The Rapid Adoption of Generative AI
+
Generative AI in the Labor Market: Evidence and Some Theory*

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*The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

This Paper

- **Growing evidence genAI increases productivity for some workers**
  - Noy, Zhang '23; Cui et al., '24; Dell'Acqua et al., '23; Brynjolfsson et al., '25; Dillon et al., '25; Kanazawa et al., '25

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- **What we do**: bring national data to bear
  - Document genAI adoption by workers (extensive + intensive margin)
  - Use adoption data to discipline model of technology adoption

Outline

The Real-Time Population Survey (RPS)

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- Design: replicate core Current Population Survey (CPS) questionnaire
  - Compatible measures with CPS $\implies$ use CPS to weight & validate

How Do We Administer the Survey?

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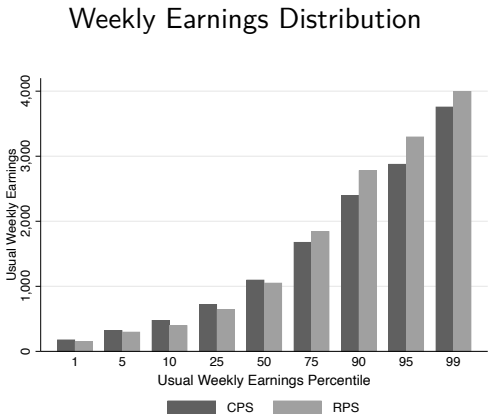
- Key potential concern: selection based on unobservables
  - Addressed in several of our prior papers
  - *AEJ: Macro*, 2023; *RED*, 2023; *St. Louis Fed Review*, 2025

Validation Checks for Unweighted Data, August 2025



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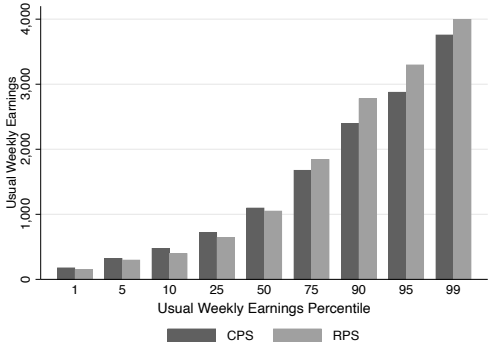
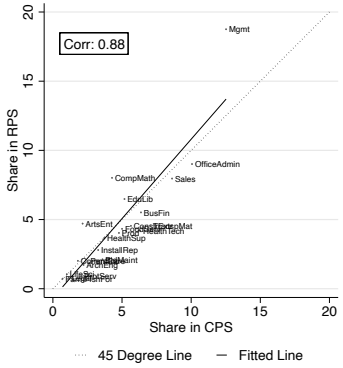


Occupation Shares



Measuring Generative AI Adoption

Eliciting Technology Adoption: The CPS as a Template

- CPS Computer and Internet Use Supplement (CIU)
- PC use: '84, '89, '93, '97, '01, '03
  - Employed: *Do you use a computer for your job? (No/Yes)*
  - Everyone: *Do you use a computer at home? (No/Yes)*

How the RPS Measures Generative AI Use

- Definition of Generative AI:

  Generative AI is a type of artificial intelligence that creates text, images, audio, or video in response to prompts. Some examples of Generative AI include ChatGPT, Gemini, and Midjourney.

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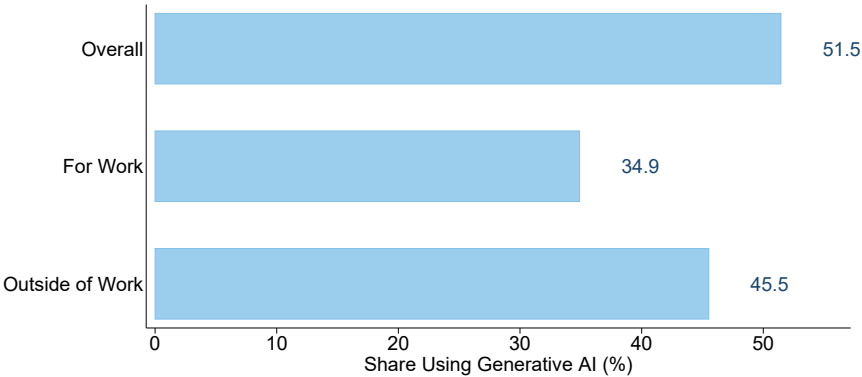
- Follow-up questions for AI users:
  - Days/week, time/day, which products, which tasks, time saved

What Share of Working Age Adults Use Generative AI?



