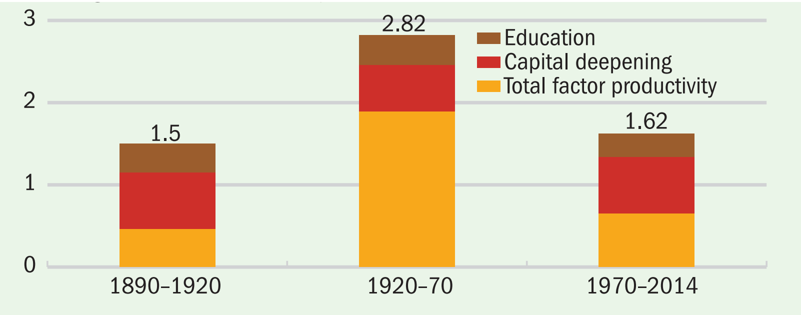
Technological progress, technology diffusion, and productivity

François Lafond

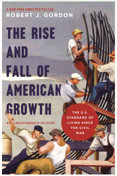
Can we predict future productivity?

How do we improve it?

Growth as large adjustment of levels



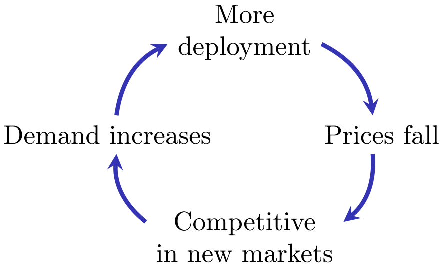
- Large technological shocks take time to diffuse
- Gordon (2016)'s "One Big Wave" / "Great Leap Forward"



Gordon (2016), *The Rise and Fall of American Growth.*

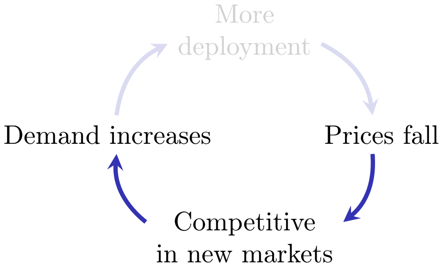
Source: On the importance of diffusion for productivity, see e.g. Andrews et al. (2016), Coyle (2026) and Van Ark (2026)

Part I: The cost–deployment feedback loop



Source: Diagram adapted from Roser (2020).

Part I: The cost–deployment feedback loop



Demand curve

Lower prices make the technology competitive in more markets, increasing demand.

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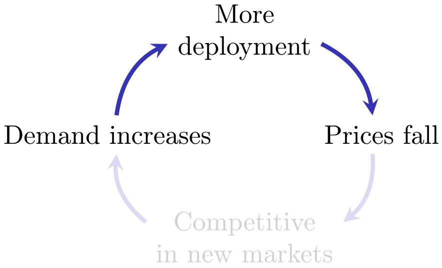

Learning curve

More deployment builds cumulative experience, which lowers cost.

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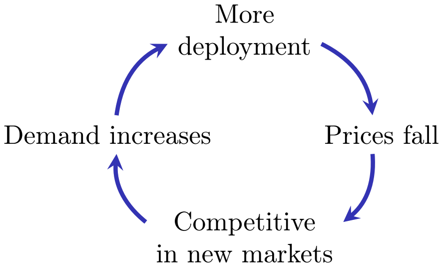

Three empirical objects

1. **Cost**
   How quickly does a technology improve?
2. **Deployment to cost**
   Does deployment cause further improvement?
3. **Deployment**
   How quickly and how far does adoption proceed?

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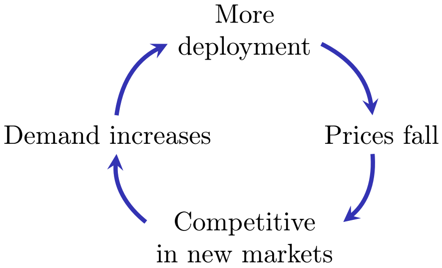

