The Market's Expectation of AI-Driven Growth

Timo Boppart (Zurich, IIES)
Peter J. Klenow (Stanford)
Reiko Laski (Stanford)
Huiyu Li (Fed SF)

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Motivation

How much will AI raise productivity growth?

Forecasts of the boost to annual labor productivity growth over the next decade differ by an order of magnitude

- Acemoglu (2024), Jones and Tonetti (2026): less than 0.1 pp
- Yotzov et al (2026) survey of firms: 0.75 pp
- Aghion and Bunel (2024): 0.1–2.1 pp, median 1.2 pp
- Davidson, Halperin, Houlden, and Korinek (2026): ∞

Investors have skin in the game, and their forecasts are in stock prices

This paper...

Uses stock market valuations to gauge how much growth investors expect from AI firms

- P/E ratios contain information about the expected growth of firm rents

Builds on our *Idea Rents and Firm Growth* (2026): idiosyncratic shocks to step sizes and R&D efficiency generate heterogeneous P/E ratios, R&D intensity, and earnings growth

Calibrates the model to 1976–2019 and 2020–2025 and backs out each firm's step size and R&D efficiency from its R&D, earnings, and market value

- AI firms' expected contribution to growth: 43% in 2014–2019 $\rightarrow$ 79% in 2020–2025
- vs. 33% of sales and 47% of earnings in 2020–2025
- contributed an estimated 133 bp to faster TFP growth

Related literature

Forecasting AI's effect on growth: Aghion, Jones, and Jones (2019); Acemoglu (2024); Aghion and Bunel (2024); Korinek and Suh (2024)

- we let investors do the forecasting

Asset prices and technological revolutions: Hobijn and Jovanovic (2001); Pástor and Veronesi (2009); Kogan, Papanikolaou, Seru, and Stoffman (2017); Eisfeldt, Schubert, and Zhang (2023); Caballero (2026); Wachter and Wachter (2026)

- we map valuations into firm growth contributions via an endogenous growth model

Firm heterogeneity in creative destruction models: Klette and Kortum (2004); Lentz and Mortensen (2008); Luttmer (2011); Berlingieri, De Ridder, Lashkari, and Rigo (2025)

- we infer step sizes and R&D efficiency from P/E ratios and R&D spending

Outline

Empirical patterns

Model

Quantification

Data sources

P: firm-level market cap, fiscal year end stock price $\times$ shares outstanding, CRSP

E: firm-level earnings, fiscal year end EPS $\times$ shares outstanding, I/B/E/S

S: firm-level sales, fiscal year end, Compustat

- remove year and fiscal-year-end month fixed effects

Sample covered

1976–2025: Publicly listed manufacturing firms plus selected AI firms

51,035 firm-year observations; 4,643 unique firms

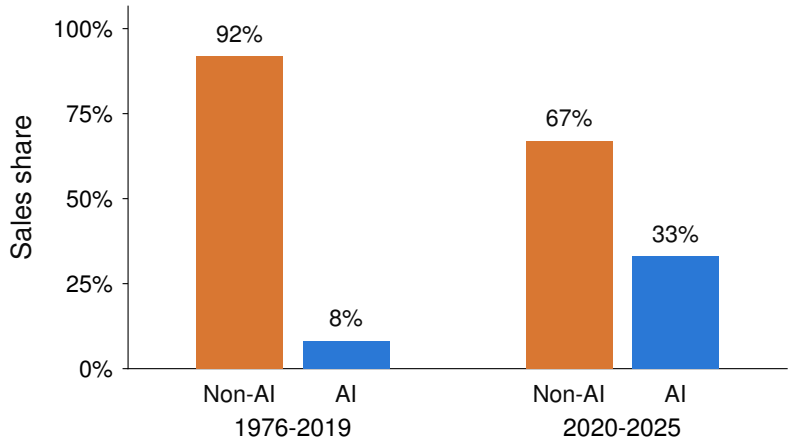
AI firms are the union of the 20 largest holdings in each of the AIQ and THNQ ETFs

