Heterogeneity in Work from Home: Evidence from Six U.S. Datasets

Alexander Bick, Adam Blandin, Aidan Caplan, and Tristan Caplan

Abstract

This article documents heterogeneity in work from home (WFH) using six nationally representative U.S. surveys. These surveys show consistent patterns indicating that pre-pandemic differences in WFH rates by sex, education, and state of residence expanded following the COVID-19 outbreak. The surveys also show similar post-pandemic trends in WFH by firm size and industry. We find that an industry's WFH potential was highly correlated with actual WFH during the first year or two of the COVID-19 pandemic. However, this correlation was much weaker before and after, suggesting that WFH potential is a necessary but not sufficient determinant of actual WFH.

JEL codes: I18, J21, J22, J24, L23

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1. INTRODUCTION

The ability to work from home (WFH) varies greatly among workers. For example, Dingel and Neiman (2020) use O*NET data to classify occupations by WFH potential and find that at most 37 percent of jobs in the U.S. could be performed entirely from home. Moreover, several articles document substantial variation in actual WFH during the COVID-19 pandemic across different demographic groups and locations (see, e.g., Mondragon and Wieland, 2022; Barrero, Bloom, and Davis, 2023; or Bick, Blandin, and Mertens, 2023). These findings show that benefits and spillover effects from WFH will be unevenly distributed across workers and locations.

Most existing work documenting variation in WFH focuses on a cross section from one particular time period and dataset. The contribution of this article is to use multiple data sources to document differences in the evolution

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of WFH across demographic groups, U.S. states, and firm characteristics since the COVID-19 outbreak in March 2020. We study four surveys run by the U.S. Census Bureau: the American Community Survey (ACS), the Current Population Survey (CPS), the American Time Use Survey (ATUS), and the Survey of Income and Program Participation (SIPP). We also study two privately run surveys: the Real-Time Population Survey (RPS) and the Survey of Working Arrangements and Attitudes (SWAA).[1]

We begin by documenting modest pre-pandemic differences in WFH by sex and education (with higher WFH rates for women and more-educated workers) and by state of residence across all six surveys. We find that these demographic differences expanded after the COVID-19 outbreak. We also find broadly similar trends in WFH differences across surveys, with some exceptions. One notable dissimilarity is that the magnitude of WFH differences by education is larger in the government-run surveys than in the RPS and SWAA.

Next, we compare firm-related differences in WFH across surveys. Because the surveys are household-based, we do not have firm-level data. However, four datasets have information on firm size (the CPS, SIPP, RPS, and SWAA), and all datasets have information on industry. We arrive at two key findings. First, the relationship between WFH and firm size is U-shaped, with the smallest and largest firms exhibiting higher WFH rates. However, this is not true for the CPS, where WFH in small and medium firms is consistently very similar. By contrast, both the SIPP and RPS show that the slope of this gradient increased following the COVID-19 outbreak.

Second, the relationship between firm industry and WFH has evolved dramatically since the COVID-19 outbreak. We start by verifying that the surveys yield closely aligned estimates of industry-level variation in WFH. We find that just before the pandemic there was very little variation in WFH across industries. However, after the COVID-19 outbreak in 2020, WFH expanded dramatically in some industries and hardly at all in others. We also find that an industry's WFH potential (Dingel and Neiman, 2020) almost perfectly predicts its WFH rate in 2020 and that, in most industries, actual WFH was close to potential. However, the relationship between industry WFH potential and actual WFH weakened substantially from 2022 onward. In particular, while some high-potential industries continued to exhibit high WFH rates (e.g., Professional/Business services, Finance, and Information), other high-potential industries saw their WFH rates revert to near pre-pandemic levels (e.g., Education). This suggests that in some industries, WFH is feasible during emergencies but less productive or less desirable under more normal conditions.

The rest of the article proceeds as follows. Section 2 provides a brief overview of the data sources used and how we measure WFH. Section 3 analyzes demographic differences in WFH, and Section 4 analyzes firm differences in WFH. Section 5 concludes.

2. MEASUREMENT AND DATA SOURCES

In this section we briefly describe our two measures of WFH and our data sources. For more details, especially regarding how each survey phrases WFH-related questions, we refer the interested reader to our companion article (Bick, Blandin, et al., 2025).

2.1 WFH Measures

The core concept of our WFH measures is a WFH workday. A WFH workday refers to a day when a worker performs paid work without commuting to their workplace. This definition is distinct from, but related to, telecommuting and remote work. For instance, a self-employed person whose workplace is their residence would be classified as WFH without working remotely, while an employee who works neither at home nor at their workplace would be classified as working remotely without WFH. This definition also excludes days on which an individual commutes to work but does some work from home. Additionally, unpaid home production is not included in our definition of work. By focusing on whether a commute takes place on a given day, this definition is well-suited for examining issues related to transportation, congestion, pollution, and geographic mobility. However, it may be less relevant for questions about how individuals spend time at home.

Based on our definition of a WFH workday, our first measure of WFH is the *WFH Share of Workdays*, which we henceforth refer to as the *WFH Share*. This is the ratio of WFH workdays to total workdays in a given week.

[1] Bick, Blandin, et al. (2025) show that all surveys depict broadly similar trajectories of aggregate WFH since the COVID-19 outbreak.

Table 1
Survey Overview

Survey	Source	Frequency (Used)	Observation Period Used	WFH Measure Share	WFH Measure Only Rate
ACS	Ruggles, Flood, et al. (2024)	Annual	2019-2023	—	✓
ATUS	Flood, Sayer, et al. (2023)	Annual	2019-2023	✓	—
CPS	Flood, King, et al. (2024)	Monthly	2022-2024	—	✓
SIPP	U.S. Census Bureau (2019-2024)	Annual	2019-2022	✓	✓
RPS	Bick and Blandin (2023)	Monthly	2020-2024	✓	✓
SWAA	Barrero, Bloom, and Davis (2021)	Monthly	2022-2024	✓	✓

Our second measure is the *WFH Only Rate*, which represents the share of workers who WFH every workday in a week. This measure excludes hybrid workers who alternate between WFH and commuting. The WFH Only Rate is particularly relevant for studying workers who can live far from their workplace, such as "work from anywhere" employees.

2.2 Data Sources

We rely on four surveys run by U.S. government agencies (the U.S. Census Bureau and the Bureau of Labor Statistics). These are the American Community Survey (ACS), the American Time Use Survey (ATUS), the Current Population Survey (CPS), and the Survey of Income and Program Participation (SIPP). In addition, we use two independent online surveys: the Real-Time Population Survey (RPS) and the Survey of Work Arrangements and Attitudes (SWAA).

Table 1 provides a brief overview of our data sources. For each survey, we list a source, the frequency and observation period we use, and which of our two measures of WFH are available. The frequency and observation period used require further explanation for some datasets.

While the ACS is conducted throughout the year, information on the survey week and month are not made publicly available, and thus we can only construct annual estimates. The ATUS is available at a monthly frequency, but because of the small monthly sample size, we pool data at the annual level. In the SIPP, information is collected annually at the job level. Accordingly, job stayers have no variation in WFH throughout the year, so we only report annual statistics for the SIPP. In 2020, we compute averages using only the months following the COVID-19 outbreak for the SIPP (April to December 2020) and the ATUS (May to December 2020; the ATUS paused data collection in March and April 2020). The CPS questions that allow us to construct a WFH Only Rate have been available only since October 2022.

The RPS collected WFH information monthly from May 2020 through June 2021, and from 2022 onward for two to three months per year. In each survey wave, the RPS also asked a retrospective question about WFH behavior in February 2020, just before the World Health Organization declared COVID-19 a pandemic. The SWAA has been fielded every month since May 2020. From May 2020 to March 2021, the SWAA only surveyed respondents who earned above $20,000 in 2019. Between April 2021 and December 2021, this threshold fell to $10,000 in 2019. Beginning in January 2022, the survey dropped the income sample criteria, and therefore we study SWAA data only from January 2022 onward.

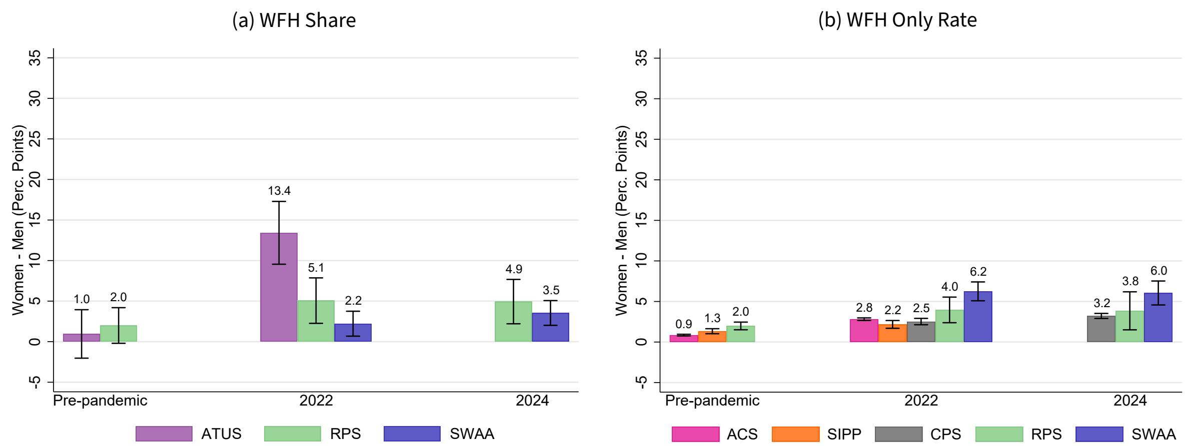
The two independent surveys—the RPS and the SWAA—collect data only for individuals aged 18-64 and 20-64, respectively. We restrict the sample in the government surveys to individuals aged 18-64, as in the RPS, to cover the working-age population in as many surveys as possible. Given the small share of 18- and 19-year-olds among the employed, further restricting the sample to those aged 20-64 would have a very modest impact on our results.

3. DEMOGRAPHIC DIFFERENCES IN WFH

We begin by documenting the evolution of WFH along three different dimensions of worker heterogeneity (sex, age, and education) and across U.S. states.