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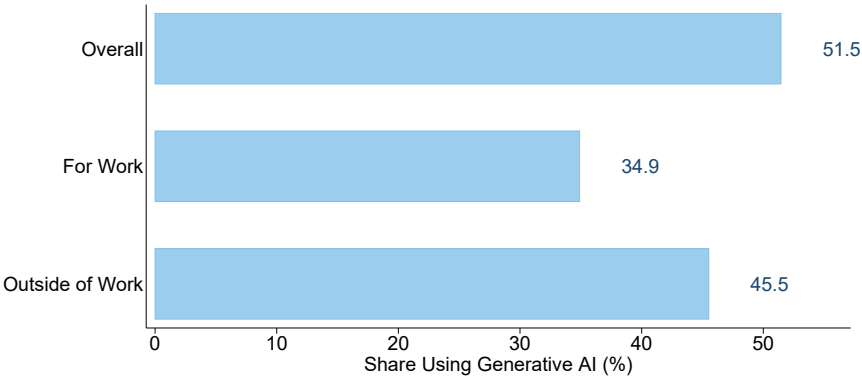

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- ChatGPT adoption rates in RPS consistent with bunch of other evidence

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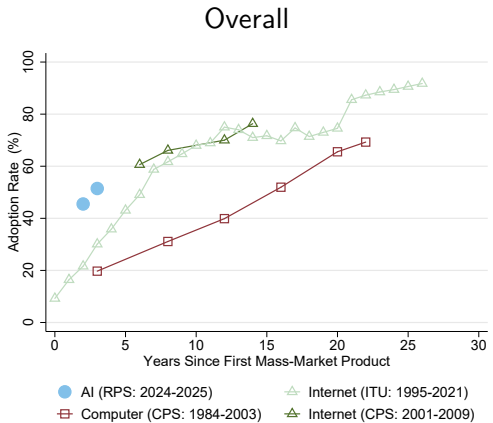

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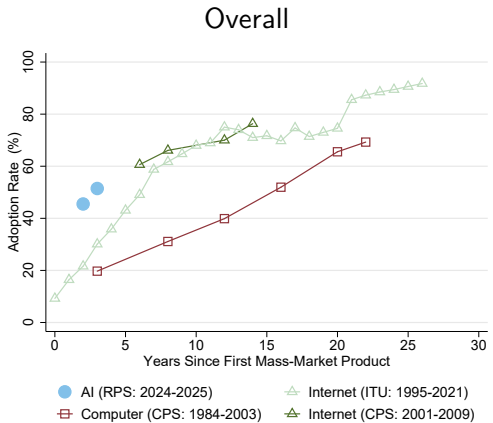
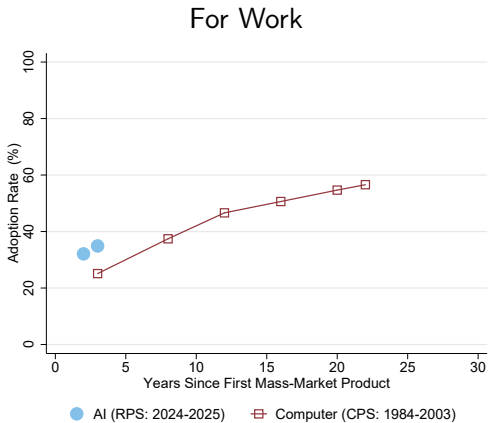
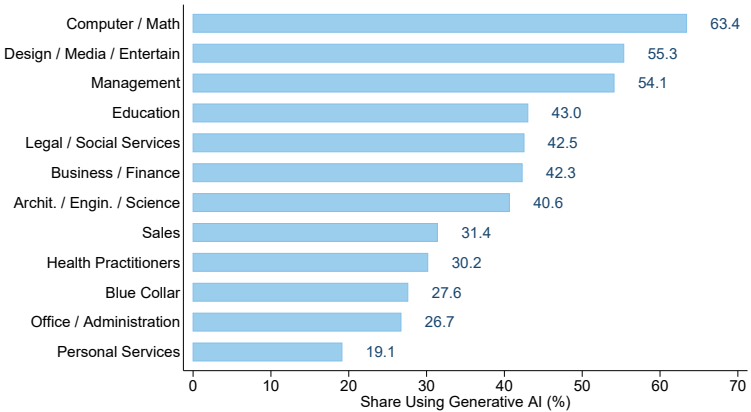




Outline

(1) Large Variation in GenAI User Shares by Occupation



(2) Measuring Time Spent Using GenAI

- *Did you use Generative AI for your job LAST WEEK?*
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  - Yes, 1 workday last week
  - Yes, more than 1 workday last week
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- *Please think back to the days LAST WEEK on which you used Generative AI for your job. On average, how much time did you spend actively using Generative AI for your job?*
  - Less than 15 minutes per day
  - Between 15 minutes and 1 hour per day
  - Between 1 and 4 hours per day
  - More than 4 hours per day

