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The Rapid Adoption of Generative AI*

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Abstract

Generative artificial intelligence (AI) is a potentially important new technology, but its impact on the economy depends on the speed and intensity of adoption. This paper reports results from a series of nationally representative U.S. surveys of generative AI use at work and at home. As of late 2024, nearly 40% of the U.S. population age 18-64 uses generative AI. Among employed respondents, 23% used generative AI for work at least once in the previous week: 9% used it every workday, and 14% on some but not all workdays. Relative to each technology's first mass-market product launch, work adoption of generative AI has been as fast as the personal computer (PC), and overall adoption has been faster than either PCs or the internet. Generative AI and PCs have very similar early work adoption patterns by education, occupation, and other characteristics. Between 1 and 5% of all work hours are currently assisted by generative AI, and respondents report time savings equivalent to 1.4% of total work hours. This suggests that substantial productivity gains from generative AI are possible.

JEL Codes: J24, O33
Keywords: Generative AI, Technology Adoption, Labor Productivity

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1 Introduction

Generative artificial intelligence (genAI) has quickly emerged as a potentially important workplace technology. The large language model ChatGPT debuted in November 2022 and, by December 2024, had over 300 million weekly users. Several studies find that genAI boosts worker productivity in specific cases (Brynjolfsson et al., 2023; Cui et al., 2024; Dell'Acqua et al., 2023; Demirci et al., 2025; Dillon et al., 2025; Kanazawa et al., 2025; Noy and Zhang, 2023; Otis et al., 2024; Peng et al., 2023), and some project genAI will have large macroeconomic effects (Chui et al., 2023; Filippucci et al., 2024). Yet others predict only modest aggregate impacts (Acemoglu, 2024). These differing views largely reflect uncertainty about the extent of genAI adoption today and in the future.[1]

This paper studies the adoption of genAI using data from the first nationally representative U.S. surveys of genAI usage at work and at home. Our data come from the Real-Time Population Survey (RPS), a national online labor market survey of working age adults aged 18-64 that has run since 2020 (Bick and Blandin, 2023). We report the combined results of two surveys fielded in August and November 2024, which collectively included more than 10,000 respondents.

The RPS asks the same core questions and follows the same timing and structure as the Current Population Survey (CPS). This parallel structure allows us to benchmark our survey estimates against the CPS and to construct weights that ensure a nationally representative sample. Benchmarking to the CPS also allows us to compare the adoption of genAI to the personal computer (PC) and the internet. Beginning in 1984, the CPS fielded the Computer and Internet Use (CIU) supplement, which fueled an influential literature studying the impact of computerization on the labor market (Autor et al., 1998; Card and DiNardo, 2002; Krueger, 1993). We closely follow the CIU question wording and structure, which allows us to compare adoption of different technologies. But we also introduce novel questions to measure how intensively individuals use the technology and how much time it saves them.

We report six main results. First, a substantial share of respondents already use genAI at work and at home. Pooling our August and November 2024 surveys, 26% of employed respondents reported using genAI for work: 9% used it every work day, 14% on some but not all work days, and 3% did not use it in the previous week. One third of respondents report using genAI outside of work. Overall, 39% of respondents report using genAI either for work

[1] Acemoglu et al. (2022) analyze online job vacancies related to AI, but their data predates ChatGPT. Albanesi et al. (2024), Eisfeldt et al. (2024), and Gathmann et al. (2024) compare occupations according to predictions of AI exposure but do not have data on actual adoption. Humlum and Vestergaard (2025) find no meaningful impacts of genAI adoption on employment and earnings in Denmark among workers in 11 occupations that are particularly exposed to genAI.

or outside of work. The most commonly used products are ChatGPT (28% of all respondents), Gemini (17%) and embedded products such as Microsoft Copilot (14%).

To validate our results, we fielded our genAI module in the December 2024 Survey of Working Arrangements and Attitudes (SWAA), an online survey that uses a different provider than the RPS (Barrero et al., 2021). The RPS and SWAA show similar adoption rates by overall use, frequency, and product type. Our findings align with other studies on ChatGPT use, including non-internet surveys (Fletcher and Nielsen, 2024; McClain, 2024). Compared to prior studies, our data offer several advantages: we ask about all genAI use, distinguish between work and non-work applications, and collect more detailed data on demographics, intensity of genAI use, and time savings.

The widespread adoption of computers and related information technologies beginning in the 1980s contributed to rising aggregate productivity and growing income inequality (Autor et al., 2003). We show that early demographic and occupation patterns of computer adoption in the 1980s were highly predictive of longer-term computer adoption, and also predicted wage gains over subsequent decades. This suggests that studying early adoption patterns may help us understand the long-term impacts of genAI on wage inequality (Autor, 2024). Our second main finding is that genAI adoption has so far been at least as fast as PCs and the internet relative to the release of each technology's first mass-market product. We define 1981, 1995, and 2022 as the mass-market release dates for PCs, the internet, and genAI, respectively (see Section 3.2 for details). 2-3 years after the first mass-market product, overall genAI adoption has outpaced both PCs and the internet. This faster pace is driven by quicker adoption outside of work compared with PCs (we cannot separate work and non-work use for the internet). By contrast, work adoption of genAI is proceeding at a similar pace to PCs. The rapid pace of genAI adoption may reflect differences in adoption costs. PC adoption required expensive, immobile hardware, and internet access required a modem and Internet Service Provider subscription, whereas many genAI products are low-cost and user-friendly. Low individual adoption costs may also explain why adoption by workers is faster than official firm-wide adoption (Babina et al., 2024; Bonney et al., 2024).[2]

Third, we find substantial variation in genAI adoption across demographic and labor market characteristics that closely matches early patterns of PC adoption. Both PC and genAI adoption have been faster for younger, more educated, and higher-wage workers, and we find

[2]The Census BTOS Survey estimates that official firm-wide genAI adoption rose from 3.7% in December 2023 to 5.4% in February 2024, a rapid rise but still far below our estimates. This suggests firm-based measures may miss an important share of genAI adoption. Aaron Levie, the founder and CEO of Box, a cloud storage provider, compares this pattern with past technologies: "It's almost a one-to-one parallel with the early wave of consumerization of IT. We saw that exact same dynamic in the early 2010s, which was employees of enterprises were pretty frustrated with their traditional document management and collaboration technology, and so they would go out and just go onto a web browser, sign up for a Box account, and then bring it into their organization." (Levine, 2024)

similar adoption patterns by occupation and industry. The one exception is gender: early genAI usage is higher for men, while PC usage was initially higher for women, reflecting rapid PC adoption among secretaries and other administrative occupations, which were predominantly female. Heterogeneity in early PC adoption persisted for several decades, which suggests that the adoptions patterns we find for genAI may also persist for some time.

Fourth, recent estimates of genAI task-based exposure are highly predictive of actual adoption. Eloundou et al. (2024) assign each occupation a predicted exposure score based on the share of tasks they believe can be substantially affected by genAI. We find a strong correlation between their measure of predicted exposure and realized adoption, and nearly all occupation groups show at least some genAI use—consistent with the broad exposure Eloundou et al. (2024) identify. This provides partial validation of task-based exposure indices and supports their usefulness for researchers. However, some occupations exhibit higher or lower adoption rates than predicted. These discrepancies may reflect mismeasurement of which tasks actually benefit from genAI, or variation in adoption frictions such as regulatory or institutional barriers.

Fifth, we find substantial variation in the intensity of genAI usage. Among work users, 34% used it every workday, 52% on some but not all workdays, and 14% not at all last week. On days workers used genAI, 32% used it for an hour or more, 47% for 15–59 minutes, and 21% for less than 15 minutes. Workers who use genAI on more days tend to use it more time per day on days that they used it. Overall, we estimate that between 1-5% of all U.S. work hours use genAI.

Sixth, we provide a rough estimate of genAI's early impact on aggregate productivity using self-reported time savings. We ask users how many extra hours they would have needed to complete last week's work without genAI. Our findings imply that, on average, genAI users would need to work 5.4% more hours to complete their work without genAI, implying 1.4% time savings across all workers (including non-users). Time savings are highly correlated with the intensity of genAI use and thus vary widely across occupations and industries. Using a standard aggregate production model, we estimate a potential aggregate productivity gain of 1.1%. To interpret this result, we highlight two points of context. First, our estimate is close to Acemoglu (2024), who uses a similar framework to estimate a 0.7% gain based on predicted task exposure rather than actual adoption. Notably, however, Acemoglu (2024) assumed these productivity gains may take a decade to materialize. In contrast, our estimates reflect current adoption and time savings, implying a faster pace of diffusion. Second, our estimate does not capture potential productivity gains from using genAI to reorganize or completely automate production processes. With previous technologies, these more systematic gains occurred with substantial time lags (Bresnahan and Trajtenberg, 1995; Brynjolfsson and Hitt, 2000; David, 1990; Jovanovic and Rousseau, 2005).

2 Data Sources and Measurement

2.1 The Real-Time Population Survey (RPS)

Our main data source is the Real-Time Population Survey (RPS), a national labor market survey of U.S. adults aged 18-64 (for a detailed discussion, see Bick and Blandin 2023). The RPS is fielded online by Qualtrics, a large commercial survey provider, and has collected multiple survey waves each year starting in 2020.

The RPS is designed to mirror the Current Population Survey (CPS) along key dimensions. The RPS matches questions on demographics and labor market outcomes in the basic CPS and CPS Outgoing Rotation Group, using the same word-for-word phrasing when practical and replicating the intricate sequence of questions necessary to elicit labor market outcomes in a manner consistent with the CPS (US Census Bureau, 2015). Replicating key portions of an existing high-quality survey ensures that survey concepts are comparable, which allows researchers to validate RPS outcomes against a widely used benchmark with a larger sample size and, where necessary, to construct sample weights. Bick and Blandin (2023) and Bick et al. (2024a,b) show that the RPS closely aligns with government household surveys on distributions of employment, hours worked, earnings, industry composition, employee tenure, and work from home.

In June 2024, the RPS introduced a novel module measuring genAI use both at work and at home.

2.1.1 RPS Sample

The Qualtrics panel includes about 15 million members and is not a random sample of the U.S. population. However, Qualtrics can target survey invitations to specific demographic groups. The RPS sample was designed to be nationally representative across key demographics. We also include measures to filter out low quality responses. (This is typically the case for 1% to 3% of the responses.) Details on sampling and data quality procedures can be found in Appendix D.1.

We fielded the RPS with a pilot AI module in June 2024 and received 2,551 responses. We then launched the full AI module with the August and November 2024 waves and received 5,014 and 5,154 responses respectively. All surveys started fielding during the same weeks that the CPS conducted its corresponding surveys. Because the results are very similar across all surveys but our June pilot featured fewer questions, we report results from the pooled August and November surveys. Appendix B replicates key figures of the paper separately by survey waves.

Table 1 compares the sample composition between the CPS and RPS along the demographics targeted in the sampling procedure for our main surveys (columns 1 and 2). The most notable discrepancies are that individuals aged 18 to 24 and with no more than a high school degree are underrepresented in the RPS relative to the CPS, while individuals with household income of $50,000 or less are overrepresented. The bottom panel of Table 1 compares employment status in the CPS and RPS, statistics that have not been targeted in the sampling procedure. Employment rates are similar across the two surveys, although individuals classified as unemployed according to the CPS definition are somewhat overrepresented in the RPS.

2.1.2 Sample Weights and Validation

To address remaining discrepancies, we construct sample weights using the raking algorithm of Deming and Stephan (1940), ensuring that the weighted sample proportions align with the demographic characteristics targeted in the sampling procedure. We weight by disaggregated categories for education, employment, and marital status and interact all categories with gender. We match these key labor market statistics both in the aggregate and conditional on demographic characteristics. Finally, occupational composition is also included in our weighting scheme; however, due to the relatively small number of observations for some occupations, we do not interact occupation categories with demographics. The weighting scheme necessitated dropping some observations due to missing occupation, resulting in a final sample size of 96.3% of the initial responses. Appendices D.1 and D.2 detail the sample restrictions and the construction of the sample weights.

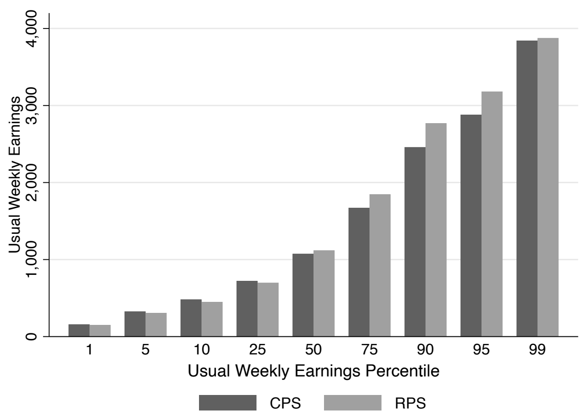
Figure 1 shows the distribution of usual weekly earnings and occupational shares in the RPS and CPS samples.[3] Occupation shares were included as targets in the weighting procedure, but earnings were not, and neither earnings nor occupation were targeted during sampling. Left-hand-side figures show unweighted distributions and right-hand-side figures show weighted distributions. The distributions are already similar without weights, and applying weights further improves the alignment.

Appendix D.4 presents analogous plots for industry and college major, neither of which were targeted during sample collection. The correlation between unweighted industry and college major shares in the RPS and the CPS are 0.89 and 0.83, respectively. Applying sample weights

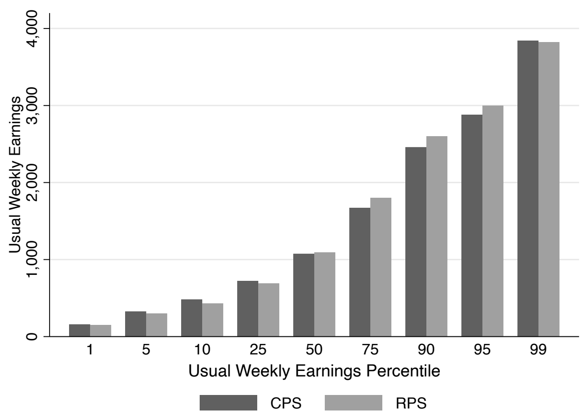
[3] We restrict both the RPS and CPS samples to individuals with (i) weekly earnings below the CPS topcode of $3,960.00, and (ii) an implied hourly wage of at least the federal minimum wage of $7.25.