3.1 Sex

Figure 1
WFH by Sex: Women-Men



NOTE: Figure 1 displays differences in WFH between men and women. Figure 1a plots the percentage point difference in the WFH Share and Figure 1b plots the percentage point difference in the WFH Only Rate. The whiskers correspond to 95 percent confidence intervals, and we display point estimates just above the whiskers. The pre-pandemic baselines are 2019 in the ACS, SIPP, and ATUS, and February 2020 in the RPS. The 2020 ATUS data only use responses from May through December 2020, while the 2020 SIPP data use responses from April through December 2020. The 2024 CPS, RPS, and SWAA data use all survey waves available between January and June 2024 inclusive. We drop low-quality observations and those who fail attention-check questions in the SWAA. See Appendix Figure 2.3 for a time series of WFH by sex.

Figure 1 displays differences in WFH between women and men. Figure 1a plots the percentage point difference in the WFH Share and Figure 1b plots the percentage point difference in the WFH Only Rate. We display differences from three time periods: pre-pandemic, 2022 (the most recent year for which the ACS and SIPP are available), and 2024. The pre-pandemic period corresponds to 2019 for the ATUS, ACS, and SIPP, and February 2020 for the RPS. (The SWAA does not have a pre-pandemic measure of WFH.) The 2024 period uses all survey waves available between January and June 2024 inclusive. The whiskers correspond to 95 percent confidence intervals, and we display point estimates just above the whiskers. In this section we do not show the WFH Share for the SIPP, because hybrid WFH is very uncommon in that dataset (Bick, Blandin, et al., 2025).

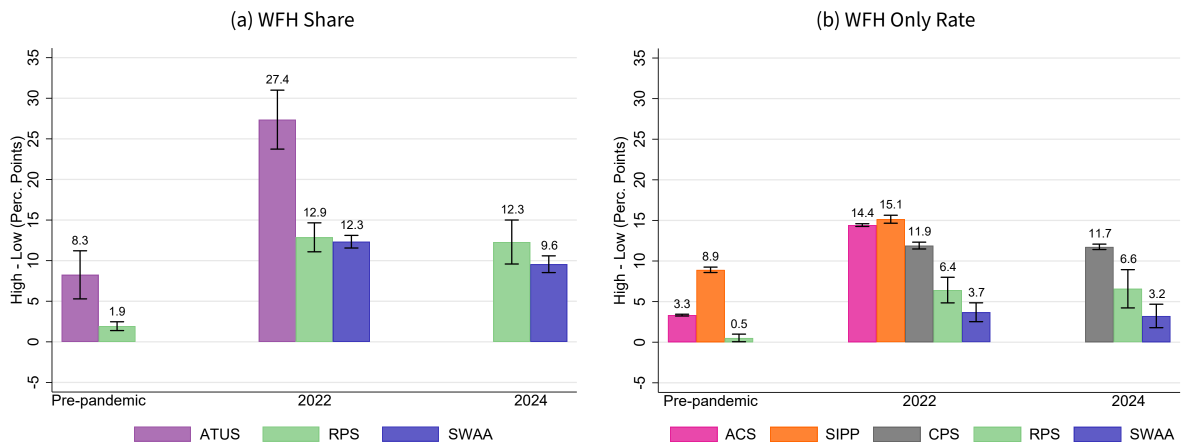
Figure 1a shows that before the pandemic, women had a slightly higher WFH Share than men in both the ATUS and RPS, though these differences were not statistically significant. In 2022 the gap between women and men expanded and was statistically significant in all datasets, with the largest gap in the ATUS (13.4 percentage points) and smaller gaps in the RPS (5.1 percentage points) and the SWAA (2.2 percentage points). From 2022–2024, the gaps remained fairly stable in the RPS and SWAA.

Figure 1b reveals broadly similar patterns for differences in the WFH Only Rate between women and men. Before the pandemic, the WFH Only Rate for women was between 0.9 and 2.0 percentage points higher than the rate for men in the ACS, SIPP, and RPS. In 2022 this gap expanded in all three datasets and was largest in the SWAA. In 2024 the gaps in the CPS (3.2 percentage points), RPS (3.8 percentage points), and SWAA (6.0 percentage points) are similar.

These figures reveal three key takeaways. First, women worked from home more than men pre-pandemic, but the differences were modest. Second, the increase in WFH since the pandemic was larger for women than for men, resulting in a larger WFH gap. Third, different datasets yield fairly similar estimates for the female-male gap in WFH, except for the ATUS, which in 2022 shows a substantially larger gap than in the RPS and SWAA.

3.2 Education

Figure 2
WFH by Education: High-Low



NOTE: Figure 2 displays differences in WFH by educational attainment. Figure 2a plots the percentage point difference in the WFH Share and Figure 2b plots the percentage point difference in the WFH Only Rate. The whiskers correspond to 95 percent confidence intervals, and we display point estimates just above the whiskers. The pre-pandemic baselines are 2019 in the ACS, SIPP, and ATUS, and February 2020 in the RPS. The 2020 ATUS data only use responses from May through December 2020, while the 2020 SIPP data use responses from April through December 2020. The 2024 CPS, RPS, and SWAA data use all survey waves available between January and June 2024 inclusive. We drop low-quality observations and those who fail attention-check questions in the SWAA. We have divided our samples into two mutually exclusive categories of educational attainment: BA or more (high) and some college or less (low). Note that "some college" includes both college graduates who did not receive a four-year degree and non-graduates. See Appendix Figure 2.4 for a time series of WFH by educational attainment.

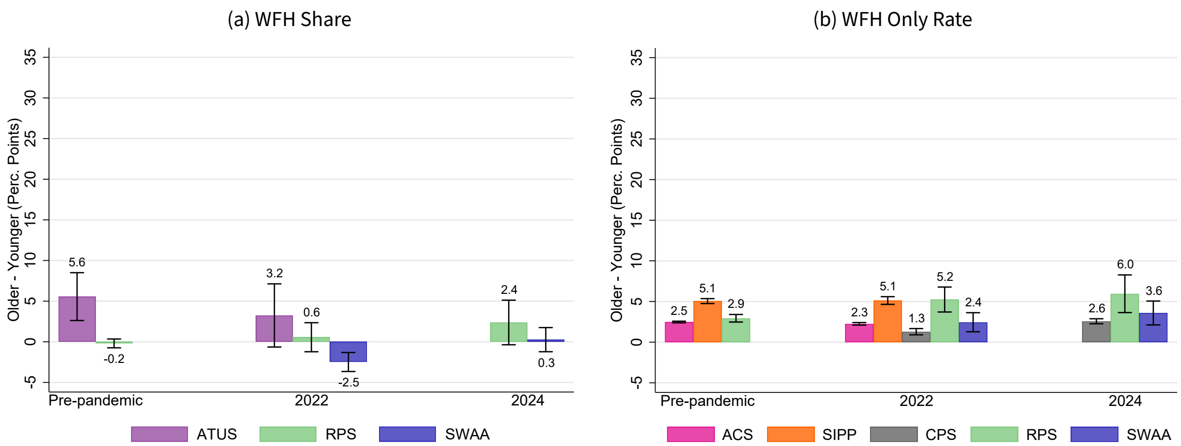
Figure 2 displays differences in WFH by educational attainment. The structure is identical to Figure 1, except that instead of displaying differences between women and men, we now display differences between workers with at least a four-year college degree and those without. Figure 2a shows that even before the pandemic, WFH was more common among college-educated workers. The magnitude of this difference is quite large in the ATUS (8.3 percentage points) compared with the RPS (1.9 percentage points). By 2022 the gap widened dramatically, reaching 27.4 percentage points in the ATUS, 12.9 percentage points in the RPS, and 12.3 percentage points in the SWAA. From 2022-2024, the gaps decreased slightly in the RPS and SWAA.

Figure 2b reveals qualitatively similar patterns for the WFH Only Rate. Before the pandemic, college-educated workers had a higher WFH Only Rate. As with the WFH Share, however, the magnitude of the gap differs across datasets: It is highest in the SIPP (8.9 percentage points), smaller in the ACS (3.3 percentage points), and smallest in the RPS (0.5 percentage points). In 2022 the gap expands in all three datasets, with larger gaps in the SIPP, ACS, and CPS and smaller gaps in the RPS and SWAA. From 2022-2024 the gaps remain relatively constant, with a decrease of 0.2 and 0.5 percentage points in the CPS and SWAA and an increase of 0.2 percentage points in the RPS.

These figures reveal three key takeaways. First, before the pandemic, workers with a four-year college degree already worked from home more than those without one. Second, the increase in WFH since the pandemic was larger for workers with a four-year degree. Third, government surveys (the ACS, SIPP, ATUS, and CPS) find larger estimates of the educational WFH gap than the independent online surveys.

3.3 Age

Figure 3
WFH by Age: Older-Younger



NOTE: Figure 3 displays differences in WFH by age. Figure 3a plots the percentage point difference in the WFH Share and Figure 3b plots the percentage point difference in the WFH Only Rate. The whiskers correspond to 95 percent confidence intervals, and we display point estimates just above the whiskers. The pre-pandemic baselines are 2019 in the ACS, SIPP, and ATUS, and February 2020 in the RPS. The 2020 ATUS data only use responses from May through December 2020, while the 2020 SIPP data use responses from April through December 2020. The 2024 CPS, RPS, and SWAA data use all survey waves available between January and June 2024 inclusive. We drop low-quality observations and those who fail attention-check questions in the SWAA. We have divided our samples into two mutually exclusive age bins: 18-39 (younger) and 40-64 (older). Note that the SWAA restricts its sample to workers aged 20 and above, but we have not restricted our sample in other datasets to adjust for this difference. See Appendix Figure 2.5 for a time series of WFH by age.

Figure 3 displays differences in WFH between older workers (aged 40–64) and younger workers (aged 18–39). Figure 3a shows that, compared with differences by sex and education, the relationship between age and the WFH Share is fairly weak. In all time periods and datasets, the difference in the WFH Share between older and younger workers is modest and statistically insignificant, with the exceptions of a higher WFH Share among older workers in the ATUS before the pandemic and a lower WFH share among older workers in the SWAA in 2022.