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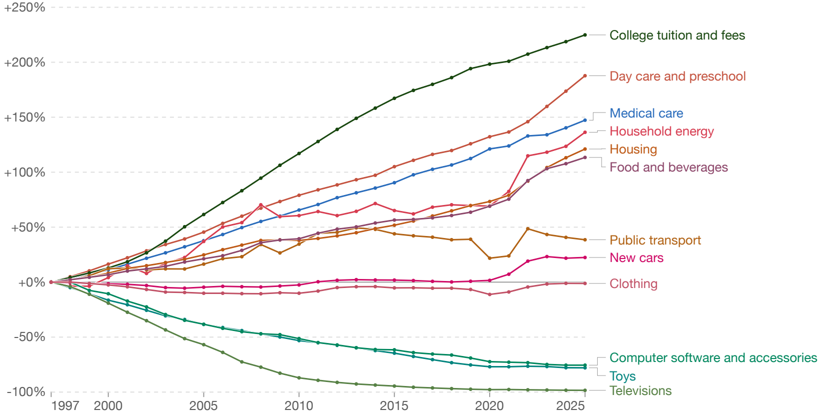
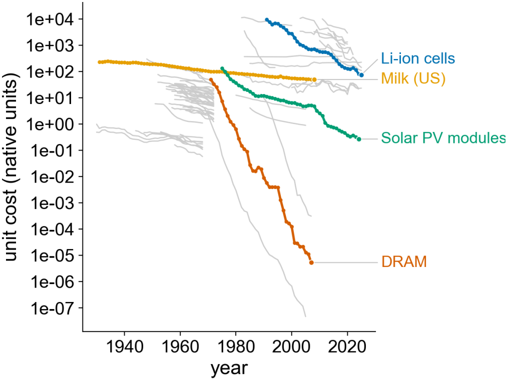
Technologies improve at different rates



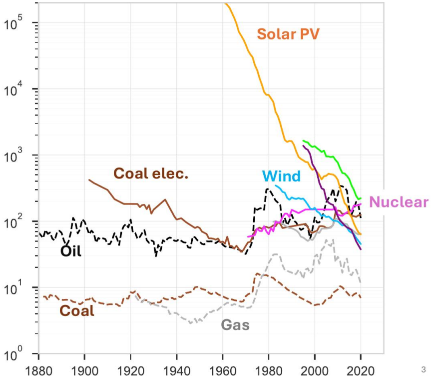
Source: Our World in Data (CC BY), from U.S. Bureau of Labor Statistics CPI data; cumulative change since 1997. Medical care is not quality-adjusted.

Technologies improve at different rates

Exponential decrease with time ("Moore's law")

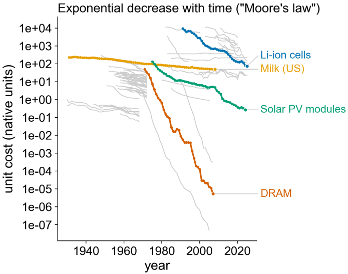


Useful energy cost ($[2020]/MWh)



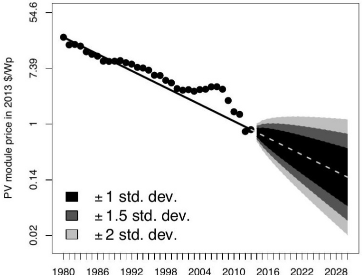
Source: Updated from Farmer and Lafond (2016) and Way et al. (2022).

Use the full database to calibrate distributional forecasts



Historical cost trajectories

$\Longrightarrow$

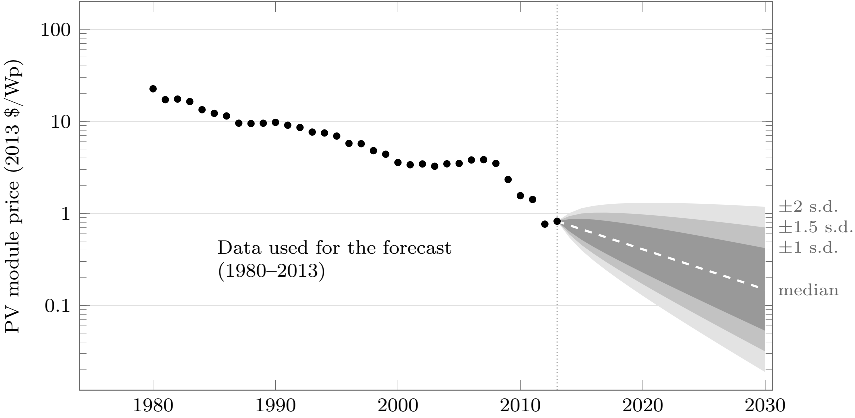


Solar forecast with calibrated bands

Many datasets $\Rightarrow$ Many forecast errors
$\Rightarrow$ Calibrated prediction intervals.

