Labor, Despite AI

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July 21, 2026

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Introduction

Motivation.

- AI tends to “collapse” when recursively trained on own output, certainly won’t improve
  (e.g., Shumailov et al (2024), Kazdan et al (2024) among others)
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2. Complementarity of labor/data fundamentally alters AI's impact on labor market.

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Approach.

- Support hypotheses by linking firm-level AI surveys to W2s
- Estimate new theory of data & job dynamics to simulate medium run, design insurance

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Empirics.

- Link W2s to 2022-2023 ABS (*today*)+ 2024-2025 BTOS (*pending*) to show

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2. Exposed workers gain relative to non-exposed workers on average (DnDs)

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$\hookrightarrow$ Motivates & disciplines model of AI requiring in-house resources & data on labor

Model.

- Workers generate data in job, firms use in- & out-of-house data to partially/fully automate
- Nest in directed search model w/ skill-weights that firms adapt (*new work*∼Lazear '09)
- Allow workers to retrain for credible medium-run dynamics

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  2. 9-fold increase in exposure
  3. 90% reduction in data obsolescence

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  - Extreme shocks (1.)-(3.) do not generate widespread displacement, long-run UR$<$6.5%.
  - Why? Workers retrain, remain valuable in production and data generation
- Optimal AI insurance fund: 0.7% profit/data sales tax yields large gains+retraining
  - Fund size robust to low degrees of verification/whistle-blower rates

Empirics

Data Sources

Four sources.

1. Annual Business Survey (ABS): R&D and AI activity, response required (460k firms ’23)
2. Business Trends and Outlook Survey (BTOS): AI activity, voluntary (1.2m firms ’25) evidence
3. Census-IRS Panel: W2s from 2005 to 2023 (today) and 2024 (pending)
4. Revelio: Detailed resume data from large online job networking site (2010 to 2023)

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- First link from firm AI adoption to worker wage histories (e.g. Humlum & Vestergaard ('26) – worker survey to earnings).

Annual Business Survey

AI definition in 2023 ABS:

"Artificial intelligence is a branch of computer science and engineering devoted to making machines intelligent. Intelligence is that quality that enables an entity to perceive, analyze, determine response and act appropriately in its environment."

Use AI if *"Used as part of the processes or methods"*, intensive if *"A lot"*

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Motivating facts from ABS 2023, 2022, 2019 ABS questions

1. Few firms use AI in production (2.9%-4.6%), affects many workers (13%-21% empl).
2. Among users, 83% report no workforce change from AI, 10% expand, 6% cut
3. Among intensive AI users, 49% conduct AI R&D in-house (77% empl), more likely to expand workforce and upskill from AI [details next]
4. Conditional on testing, firms say data access (9%), data quality (8%), talent (10%) adversely affect use

AI Usage and AI R&D in Annual Business Survey

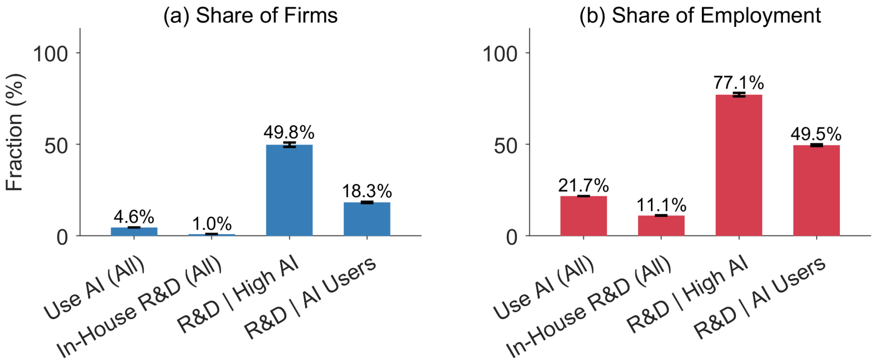

Figure: AI use and in-house AI R&D, 2022 ABS

AI use question: "To what extent did this business use Artificial Intelligence?" (response "A lot" = high intensity.)
R&D question: "During 2021, did this business perform or fund R&D on the following technologies?" AI=RD

AI R&D and Employment in Annual Business Survey

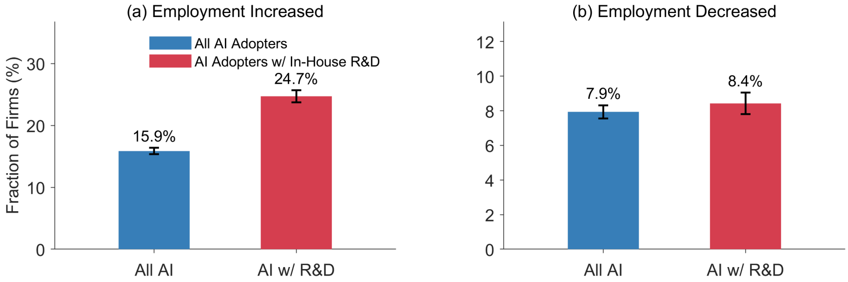

Figure: Employment effects of AI adoption by in-house AI R&D, 2022 ABS

Employment question: "To what extent did this business's use of AI technology impact your workforce? The number of workers employed at this business."

AI R&D and Upskilling in Annual Business Survey

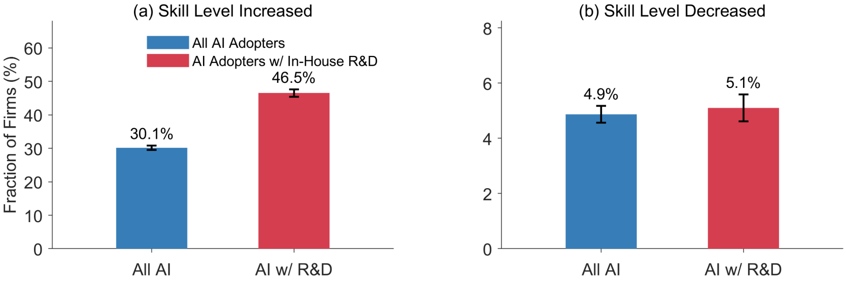

Figure: Workforce skill-level effects of AI adoption by in-house R&D status, 2022 ABS

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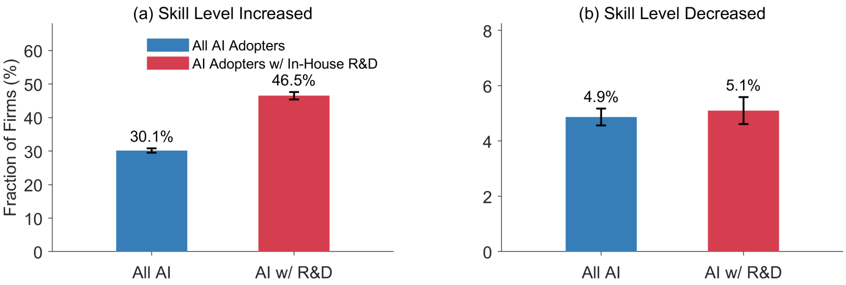

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Employment question: "To what extent did this business's use of AI technology impact your workforce? The skill level of workers employed at this business."

- Importance of in-house AI R&D motivate key model assumptions
- Does this complementarity appear in employment/wage data? Next.

AI and Worker Complementarity: ABS Linked to W2s

New Panel: Spine is W2s from 2015 to 2023 +

- Link to 2023 ABS which has retrospective question on the timing of AI adoption
- We restrict attention to firms adopting AI in the 2021–2022 window
- Link in ACS from 2015-2023, yielding occupations for roughly 16% of W2s (500k obs)

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Approach: compare wage growth of high v. low exposure *within-firm*

- Exposure 1: AI resume text to ONET task similarity by occ. (Hampole et al '25) + occ.
  - Most exposed: Health record tech specialists, management analytics, economists
- Exposure 2: Share of AI adopting firms reporting AI R&D by occ. (ACS-to-ABS) occ.
  - Most exposed to AI R&D: Aerospace engineers, EE, ME, scientists

AI and Worker Complementarity: ABS Linked to W2s

Notation: sum. stats

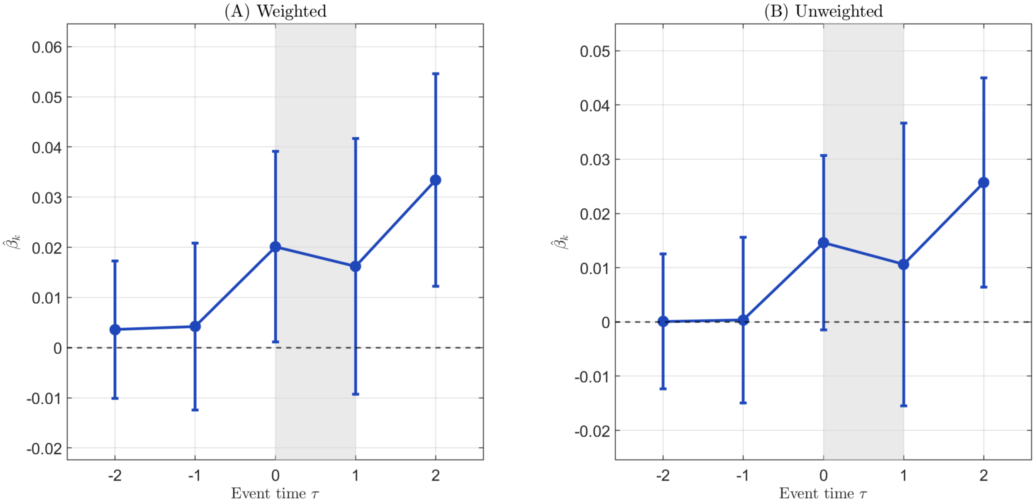
- i is individual, j firm, t year, τ years since AI adoption
- Map worker occupations to AI exposure e_i
- Let treatment T_i denote high exposure, e.g. $T_i = 1(e_i > p_{90})$

Primary specification: exploits within firm-year variation in exposure:

$$\Delta \log w_{it} = \alpha_i + \alpha_{jt} + \sum_{k=-2}^{2} \beta_k \cdot \mathbf{1}(\tau_{it} = k) \cdot T_i + \Gamma X_{ijt} + \epsilon_{it}, \tag{1}$$

- β_{+1}: within firm j at $\tau = +1$, extra % wage growth among exposed v. non-exposed

$\Delta \ln w_{it}$ around AI adoption ($\tau = 0$), Revelio exposure>p90

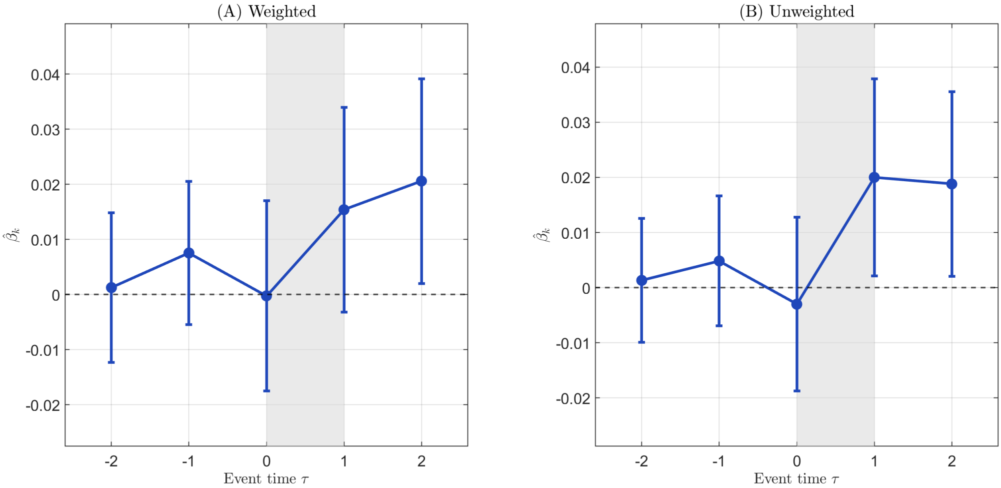


- 2% to 3% greater wage growth among p90 exposed v. non-exposed

$\Delta \ln w_{it}$ around AI adoption ($\tau = 0$), AI R&D exposure>p90

- Treatment is high AI R&D in occ: $T_i^{RD} = \mathbf{1}(e_i^{RD} > e_{RD}^{90})$ (keep Revelio exposure control)

occ.