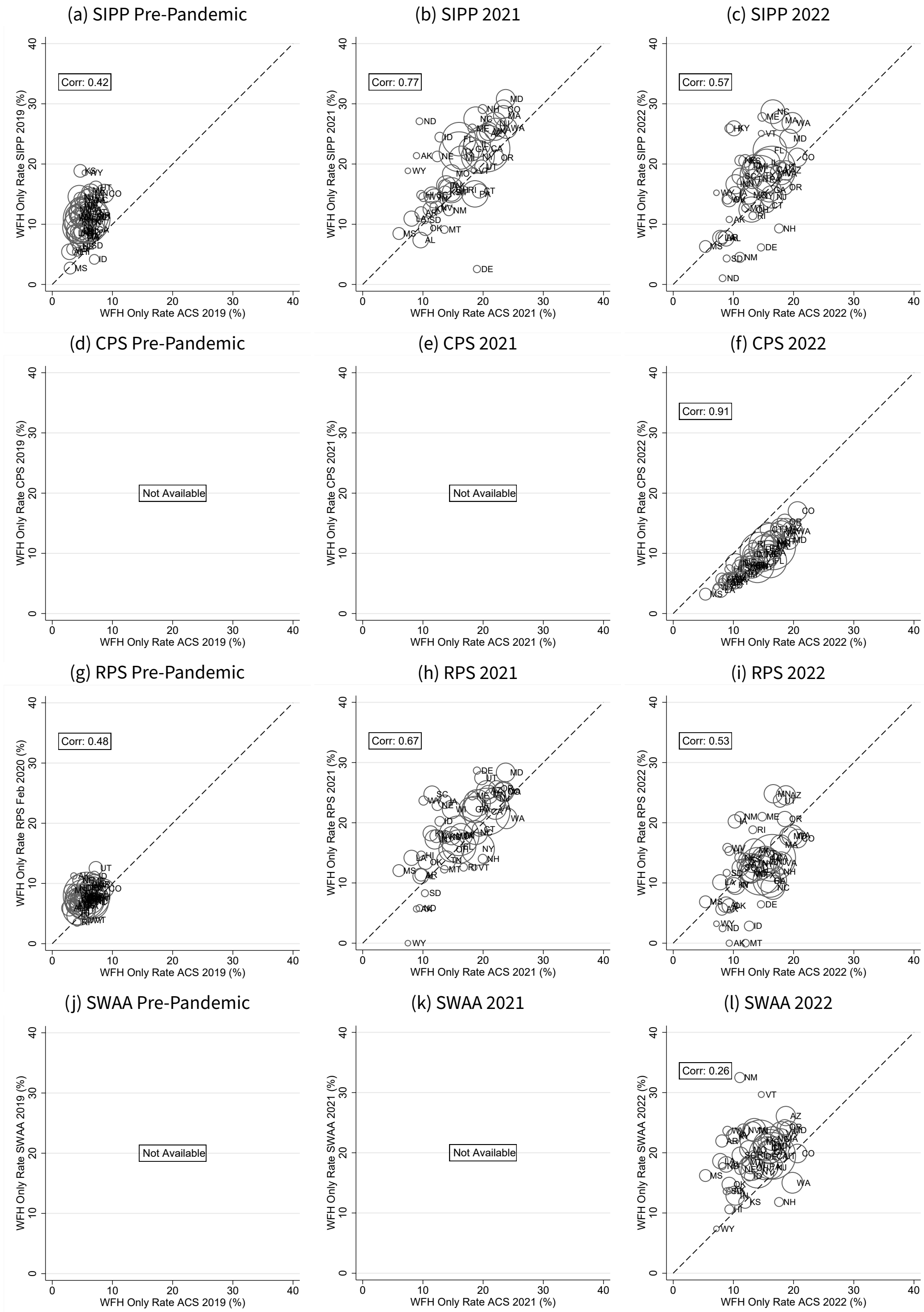
By contrast, Figure 3b does reveal large age differences in the WFH Only Rate. Before the pandemic, older workers had a significantly higher WFH Only Rate than younger workers in all datasets, with differences of 2.5, 5.1, and 2.9 percentage points in the ACS, SIPP, and RPS, respectively. In 2022 these gaps were fairly stable, ranging from 1.3 percentage points in the CPS to 5.2 percentage points in the RPS. They modestly expanded from 2022–2024 in the CPS, RPS, and SWAA, though the increase was not significant for the RPS or SWAA.

The figures in this section reveal four key takeaways. First, there is only a weak relationship between the WFH Share and age, and unlike with sex or education the relationship with age did not become stronger since the COVID-19 outbreak. Second, older workers do have a substantially higher WFH Only Rate. Taken together, these first two points imply that WFH Only is higher for older workers, but partial WFH is higher among younger workers. Third, unlike differences by education, the gap in WFH Only by age continued to increase from 2022–2024. Fourth, the RPS and SIPP tend to find larger age gaps than the ACS and SWAA.

3.4 States

Figure 4

WFH Only Rate by Dataset and State



NOTE: Figure 4 displays heterogeneity in WFH by state. Each panel plots the WFH Only Rate by state in the ACS on the horizontal axis against the WFH Only Rate by state in the SIPP, CPS, RPS, or SWAA on the vertical axis for one of three time periods: a pre-pandemic baseline, 2021, and 2022. The pre-pandemic baseline is 2019 in the SIPP and February 2020 in the RPS. We drop low-quality observations and those who fail attention-check questions in the SWAA. States are plotted as bubbles with areas directly proportional to their population share in the 2019 ACS release. The (rounded) population-weighted correlation between the state-level WFH Only Rate in the ACS and that in another dataset is plotted in the upper left-hand corner of each panel. The 45-degree line is also plotted.

Figure 4 documents variation in WFH by state, with each panel plotting the WFH Only Rate by state in the ACS on the horizontal axis against the corresponding rate from another dataset on the vertical axis. We use the ACS as our benchmark because its large sample size provides the most precise estimates, even for relatively small states. We focus solely on the WFH Only Rate to allow comparison with the ACS, and we omit the ATUS because it does not include this measure. We arrange the panels so that rows correspond to datasets and columns correspond to one of three distinct time periods: a pre-pandemic baseline, 2021, and 2022. We do not show data for 2020, because in that year there is no way to disentangle pre- and post-pandemic outcomes in the ACS. CPS and SWAA data are also not available for 2020 and 2021. See Appendix Figure 2.9 for results from 2023 data. We drop low-quality observations and those who fail attention-check questions in the SWAA. States are plotted as bubbles with areas proportional to their population share in the 2019 ACS.

Figures 4a and 4g display pre-pandemic WFH by state in the ACS, SIPP, and RPS. SIPP estimates of WFH across states are higher and more dispersed than in the the RPS and ACS. Figures 4b and 4h show a large increase in both the mean and dispersion of state-level WFH.[2] The correlation of state-level WFH with the ACS is 0.67 in the RPS and 0.77 in the SIPP, indicating fairly strong alignment in state-level variation across datasets. Figures 4c, 4f, 4i, and 4l display state-level WFH in all four datasets for 2022. The dispersion in WFH across states declines from 2021 to 2022 but remains far above pre-pandemic dispersion.[3] The CPS displays the highest correlation with the ACS (0.91), followed by the SIPP (0.57), RPS (0.53), and SWAA (0.26). For 2023, the correlation with the ACS is the same for the CPS and SIPP but lower for the RPS (0.19; see Appendix Figure 2.9).

These panels reveal three key takeaways. First, before the pandemic, there was minimal variation in WFH Only across states. Second, cross-state variation in WFH Only increased dramatically in 2021 and only slightly declined in 2022. Third, all datasets generally show consistent patterns in which states had a higher WFH Only Rate, though the strength of this consistency varies across datasets.

4. FIRM-LEVEL DIFFERENCES IN WFH

4.1 Firm Size

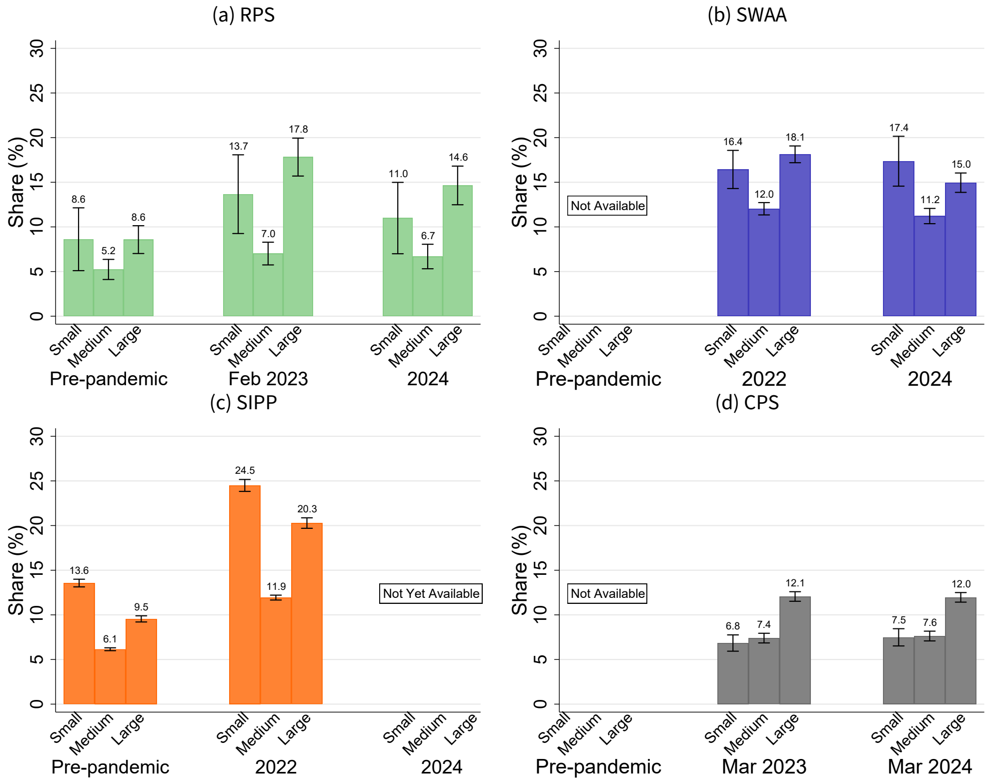
Barrero, Bloom, and Davis (2023) document a U-shaped relationship between firm size and fully remote work among employees using pooled SWAA data from 2020-2023. Figure 5 documents this relationship over time, also focusing on employees, using the RPS, SWAA, SIPP, and CPS. Each panel corresponds to a different dataset and covers one of three distinct time periods: a pre-pandemic baseline, 2022/2023, and 2024. The SWAA and CPS do not measure pre-pandemic WFH. Information on both WFH and firm size has only been available in the RPS since 2023 and is only available in the CPS using the ASEC March Supplement in 2023 and 2024. We partition firms into three groups based on firm size categories that are observable in all three datasets: small (1-9 employees), medium (10-499 employees), and large (500 or more employees). These three groups represent 17/48/36 percent of employees in the RPS, 9/54/37 percent in the SWAA, 18/62/20 percent in the SIPP, and 11/35/54 percent in the CPS.