Source: Farmer and Lafond (2016).

The 2013 solar forecast, ten years on



Source: Forecast: Farmer and Lafond (2016), Fig. 10, recomputed on the module prices it used (1980–2013, 2013 dollars). Series today: Our World in Data (2026), 2025 dollars converted to 2013 dollars with the US GDP deflator (World Bank, 2026).

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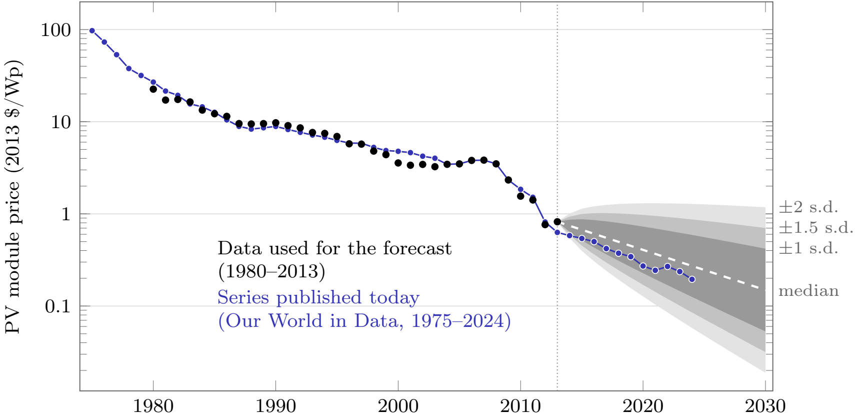

(*Note the data revisions including −23% in 2013.*)

Source: Forecast: Farmer and Lafond (2016), Fig. 10, recomputed on the module prices it used (1980–2013, 2013 dollars). Series today: Our World in Data (2026), 2025 dollars converted to 2013 dollars with the US GDP deflator (World Bank, 2026).

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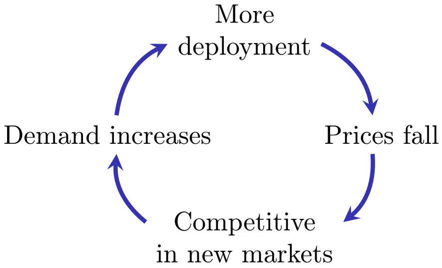

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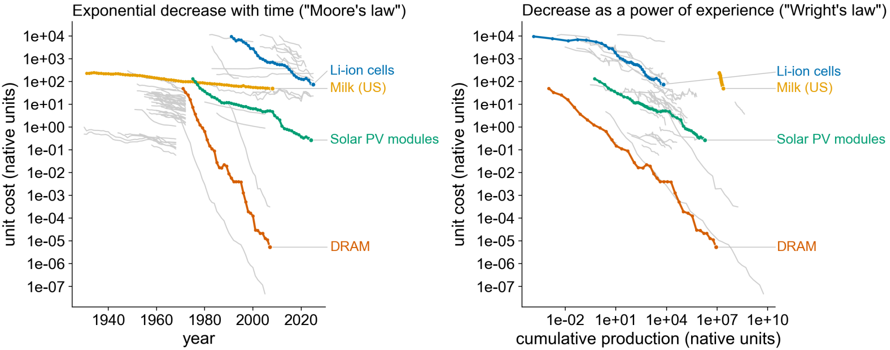
Cost declines with time and cumulative deployment

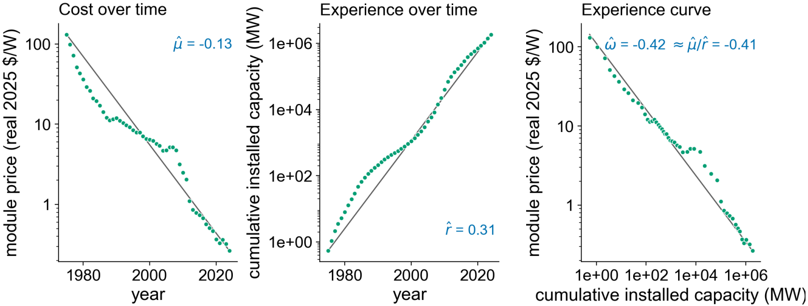


$$c_t = c_0 \exp(\mu t)$$

$$c_t = \widetilde{c}_0 Z_t^{\omega}$$

Source: Updated from Farmer and Lafond (2016) and Lafond et al. (2018).