Additional Results: Extensive Margin, Mobility, and Heterogeneity

Extensive margin and mobility.

- Re-run baseline with a **low-earnings** (layoff proxy) and **job-change** indicator
- No differential layoff of exposed workers on average low earn.
- Job-changes rise mildly after adoption job chg.

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Triple difference by firm employment response

- Add $T_i \times J_j^+$ (expanders) and $T_i \times J_j^-$ (contractors)
- At **contracting** firms, exposed workers lose: $\gamma_{+2}^- \in [-7.3, -5.7]$ log pts (sig.) DDD
- At **expanding** firms (J_j^+): small and insignificant
- $\Rightarrow$ average exposed gains mask heterogeneity: many lose where firms shed labor

Annual Business Survey Summary and Caveats

Summary:

- High exposure workers fare better, and moreso in high AI R&D occupations
- Adopters tend to expand employment, particularly so at firms conducting AI R&D

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Pending Census Release: BTOS evidence

- Linked 2024 W2s to 2024 BTOS and re-run the analysis among **"chatbot"** adopters
- Self-reported business changes (data practices, vendor use, hiring AI experts, retraining, no change) required to automate labor
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Next: Use empirics to motivate/discipline model that can be used for SR-LR counterfactuals

Model

Environment without Aggregate Risk

Workers. +

- Unit measure of risk-averse workers (die at rate λ)
- Differ by stochastic automatable/non-automatable human capital $\mathbf{h} = (h_a, h_n)$
- Workers direct search for jobs, indexed by piece-rate wage ϕ and skill $\mathbf{h}$
- Employed workers learn by doing, unemployed can retrain & augment h_n

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Firms. +

- Setup cost $\psi(\mathbf{h})$ to operate, can buy out-of-house data at exogenous cost $c(d)$
- Firms learn from workers and stochastically accumulate in-house data $d \leq h_a$
- With enough data, firms can partially or fully automate worker
  - Partial automation: retain worker, replace automatable human capital with data
  - Full automation: fire worker, replace entirely with data

Firms

- Enter submarket $(\mathbf{h}, \phi)$ at cost $\psi(\mathbf{h})$, find worker $q\left(\theta(\mathbf{h}, \phi)\right)$, or operate w/o worker
- Purchase out-of-house data d at exogenous cost $c(d)$, free entry implies

$$\psi(\mathbf{h}) \geq q(\theta(\mathbf{h}, \phi)) \left(\max_{d \leq h_a} J(\mathbf{h}, \phi, d) - c(d) \right) + (1 - q(\theta(\mathbf{h}, \phi))) \left(\max_{d \leq h_a} \beta J^F(d) - c(d) \right)$$

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- Non-automated firms $J(\cdot)$ accumulate in-house data stochastically on operations

$$d' = \begin{cases} \min\{d + \Delta, h_a\} & \text{w/ prob } p_d \\ \min\{d \quad\quad, h_a\} & \text{otherwise} \end{cases}$$

- End of period, may automate $\hat{J}$ or sell data if exit (δ) or worker dies (λ)

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- End of period, may automate $\hat{J}$ or sell data if exit (δ) or worker dies (λ)
- Firm chooses skill weights s to produce (Lazear '09), ρ governs complementarity

$$J(\mathbf{h}, \phi, d) = \max_{s \in [0,1]} \left((s h_n)^\rho + ((1 - s) h_a)^\rho\right)^{1/\rho} \cdot (1 - \phi)$$
$$+ \beta E_{\mathbf{h}', d' | \mathbf{h}, d} \left[(1 - \lambda)(1 - \delta) \widehat{J}(\mathbf{h}', \phi, d') + (\delta(1 - \lambda) + \lambda) c(d') \right]$$

Firms

Each period, firms choose between partial/full automation,

$$\widehat{J}(\mathbf{h}, \phi, d) = \max \left\{ J(\mathbf{h}, \phi, d),\ J^P(\mathbf{h}, \phi, d),\ J^F(d) \right\}$$

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Partial automation (PA).

- Flow cost κ of production (same for PA and FA), accumulate data as before
- Worker continues but job's skill weights change ($s = 1$) and data replaces h_a:

$$\begin{aligned} J^P(\mathbf{h}, \phi, d) = & \left(h_n^\rho + d^\rho\right)^{1/\rho} (1-\kappa)(1-\phi) \\ & + \beta E_{\mathbf{h}', d' | \mathbf{h}, d}\left[(1-\lambda)(1-\delta)\widehat{J}(\mathbf{h}', \phi, d') + (\delta(1-\lambda)+\lambda)c(d')\right] \end{aligned}$$

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Full automation (FA).

- The worker is fired and only accumulated data is used to produce

$$J^F(d) = d(1-\kappa) + \beta[(1-\delta_F)J^F(d) + \delta_F c(d)]$$

Workers

Unemployed.

- Home production $z(\mathbf{h})$ *[version with assets b, today hand-to-mouth]*
- Can retrain and learn R non-automatable skills at cost $R^{\eta} \cdot \chi \to \mathbf{h}' = (h_n + R, h'_a)$.

$$U(\mathbf{h}) = \max_{R \geq 0} u(z(\mathbf{h}) - R^{\eta} \cdot \chi)$$
$$+ \beta(1-\lambda) E_{\mathbf{h}'|\mathbf{h},R,U} \left[\max_{\phi} p(\theta(\mathbf{h}',\phi)) W(\mathbf{h}',\phi,d(\mathbf{h}',\phi)) + \left(1 - p(\theta(\mathbf{h}',\phi))\right) U(\mathbf{h}') \right]$$

Employed.

- Earn piece-rate ϕ of production (or marginal product) and learn on the job
- Take automation decisions of firm f^F and f^P as given More

Newborns start unemployed, zero assets.

- Draw total h.c. $h = h_a + h_n$ and fraction automatable skills $f_a = \frac{h_a}{h}$ from $G(h, f_a)$

Equilibrium

Equilibrium. characterization

Given r_f, a *Block Recursive Equilibrium* consists of firm policy functions $\{f^P(\mathbf{h}, \phi, d), f^F(\mathbf{h}, \phi, d), \hat{s}(\mathbf{h}), d(\mathbf{h}, \phi)\}$, search and human capital investment policy functions for workers $\{\phi(b, \mathbf{h}), \hat{R}(b, \mathbf{h})\}$, and a market tightness function, $\{\theta(\mathbf{h}, \phi)\}$ such that households and firms optimize, and free entry holds.

- Keeps non-linear aggregate dynamics tractable, lets us estimate model along transition

Consider four aggregate shocks.

- Cost of initial data $c(d)$
- Cost of automation κ
- Share of skills automatable $f_a = h_a/(h_a + h_n)$
- Complementarity ρ

Quarterly Estimation

External: $\beta = 0.99$, 46yr working life, $\delta = 0.034$ (JOLTS), $u(c) = ln(c)$ functional forms

- Den Haan et al '00 matching, elast. $\alpha = 1.6$ (Schaal '17), birth exposure (Revelio, next) learning moments

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   - Retraining: χ and η $\rightarrow$ retraining rate/gains from JLS '05, Lahey et al '25

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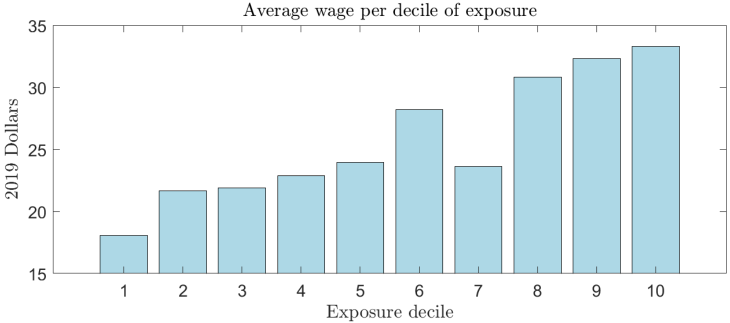
3. Run identical regressions to first half of paper, estimate key parameters
   - Complementarity ρ $\rightarrow \tau = 0$ wage effect $>$p90 exposed v. $<$p90
   - In-house learning p_d $\rightarrow \tau = +1$ wage effect $>$p90 exposed v. $<$p90

Estimation: Exposure distribution of newborns

- Assume $\log h_n$ and f_a jointly normal (over grids), with correlation Γ
- (1) Marginal of f_a is Revelio exposure (mean μ_{f_a}), (2) Normalize mean h, (3) $\Gamma \rightarrow corr(f_a, w)$

Figure: Correlation of Revelio exposure and wages in CPS (2010-2022)

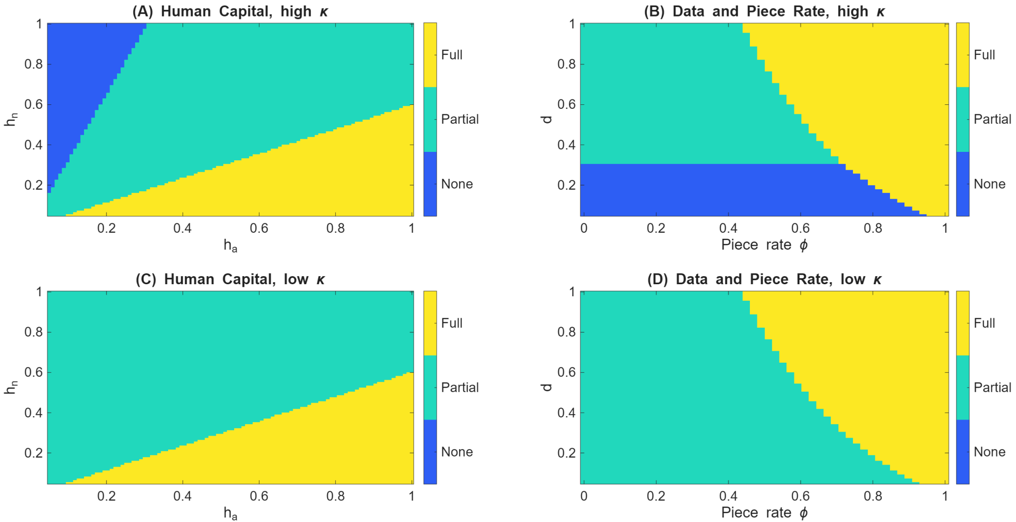


Estimation: Model v. Data Moments

Var.	Description	Value	Moment	Model	Data
A. 2023 Transition					
ρ	Complementarity (Sup. $\rho < 1$)	0.484	β_0: exposed wage diff. (τ=0) ('23 ABS)	0.025	0.020
p_d	Pr. data accumulation	0.191	β_{+1}: exposed wage diff. (τ=1) ('23 ABS)	0.015	0.016
δ_κ	Drop in AI adoption cost	0.461	AI use & cut employment ('23 ABS)	0.018	0.004
B. Steady State					
c_0	Cost of data	0.160	Immediate partial automation ('22 ABS, Use AI+No R&D)	0.597	0.505
χ	Cost of re-training h_n	0.757	Re-training rate (JLS)	0.174	0.150
η	Convexity of re-training cost	1.621	Re-training gains (HLNP)	0.081	0.090
κ	AI adoption cost	0.462	Partial automation rate ('22 ABS, Use AI)	0.172	0.217
p_h^-	Pr. h decrease	0.448	Mean 4y earnings losses (BHP)	-0.113	-0.090
p_h^+	Pr. h increase	0.020	Mean wage growth (CPS)	0.006	0.020
σ_h	S.D. of $\log h_n$ at birth	0.321	Standard deviation of log wages (CPS)	0.222	0.305
ψ	Cost of vacancy	0.178	Unemployment rate (CPS)	0.045	0.062
z_0	Home production rep. rate	0.293	Home production replacement rate (Shimer)	0.391	0.400
Γ	Corr. of h_n and e $(= \frac{h_a}{h_a+h_n})$	0.917	Corr. of e and wages (Revelio and CPS)	0.531	0.496
δ_F	Full-auto. firm death rate	0.011	Labor share (BEA)	0.488	0.529