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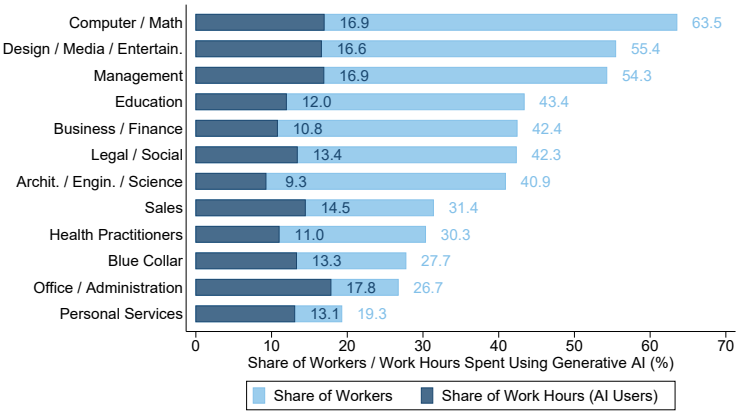
- Combined with days and hours worked last $\Longrightarrow$ 2.0% - 8.1% of total work hours spent using genAI

(2) Much Less Variation in Time Spent Using GenAI by Occupation



(3) Measuring Time Savings from GenAI

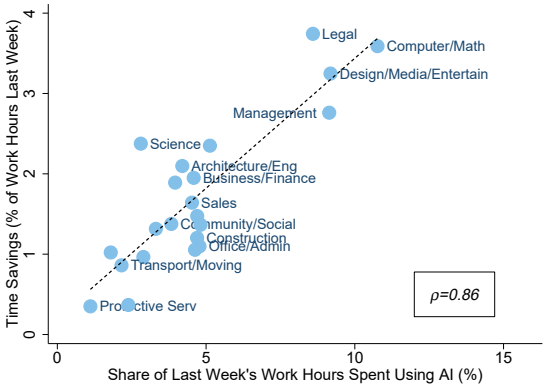
- *You indicated that LAST WEEK you worked __X__ hours and that you used Generative AI for your job.*

  Now, imagine that LAST WEEK you did not have access to Generative AI.

  How many additional hours of work would you have needed to complete the same amount of work?

  - Less than 1 additional hour of work
  - 1 additional hour of work
  - 2 additional hours of work
  - 3 additional hours of work
  - 4 additional hours of work
  - More than 4 additional hours of work

(3) Time Savings Strongly Increase in GenAI Use



- 10 pp. ↑ genAI time → 3.5 pp. ↑ time saved (similar to micro estimates)

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- **Other papers**: potential of genAI
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- **This paper**: current usage of genAI
  - Use survey measures of genAI adoption along extensive & intensive margin
  - Infer generic labor share using model structure
  - Agnostic about which tasks / activities this labor captures

Worker i in Occupation o

- Output: $y_{o,i} = \left(\alpha_o^{\frac{1}{\phi}} (\pi_o p_i + \gamma_i g_i)^{\frac{\phi-1}{\phi}} + (1-\alpha_o)^{\frac{1}{\phi}} (\nu_i n_i)^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}}$
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- A worker i in occupation o with productivity (γ_i, ν_i) solves:

$$\begin{aligned} \max_{g,p,n} \quad & w_o y_{o,i}(g,p,n) \\ s.t. \quad & g + p + n \leq 1 \end{aligned}$$

Aggregate Output

- Occupations $o = 1, ..., O$ with mass of workers $i = [0, I_o]$
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  - In competitive equilibrium, wage rate of occupation o: $w_o = \frac{\partial Y}{\partial Y_o}$ Eq Definition

Worker's Optimal Time Allocation

- Non-AI-user $(0 \leq \pi_o < \gamma)$: $\frac{g}{n} = \left(\frac{\alpha_o}{1-\alpha_o}\right)\left(\frac{\gamma}{\nu}\right)^{\phi-1}$

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- AI-user $(\pi_o > \gamma)$: same as above but replace g with p and γ with π_o
  - Adopting AI is effectively an **increase** in γ

Impact of an Rise in GenAI Productivity, $\pi_o \rightarrow \pi'_o$

- **All workers**:
  - $\frac{\partial w_o}{\partial \pi_j} > 0$: Wage rate $\uparrow$ in other occupations' π_j
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  - $\frac{\partial (\Delta \hat{y})}{\partial \nu_i}$: Sign depends on ϕ
    - $\phi < 1$: More nuanced skill $\implies$ benefit more from genAI
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Discussion: Technology Adoption in Our Model

- Technology adoption in our model vs. most of AI/SBTC literature
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- Advantages of our framework
  - Adoption data reveals generic labor shares by occupation
  - Speaks to finding that more intensive users save more time
- Disadvantage of our framework so far
  - Workers need to operate technology $\implies$ no jobs fully automated away
  - Workers are stuck in an occupation
  - This is something we are working on ...

