

# The Rapid Adoption of Generative AI

Alexander Bick

Adam Blandin

David Deming

ONLINE APPENDIX

## A RPS: Measurement and Definitions

### A.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.<sup>1</sup> Finally, once fielding is completed Qualtrics staff goes over all responses and filters out any that look suspicious. This is typically the case for around 10% of the responses. We also screened manually out responses whose responses to the free text question about the industry appear to be generated by a bot taking the survey. This was the case for less than 10 responses in each survey.

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. In each survey, we dropped less than 40 respondents because they either reported their industry and/or occupation as military or because they reported being employed but also reported being homemakers, retired, or unemployed as their occupation. Table A.1 show the raw sample composition for the pooled August and November 2024 surveys after these observations were dropped.

We also include occupation in our weighting scheme. This requires us to drop another 108, 112, and 113 observations due to missing occupation codes for the June, August, and November surveys, respectively. We drop another 70, 154, and 145 employed respondents after constructing weights because we lack information on their Generative AI use at work last week. 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 94.7%, 96.8%, and 96.9% of the initially collected responses for the June and August surveys, respectively.

Table A.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

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<sup>1</sup>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.

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 A.1 compares employment 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.

## A.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 A.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).

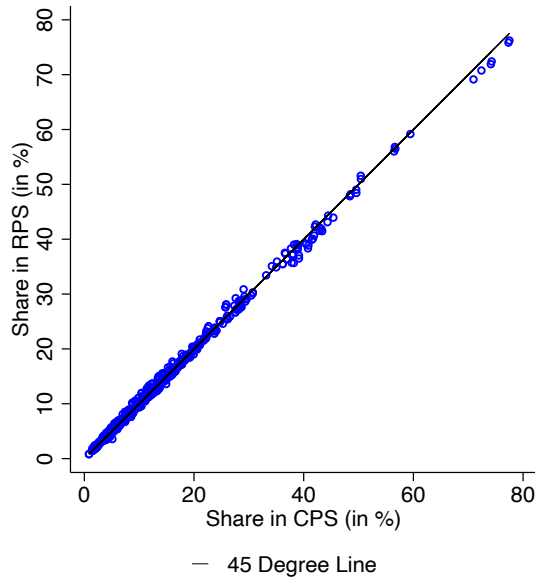
In addition, our sampling weights replicate the employed-at-work rates, the employment rates, and the labor force participation rates in each of the subsequent months. We match these key labor market statistics not only in the aggregate but also conditional on demographic characteristics. More specifically, 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-

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

	<i>Everyone</i>		<i>Employed</i>	
	CPS (1)	RPS (2)	CPS (3)	RPS (4)
<i>Gender: Women</i>	50.4	52.2	47.3	47.5
<i>Age</i>				
18-24	15.0	11.7	12.0	12.0
25-34	22.2	22.0	23.9	23.8
35-44	22.2	23.8	24.4	25.0
45-54	20.1	21.2	21.7	21.7
55-64	20.6	21.2	17.9	17.5
<i>Race/Ethnicity</i>				
Non-hispanic White	56.5	56.4	57.8	57.8
Non-hispanic Black	12.9	13.2	12.1	12.3
Hispanic	20.5	20.4	20.2	19.8
Other	10.1	10.0	9.9	10.1
<i>Education</i>				
Highschool or less	37.1	32.9	32.8	27.1
Some college/Associate's degree	25.8	27.6	25.2	27.6
Bachelor's or Graduate degree	37.1	39.5	42.0	45.3
<i>Marital Status: Married</i>	50.1	49.0	52.8	52.4
<i>Number of children</i>				
0	58.1	55.7	57.2	52.8
1	17.8	19.7	18.1	21.2
2	14.7	16.5	15.5	18.4
3+	9.3	8.1	9.2	7.6
<i>Household Income in Last 12 Months</i>				
\$0-\$50,000	26.1	31.4	19.9	22.6
\$50,000-\$100,000	29.9	29.5	30.7	32.1
\$100,000+	44.0	39.1	49.5	45.3
<i>Region</i>				
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	37.9
West	23.8	24.2	23.9	24.2
<i>Employment Status</i>				
Employed, at work last week	71.7	69.8		
Employed, absent from work last week	2.5	2.9		
Unemployed	3.2	8.0		
Not in the labor force	22.6	19.3		
<i>Observations</i>	115477	10241	85546	7450

*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).

