The Rapid Adoption of Generative AI

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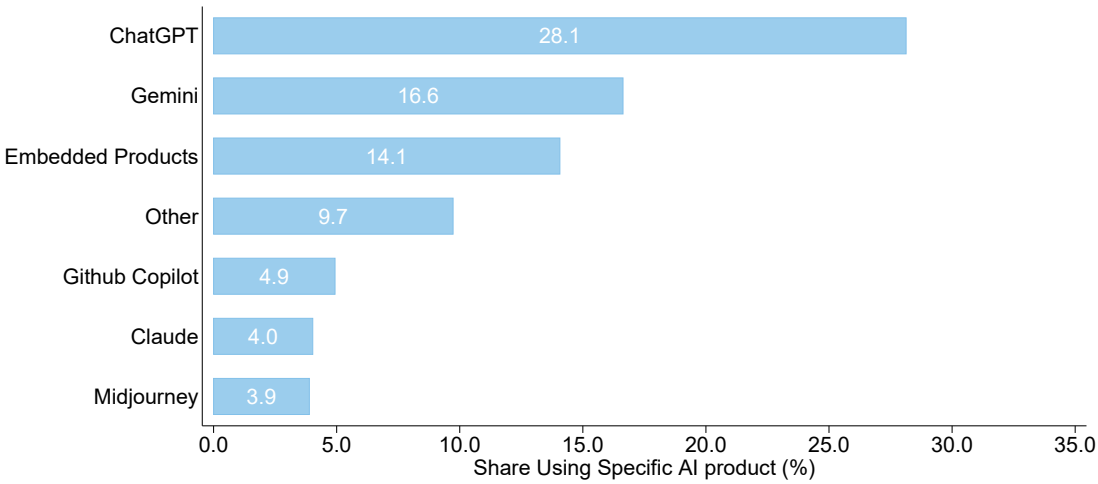
ONLINE APPENDIX

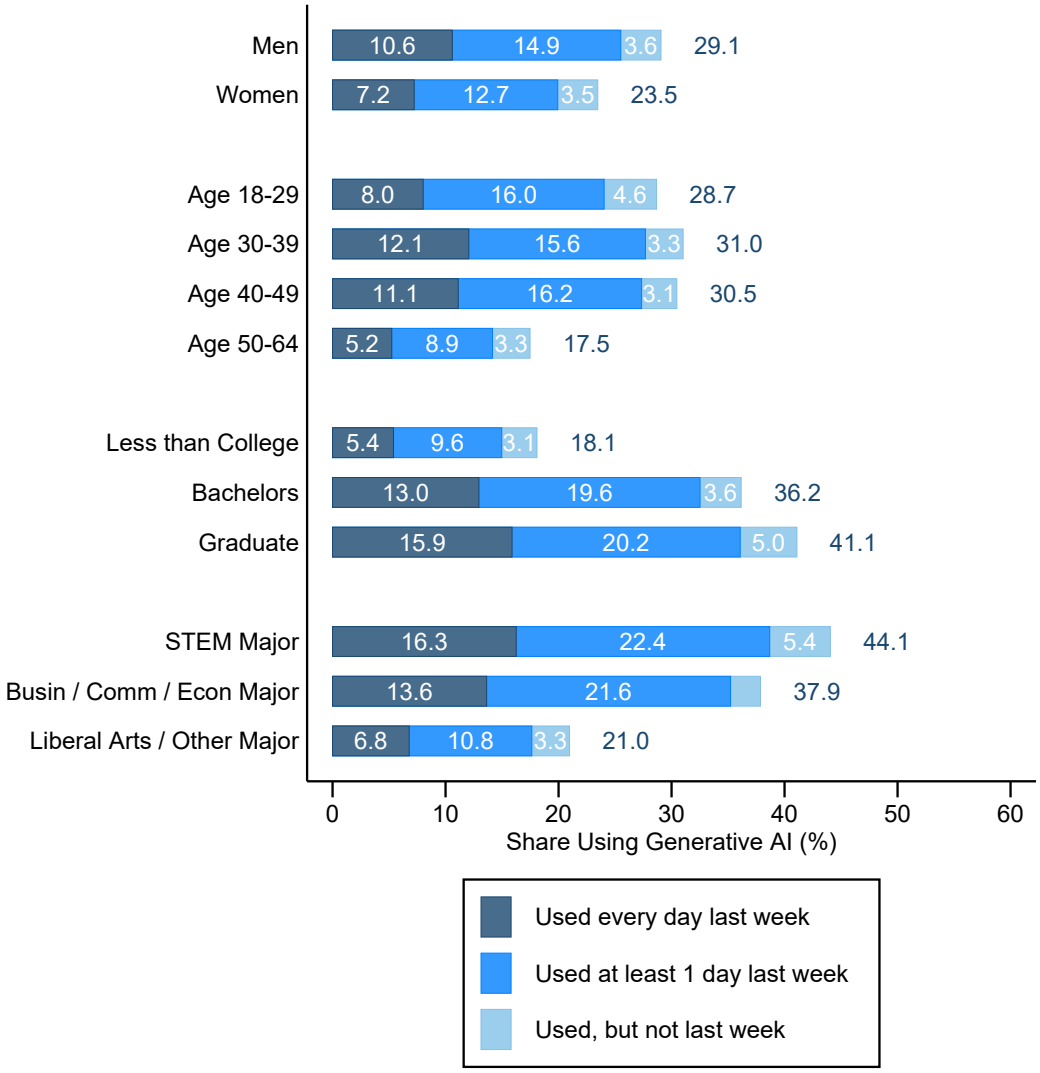
A Additional Results on Generative AI and PC Adoption

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.

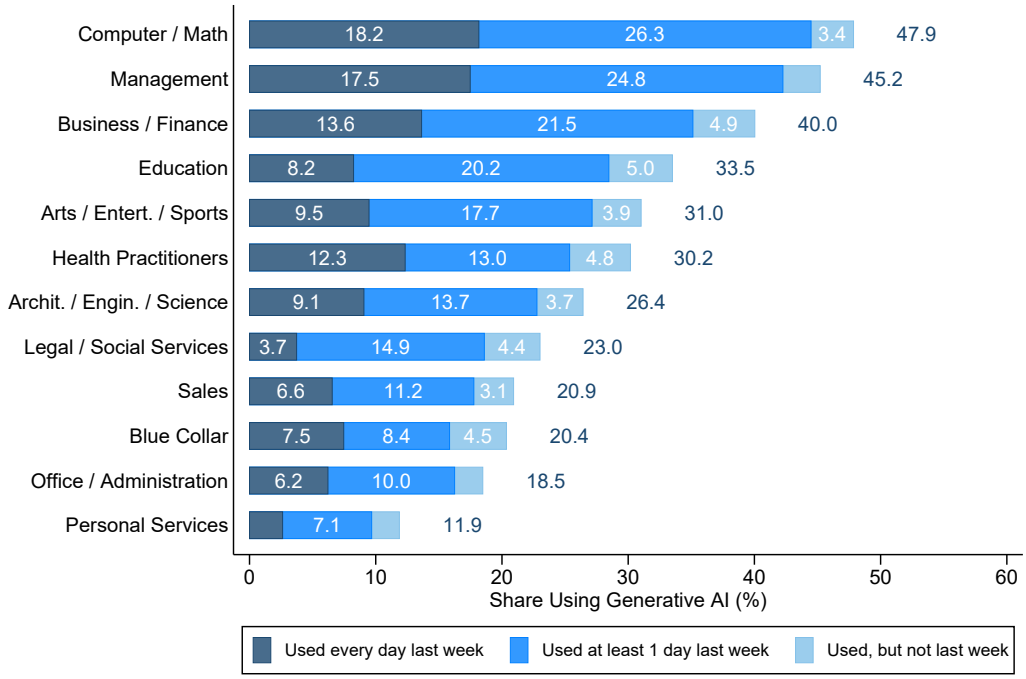
FIGURE A.2: Demographic Differences in Generative AI Use At Work



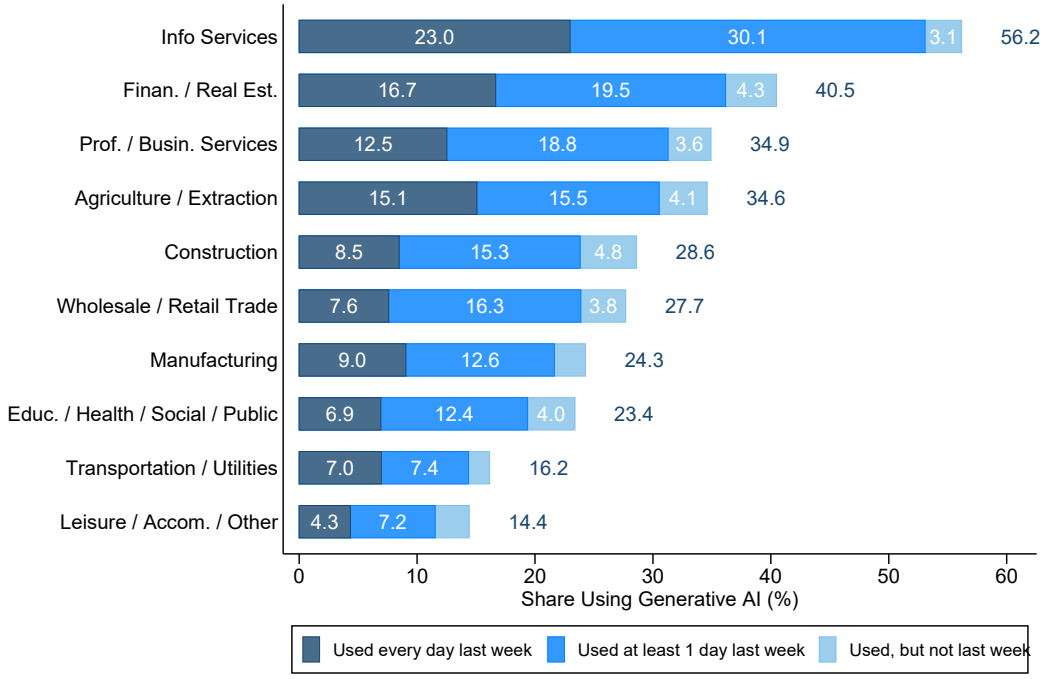
Notes: The figure shows the share of respondents who use genAI for work, broken down by gender, age, education, and college major. Intensity of use is broken down into every day last week (dark blue), at least one day but not every day last week (medium blue), and not last week (light blue). Data source is the August and November 2024 waves of the RPS, ages 18-64. The sample for this figure is employed individuals ($N = 6951$). The sample for college majors is employed individuals with at a bachelor's degree or more. STEM majors include biological, agricultural, environmental, physical, and related sciences; computers, mathematics, and statistics; and engineering. "Busin / Comm / Econ" includes business, communications, and economics majors. "Liberal Arts / Other" includes all other majors.