Sahal's identity



$$c_t = c_0 \exp(\mu t) \qquad Z_t = Z_0 \exp(rt) \qquad c_t = \widetilde{c}_0 Z_t^{\omega}$$

If any two relations hold, the third follows mechanically.

Source: Sahal (1979); solar PV updated data.

Exogenous or endogenous technological change?

The Perils of the Learning Model for Modeling Endogenous Technological Change

*William D. Nordhaus**

ABSTRACT

Modeling of technological change has been a major empirical and analytical obstacle for many years. One approach to modeling technology is learning or experience curves, which originated in techniques used to estimate cost functions

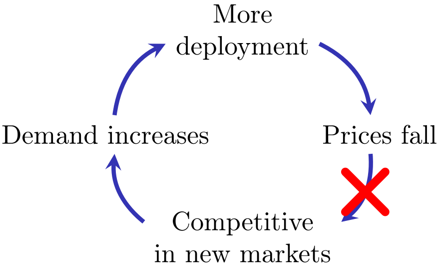
- Is the experience curve just a demand curve in reverse?

More deployment $\rightleftarrows$ Lower costs

- Regressing costs on both time and experience gives very wild answers

Source: Nordhaus (2014), *The Energy Journal*.

WWII as a natural experiment



Identifying assumption

WWII procurement followed battlefield needs, not prices.

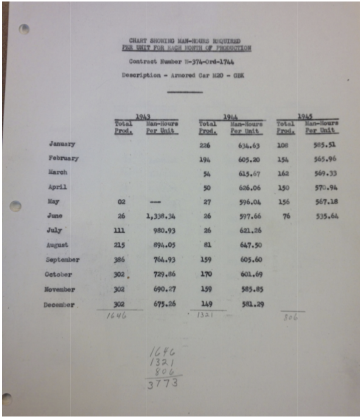


CHART SHOWING MAN-HOURS REQUIRED
PER UNIT FOR EACH MONTH OF PRODUCTION

Contract Number W-374-Ord-1744

Description - Armored Car M20 - GBK

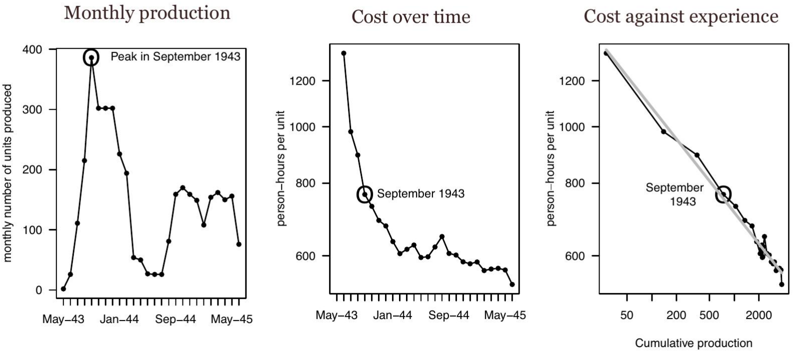
	1943		1944		1945	
	Total Prod.	Man-Hours Per Unit	Total Prod.	Man-Hours Per Unit	Total Prod.	Man-Hours Per Unit
January			226	634.63	108	585.51
February			194	605.20	154	565.96
March			54	615.67	162	569.33
April			50	626.06	150	570.94
May	02	---	27	596.04	156	567.18
June	26	1,338.34	26	597.66	76	535.64
July	111	980.93	26	621.26		
August	215	894.05	81	647.50		
September	386	764.93	159	605.60		
October	302	729.86	170	601.69		
November	302	690.27	159	585.85		
December	302	675.26	149	581.29		
	1646		1321		806	

1646
1321
806
3773

Ford archives: man-hours per unit, armored car M20, 1943–45.

Source: Diagram from Roser (2020); Ford archives; Lafond et al. (2022).