Identification moment details

Policy Functions



- High $h_a \to$ f.a. (yellow), mid non-auto $h_n \to$ p.a. (turquoise), high $h_n \to$ non (blue)

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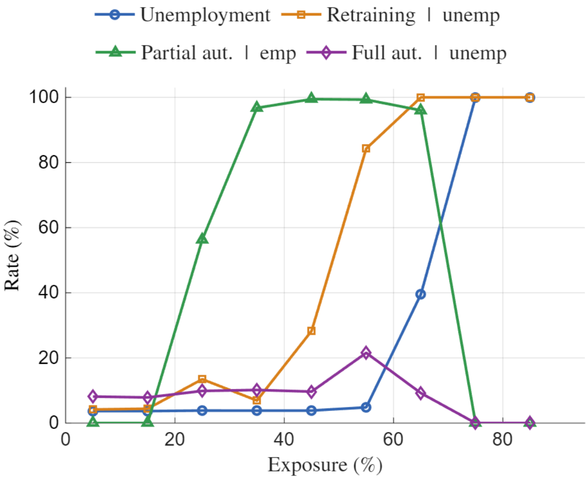
Policy Functions



- Partial automation among mid-exposure, Full automation in tail and motivates retraining

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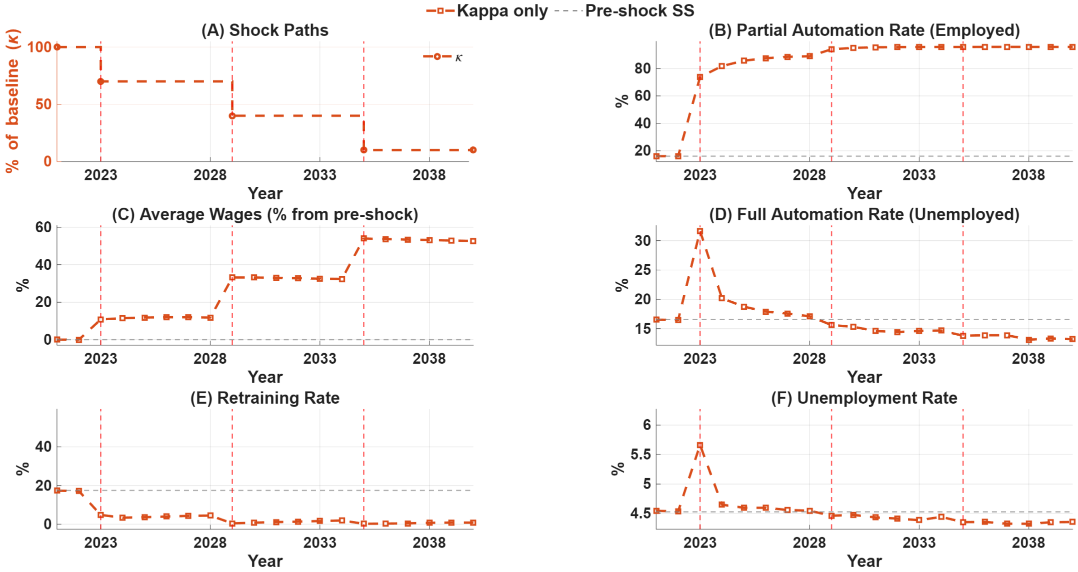
Counterfactuals

1. Lower κ (or c_0) by 15% to match 2026 AI use ($\approx$ 50% Bonney et al 2026) BTOS evidence
   - From 2022 to 2026, we infer 4% cost reduction *per year* in κ (or c_0)
2. Extrapolate: 4% cost reduction in κ per year until 2042 (90% reduction)
3. Exposure hard to measure over time, assume newborn exposure 75% by 2042 (9x incr)
4. Data obsolescence falls 90% by 2042 (AI retraining less frequent)
5. Complementarity undone to perfect substitutes by 2042
6. Last: all changes compressed into next 10 years.

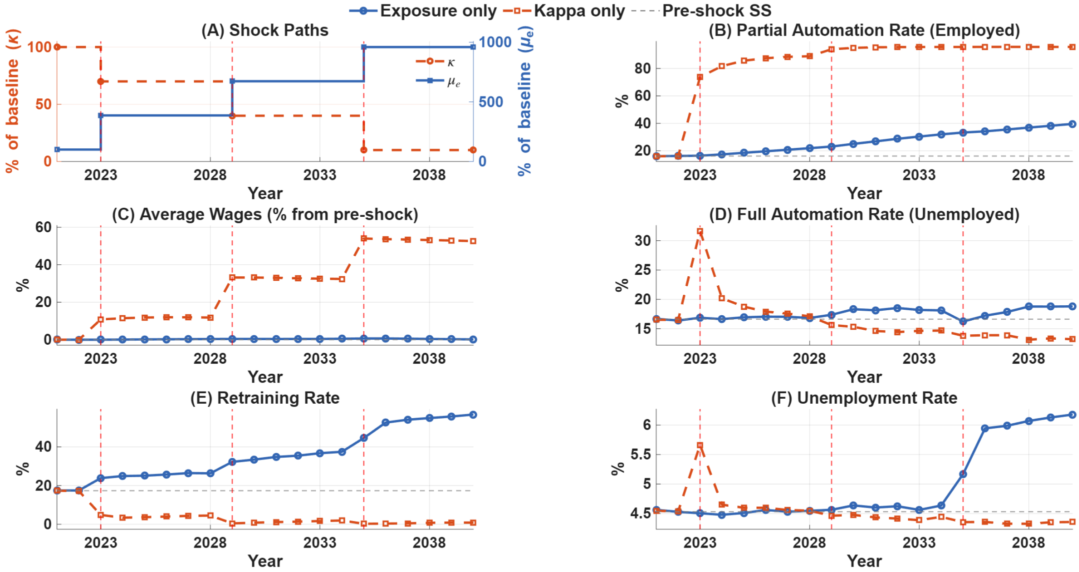
- Beliefs: first shock is surprise, rational expectations henceforth