Figure A.3: AI Use At Work by Occupation and Industry Groups

(a) Occupation Groups



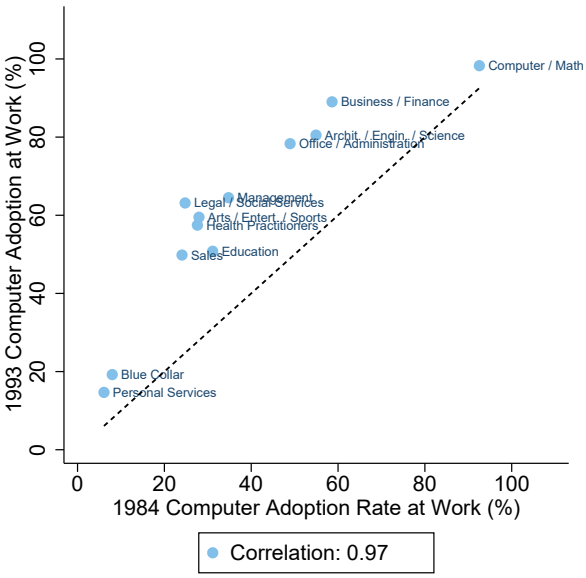
(b) Industry Groups



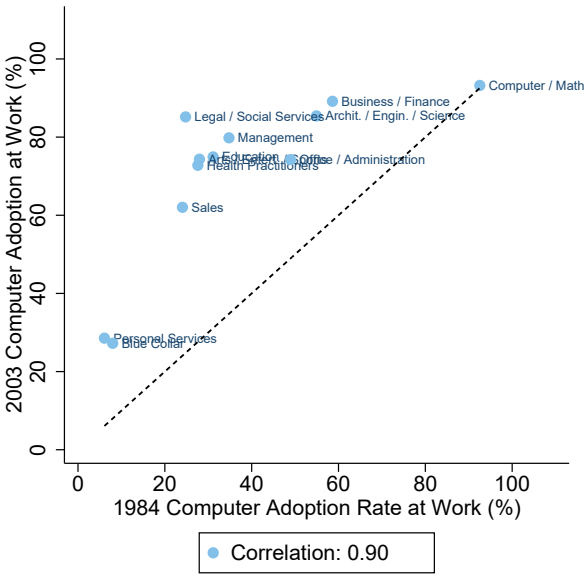
Notes: The figure shows the share of respondents who use genAI for work, by occupation and industry. For Panel a, Personal Services occupations combine SOC codes 31-39: Healthcare support, Protective services, Food preparation and serving, Cleaning and maintenance, and Personal care. Blue Collar occupations combine SOC codes 47-53: Construction, Extraction, Installation, Maintenance and Repair, Production, Transportation, and Moving. 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 August and November 2024 waves of the RPS, ages 18-64. For panel (b), the industry groupings 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). The sample for this figure is employed individuals with valid occupation and industry ($N = 6898$).

FIGURE A.4: The Persistence of Early Computer Adoption Patterns

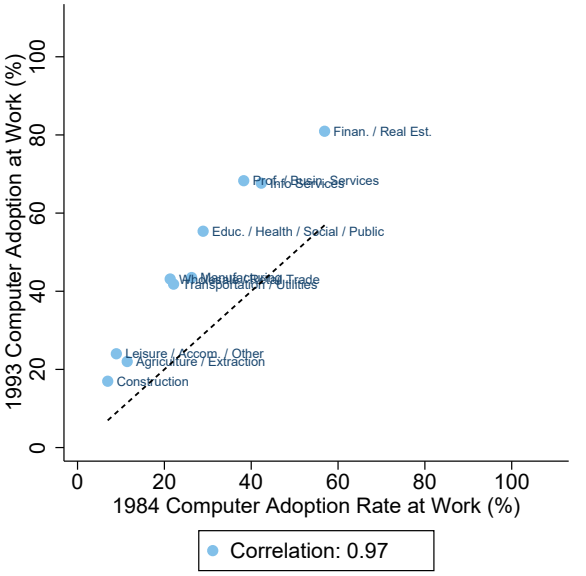
(a) By Occupation: 1984 vs. 1993



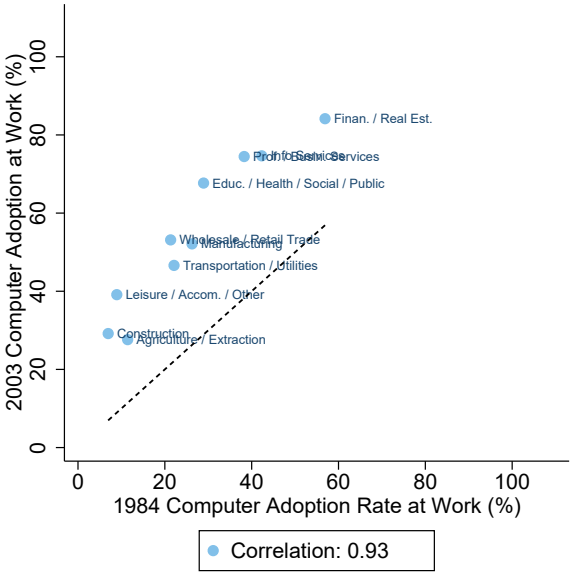
(b) By Occupation: 1984 vs. 2003



(c) By Industry: 1984 vs. 1993



(d) By Industry: 1984 vs. 2003

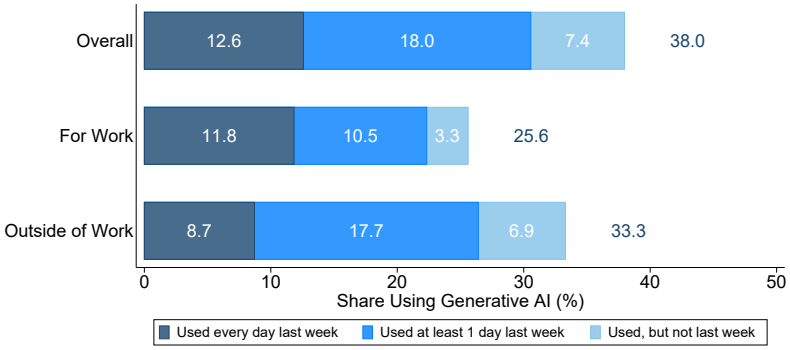


Notes: The figure shows PC work adoption rates by in the 1984, 1993, and 2003 Computer and Internet use Supplement of the CPS. Panels a and b group observations by occupation; panels c and d group observations by industry. The sample is employed individuals ages 18-64.

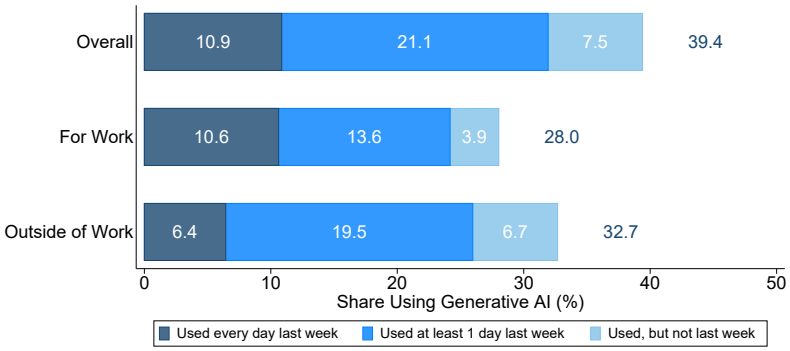
B Results on Generative AI Use: Comparing the June (Pilot), August, and November 2024 Waves

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

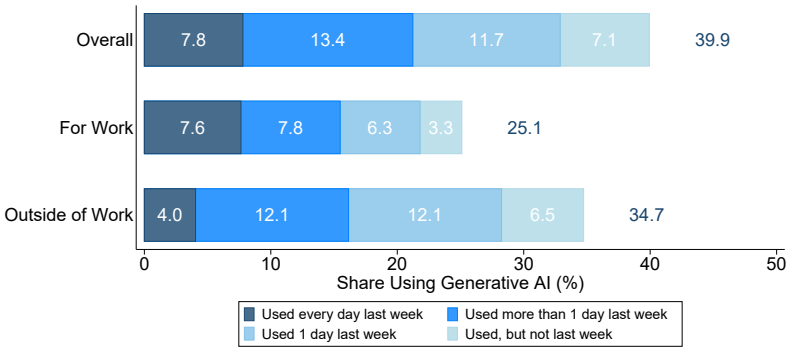
(a) June 2024 (Pilot)



(b) August 2024

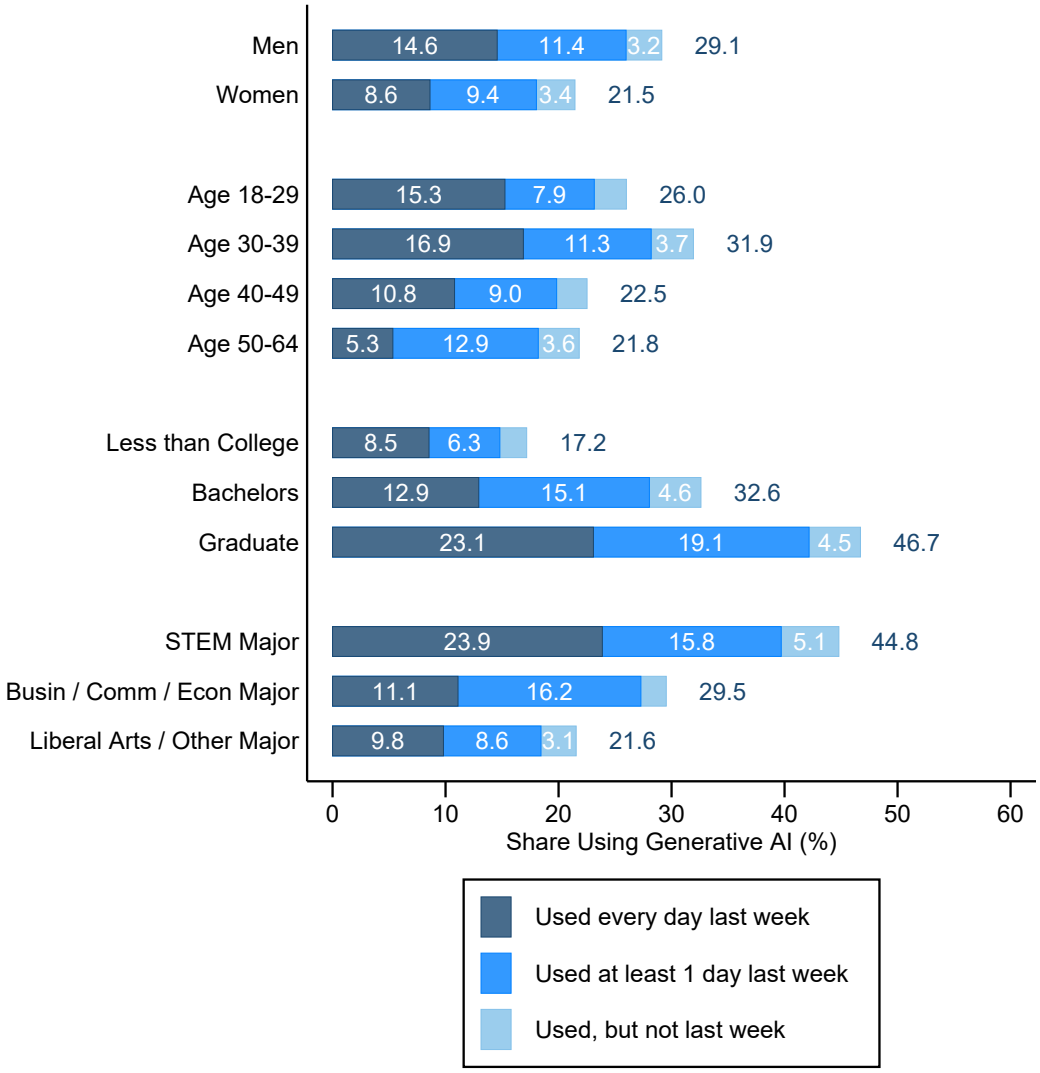


(c) November 2024 (More Detailed Breakdown)