Figure 1: Validation Checks – Usual Weekly Earnings and Occupation Shares

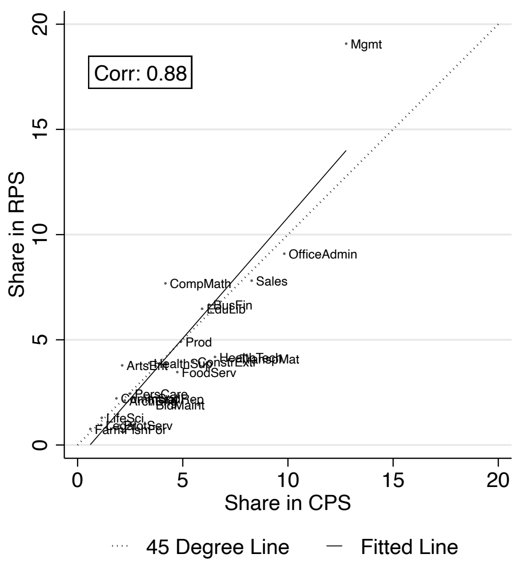
(a) Weekly Earnings Percentiles: Unweighted



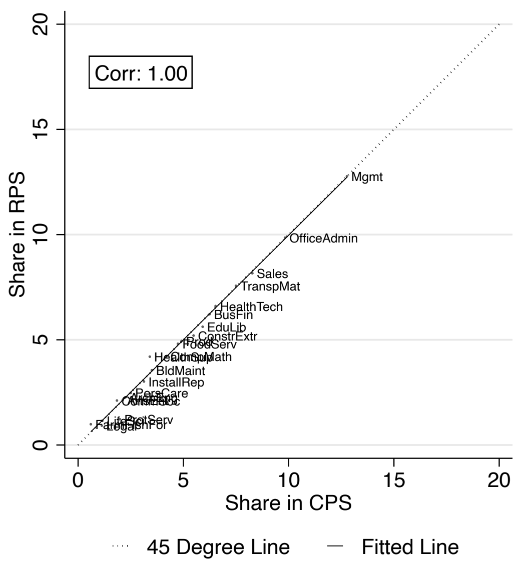
(b) Weekly Earnings Percentiles: Weighted



(c) Occupation Shares: Unweighted



(d) Occupation Shares: Weighted



Notes: Figures on the left use unweighted RPS data, figures on the right use weighted RPS data. We use the same sample of RPS respondents in both figures. All figures use weighted CPS data. Data samples for the weekly earnings figures are employees ages 18-64 in the pooled August and November 2024 RPS and CPS-ORG with weekly earnings below the CPS topcode of $4140 and an implied hourly wage of at least the federal minimum wage of $7.25. Since the CPS topcode varies across month, we apply the lower topcode in both months. Sample sizes for the RPS and CPS are 4786 and 12133, respectively. Data samples for the occupation comparison are employed respondents ages 18-64 in the pooled August and November 2024 RPS and CPS with sample sizes of 6951 and 85546, respectively.

Table 1: Sample Composition in the Pooled August and November 2024 CPS and RPS

	Everyone		*Employed*	
	CPS	RPS	CPS	RPS
	(1)	(2)	(3)	(4)
Gender: Women	50.4	52.1	47.3	47.4
Age				
18-24	15.0	11.7	12.0	12.0
25-34	22.2	22.0	23.9	23.8
35-44	22.2	23.9	24.4	25.0
45-54	20.1	21.2	21.7	21.7
55-64	20.6	21.2	17.9	17.4
Race/Ethnicity				
Non-hispanic White	56.5	56.5	57.8	57.9
Non-hispanic Black	12.9	13.1	12.1	12.3
Hispanic	20.5	20.3	20.2	19.8
Other	10.1	10.0	9.9	10.1
Education				
Highschool or less	37.1	32.9	32.8	27.1
Some college/Associate's degree	25.8	27.5	25.2	27.6
Bachelor's or Graduate degree	37.1	39.5	42.0	45.4
Marital Status: Married	50.1	49.1	52.8	52.4
Number of children				
0	58.1	55.7	57.2	52.7
1	17.8	19.7	18.1	21.2
2	14.7	16.5	15.5	18.5
3+	9.3	8.1	9.2	7.6
Household Income in Last 12 Months				
\$0-\$50,000	26.1	31.3	19.9	22.6
\$50,000-\$100,000	29.9	29.5	30.7	32.0
\$100,000+	44.0	39.2	49.5	45.4
Region				
Northeast	17.0	18.3	16.9	18.8
Midwest	20.3	19.4	21.1	19.2
South	38.8	38.1	38.1	37.8
West	23.8	24.2	23.9	24.2
Employment Status				
Employed, at work last week	71.7	69.9		
Employed, absent from work last week	2.5	2.9		
Unemployed	3.2	8.0		
Not in the labor force	22.6	19.2		
Observations	115477	10264	85546	7473

Notes: Column 1 reports the sample composition in the pooled August and November 2024 Current Population Survey (CPS) for the variables targeted by Qualtrics in the sampling procedure. The employment status was the only variable not targeted. Column 2 reports the sample composition in the pooled August and November 2024 Real-Time Population Survey (RPS). The sample in both data sets is restricted to the civilian population ages 18-64. Columns 3 and 4 report the same outcomes for the employed (at work and absent from work last week).

increases these correlations slightly, to 0.91 and 0.85, respectfully.

2.2 Measurement of Generative AI Use

When designing our survey, a key goal was to enable comparisons to the historical adoption of other technologies. To facilitate these comparisons, we use existing technology adoption questions from the CPS Computer and Internet Use supplement (CIU) as a template for our own questions regarding genAI. In the CIU, the leading question about computer adoption at work for employed respondents was:

> *Do you [directly] use a computer for your job? (No/Yes)*

A second question asks about computer use at home:

> *Do you [directly] use a computer at home? (No/Yes)*

These questions were asked in 1984, 1989, 1993, 1997, 2001, and 2003, with the word "directly" being omitted in the last two years. In 2001 a question about internet usage was added:

> *Do you use the internet at any location? (No/Yes)*

This question was asked in the 2001, 2003, 2007, and 2009 waves of the CIU. Unlike the computer-related questions, it does not condition on location.

The RPS genAI module begins with a definition of genAI:

> *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.*

We included examples of popular genAI products because we thought some respondents may be more familiar with those product names than with the broader concept of genAI. After defining genAI, the module asks respondents whether they had heard of the concept prior to the survey. Overall, 74.5% report having heard of genAI; the remaining 25.5% who answered "No" skip the remainder of the module. Respondents who answer "Yes" continue with the survey.

For employed respondents, the next question asks about genAI use at work:

> *Do you use Generative AI for your job? (No/Yes)*

This question is designed to mirror the analogous computer use question from the CIU, discussed above. We opted for the version asked from 2001 onwards that omitted the word "directly."

Another question later in the survey asks about genAI usage outside work:

Do you use Generative AI [outside your job]? (No/Yes)

Non-employed respondents are not shown the term in brackets. While the CIU asks about computer use "at home", we use slightly different language to account for respondents who access genAI on mobile devices outside of their home.

The survey asks several follow-up questions of genAI users regarding which products they used, how intensively they used it, and how much time they saved, always distinguishing between work and non-work use.

3 How Prevalent is Generative AI Use?

Figure 2a displays the share of August and November 2024 RPS respondents who report using genAI. The samples for the "Overall" and "Outside of Work" bars are all respondents, while the sample for the "For Work" bar is employed respondents. The Overall estimates reflect the share who use genAI either for work or outside of work.

The first bar shows that 39.6% of respondents report using genAI either at work or at home: 9.3% used it every day, 23.1% used it some but not all days, and 7.2% did not use it in the last week. The second bar shows that 26.4% of workers used genAI at work: 9.0% used it every work day and 13.8% on some but not all workdays, bringing total weekly usage to 22.8%. Outside of work, usage is higher overall (33.7%) but less intensive, with only 5.2% of all respondents using it every day last week.

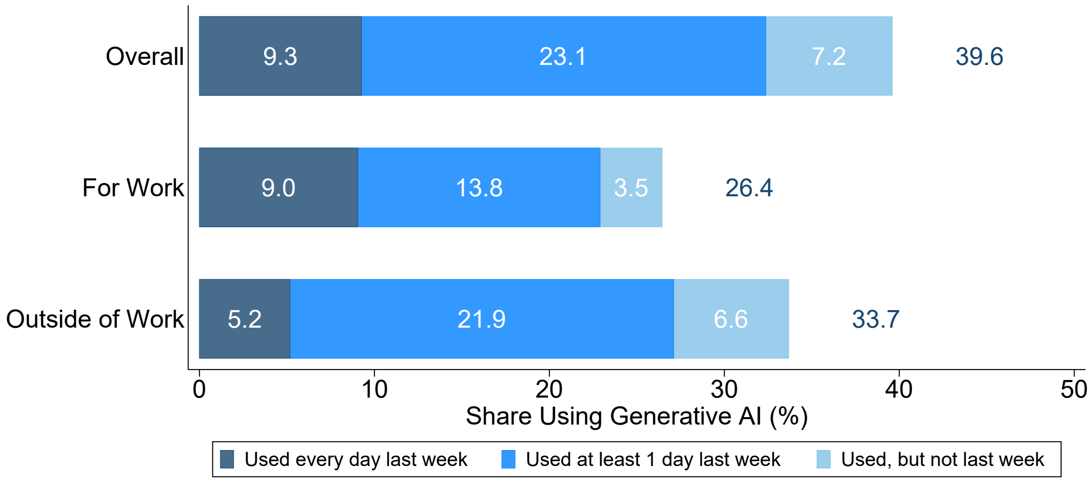
3.1 How Do Our Results Compare to Other Estimates?

The RPS is administered by Qualtrics. To provide a second source of data, in December 2024 we fielded our genAI module through the Survey of Working Arrangements and Attitudes (SWAA) (Barrero et al., 2021). The SWAA uses a different survey provider (IncQuery) but targets a similar sample intended to be representative of the U.S. ages 20-64.

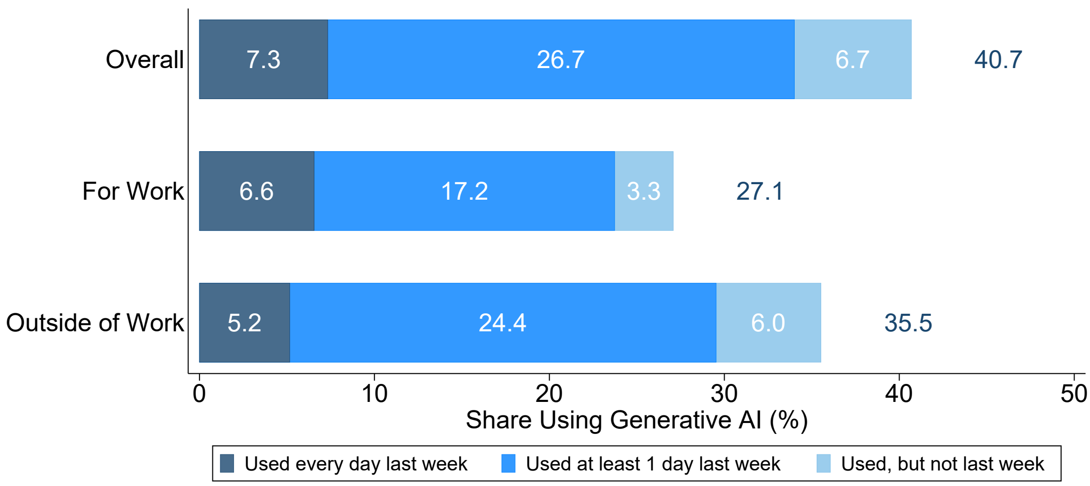
Figure 2b displays similar results from the SWAA. 40.7% of SWAA respondents reported using genAI overall, versus 39.6% of RPS respondents. We find similar estimates for work (27.1% SWAA, 26.4% RPS) and outside work (35.5% SWAA, 33.7% RPS). Appendix C includes additional comparisons between the SWAA and RPS. Because the two surveys yield

Figure 2: Share of Working Age Adults Using Generative AI

(a) RPS: August & November 2024



(b) SWAA: December 2024



Notes: The figure shows the share of respondents who use genAI for work, outside of work, and overall (either for work or outside of work). Intensity of use is broken down into every day last week (dark blue), at least one day but not every day last week (medium blue), and not last week (light blue). Data source for panel (a) is the August and November 2024 waves of the RPS, ages 18-64. The "For Work" sample is employed individuals ($N = 6951$); the other bars include all respondents ($N = 9742$). Data source for panel (b) is the December 2024 wave of the SWAA, ages 20-64. The "For Work" sample is employed individuals ($N = 3516$); the other bars include all respondents ($N = 4698$).

similar estimates but the SWAA only includes a subset of the genAI questions in the RPS, the remainder of the main text reports results only from the RPS.

We presented genAI users a list of common products (and a write-in option) and asked them to select the ones they used. Respondents could select multiple products. This allows us to compare ChatGPT use in the RPS with other surveys. The three most used genAI products were ChatGPT (28.1% of all respondents), Gemini (16.6%), and embedded tools like Microsoft Copilot (14.1%). Appendix Figure A.1 shows the full distribution of product usage. In April 2024, Fletcher and Nielsen (2024) conducted an online survey of ChatGPT adoption using a different survey provider (YouGov). They found that 18% of U.S. adults used ChatGPT at least weekly, compared to 19% who used ChatGPT in the previous week in our study.[4]

A potential concern with online-based surveys is that they may suffer from selection based on unobservable characteristics that are correlated with genAI use. For example, online survey respondents may be more comfortable using technology and therefore be more likely to use genAI than the overall U.S. population. From this perspective, a valuable point of comparison is a survey conducted by the Pew Research Center (McClain, 2024). That survey sampled respondents using a nationally representative sample of U.S. Postal Services addresses. Importantly, the survey included respondents without internet access. (Internet access per se is unlikely to substantially impact our results: in the 2022 ACS, 96.8% of individuals aged 18-64 report having access to the internet.) They find that in February 2024, 27% of U.S. adults age 18-64 reported ever having used ChatGPT, compared to 29% of individuals who report using ChatGPT in our survey in August and November 2024.

3.2 How Fast is Generative AI Being Adopted Compared to Other Technologies?

Figure 3a compares the pace of genAI adoption with PCs and the internet. (As described in Section 2.2, adoption was measured using very similar questions for all three technologies.) The horizontal axis represents years since the release of the first mass-market product for a given technology. The first mass-market computer was the IBM PC, which was released in August 1981. We date mass-market availability of the internet to April 1995, when the National Science Foundation (NSF) decommissioned NSFNet and allowed the internet to carry commercial traffic (Leiner et al., 2009). The first mass-market genAI product was ChatGPT, which was released in November 2022.[5]

The blue dot in Figure 3a repeats the 39% adoption rate for genAI reported in Figure 2a,

[4]Humlum and Vestergaard (2024) survey a representative sample of workers in eleven occupations in Denmark about their usage of ChatGPT at work. We find similar patterns by age, education and gender in the occupations covered by both surveys.