belief process policy functions other predictions

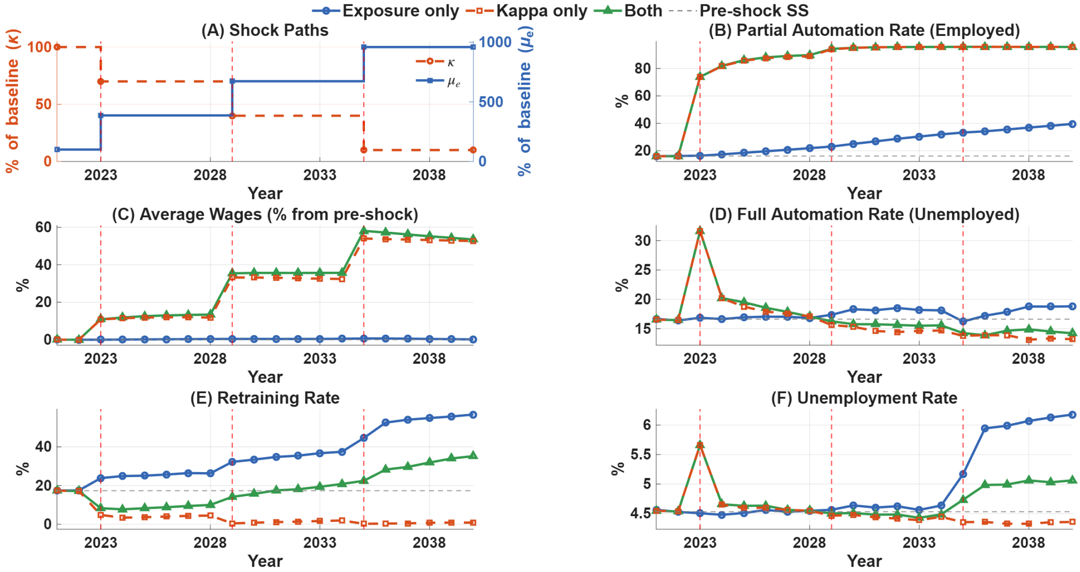
Results - Automation Cost/Exposure



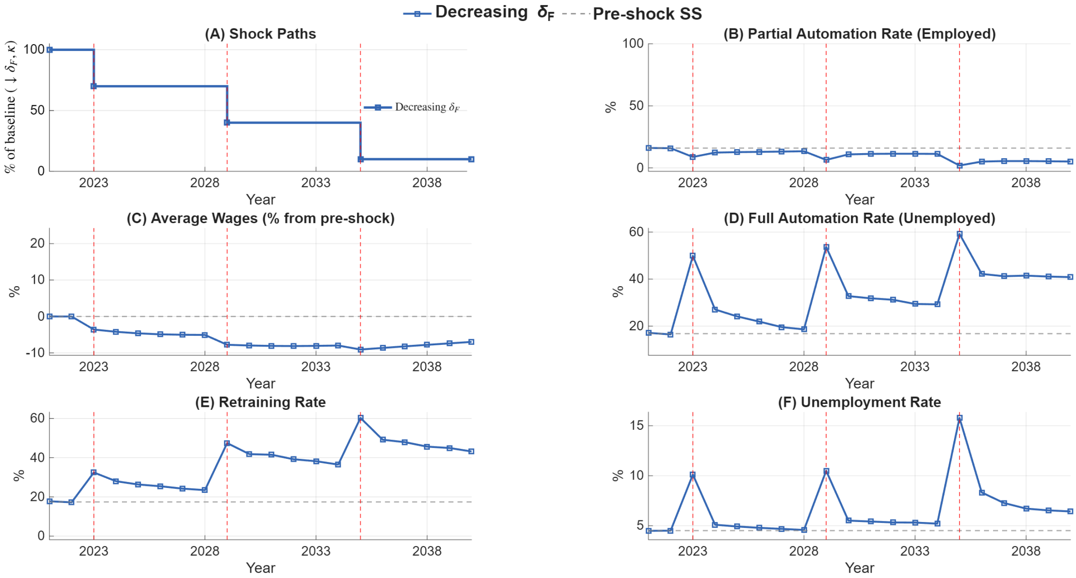
Results - Automation Cost/Exposure



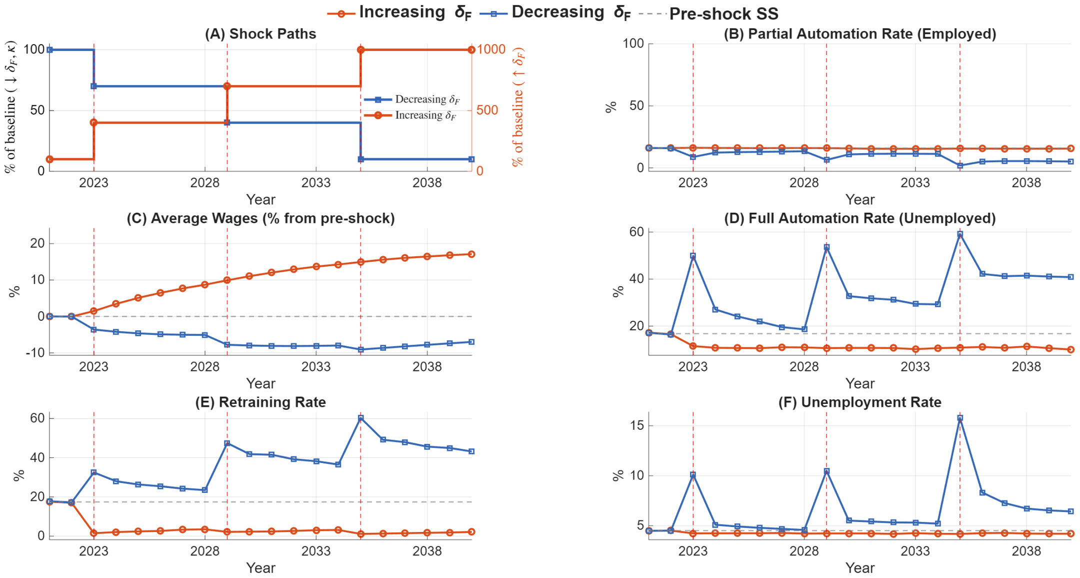
Results - Automation Cost/Exposure



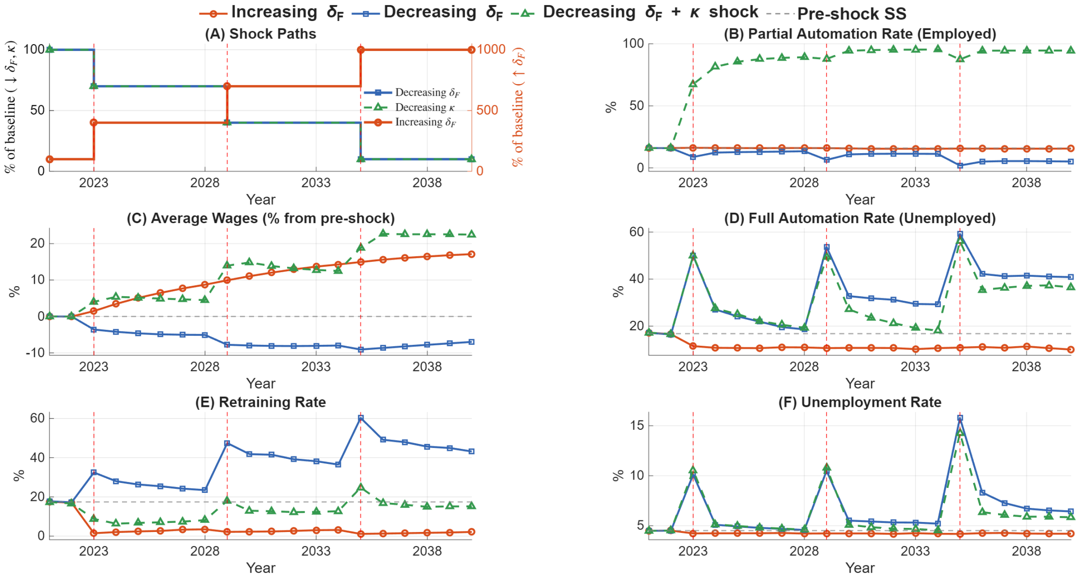
Results - Data Depreciation



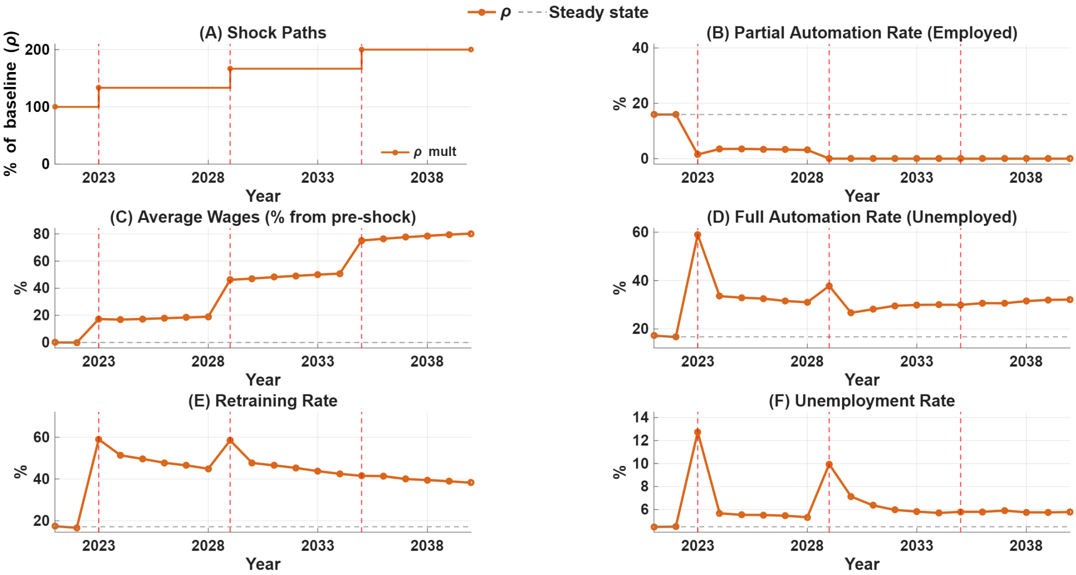
Results - Data Depreciation



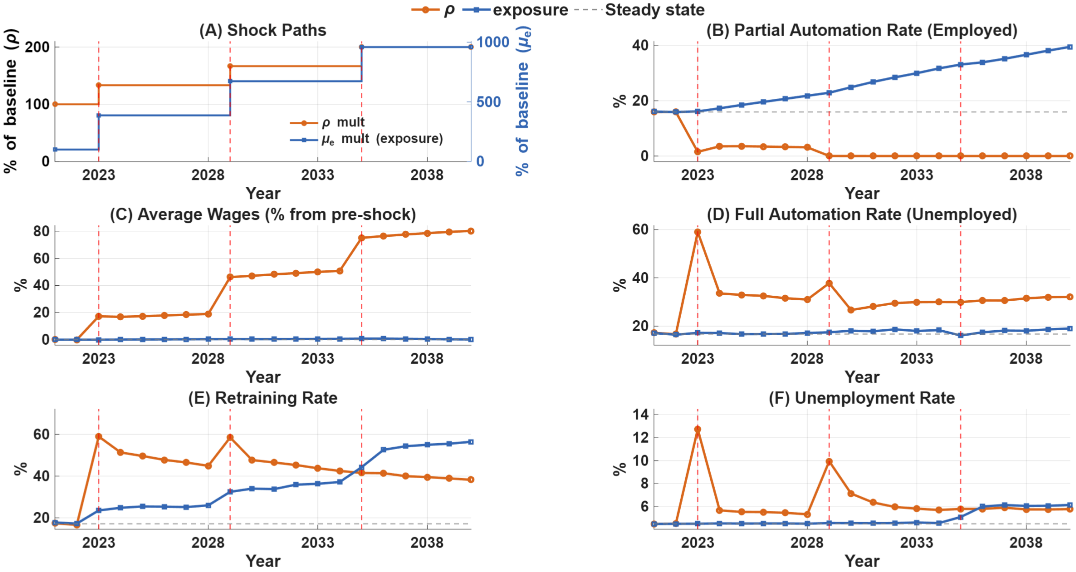
Results - Data Depreciation



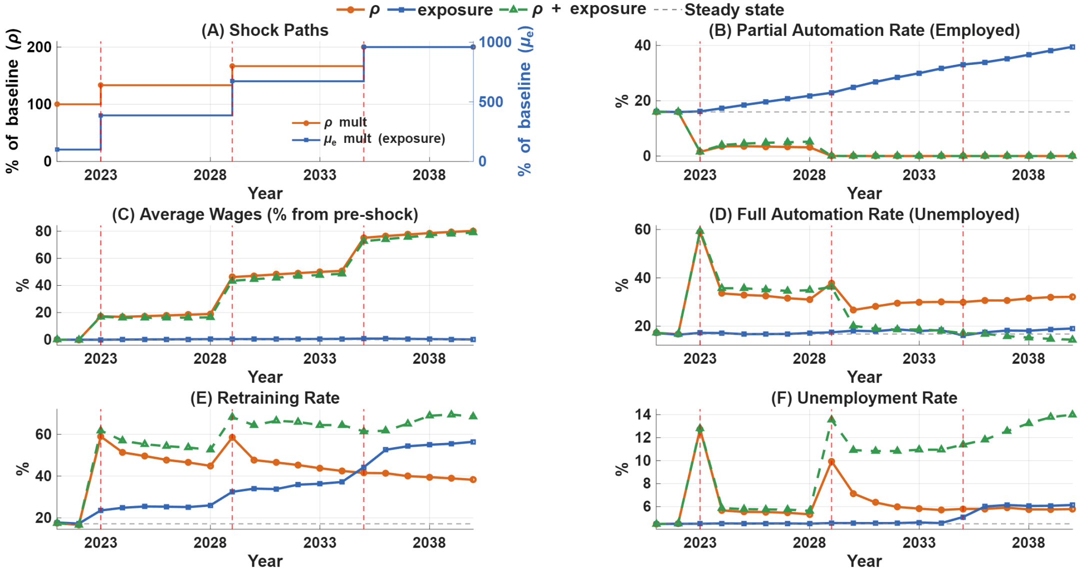
Results - Complementarity



Results - Complementarity



Results - Complementarity



Steady-State Moments Under the Counterfactual Shocks

	(1) Baseline	(2) Exposure	(3) κ	(4) κ+Exp	(5) $\delta_F \downarrow$	(6) $c_0 \downarrow$
Shock	—	$\uparrow 9\times$	$\downarrow$ 90%	both	$\downarrow$ 90%	$\downarrow$ 90%
Unemployment rate (%)	4.5	6.3	4.4	5.0	6.2	4.6
Partial automation rate (%)	17.2	92.7	95.7	96.3	1.9	19.3
Full automation rate (%)	16.8	18.9	13.4	14.2	41.2	17.4
Retraining rate (%)	17.4	68.7	3.7	56.5	34.1	17.7
Δ wages (%)	—	+9.8	+46.5	+59.2	-1.5	+0.0

- Fixing complementarity, highest long-run unemployment rate is 6.3% from rising exposure

Steady-State Moments Under the Counterfactual Shocks

	(1) Baseline	(2) Exposure	(3) κ	(4) κ+Exp	(5) $\delta_F \downarrow$	(6) $c_0 \downarrow$	(7) ρ	(8) ρ+Exp
Shock	—	$\uparrow 9\times$	$\downarrow$ 90%	both	$\downarrow$ 90%	$\downarrow$ 90%	perf. subs.	both
Unemployment rate (%)	4.5	6.3	4.4	5.0	6.2	4.6	5.6	14.8
Partial automation rate (%)	17.2	92.7	95.7	96.3	1.9	19.3	0.0	0.0
Full automation rate (%)	16.8	18.9	13.4	14.2	41.2	17.4	33.5	14.6
Retraining rate (%)	17.4	68.7	3.7	56.5	34.1	17.7	32.8	62.0
Δ wages (%)	—	+9.8	+46.5	+59.2	-1.5	+0.0	+89.2	+93.4

- Fixing complementarity, highest long-run unemployment rate is 6.3% from rising exposure
- If we undo complementarity $\rho \approx 1$ and raise exposure, unemp. rate reaches 15%

Optimal Automation Insurance Fund

Motivation. Can't insure automation and job loss$\rightarrow$ markets incomplete.