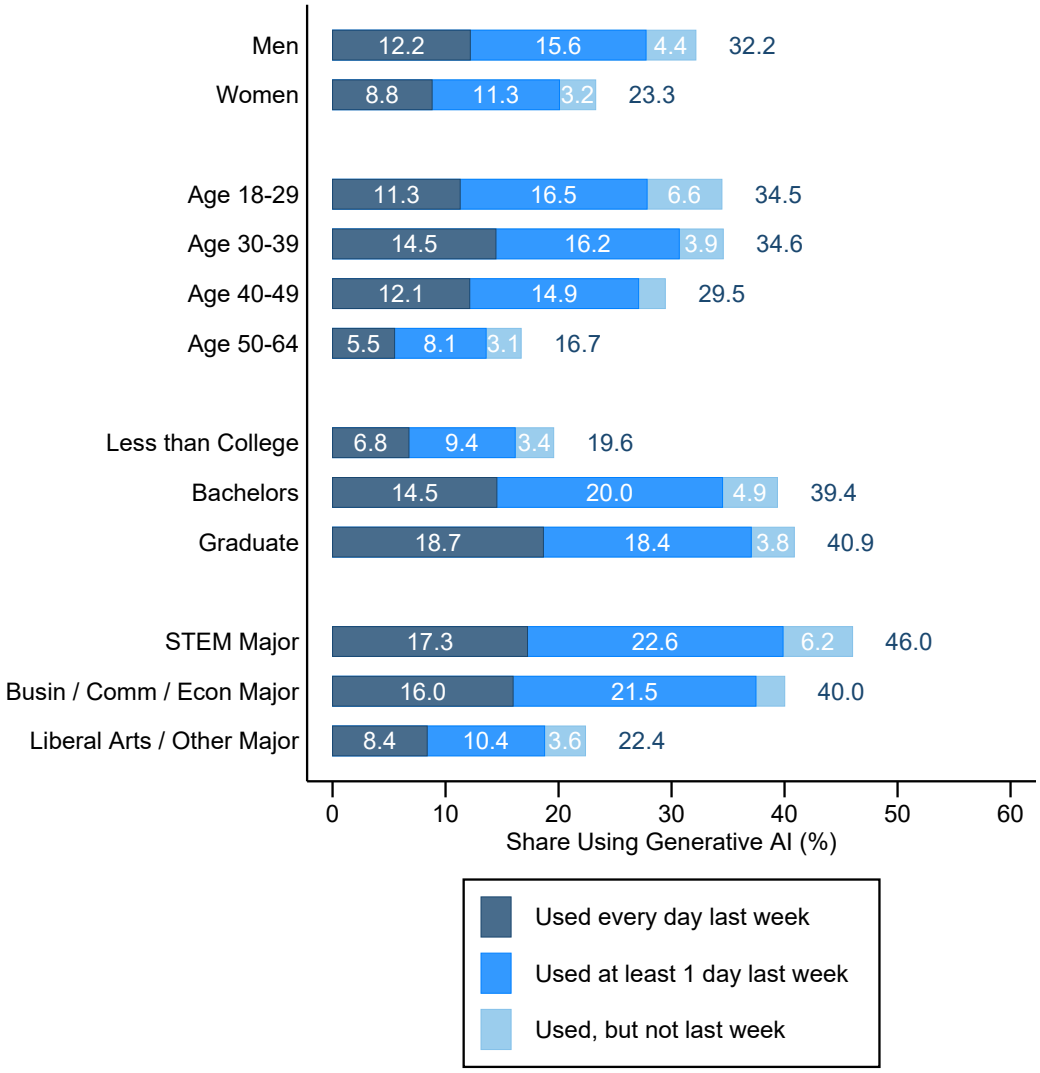
Notes: The figure shows the share of respondents who use genAI for work, outside of work, and overall (either for work or outside of work). Intensity of use is broken down into every day last week (dark blue), at least one day but not every day last week (medium blue), and not last week (light blue). 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: Demographic Differences in Generative AI Use At Work: June 2024 (Pilot)



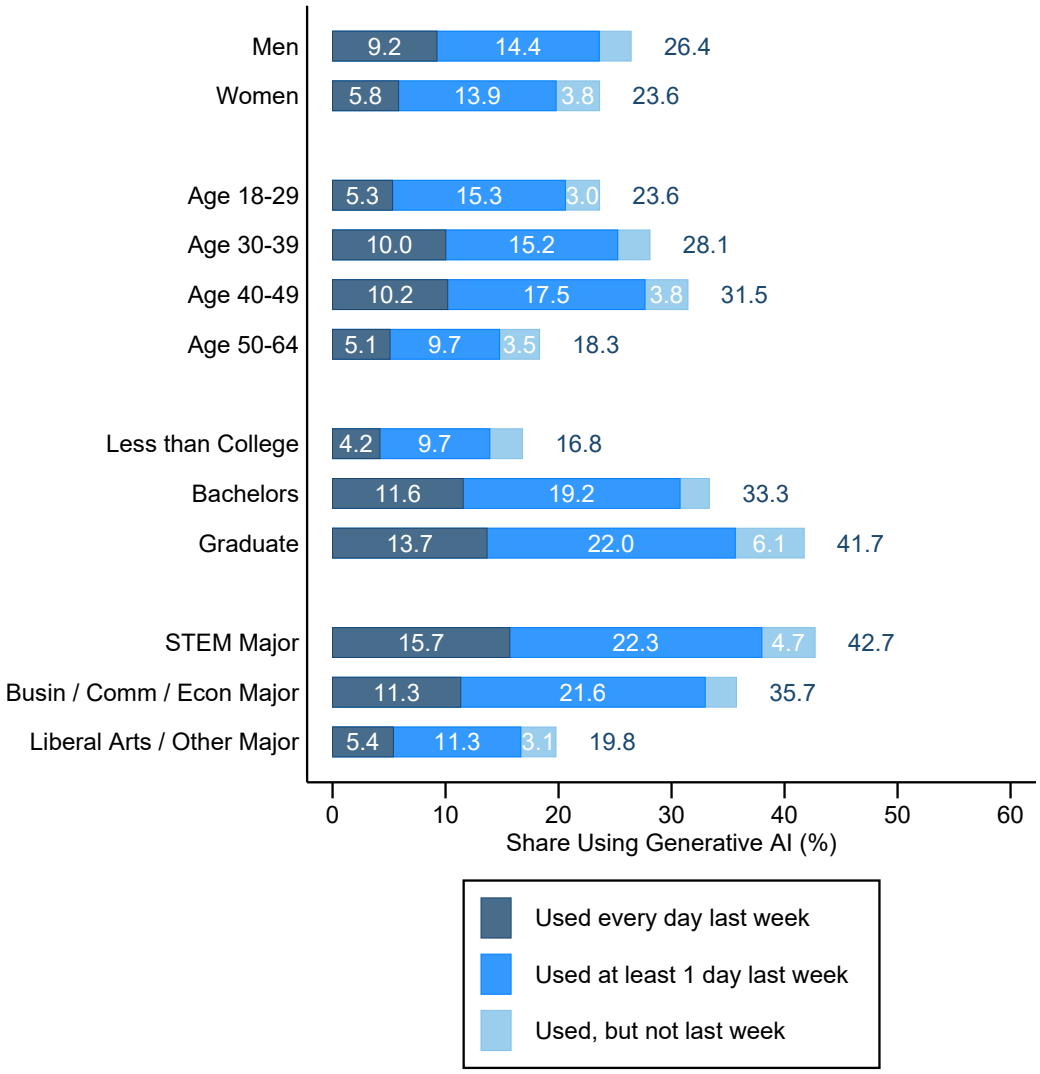
Notes: The figure shows the share of respondents who use genAI for work, broken down by gender, age, education, and college major. Intensity of use is broken down into every day last week (dark blue), at least one day but not every day last week (medium blue), and not last week (light blue). Data source is the August and November 2024 waves of the RPS, ages 18-64. The sample for this figure is employed individuals ($N = 1576$). The sample for college majors is employed individuals with at a bachelor's degree or more. STEM majors include biological, agricultural, environmental, physical, and related sciences; computers, mathematics, and statistics; and engineering. "Busin / Comm / Econ" includes business, communications, and economics majors. "Liberal Arts / Other" includes all other majors.

FIGURE B.3: Demographic Differences in Generative AI Use At Work: August 2024



Notes: The figure shows the share of respondents who use genAI for work, broken down by gender, age, education, and college major. 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 August and November 2024 waves of the RPS, ages 18-64. The sample for this figure is employed individuals ($N = 3216$). The sample for college majors is employed individuals with at a bachelor's degree or more. STEM majors include biological, agricultural, environmental, physical, and related sciences; computers, mathematics, and statistics; and engineering. "Busin / Comm / Econ" includes business, communications, and economics majors. "Liberal Arts / Other" includes all other majors.

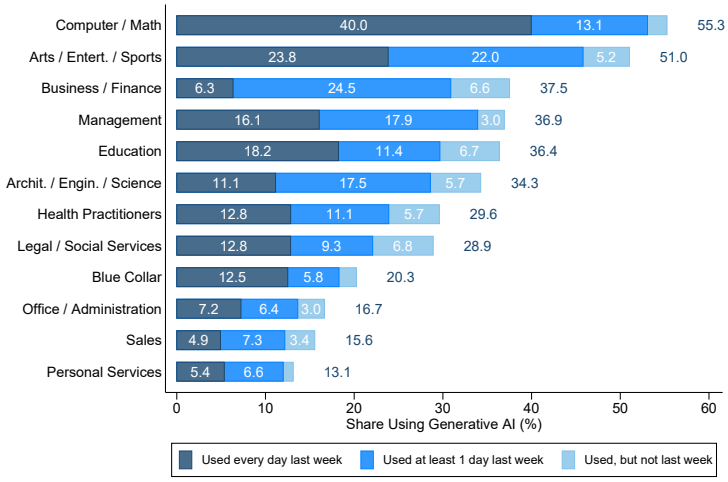
FIGURE B.4: Demographic Differences in Generative AI Use At Work: November 2024



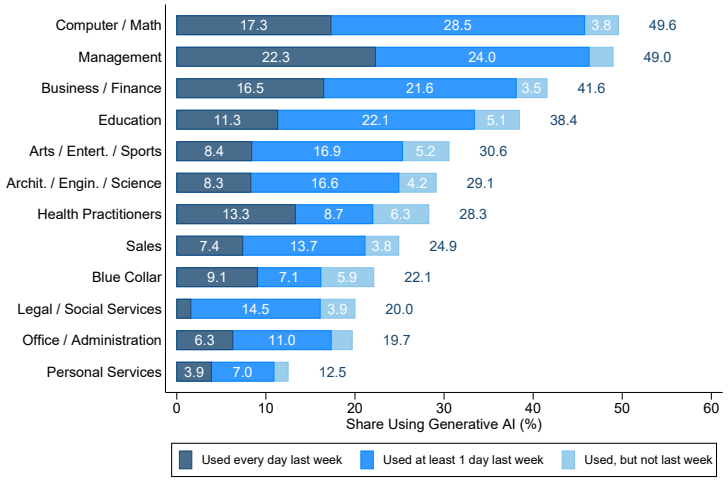
Notes: The figure shows the share of respondents who use genAI for work, broken down by gender, age, education, and college major. Intensity of use is broken down into every day last week (dark blue), at least one day but not every day last week (medium blue), and not last week (light blue). Data source is the August and November 2024 waves of the RPS, ages 18-64. The sample for this figure is employed individuals ($N = 3703$). The sample for college majors is employed individuals with at a bachelor's degree or more. STEM majors include biological, agricultural, environmental, physical, and related sciences; computers, mathematics, and statistics; and engineering. "Busin / Comm / Econ" includes business, communications, and economics majors. "Liberal Arts / Other" includes all other majors.

