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Authors	Alexander Bick, Adam Blandin, Aidan Caplan, and Tristan Caplan
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Federal Reserve Bank of St. Louis, Research Division, P.O. Box 442, St. Louis, MO 63166

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

Alexander Bick
Federal Reserve Bank of St. Louis, CEPR

Adam Blandin
Vanderbilt University

Aidan Caplan
Vanderbilt University

Tristan Caplan
Vanderbilt University

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Abstract

This paper documents heterogeneity in work from home (WFH) across six U.S. data sets. These surveys agree 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 show that an industry's WFH potential was highly correlated with actual WFH during the first year or two of the Covid-19 pandemic, but that this correlation was much weaker before and after the pandemic, suggesting that WFH potential is a necessary but not sufficient determinant in the decision to WFH.

JEL Codes: I18, J21, J22, J24, L23
Keywords: Work from Home, Remote Work, Telecommuting, Commuting, Data Set Comparisons

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*Contact: alexander.bick@stls.frb.org; adam.blandin@vanderbilt.edu; aidan.caplan@vanderbilt.edu; tristan.caplan@vanderbilt.edu. We thank Kevin Bloodworth II and Grace Ozor for excellent research assistance. The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

1 Introduction

The ability to 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 papers document substantial variation in actual WFH during the Covid-19 pandemic across different demographic groups and locations; see, for example Mondragon and Wieland (2022); Barrero et al. (2023); or Bick et al. (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 paper is to use multiple data sources to document differences in the evolution of WFH across demographic groups, geography, 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 Work 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. Second, we show that these demographic differences expanded after the Covid-19 outbreak. We find broadly similar trends in WFH differences across surveys, with some exceptions. One notable difference between surveys is that the magnitude of WFH differences by education is larger in the government-run surveys than in the RPS and the SWAA.

Next, we compare firm-related differences in WFH across surveys. Because our surveys are household-based, we do not have firm-level data. However, four datasets have information on firm size (the CPS, SIPP, the RPS, and the SWAA) and all datasets have information on industry. We arrive at two key findings.

Our first finding is that the relationship between WFH and firm size is U-shaped, with the smallest and largest firms exhibiting higher rates of WFH. This is however not true for the CPS, where WFH in small and medium are very similar. Moreover, the SIPP and the RPS show that the slope of this gradient increased following the Covid-19 outbreak.

Our second firm-related finding is that the relationship between firm industry and WFH evolved dramatically since the Covid-19 outbreak. We start by verifying that surveys agree quite closely about industry-level variation in WFH. We then show that just

[1] Bick et al. (2024) show that all surveys broadly agree about the trajectory of aggregate WFH since the Covid-19 outbreak.

before the pandemic there was very little variation in WFH across industries. However, in 2020 after the Covid-19 outbreak WFH expanded dramatically in some industries and hardly at all in others. We show 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 continue to exhibit high rates of WFH (e.g., Professional and Business services, Information services, and Financial services), 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.

We proceed with Section 2 providing a brief overview of the data sources covered and how we measure WFH. We analyze demographic differences in WFH in Section 3. 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 the data sources we use. For more details, especially regarding how each survey phrases WFH-related questions, we refer the interested reader to our companion paper (Bick et al., 2024).

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 a 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 employer's workplace would be considered to work remotely without WFH. The definition also excludes days when an individual commutes to work but also 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.

Table 1: Survey Overview

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

Our second measure is the *WFH Only Rate*, which represents the share of workers who WFH every workday within a week. This 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 on 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 only using the months following the COVID-19 outbreak for the SIPP (April-December 2020) and the ATUS (May-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 only been available since October 2022.

The RPS collected WFH information on a monthly basis from May 2020 through June 2021, and from 2022 on 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 WHO 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 we therefore study SWAA data only from January 2022 onwards.

The two independent surveys collect data only for individuals aged 18 to 64 (RPS) and for individuals aged 20 to 64 (SWAA), respectively. We restrict the sample in the government surveys to individuals aged 18 to 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 to 64 would have a very modest impact on our results.