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- **Exogenously-set parameters**:
  - $\mu_{\gamma,o} = \mu_{\nu,o} = 0$ (Normalization)
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- **Need to set values for**:
  - β_o $\to$ variation in wages between occupations
  - $\sigma_{\nu,o}$ $\to$ variation in wages within occupations
  - π_o $\to$ share of occupation using genAI
  - α_o $\to$ genAI time use among users
  - $\sigma_{\gamma,o}$ $\to$ mean time savings by occupation
  - ρ_{γ_o,ν_o} $\to$ mean wage difference: genAI users vs. non-users

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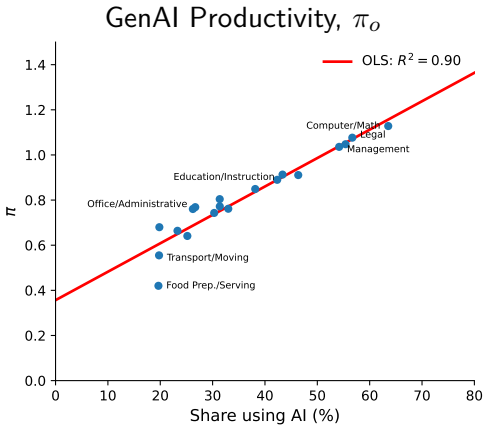
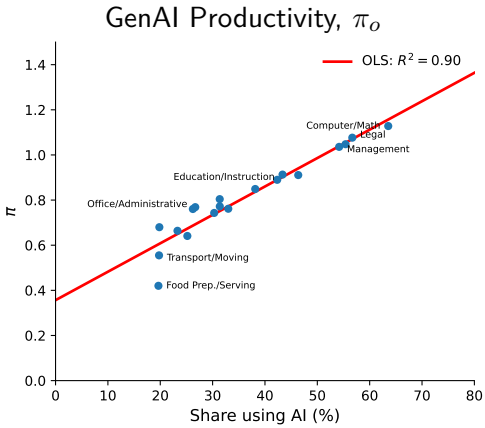
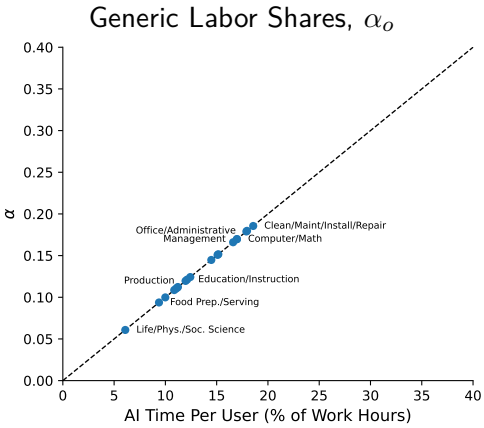
  - ρ_{γ_o,ν_o} $\to$ mean wage difference: genAI users vs. non-users
- **Quantitative exercise**: compare outcomes to $\pi_o = 0$ case ($\approx$ 2022)

Calibration: Variation Substantial in π_o



Calibration: Variation Substantial in π_o but Modest in α_o

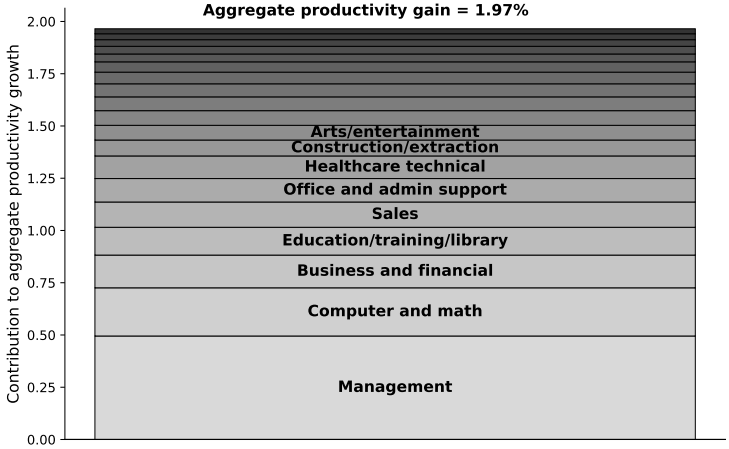




Quantitative Impact of Generative AI:

Very Preliminary Results

Impact of GenAI on Aggregate Labor Productivity



- Computer, Math and Management $\rightarrow 1/3$ of agg. productivity gain

The Heterogeneous Impact of GenAI

- Wage inequality increases: Variance of $\log$ wages $\uparrow 0.9\%$
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- In most occupations, all workers' wages increase
  - If $w_o \uparrow$, then genAI can only benefit
- In the 6 most-impacted (highest adoption) occupations, $w_o \downarrow$:
  - *Computer / Math, Management, Legal, Media/Entertain., Science, Education*
  - $\approx 1/2$ of workers' wages fall: $\approx 1\%$ on average
  - $\approx 1/2$ of workers' wages rise: $\approx 5\%$ on average

Evaluation: Are the Model's Predictions Plausible?