FIGURE B.5: AI Use At Work by Occupation Groups

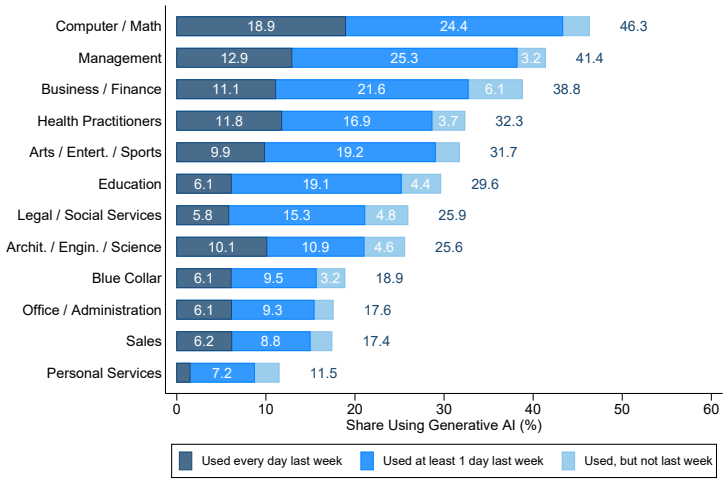
(a) June 2024 (Pilot)



(b) August 2024



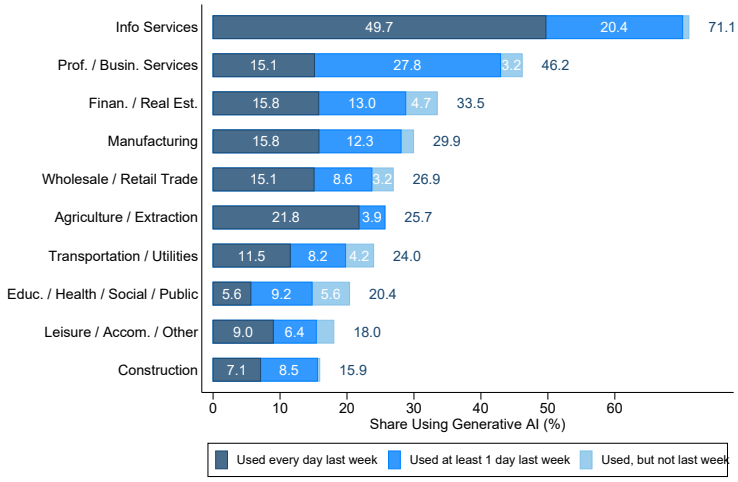
(c) November 2024



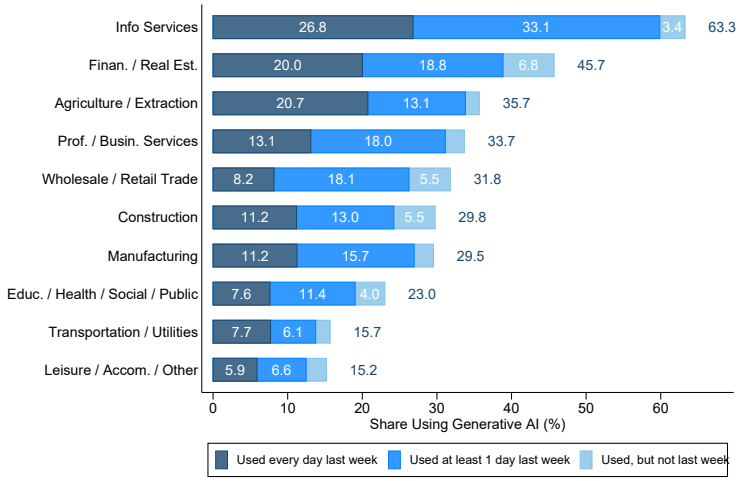
Notes: The figure shows the share of respondents who use genAI for work, broken down by occupation. Personal Services occupations combine SOC codes 31-39: Healthcare support, Protective services, Food preparation and serving, Cleaning and maintenance, and Personal care. Blue Collar occupations combine SOC codes 47-53: Construction, Extraction, Installation, Maintenance and Repair, Production, Transportation, and Moving. 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, ages 18-64. The sample for this figure is employed individuals with a valid occupation (June, $N = 1570$; August, $N = 3191$; November, $N = 3677$).

FIGURE B.6: AI Use At Work by Industry Groups

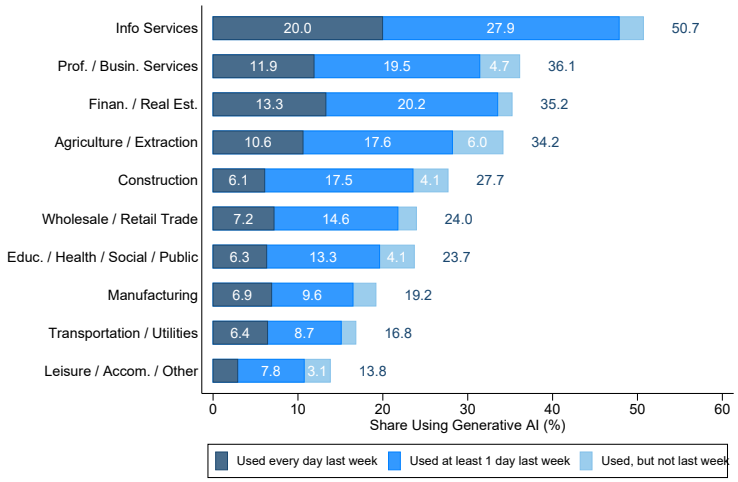
(a) June 2024 (Pilot)



(b) August 2024



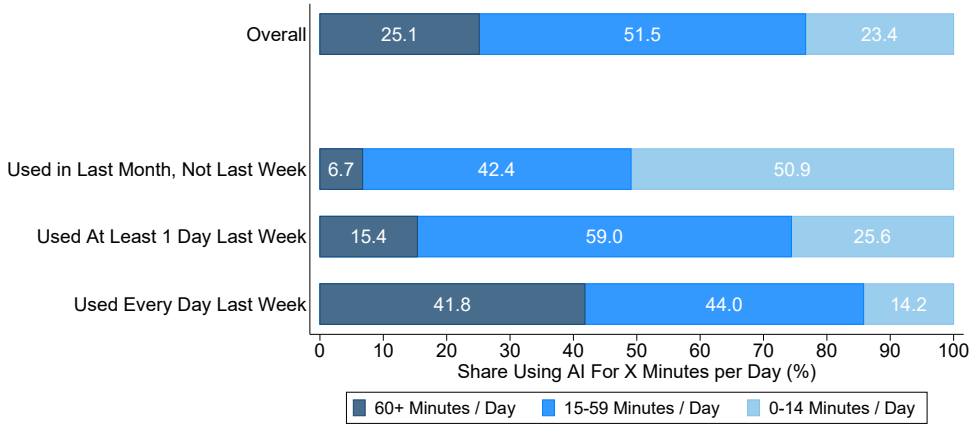
(c) November 2024



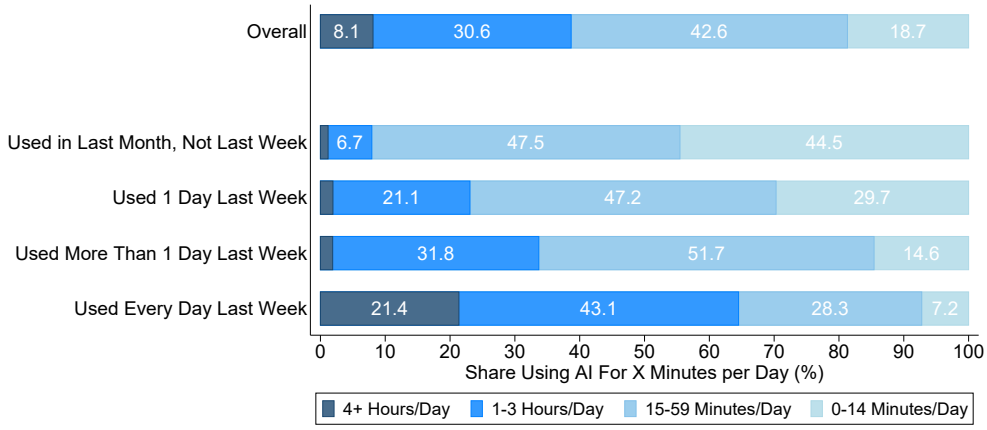
Notes: The figure shows the share of respondents who use genAI for work, broken down by industry. Intensity of use is broken down into every day last week (dark blue), at least one day but not every day last week (medium blue), and not last week (light blue). The industry groupings are: Agriculture / 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). Data source is the June, August, and November 2024 waves of the RPS, ages 18-64. The sample for this figure is employed individuals with a valid industry (June, $N = 1570$; August, $N = 3191$; November, $N = 3677$).

FIGURE B.7: Intensity of genAI Use For Work

(a) August 2024



(b) November 2024 (More Detailed Breakdown)

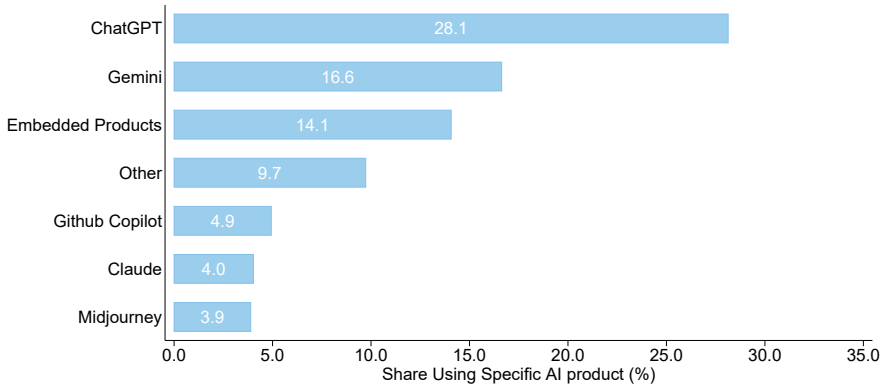


Notes: The figure shows the distribution of daily time spent actively using genAI for work, among genAI users. In August, usage time is broken down into 0-14 minutes per day (light blue), 15-59 minutes per day (medium blue), and 60 or more minutes per day (dark blue). In November, usage time is broken 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, $N = 1008$).

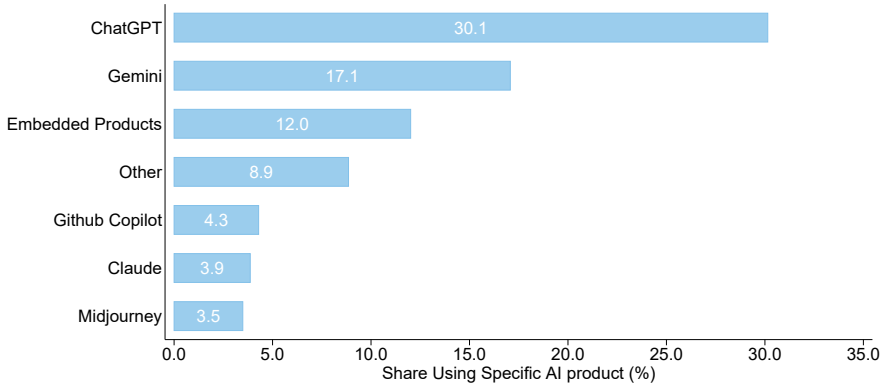
C Results on Generative AI Use: Comparing the RPS and SWAA

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

(a) RPS: August & November 2024



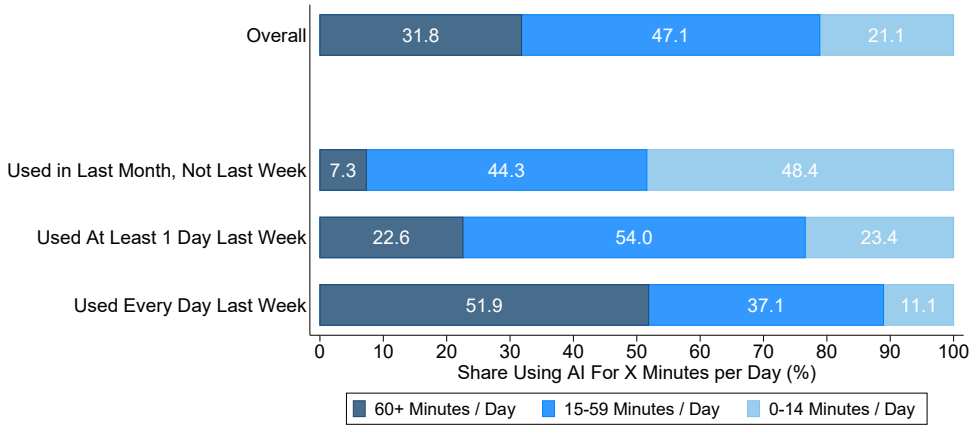
(b) SWAA: December 2024



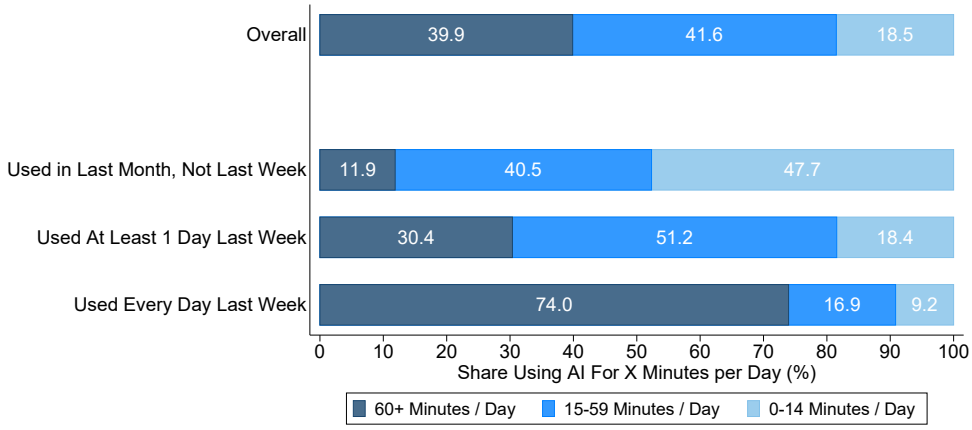
Notes: The figure shows the share of respondents who report using particular genAI products. "Embedded products" are genAI features embedded within existing software, such as Microsoft Copilot. Data source is the August and November 2024 waves of the RPS, ages 18-64 ($N = 9742$) and the December 2024 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 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. Tables D.1 to D.3 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.

