.00%**

Machinery, software, and IP products are at most 7% of R&D spending in the US. There may be some rental of capital hidden in current cost, but it is unlikely to increase the number to 33%. Of course, much AI use in R&D may be one-off own development and therefore is in labor cost.

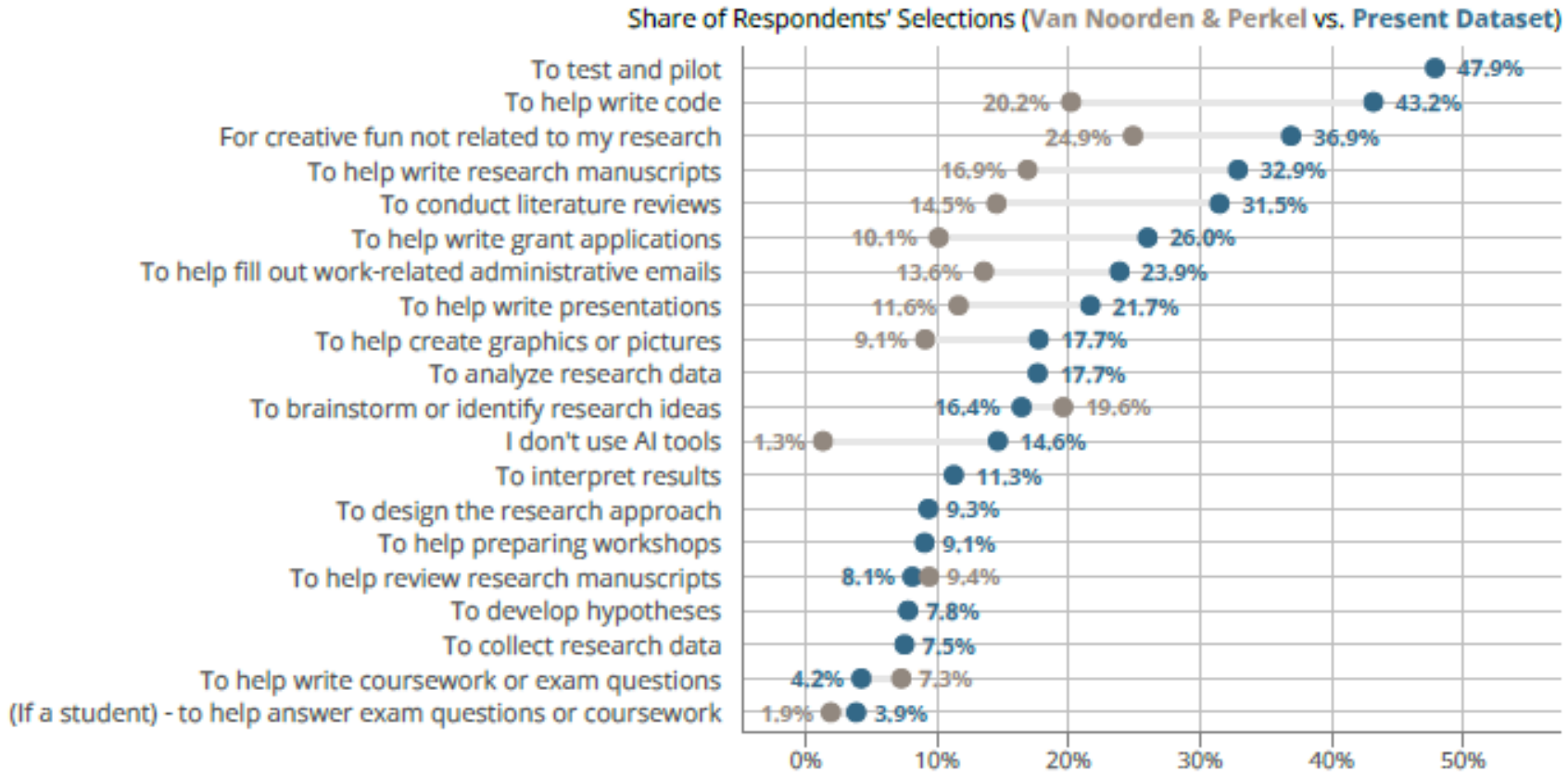
Implication of a low capital share

- With 10% Capital Share, $\theta = -1$, and $\gamma = 0.5$:
  - An infinite increase in machine intelligence would increase progress by a factor of 1.23 (not 2.25).
  - If half of the machines have infinite intelligence, progress increases by 1.11 (not 1.44).
  - If the share of tasks performed by machines shifts completely to AI, the productivity gain would be 25 (versus Jones' 2.25), due to the initial high productivity of capital (cost-effective at half the tasks) relative to its small share of cost (10%).

Reconciling the model with the data (2)

- HOWEVER….at least at the present time, much AI use in research is programmed, executed, and interpreted by labor, so a higher share may be appropriate.
- Survey evidence shows that AI partners labor in many tasks.

Figure 2: "In your research, what do you use AI tools for? Select all that apply." Comparison to Van Noorden and Perkel (2023).



Notes. Some areas of use were newly introduced in our survey and are therefore not available for comparison with the previous study.

Source: Marina Chugunova, Dietmar Harhoff, Katharina Hölzle, Verena Kaschub, Sona Malagimani, Ulrike Morgalla, and Robert Rose (2025). Who Uses AI in Research, and for What? Large-scale Survey Evidence from Germany. Research Policy, forthcoming.

Case study: “bump hunting” in particle physics

- 1960s-1970s: A manual, human-centric process involving manual plotting of data and visual scanning, accompanied by some use of software for fitting observed interactions and simulation.
- Later Advances:
  - Development of statistical techniques to reduce false positives.
  - Replacement of bubble chambers with electronic detectors, allowing screening for interesting events.
  - Crucial Shift: Computing advances allowed many tasks to move from humans to machines.