- Proportional tax τ on firm profits+data sales, impose budget balance
- Rebate T to fully automated unemployed workers with prob. $\pi = 10\%$ ("whistleblower")
- Whistleblower transit into the U^F Bellman for 1 period after full automation:

$$U^F(\boldsymbol{h}) = \max_{R\geq 0} u(z(\boldsymbol{h}) + T - \chi R^\eta) + \beta(1-\lambda)\, E_{\boldsymbol{h}'|\boldsymbol{h},R,U}\left[\max_{\phi} p(\theta(\boldsymbol{h}',\phi))\, W(\boldsymbol{h}',\phi,d(\boldsymbol{h}',\phi)) + \left(1-p(\theta(\boldsymbol{h}',\phi))\right) U(\boldsymbol{h}')\right]$$

- Choose $\{\tau, T\}$ to maximize SS ex-ante newborn welfare, before drawing $(\boldsymbol{h}, f_a) \sim G$
- Optimal τ^* is 0.74% and $T^* \approx 120k$, CEV welfare gain: 0.7%
- Large welfare gain of 0.4% CEV for $\tau = 0.1\%$, larger gains than UI due to targeting +

Conclusion

- First link of firm-reported AI adoption (ABS) to U.S. tax records:

▶ **Result I:** Exposed workers gain after adoption, and AI not "out of box"

- New framework in which AI must be trained by workers, i.e. AI is part "experience good"

▶ **Result II:** Extreme shocks fail to generate widespread LR displacement

Why? workers generate data, retrain, and remain valuable

▶ **Result III:** Small automation insurance fund generates large gains behind-the-veil

Appendix

Motivating Facts from Annual Business Survey Administrative (ABS) Microdata

Fact 1: Relatively few firms have adopted ai ("Used as part of the processes or methods"), but it affects a substantial fraction of workers. Census AI definition: "Artificial intelligence is a branch of computer science and engineering devoted to making machines intelligent. Intelligence is that quality that enables an entity to perceive, analyze, determine response and act appropriately in its environment." Robots: "Robotic equipment (or robots) are automatically controlled, reprogrammable, and multipurpose machines used in automated operations in industrial and service environments."

Variable	Sample	Mean	Mean (Empl-wtd)	N
Use AI (d)	2022 ABS, weighted	2.9%	13.5%	460,000

Fact 2: Among AI adopters, many say their intention is "To automate tasks performed by labor"

Variable	Sample	Mean	Mean (Empl-wtd)	N
Labor Saving Intent (d)	2022 ABS Adopters	36.8%	62.6%	16,000

Motivating Facts from Annual Business Survey Administrative (ABS) Microdata

Fact 3: Among AI adopters, most report no workforce change, but non-trivial fractions report expansions and contractions of employment as the result of AI ("During the three years 2020 to 2022, what were the effects of adopting or using Artificial Intelligence on the following? a. The number of workers employed by this business, increased, decreased or did not change"

Variable	Sample	Mean	Mean (Empl-wtd)	N
Increase Workforce	2022 ABS Adopters	10.7%	18.8%	16,000
Decrease Workforce	2022 ABS Adopters	6.1%	3.0%	16,000
No Change	2022 ABS Adopters	83.2%	78.2%	16,000

Fact 4: Among those who use AI ("Artificial intelligence (e.g., machine learning, planning, reasoning, and decision making)") intensively ("A lot"), the near majority of firms are doing R&D in-house ("During 2021, did this business perform or fund R&D on the following technologies?")

Variable	Sample	Mean	Mean (Empl-wtd)	N
Use AI (d)	2021 ABS	4.6%	21.7%	179,000
In House R&D	2021 ABS	1.0%	11.1%	179,000
In House R&D	2021 ABS, High AI	49.8%	77.1%	2,000
In House R&D	2021 ABS, Any AI	18.3%	49.5%	13,000

Motivating Facts from Annual Business Survey Administrative (ABS) Microdata

Fact 5: In the 2018 ABS, the intensity of use of technologies in production was measured and a a significant number of firms reported "In use for more than 25% of production or service"

Variable	**Sample**	**Mean**	**Mean (Empl-wtd)**	**N**
High AI (d)	2017 ABS, weighted	4.1%	12.7%	496,000
High LLM (d)	2017 ABS, weighted	0.4%	0.6%	496,000
High ML (d)	2017 ABS, weighted	0.8%	3.7%	496,000
High Robot (d)	2017 ABS, weighted	0.4%	3.7%	496,000
High Robot and LLM (d)	2017 ABS, weighted	0.1%	0.1%	496,000
Use AI (d)	2017 ABS, weighted	8.9%	25.6%	496,000
Use LLM (d)	2017 ABS, weighted	1.0%	5.9%	496,000
Use ML (d)	2017 ABS, weighted	2.3%	8.3%	496,000
Use Robot (d)	2017 ABS, weighted	1.1%	9.0%	496,000

Motivating Facts from Annual Business Survey Administrative (ABS) Microdata

Fact 6: Conditional on testing AI, a large fraction of firms claim that data access, data quality, or human capital talent adversely affected adoption ("During the three years 2016 to 2018, indicate which factors adversely affected the adoption or utilization of the following technologies to produce goods or services. Select all that apply for each technology.")

Variable	**Sample**	**Mean**	**Mean (Empl-wtd)**	**N**
Too Expensive (d)	2018 ABS, Test AI	23.9%	30.5%	2,000
Lack data access (d)	2018 ABS, Test AI	9.4%	21.4%	2,000
Unreliable data (d)	2018 ABS, Test AI	8.0%	35.7%	2,000
Lack talent (d)	2018 ABS, Test AI	10.9%	35.7%	2,000
No Barriers (d)	2018 ABS, Test AI	26.9%	15.7%	2,000

Fact 7: Unconditionally, AI has different adoption barriers than robots, and firms report talent and data as AI adoption barriers relatively more then robots

Variable	**Sample**	**Mean**	**Mean (Empl-wtd)**	**N**
Lack data access for AI (d)	2018 ABS	0.9%	3.5%	188000
Lack talent for AI (d)	2018 ABS	1.2%	5.0%	188000
Lack data access for robot (d)	2018 ABS	0.4%	1.0%	188000
Lack talent for robot (d)	2018 ABS	0.7%	3.1%	188000

Hampole et al (2025) AI Exposure ABS+W2

Compute similarity (**exposure**) for all pairwise AI resume text embeddings & O*NET tasks

1. First step is bag of words to isolate AI resume text
2. E.g. AI resume text:
   "...AI/ML model delivery in public cloud, private cloud and on prem. managing credit risk deployment services platform with continuou s delivery..."
3. Embed with General Text Embeddings (GTE) "large" model
4. Let N_t is no. of AI resume texts in year t
5. Compute cosine similarity for all AI text (i) by O*NET task (j) pairs

$$e_o(x) = \frac{1}{N} \cdot \sum_{i=1}^{N_{f,t}} \sum_{j \in J(o)} \omega_{o,j} \cdot \mathbb{1}(\text{similarity}(\text{AI resume text } i, \text{O*NET task } j) \geq x).$$

6. $x = p95$ of similarity dist, $\omega_{o,j} =$ importance weight of task j in occ o, $J(o) =$all tasks in occ o

Exposure 1: Example Hampole et al. (2025) Exposed Occupations

Table: Highest (top) v. lowest (bottom) AI-exposure occupations, ONET-task similarity score

	Score	
1.	.7557775	Health record tech specialists
2.	.7355667	Mathematicians and mathematical scientists
3.	.6802118	Farmers (owners and tenants)
4.	.648904	Operations and systems researchers and analysts
5.	.6474488	Economists, market researchers, and survey researchers
6.	.6388968	Management analysts
7.	.6218218	Managers of medicine and health occupations
8.	.6164278	Physical scientists, n.e.c.
9.	.5776188	Statistical clerks
10.	.5733104	Industrial engineers
	Score	
1.	0	Repairers of mechanical controls and valves
2.	0	Insurance underwriters
3.	0	Janitors
4.	0	Concrete and cement workers
5.	0	Furniture and wood finishers
6.	0	Dancers
7.	0	Explosives workers
8.	0	Pressing machine operators (clothing)
9.	0	Postal clerks, excluding mail carriers
10.	0	Musician or composer

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Exposure 2: Example R&D Exposed Occupations

Construction.

- Use 2022 ABS linked to W2 panel, isolate AI using firms
- "Collapse" share of firms reporting positive AI by occupation ($P(AI\ RD|occ)$)
- $e_i^{RD} =$ share of each occupation's employment at R&D-performing firms
- Treatment $T_i^{RD} = \mathbf{1}(e_i^{RD} > e_{RD}^{90})$; all specs control for AI exposure T_i^{AI}

Highest R&D-exposure occupations.

- Aerospace engineers
- Electrical engineers
- Mechanical engineers
- Atmospheric and space scientists

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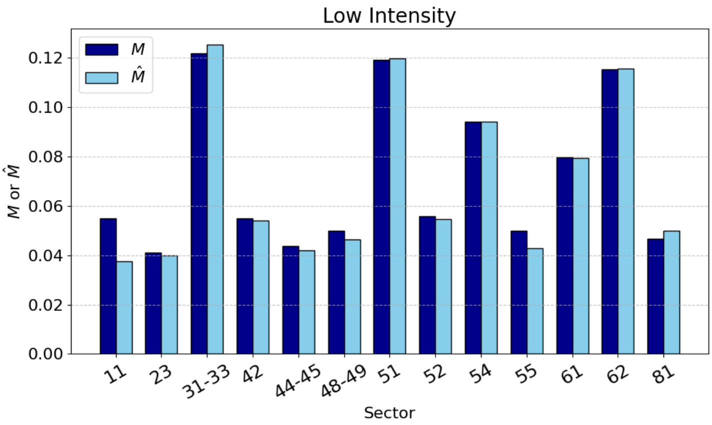
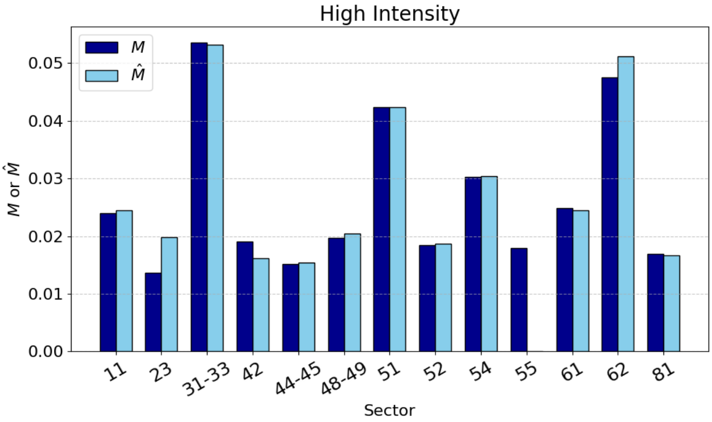
Estimation: Share low AI use Annual Business Survey (ABS)

Figure: Fraction of firms with "low" AI use (5% to 25% of production) versus ABS data



Estimation: Share high AI use Annual Business Survey (ABS)

Figure: Fraction of firms with "high" AI (25%+ of production) use versus ABS data



Empirics: Questions Used in the Annual Business Survey

- Adoption (2023 ABS): "During the 3 years from 2020 to 2022, did this business adopt/use the following technologies? Artificial Intelligence." (code as use if "Used as part of processes or methods")
- Intent (2023 ABS): "What is this business's intention for adopting or using AI? To automate tasks performed by labor."
- Employment effect (2023 ABS): "During 2020–2022, what were the effects of adopting/using AI on the number of workers employed by this business?" (increase/decrease/no change)
- Intensity (2022 ABS): "To what extent did this business use Artificial Intelligence?" ("A lot" = high intensity)
- In-house R&D (2022 ABS): "During 2021, did this business perform or fund R&D on the following technologies?"
- Skill/STEM (2022/2023 ABS): "... impact your workforce? The skill level of workers employed."
- Barriers (2019 ABS): "During 2016–2018, indicate which factors adversely affected the adoption or utilization of the following technologies." (data access, data quality, talent, cost)

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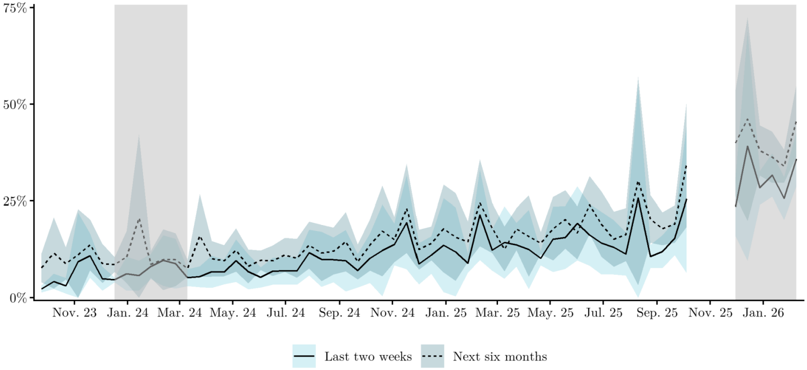
BTOS Evidence: AI Use Over Time (Haltiwanger 2026)

(b) Employment-weighted



Note: Shaded areas indicate 95% confidence intervals around BTOS estimates given BTOS response standard errors. Grey shaded areas represent AI supplement collection periods.