[5]Three notable computer products had already been released in 1977 (the Apple II, the Commodore PET, and the TRS-80). Choosing earlier introduction dates would imply slower adoption rates for a given technology. The 1981 IBM PC was the first computer to sell over one million units (Abbate, 1999). With regards to the internet, 1995 was also the year of Netscape's initial public offering and the year that AOL 3.0 was released. We chose these dates based in part on ChatGPT's answers to questions about the year of the first mass market product for each technology. The exact prompts and answers are available upon request.

which corresponds to 2 years since the first mass-market genAI product. The red squares plot PC adoption in the CPS between years 3 to 22 (1984 to 2003). The dark green triangles plot internet adoption in the CPS between years 6 to 14 (2001 to 2009). The light green triangles are based on data from the International Telecommunication Union (ITU), which has gathered U.S. and global internet usage data since 1995, in partnership with the World Bank. The ITU combines subscriber data from national regulatory bodies and service providers to estimate the population's internet access rate (Peña-López et al., 2009). We plot internet adoption in the ITU between years 0 to 26 (1995 to 2021). The two series for the internet align closely for the years that overlap.

PC adoption rose steadily from 20% in year three to 70% in year 22. Internet adoption increased rapidly from 20% in year two to 60% in year seven, and then more gradually to 90% over the ensuing two decades. We conclude that, relative to the introduction of the first mass-market product, genAI has been adopted at a faster pace than both PCs and the internet.

A key question is whether genAI's faster adoption was driven by work or non-work use. While we cannot separate work and non-work internet use, we can do so for PCs and genAI.

The faster overall pace of genAI adoption compared with PCs is driven by non-work adoption. Figure 3b plots work adoption of PCs and genAI. We find very similar work adoption rates for genAI after two years (26%) and PCs after three years (25%). By contrast, Figure 3c reveals much higher non-work adoption rates for genAI (34%) compared with PCs (5%).

The choice of whether to adopt a technology depends on both benefits and costs. PCs required purchasing expensive immobile hardware, while internet adoption required purchasing a modem and Internet Service Provider subscription. In contrast, many genAI products are free or inexpensive and user-friendly. On the one hand, this lower adoption cost likely contributes to genAI's rapid uptake. On the other hand, this means that similar adoption rates for PCs and genAI at work do not necessarily imply equivalent benefits.

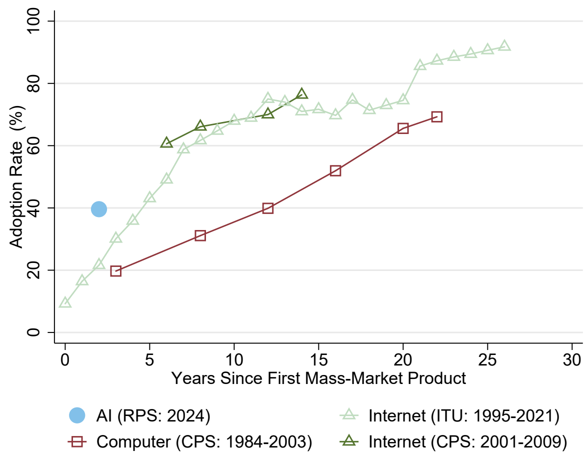
4 Which Workers Use Generative AI?

Figure 3b documented a very similar work adoption rate for PCs in 1984 compared with genAI in 2024. Did the same groups of workers that drove PC adoption in 1984 also drive genAI adoption 40 years later? Answering this question is a preliminary step toward understanding the potentially heterogeneous labor market impact of genAI (Acemoglu, 2024; Autor, 2024; Autor et al., 2003).

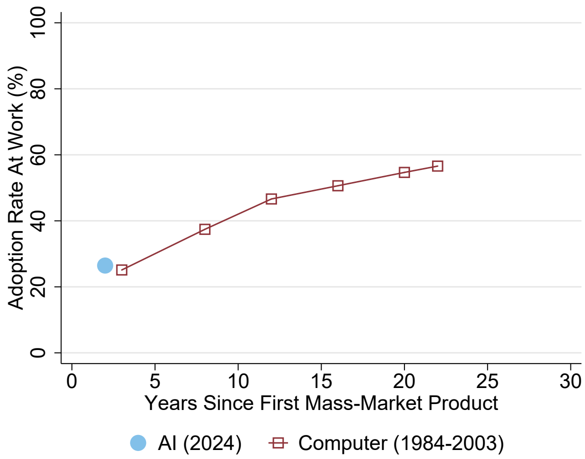
Figure 4 documents demographic heterogeneity in work adoption for PCs (1984) and genAI (2024). Figure 4a indicates that genAI adoption among workers with a Bachelor's or Graduate

Figure 3: The Trajectory of Computer, Internet, and Generative AI Adoption

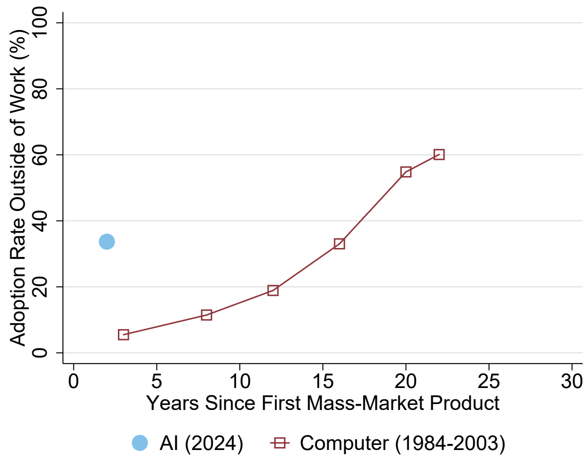
(a) Overall Adoption



(b) Work Adoption

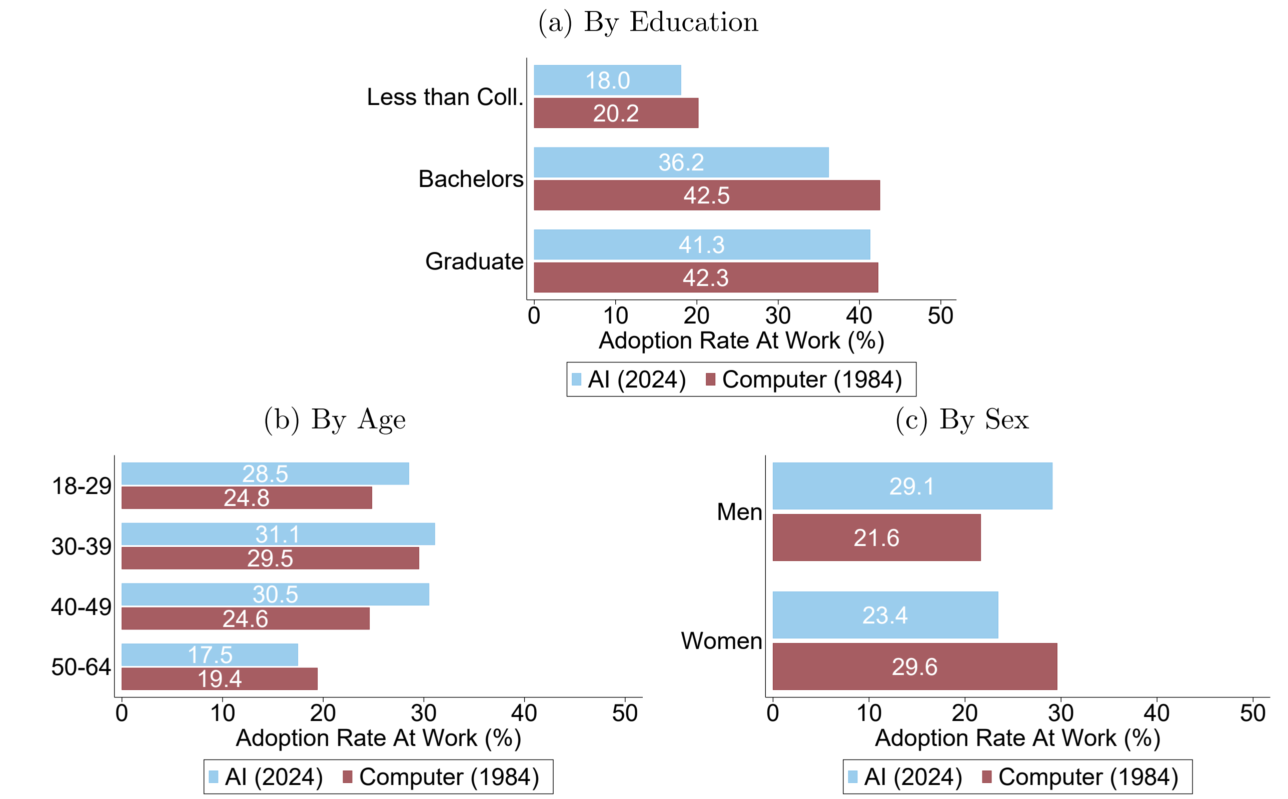


(c) Adoption Outside of Work



Notes: Panel (a) shows overall usage rates for three technologies: genAI, computers, and the internet. The horizontal axis represents years since the introduction of the first mass-market product for each technology. We use 1981 as the introduction year for computers, which was the year the IBM PC was released. We use 1995 as the introduction year for the internet, which was the year that the NSF decommissioned NSFNet and allowed the internet to carry commercial traffic. We use 2022 as the introduction year for genAI, which was the year ChatGPT was released. The data source for genAI is the August and November 2024 wave of the RPS (solid blue circle). The data source for computers is the 1984-2003 Computer and Internet Use Supplement of the CPS (hollow red squares). We plot two estimates of internet use: the 2001-2009 Computer and Internet Use Supplement of the CPS (dark green triangles) and the ITU (teal triangles). The sample for the RPS and CPS is all individuals ages 18-64. The RPS sample size is $N = 9742$. The sample for the ITU is individuals of all ages. Panels (b) and (c) show usage rates for computers and genAI for work and outside of work, respectively. The sample for Panel (b) is employed individuals ages 18-64 (RPS, $N = 6951$). The sample for Panel (c) is all individuals ages 18-64 (RPS, $N = 9742$).

Figure 4: Demographic Heterogeneity in Work Adoption of Generative AI and PCs



Notes: The figure shows adoption rates at work for genAI and PCs by education (Panel a), age (Panel b), and sex (Panel c). The data source for genAI is the August and November 2024 waves of the RPS (blue bars). The data source for computers is the 1984 Computer and Internet Use Supplement of the CPS (red bars). The sample for each dataset is employed individuals ages 18-64 (RPS, $N = 6951$).

degree is double that of non-college workers, mirroring PC adoption patterns. Similarly, Figure 4b shows higher adoption among workers under 50 for both technologies. However, we find different adoption patterns by sex: Figure 4c shows genAI adoption is 5.7 percentage points higher for men, whereas PC adoption was 8 points higher for women. High PC adoption by women is driven by high adoption among office and administrative support occupations (see Figure 6a), which was a highly female occupation in 1984.

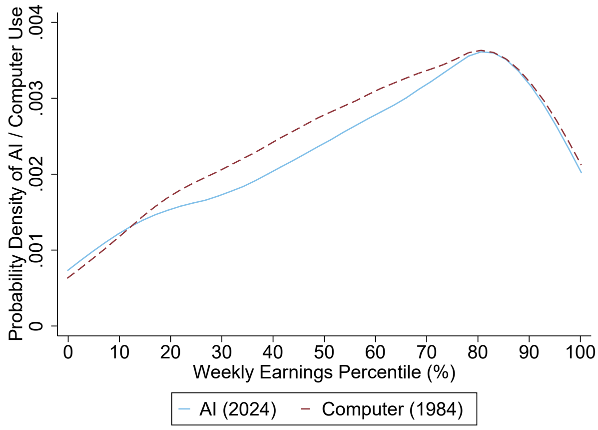
Figure 5a plots the kernel density of PC and genAI adoption by weekly earnings percentile. We again find strikingly similar patterns for the two technologies. Adoption rates increase steadily with income until roughly the 80th percentile, and then decline.

To better understand the relationship between technology use and labor market outcomes, we regress earnings, wages, and hours on indicators for PC and genAI use on while also controlling for occupation, industry, education, and demographic characteristics.[6] The results are displayed in Figure 5b. We estimate nearly identical coefficients for PCs and genAI. Use of both

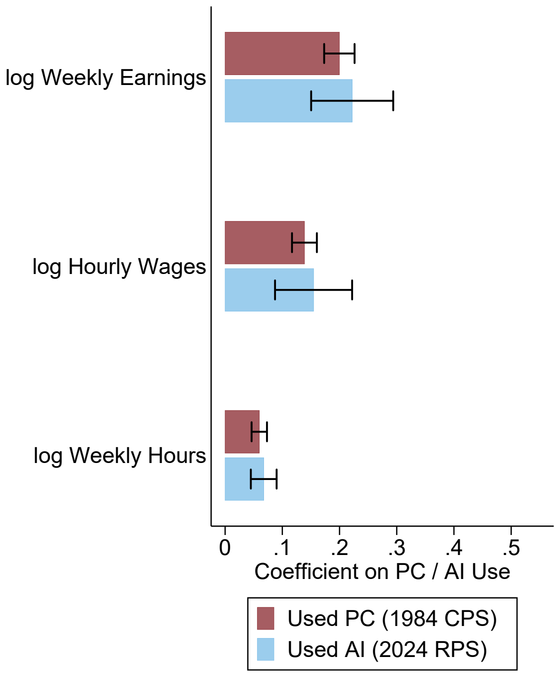
[6]The control variables used in these regressions are indicators for: female, age 18-29, age 40-49, age 50-54, a bachelor's degree, a graduate degree, Black, Hispanic, occupation group, and industry.