FIGURE A.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).

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.”

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  $2 \times 6 = 12$  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 A.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.

### A.2.1 Weighting Adjustment Based on Awareness

In addition to the raking procedure described above to ensure representativeness along demographic characteristics, our weighting scheme incorporates results from a new experimental survey that tested alternative question sequences for measuring genAI awareness and use. This experiment revealed that our original question sequence likely underestimated genAI awareness. In response, we applied a reweighting adjustment to our 2024 survey waves to align them with the higher awareness rates observed under the alternative design. This raises reported usage levels modestly (by about 5–6 percentage points) without altering any qualitative patterns in the results.

**Details.** In survey waves prior to August 2025, respondents were first asked whether they had heard of generative AI and, conditional on having heard of it, about their usage. To assess whether this structure induced systematic differences in reporting, we introduced a randomized experiment in a survey conducted in August 2025. Respondents were randomly assigned to one of two groups. Group 1 received the original sequential flow, where they were first asked whether they had heard of genAI, and then whether they used it. Alternatively, Group 2 was first asked whether they used genAI, and if they did not use it they were asked why, with one option being that they had not heard of it.

**Measurement differences across groups.** We found that a larger share of respondents reported having heard of genAI in Group 2. Specifically, 79.6 percent of Group 1 reported having heard of genAI, compared with 88.4 percent of Group 2. Across the two groups, a similar share of respondents reported using genAI conditional on having heard of genAI, suggesting that differential awareness reporting was evenly split between genAI users and non-users. The higher awareness rate in Group 2, combined with similar usage rates conditional on awareness between Groups 1 and 2, translated into higher overall usage rates in Group 2. Similar patterns held across employment status and for usage at home and at work. These results indicate that the initial awareness question (for Group 1) generated a downward bias in reported usage rates. One possible explanation for this pattern is that some respondents strategically reported that they had not heard of genAI because they guessed they would receive fewer questions with that answer.

**Reweighting strategy.** In the August 2025 wave, we can adjust for this bias by reweighting Group 1 respondents to match Group 2 usage rates. We constructed adjustment weights across gender, age, education, employment status, and usage (at work and at home) using a raking algorithm that increases the weight of Group 1 users relative to non-users while leaving Group 2 weights unchanged. To maintain coverage across demographic–usage cells, we did not incorporate intensity of usage into the adjustment. (Alternatively, we find that weighting on intensity of genAI interacted with only one demographic characteristics leads to very similar results.)

We then apply this adjustment to the 2024 survey waves used in this paper. Since all respondents in these prior waves received the question sequence of Group 1, we apply the adjustment to all respondents in these waves. Furthermore, the share of respondents stating they have heard of genAI (prior to our weighting adjustment) shows no trend between the surveys prior to the August 2025 survey and is very similar to Group 1 in the August 2025 survey (79.6% in vs. 79.4% in the August 2024 survey. This stability suggests that the bias in August 2025 likely existed consistently across earlier waves as well.