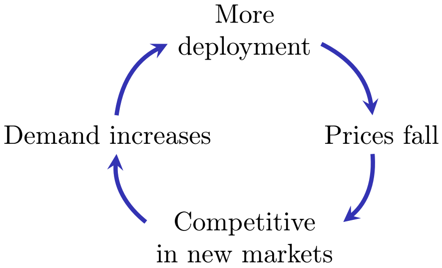
Wartime production separates time from experience



Data: Ford's M-20GBK.

- Production ceased to be exponential, while cost continued to track experience
- Across broader datasets, experience and time account for roughly equal shares of cost decline

Source: Lafond et al. (2022).



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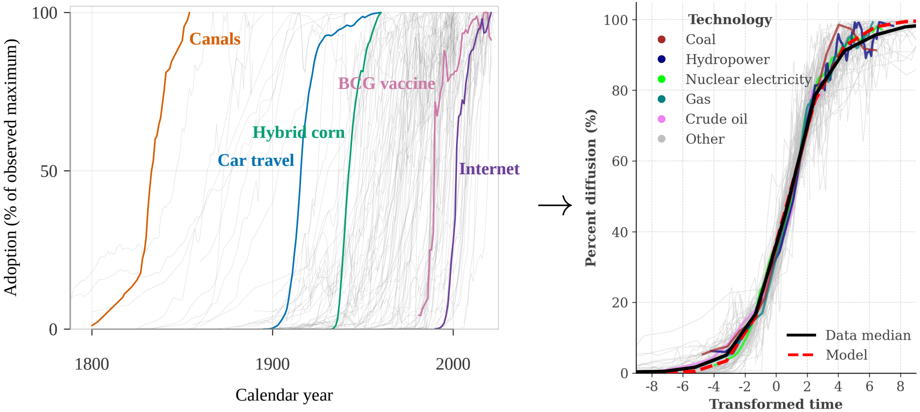
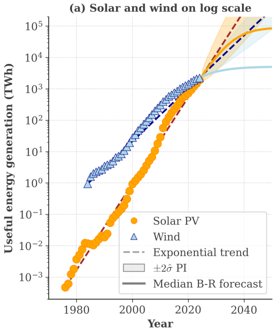
Diffusion curves share a common shape after rescaling

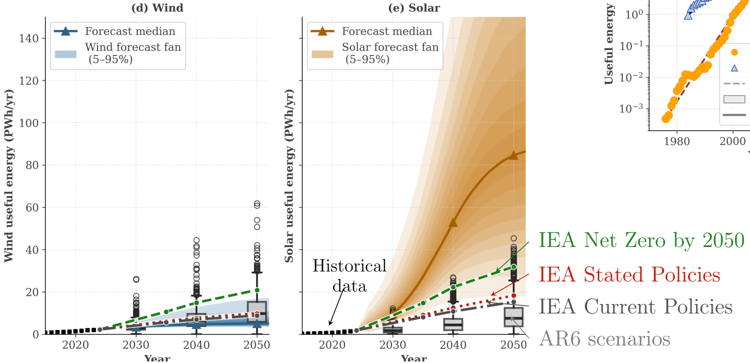


Rescaling of technologies performed assuming they all follow a Bertallanfy–Richards curve with $\beta = 2/3$ and otherwise technology-specific parameters.

Source: Wagenvoort et al. (2026).

Forecasting solar and wind deployment



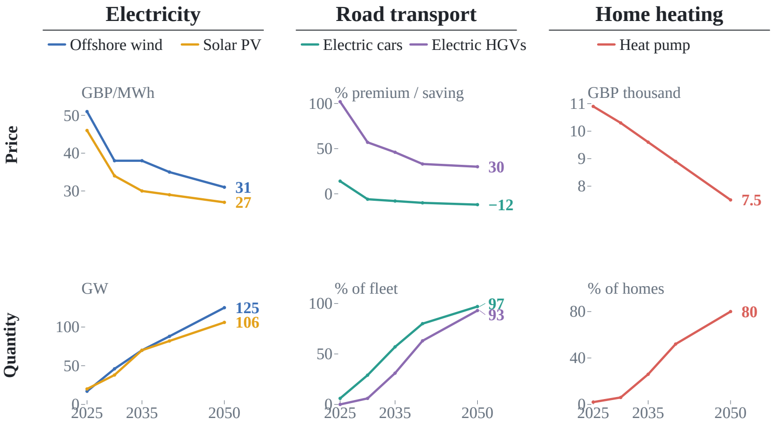


Source: Wagenvoort et al. (2026); historical data through 2024.