Includes NVIDIA, TSMC, Microsoft, Meta, Tesla, Alphabet, Amazon, Apple

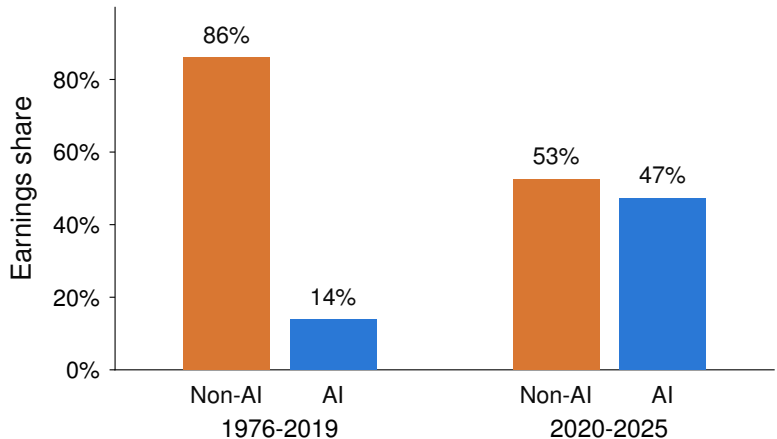
AI firms

Alibaba Group	Cisco Systems	Meta Platforms	Pure Storage
Alphabet	Cloudflare	Micron Technology	Samsung Electronics
Amazon.com	Cognex	Microsoft	SK hynix
AMD	Global Unichip	Nebius Group	Tencent Holdings
Analog Devices	IBM	Netflix	Teradyne
Apple	Infineon Technologies	NVIDIA	Tesla
Arista Networks	Lam Research	Oracle	TSMC
ASML Holding	Lumentum Holdings	Palantir Technologies	
Broadcom	MediaTek	Palo Alto Networks	

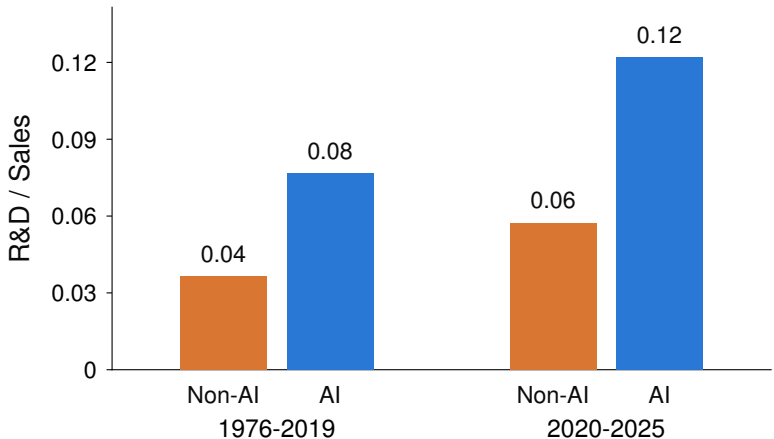
Sales share of AI firms has increased relative to non-AI firms



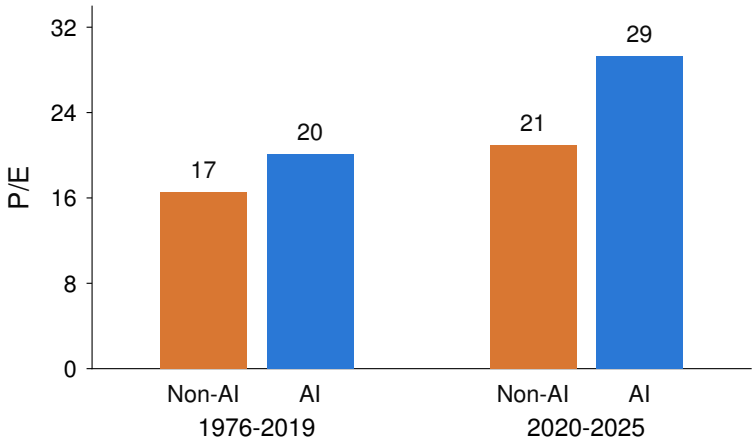
Earnings share of AI firms has increased relative to non-AI firms



R&D intensity has increased for both AI firms and non-AI firms



P/E ratios have increased more for AI firms than non-AI firms



Summary of stylized facts

AI firms account for growing shares of sales and earnings.