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. Columns 1 and 2 of Tables D.1 to D.3 and of Table 1 for the pooled August and November data compare the sample composition between the CPS and RPS along the demographics targeted in the sampling procedure for our main survey. 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

Table D.1: Sample Composition in the June 2024 CPS and RPS

	Everyone		*Employed*	
	CPS	RPS	CPS	RPS
	(1)	(2)	(3)	(4)
Gender: Women	50.4	53.2	47.0	44.8
Age				
18-24	14.9	9.4	12.5	10.0
25-34	22.3	23.0	23.9	24.9
35-44	22.1	24.4	24.2	25.4
45-54	20.1	21.9	21.7	22.2
55-64	20.7	21.4	17.7	17.5
Race/Ethnicity				
Non-hispanic White	56.8	54.5	58.2	58.9
Non-hispanic Black	12.9	14.0	12.0	11.9
Hispanic	20.4	21.1	20.1	19.5
Other	9.9	10.4	9.7	9.8
Education				
Highschool or less	37.0	32.7	32.9	24.5
Some college/Associate's degree	25.8	28.5	25.5	29.1
Bachelor's or Graduate degree	37.2	38.8	41.6	46.5
Marital Status: Married	50.3	52.2	52.6	56.7
Number of children				
0	59.0	56.5	58.2	53.3
1	17.8	19.8	18.1	21.9
2	14.7	15.5	15.5	17.1
3+	8.5	8.2	8.3	7.8
Household Income in Last 12 Months				
\$0-\$50,000	25.6	31.0	19.6	19.8
\$50,000-\$100,000	29.9	28.4	30.6	31.0
\$100,000+	44.5	40.7	49.8	49.1
Region				
Midwest	20.2	19.8	20.8	19.7
Northeast	17.0	18.9	17.4	18.7
South	38.7	38.8	38.0	38.3
West	24.0	22.5	23.8	23.4
Employment Status				
Employed, at work last week	71.0	66.4		
Employed, absent from work last week	3.5	2.8		
Unemployed	3.3	8.4		
Not in the labor force	22.3	22.3		
Observations	56969	2528	42365	1750

Notes: Column 1 reports the sample composition in the June 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 June 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).

Table D.2: Sample Composition in the August 2024 CPS and RPS

	Everyone		*Employed*	
	CPS	RPS	CPS	RPS
	(1)	(2)	(3)	(4)
Gender: Women	50.4	52.2	47.2	46.7
Age				
18-24	14.9	8.1	12.0	9.2
25-34	22.2	23.0	23.9	24.4
35-44	22.2	24.7	24.5	26.1
45-54	20.1	22.0	21.8	22.5
55-64	20.6	22.1	17.8	17.8
Race/Ethnicity				
Non-hispanic White	56.6	56.2	57.9	59.0
Non-hispanic Black	12.9	13.0	12.1	10.9
Hispanic	20.5	20.6	20.2	19.5
Other	10.0	10.3	9.9	10.5
Education				
Highschool or less	37.5	32.4	33.2	25.5
Some college/Associate's degree	25.6	26.7	25.1	27.1
Bachelor's or Graduate degree	36.9	40.8	41.7	47.4
Marital Status: Married	50.2	48.6	52.9	52.7
Number of children				
0	59.4	57.6	58.5	54.2
1	17.3	19.3	17.5	20.8
2	14.5	15.7	15.2	17.9
3+	8.8	7.4	8.7	7.1
Household Income in Last 12 Months				
$0-$50,000	25.8	32.7	19.8	22.7
$50,000-$100,000	30.3	28.0	31.0	31.1
$100,000+	43.9	39.3	49.2	46.2
Region				
Midwest	16.9	18.6	16.8	19.3
Northeast	20.3	18.1	20.9	17.4
South	39.0	37.8	38.3	37.7
West	23.8	25.5	24.0	25.6
Employment Status				
Employed, at work last week	71.0	67.4		
Employed, absent from work last week	3.2	3.1		
Unemployed	3.4	8.7		
Not in the labor force	22.5	20.8		
Observations	58068	4972	42987	3506

Notes: Column 1 reports the sample composition in the August 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 August 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).

Table D.3: Sample Composition in the November 2024 CPS and RPS

	Everyone		*Employed*	
	CPS	RPS	CPS	RPS
	(1)	(2)	(3)	(4)
Gender: Women	50.4	52.1	47.3	48.0
Age				
18-24	15.0	15.0	12.1	14.5
25-34	22.2	21.1	24.0	23.3
35-44	22.2	23.1	24.4	24.1
45-54	20.0	20.4	21.6	21.0
55-64	20.6	20.2	18.0	17.1
Race/Ethnicity				
Non-hispanic White	56.5	56.7	57.8	56.8
Non-hispanic Black	12.8	13.3	12.1	13.4
Hispanic	20.5	20.1	20.1	20.1
Other	10.1	9.8	9.9	9.7
Education				
Highschool or less	36.7	33.4	32.3	28.5
Some college/Associate's degree	26.0	28.3	25.4	28.0
Bachelor's or Graduate degree	37.3	38.3	42.3	43.5
Marital Status: Married	49.9	49.6	52.8	52.2
Number of children				
0	56.7	53.9	55.8	51.4
1	18.4	20.0	18.7	21.5
2	15.0	17.3	15.7	19.1
3+	9.9	8.8	9.8	8.0
Household Income in Last 12 Months				
\$0-\$50,000	26.3	30.1	20.0	22.6
\$50,000-\$100,000	29.5	30.8	30.3	32.8
\$100,000+	44.2	39.1	49.7	44.6
Region				
Northeast	17.0	18.1	17.0	18.4
Midwest	20.4	20.6	21.4	20.7
South	38.7	38.4	37.9	37.9
West	23.9	22.9	23.7	23.0
Employment Status				
Employed, at work last week	72.4	72.2		
Employed, absent from work last week	1.9	2.7		
Unemployed	3.1	7.3		
Not in the labor force	22.7	17.8		
Observations	57409	5292	42559	3967

Notes: Column 1 reports the sample composition in the 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 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).

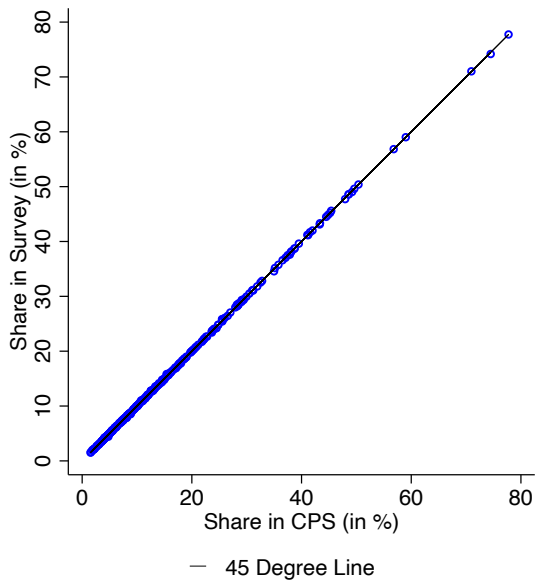
overall sample, i.e., independent of employment status. However, we use more disaggregated categories for education and marital status, and we interact all categories with gender. In particular, for education, we distinguish between less than high school, high school graduate or equivalent, some college 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."

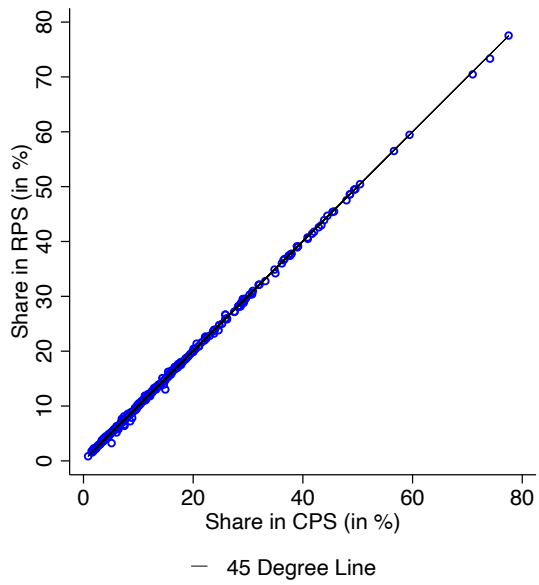
Including all the interaction terms, we have a total of 48 statistics (e.g., gender is one, and gender x education is another) which we weight on, with a combined 295 categories (e.g., gender has two categories, and gender x education has 2 x 6 = 12 categories; for the June 2024 we only have 294 categories 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). The lack of sizeable deviations from the 45-degree line demonstrates how well the weighting procedure works.

Figure D.1: Sample Composition in the Weighted RPS vs. CPS

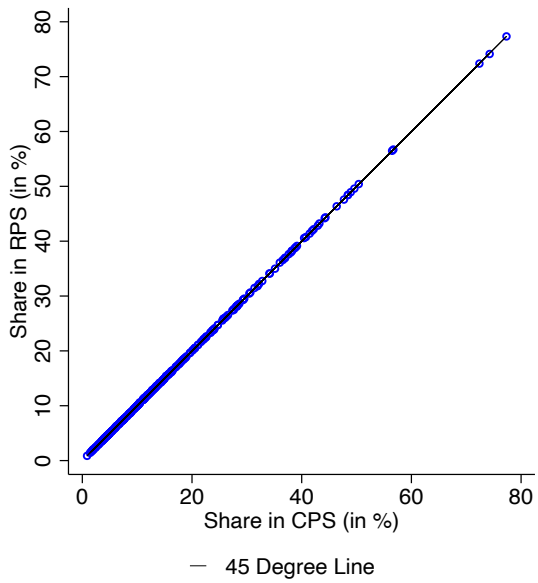
(a) June 2024



(b) August 2024



(c) 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).