Employment-weighted BTOS AI-use rate; rising sharply by 2025–26 (Haltiwanger 2026).

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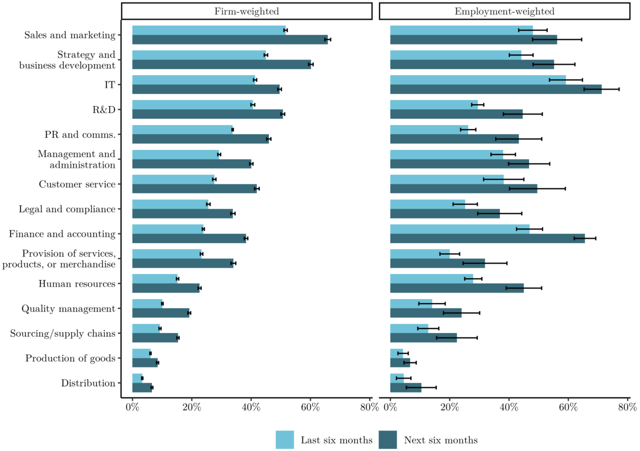
BTOS Evidence: AI Use by Business Function

Figure 7: AI use rate by business function – conditional on use in at least one function

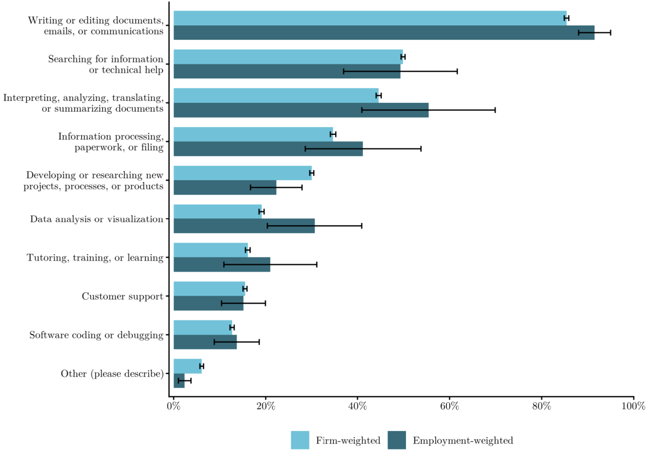


Note: Error bars indicate 95% confidence intervals around BTOS estimates given BTOS response standard errors. Response rates are conditional on answering 'Yes' to AI use for at least one business function.

AI use rate by business function, conditional on use in $\geq$ 1 function (Haltiwanger 2026).

BTOS Evidence: Worker GenAI Use by Task

Figure 9: Worker GenAI use rates by task – conditional on use in at least one task

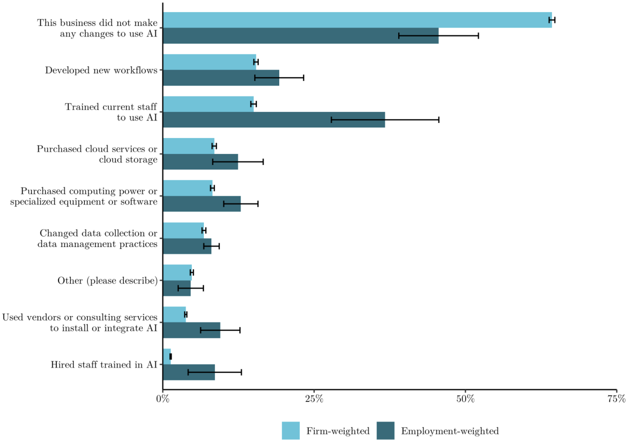


Note: Error bars indicate 95% confidence intervals around BTOS estimates given BTOS response standard errors. Q32 is conditional on responding 'Yes' to Q31: Generative AI use by employees.

Worker GenAI use rates by task, conditional on use in $\geq$ 1 task (Haltiwanger 2026).

BTOS Evidence: Organizational Adjustments to Use AI

Figure 18: Organizational adjustments to use AI



Note: Error bars indicate 95% confidence intervals around BTOS estimates given BTOS response standard errors. Q29 is conditional on AI use in at least one business function.

Organizational adjustments to use AI (Haltiwanger 2026): most make no change; else new workflows / staff training lead.

Empirics: Construction of the ABS→W2 Panel

Four linked sources.

1. **Spine:** 1040 tax returns 2015–2023 (annual W2 wage/salary income)
2. **Firm:** TIN + EIN on returns; EIN-to-firmid crosswalk assigns Census firmid by year
3. **Adoption:** 2023 ABS retrospective timing question; keep 2021–2022 adopters
4. **Occupation:** ACS occupation codes; AI exposure from Hampole et al. ’25

Key choices.

- Most recent occupation observed before 2020, filled forward/backward (time-invariant)
- Exposure mapped on 1990 Census occ. codes (Dorn crosswalk), predetermined to adoption
- Require ≥ 2 exposure categories within firm (ensures within-firm-year variation)
- $\approx$95k worker-year obs at 900 firms; earnings deflated to 2024 by CPI Back

Empirics: ABS$\rightarrow$W2 Estimation Sample Summary Statistics

Table: Summary statistics at $\tau = -1$ (2020), firms reporting AI adoption in 2021–2022 (ABS)

Variable	Mean	SD	N
W-2 Earnings ($)	108,100	94,030	95,000
Age	44.0	11.7	95,000
Male	0.545	0.498	95,000
White	0.707	0.455	95,000
College Degree	0.455	0.498	95,000
Some College	0.315	0.465	95,000
High School	0.204	0.403	95,000
$\Delta \ln w_2$	-0.005	0.467	95,000
AI Exposure Score	0.070	0.043	95,000
High Exposure (T_i)	0.120	0.325	95,000
Unique firms: 900			

W-2 earnings in 2024 dollars. $T_i = \mathbf{1}(e_i > e^{90})$: above 90th pctile of AI exposure. N rounded.

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Empirics: Estimating Equations

Outcome and timing.

- Residualize $\ln W2_{it}$ on age dummies; outcome $\Delta \ln w_{2,it} = \Delta\hat{\epsilon}_{it}$
- Event time τ ($\tau = 0$ is 2021), window $\tau \in \{-3, \ldots, +2\}$, $\tau = -3$ omitted

Baseline (within firm-year): worker FE α_i, firm×year FE α_{jt}

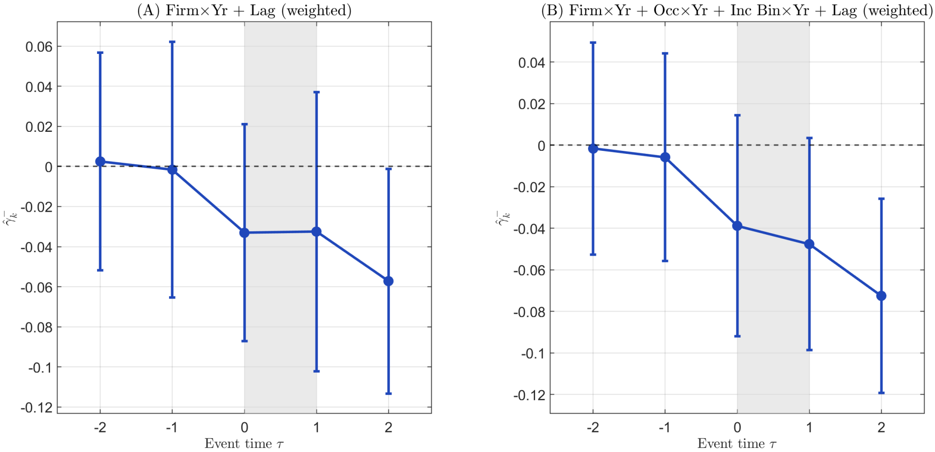
$$y_{it} = \alpha_i + \alpha_{jt} + \sum_{k=-2}^{2} \beta_k \cdot \mathbf{1}(\tau_{it} = k) \cdot T_i + \epsilon_{it}$$

Triple difference (heterogeneity by firm employment response):

$$y_{it} = \alpha_i + \alpha_{jt} + \sum_k \beta_k \mathbf{1}(\tau_{it}{=}k)\, T_i + \sum_k \gamma_k^+ \mathbf{1}(\tau_{it}{=}k)\, T_i J_j^+ + \sum_k \gamma_k^- \mathbf{1}(\tau_{it}{=}k)\, T_i J_j^- + \epsilon_{it}$$

- Progressively add income-bin×year FE and lagged outcome; $J_j^{\pm}$: firm expands/contracts
- DDD adds occupation×year FE (absorbs national occ. shocks), but then β_k not identified

Empirics: Triple Difference (J_j^-), AI Exposure



$\hat{\gamma}_k^-$: extra effect for exposed workers at firms that *contract* employment post-AI. Panel A: firm$\times$year + worker FE + lagged outcome. Panel B: adds occupation$\times$year and income-bin$\times$year FE. $\tau = 0$ is 2021.

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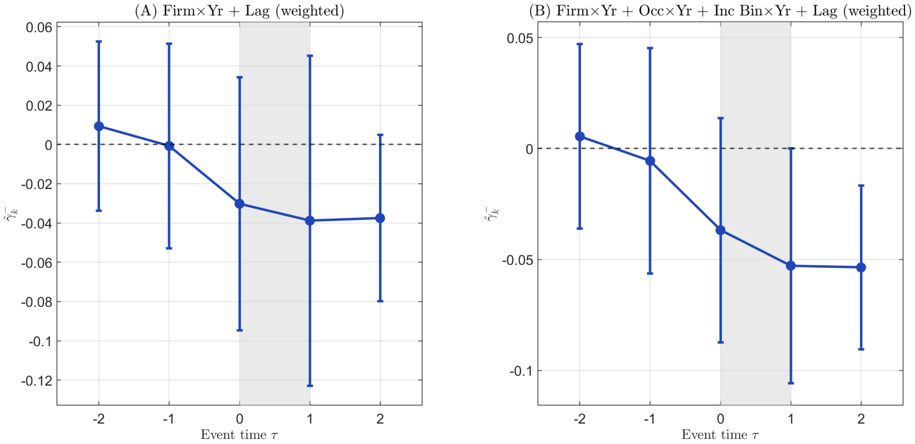
Empirics: Triple Difference (J_j^-), R&D Exposure



$\hat{\gamma}_k^-$ for R&D occupation exposure, controlling for AI exposure. At contracting firms, high R&D-exposure workers lose ($\gamma_{+2}^- \in [-5.4, -3.8]$ log pts). $\tau = 0$ is 2021.