### A.3 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 A.2 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.

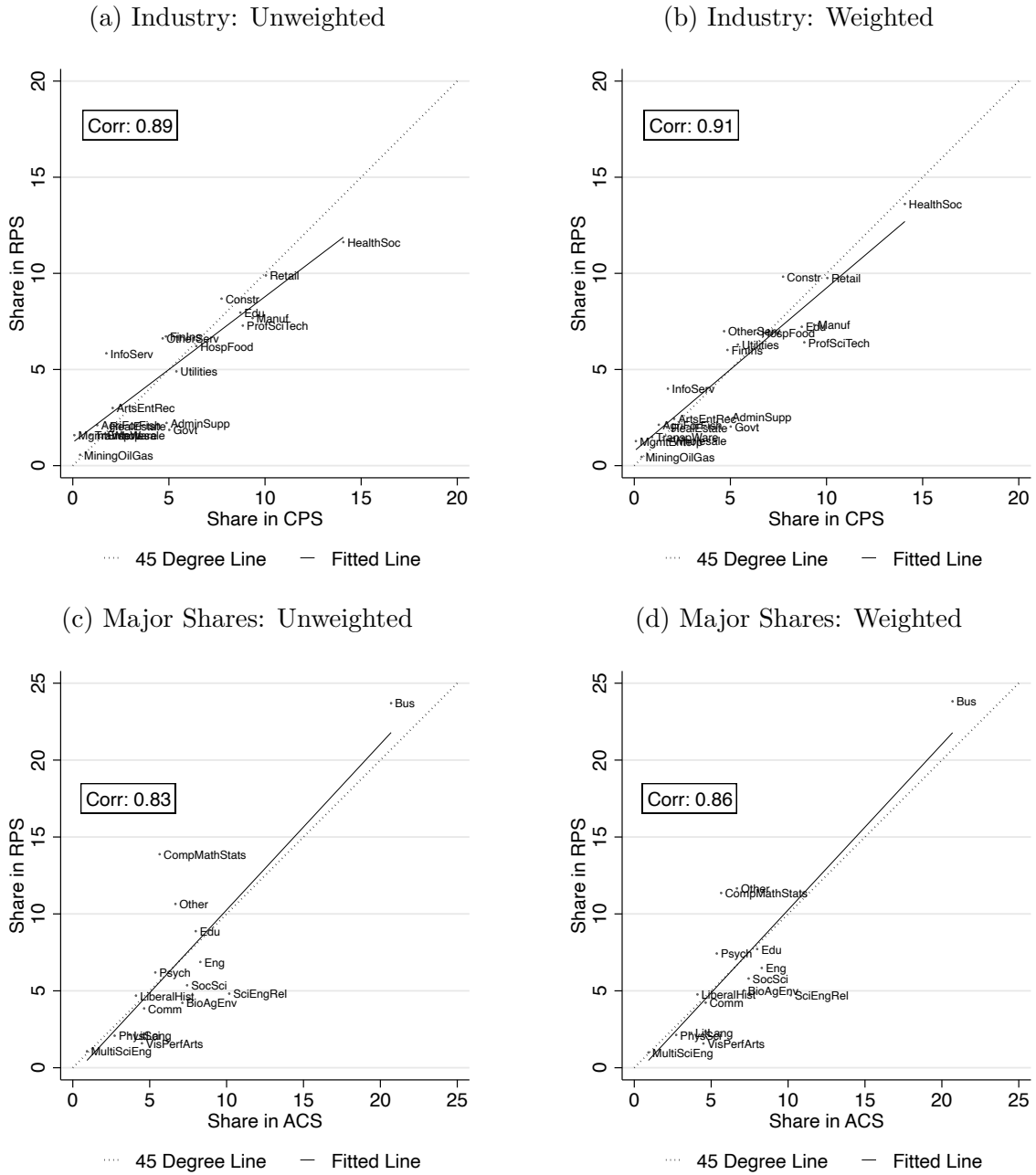
Panels (c) and (d) of Figure A.2 compare occupation shares in the RPS and the CPS, unweighted and weighted respectively. The unweighted correlation is 0.88, with Management as the only major outlier. Applying the weights corrects this imbalance and mechanically increases the correlation to 1.

Figure A.3 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 avail-



FIGURE A.3: Validation Checks – Industry and Major Shares



*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 6935 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 3840 and 85546 in the 2022 ACS, respectively.

able 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 A.3 confirms this resolved the issue.

#### A.4 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); 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).

## A.5 Reasons for Not Using Generative AI at Work

In the November 2024 wave, we asked people who know about genAI but do not use it at work the following question.

*You indicated that you do not use Generative AI for your job. Below is a list of common reasons why people do not use Generative AI for their job. Please select all that apply to you.*

The answer options were:

1. Generative AI cannot help with my job.
2. I am unsure how to use Generative AI effectively for my job.
3. My employer does not allow me to use Generative AI.