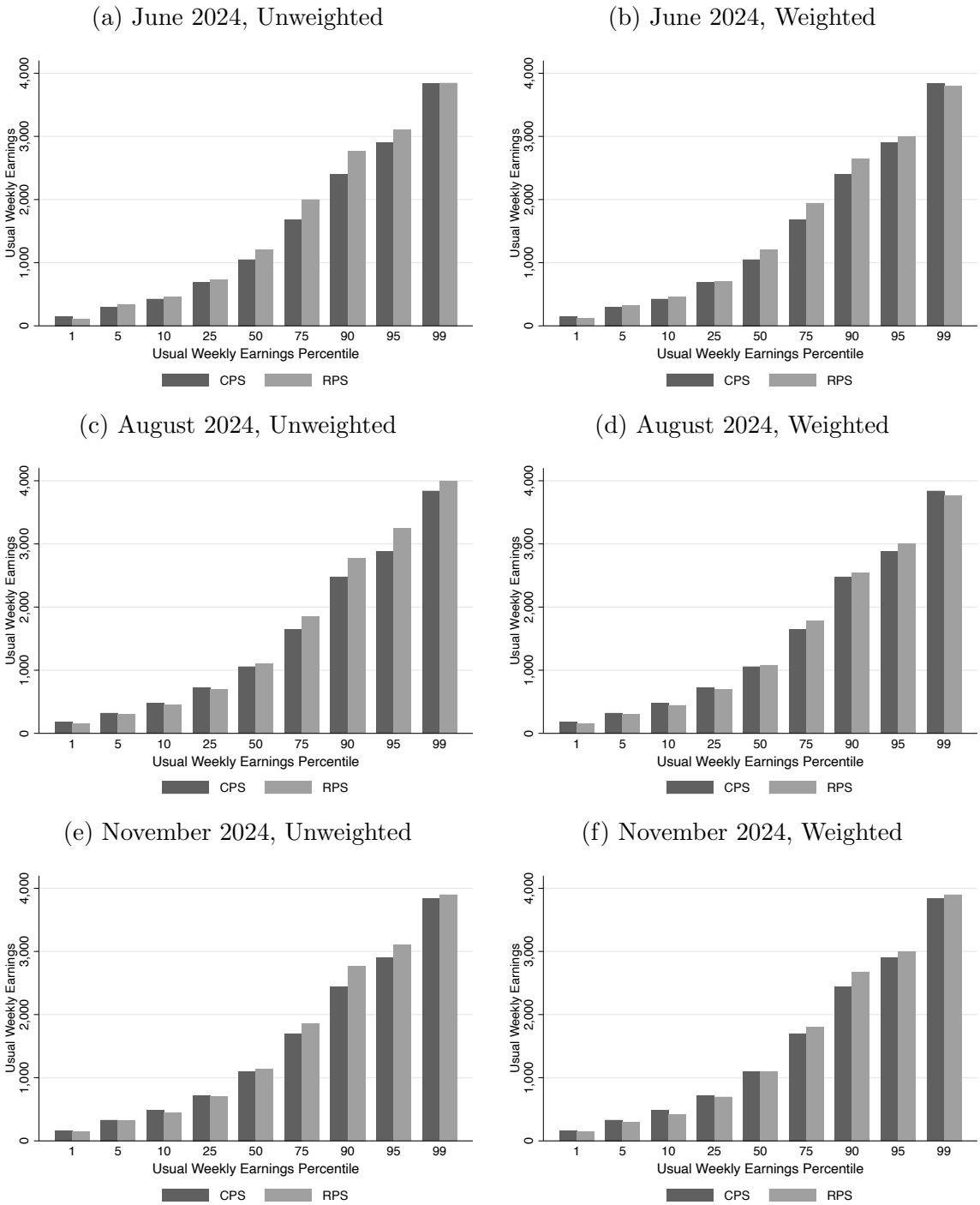
D.3 Validation Checks

Figures D.2 and D.3 show that the usual weekly earnings distribution for employees and the occupation and industry composition among all employed respondents in the RPS are very similar to the CPS for each of our three survey waves individually.

Figure D.4 compares the industry composition in the RPS with the CPS. In the August and November surveys, the unweighted correlations are at 0.89 comparable to those for occupations. In the June 2024 survey, "Other Services" has a much higher industry share in the RPS than in the CPS, lowering the correlation to 0.74. This pattern has been prevalent in all previous versions of the RPS (see Bick and Blandin, 2023). In the June 2024 survey, we asked employed respondents to first choose from a list of 22 2-digit NAICS industries. Based on that choice, we then presented them with a list of more detailed (sub)industries. The over-representation of "Other Services" in the RPS stems from the over-representation of "Other Personal Services" in the follow-up question. This suggests that many individuals in the service sector are uncertain about which industry to select. This issue is not relevant for the CPS because, in that survey, respondents report a business or industry orally, and professional coders make the assignment after the fact. Starting in the August 2024 survey, we addressed this issue by asking individuals from this group: "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." The comparison between Figures D.4a and D.4c suggests that this change resolved the issue.

Figure D.5 shows that the distribution of college majors in the RPS is similar to the ACS with the correlation ranging from 0.80 to 0.86. 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 agreement between the RPS and ACS.

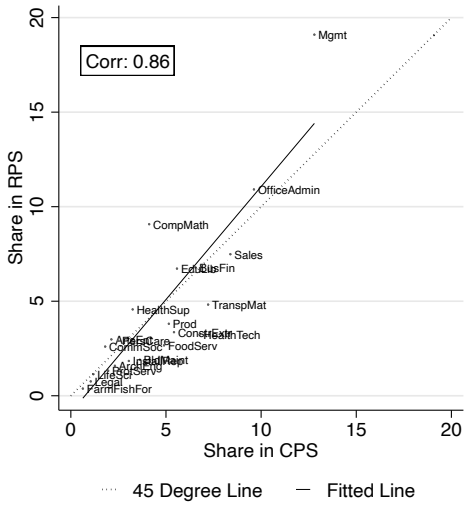
Figure D.2: Validation Checks: Usual Weekly Earnings



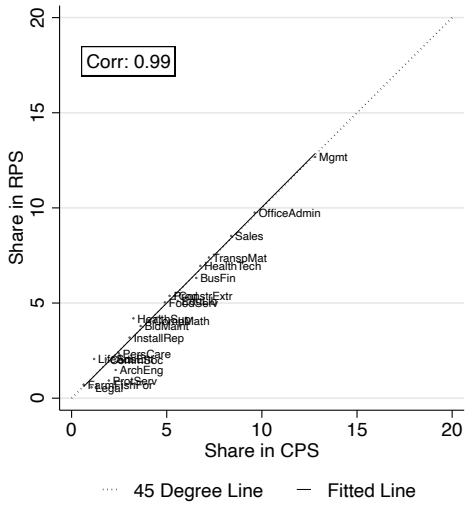
Notes: Figures on the left use unweighted RPS data, figures on the right use weighted RPS data. We use the same sample of RPS respondents in both figures. All figures use weighted CPS data. Data samples are employees ages 18-64 in the RPS and CPS-ORG with weekly earnings below the month-specific CPS topcode ($4160, $4240, and $4140 for June, August, and November 2024, respectively) and an implied hourly wage of at least the federal minimum wage of $7.25. Sample sizes for the RPS are 1127, 2228, and 2564 and for the CPS 5919, 6095, and 6039, respectively.

Figure D.3: Validation Checks: Occupational Shares

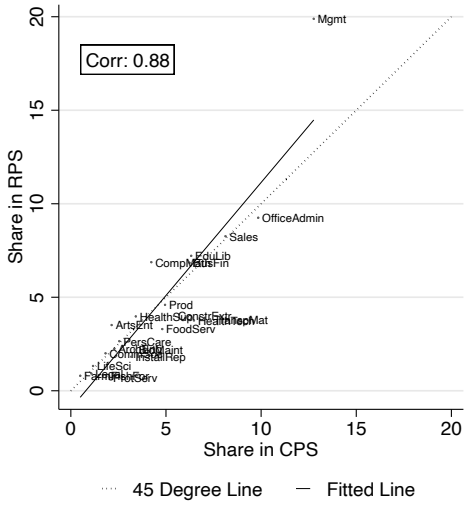
(a) June 2024, Unweighted



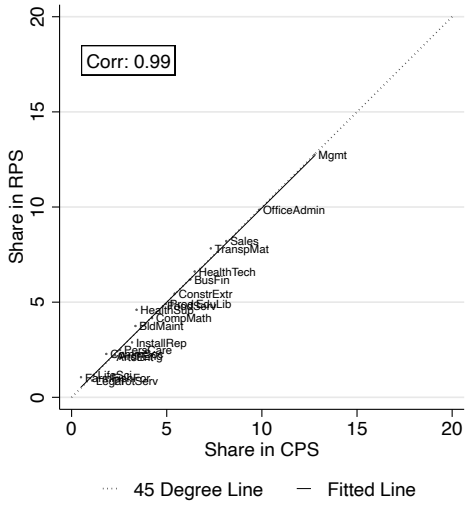
(b) June 2024, Weighted



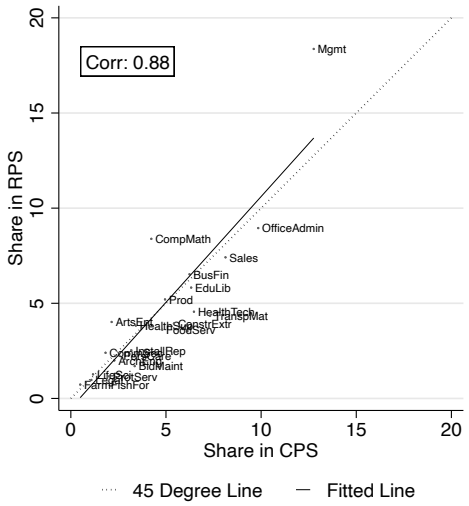
(c) August 2024, Unweighted



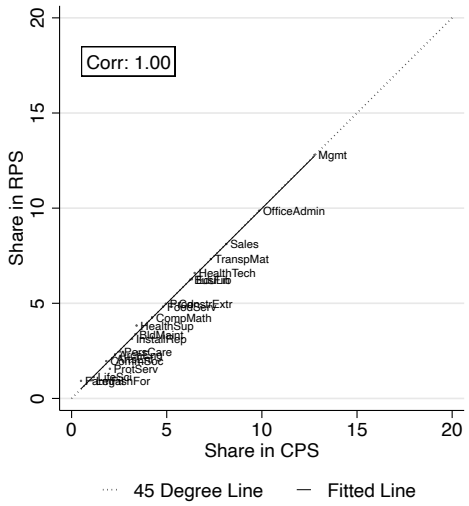
(d) August 2024, Weighted



(e) November 2024, Unweighted



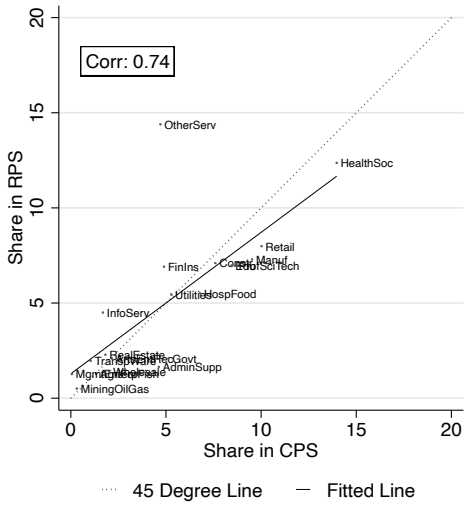
(f) November 2024, Weighted



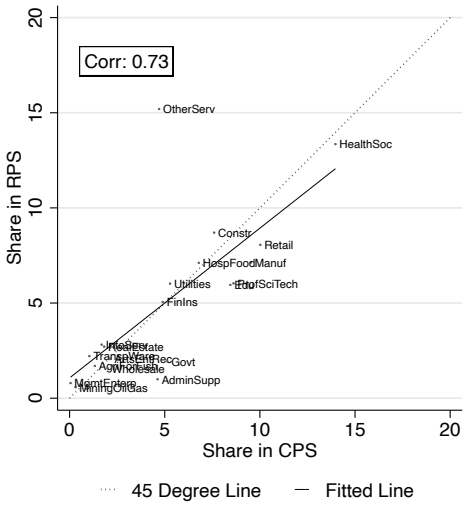
Notes: Figures on the left use unweighted RPS data, figures on the right use weighted RPS data. We use the same sample of RPS respondents in both figures. All figures use weighted CPS data. Data samples are employed respondents ages 18-64. Sample sizes for the RPS are 1576, 3243, and 3708 and for the CPS 42365, 42559, and 42559, respectively.