[2] In the ACS, the population-weighted standard deviation in WFH across states increases from 1.1 percentage points pre-pandemic to 4.0 percentage points in 2021. In the RPS, this standard deviation increases from 1.3 to 4.3; in the SIPP, it increases from 2.5 to 5.3.

[3] In the ACS, the population-weighted standard deviation declines from 4.0 percentage points in 2021 to 3.0 percentage points in 2022. In the RPS it declines from 4.3 to 4.1, and in the SIPP it declines from 5.3 to 4.9.

Figure 5

WFH Only Rate by Firm Size, Employees Only



NOTE: Pre-pandemic refers to February 2020 in the RPS and to the 2019 SIPP administration in the SIPP. Information on firm size is unavailable in the RPS and CPS in 2022. For the RPS, we plot data from the February 2023 survey wave instead. For the CPS, 2023 and 2024 data come from the respective ASEC March supplements. The 2024 RPS and SWAA data use all survey waves available between January and June 2024 inclusive. We cannot construct a comparable pre-pandemic baseline in the SWAA, while the 2024 SIPP microdata have not been released as of the publication of this article. We drop low-quality observations and those who fail attention-check questions in the SWAA. We classify firms into one of three mutually exclusive categories: small (1-9 employees), medium (10-499 employees), and large (500 or more employees). See Appendix Figure 2.6 for the WFH Share by firm size among employees. See Appendix Figure 2.7 and Appendix Figure 2.8 for the time series of the WFH Only Rate and WFH Share by firm size among employees.

The figure generally confirms the U-shaped relationship between firm size and the WFH Only Rate documented by Barrero, Bloom, and Davis (2023). In all datasets except the CPS, WFH is lowest for medium firms in all time periods. WFH is most common among large firms in the RPS and CPS and among small firms in the SIPP.

The gradient between firm size and WFH increased after the COVID-19 outbreak in the RPS and SIPP. Specifically, the percentage point difference between small and medium firms increased from 3.4 to 6.7 in the RPS and from 7.5 to 12.6 in the SIPP. Similarly, the percentage point difference between large and medium firms increased from 3.4 to 10.8 in the RPS and from 3.4 to 8.4 in the SIPP.

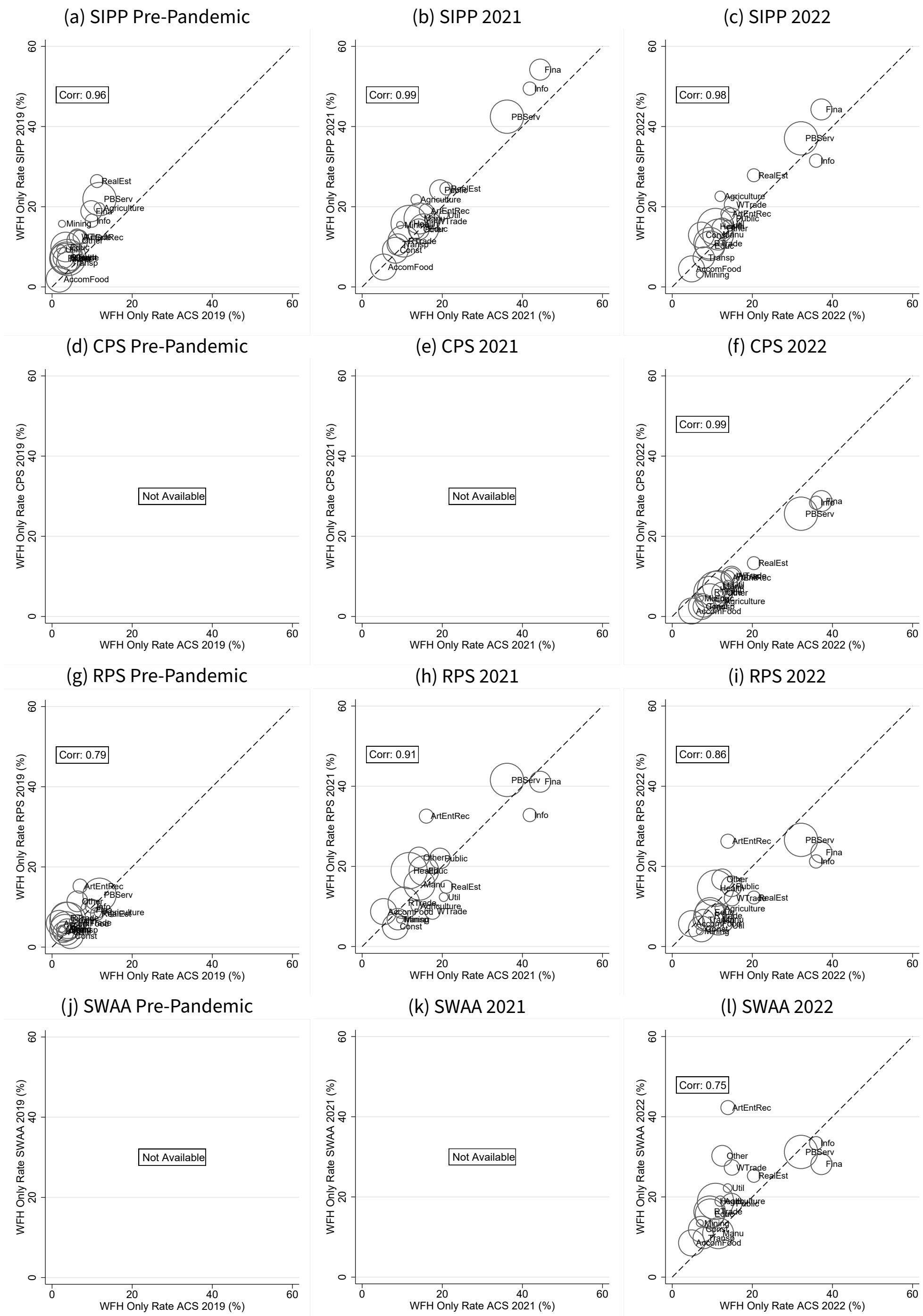
The changes between 2022/2023 and 2024 were much smaller and not statistically significant. The difference in WFH between small and medium firms decreased slightly in the RPS (from 6.7 to 4.3) and increased slightly in the SWAA (from 4.4 to 6.2). Over the same time period, the difference in WFH between large and medium firms decreased slightly in both the RPS (from 10.8 to 7.9) and the SWAA (from 6.1 to 3.8). Despite the flattening from 2023-2024, the gradient between firm size and WFH in the RPS is steeper in 2024 than before the pandemic.

Figure 5 shows that in the CPS alone, medium firms consistently had a higher WFH rate than small firms. However, the flattening gradient between firm size and WFH from 2023-2024 remains evident. As in the RPS, WFH rates in small and medium firms converged over this period. The difference in WFH between medium and small firms decreased slightly (from 0.6 to 0.1 percentage points), as did the difference between large and medium firms (from 4.7 to 4.4 percentage points).

4.2 Industries

Figure 6

WFH Only Rate by Dataset and Industry



NOTE: Figure 6 displays heterogeneity in WFH by industry. Each panel plots the WFH Only Rate by industry in the ACS on the horizontal axis against the WFH Only Rate by industry in either the SIPP, CPS, RPS, or SWAA on the vertical axis for one of three time periods: a pre-pandemic baseline, 2021, and 2022. The pre-pandemic baseline is 2019 in the SIPP and February 2020 in the RPS. We drop low-quality observations and those who fail attention-check questions in the SWAA. Industries are plotted as bubbles with areas directly proportional to their share of employment in the 2019 ACS release. The (rounded) population-weighted correlation between the industry-level WFH Only Rate in the ACS and that in another dataset is plotted in the upper left-hand corner of each panel. The 45-degree line is also plotted.

Figure 6 displays variation in WFH by industry, with each panel plotting the WFH Only Rate by industry in the ACS on the horizontal axis against the corresponding rate from another dataset on the vertical axis. These other datasets are the SIPP, CPS, RPS, and SWAA. We use the ACS as our benchmark because its large sample size provides the most precise estimates, even for relatively small industries. We arrange the panels so that rows correspond to datasets and columns correspond to one of three distinct time periods: a pre-pandemic baseline, 2021, and 2022. Industries are categorized according to NAICS classifications and are plotted as bubbles with areas directly proportional to their share of employment in the 2019 ACS.

Figures 6a and 6g display WFH by industry before the pandemic in the ACS, SIPP, and RPS. SIPP estimates are higher and more dispersed than in the ACS and RPS. The correlation of industry-level WFH with the ACS is 0.79 in the RPS and 0.96 in the SIPP, indicating close consistency in industry-level variation across datasets before the pandemic.

Figures 6b and 6h show the mean and dispersion of industry-level WFH increased considerably across all datasets in 2021. The population-weighted standard deviation increased from 3.3 to 11.9 percentage points in the RPS, from 3.3 to 11.4 percentage points in the ACS, and from 6.2 to 13.9 percentage points in the SIPP. These figures also exhibit even closer consistency across datasets in 2021: The correlation of industry-level WFH with the ACS rises to 0.91 in the RPS and to 0.99 in the SIPP. Although WFH rose in nearly every industry, all datasets show that WFH increased most in the Professional/Business services, Finance, and Information industries.

Figures 6c, 6f, 6i, and 6l display results for 2022. From 2021-2022, the population-weighted standard deviation decreased from 11.9 to 7.6 percentage points in the RPS, from 11.4 to 10.0 in the ACS, and from 13.9 to 11.3 in the SIPP. However, this variation still far exceeds pre-pandemic levels. In particular, in all of these datasets, the 2022 WFH Only Rate in the Professional/Business services, Finance, and Information industries is more than 1.8 times its pre-pandemic value (more than triple in the ACS, more than double in the RPS, and 1.86 times in the SIPP).

Industry-level information is also available for the SWAA and CPS in 2022. Figure 6f shows that the WFH Only Rate is consistently lower in the CPS than the ACS for all industries, but the correlation between industries is nearly perfect. By contrast, Figures 6i and 6l exhibit a slightly lower correlation with the ACS for the RPS and SWAA. The patterns are qualitatively and quantitatively similar in the CPS, RPS, and SWAA for 2023 (see Appendix Figure 2.10).