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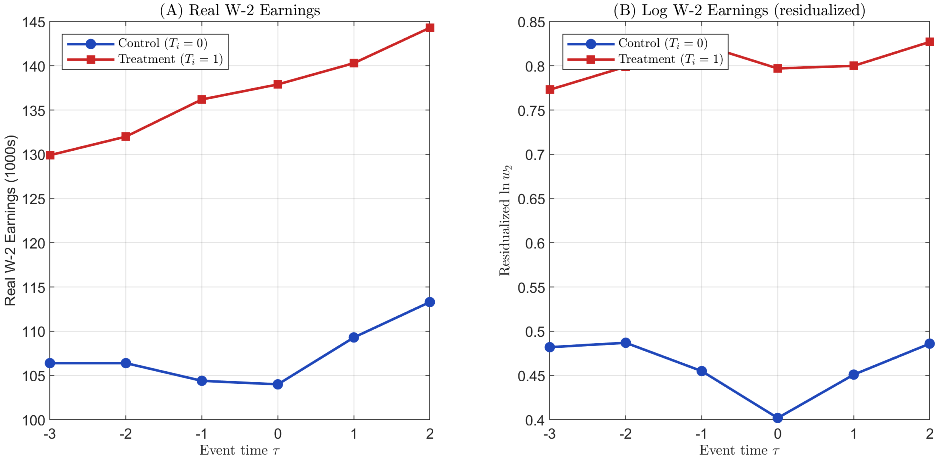
Empirics: Earnings Dynamics by AI Exposure Group



Panel A: real W-2 earnings ($1000s). Panel B: residualized log W-2 earnings. Treatment $T_i = 1$ (>p90 exposure) vs. control. $\tau = 0$ is 2021. ABS survey-weighted.

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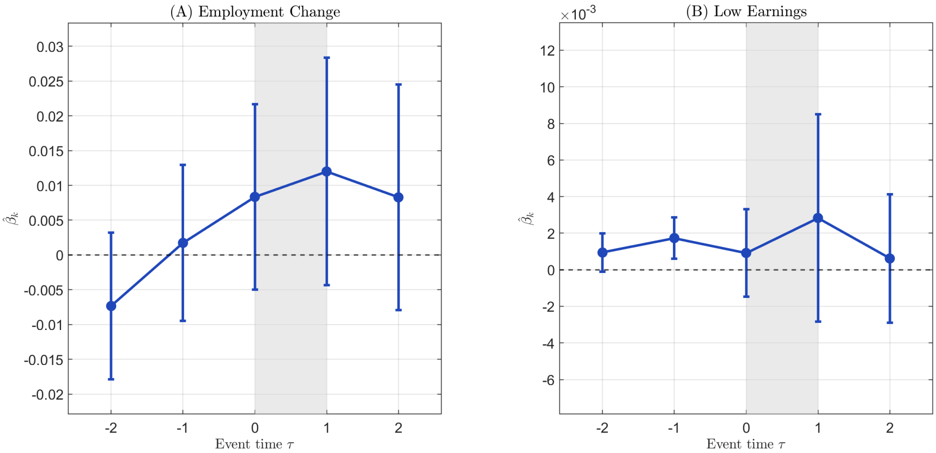
Empirics: Job Change and Low Earnings Around AI Adoption



Baseline $\hat{\beta}_k$ (firm$\times$year, worker, income-bin$\times$year FE $+$ lagged outcome). Panel A: job-change (firm-switch) indicator. Panel B: low-earnings (layoff proxy) indicator. $\tau = 0$ is 2021.

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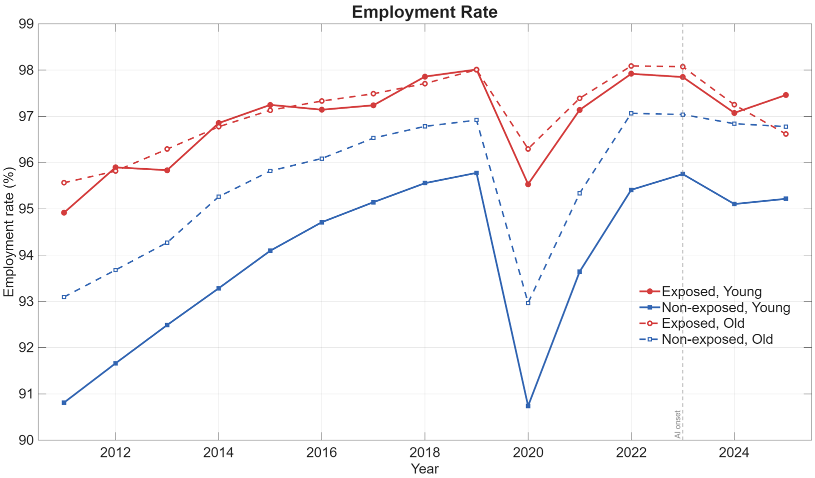
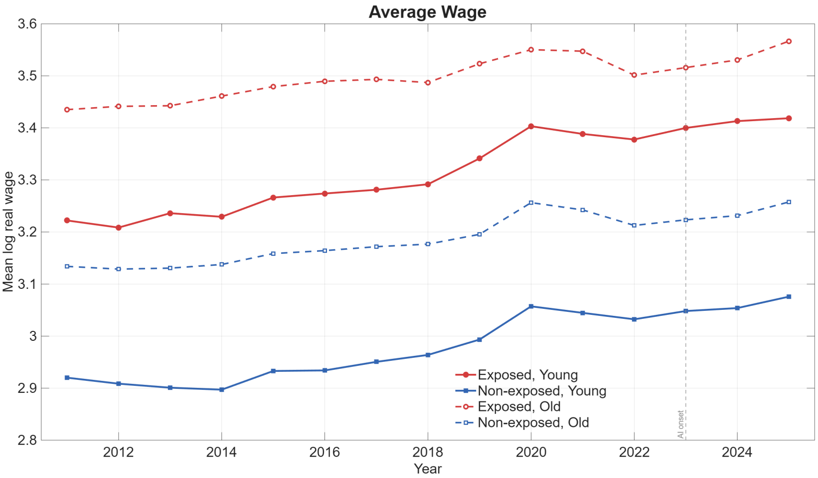
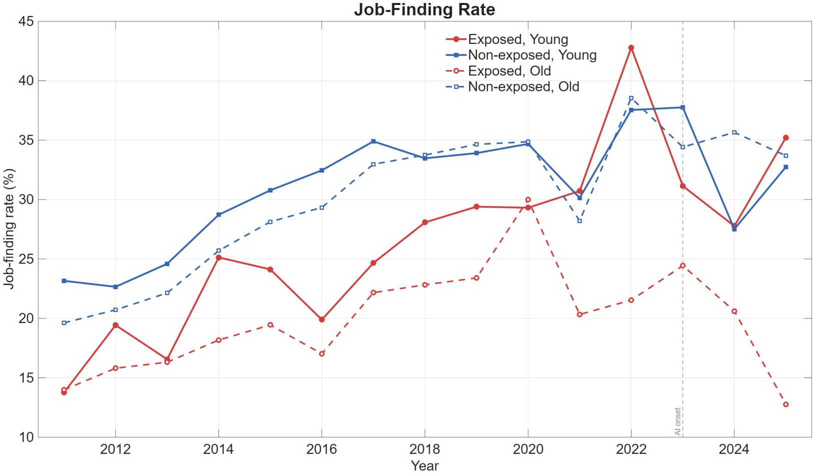
Empirics: CPS Employment Rate



Empirics: CPS Wages



Empirics: CPS Job-Finding Rate



Theory: Firms

Piece-rate on production implies spot-wage increase after partial automation in equilibrium

$$
\begin{aligned}
J^P(\mathbf{h}, w, d) = {} & \left(h_n^\rho + d^\rho\right)^{1/\rho}(1-w) - \kappa \\
& + \beta E_{d',\mathbf{h}'|\mathbf{h}}\left[(1-\lambda)(1-\delta)\hat{J}(\mathbf{h}', w, d') + (\delta(1-\lambda)+\lambda)c(d')\right]
\end{aligned} \tag{2}
$$

Piece-rate on marginal product implies ambiguous wage dynamics after partial automation

$$
\begin{aligned}
J^P(\mathbf{h}, w, d) = {} & \left(h_n^\rho + d^\rho\right)^{1/\rho} - wMP(h_n, d) - \kappa \\
& + \beta E_{d',\mathbf{h}'|\mathbf{h}}\left[(1-\lambda)(1-\delta)\hat{J}(\mathbf{h}', w, d') + (\delta(1-\lambda)+\lambda)c(d')\right]
\end{aligned} \tag{3}
$$

$$
MP(h_n, d) = \left(h_n^\rho + d^\rho\right)^{1/\rho} - (0^\rho + d^\rho)^{1/\rho}
$$

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Theory: Workers

Employed. The Bellman equation for an employed worker is given by

$$\begin{aligned} W(\mathbf{h}, \phi, d) = u\left(w(\mathbf{h}, \phi, d)\right) + \beta(1-\lambda) E_{\mathbf{h}', d' | \mathbf{h}, d, W} \Big[(1-\delta)(1 - f^F(\mathbf{h}', \phi, d')) \cdot W(\mathbf{h}', \phi, d') \\ + \left\{ \delta + (1-\delta) f^F(\mathbf{h}', \phi, d') \right\} \cdot U(\mathbf{h}') \Big] \end{aligned} \tag{4}$$

where workers take as given the firm's task and automation policies, d' evolves and the worker's labor income is a piece-rate of non-automated or partially automated firm's revenue,

$$w(\mathbf{h}, \phi, d) = \phi \cdot \begin{cases} \left((\widehat{s}(\mathbf{h}) h_n)^{\rho} + ((1 - \widehat{s}(\mathbf{h})) h_a)^{\rho}\right)^{1/\rho}, & \text{if } f^F(\mathbf{h}, \phi, d) + f^P(\mathbf{h}, \phi, d) = 0 \\ \left(h_n^{\rho} + d^{\rho}\right)^{1/\rho} (1-\kappa), & \text{if } f^P(\mathbf{h}, \phi, d) = 1 \end{cases} \tag{5}$$

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Theory: Key Model Assumptions

AI as an experience good.

- Part experience good (in-house data on worker tasks) + part inspection good (buy d at $c(d)$)
- Nests pure experience ($c(d) = \infty$) and pure inspection ($\Delta = 0$) models
- Data bounded by automatable human capital, $d \leq h_a$; AI keeps learning after partial auto.

Contracts, workers, and markets.

- Firms commit to piece-rate ϕ (not a fixed wage) $\Rightarrow$ on-the-job wage growth
- Adaptive skill weights s (Lazear '09) $\Rightarrow$ "new work" as jobs are automated
- Partial vs. full automation, common per-period flow cost κ; full auto. takes one period
- Workers hand-to-mouth today (role for insurance); perpetual-youth OLG, retraining when unemployed
- CRS matching + directed search $\Rightarrow$ block recursive

Estimation: Functional Forms

Production (CES, skill weight s)	$((sh_n)^\rho + ((1-s)h_a)^\rho)^{1/\rho}$
Utility	$u(c) = \ln(c)$
Matching (Den Haan et al. '00)	$M(u,v) = uv/\left(u^\alpha + v^\alpha\right)^{1/\alpha},\ \alpha = 1.6$
Home production	$z(\mathbf{h}) = z_0$
Out-of-house data cost (resale $=$ cost)	$c(d) = c_0 \cdot \bar{c} \cdot d,\ \bar{c} =$ max non-aut. production
Setup cost	$\widetilde{\psi}(\mathbf{h}) = \psi(\mathbf{h}) - \left(\max_{d \le h_a} \beta J^F(d) - c(d)\right)$
Retraining cost	$R^\eta \cdot \chi,\ h_n' = h_n + R$
Data accumulation	$d' = \min\{d + \Delta, h_a\}$ w.p. p_d; else $\min\{d, h_a\}$
Human-capital shocks	each type $\uparrow$ w.p. p_h^+, $\downarrow$ w.p. p_h^-
Exposure	$e(\mathbf{h}) = h_a/(h_a + h_n)$
Newborn draws	$\log h_n \sim \mathcal{N}\left(\mu_{h_n}, \sigma_{h_n}^2\right),\ f_a \mid \log h_n \sim \mathcal{N}\Big(\underbrace{\mu_{f_a} + \Gamma \frac{\sigma_{f_a}}{\sigma_{h_n}} (\log h_n - \mu_{h_n})}_{\mu_{f_a \mid h_n}},\ \sigma_{f_a}^2\,(1-\Gamma^2)\Big)$

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Theory: Characterization (1/2)

Lemma 1 (skill weights). For a non-automated firm:

- If $\rho < 1$ (complements), both tasks used; $s^* = h_n^{\frac{\rho}{1-\rho}} / (h_n^{\frac{\rho}{1-\rho}} + h_a^{\frac{\rho}{1-\rho}})$
- If $\rho \geq 1$ (substitutes), only the most productive task is used ($s^* \in \{0, 1\}$)
- $\Rightarrow \rho$ governs which workers are most exposed to replacement

Proposition 1 (block recursivity).