(1) GenAI ↑ aggregate labor productivity by 2.0%

(2) GenAI ↑ labor productivity more in high-adoption occupations

(3) GenAI ↑ wage bill of high-adoption occupations

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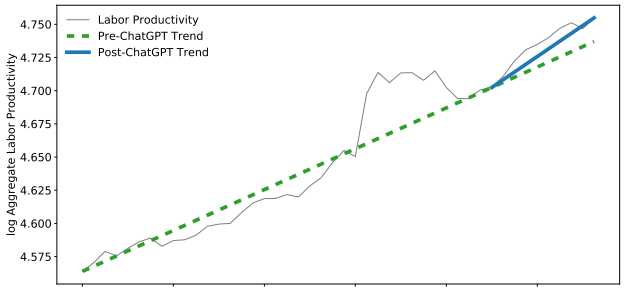
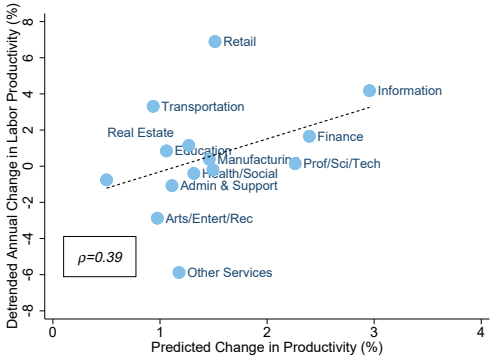


Source: BLS output per hour worked in nonfarm business sector.

(2) GenAI ↑ Productivity More in High-Adoption Occ's

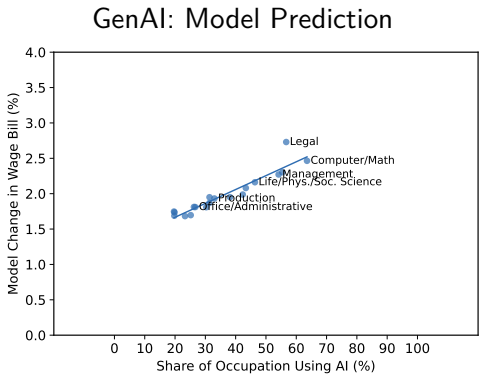
Labor Productivity Growth:
US ('22-'25) vs. Model Prediction

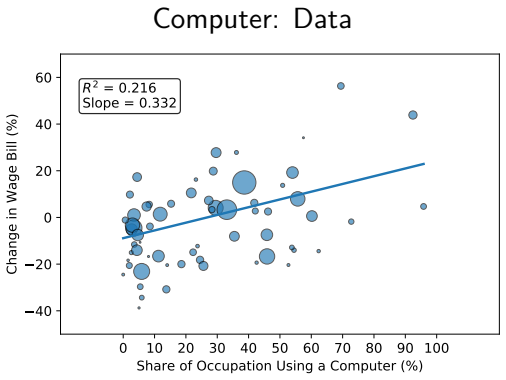


Source: BLS output per hour worked

- Use occupation composition to predict industry productivity gains

(3) GenAI ↑ Wage Bill of High-Adoption Occupations





Source: CPS computer adoption (1984 CIU); CPS wage & employment changes: 1982-1990

Bin scatter | Wages & Employment

- High PC adoption (1984) $\Longrightarrow$ larger growth in wages & employment

A Potential Generative AI Future

Quantitative Impact of Eloundou et al. (2024) Exposures

- Parametrization
  - GenAI labor shares, $\alpha_o = \texttt{ChatGPT } (\beta) \texttt{ exposure score}$
  - GenAI productivities, $\pi_o = 2.0$

Labor Market Impact of GenAI

	RPS (2025)	Eloundou et al. (2024)
GenAI adoption share (%)	34.9	90.8
GenAI work time share (%)	5.0	34.0
Δ Aggregate productivity (%)	+2.0	+27.2

Outline

Conclusion

- **GenAI may continue to rapidly improve — or not**
  - If it does rapidly improve, difficult to forecast where and how much
  - Our framework can be used to evaluate the evolving impact of genAI
    - Need to add/allow for full automization & endogenous occupational choices

Conclusion

- **GenAI may continue to rapidly improve — or not**
  - If it does rapidly improve, difficult to forecast where and how much
  - Our framework can be used to evaluate the evolving impact of genAI
    - Need to add/allow for full automization & endogenous occupational choices
- **(Preliminary) results given current data**
  - Even highly-exposed occupations have modest generic labor shares
  - GenAI modestly increases wage inequality between and within occupations
  - The most-impacted occupations experience more uneven wage impacts
  - GenAI increases aggregate labor productivity $\approx 2\%$

Thank you!