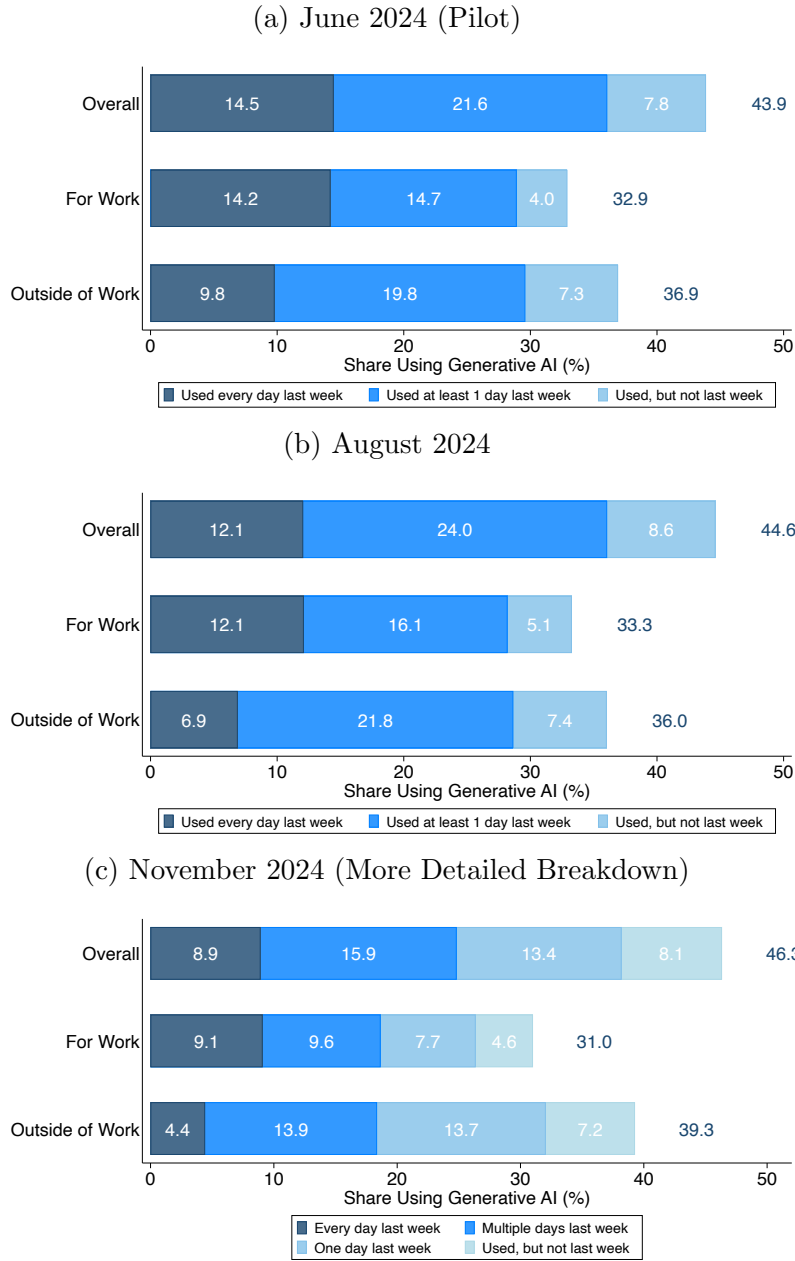
4. I am unsure whether my employer allows me to use Generative AI.
5. I feel pressure from coworkers to not use Generative AI.
6. I have privacy or security concerns.
7. I have ethical concerns.
8. I am skeptical about the quality and accuracy of AI-generated output.
9. I am worried that using Generative AI could eventually replace some or all parts of my job.
10. I am worried that using Generative AI would dilute my personal style or the creativity and authenticity of my work output.
11. Other reasons

We then followed up with the following question, displaying only the answer options selected in the previous question.