Part II: Technology trajectories and aggregate productivity

- Net-Zero
- Artificial Intelligence

Technology scenarios from the Climate Change Committee



How do these price and deployment paths affect aggregate productivity?

Source: Climate Change Committee (2025), Balanced Pathway; costs in 2023 prices.

Our approach

Aggregate productivity can be retrieved from industry-level productivity via **Domar aggregation** (motivated by an accounting version of Hulten's theorem (McNerney et al., 2022))

$$\hat{A}_t = \sum_{i=1}^{N} \lambda_i \hat{A}_{it}, \quad \lambda_i \equiv \frac{p_i X_i}{pY} = \frac{\text{Sales}_i}{\text{GDP}}$$

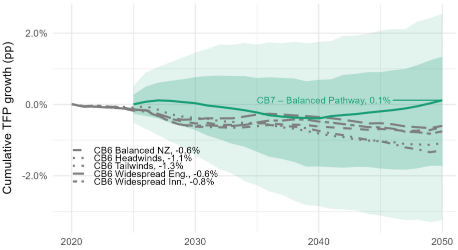
How can we get industry-level productivity from prices and quantities? We use the following **data-driven assumption**

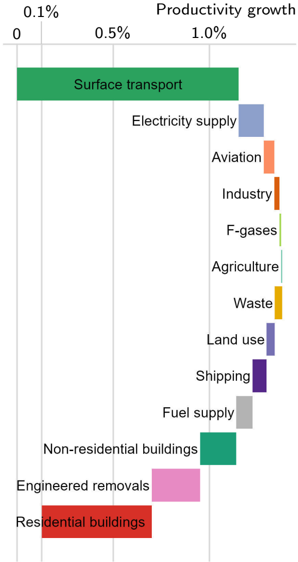
$$\hat{A}_{it} = \zeta \hat{X}_{it} + (\zeta - 1)\hat{p}_{it} + \text{Error}, \quad \zeta \approx 0.13$$

$$\boxed{\mathbb{P}\Big(\text{TFP gr.}\Big) \approx \sum_i \underbrace{\frac{\text{Sales}_{i,t}}{\text{GDP}_t}}_{\substack{\text{Domar}\\ \text{weights}}} \times \underbrace{\Big(\zeta \text{Quantity gr.} + (\zeta - 1)\text{Price gr.} + \mathbb{P}\big(\text{Error}\big)\Big)}_{\text{Predicted industry TFP growth}}}$$

Source: Ravigné and Lafond (2026), work in progress.

Sectoral gains and losses partly offset





Under the CCC Balanced Pathway, the aggregate effect remains close to zero within the prediction interval.

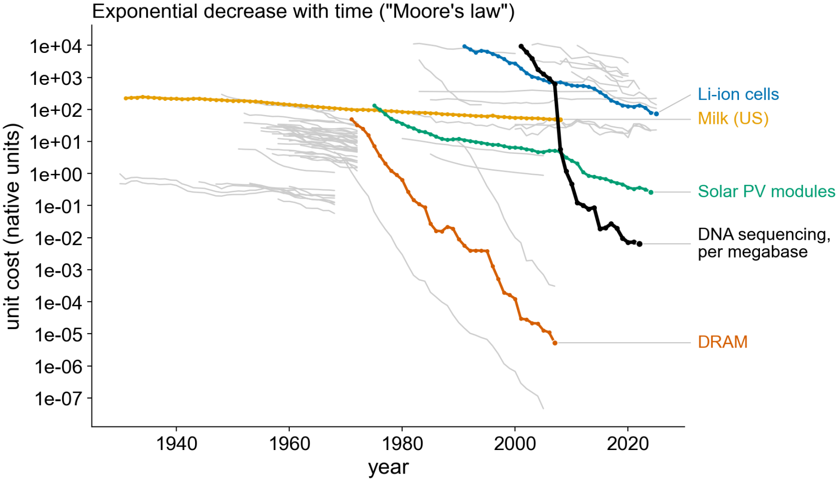
Source: Ravigné and Lafond (2026), work in progress.