Figure D.4: Validation Checks: Industry Shares

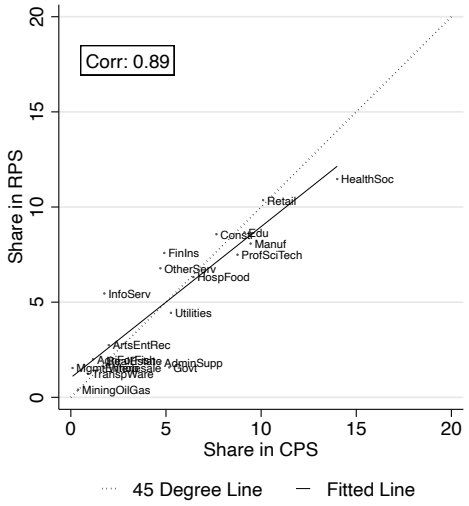
(a) June 2024, Unweighted



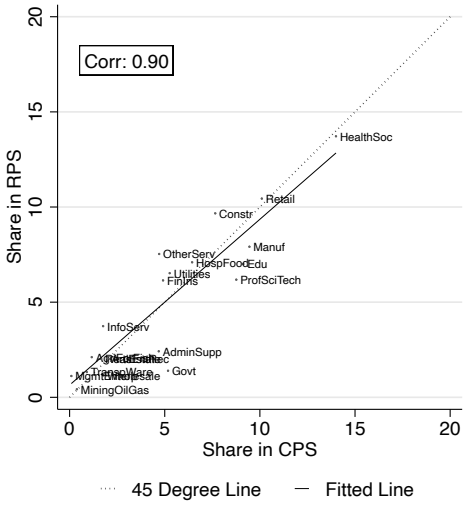
(b) June 2024, Weighted



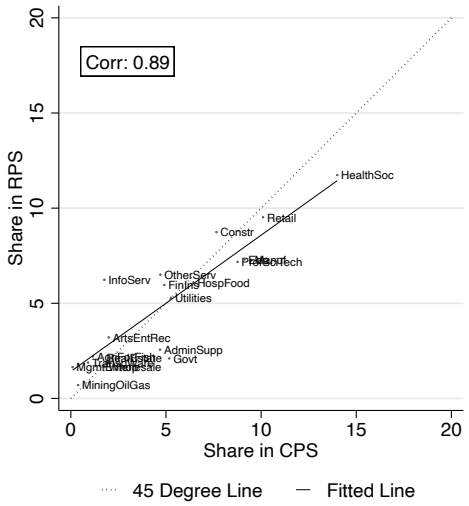
(c) August 2024, Unweighted



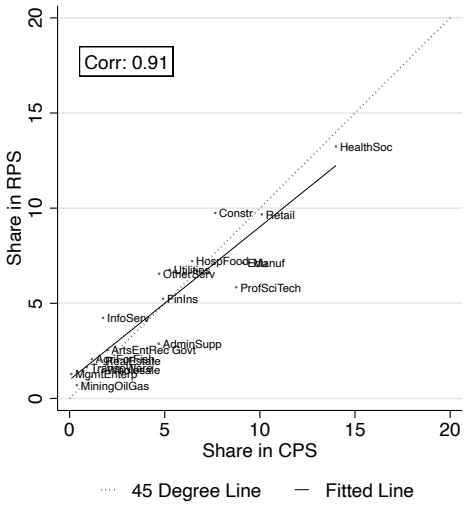
(d) August 2024, Weighted



(e) November 2024, Unweighted



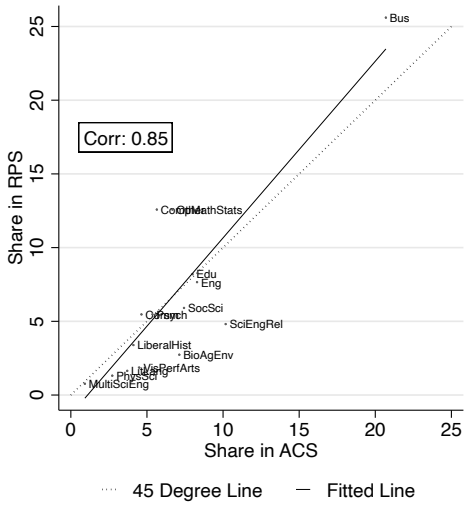
(f) November 2024, Weighted



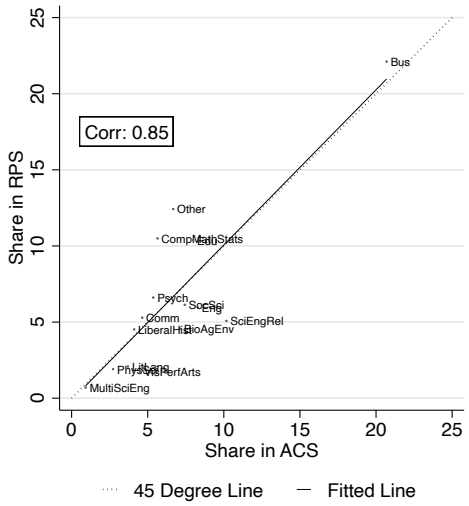
Notes: Figures on the left use unweighted RPS data, figures on the right use weighted RPS data. We use the same sample of RPS respondents in both figures. All figures use weighted CPS data. Data samples are employed respondents ages 18-64. Sample sizes for the RPS are 1577, 3243, and 3706 and for the CPS 44220, 44362, and 44362, respectively.

Figure D.5: Validation Checks: Major Shares

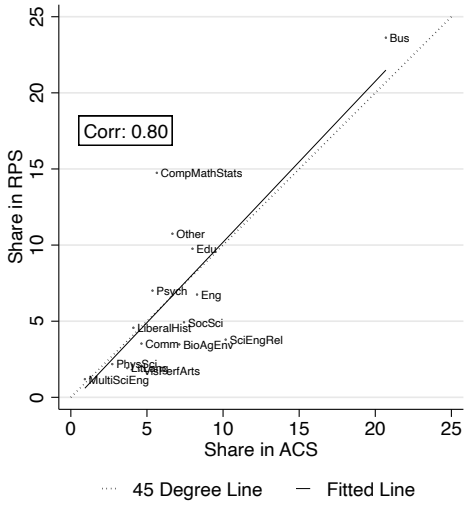
(a) June 2024, Unweighted



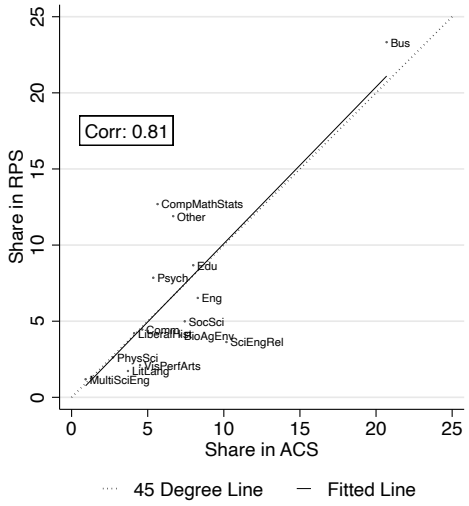
(b) June 2024, Weighted



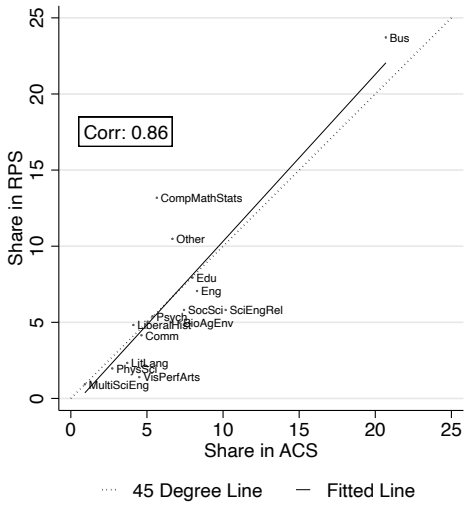
(c) August 2024, Unweighted



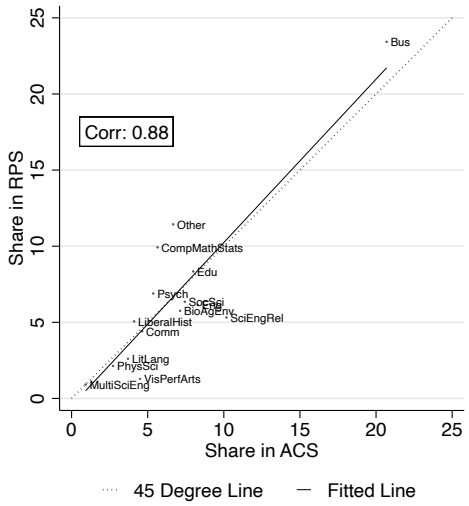
(d) August 2024, Weighted



(e) November 2024, Unweighted



(f) November 2024, 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 2022 ACS data. Data samples are respondents with a college degree ages 18-64. Sample sizes for the RPS are 914, 1926, and 1927 and for the 2022 ACS are 694022 .

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 Tables D.1-D.3 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.[1]

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.[2] 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.

[1] 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.

[2] 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%).

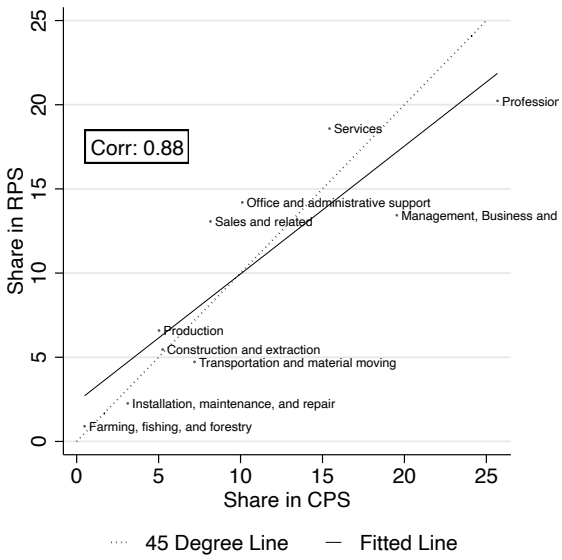
Table E.1: Sample Composition in the December 2024 CPS and SWAA

	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

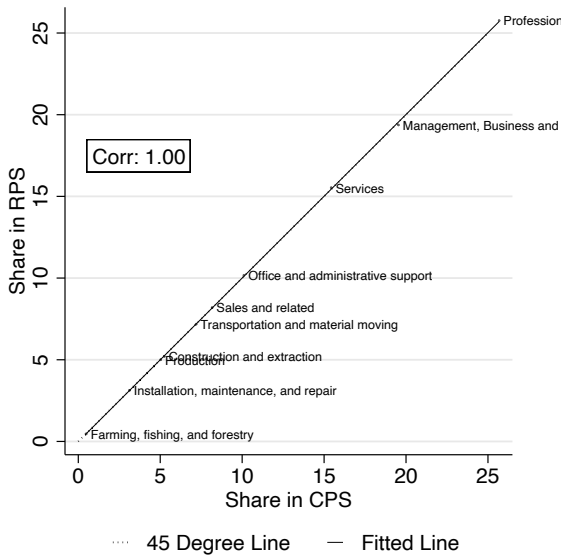
Notes: Column 1 reports the sample composition in the December 2024 Current Population Survey (CPS) for the variables most comparable to those targeted in the RPS in the sampling procedure. The SWAA targets only the variables marked with an asteriks. The employment status is neither targeted in the RPS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

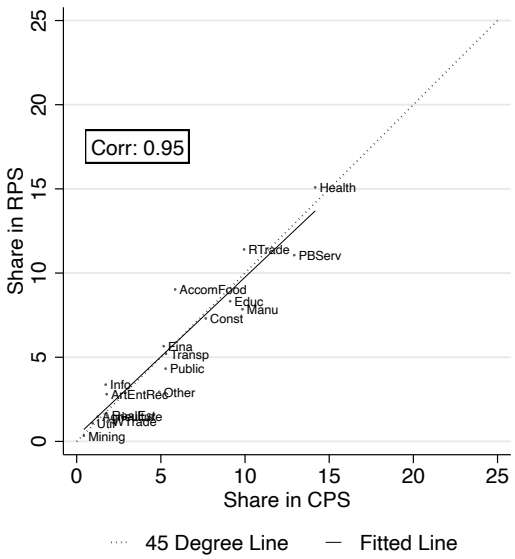
(a) Occupation Shares: Unweighted



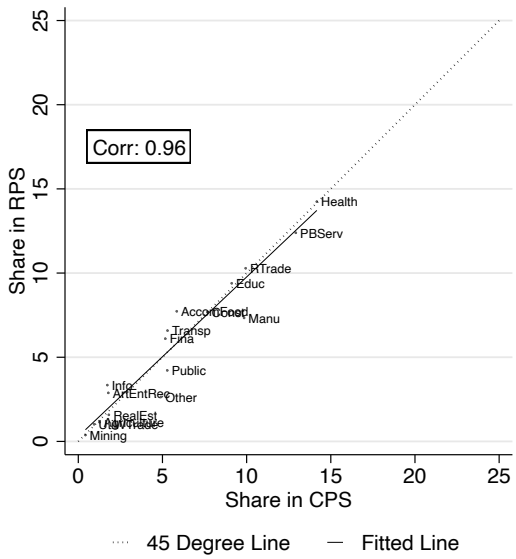
(b) Occupation Shares: Weighted



(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 ChatGPT Answers about the Year of the First-Mass Market Product

F.1 First-Mass Product of the PC

- Question: What do you think would be the first mass market product for the PC in terms of hardware and to which year would you date this?