Figure 5: Earnings and Generative AI / PC Adoption

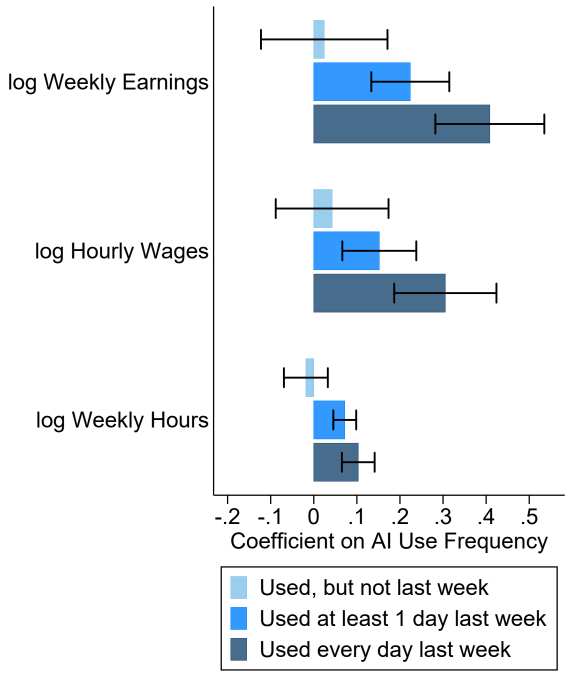
(a) By Weekly Earnings percentile



(b) Reg. Coefficient of PC / genAI Use



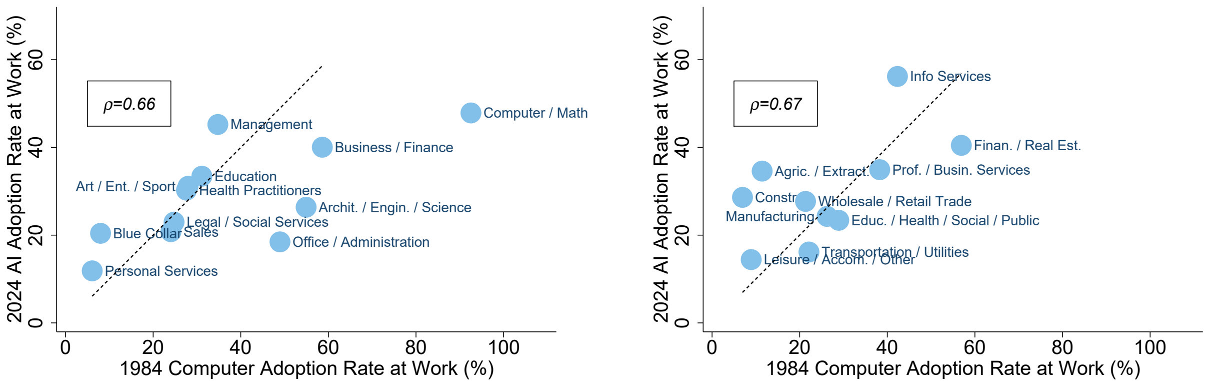
(c) Reg. Coefficient of Intensity of genAI Use



Notes: Panel (a) shows adoption rates at work for genAI and PCs by weekly earnings percentile (kernel density). Panel (a) shows the coefficient on PC adoption (red bars) and genAI adoption (blue bars) in a regression of (i) log weekly earnings, (ii) log hourly wages, and (iii) log weekly hours worked. Panel (b) shows the coefficients on genAI intensity-of-use (zero days last week, some but not all workdays last week, and every workday last week) for the same variables (i-iii). For all regressions, the additional control variable used are indicators for: female, age 18-29, age 40-49, age 50-64, a bachelor's degree, a graduate degree, Black, Hispanic, occupation group, and industry. The data source for genAI is the August and November 2024 waves of the RPS. The data source for computers is the Outgoing Rotation Group (ORG) subset of the 1984 Computer and Internet Use Supplement of the CPS. The sample for each dataset is employed individuals ages 18-64 whose implied hourly wage is at least the federal minimum wage in the relevant year (RPS, $N = 6076$).

Figure 6: Generative AI and PC Work Adoption By Occupation and Industry

(a) By Occupation (b) By Industry



Notes: The figure shows adoption rates at work for genAI and PCs by occupation (Panel a), and industry (Panel b). The data source for genAI is the August and November 2024 waves of the RPS (blue bars). The data source for computers is the 1984 Computer and Internet Use Supplement of the CPS (red bars). The sample is employed individuals with valid occupation and industry (RPS, $N = 6898$). For details on occupation and industry groups, see Appendix D.3.

technologies is associated with a weekly earnings premium of 21 log points, a wage premium of about 15 log pints, and 5 log points for weekly hours.

Figure 5c estimates a version of our regression with separate indicators for infrequent, weekly, and daily users of genAI. (We cannot run an analogous regression for PCs because the CPS does not ask about usage frequency.) The coefficients on earnings, wages, and hours are all increasing in genAI intensity, and infrequent users show no statistical difference between non-users.

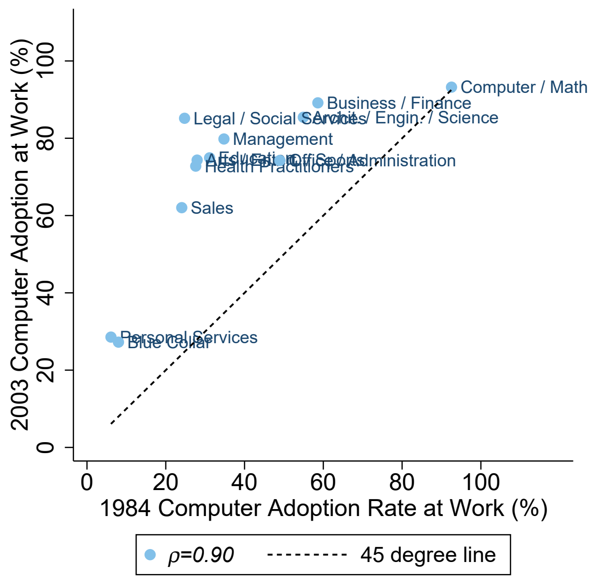
Higher wages by (more intensive) users could reflect several factors. First, within an occupation and industry jobs that benefit more from genAI assistance may be associated with higher wages (Deming and Kahn, 2018). Second, productive workers may adopt new technologies more rapidly (Nelson and Phelps, 1966). Third, genAI may directly increase workers' productivity and wages. Our data do not allow us to distinguish between these explanations.

Figure 6a plots genAI adoption against PC adoption by occupation group. (For details on how we elicit occupation, see Appendix D.3.) GenAI adoption at work is highest in computer and mathematical, management, and business and finance jobs (43%, 42%, and 41% respectively). Overall, though, genAI use is broadly distributed, with adoption above 15% for each occupation group. In contrast, PC use is more concentrated, with three occupation groups above 50% and two occupation groups below 10%. Still, early adoption rates are highly correlated across the two technologies ($\rho = 0.66$).

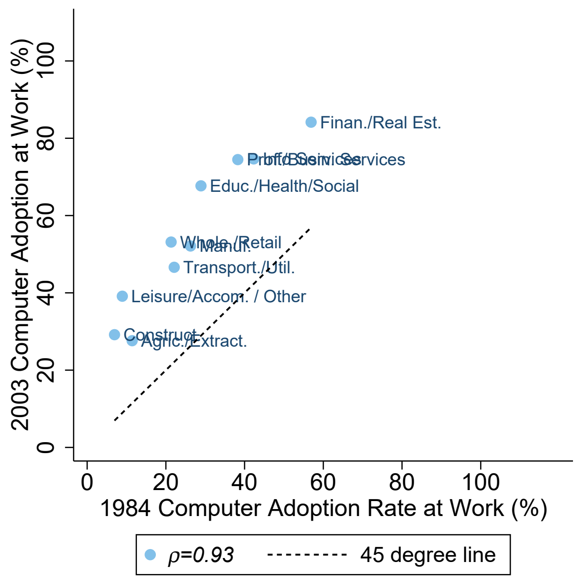
Figure 6b plots genAI adoption against PC adoption by industry. GenAI adoption at work

Figure 7: The Persistence of Early Computer Adoption: 1984 - 2003

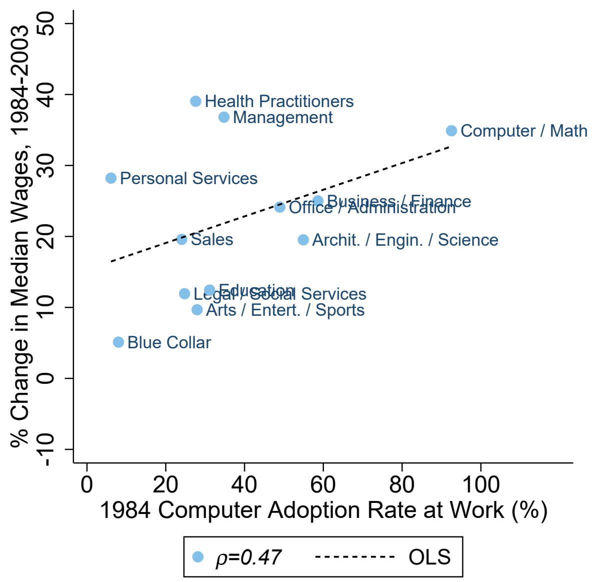
(a) By Occupation: Adoption in 1984 vs. 2003



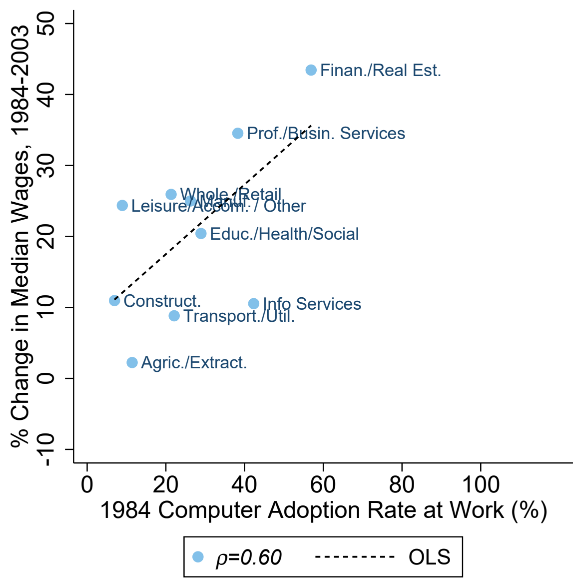
(b) By Industry: Adoption in 1984 vs. 2003



(c) By Occupation: Wage Growth 2003 - 1984



(d) By Industry: Wage Growth 2003 - 1984



Notes: The figure compares PC work adoption rates in 1984 to PC work adoption in 2003 and growth in median wages from 1984 - 2003. The source for adoption rates is the Computer and Internet use Supplement of the CPS. Panels a and c group observations by occupation; panels b and d group observations by industry. The sample is employed individuals ages 18-64.

is highest in information services (58%). GenAI adoption is lowest in leisure, accommodation, and other services (15%) and transportation and utilities (17%). Overall, adoption rates by industry are highly correlated across the two technologies ($\rho = 0.67$).

Early heterogeneity in PC adoption by occupation and industry was highly persistent over subsequent decades. Figures 7a and 7b show that occupations and industries with higher computer adoption in 1984 continued to have higher adoption in 2003. Moreover, Figures 7c and 7d show that occupations and industries with higher computer adoption in 1984 experienced higher wage growth over the next two decades, consistent with skill-biased technical change explanations (Autor et al., 2003). The close similarities between early adoption of PCs and genAI, combined with the fact that early PC adoption is highly predictive of later adoption and wage growth, suggests that these early genAI adoption patterns may be informative about the technology's future labor market effects.

4.1 Tasks, Predicted Exposure, and Generative AI Adoption

Why do some groups of workers adopt genAI at higher rates than others? One reason could be that the technology is simply more helpful in some jobs than others. To investigate this, we use the predicted-task-exposure analysis of Eloundou et al. (2024). They construct a rubric that assigns each task in the O*NET database a zero or one corresponding to whether LLMs (a popular class of genAI) could feasibly produce large productivity gains for that task. They then aggregate these task exposure scores by occupation to assign each occupation a predicted exposure score.

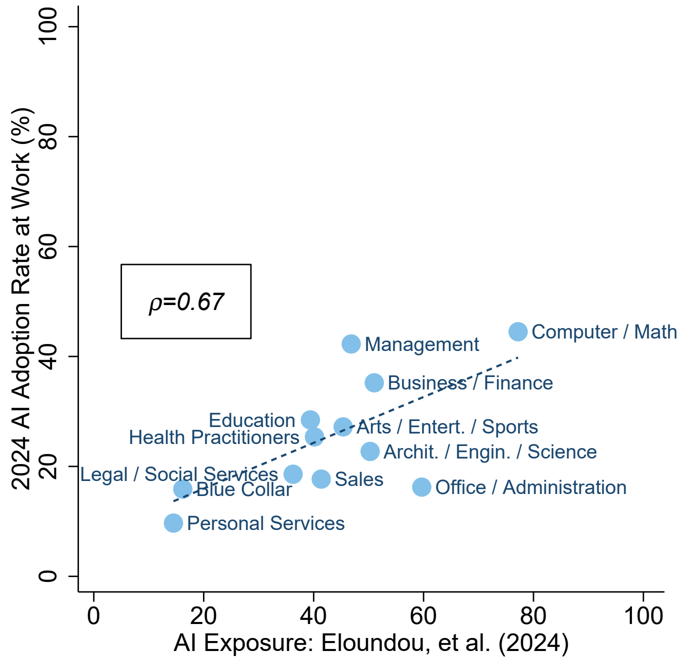
Figure 8a plots an occupation group's predicted genAI exposure from Eloundou et al. (2024) against actual genAI adoption in the 2024 RPS. We find that predicted genAI exposure is highly correlated with actual genAI adoption ($\rho = 0.67$). Personal service and blue-collar occupations have relatively low predicted exposure and also relatively low adoption, while computer and mathematical occupations have both high predicted exposure and high adoption.

Our results offer partial validation of task-based exposure predictions, supporting their utility for researchers. However, managers adopt genAI at high rates relative to predicted exposure, while legal, social services, and administrative occupations adopt at lower rates. These gaps may stem from mismeasurement as to which tasks benefit from genAI, or differences in adoption costs such as regulatory barriers. Understanding the source of these disparities is an important question for future research.

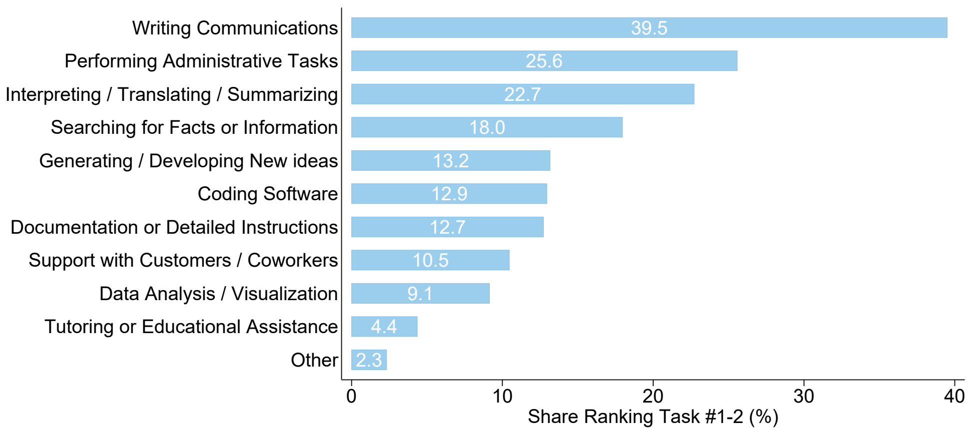
Given the high correlation between job tasks and adoption, a natural follow up question is to ask which tasks genAI helps workers complete. We present genAI users with the list of tasks in Figure 8b and ask them to select any for which they had used genAI in the last week. (They

Figure 8: Work Tasks and Generative AI Adoption

(a) Task-Based Predicted Exposure vs. Adoption By Occupation



(b) In Which Specific Work Tasks Is Generative AI Most Useful?