3 Demographic Differences in Work from Home

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

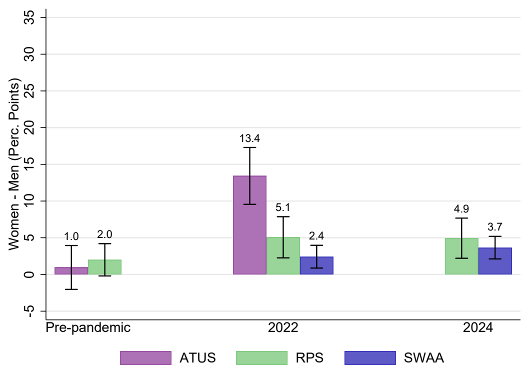
3.1 Sex

Figure 1 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 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 et al., 2024).

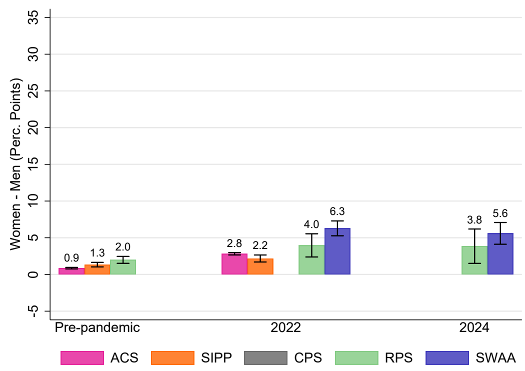
Figure 1a shows that before the pandemic women had a slightly higher WFH Share than men in both the ATUS and RPS, though these differences were not statistically significant. In 2022 the gap between women and men expanded and was statistically significant in all datasets, with the largest gap in the ATUS (13.4 percentage points) and smaller gaps in the RPS (5.1 percentage points) and the SWAA (2.4 percentage points). From 2022-2024, the gaps remained fairly stable in the RPS and SWAA.

Figure 1: WFH By Sex: Women-Men

(a) WFH Share



(b) WFH Only Rate



Notes: Figure 1 displays differences in WFH between men and women. Figure 1a plots the percentage point difference in the WFH Share and Figure 1 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 prepandemic baselines are 2019 in the ACS, SIPP, and ATUS, and February 2020 in the RPS. The 2020 ATUS data only uses responses from May through December 2020, while the 2020 SIPP data uses responses from April through December 2020. See Figure B.3 for a time series of WFH by sex.

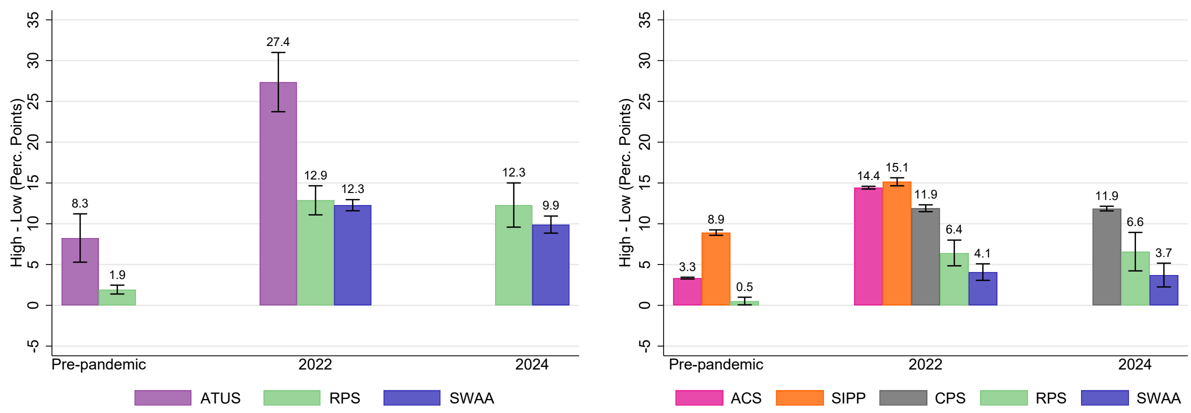
Figure 1b reveals broadly similar patterns for differences in the WFH Only Rate between women and men. Prior to the pandemic, the female WFH Only Rate was between 0.9-2.0 percentage points higher than the male rate in the ACS, SIPP, and RPS. In 2022 this gap expanded in all three datasets and was largest in the SWAA. In 2024 the gap in the CPS (3.0 percentage points), RPS (3.8 percentage points) and SWAA (5.6 percentage points) is similar.