- Answer: When it comes to personal computer hardware, the first mass-market product is generally considered to be the IBM Personal Computer (IBM PC 5150), released in 1981. This machine played a pivotal role in the mass adoption of personal computers and set the standard for the PC architecture that remains influential today.

  Here's why the IBM PC 5150 is considered the first mass-market PC hardware product:

  1. IBM PC (1981): Launch of the IBM PC 5150: IBM introduced this model in August 1981, and it became a watershed moment for the personal computing market. Although personal computers existed before the IBM PC, including machines like the Apple II (1977) and Commodore PET (1977), IBM's entry into the market legitimized and greatly expanded the appeal of personal computers for businesses, educational institutions, and individual consumers.

     Open Architecture: The IBM PC's architecture was designed to be open, meaning third-party developers and manufacturers could create compatible software and hardware. This openness helped create a thriving ecosystem around the IBM PC, and its architecture became the blueprint for future PCs.

     Widespread Use: The IBM PC quickly became the go-to machine for businesses, and it sparked the development of a wide range of compatible software and hardware. Other manufacturers began producing IBM-compatible PCs, which led to rapid market expansion.

  2. Earlier PCs (Pre-1981):

     (a) Apple II (1977): Before the IBM PC, the Apple II was already a popular personal computer, particularly in homes, schools, and small businesses. It was one of the first commercially successful personal computers and remained influential for years. However, it wasn't considered a "mass-market" product in the same sense as the IBM PC because it didn't create a broad standard in the industry.

     (b) Commodore PET and TRS-80 (1977): These early computers were aimed at hobbyists and educational users, and while successful, they didn't have the same broad appeal or market penetration as the IBM PC later achieved.

3. Mass Market Impact:
   (a) Widespread Software Availability: The IBM PC's compatibility with a growing library of software (like VisiCalc and later Lotus 1-2-3) made it a practical tool for businesses and home users alike. The machine also supported early versions of MS-DOS, which further solidified the standardization of the PC platform.
   (b) Expansion of the PC Ecosystem: IBM's success prompted other companies, like Compaq, Dell, and HP, to enter the market with IBM PC-compatible hardware. This "IBM-compatible" standard created a competitive, rapidly growing market for personal computers.
4. Date: 1981: While personal computers existed before 1981, the launch of the IBM PC in 1981 is often marked as the true beginning of the mass market for personal computers because it made the PC mainstream, especially in business and professional environments. It also led to the dominance of the IBM-compatible PC standard, which continues to influence modern PCs today.
5. Legacy of the IBM PC: The IBM PC was more than just a product; it became the foundation for what we now know as the PC industry. Its open architecture, use of the Intel 8088 processor, and reliance on MS-DOS created a standard that allowed other manufacturers to develop "clones" or compatible systems, which lowered prices and expanded the market further.

Summary: The IBM PC 5150 (1981) is considered the first mass-market PC hardware product. Its introduction marked a turning point for personal computers, transforming them from niche products for hobbyists and small businesses into essential tools for businesses, schools, and homes.

F.2 First-Mass Product of Generative AI

- Question: If you would draw a parallel to generative AI, when what you date the first mass market product of generative AI and which product would that be.
- Answer: Drawing a parallel to the first mass-market product for Generative AI, I would date it to 2022 with the launch of ChatGPT by OpenAI. Here's why:

  1. ChatGPT (November 2022):
     (a) Broad Adoption and Accessibility: ChatGPT, especially with its free version, brought Generative AI to the mass market in a way that no previous AI product had. Before ChatGPT, AI tools existed but were mainly used in specialized fields (e.g., GPT-3 in research or enterprise applications). ChatGPT made Generative

AI accessible to anyone with an internet connection, allowing millions of users to interact with AI in natural language.

(b) Ease of Use: ChatGPT's simple, conversational interface made it intuitive for non-technical users to interact with advanced AI without needing to understand programming or complex machine learning concepts. This democratized the technology, similar to how VisiCalc made personal computers indispensable for non-tech users in the late 1970s.

(c) Wide Range of Applications: Much like the IBM PC's flexibility in handling different tasks, ChatGPT could be used for a variety of applications right out of the gate—creative writing, answering questions, tutoring, drafting emails, coding, and even producing creative content like poems and stories. Its versatility helped it go mainstream rapidly.

(d) Public Awareness and Cultural Impact: Just as the IBM PC became synonymous with the personal computer, ChatGPT quickly became the face of Generative AI for the public. It sparked widespread discussions about AI's capabilities, limitations, and societal impact, bringing the technology into the mainstream.

2. Other Early Generative AI Products:

   (a) GPT-3 (2020): OpenAI's GPT-3, launched in 2020, was a significant milestone, but its use was initially limited to research, business applications, and tech enthusiasts via API access. It wasn't considered a mass-market product because it required technical expertise to use effectively, and widespread public access wasn't available until ChatGPT.

   (b) DALL·E 2 (2022): Another important Generative AI product, DALL·E 2, also from OpenAI, made significant strides in image generation but didn't achieve the mass appeal and use cases that ChatGPT did for text-based interactions. However, DALL·E's image generation capabilities set the stage for widespread interest in AI's creative potential.

3. Why 2022 and ChatGPT?:

   (a) Massive User Base: Within just a few months of its launch, ChatGPT reached millions of users, including both professionals and everyday people. It had a profound effect on how people interact with AI and integrate it into their daily lives. This wide adoption is similar to the way VisiCalc became the reason many people bought their first personal computer.

   (b) Cultural Penetration: ChatGPT quickly became part of popular culture, with its outputs being shared widely on social media, discussed in news outlets, and used in businesses. Its visibility and impact on daily life marked a tipping point for Generative AI's acceptance and integration into society.

(c) User-Friendly Design: Just as the IBM PC was a standardized, user-friendly platform that businesses and individuals could adopt, ChatGPT provided a user-friendly interface for engaging with a complex technology, which opened the doors for millions of users who previously had no experience with AI.

(d) Comparison to Early Mass-Market Products: Generative AI's "VisiCalc" Moment: In many ways, ChatGPT's launch is analogous to the launch of VisiCalc for PCs—both were breakthrough applications that made a technology that had existed primarily for enthusiasts or niche markets suddenly relevant to a much larger audience. ChatGPT did for AI what VisiCalc did for personal computing: it provided an easy, compelling reason for the public to engage with the technology.

(e) Generative AI's "IBM PC" Moment: ChatGPT is also similar to the IBM PC's launch in 1981. Just as the IBM PC set the stage for a broader ecosystem of software and hardware, ChatGPT has led to the rapid development of various applications (chatbots, virtual assistants, content generators) that leverage large language models (LLMs) in creative, professional, and educational domains.

Summary: The first mass-market product for Generative AI would be ChatGPT, released in November 2022. Its wide accessibility, versatility, ease of use, and rapid cultural penetration marked a transformative moment in making Generative AI a mainstream technology, much like how the IBM PC and VisiCalc transformed the personal computing industry in the late 1970s and early 1980s.

F.3 First-Mass Product of the Internet

- Question: What would be the analogue for the internet in the US?
- Answer: The mass-market product for the internet in the U.S. is often considered to be America Online (AOL), which reached its peak popularity in the mid-to-late 1990s. If I had to date the beginning of widespread internet adoption in the U.S., it would be around 1995 when AOL made getting online accessible, easy, and user-friendly for millions of households.

  Here's why AOL, particularly around 1995, stands as the mass-market analogue for the internet:

  1. America Online (AOL, 1995):

     (a) Ease of Access: AOL's software made getting online simple for average users. It bundled internet access, email, chat rooms, and news, all within one platform.

The service famously came on CD-ROMs that were distributed everywhere (by mail, in magazines, even in cereal boxes), which drastically reduced the friction for people to get online.

(b) User-Friendly Interface: AOL made the internet approachable with its intuitive "point-and-click" graphical interface, making it easy for non-technical users to navigate. The famous "You've Got Mail" notification became an iconic sound for internet users of the era.

(c) Dial-Up Service: AOL provided dial-up internet access, which was affordable and available to millions of households across the U.S. While dial-up speeds were slow by today's standards, it marked a significant leap in connecting everyday people to the internet from their homes.

(d) Content and Community: AOL wasn't just an ISP; it was a portal that provided users with access to news, games, email, chat rooms, and other forms of online interaction. These features turned AOL into a gateway for early internet users, encouraging exploration and social interaction online.

2. Why 1995?:

   (a) Launch of AOL 3.0 (1995): AOL 3.0 was a turning point because it made the service compatible with Windows 95, which was gaining mass adoption at the time. This combination helped push the internet into mainstream U.S. households.

   (b) Explosion of Internet Users: By 1995, the number of internet users began to grow exponentially, largely due to services like AOL making it easy for non-tech-savvy people to get online. The internet became a mainstream phenomenon, with millions of users joining for the first time between 1995 and 2000.

   (c) Emergence of Web Browsers: While AOL was the main driver for getting people online, it was also during this period that web browsers like Netscape Navigator and Microsoft's Internet Explorer emerged, making it easier for people to browse the wider internet beyond AOL's walled garden.

3. Other Early Internet Products:

   (a) CompuServe (1980s): Before AOL, services like CompuServe provided online access, but they were more technical and catered to business users or hobbyists. They didn't achieve the same mainstream success as AOL did in the 1990s.

   (b) Netscape Navigator (1994): Netscape was the first widely adopted web browser, which contributed to the internet boom by making the World Wide Web easy to navigate. However, it wasn't as mass-market friendly as AOL, which handled both internet access and online services in one package.

4. Why AOL Was the "Internet's IBM PC":
   (a) Mass Market Accessibility: Just as the IBM PC set a standard for personal computing, AOL made the internet accessible to the masses. It created a user-friendly interface and provided a relatively simple way to connect to the web at a time when most people found the technology daunting.
   (b) Cultural Penetration: Much like ChatGPT in 2022 or VisiCalc in 1979, AOL captured the public's imagination. It became a household name and was synonymous with the internet for many Americans in the 1990s.
   (c) Catalyst for Growth: AOL's success prompted millions of people to go online, encouraging the development of websites, online businesses, and digital communication tools like email, paving the way for the broader internet revolution.
5. Comparison to Other Technologies:
   (a) Dial-Up Modems (1980s): Dial-up modems predate AOL, but their use was largely limited to hobbyists and tech enthusiasts until services like AOL came along and simplified the process.
   (b) The World Wide Web: Although the web itself started to gain traction in the early 1990s, it was services like AOL that made it accessible to the general public. The web's breakthrough moment came when graphical browsers like Netscape combined with easy-to-use internet services like AOL.

Summary: The first mass-market product for the internet in the U.S. was AOL, particularly around 1995, when it became widely used and offered a simple way for average users to access the internet. Just as the IBM PC and VisiCalc drove mass adoption of personal computers, AOL made the internet mainstream, helping millions of people get online for the first time.