*You indicated that you not using Generative AI for your job for the following reasons. Please rank these tasks from “most important” (top) to “least important” (bottom) by dragging them.*

## B Comparison of Generative AI Use in the June (Pilot), August, and November 2024 Waves

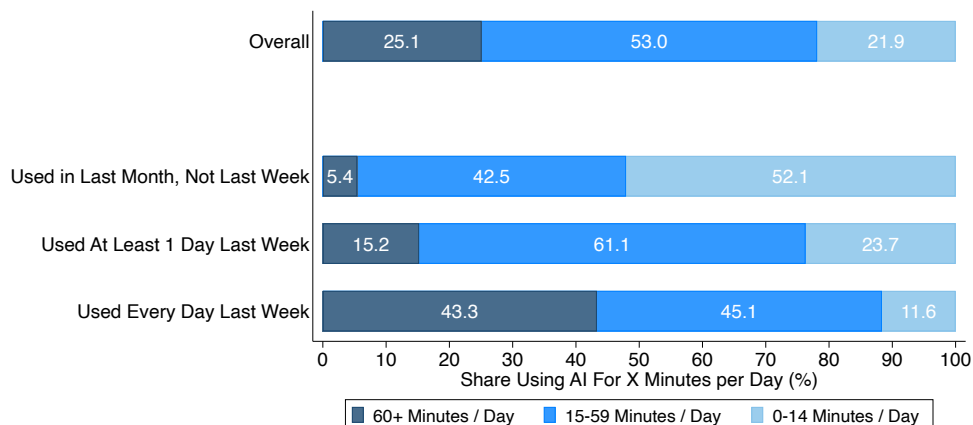
FIGURE B.1: Share of Working Age Adults Using Generative AI



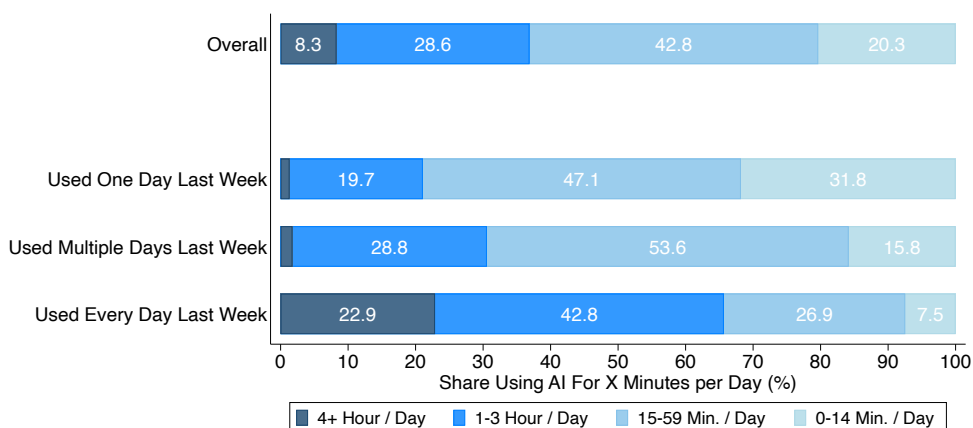
*Notes:* The figure shows the share of respondents who use genAI for work, outside of work, and overall (either for work or outside of work). Intensity of use is broken down into every day last week (dark blue), at least one day but not every day last week (medium blue), and not last week (light blue). 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,  $N = 1573$ ; August,  $N = 3238$ ; November,  $N = 3697$ ). The other bars include all respondents (June,  $N = 2351$ ; August,  $N = 4704$ ; November,  $N = 5022$ ).

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,  $N = 983$ ; November,  $N = 1000$ ).

## C 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 C.1 shows the analogue of Table A.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.<sup>2</sup>

### C.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.<sup>3</sup> 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 C.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.

### C.2 Validation

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

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<sup>2</sup>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.

<sup>3</sup>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%).