These figures reveal three key takeaways. First, women WFH 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, with the exception of the ATUS, which in 2022 features a substantially larger gap than in the RPS and SWAA.

3.2 Education

Figure 2: WFH By Education: High-Low

(a) WFH Share (b) WFH Only



Notes: 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 prepandemic baselines are 2019 in the ACS, SIPP, and ATUS, and February 2020 in the RPS. The 2020 ATUS data only uses responses from May through December 2020, while the 2020 SIPP data uses responses from April through December 2020. 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 Figure B.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 workers without a four-year degree.

Figure 2a shows that even before the pandemic WFH was already 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 gap decreased slightly in the RPS and SWAA.

Figure 2b reveals qualitatively similar patterns for the WFH Only Rate. Prior to 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

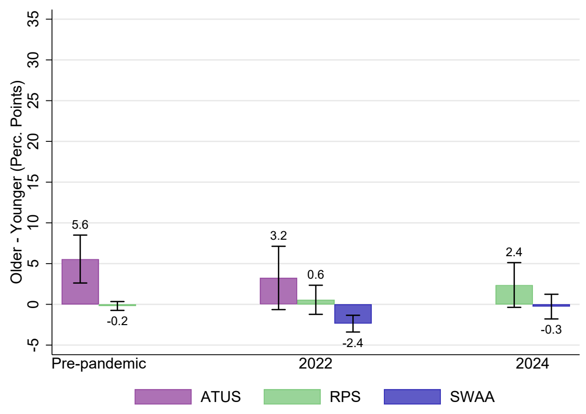
2022-2024 the gaps remain relatively constant, with a decrease of 0.3 and 0.4 percentage points in the CPS and SWAA, and an increase of 0.2 percentage points in the RPS.

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

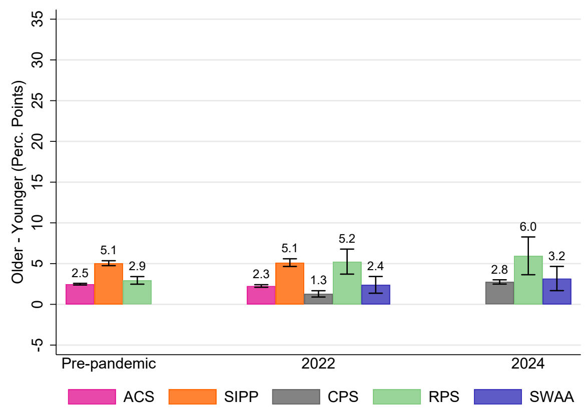
3.3 Age

Figure 3: WFH By Age: Older-Younger

(a) WFH Share



(b) WFH Only



Notes: Figure 3 displays differences in WFH by educational attainment. 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 prepandemic baselines are 2019 in the ACS, SIPP, and ATUS, and February 2020 in the RPS. The 2020 ATUS data only uses responses from May through December 2020, while the 2020 SIPP data uses responses from April through December 2020. 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 Figure B.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 exception of a higher WFH Share among older workers in the ATUS before the pandemic.

By contrast, Figure 3b does reveal large age differences in the WFH Only Rate. Prior to the pandemic, Older workers had a significantly higher WFH Only Rate than

Younger workers in all datasets, with differences of 2.5 percentage points in the ACS, 5.1 percentage points in the SIPP, and 2.9 percentage points in the RPS. In 2022 these gaps were fairly stable, ranging from 1.3 percentage points in the CPS to 5.2 percentage points in the RPS. These gaps 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 do the ACS and SWAA.