R&D intensity among AI firms has increased over time.

P/E ratios among AI firms has increased over time.

Outline

Empirical patterns

Model

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Model outline

- We build on Klette and Kortum (2004)
  - Quality-driven growth
  - All innovation takes the form of creative destruction
  - Multi-product firms
- Ways we deviate from Klette-Kortum
  - Idiosyncratic shocks to firm step sizes and R&D efficiency
  - Arrival rate does not scale with a firm's number of products
  - Fixed number of firms (no entry or exit)

Environment

Representative household with preference

$$U_0 = \sum_{t=0}^{\infty} \beta^t \log C_t.$$

Final output is produced using intermediate goods via

$$Y = \exp\left(\int_0^1 \log\left[q(i)\, y(i) \right] di \right).$$

Fixed number J of intermediate good producers who can produce one unit of product i at quality $q(i, j)$ using one unit of labor.

Innovation

Firms can gain lines by investing in R&D.

Spending $\frac{1}{\varphi_{jt}} \cdot x_{jt}^{\nu} \cdot Y$ in goods increases the best quality of x_{jt} randomly drawn lines.

Step sizes are factor $\gamma_{jt} > 1$.

$\{\gamma_{jt}, \varphi_{jt}\}$ follows a Markov chain with states (γ_k, φ_k) and transition matrix M.

Price setting and firm earnings in each period

Bertrand competition within each product line $i \in [0, 1]$.

Markup for product i equals the step size of leading firm $j(i)$ when it took over the line.

Let n_{jt} be the number of lines where firm j is the highest quality producer in period t and let ω_{jt}^k be the share of j's lines that have markups γ_k.

Firm j's period t earnings relative to output Y_t when innovating on x_{jt} lines is

$$E(n_{jt}, \{\omega_{jt}^k\}, x_{jt}, \varphi_{jt}) = n_{jt} \cdot \sum_k \omega_{jt}^k \left(1 - \frac{1}{\gamma_k}\right) - \frac{1}{\varphi_{jt}} \cdot x_{jt}^{\nu}.$$

Dynamic firm problem

Consider a stationary equilibrium with a constant aggregate rate of creative destruction $x^\star$, output growth $g^\star$, and interest rate $r^\star$.

Given current $\{\gamma_{j0}, \varphi_{j0}\}$, a firm chooses innovation x_{jt} to maximize the EPDV of its profits:

$$V(n_{j0}, \{\omega_{j0}^k\}, \gamma_{j0}, \varphi_{j0}) \;=\; \max_{\{x_{jt}, n_{j,t+1}\}_{t=0}^{\infty}} \mathbb{E}_{\gamma_{j0}, \varphi_{j0}} \sum_{t=0}^{\infty} E(n_{jt}, \{\omega_{jt}^k\}, x_{jt}, \varphi_{jt}) \left(\frac{1+g^\star}{1+r^\star}\right)^t$$

subject to

$$n_{j,t+1} \;=\; n_{j,t} \cdot (1 - x^\star) \;+\; x_{jt}$$

$$\omega_{j,t+1}^k n_{j,t+1} \;=\; (1 - x^\star)\omega_{jt}^k n_{j,t} \;+\; \mathbf{1}\{\gamma_{jt} = \gamma_k\} x_{jt}.$$

- The P/E ratio reflects expected earnings growth.

Privately-optimal R&D

Choice for the arrival rate:

$$x_{jt} = x(\gamma_{jt}, \varphi_{jt}) = \left(\frac{1+g^\star}{1+r^\star} \frac{\varphi_{jt}}{\nu} v(\gamma_{jt}) \right)^{1/(\nu-1)}$$

where $v(\gamma) = (1 - \frac{1}{\gamma}) \frac{1+r^\star}{1+r^\star-(1+g^\star)(1-x^\star)}$ is the PDV of a line relative to output Y.