4.2.1 The Changing Role of Industry WFH Potential

In an influential article, Dingel and Neiman (2020) argue that industries have very different WFH potential due to their different occupational mixes. To investigate the importance of this factor in explaining industry differences in WFH, Figure 7 plots the Dingel-Neiman measure of WFH potential by industry on the horizontal axis against the actual WFH Only Rate on the vertical axis. The solid line is the line of best fit using these industry weightings, while the dashed line is simply the 45-degree line. The slope of the line of best fit (β) and correlation coefficient are reported in the upper left-hand corner. The first row of Figure 7 shows three distinct time periods: February 2020 (pre-pandemic), May 2020 (just after the pandemic), and 2022 (post-pandemic).

We rely mainly on RPS data for two reasons. First, Figure 6 demonstrated substantial consistency across all datasets in the WFH Only Rate by industry. Second, only the RPS contains estimates of WFH Only spanning from before the pandemic through to 2024.

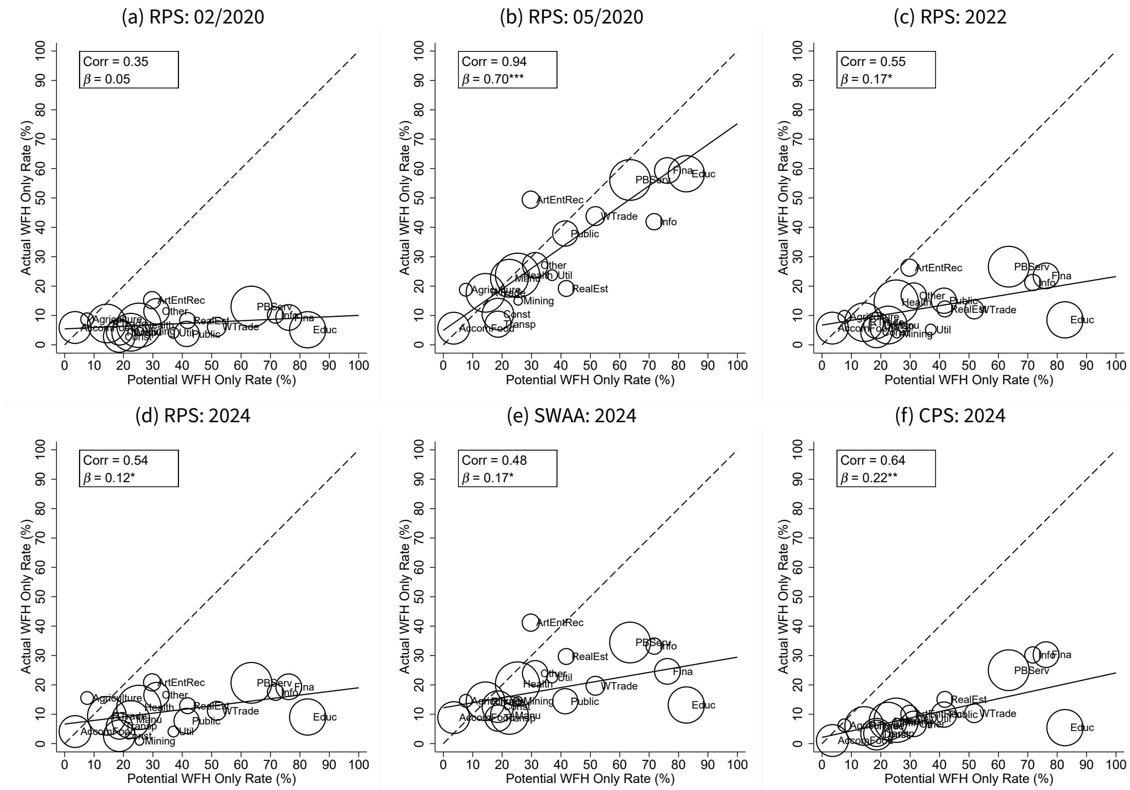
Figure 7a shows that the Dingel-Neiman measure of WFH potential was weakly predictive of actual WFH before the pandemic. On average, a 1-percentage-point increase in WFH potential was associated with only a 0.05-percentage-point increase in actual WFH, and this relationship was not statistically significant. The population-weighted correlation between these is 0.35. Nearly all industries lie considerably below the 45-degree line, suggesting that most industries had attained only a small fraction of their WFH capacity.

This narrative completely changed in May 2020, as shown in Figure 7b. A 1-percentage-point increase in WFH potential was associated with a 0.70-percentage-point increase in actual WFH, and the population-weighted correlation between the Dingel-Neiman measure of WFH potential and actual WFH was 0.94. Most industries lie close to the 45-degree line, suggesting that in the months after the COVID-19 outbreak, they were close to their maximum WFH potential.

However, Figure 7c shows that by 2022 the predictive power of WFH potential had again weakened. On average, a 1-percentage-point increase in WFH potential was associated with a 0.17-percentage-point increase in actual

Figure 7

WFH Potential and Actual WFH by Industry



NOTE: Figure 7 plots the measure of WFH potential by industry from Dingel and Neiman (2020) on the horizontal axis against the actual WFH Only Rate in the RPS, SWAA, or CPS by industry on the vertical axis. Industries are categorized according to NAICS classifications and are plotted as bubbles with areas directly proportional to their share of employment in the 2019 ACS release. The solid line is the line of best fit using these industry weightings, while the dashed line is simply the 45-degree line. The slope of the line of best fit and correlation coefficient are reported in the upper left-hand corner. Each panel in the first row corresponds to one of three distinct time periods: February 2020, May 2020, and 2022. The second row uses all survey waves available between January and June 2024 inclusive as a post-pandemic baseline to best distinguish the short-run impact of the pandemic on the WFH Only Rate from longer-run trends. We drop low-quality observations and those who fail attention-check questions in the SWAA.

WFH, compared with 0.70 in May 2020. In particular, while some industries with high WFH potential continue to exhibit elevated levels of WFH (such as Professional/Business services, Finance, and Information), WFH rates had fallen dramatically in other high-potential industries (such as Education). Figures 7d, 7e, and 7f show that this pattern remains present as late as 2024, when the coefficient of WFH potential for actual WFH was 0.12 in the RPS, 0.17 in the SWAA, and 0.22 in the CPS. In all three datasets, most industries continue to lie well below the 45-degree line.

To summarize, we find that industry WFH potential was not predictive of actual WFH before the pandemic, highly predictive of actual WFH near the onset of the pandemic, and then only moderately predictive of WFH after the pandemic. One possible explanation of these patterns is that WFH potential presents an upper rather than a lower bound for actual WFH. Industries with low WFH potential will never exhibit high WFH rates, regardless of the circumstances. Alternatively, industries with high WFH potential may exhibit high or low WFH rates depending on the economic environment. For example, if education industries have high WFH potential but remote schooling is less productive than in-person schooling, then WFH in education may be rare in normal times but high during emergencies like a global pandemic (Jack and Oster, 2023; Lewis, Kuhfeld, et al., 2021; Maldonado and De Witte, 2022).

5. CONCLUSION

The prevalence of WFH varies greatly across groups. In this article, we show that different surveys generally yield similar estimates of differences in WFH rates by sex, education, state of residence, firm size, and industry. We also document consistent patterns across surveys suggesting that pre-pandemic differences in WFH rates among these groups expanded following the COVID-19 outbreak. At the same time, we note some instances in which surveys differ quantitatively on WFH disparities, such as differences between education groups or the self-employed versus employees.

The results in this article regarding persistent disparities in WFH by demographic and firm characteristics may offer some helpful clues for future researchers investigating why aggregate WFH rates have declined from their pandemic peaks while remaining above their pre-pandemic levels (Bick, Blandin, et al., 2025). Another important topic for future research concerns the consequences of persistently higher WFH rates. One example is higher WFH rates among women compared with men. In one direction, if there are wage or career penalties of WFH relative to commuting, greater WFH by women could exacerbate income gaps between men and women (Arntz, Ben Yahmed, and Berlingieri, 2020). In the other direction, WFH may increase labor force participation among marginal workers (Bick, Blandin, and Fuchs-Schündeln, 2022; Tito, 2024), which could disproportionately impact women, especially those with young children. If WFH makes it easier to balance work and childcare, greater access to WFH could also increase fertility (Kurowska, Matysiak, and Osiewalska, 2023).

Another example is higher WFH rates among college-educated workers. Because more-educated workers also tend to have higher earnings, the expansion in WFH could widen inequality in welfare between more- and less-educated households. However, if WFH is a desirable amenity that must be paid for via a compensating differential, this welfare gain could come at the expense of lower wages, which could reduce measured income inequality between education groups.

A final example concerns geographic variation in WFH. For instance, WFH could raise the demand for housing if WFH workers require more workspace (Mondragon and Wieland, 2022), which might disproportionately increase housing prices in locations where WFH workers live. Moreover, a nascent literature on the connection between WFH and migration suggests that WFH workers migrate between states at higher rates (Bick, Blandin, et al., 2024), which could impact local or state tax revenues, housing prices, and emissions.