Validation Check: Industry Shares, 2025 Data

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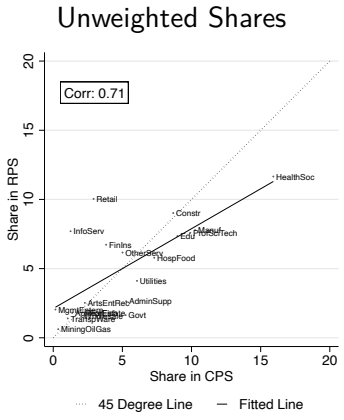

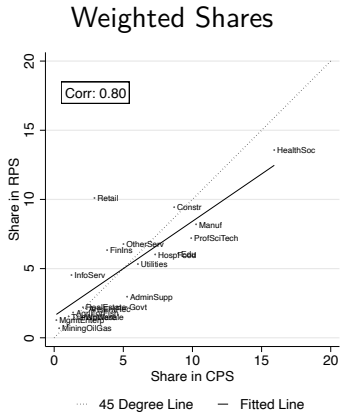

- Similar industry composition in CPS & RPS

Validation Check: College Major, 2025 Data

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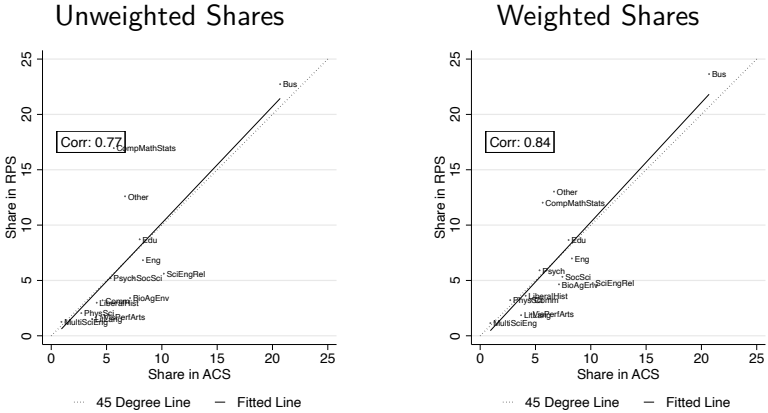

- Similar distribution of college majors in ACS & RPS

Worker's Time Allocation Problem

back

- A worker with productivity (γ, ν) in occupation with (α, π) solves:

$$\begin{aligned} \max_{g,p,n} \quad & \left(\alpha_o^{\frac{1}{\phi}} (\gamma_i g + \pi_o p)^{\frac{\phi-1}{\phi}} + (1-\alpha_o)^{\frac{1}{\phi}} (\nu n_i)^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}} \\ s.t. \quad & g + p + n = 1 \end{aligned}$$

What Share of **Work Days** Use GenAI?

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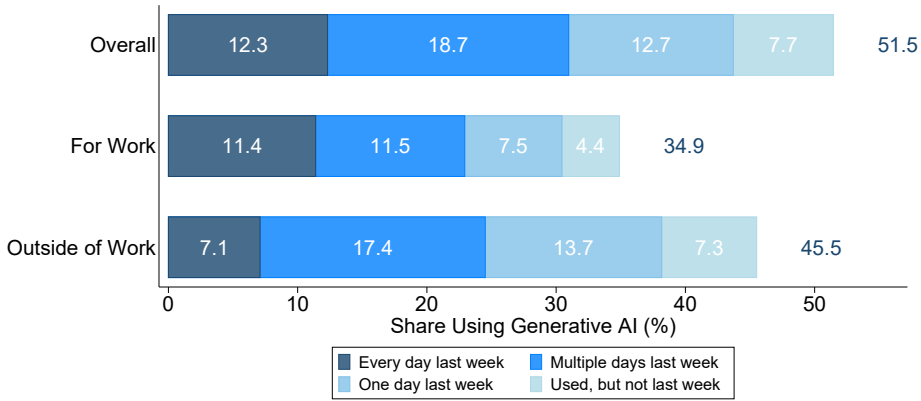

- Estimates imply genAI used in 13.8% - 18.5% of all work days

What Share of **Work Hours** Are Spent Using GenAI?

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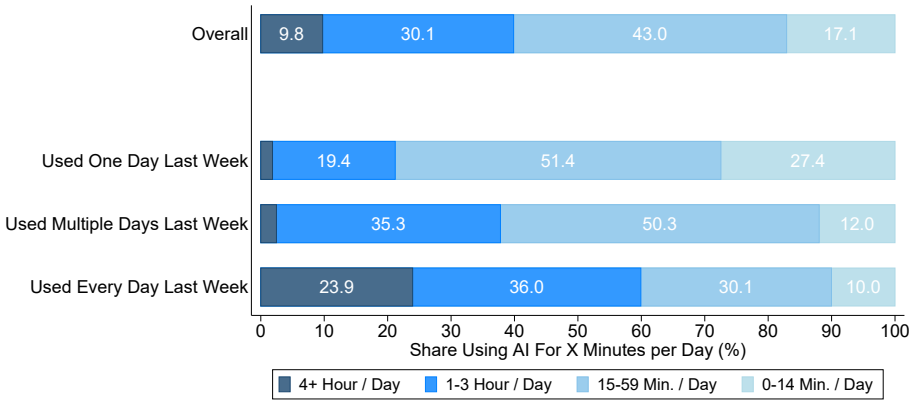