Implies higher R&D spending for firms with higher step size and R&D efficiency:

$$\frac{1}{\varphi_{jt}} x(\gamma_{jt}, \varphi_{jt})^\nu = \left(\varphi_{jt}\right)^{\frac{1}{\nu-1}} \left(\frac{1+g^\star}{1+r^\star} v(\gamma_{jt}) \frac{1}{\nu} \right)^{\nu/(\nu-1)}.$$

P/E ratio and earnings growth

The optimal R&D policy of a firm yields the ex-dividend $P/(E+R\&D)$ ratio

$$\begin{aligned}\frac{P(\{\omega_{kt}^j\},n_{jt},\gamma_{jt},\varphi_{jt})}{\tilde{E}(\{\omega_{kt}^j\},n_{jt})} &= \frac{(1+g^\star)(1-x^\star)}{1+r^\star-(1+g^\star)(1-x^\star)} \\ &+ \frac{\left(\frac{1+g^\star}{1+r^\star}v(\gamma_{j,t})\right)^{\nu/(\nu-1)}\left(\frac{\varphi_{j,t}}{\nu}\right)^{1/(\nu-1)}}{\tilde{E}(\{\omega_{kt}^j\},n_{jt})} \\ &+ \left(1-\frac{1}{\nu}\right)\cdot\mathbb{E}_{\gamma_{jt},\varphi_{jt}}\frac{\sum_{\tau=1}^{\infty}\left(\frac{1+g^\star}{1+r^\star}\right)^{\tau}\left(\frac{1+g^\star}{1+r^\star}v(\gamma_{j,t+\tau})\right)^{\nu/(\nu-1)}\left(\frac{\varphi_{j,t+\tau}}{\nu}\right)^{1/(\nu-1)}}{\tilde{E}(\{\omega_{kt}^j\},n_{jt})}.\end{aligned}$$

The growth rate on the BGP

Household problem implies a standard Euler equation: $1 + g^\star = \beta(1 + r^\star)$.

Final output can be used for consumption or to cover R&D costs: $Y = C + \sum_j \varphi_j \cdot x_j^\nu \cdot Y$.

The aggregate rate of creative destruction is

$$x^\star = \sum_j x_j = \sum_k J \cdot s_k \cdot x(\gamma_k, \varphi_k),$$

where s_k are the shares of each firm type in the ergodic distribution.

The growth rate is the innovation-weighted geometric mean of the step sizes:

$$\ln(1 + g^\star) = x^\star \cdot \sum_k \frac{s_k \cdot x(\gamma_k, \varphi_k)}{\sum_{k'} s_{k'} \cdot x(\gamma_{k'}, \varphi_{k'})} \gamma_k.$$

Contribution to growth

A firm's current size depends on the entire history of its step sizes and R&D efficiency.

A firm's current R&D spending and contribution to growth depends only on its current step size and R&D efficiency.

A firm's contribution to growth is

- independent of its size if step sizes and R&D efficiency are iid
- positively correlated with its size if step sizes or R&D efficiency are persistent

P/E ratios can be used to infer expected future step-size and R&D efficiency dynamics.

Job Reallocation

Product level gross job creation = product level gross job destruction = rate of creative destruction $x^\star$.

Firm j's employment L_{jt} sums over its lines. Its Davis, Haltiwanger, and Schuh (1996) growth rate is $g^L_{jt} \equiv \frac{L_{jt}-L_{j,t-1}}{\bar{L}_{jt}} \in [-2,2]$, where $\bar{L}_{jt} \equiv \frac{L_{jt}+L_{j,t-1}}{2}$.