Notes: Panel (a) compares predicted genAI exposure with genAI use by occupation group. The data source for predicted genAI exposure is ChatGPT-β predicted exposure from Eloundou et al. (2024). The data source for genAI use is the August and November 2024 RPS. The sample for the RPS is employed individuals age 18-64 with a valid occupation ($N = 6898$). Panel (b) shows which work tasks genAI users report that genAI is most helpful in completing. Employed respondents who used genAI were first provided with a list of tasks and asked to select those that they had used genAI to help with last week. Respondents were then asked to rank these selected tasks according to how helpful genAI was in completing the task. The figure reports the share of genAI users who ranked a particular task either #1 (AI was most helpful in this task) or #2. The bars do not have a natural sum because some respondents selected fewer than two tasks. Data source is employed respondents ages 18-64 who used genAI for work and selected at least one task in the August and November 2024 waves of the RPS.

were also allowed to write in other tasks.) Respondents were then asked to rank these tasks according to how helpful genAI was in completing them.

Figure 8b reports the share of respondents who ranked each task in the top two in terms of importance. The highest ranked tasks at work were writing (39.5%), administrative tasks (25.6%), and interpreting/translating/summarizing text or data (22.7%). While genAI seems most useful for creating, absorbing, and organizing written information or communications, eight of the ten tasks in our list were ranked in the top two by at least 10% of users, indicating a variety of use cases for genAI.

5 Frequency of Generative AI Use and Time Savings

5.1 How Much Do Workers Use Generative AI?

Figure 9a reports how much time genAI users spent using the technology in a given day. Specifically, we ask "*Please think back to the days LAST WEEK on which you used Generative AI at work. On average, how much time did you spend actively using Generative AI at work?*" Respondents could select from three options: 15 minutes or less per day, between 15 minutes and one hour per day, or more than an hour per day.[7]

Figure 9a shows that 31.9% of genAI users report using genAI for an hour or more per day at work, 47.0% used it for between 15 and 60 minutes per day, and 21.0% used it for less than 15 minutes per day. We also show these estimates separately by workers' daily frequency of use. Frequency and intensity of genAI use are positively correlated. 52.0% of daily genAI users report using it an hour or more each day, compared to only 7.3% of those who used it in the last month but not the last week. Overall, our results indicate wide variation in the frequency and intensity of genAI use at work.

We estimate bounds on the share of total work hours assisted by genAI by combining data on usage intensity with data on days and hours worked in the previous week. For this calculation we restrict attention to our November 2024 wave, which contains more detailed intensity categories (see Appendix Figure B.2). For example, consider a worker who reports (i) working 40 hours last week over 5 days, (ii) using genAI on multiple but not all workdays last week, and (iii) using genAI for between 15 and 59 minutes per day on days that they used it. The lower bound implies the respondent used genAI on two days for 15 minutes each day ($15/59 \cdot 2/40 = 1.3\%$ of their weekly hours); the upper bound implies using genAI on four workdays for 1 hour each day ($1 \cdot 4/40 = 10\%$ of their weekly hours).

[7] Respondents who did not use genAI last week but did use it in the last four weeks were asked about their average usage on the days they used genAI over the last four weeks.

We first aggregate these estimates across the 21.8% of workers in the November 2024 wave who report using genAI in the past week. Among workers who use genAI, between 6.0 and 24.9% of all work hours were assisted by genAI. Next, we include the 78.2% of non-genAI-workers in our calculation, who spend no time using genAI by construction. Among all workers, between 1.3% and 5.4% of total work hours were assisted by genAI.

5.2 Reported Time Savings Due to Generative AI

In the November 2024 wave, we asked workers who used genAI in the previous week to estimate how much time genAI saved them in the past week:

> *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?* *[For X we fill in the respondent's reported hours worked last week.]*

The answer options were: Less than 1 hour, 1 hour, 2 hours, 3 hours, 4 hours, More than 4 hours. For respondents who selected "less than 1 hour", we assume that genAI saved zero hours of work. For respondents who selected "more than 4 hours," we assume that genAI saved 4 hours of work. These assumptions are conservative in the sense that they reflect a lower bound of time savings.

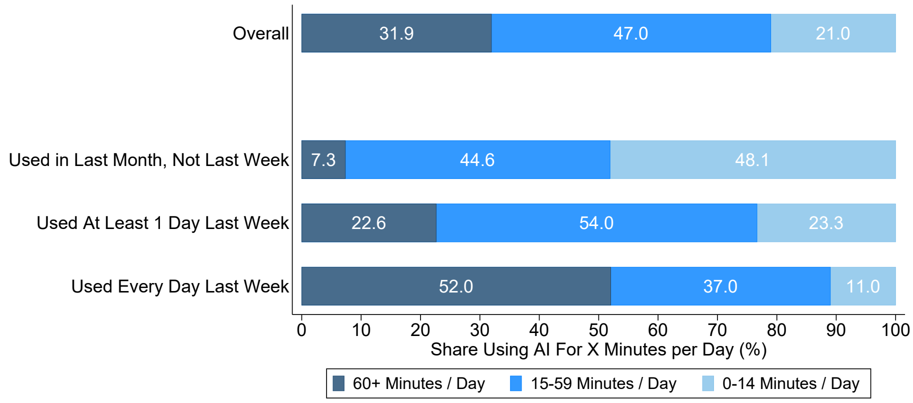
Figure 9 reports the results: 33.0% said genAI saved them an hour or less last week, 26.4% reported two hours, 20.1% reported three hours, and 20.5% reported four hours or more. More frequent users report higher average time savings. Among workers who used genAI every day last week, 33.5% reported saving four hours or more, compared to 11.5% of respondents who used it one day last week.

For each genAI user, we compute the share of working hours saved as the ratio of time saved last week to hours worked last week. We find an average time savings of 5.4% of work hours by genAI users in the November 2024 wave, or about 2.2 hours for a 40-weekly-hour worker. When we include all workers, including non-users, on average genAI saved workers saved 1.4% of total hours.

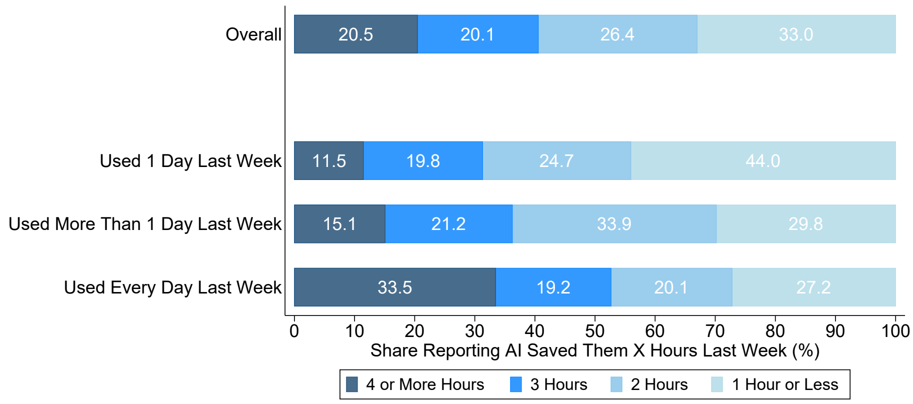
Figures 9c and 9d show that usage and time savings are highly correlated. Workers in computer, mathematical, and management occupations spend 9–12% of work hours using genAI and save 2.1–2.5% of their time, while personal service workers use it for just 1.3% of work hours and save only 0.4%. Across industries, information services has the highest genAI use (14.0%) and time savings (2.6%), while leisure, accommodation, and other services have the lowest use (2.3%) and time savings (0.6%). In both figures, the slope of the dashed OLS line

Figure 9: Reported Time Savings Due to Generative AI

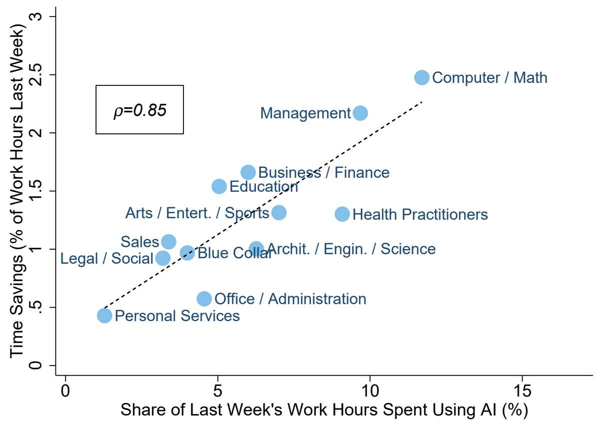
(a) Intensity of Generative AI Use For Work



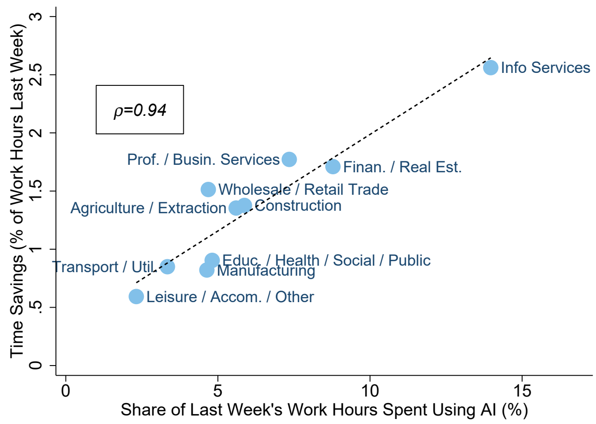
(b) Reported Time Savings Due to Generative AI



(c) genAI Time Savings and Use by Occupation



(d) genAI Time Savings and Use by Industry



Notes: Panel (a) shows the distribution of daily time spent actively using genAI for work, among genAI users. The "Overall" bar reflects the distribution among all workers who use genAI. Other bars break down daily time use by daily frequency of use. Data source is the August and November 2024 waves of the RPS, ages 18-64. The sample is employed respondents who use genAI for work ($N = 1918$). Panel (b) shows the distribution of work time saved in the previous week due to genAI, among individuals who use genAI for work. The "Overall" bar reflects the distribution among all workers who use genAI. Other bars break down time savings by daily frequency of use. Data source is the November 2024 wave of the RPS, ages 18-64 (the August 2024 wave did not ask about time savings). The bottom two panels plot the mean share of last week's work hours spent using genAI against the mean time savings due to genAI by occupation group (Panel c) and industry group (Panel d). The sample is employed respondents who use genAI for work ($N = 933$).

is 0.17, indicating that a 10 percentage point increase in genAI use is associated with a 1.7% rise in time savings.

5.3 The Aggregate Productivity Gain from Generative AI

We now present a standard model of aggregate production to illustrate how our data can be used to estimate the increase in aggregate productivity due to genAI. Detailed derivations can be found in Appendix F.1.

We model aggregate output with a Cobb-Douglas function:

$$Y = AK^{\alpha}L^{1-\alpha}, \tag{1}$$

$$L = \sum_{i=1}^{N} \ell_i e_i, \tag{2}$$

where L is aggregate effective labor supply (where ℓ_i is hours worked and e_i is efficiency for worker i). If worker i saves s_i hours per week due to genAI and spends this time on additional production within their job, their effective labor becomes $\ell_i + s_i$ and the change in effective labor supply is

$$\Delta L = \sum_{i=1}^{N} s_i e_i. \tag{3}$$

Assuming a competitive labor market and constant TFP, capital, and hours worked, Appendix F.1 shows that we can write the approximate percent change in aggregate output from genAI as:

$$\frac{\Delta Y}{Y} \approx \underbrace{(1-\alpha)}_{\text{labor cost share}} \times \underbrace{\frac{\sum_i s_i \tilde{w}_i}{\sum_i \ell_i \tilde{w}_i}}_{\Delta\%\text{effective labor}} \tag{4}$$

where $\tilde{w}_i$ is worker i's wage relative to mean wages. This equation states that the percent change in output due to genAI is the ratio of mean time savings to mean hours worked, weighted by worker's wages, and scaled by labor's share of production costs.

Using November 2024 RPS data on hourly wages w_i, weekly hours worked ℓ_i, and weekly genAI time savings s_i, we use (4) to estimate that genAI currently increases the aggregate effective labor supply by 1.9%. We use an AI-exposure-adjusted labor share of 0.57, following Acemoglu (2024), which implies a potential productivity gain of 1.1%.

When interpreting these estimates, we emphasize that official firm-level adoption still lags worker adoption, suggesting that worker adoption is still mostly informal (Bonney et al., 2024). Therefore, *potential* productivity gains from genAI may not be fully captured by productivity statistics, at least in the short run, if some workers take their time savings as on-the-job leisure, which would increase welfare but not output.

5.4 Comparisons to Micro and Macro Estimates of GenAI Productivity Gains

To compare our estimate of the aggregate productivity gain from genAI with experimental estimates from the literature, we reformulate the model to express time savings as a linear function of time spent using genAI, $s_i = \gamma u_i$:

$$\Delta L = \sum_{i=1}^{N} \gamma u_i e_i. \tag{5}$$

In this expression, u_i is weekly hours spent using genAI by worker i and γ is the productivity gain associated with one hour of genAI use.

Given our estimates of genAI use, Appendix F.1 shows that the value of γ that would generate a 1.9% increase in aggregate effective labor supply can be written:

$$\gamma = 1.9\% \cdot \left(\frac{\sum_i \tilde{w}_i l_i}{\sum_i \tilde{w}_i u_i} \right) \tag{6}$$

As discussed in Section 5.1, RPS data provide a lower and upper bound for l_i, $\underline{l}_i$ and $\bar{l}_i$. Evaluating (6) using the midpoint of these bounds, $l_i \equiv (\underline{l}_i + \bar{l}_i)/2$ yields a wage-weighted share of total work hours spent using genAI of 5.7%, which yields $\gamma = 0.33$. This implies that each hour spent using genAI increases the worker's productivity for that hour by 33%. This is similar in magnitude to the average productivity gain of 27% from several randomized experiments of genAI usage (Cui et al., 2024; Dell'Acqua et al., 2023; Noy and Zhang, 2023; Peng et al., 2023).

Our estimated aggregate productivity gain from genAI (1.1%) exceeds the 0.7% estimate by Acemoglu (2024) based on a similar framework. In our framework and in Acemoglu (2024), the aggregate productivity gain is the product of three numbers: the AI-exposure-adjusted labor share of GDP, the wage-weighted share of labor that is automated by genAI, and the productivity gain from genAI automation. We use the same labor share as Acemoglu (2024). Our survey data imply a wage-weighted adoption share of 5.7%, while Acemoglu (2024) assumes a slightly lower wage-weighted adoption share of 4.6% based on task-exposure predictions. As discussed above, we estimate a productivity gain from genAI of 33%; Acemoglu (2024) assumes a productivity gain from genAI automation of 27% based on micro experimental evidence. Adjusting our productivity value γ from 33% to 27% lowers our estimated aggregate productivity gain to 0.9%; the remaining 0.2 percentage point gap is due to our higher adoption estimate.