- Estimates imply 2.0% - 8.1% of all work hours spent using genAI

Reported Time Savings Due to GenAI

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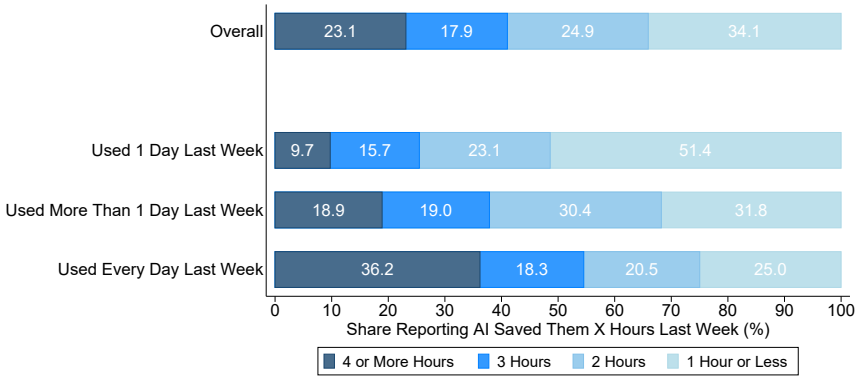

- Workers who use genAI more report saving more time
- Mean time savings among genAI users: 5.6% of work hours

Competitive Equilibrium

- A competitive equilibrium is a collection of:
  - Time choices for each worker, (g_i, p_i, n_i)
  - Occupational output Y_o
  - Wage rates for each occupation, w_o

s.t.

1. Given (γ_i, ν_i), π_o, and w_o, (g_i, p_i, n_i) solves the worker's problem
2. $Y_o = \int_0^{I_o} y_{o,i}(g_i, p_i, n_i)di$
3. $w_o = \frac{\partial Y}{\partial Y_o}$

Back

For Which Work Activities Do Workers Use GenAI?

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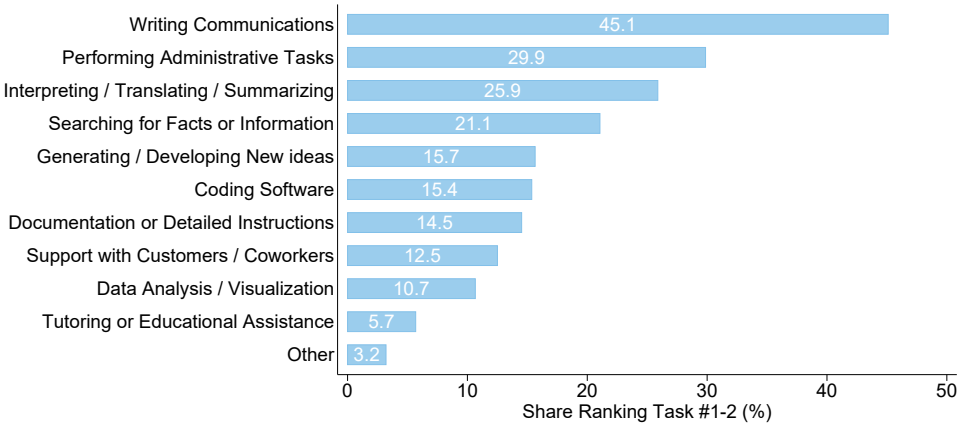

Discussion: The Price of GenAI

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- Currently, workers in the model can adopt genAI at zero price
  - (Annual ChatGPT Plus subscription is $250)

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- Currently, workers in the model can adopt genAI at zero price
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- Alternative cases to consider
  - Non-zero competitive pricing
  - Monopsony power: firms may capture some surplus
  - Pricing power: genAI companies may capture some surplus

Comparisons to Other Estimates of GenAI Use

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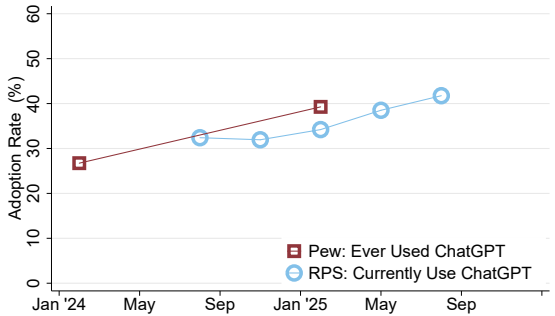

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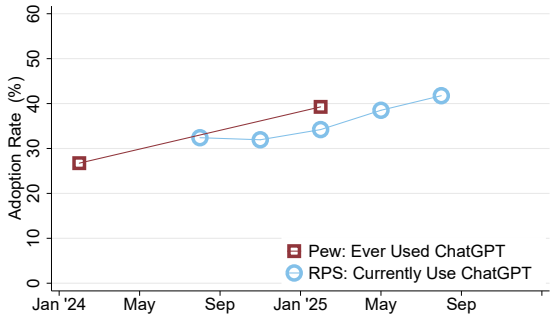

Sample: Ages 18-64. Pew survey includes those without internet access.