Aggregate job reallocation rate across firms (job creation rate + job destruction rate):

$$\mathrm{JR}_t \equiv \frac{\sum_j \left|L_{jt}-L_{j,t-1}\right|}{\sum_j \bar{L}_{jt}} = \sum_j \frac{\bar{L}_{jt}}{\bar{L}_t}\left|g^L_{jt}\right|, \qquad \bar{L}_t \equiv \sum_j \bar{L}_{jt}.$$

Share from bin B_b of g^L_{jt} (bins as in Figure 1 of Garcia-Macia, Hsieh, and Klenow 2019):

$$s_{bt} \equiv \frac{\sum_{j:\, g^L_{jt}\in B_b}\left|L_{jt}-L_{j,t-1}\right|}{\sum_j \left|L_{jt}-L_{j,t-1}\right|} = \frac{1}{\mathrm{JR}_t}\sum_{j:\, g^L_{jt}\in B_b}\frac{\bar{L}_{jt}}{\bar{L}_t}\left|g^L_{jt}\right|, \qquad \sum_b s_{bt} = 1.$$

Lines gained and lost within a firm net out $\Rightarrow$ firm-level $<$ product-level job reallocation.

Outline

Empirical patterns

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Parameterizing the Markov process

Model has a discrete number of step sizes and R&D efficiency levels (γ and φ).

Parsimonious to assume that $z_t = \log(\gamma_t - 1)$ and $\log \varphi_t$ follow a VAR(1) process

$$\begin{pmatrix} z_t \\ \log \varphi_t \end{pmatrix} = \begin{pmatrix} \rho_\gamma \, z_{t-1} \\ \rho_\varphi \, \log \varphi_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{\gamma,t} \\ \varepsilon_{\varphi,t} \end{pmatrix}, \quad \begin{pmatrix} \epsilon_{\gamma,t} \\ \epsilon_{\varphi,t} \end{pmatrix} \overset{iid}{\sim} N\left(\begin{pmatrix} \mu_\gamma \\ \mu_\varphi \end{pmatrix}, \begin{bmatrix} \sigma_\gamma^2 & \sigma_{\gamma,\varphi} \\ \sigma_{\gamma,\varphi} & \sigma_\varphi^2 \end{bmatrix} \right)$$

and use the Gospodinov and Lkhagvasuren (2014) method to select N discrete states $\{(\gamma_1, \varphi_1), ..., (\gamma_N, \varphi_N)\}$.

Currently we set $N = 5625$, with an $N \times N$ transition matrix M between states.

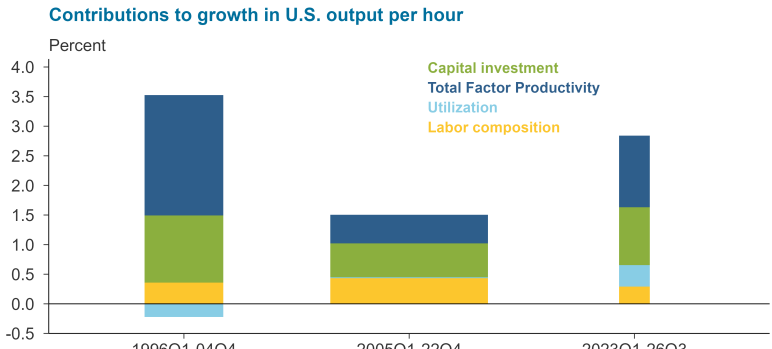
Calibration

Empirical Targets	1976–2019	2020–2025
1. Growth in aggregate earnings, net of labor input growth, $g^{\star}$	1.2%	2.2%
2. Average firm-specific discount rate, $r^{\star}$	10.1%	9.7%
3. Contribution of $g_{E/S}$ to g_E on log $P/(E+R\&D)$	44%	43%
4. Contribution of $g_{(E+R\&D)/S}$ to $g_{E/S}$ on log $P/(E+R\&D)$	90%	68%
5. Aggregate earnings/aggregate sales	0.11	0.20
6. 90–10 range of fitted g_E	0.09	0.11
7. 90–10 range of fitted $g_{E+R\&D}$	0.15	0.17
8. R&D/sales projected on log sales	-0.027	-0.035
9. 90:50 sales ratio	18.4	14.8
10. Standard deviation of log $P/(E+R\&D)$	0.63	0.79