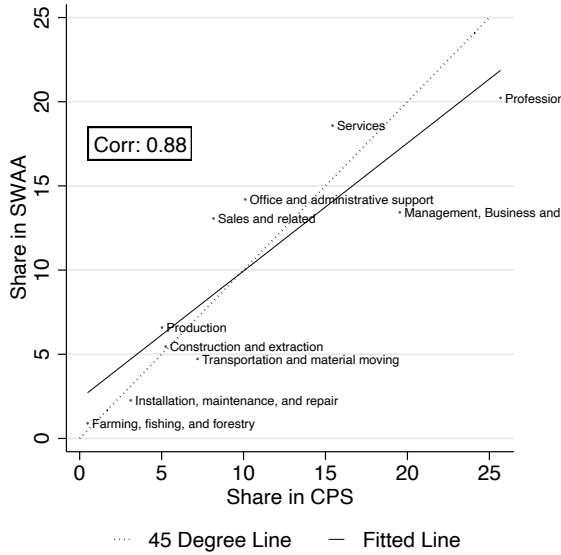
Table C.1: Sample Composition in the December 2024 CPS and SWAA

	<i>Everyone</i>		<i>Employed</i>	
	CPS (1)	SWAA (2)	CPS (3)	SWAA (4)
<i>Gender: Women*</i>	50.5	58.6	47.3	54.7
<i>Age*</i>				
20-24	11.2	6.8	9.9	7.2
25-34	23.2	20.4	24.5	21.8
35-44	23.2	26.1	25.0	28.8
45-54	20.9	23.9	22.1	24.1
55-64	21.5	22.7	18.5	18.2
<i>Race/Ethnicity*</i>				
Non-hispanic White	56.8	64.4	57.9	63.0
Non-hispanic Black	12.8	10.1	12.1	10.3
Hispanic	20.3	19.3	20.1	20.5
Other	10.1	6.2	9.9	6.2
<i>Education*</i>				
Highschool or less	35.4	34.6	31.8	30.3
Some college/Associate's degree	25.7	29.1	25.1	28.5
Bachelor's or Graduate degree	38.9	36.3	43.1	41.2
<i>Live-in-Partner</i>	60.1	55.4	62.7	55.5
<i>Number of children</i>				
0	58.1	56.4	57.0	53.3
1	17.6	21.3	18.0	23.1
2	14.8	15.6	15.7	16.9
3+	9.5	6.8	9.3	6.8
<i>Region*</i>				
Northeast	17.0	18.5	17.0	19.6
Midwest	20.3	20.6	21.0	20.4
South	38.7	44.0	38.2	43.3
West	24.0	16.9	23.8	16.7
<i>Employment Status</i>				
Employed, at work last week	73.7	71.6		
Employed, absent from work last week	2.0	4.4		
Unemployed	2.8	9.7		
Not in the labor force	21.5	14.3		
<i>Observations</i>	54949	4914	41481	3732

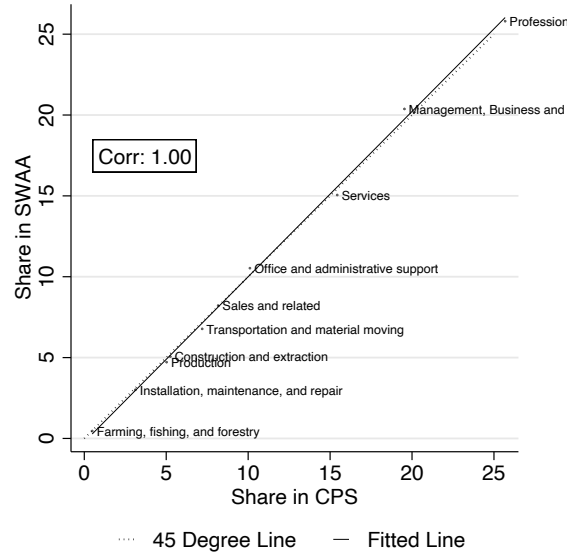
*Notes:* Column 1 reports the sample composition in the December 2024 Current Population Survey (CPS) for the variables most comparable to those targeted in the RPS in the sampling procedure. The SWAA targets only the variables marked with an asteriks. The employment status is neither targeted in the 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 C.1: SWAA Validation Checks