- Reuters 2024: similar share using ChatGPT at least weekly
- Humlum, Vestergaard 2024: similar results for select occ's in Denmark
- November 2024: similar estimates from fielding RPS in SWAA

The Task-Based Approach To GenAI

back

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  - Example: Economics Teachers, Postsecondary
    - "Prepare and deliver lectures ..." $\rightarrow$ exposed
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  - Example: Economics Teachers, Postsecondary
    - "Prepare and deliver lectures ..." $\rightarrow$ exposed
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- **Emerging literature**: treat exposed tasks as genAI substitutes

  $\Longrightarrow$ genAI will decrease the labor market price of these tasks

GenAI Is Used For a Wide Variety of Tasks

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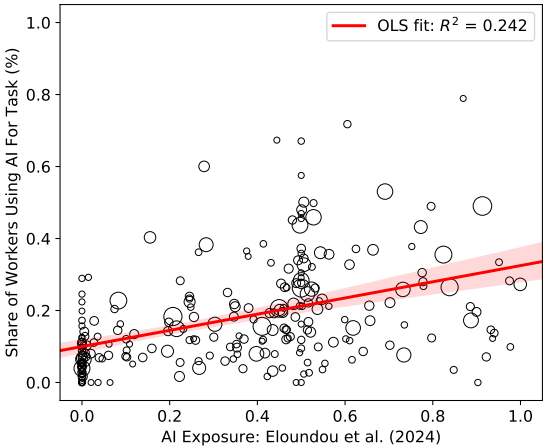

- Workers report using genAI even for some low-exposure tasks

Examples of GenAI Use in Low-Exposure Tasks/Occupations

- Painting, Coating, and Decorating Worker:
  - `"how changes to structure will look and how, multiple colors look so that i wont have to repaint.  bc the color look different on sample."`

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- Chatterji, et al. (2025): "How People Use ChatGPT"
  - *"'Practical Guidance,' 'Seeking Information,' and 'Writing' are the three most common topics and collectively account for nearly 80% of all conversations."*

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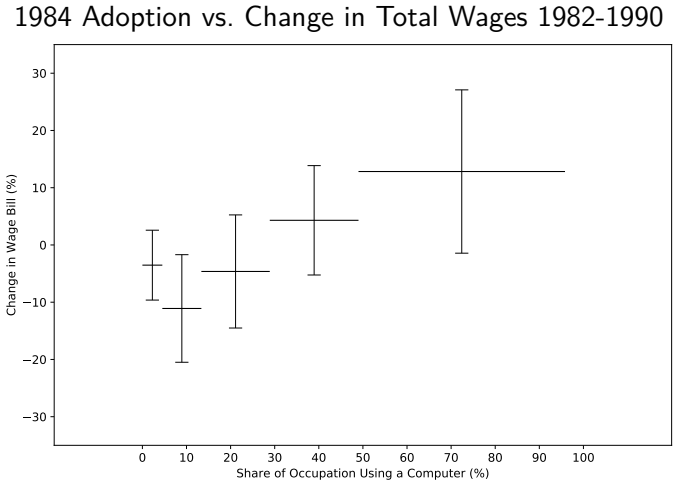
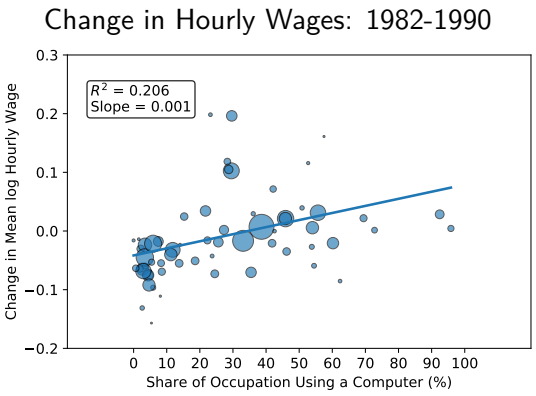
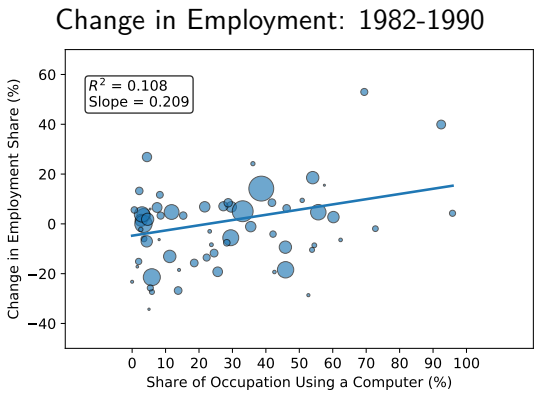
Changes in Total Wages: Bin Scatter back



Computer Adoption & Changes in Wages, Employment back





- High PC adoption (1984): $\Longrightarrow$ larger growth in wages & employment