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APPENDIX 1. DATASETS AND DEFINITIONS

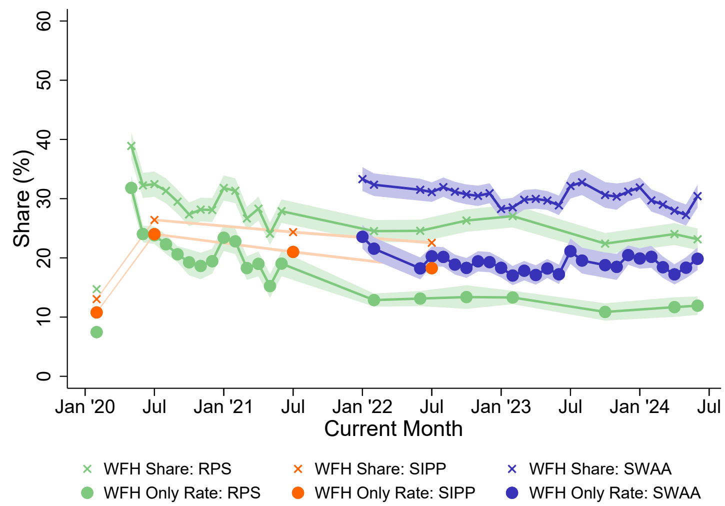
Appendix 1.1 Definition of Demographic Groups and Industries

The figures in Section 4 report results separately for different demographic groups. This appendix includes cross-dataset time series that correspond to the bar graphs in Section 4 and also report results by race and ethnicity. Demographic groups are defined as follows:

- Age
  - **Younger**: 18-39
  - **Older**: 40-64
- Education
  - **Lower**: No bachelor's degree
  - **Higher**: Bachelor's degree or higher
- Industry
  - **Agriculture** (NAICS 11): Agriculture, Forestry, Fishing and Hunting
  - **Mining** (NAICS 21): Mining, Quarrying, and Oil and Gas Extraction
  - **Util** (NAICS 22): Utilities
  - **Const** (NAICS 23): Construction
  - **Manu** (NAICS 31-33): Manufacturing
  - **WTrade** (NAICS 42): Wholesale Trade
  - **RTrade** (NAICS 44-45): Retail Trade
  - **Transp** (NAICS 48-49): Transportation and Warehousing
  - **Info** (NAICS 51): Information
  - **Fina** (NAICS 52): Finance and Insurance
  - **RealEst** (NAICS 53): Real Estate and Rental and Leasing
  - **PBServ** (NAICS 54-56): Professional, Scientific, and Technical Services and Management of Companies and Enterprises and Administrative and Support and Waste Management and Remediation Services
  - **Educ** (NAICS 61): Educational Services
  - **Health** (NAICS 62): Health Care and Social Assistance
  - **ArtEntRec** (NAICS 71): Arts, Entertainment, and Recreation
  - **AccomFood** (NAICS 72): Accommodation and Food Services
  - **Other** (NAICS 81): Other Services (except Public Administration)
  - **Public** (NAICS 99): Federal, State, and Local Government, excluding State and Local Schools and Hospitals and the U.S. Postal Service (OES Designation)

Appendix 1.2 WFH Only Versus WFH Share

Appendix Figure 1.1
WFH Only Rate and WFH Share in the RPS, SWAA, and SIPP

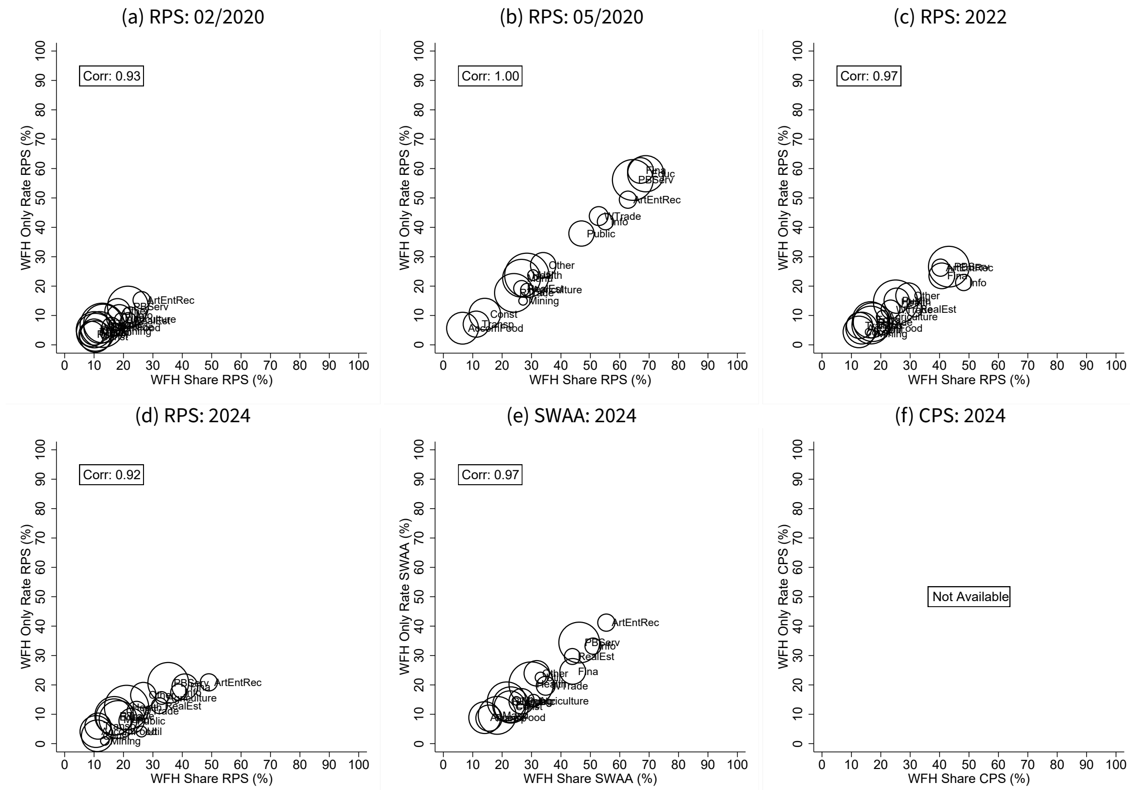


NOTE: Appendix Figure 1.1 shows the evolution of the WFH Only Rate and the WFH Share in the RPS, SWAA, and SIPP over time. The shaded regions represent 95 percent confidence intervals. We plot data from the 2019 release of the SIPP in February 2020. The 2020 SIPP data use responses from April through December 2020. We drop low-quality observations and those who fail attention-check questions in the SWAA.

Appendix Figure 1.1 illustrates that the WFH Only Rate and WFH Share follow broadly similar trends across datasets where they are both available. Consequently, Sections 4–4.2 focus exclusively on the WFH Only Rate. Agreement between our two WFH measures is especially pronounced in the SIPP. Therefore, with rare exceptions, we do not report the WFH Share when analyzing the SIPP. The SIPP WFH Share is reported in other appendix figures.

Appendix Figure 1.2

WFH Only Rate Against WFH Share by Dataset



NOTE: Appendix Figure 1.2 plots the WFH Only Rate by industry on the vertical axis against the WFH Share by industry on the horizontal axis in the RPS, SWAA, and CPS. The correlation is reported in the upper left-hand corner. A measure of the WFH Share is not available in the CPS. The 2024 RPS, SWAA, and CPS data use all survey waves available between January and June 2024 inclusive. We drop low-quality observations and those who fail attention-check questions in the SWAA.

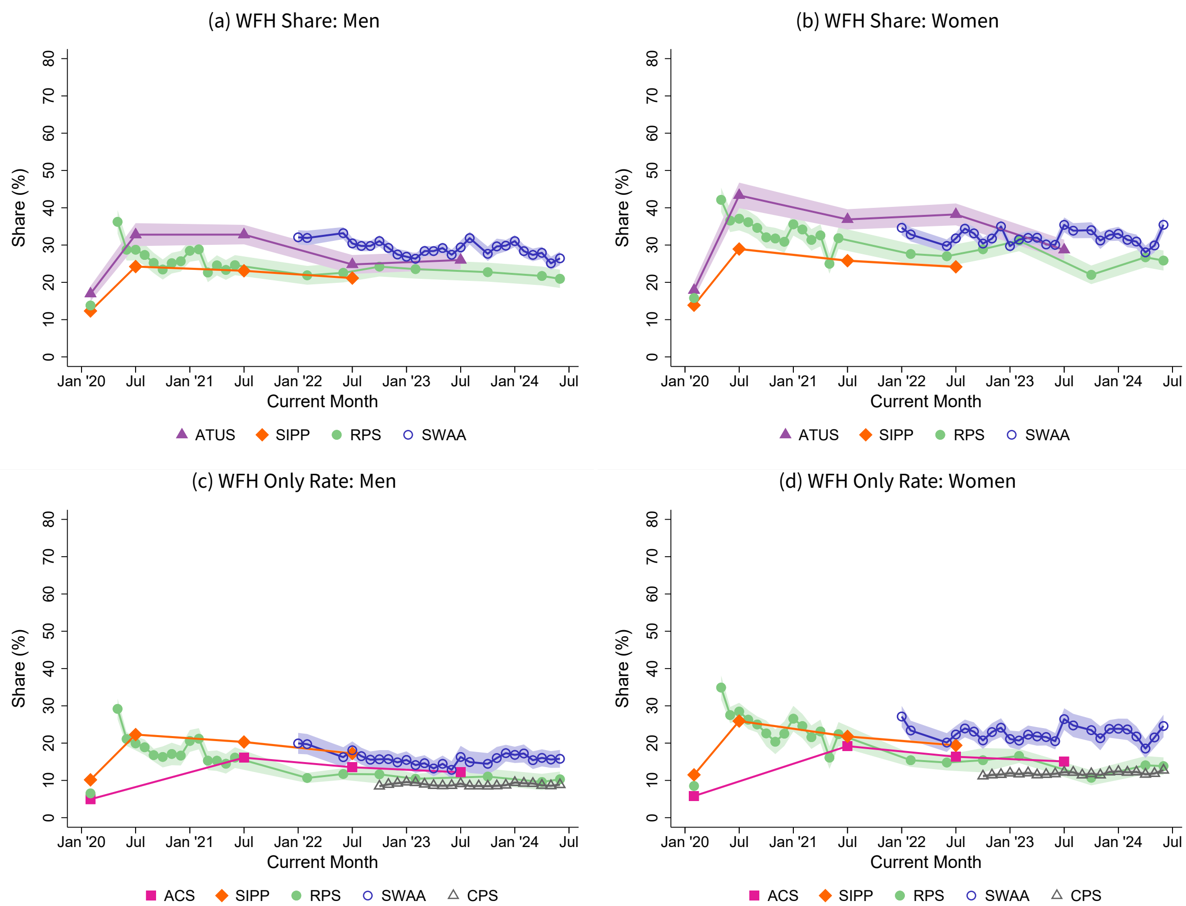
Figure 7 shows that WFH potential as estimated by Dingel and Neiman (2020) was somewhat predictive of the WFH Only Rate in the RPS, CPS, and SWAA. Appendix Figure 1.2 shows that the WFH Share is highly correlated with the WFH Only Rate in the RPS and SWAA, suggesting that this relationship is robust to changing the WFH measure.