We make two points about these estimates of aggregate productivity gains. First, Acemoglu (2024) assumes these productivity gains take a decade to materialize. In contrast, our estimates reflect current adoption and time savings, implying a faster pace of diffusion. Second, our estimate does not capture potential productivity gains from using genAI to reorganize or completely automate production processes. With previous technologies, these more systematic gains occurred with substantial time lags, implying that this omission may be modest in the short run (Bresnahan and Trajtenberg, 1995; Brynjolfsson and Hitt, 2000; David, 1990; Jovanovic and Rousseau, 2005).

6 Conclusion

Predictions about genAI's labor market impact vary widely, driven by uncertainty over how many jobs it can assist and the size of its productivity gains. This paper presents evidence from the first nationally representative U.S. surveys on generative AI use at work and home. We find that a substantial share of individuals already use genAI. Thus far, the pace of overall adoption is rapid compared with past ICT technologies. At work, genAI adoption has followed a similar pace to PCs, driven by many of the same types of workers. Although the intensity of genAI use varies widely, genAI already assists a noticeable share of total work hours, suggesting the potential for meaningful aggregate productivity gains. These findings help lay the groundwork for a more accurate understanding of the labor market impact of genAI.

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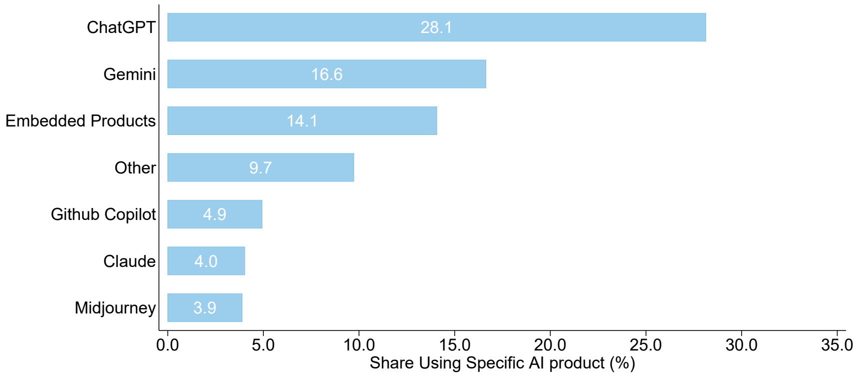
The Rapid Adoption of Generative AI

ONLINE APPENDIX

A Additional Results on Generative AI and PC Adoption

Figure A.1: Share of Respondents Using Specific Generative AI Products

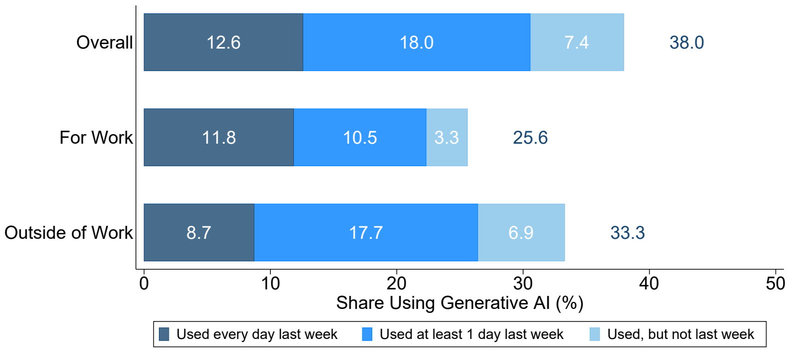


Notes: The figure shows the share of respondents who report using particular genAI products. "Embedded products" are genAI features embedded within existing software, such as Microsoft Copilot. Data source is the August and November 2024 waves of the RPS, ages 18-64 ($N = 9742$). Individuals who report using multiple genAI products are reflected in multiple bars.

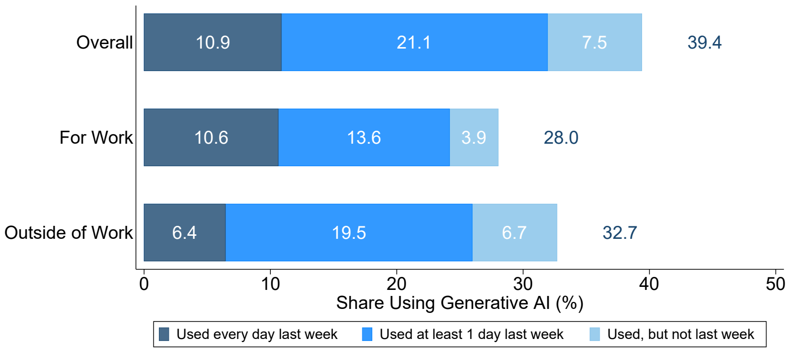
B Results on Generative AI Use: Comparing the June (Pilot), August, and November 2024 Waves

Figure B.1: Share of Working Age Adults Using Generative AI

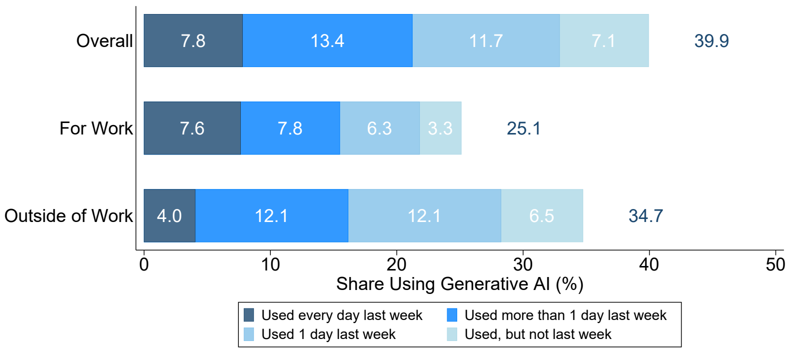
(a) June 2024 (Pilot)



(b) August 2024



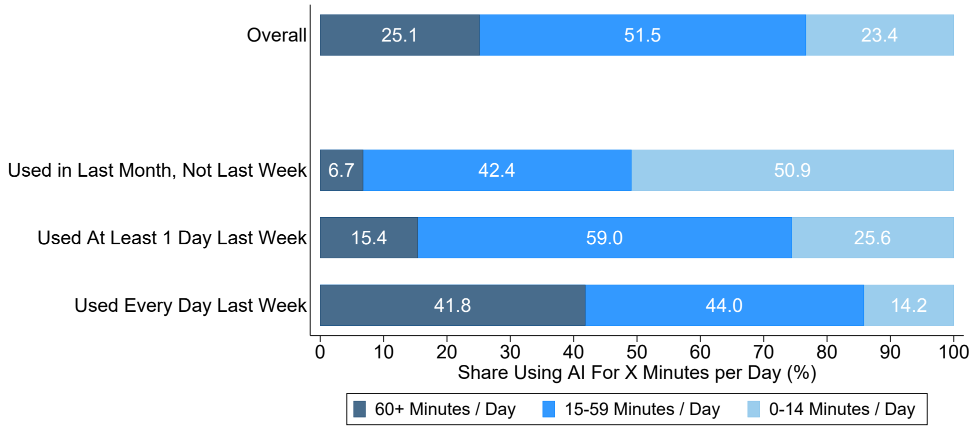
(c) November 2024 (More Detailed Breakdown)



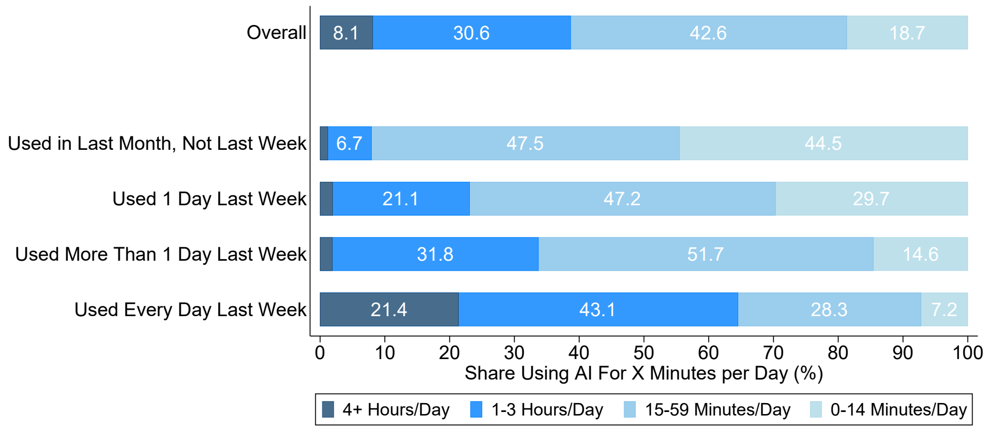
Notes: The figure shows the share of respondents who use genAI for work, outside of work, and overall (either for work or outside of work). Intensity of use is broken down into every day last week (dark blue), at least one day but not every day last week (medium blue), and not last week (light blue). Data source is the June 2024 wave of the RPS (Panel a), the August 2024 wave (Panel b), and the November 2024 wave (Panel c). The "For Work" samples are employed individuals (June, $N = 1576$; August, $N = 3216$; November, $N = 3708$). The other bars include all respondents (June, $N = 2354$; August, $N = 4682$; November, $N = 5033$).

Figure B.2: Intensity of genAI Use For Work

(a) August 2024



(b) November 2024 (More Detailed Breakdown)

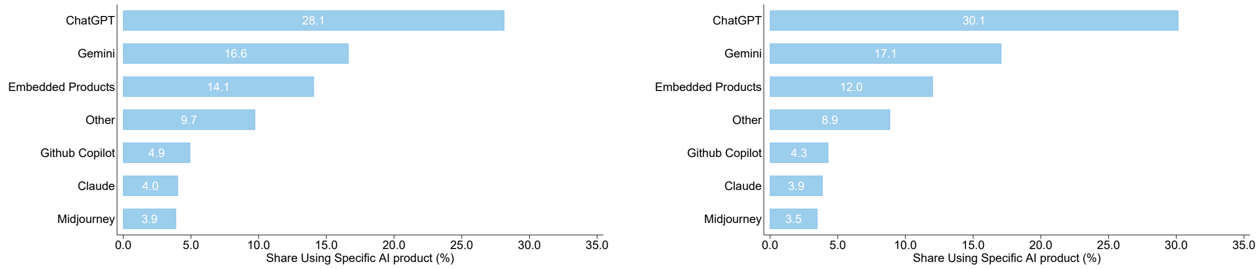


Notes: The figure shows the distribution of daily time spent actively using genAI for work, among genAI users. In August, usage time is broken down into 0-14 minutes per day (light blue), 15-59 minutes per day (medium blue), and 60 or more minutes per day (dark blue). In November, usage time is broken down into 0-14 minutes per day (lightest blue), 15-59 minutes per day (light blue), 1-4 hours per day (medium blue), and 4 or more hours per day (dark blue). The "Overall" bar reflects the distribution among all genAI users. Data source is the August and November 2024 waves of the RPS, ages 18-64 (the June 2024 Pilot did not ask about time spent using genAI). The sample is employed respondents who use genAI for work The sample for this figure is employed individuals with a valid occupation (August, $N = 984$; November, $N = 1008$).

C Results on Generative AI Use: Comparing the RPS and SWAA

Figure C.1: Share of Respondents Using Specific Generative AI Products

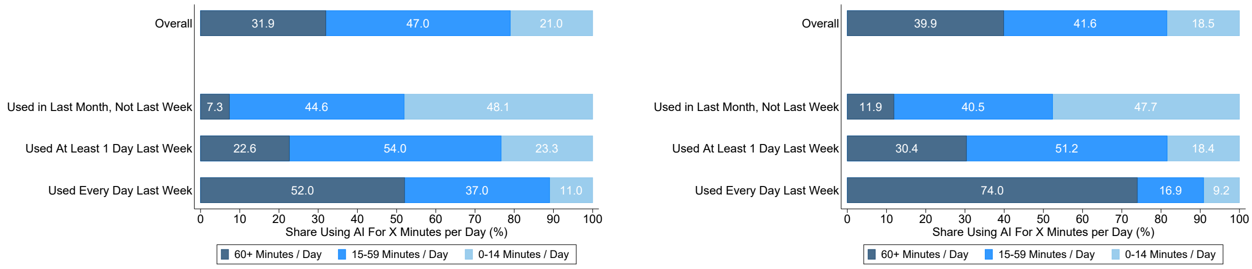
(a) RPS: August & November 2024 (b) SWAA: December 2024



Notes: The figure shows the share of respondents who report using particular genAI products. "Embedded products" are genAI features embedded within existing software, such as Microsoft Copilot. Data source is the August and November 2024 waves of the RPS, ages 18-64 ($N = 9742$) and the December 2024 SWAA, ages 20-64 ($N = 4698$). Individuals who report using multiple genAI products are reflected in multiple bars.

Figure C.2: Intensity of genAI Use For Work

(a) RPS: August & November 2024 (b) SWAA: December 2024



Notes: The figure shows the distribution of daily time spent actively using genAI for work, among genAI users. Usage time is broken down into 0-14 minutes per day (light blue), 15-59 minutes per day (medium blue), and 60 or more minutes per day (dark blue). The "Overall" bar reflects the distribution among all genAI users. In Panel a, data source is the August and November 2024 waves of the RPS, ages 18-64. In Panel b, data source is the December 2024 SWAA, ages 20-64. The sample for both data sources is employed respondents who use genAI for work. (RPS, $N = 1918$; SWAA, $N = 861$).

D RPS: Measurement and Definitions

D.1 Sample Restrictions

The Qualtrics panel includes about 15 million members and is not a random sample of the U.S. population. However, researchers can instruct Qualtrics to target survey invitations to specific demographic groups. The RPS sample was designed to be nationally representative of the U.S. across gender, age, education, household income, and other demographic characteristics. Individuals who take the survey too fast, i.e. in less than 50% of the median time in a soft launch, or who do not state that they will provide their best answers, are automatically dropped from the sample.[1] Finally, once fielding is completed Qualtrics staff goes over all responses and filters out any that look suspicious. This is typically the case for 1% to 3% of the responses.

The pilot survey in June 2024 received 2,551 responses. Our full surveys in August and November 2024 received 5,014 and 5,329 responses, respectively. We dropped 14, 33, and 26 respondents, respectively, from the June, August, and November surveys because they reported their industry and/or occupation as military. An additional 9, 9, and 11 respondents were dropped from the June, August, and November survey because they reported being employed but also reported being homemakers, retired, or unemployed as their occupation. Table 1 show the raw sample composition for each survey after these observations were dropped.

We also include occupation in our weighting scheme. This requires us to drop another 108, 112, and 115 observations due to missing occupation codes for the June, August, and November surveys, respectively. We drop another 72, 157, and 148 employed respondents after constructing weights because we lack information on their Generative AI use at work last week. Almost all of these dropped respondents were classified as "employed, absent from work last week" as they by construction cannot have used Generative AI last week. Accounting for all individuals dropped from our analysis, this leaves us with a final sample size of 94.9%, 96.3%, and 95.2% of the initially collected responses for the June and August surveys, respectively.