  - Today: Extensive use of machine learning and AI for data analysis, exemplified by the Higgs boson discovery.
- During this evolution, number of authors on a published article increased from a handful to hundreds; articles also got longer and more detailed.

Lessons from the example

- Diminishing Returns: As research advanced, the budget and number of researchers increased, suggesting that new discoveries may be getting harder to find (Bloom et al. 2020).
- Moving Target: Improvements in technology (like computing speed) allowed researchers to tackle more ambitious problems, increasing the complexity and cost of research.
- New Tasks: Increased automation did not simply replace human tasks; it created new ones, such as software design and development, which are still done by humans.

Conclusion

- Model assumes constant goal and fixed budget.
  - Example suggests that AI's impact may be less about pure efficiency gains and more about enabling the pursuit of previously intractable problems.
- Future Research Priorities:
  - Detailed empirical work on R&D task structures.
  - Dynamic models that account for expanding research frontiers.
  - Studying the impact of AI on the organization of research teams.
  - In what ways can past experience with computing enhancements inform us about the impact of AI?

My puzzle with the model

- The model is used to analyze the impact of AI's productivity and the share of tasks it performs separately.
  - But these two factors are not truly independent; they are jointly determined from the primitives of machine productivity m_t and cost μ_t (as well as labor productivity and cost):

$$M_t = \left[\frac{1}{\gamma_t} \int_0^{\gamma_t} m_t(j)^{\theta/(1-\theta)} dj \right]^{\frac{1-\theta}{\theta}}$$

$$m_t(j) \geq H \mu_t / w_t \text{ for all } j \in [0, \gamma_t]$$

- A large enough increase in AI productivity will lead to a greater share of tasks being performed by machines.
- Implication: This joint determination might make it difficult to isolate the effects of different advances in AI.
- For example, Corollary 2 refers to the share of machine expenditure as a function of exogenous parameters, but equation (9) for the share includes γ_t, which is clearly not exogenous.