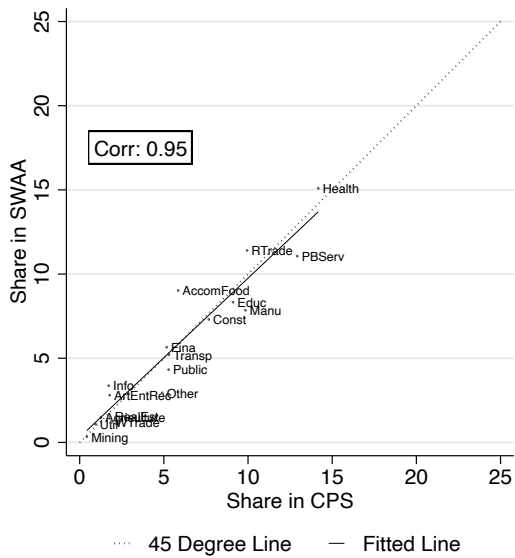
(a) Occupation Shares: Unweighted



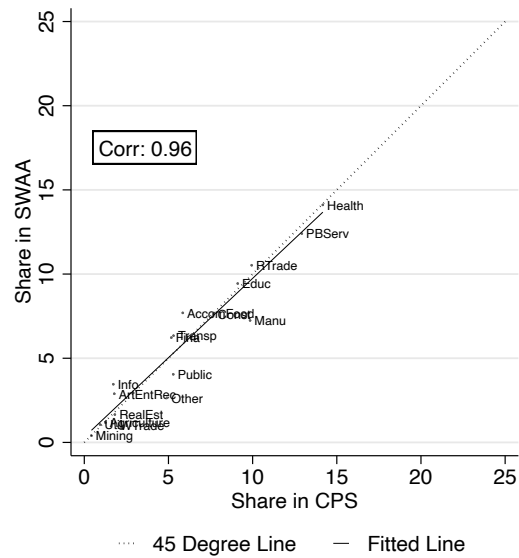
(b) Occupation Shares: Weighted



(c) Industry: Unweighted



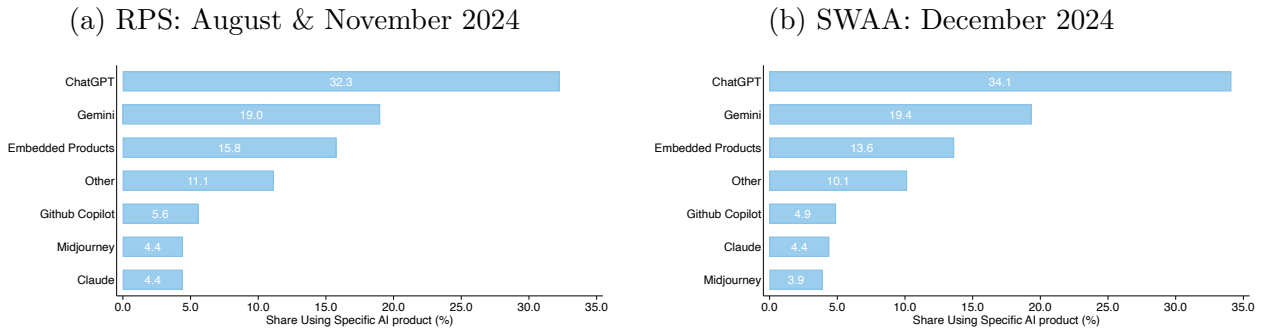
(d) Industry: Weighted



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.

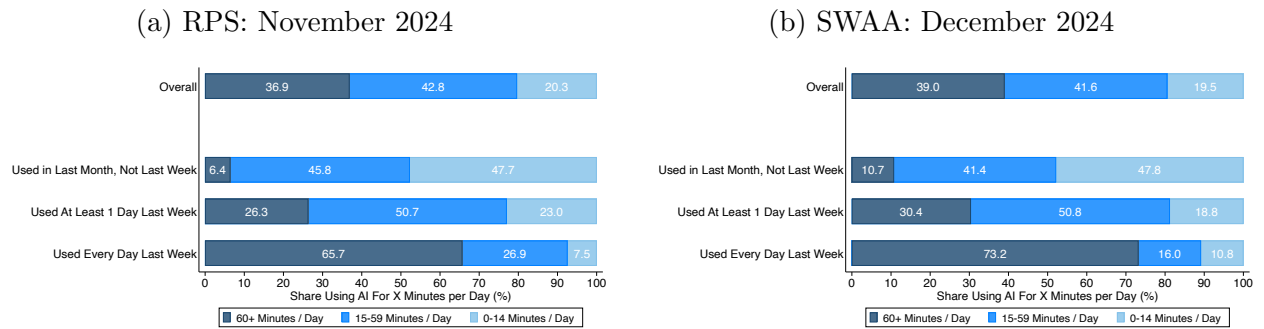
### C.3 Comparison of Generative AI Use in the RPS and SWAA

FIGURE C.2: 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 ( $N = 9742$ ) and the December 2024 SWAA, ages 20-64 ( $N = 4698$ ). Individuals who report using multiple genAI products are reflected in multiple bars.