Table 1 compares the sample composition between the CPS and RPS along the demographics targeted in the sampling procedure for our main surveys (columns 1 and 2). The most notable discrepancies are that individuals aged 18 to 24 and with no more than a high school degree are underrepresented in the RPS relative to the CPS, while individuals with household income of $50,000 or less are overrepresented. The bottom panel of Table 1 compares employment

[1] The exact phrasing of the screener question is: "We care about the quality of our survey data and hope to receive the most accurate measure of your opinions, so it is important to us that you thoughtfully provide your best answer to each question in the survey. Do you commit to providing your thoughtful and honest answers to the questions in this survey?" with the following three answer options (1) I will provide my best answers, (2) I will not provide my best answers, and (3) I can't promise either way. According to Qualtrics staff, this question provides the best results in terms of screening out respondents.

status in the CPS and RPS, statistics that have not been targeted in the sampling procedure. Employment rates are very similar across the two surveys, although individuals classified as unemployed according to the CPS definition are somewhat overrepresented in the RPS.

D.2 Weighting

As described in the body of the paper, we asked Qualtrics to administer the survey to a sample of respondents who match the U.S. population along a few broad demographic characteristics: gender, five age bins (18-24, 25-34, 35-44, 45-54, 55-64), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, other), education (high school or less, some college or associate degree, bachelor's degree or more), marital status (married or not), number of children in the household (0, 1, 2, 3 or more), three income bins for household income over the last 12 months (<\$50k, \$50k-100k, >\$100k), and four Census regions. Table 1 compare the sample composition between the pooled August and November RPS and the CPS along the demographics targeted in the sampling procedure for our main survey. The tables look very similarly for each survey wave separately, including the June pilot, and are available upon request. As discussed in the paper, we also compare at the bottom of the table employment status in the CPS and RPS, as well as the demographic composition for the employed. None of this latter sets of moments were targeted during the sampling of survey respondents.

Using the iterative proportional fitting (raking) algorithm of Deming and Stephan (1940), we construct sampling weights to ensure the RPS matches the CPS sample proportions for the same set of demographic characteristics included in the Qualtrics sampling targets for the overall sample, i.e., independent of employment status. However, we use more disaggregated categories for education and marital status, and we interact all categories with gender. In particular, for education, we distinguish between less than high school, high school graduate or equivalent, some college but no degree, associate degree, bachelor's degree, and graduate degree. For marital status, we distinguish between married + spouse present, divorced, never married, and "other." We also condition on relationship status (spouse living in the same household, partner living in the same household, other).

In addition, our sampling weights replicate the employed-at-work rates, the employment rates, and the labor force participation rates in each of the subsequent months. We match these key labor market statistics not only in the aggregate but also conditional on demographic characteristics. More specifically, we match the employed-at-work rate, the employment rate, and the labor force participation rate for the current month by gender, age (18-24, 25-34, 35-44, 45-54, 55-64), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, all other racial and ethnic groups), education (high school or less, some college or associate degree, bachelor's degree or more), marital status (married + spouse present, never married, other), relationship status (spouse living in the same household, partner living in the same household, other), presence of children in the household (yes or no), household income over the last 12 months (<\$50k, \$50k-100k, >\$100k), and region (Midwest, Northeast, South, and West using the Census definition). These groupings were chosen to ensure that each cell size is at least 30. We also include 2-digit occupation codes in our weighting scheme. Among the 22 occupations, we merge several occupations to ensure a sufficient sample size. In particular, for the June 2024 survey, we merge a) "Architecture and Engineering Occupations" and "Life, Physical, and Social Science Occupations", b) "Community and Social Service Occupations" and "Legal Occupations", c) "Healthcare Support Occupations" and "Protective Service Occupations", and d) "Farming, Fishing, and Forestry Occupations" and "Construction and Extraction Occupations." For the August and November 2024 survey, we proceeded similarly but, due to the larger sample size, did not need to merge "Architecture and Engineering Occupations" and "Life, Physical, and Social Science Occupations."

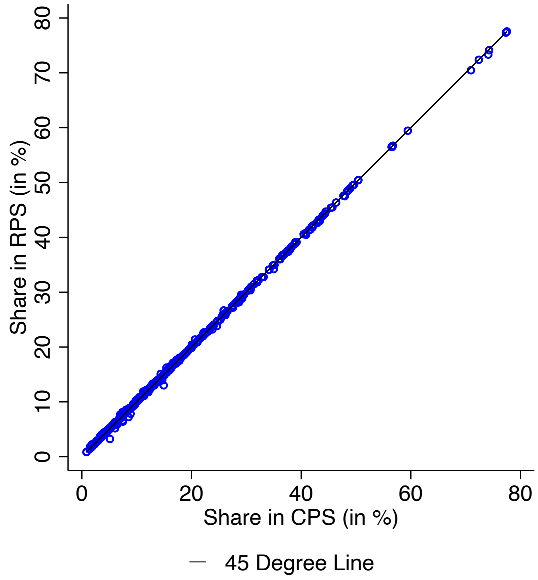
The weighting scheme necessitated dropping some observations due to missing occupation and other discrepancies, resulting in a final sample size of 96.3% of initially collected responses.

Including all the interaction terms, we have a total of 48 statistics (e.g., gender is one, and gender x education is another) which we weight on, with a combined 295 categories (e.g., gender has two categories, and gender x education has 2 x 6 = 12 categories; for the June 2024 we only have 294 categories because of the additional occupational grouping). To visualize the goodness of fit, we plot in Figure D.1 for all statistics used in the weighting scheme, the weighted fraction of individuals with the respective characteristics in the RPS (on the y-axis) and the CPS (on the x-axis) for August and November 2024. The lack of sizeable deviations from the 45-degree line demonstrates how well the weighting procedure works. The results are similar for each survey wave separately, including the June pilot, and are available upon request.

D.3 Definition of Industries and Occupations

Industries correspond to the 22 major industries in the NAICS: Agriculture, Forestry, Fishing, and Hunting (NAICS=11); Mining, Quarrying, and Oil and Gas Extraction (NAICS=21); Utilities (NAICS=22); Construction (NAICS=23); Manufacturing (NAICS=31-33); Wholesale Trade (NAICS=42); Retail Trade (NAICS=44-45); Transportation and Warehousing (NAICS=48-49); Information (NAICS=51); Finance and Insurance (NAICS=52); Real Estate and Rental and Leasing (NAICS=53); Professional, Scientific, and Technical Services (NAICS=54); Management of Companies and Enterprises (NAICS=55); Administrative and Support and Waste Management Services (NAICS=56); Educational Services (NAICS=61); Health Care and Social Assistance (NAICS=62); Arts, Entertainment, and Recreation (NAICS=71); Accommodation and Food Services (NAICS=72); Other Services (except Public Administration) (NAICS=81);

Figure D.1: Sample Composition in the Weighted RPS vs. CPS for August and November 2024



Notes: The figure shows for all statistics used in the weighting scheme, the weighted fraction of individuals with the respective characteristics in the RPS (on the y-axis) and the CPS (on the x-axis).

Public Administration (NAICS=99).

The industry groupings used in the main text figures are: Agriculture / Extraction (sectors 11, 21), Construction (23), Manufacturing (31-33), Wholesale / Retail Trade (42, 44-45), Transportation / Utilities (22, 48-49), Info Services (51), Finance / Real Estate (52, 53), Professional / Business Services (54, 55, 56), Education / Health/ Social / Public Services (61, 62, 92), Leisure / Accommodation / Other (71, 72, 81).

Occupations correspond to the 22 major occupations in the SOC: Management Occupations (SOC=11); Business and Financial Operations Occupations (SOC=13); Computer and Mathematical Occupations (SOC=15); Architecture and Engineering Occupations (SOC=17); Life, Physical, and Social Science Occupations (SOC=19); Community and Social Service Occupations (SOC=21); Legal Occupations (SOC=23); Educational Instruction and Library Occupations (SOC=25); Arts, Design, Entertainment, Sports, and Media Occupations (SOC=27); Healthcare Practitioners and Technical Occupations (SOC=29); Healthcare Support Occupations (SOC=31); Protective Service Occupations (SOC=33); Food Preparation and Serving Related Occupations (SOC=35); Building and Grounds Cleaning and Maintenance Occupations (SOC=37); Personal Care and Service Occupations (SOC=39); Sales and Related Occupations (SOC=41); Office and Administrative Support Occupations (SOC=43); Farming, Fishing, and Forestry Occupations (SOC=45); Construction and Extraction Occupations (SOC=47); Installation, Maintenance, and Repair Occupations (SOC=49); Production Occupations (SOC=51);

Transportation and Material Moving Occupations (SOC=53).

The occupation groupings used in the main text figures are: Personal Services occupations combine SOC codes 31-39: Healthcare support, Protective services, Food preparation and serving, Cleaning and maintenance, and Personal care. Blue Collar occupations combine SOC codes 47-53: Construction, Extraction, Installation, Maintenance and Repair, Production, Transportation, and Moving.

We elicited respondents' job titles through a free text response with autocomplete suggestions covering over 40,000 occupations from O*NET and the Occupational Outlook Handbook and then match them to Standard Occupation Classification (SOC) codes using a parsing algorithm that identifies occupations in 97 percent of cases. For job titles that do not exactly match a unique SOC code, we present respondents with a choice of probabilistic matches using the job title to SOC code matching algorithm developed by the National Institute for Occupational Safety and Health (Laughlin et al., 2024).

D.4 Validation Checks

To illustrate how the RPS and CPS compare for characteristics that are not part of the sampling scheme and the effect of weighting, panels (a) and (b) of Figure 1 compare the usual weekly earnings distribution in the RPS and CPS in the pooled August and November 2024 waves, with and without weights, respectively. The unweighted distributions are already similar, and the weights improve the fit further.

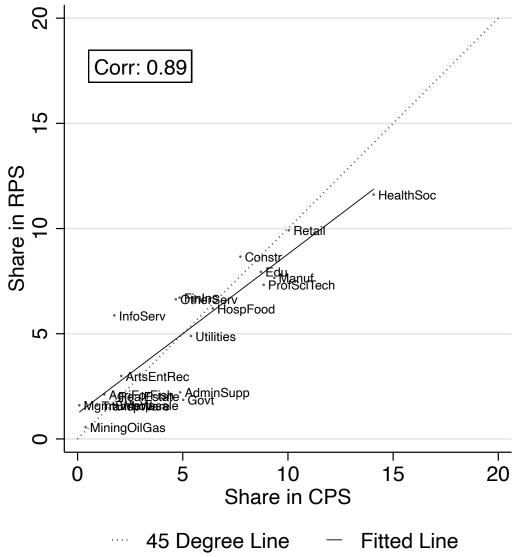
Panels (c) and (d) of Figure 1 compare occupation shares in the RPS and the CPS, unweighted and weighted respectively. The unweighted correlation is 0.88, with Management as the only major outlier. Applying the weights corrects this imbalance and mechanically increases the correlation to 1.

Figure D.2 compare the industry shares in the RPS and CPS in the pooled August and November 2024 waves, with and without weights, as well as college major shares in the RPS and 2022 American Community Survey (ACS). The unweighted correlations of the industry shares is 0.89, comparable to those for occupations. The correlation of college majors in the RPS and the ACS is 0.83. The major with the highest share relative to the ACS is Computers, Mathematics, & Statistics, while the major with the lowest share relative to the ACS is Science and Engineering Related Fields. Weighting the data marginally improves the fit between the RPS and the two other data sets.

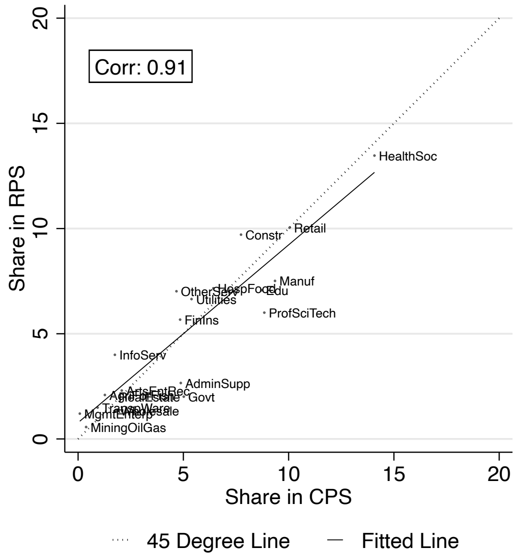
All four variables align closely across survey waves, including the June pilot, and are available upon request. The only exception is industry composition in the June 2024 survey (excluded from the main text), where the correlation is 0.74. This results from a higher Other Services" share in the RPS than in the CPS, a recurring issue in past RPS waves Bick and Blandin, 2023. We attribute this to respondents selecting Other" when unsure of their industry, unlike in the CPS, where professional coders classify responses. To address this, starting in the August 2024 survey, we prompted those selecting "Other Services" with the following question: "We would like to know some more details about what kind of business or industry this job is. Please include the main activity, product, or service provided at the location where you are employed. (For example: elementary school, residential construction)." We provided an open text field for respondents to type their answers. These responses were routed to an industry and occupational coder at the National Institute for Occupational Safety and Health (NIOSH) (`https://csams.cdc.gov/nioccs/SingleCoding.aspx`). Based on the provided responses, the system suggested the top five 6-digit NAICS codes plus an "Other" option. We assigned industry based on their choice, with "Other" being classified as "Other Services - Other Personal Services." Figure D.2 confirms this resolved the issue.

Figure D.2: Validation Checks – Industry and Major Shares

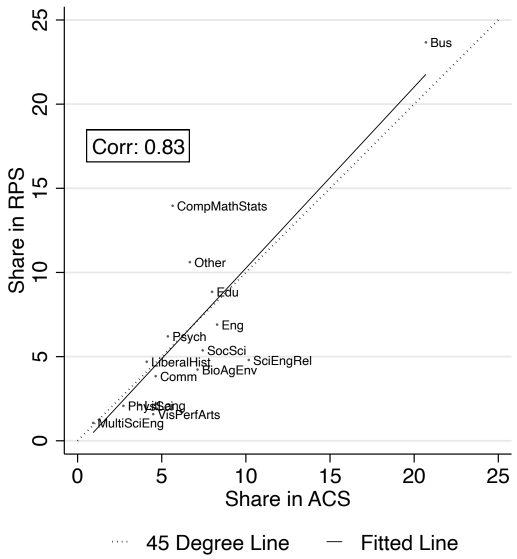
(a) Industry: Unweighted



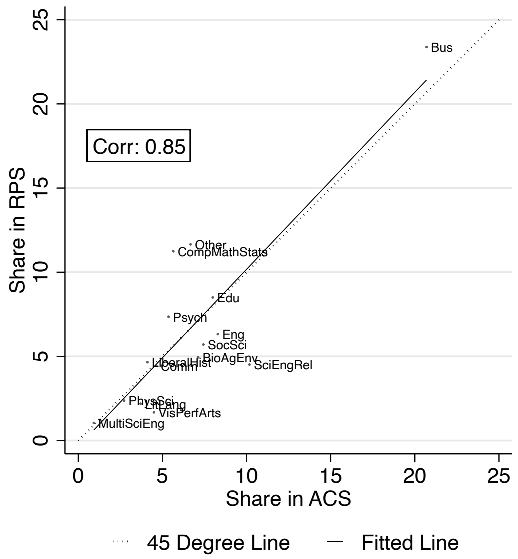
(b) Industry: Weighted



(c) Major Shares: Unweighted



(d) Major Shares: Weighted



Notes: Figures on the left use unweighted RPS data, figures on the right use weighted RPS data. We use the same sample of RPS respondents in both figures. All figures use weighted CPS and ACS data, respectively. Data samples for the industry comparison are employed respondents ages 18-64 in the pooled August and November 2024 RPS and CPS with sample sizes of 6951 and 85546 , respectively. Data samples for the college major comparison are respondents with a college degree ages 18-64 in the pooled August and November 2024 RPS with sample sizes of 3853 and 85546 in the 2022 ACS, respectively.