APPENDIX 2. ADDITIONAL WFH GRAPHS

Appendix 2.1 Sex

Appendix Figure 2.3

WFH by Sex

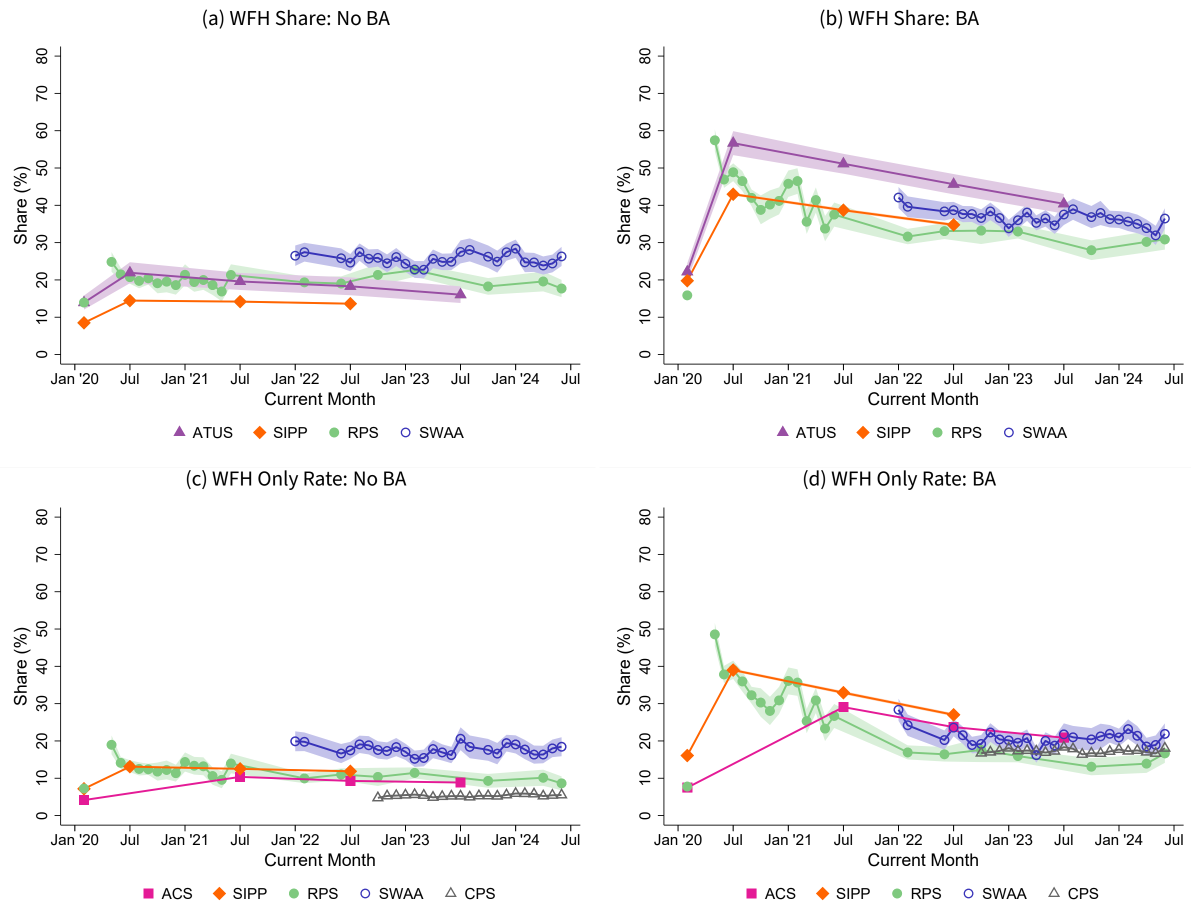


NOTE: Appendix Figure 2.3 compares the prevalence of WFH between men and women over time. Appendix Figures 2.3a and 2.3b plot the WFH Share, while Appendix Figures 2.3c and 2.3d plot the WFH Only Rate. The shaded regions represent 95 percent confidence intervals. We compute moments at the annual level in the ACS, SIPP, and ATUS and plot these in July of the corresponding year. We plot data from the 2019 releases of the ACS, SIPP, and ATUS in February 2020. We omit the 2020 ACS release because we cannot distinguish pre-pandemic months from post-pandemic months. The 2020 ATUS data only use responses from May through December 2020, while the 2020 SIPP data use responses from April through December 2020. We drop low-quality observations and those who fail attention-check questions in the SWAA.

Figure 1 displays gaps in WFH rates between men and women across three distinct time periods. Appendix Figure 2.3 displays the full time series and plots WFH rates for men and women separately. As suggested by Figure 1, men consistently have lower WFH rates than women.

Appendix 2.2 Education

Appendix Figure 2.4
WFH by Education

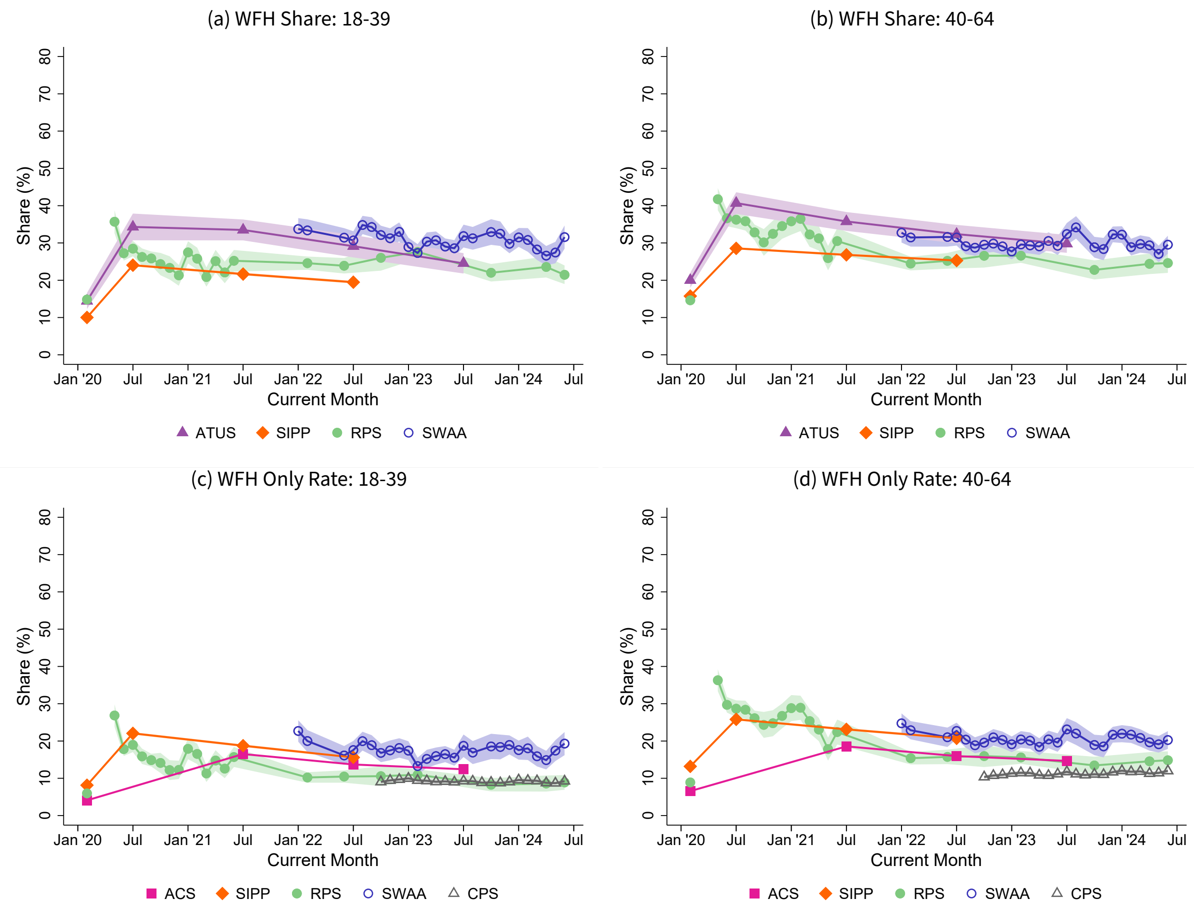


NOTE: Appendix Figure 2.4 compares the prevalence of WFH between workers with higher education and those with lower education over time. Appendix Figures 2.4a and 2.4b plot the WFH Share, while Appendix Figures 2.4c and 2.4d plot the WFH Only Rate. The shaded regions represent 95 percent confidence intervals. We compute moments at the annual level in the ACS, SIPP, and ATUS and plot these in July of the corresponding year. We plot data from the 2019 releases of the ACS, SIPP, and ATUS in February 2020. We omit the 2020 ACS release because we cannot distinguish pre-pandemic months from post-pandemic months. The 2020 ATUS data only use responses from May through December 2020, while the 2020 SIPP data use responses from April through December 2020. We drop low-quality observations and those who fail attention-check questions in the SWAA.

Figure 2 displays gaps in WFH rates between workers with higher education and those with lower education across three distinct time periods. Appendix Figure 2.4 displays the full time series and plots WFH rates for these workers separately. As suggested by Figure 2, workers with higher education consistently have greater WFH rates than those with lower education.

Appendix 2.3 Age

Appendix Figure 2.5
WFH by Age

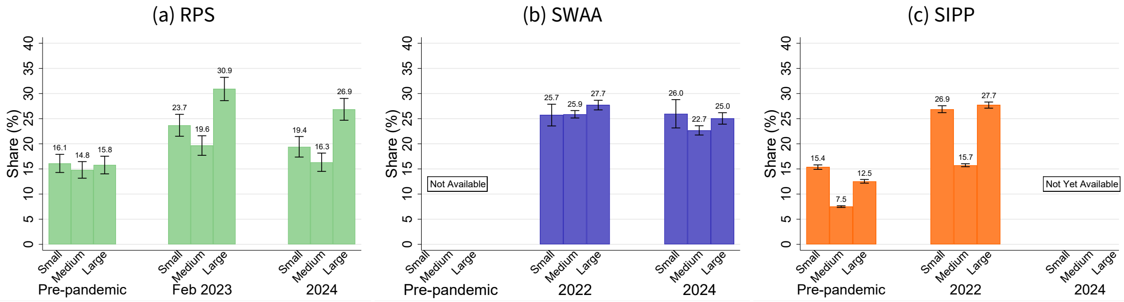


NOTE: Appendix Figure 2.5 compares the prevalence of WFH between younger and older workers over time. Appendix Figures 2.5a and 2.5b plot the WFH Share, while Appendix Figures 2.5c and 2.5d plot the WFH Only Rate. The shaded regions represent 95 percent confidence intervals. We compute moments at the annual level in the ACS, SIPP, and ATUS and plot these in July of the corresponding year. We plot data from the 2019 releases of the ACS, SIPP, and ATUS in February 2020. We omit the 2020 ACS release because we cannot distinguish pre-pandemic months from post-pandemic months. The 2020 ATUS data only use responses from May through December 2020, while the 2020 SIPP data use responses from April through December 2020. We drop low-quality observations and those who fail attention-check questions in the SWAA.