The impact of AI on aggregate productivity

Save time to do the same work = productivity growth

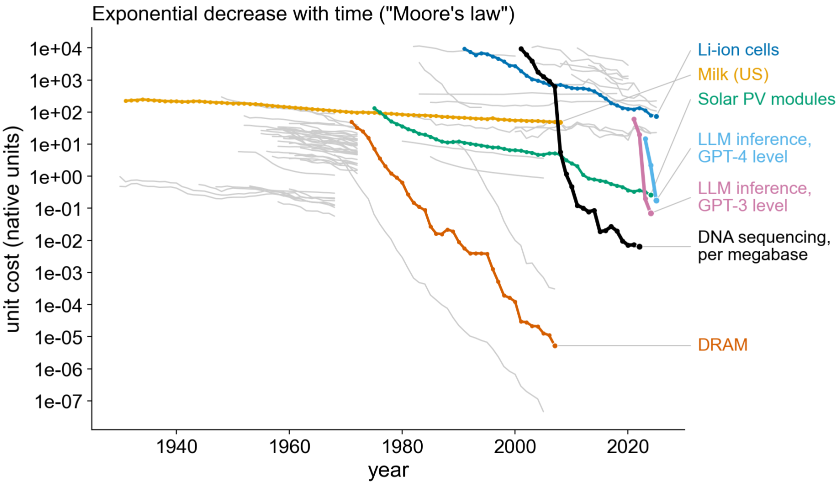
Impact		*Potential*		*Exposure*		*Adoption*
Productivity growth in a given industry	=	**Percent time saved if AI is used in a task**	×	**Share of tasks exposed to AI**	×	**Fraction of exposed tasks for which AI is actually adopted**
				Ranges across studies		
0.5–12% 0.05–1.2% per year over a decade		25–30%		10–50%		20–80%

Source: Elaboration of OECD (2024).



Source: Updated from Farmer and Lafond (2016) and Way et al. (2022).

AI capability costs are falling extraordinarily quickly

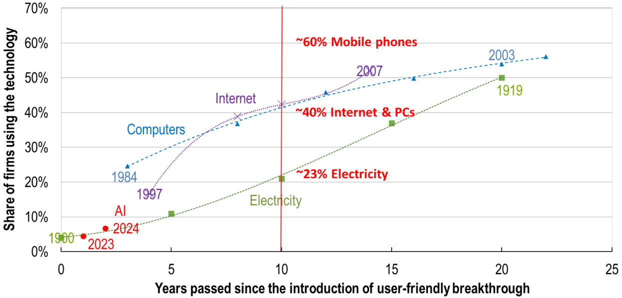


Cheapest observed price for a fixed capability threshold measured using MMLU.

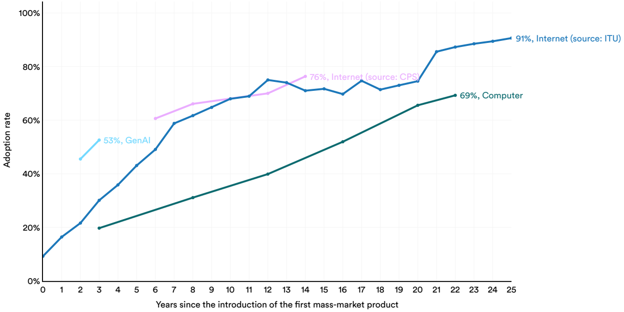
Source: Updated from Farmer and Lafond (2016) and Way et al. (2022); LLM inference prices from Cottier et al. (2025).

AI diffusion depends on what counts as adoption

OECD (firm use in production)



Stanford HAI (individual use)



Sources: OECD (2025), Figure 6, share of US firms (mobile phones: individuals); Stanford HAI (2026), Figure 4.3.9, share of US adults aged 18–64.

Part III: From forecasts to explanation - an agenda

The technology observatory

Hypothesis: Many economic causal factors of progress and diffusion (e.g. regulation, market structure) are the results of deeper, ultimate factors related to technology features

Candidate features

- Modularity
- Granularity
- Position in technological space
- Complementarities
- etc.

Sample technologies deliberately

- Diverse across sectors
- Variance across specific features
- Mature, emerging and failed technologies

Conclusion

Can we predict future productivity, and how do we improve it?

Useful tools to predict productivity

- Cost and diffusion follow specific patterns well enough to make probabilistic forecasts useful
- Granular price and quantity scenarios are useful for estimating aggregate productivity consequences

Technology choice is not a solved problem

- Why improvement and diffusion rates differ across technologies

Thanks

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