Model fit to empirical targets

Model Moments	1976–2019	2020–2025
1. Growth in aggregate earnings, net of labor input growth, $g^{\star}$	1.1%	2.3%
2. Average firm-specific discount rate, $r^{\star}$	10.0%	9.8%
3. Contribution of $g_{E/S}$ to g_E on log $P/(E + R\&D)$	48%	35%
4. Contribution of $g_{(E+R\&D)/S}$ to $g_{E/S}$ on log $P/(E + R\&D)$	100%	88%
5. Aggregate earnings/aggregate sales	0.11	0.17
6. 90–10 range of fitted g_E	0.10	0.10
7. 90–10 range of fitted $g_{E+R\&D}$	0.16	0.15
8. R&D/sales projected on log sales	-0.023	-0.036
9. 90:50 sales ratio	18.7	11.9
10. Standard deviation of log $P/(E + R\&D)$	0.66	0.79

U.S. labor productivity growth in recent years



Note: Average quarterly growth expressed as annual rate, business sector.
Source: FRBSF/Fernald Total Factor Productivity data.

Estimated parameters

Parameter		1976–2019	2020–2025
Curvature of R&D cost function	ν	4.02	3.89
Persistence of γ process	ρ_γ	0.95	0.88
Mean of shocks to γ process	μ_γ	-0.05	0.20
Variance of shocks to γ process	σ^2_γ	0.92	4.90
Persistence of φ process	ρ_φ	0.84	0.81
Mean of shocks to φ process	μ_φ	-4.82	-4.77
Variance of shocks to φ process	σ^2_φ	49.9	48.2
Correlation between shocks	$\frac{\sigma_{\gamma\varphi}}{\sigma_\gamma \sigma_\varphi}$	-0.57	-0.66
Discount factor	β	0.92	0.93

Calibrated model results

	1976–2019	2020–2025
Average markup	1.13	1.21
Arrivals, $x^\star$	0.06	0.06
Growth per arrival, $g/x^\star$	0.18	0.36
Arrivals per unit of R&D, $x^\star/\text{R\&D}$	5.42	3.10

Backing out innovation step size and R&D efficiency

Given the calibrated model, use each firm's R&D spending, earnings, and market value to recover its current $\{\gamma_{jt}, \varphi_{jt}\}$.

R&D spending depends on the firm's current step size and R&D efficiency:

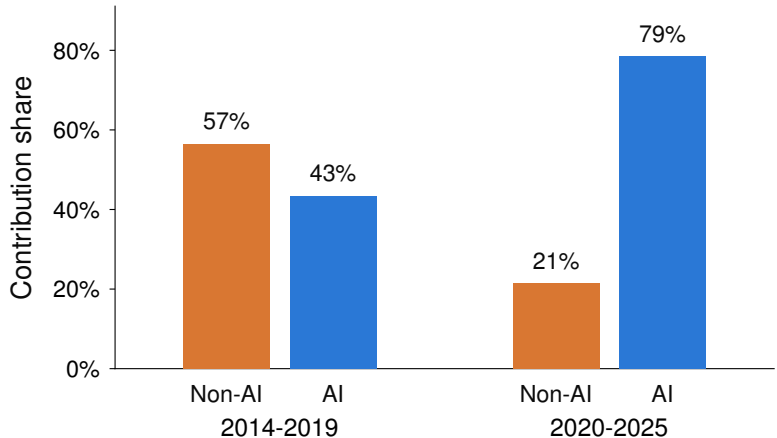
$$R_{jt} = \frac{x(\gamma_{jt}, \varphi_{jt})^{\nu}}{\varphi_{jt}}.$$

Subtract the profits from existing products from firm value to obtain the value of innovation:

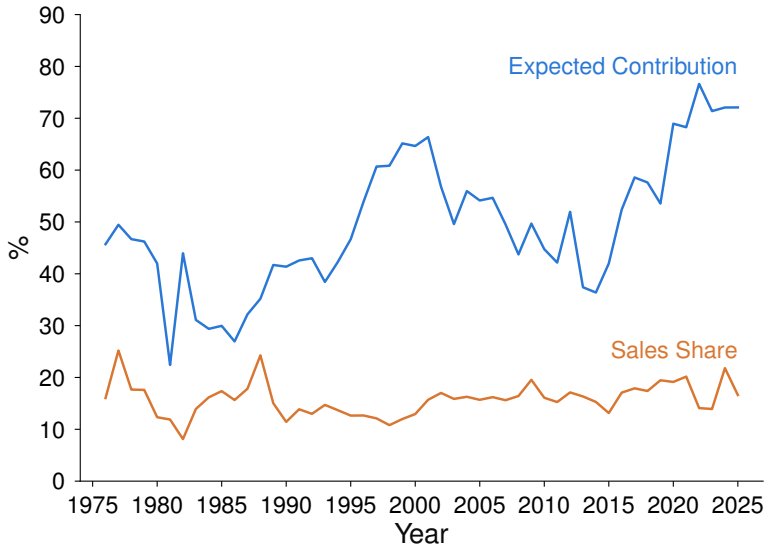
$$V_{jt} - \frac{1 + r^{\star}}{1 + r^{\star} - (1 + g^{\star})(1 - x^{\star})}(E_{jt} + R_{jt}) = (\nu - 1)\,\mathbb{E}_{jt} \sum_{\tau=0}^{\infty} \left(\frac{1 + g^{\star}}{1 + r^{\star}}\right)^{\tau} R_{j,t+\tau}.$$

Choose $\{\gamma_{jt}, \varphi_{jt}\}$ on the grid to jointly match R&D spending and the value of innovation.

Growth contribution share of AI firms has increased relative to non-AI firms



Expected contribution of the top 7 contributors over time

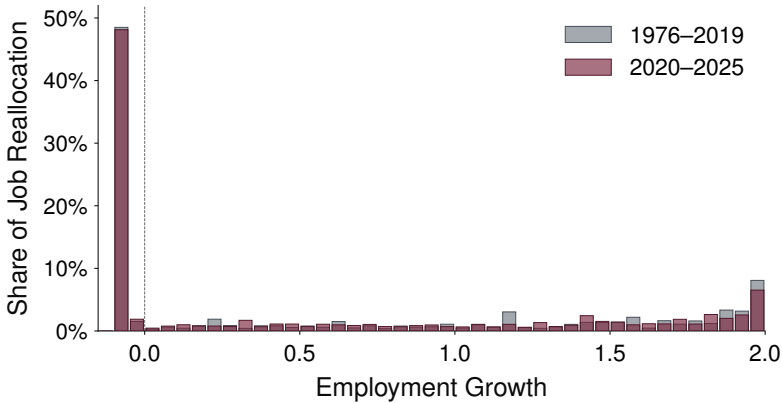


Sensitivity of AI firms' contribution to faster TFP growth

TFP growth acceleration under a X% price drop for Nvidia only and for all AI firms

Affected firms	Baseline	-10%	-20%	-30%
Nvidia only	133	132	132	131
All AI	133	125	113	95

Faster growth is accompanied by little change in job reallocation



Overall job reallocation remained roughly 11.3%.

Conclusion

AI firms' shares of sales and earnings, R&D intensity, and P/E ratios have risen since 2020

Through the lens of our model, AI firms accounted for 79% of growth in 2020–2025, up from 43% in 2014–2019

- well above their 33% share of sales and 47% share of earnings
- contributed an estimated 133 bp to faster TFP growth

Growth doubled through bigger innovation steps, not more creative destruction

- growth per arrival up from 0.18 to 0.36; average markup up from 1.13 to 1.21
- arrival rate, and hence product-level job reallocation, steady at 6% per year

To be done: privately-held AI firms (OpenAI, Anthropic)