- Equilibrium is block recursive; exists and is unique
- Blocks: (i) firm values $\{J, J^P, J^F\} \to$ (ii) tightness θ (free entry) $\to$ (iii) $\{U, W\}$
- CRS matching: free entry pins θ independent of the agent distribution
- Survives aggregate shocks (κ, Δ, c_0, ρ) $\Rightarrow$ tractable transition paths

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Theory: Characterization (2/2) – Drop in κ

Deterministic automation policy (in piece-rate ϕ). surplus fig.

- Ordering $P \to N \to F$ as ϕ rises: automation is a firm investment
- High-ϕ, high-h_a/low-h_n matches $\Rightarrow$ **pace-setter**: one period of work, then full automation
- Model exposure: $e(\mathbf{h}) = h_a / (h_a + h_n)$

Winners and losers from a fall $\kappa \to \kappa'$ (no retraining).

- **Prop. 2:** partial/marginally-automated/pace-setter gain; marginally non-automated lose; non-automated unchanged
- **Prop. 3:** only highly exposed unemployed ($e \geq \bar{e}$) switch to pace-setting search
- **Prop. 4:** all partially automated gain; large drop $\Rightarrow$ extremes of exposure get fully automated, middle becomes partial (gains)

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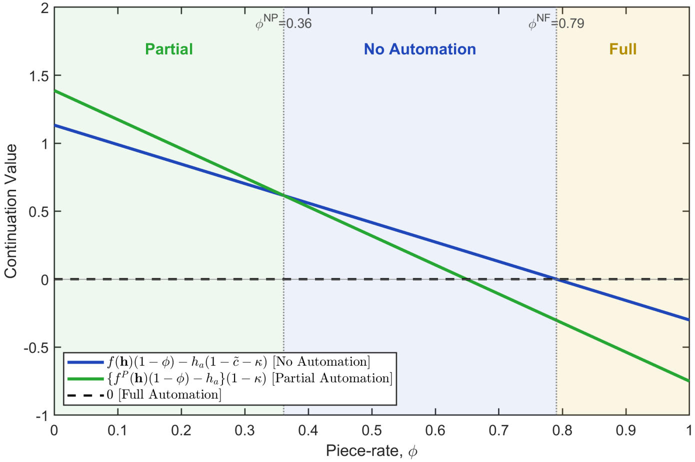
Theory: Continuation Surplus by Automation Policy



Deterministic model, $\rho < 1$: green = partial, blue = none, yellow = full automation. Ordering $P \to N \to F$ as ϕ rises.

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Estimation: Moment-to-Parameter Identification

Steady state (pre-2021).

- Unemployment rate $\rightarrow$ setup cost ψ; partial automation rate $\rightarrow$ cost of automation κ
- Replacement rate $\rightarrow$ home production z_0; re-training rate $\rightarrow$ cost of retraining χ
- Avg. time to automate $\rightarrow$ data learning prob. p_d; immediate p.a. rate $\rightarrow$ price of data c_0
- SD / corr. of exposure $\rightarrow$ σ_h, $corr(f_a, h)$; prob. wage gain $\rightarrow$ HC growth p_h

Natural experiment (unexpected κ drop).

- Post-shock layoff rate (adopter share $\times$ employment-decrease rate) $\rightarrow$ cost drop δ_κ
- Post-shock exposed-vs-non wage differential $\rightarrow$ production complementarity ρ

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Estimation: Targeted Moments and Their Calculation

2023 transition (natural experiment).

- **AI use & cut empl. (0.4%):** 2023-ABS adopter share $\times$ employment-decrease rate $= 13.52\% \times 3.04\%$
- $\beta_0, \ \beta_{+1}$ **(2.0, 1.6 log pts):** within firm$\times$year event-study coeff. on T_i ($>$p90 exposed v. $<$p90) at $\tau = 0, +1$

Steady state (2022).

- **Partial automation (21.7%):** share of employed at 2022-ABS firms using AI
- **Immediate partial auto. (50.5%):** share of AI users reporting *no* in-house R&D (buy data, skip learning)
- **Re-training rate / gains (15.0%, 9.0%):** Jacobson-LaLonde-Sullivan '05; gains Lahey et al. '25
- **Mean 4y earnings loss (-9.0%):** displaced-worker losses, Braxton-Herkenhoff-...
- **Mean wage growth / SD log wage / unemp. (2.0%, 0.305, 6.2%):** CPS
- **Home-prod. replacement rate (50%):** literature **Corr(f_a, w) (0.496):** Revelio **Labor share (52%):** BLS

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Estimation: Learning (Time-to-Adoption) Moments in Revelio

Table: Adoption-timing sample (Revelio 2010–2023; timing moments in Revelio-merged CPS)

Statistic	Value
AI resumes	708,329
AI applications	1,056,747
Firms	85,472
Immediate adoption rate (CPS)	0.895
Mean time to adoption, incl. immediate	0.20
below-median exposure	0.26
above-median exposure	0.14
Mean time to adoption, excl. immediate	1.89
below-median exposure	2.11
above-median exposure	1.65

Higher-exposure jobs adopt faster both in the full sample and conditional on positive delay. Discipline data-accumulation p_d / out-of-house data c_0.

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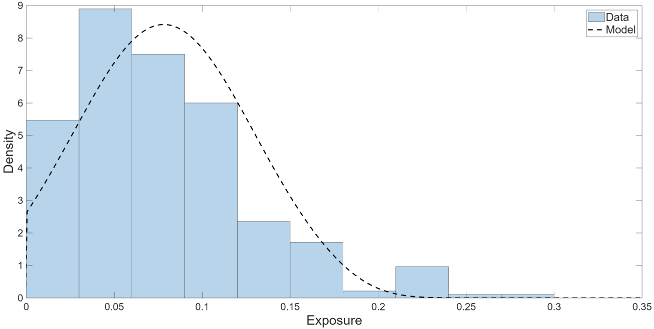
Newborn Exposure Distribution (Model vs. Data)



Newborns draw exposure $e(\mathbf{h}) = h_a/(h_a + h_n)$ from a log-normal (bars: empirical, line: parametrized).

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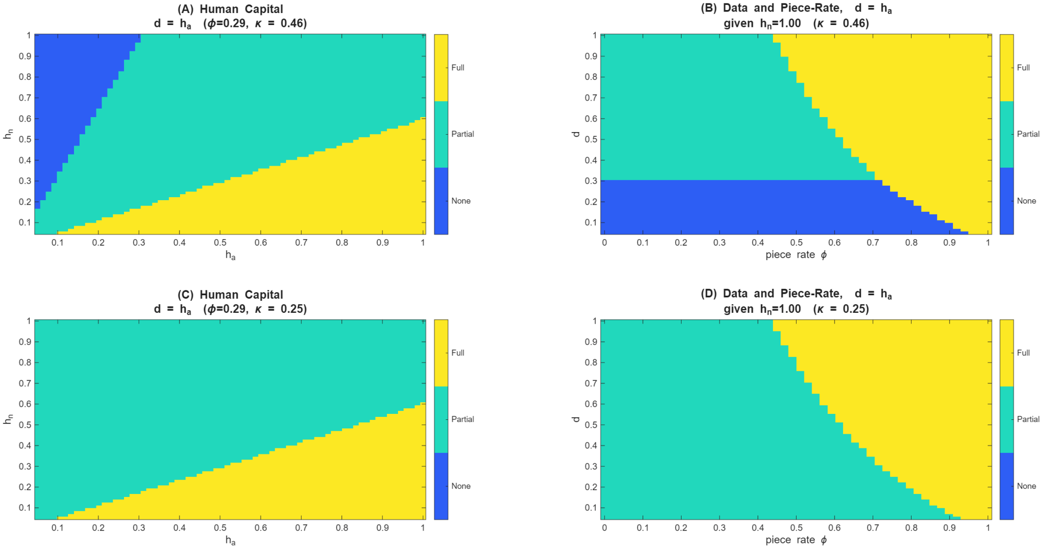
Estimated Automation Policies



- High h_a → f.a. (yellow), mid non-auto h_n → p.a. (turquoise), high h_n → non (blue)

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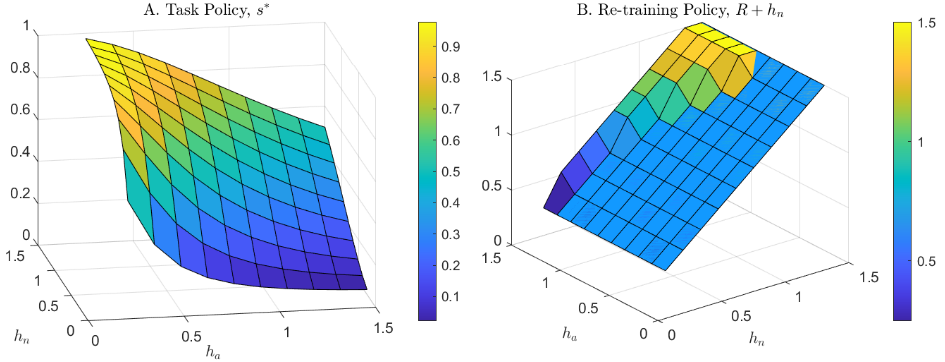
Skill Weight and Retraining Policies



- High h_n (higher wage) workers more likely to retrain

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Other Model Predictions

1. Time to AI adoption is faster for higher wage workers, conditional on **h**
2. Some workers become "**pace setters**" with short, high wage stints at firms, setting up AI
3. If data and non-automatable human capital are complements, partial automation occurs faster.
4. If data and non-automatable human capital are substitutes, full automation occurs faster.
5. Lastly, skill weights (time use) shifts to non-automatable tasks (i.e. the nature of work changes)

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Counterfactuals: Transition-Path Beliefs

Belief process. First shock is a surprise; rational expectations henceforth.

- Agents initially believe they are in the steady state (absorbing)
- Once the first shock hits, each quarter they stay with prob. $1 - \frac{1}{24}$ and advance to the next aggregate state with prob. $\frac{1}{24}$
- The terminal (2046) AI regime is absorbing

Transition matrix over aggregate states (per quarter):

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & .96 & .04 & 0 \\ 0 & 0 & .96 & .04 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

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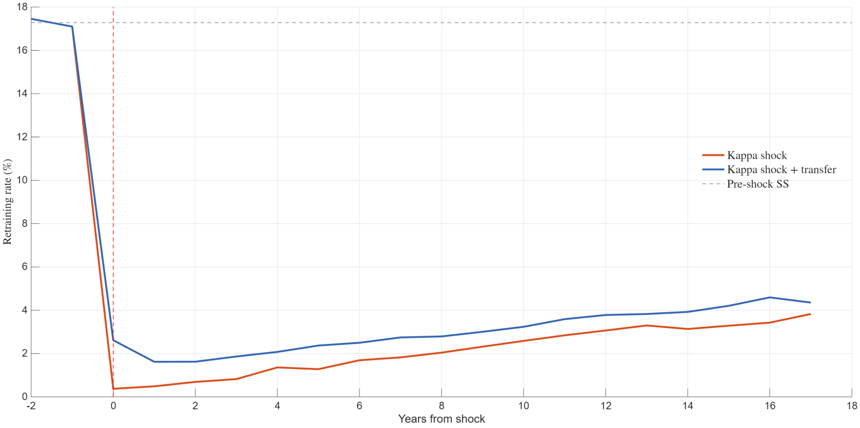
Optimal Automation Insurance Fund



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