FIGURE C.3: Intensity of genAI Use For Work



*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 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,  $N = 1000$ ; SWAA,  $N = 861$ ).

## D Details on Time Savings and Productivity Calculations

### D.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:

$$Y = AK^\alpha L^{1-\alpha}, \quad (\text{D.1})$$

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

$$L = \sum_{i=1}^N \ell_i e_i \quad (\text{D.2})$$

where  $\ell_i$  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:

$$w_i = (1 - \alpha)A(K/L)^\alpha e_i \quad (\text{D.3})$$

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

$$\tilde{w}_i \equiv \frac{w_i}{\bar{w}} = \frac{w_i}{(\sum_i w_i)/N} = \frac{(1 - \alpha)A(K/L)^\alpha e_i}{(\sum_i (1 - \alpha)A(K/L)^\alpha e_i)/N} = \frac{(1 - \alpha)A(K/L)^\alpha e_i}{(1 - \alpha)A(K/L)^\alpha \bar{e}} = e_i \quad (\text{D.4})$$

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

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:

$$L' = \sum_i (\ell_i + s_i) e_i = \sum_i \ell_i e_i + \sum_i s_i e_i. \quad (\text{D.5})$$

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

is:

$$\Delta L \equiv L' - L = \sum_i s_i e_i = \sum_i s_i \tilde{w}_i \quad (\text{D.6})$$

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:

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

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 (D.7) to estimate that genAI currently increases aggregate effective labor supply by 2.1%. If we assume an AI-exposure-adjusted labor share of 0.57, following Acemoglu (2024), the implied potential productivity gain is 1.2%.

### 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:

$$L' = \sum_i (l_i + \gamma u_i) e_i = \sum_i l_i e_i + \gamma \sum_i u_i e_i \quad (\text{D.8})$$

In this expression,  $u_i$  is the weekly hours spent using genAI by worker  $i$ , and  $\gamma$  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

$$\frac{\Delta L}{L} = \frac{\gamma \sum_i \tilde{w}_i u_i}{\sum_i \tilde{w}_i l_i} \quad (\text{D.9})$$

Next, we solve for the value of  $\gamma$  that would generate a 2.1 percent increase in aggregate effective labor supply given our estimates of genAI use:

$$\gamma = 2.1\% \cdot \left( \frac{\sum_i \tilde{w}_i l_i}{\sum_i \tilde{w}_i u_i} \right) \quad (\text{D.10})$$

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 (D.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 7.0%, which implies a productivity parameter value of  $\gamma = 0.30$ . This implies that each hour spent using genAI increases the worker's productivity for that hour by 30%. 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).

## D.2 Industry Labor Shares

Table D.1: Labor Shares by Industry

<b>Industry (NAICS2)</b>	<b>Labor Share</b>
Mining, quarrying, and oil and gas extraction	0.227
Utilities	0.237
Construction	0.717
Manufacturing	0.479
Wholesale trade	0.528
Retail Trade	0.583
Transportation and Warehousing	0.660
Information	0.389
Finance and Insurance	0.547
Real Estate and Rental and Leasing	0.070
Professional, Scientific, and Technical Services	0.759
Management of Companies and Enterprises	0.887
Administrative and Support and Waste Management and Remediation Services	0.780
Educational Services	0.849
Health Care and Social Assistance	0.846
Arts, Entertainment, and Recreation	0.806
Accommodation and Food Services	0.696
Other Services (except Public Administration)	0.837
Public Administration	0.503

Notes: Estimates are for the BLS in 2023 from Karabarbounis ([2024](#)).