Figure 3 displays gaps in WFH rates between older and younger workers across three distinct time periods. Appendix Figure 2.5 displays the full time series and plots WFH rates for older and younger workers separately. As suggested by Figure 3, the series are fairly close together.

Appendix Figure 2.6

WFH Share by Firm Size, Employees Only

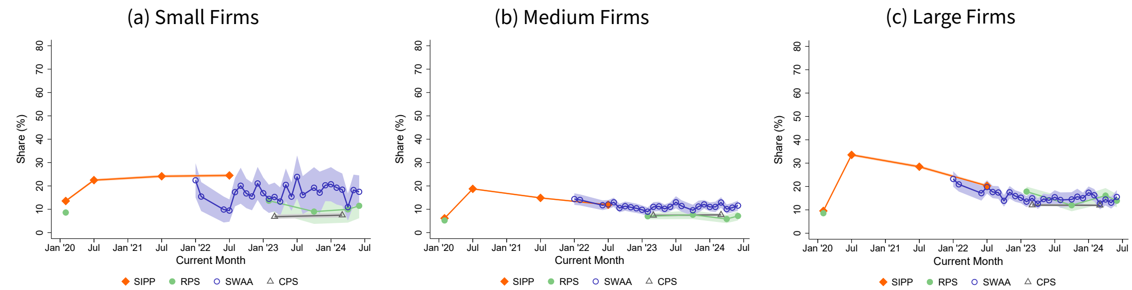


NOTE: Pre-pandemic refers to February 2020 in the RPS and to the 2019 SIPP administration in the SIPP. We plot data from the February 2023 RPS survey wave as 2022 data. We cannot construct a comparable pre-pandemic baseline in the SWAA, while the 2024 SIPP microdata have not been released as of the publication of this article. The 2024 RPS and SWAA data use all survey waves available between January and June 2024 inclusive. We drop low-quality observations and those who fail attention-check questions in the SWAA. We classify firms into one of three mutually exclusive categories: small (1-9 employees), medium (10-499 employees), and large (500 or more employees). See Appendix Figure 2.8 for the time series of WFH Share by firm size among employees.

Figure 5 plots the WFH Only Rate by firm size among employees in the RPS, SWAA, SIPP, and CPS in each of three distinct time periods. Appendix Figure 2.6 plots the WFH Share by firm size among employees in each of these time periods. Note that the WFH Share is unavailable in the CPS.

Appendix Figure 2.7

WFH Only by Firm Size, Employees

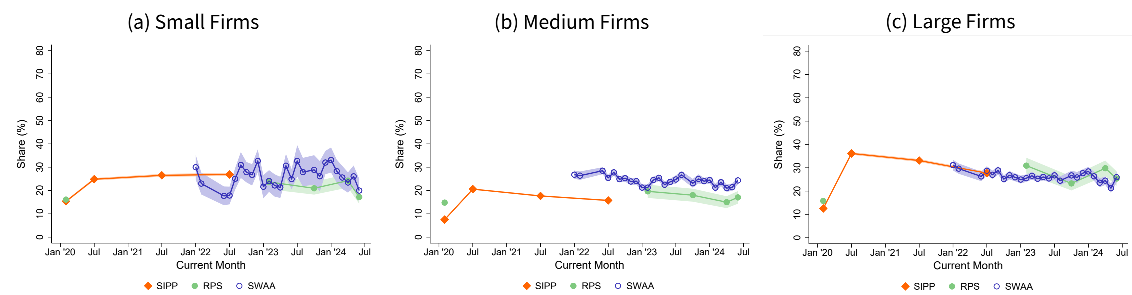


NOTE: Appendix Figure 2.7 compares the prevalence of WFH Only by firm size over time. Appendix Figures 2.7a, 2.7b, and 2.7c plot the WFH Only Rate among workers in small, medium, and large firms, respectively. The shaded regions represent 95 percent confidence intervals. We compute moments at the annual level in the SIPP and plot these in July of the corresponding year. We plot data from the 2019 release of the SIPP in February 2020, and the 2020 SIPP data use responses from April through December 2020. The CPS data points correspond to data from the 2023 and 2024 ASEC March supplements. We drop low-quality observations and those who fail attention-check questions in the SWAA.

Figure 5 displays the WFH Only Rate by firm size across three distinct time periods. Appendix Figure 2.7 displays the full time series and plots WFH rates for small, medium, and large firms separately. As suggested by Figure 5, the RPS series for large firms lies well above the RPS series for small and medium firms. The SWAA and SIPP show more variation in WFH rates by firm size over time.

Appendix Figure 2.8

WFH Share by Firm Size, Employees

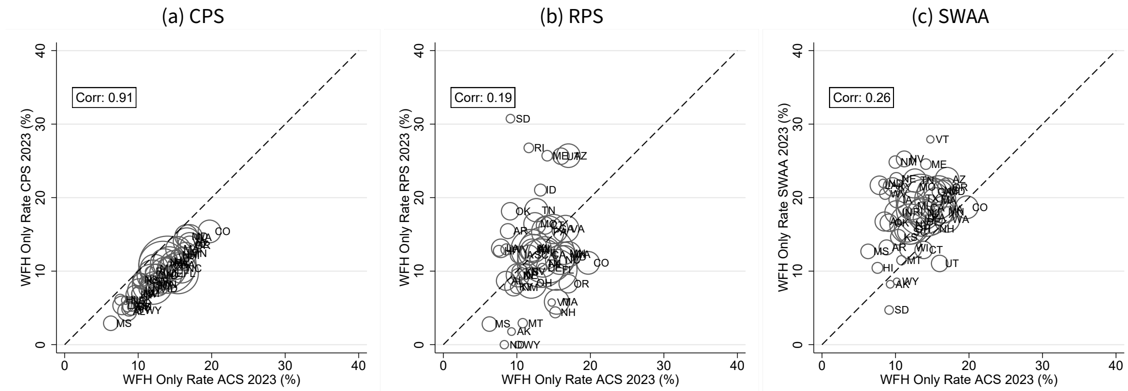


NOTE: Appendix Figure 2.8 compares the WFH Share by firm size over time. Appendix Figures 2.8a, 2.8b, and 2.8c plot the WFH Share among workers in small, medium, and large firms, respectively. The shaded regions represent 95 percent confidence intervals. We compute moments at the annual level in the SIPP and plot these in July of the corresponding year. We plot data from the 2019 release of the SIPP in February 2020, and the 2020 SIPP data use responses from April through December 2020. The CPS data points correspond to data from the 2023 and 2024 ASEC March supplements. We drop low-quality observations and those who fail attention-check questions in the SWAA.

Appendix Figure 2.6 displayed the WFH Share by firm size across three distinct time periods. Appendix Figure 2.8 displays the full time series and plots the WFH Share for small, medium, and large firms separately. As suggested by Appendix Figure 2.6, the RPS series for large firms lies well above the RPS series for small and medium firms. The SWAA and SIPP show more variation in the WFH Share by firm size over time.

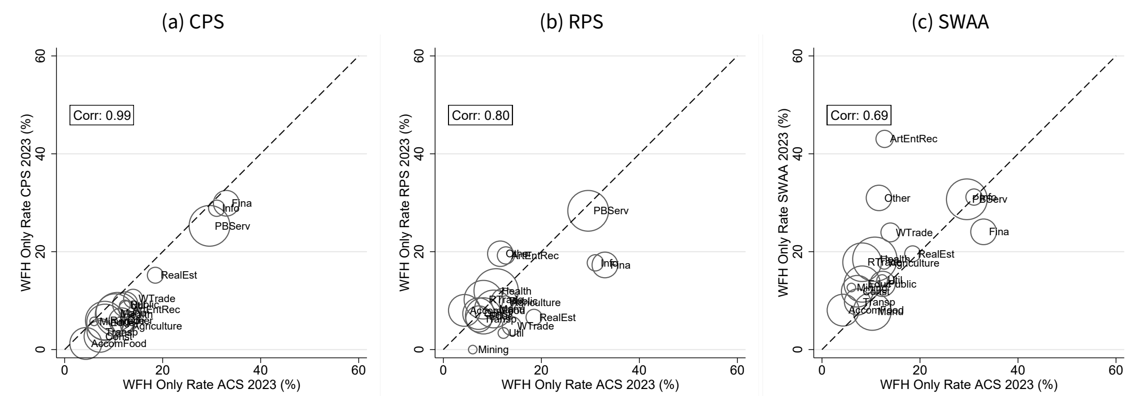
Appendix 2.4 WFH by State and Industry

Appendix Figure 2.9
WFH Only Rate by Dataset and State, 2023



NOTE: Appendix Figure 2.9 displays heterogeneity in WFH by state. Each panel plots the WFH Only Rate by state in the ACS in 2023 on the horizontal axis against the WFH Only Rate by state in either the CPS, RPS, or SWAA in 2023. We drop low-quality observations and those who fail attention-check questions in the SWAA. States are plotted as bubbles with areas directly proportional to their population share in the 2019 ACS release. The (rounded) population-weighted correlation between the state-level WFH Only Rate in the ACS and that in another dataset is plotted in the upper left-hand corner of each panel. The 45-degree line is also plotted.

Appendix Figure 2.10
WFH Only Rate by Dataset and Industry, 2023



NOTE: Appendix Figure 2.10 displays heterogeneity in WFH by industry. Each panel plots the WFH Only Rate by industry in the ACS in 2023 on the horizontal axis against the WFH Only Rate by industry in either the CPS, RPS, or SWAA in 2023. We drop low-quality observations and those who fail attention-check questions in the SWAA. Industries are plotted as bubbles with areas directly proportional to their population share in the 2019 ACS release. The (rounded) population-weighted correlation between the industry-level WFH Only Rate in the ACS and that in another dataset is plotted in the upper left-hand corner of each panel. The 45-degree line is also plotted.