E SWAA

The Survey of Working Arrangements and Attitudes (SWAA) is a monthly cross-sectional survey of Americans aged 20 to 64 that has been running since May 2020. In December 2024, we incorporated a subset of our questions on genAI usage into the SWAA. Similar to the RPS, the SWAA is fielded online, though it is conducted by a different commercial survey provider (IncQuery) and targets a sample representative of the U.S. population aged 20–64 by age, sex, income, race, and region. Table E.1 shows the analogue of Table 1 and compares the unweighted SWAA to the weighted CPS. In addition to the targeted variables by the SWAA, we also include live-in-partner (in lieu of marital status) and the number of children. Individual income in the last 12 months is not collected by the SWAA. Similar to the RPS, the SWAA matches the targeted (and non-targeted) quotas fairly closely and the unemployed are somewhat overrepresented. We note that the SWAA uses a single question to determine employment status, which differs from the more detailed protocol used in the CPS and RPS, and map the SWAA's employment categories into the CPS definitions.[2]

E.1 Weights

To maximize comparability between the RPS and SWAA, we construct our own set of weights rather than using the weights provided by the SWAA.[3] In particular, we use again the iterative proportional fitting (raking) algorithm of Deming and Stephan (1940). We include all the demographic variables shown in Table E.1 and also interact all of them with gender. The sampling weights further replicate the employed-at-work rate, the employment rate, and the labor force participation rate in the aggregate and interacted with the demographic variables used for overall weighting. To ensure a sufficient sample size for these latter interactions, we use a broader group for age (20-29, 30-39, 40-49, 50-64) and a dummy variable for whether there is a child in the house. We also include the broad occupation groups in our weighting scheme, and as for the RPS, without any interaction.

E.2 Validation

Figure E.1 shows that similar to the RPS the occupation and industry distribution in SWAA closely aligns with CPS in December 2024.

[2]In particular, the SWAA asks: "Last week what was your work status?" with the following answer options (a) Working for pay, whether on business premises or working from home, (b) Still employed and paid, but not working, (c) Unemployed, looking for work, (d) Unemployed, awaiting recall for my old job, and (e) Not working, and not looking for work.

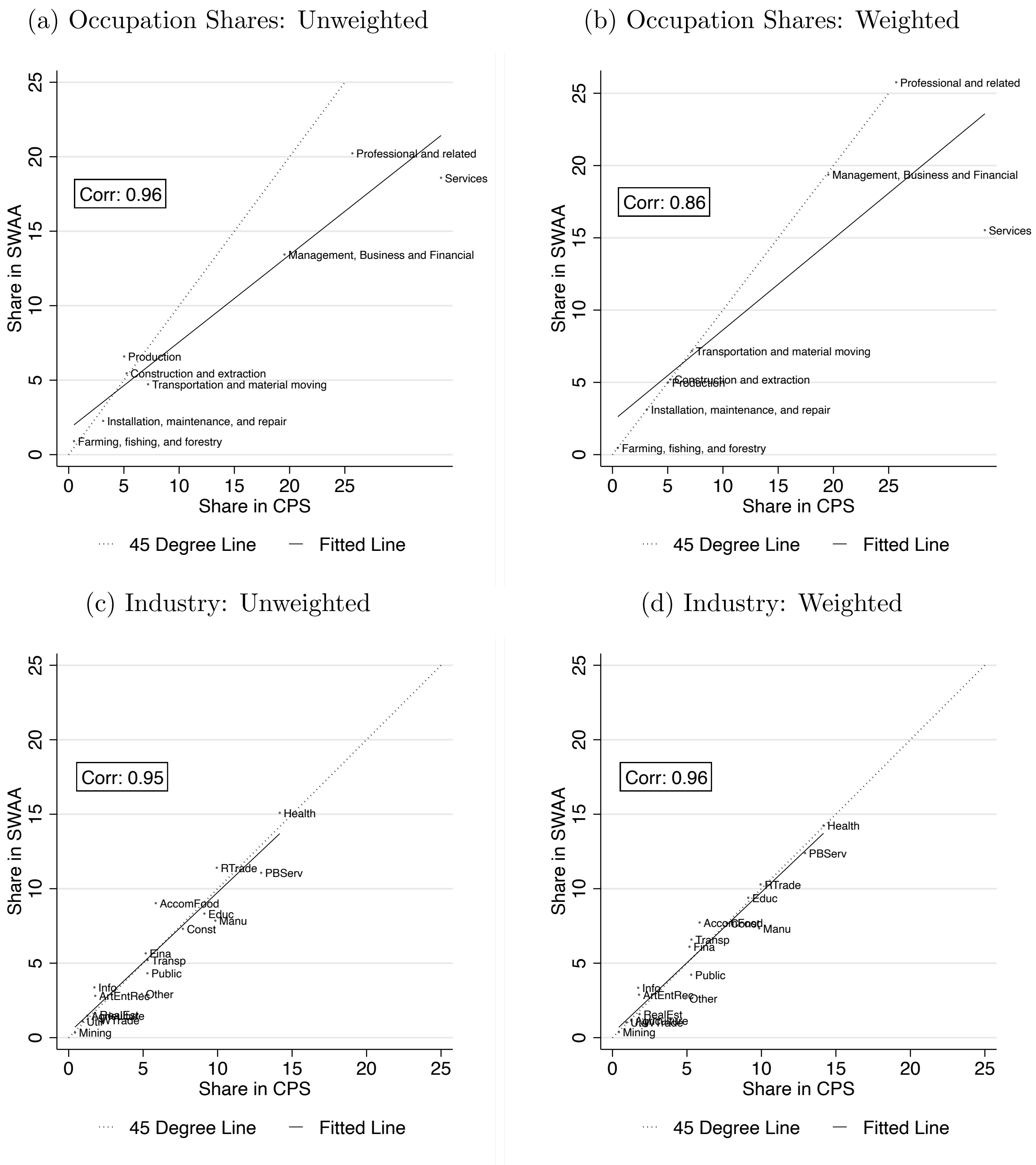
[3]Notably, the employment-to-population ratio calculated using the SWAA's provided weights is with 59% much lower than in the raw SWAA data (76.2%) and in the CPS (75.7%).

Table E.1: Sample Composition in the December 2024 CPS and SWAA

	Everyone		*Employed*	
	CPS	SWAA	CPS	SWAA
	(1)	(2)	(3)	(4)
*Gender: Women**	50.5	58.3	47.3	54.4
*Age**				
20-24	11.2	6.9	9.9	7.2
25-34	23.2	20.6	24.5	22.0
35-44	23.2	26.2	25.0	28.8
45-54	20.9	23.8	22.1	23.9
55-64	21.5	22.6	18.5	18.2
*Race/Ethnicity**				
Non-hispanic White	56.8	64.2	57.9	62.7
Non-hispanic Black	12.8	10.0	12.1	10.1
Hispanic	20.3	19.6	20.1	20.9
Other	10.1	6.2	9.9	6.2
*Education**				
Highschool or less	35.4	34.6	31.8	30.4
Some college/Associate's degree	25.7	28.9	25.1	28.3
Bachelor's or Graduate degree	38.9	36.5	43.1	41.3
Live-in-Partner	60.1	55.5	62.7	55.6
Number of children				
0	58.1	56.4	57.0	53.4
1	17.6	21.3	18.0	23.1
2	14.8	15.6	15.7	16.8
3+	9.5	6.7	9.3	6.7
*Region**				
Northeast	17.0	18.6	17.0	19.7
Midwest	20.3	20.6	21.0	20.3
South	38.7	44.0	38.2	43.3
West	24.0	16.9	23.8	16.6
Employment Status				
Employed, at work last week	73.7	71.7		
Employed, absent from work last week	2.0	4.5		
Unemployed	2.8	9.6		
Not in the labor force	21.5	14.2		
Observations	54949	4975	41481	3793

Notes: Column 1 reports the sample composition in the December 2024 Current Population Survey (CPS) for the variables most comparable to those targeted in the RPS in the sampling procedure. The SWAA targets only the variables marked with an asteriks. The employment status is neither targeted in the RPS nor the SWAA. Column 2 reports the sample composition in the December 2024 SWAA. The sample in both data sets is restricted to the civilian population ages 20-64. Columns 3 and 4 report the same outcomes for the employed (at work and absent from work last week).

Figure E.1: SWAA Validation Checks



(a) Occupation Shares: Unweighted

(b) Occupation Shares: Weighted

(c) Industry: Unweighted

(d) Industry: Weighted

Notes: Figures on the left use unweighted SWAA data, figures on the right use weighted SWAA data using our own weights. All figures use weighted CPS data. Data samples are all employed respondents. Sample sizes for the December 2024 SWAA and CPS are 4419 and 43202, respectively.

F Details on Time Savings and Productivity Calculations

F.1 Derivations Using the Aggregate Production Model

The Aggregate Productivity Gain from Generative AI

We model the economy's aggregate output using a Cobb-Douglas aggregate production function where labor supply is perfectly substitutable across workers. The economy contains N workers. Let Y denote the aggregate output, and let L denote the aggregate supply of labor measured in efficiency units (going forward we refer to this as aggregate effective labor supply). The aggregate production function is given by:

$$Y = AK^{\alpha}L^{1-\alpha}, \tag{F.1}$$

where A is TFP, K is the aggregate capital stock, and α is the Cobb-Douglas share on capital. The aggregate effective supply of labor L is defined as the weighted sum of individual labor supplies:

$$L = \sum_{i=1}^{N} \ell_i e_i \tag{F.2}$$

where ℓ_i is the number of hours worked per week by worker i, and e_i is the efficiency units of labor supplied by worker i.

In a competitive labor market, each worker is paid their marginal product of labor:

$$w_i = (1-\alpha)A(K/L)^{\alpha}e_i \tag{F.3}$$

where w_i is the worker's hourly wage. Normalizing the mean efficiency unit to $\overline{e} = 1$, we have:

$$\tilde{w}_i \equiv \frac{w_i}{\overline{w}} = \frac{w_i}{\left(\sum_i w_i\right)/N} = \frac{(1-\alpha)A(K/L)^{\alpha}e_i}{\left(\sum_i (1-\alpha)A(K/L)^{\alpha}e_i\right)/N} = \frac{(1-\alpha)A(K/L)^{\alpha}e_i}{(1-\alpha)A(K/L)^{\alpha}\overline{e}} = e_i \tag{F.4}$$

where $\tilde{w}_i$ is worker i's wage relative to mean wages $\overline{w}$.

Suppose that worker i saves s_i hours per week due to genAI and spends this time on additional production within their job. The effective weekly labor supply for worker i is then $\ell_i + s_i$. Substituting this into the expression for aggregate effective labor supply, we have:

$$L' = \sum_i (\ell_i + s_i)e_i = \sum_i \ell_i e_i + \sum_i s_i e_i. \tag{F.5}$$

The change in aggregate effective labor supply attributable to genAI-induced time savings is:

$$\Delta L \equiv L' - L = \sum_i s_i e_i = \sum_i s_i \tilde{w}_i \tag{F.6}$$

Assuming no change in TFP, capital, and hours worked, the percent change in aggregate productivity from genAI equals the percent change in aggregate output. The approximate percent change in aggregate output from genAI is given by:

$$\frac{\Delta Y}{Y} \approx (1-\alpha)\frac{\Delta L}{L} = \underbrace{(1-\alpha)}_{\text{labor cost share}} \times \underbrace{\frac{\sum_i s_i \tilde{w}_i}{\sum_i \ell_i \tilde{w}_i}}_{\Delta\%\text{effective labor}} \tag{F.7}$$

This equation states that the percent change in output due to genAI is the ratio of mean time savings to mean hours worked, weighted by worker's wages, and scaled by labor's share of production costs.

Using November 2024 RPS data on hourly wages w_i, weekly hours worked ℓ_i, and weekly genAI time savings s_i, we use (F.7) to estimate that genAI currently increases aggregate effective labor supply by 1.9%.[4]If we assume an AI-exposure-adjusted labor share of 0.57, following Acemoglu (2024), the implied potential productivity gain is 1.1%.

Comparisons to Micro and Macro Estimates of GenAI Productivity Gains

How does our estimate of the aggregate productivity gain from genAI compare with experimental estimates from the literature? To answer this question, we reformulate the model to express time savings as a linear function of time spent using the technology:

$$L' = \sum_i (l_i + \gamma u_i) e_i = \sum_i l_i e_i + \gamma \sum_i u_i e_i \tag{F.8}$$

In this expression, u_i is the weekly hours spent using genAI by worker i, and γ is the productivity gain associated with one hour of genAI use.

We can then write the percent increase in aggregate effective labor supply due to genAI as

$$\frac{\Delta L}{L} = \frac{\gamma \sum_i \tilde{w}_i u_i}{\sum_i \tilde{w}_i l_i} \tag{F.9}$$

Next, we solve for the value of γ that would generate a 1.9 percent increase in aggregate effective

[4]This estimate is slightly higher than the average time savings due to genAI from the previous section (1.4 percent). Intuitively, this is because (more intensive) genAI users tend to have above-average wages (see Figure 5c).

labor supply given our estimates of genAI use:

$$\gamma = 1.9\% \cdot \left(\frac{\sum_i \tilde{w}_i l_i}{\sum_i \tilde{w}_i u_i} \right) \tag{F.10}$$

Recall that for each worker in the RPS data we do not have a single estimate for l_i; instead, we have a lower and upper bound, $\underline{l}_i$ and $\bar{l}_i$, respectively. Evaluating (F.10) using the midpoint of these bounds, $l_i \equiv (\underline{l}_i + \bar{l}_i)/2$, yields a wage-weighted share of total work hours spent using genAI of 5.7%, which implies a productivity parameter value of $\gamma = 0.33$. This implies that each hour spent using genAI increases the worker's productivity for that hour by 33%. This is similar in magnitude to the average value of 27% from several randomized experiments of genAI usage (Cui et al., 2024; Dell'Acqua et al., 2023; Noy and Zhang, 2023; Peng et al., 2023).