3.4 States

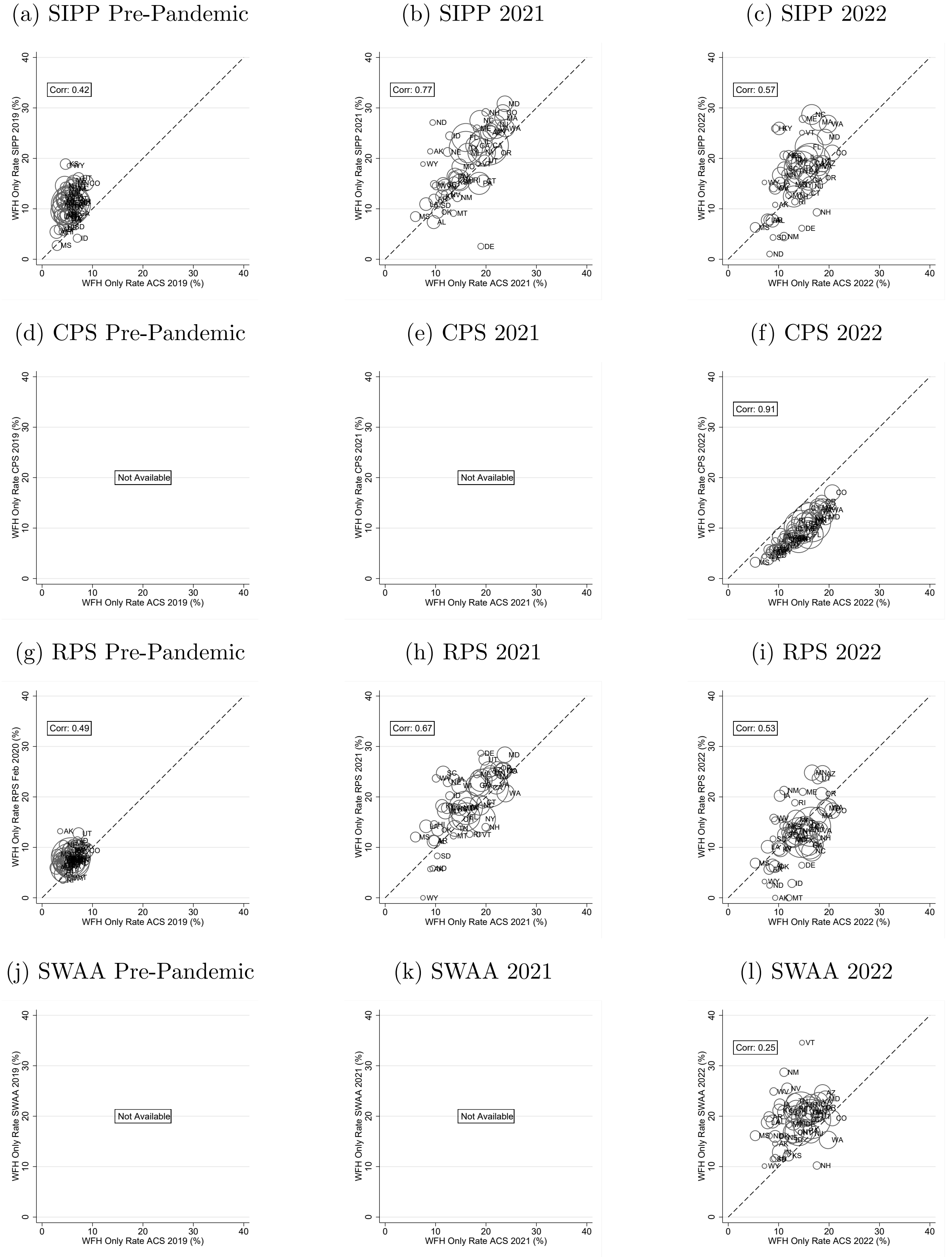
Figure 4 documents variation in WFH by state. Each panel plots the WFH Only Rate by state in the ACS on the horizontal axis against the corresponding rate from another dataset on the vertical axis. We use the ACS as our benchmark because its large sample size provides the most precise estimates, even for relatively small states. We focus solely on the WFH Only Rate because this allows us to compare our datasets with the ACS. We omit the ATUS because it does not have a WFH Only 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-pandemic and post-pandemic outcomes in the ACS. We stop in 2022 because ACS data is not yet available for later years. CPS and SWAA data are not available for 2020 and 2021. 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 agreement 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 prepandemic dispersion.[3] The CPS displays the highest correlation with the ACS

[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 1.4 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

Figure 4: WFH Only Rate By Dataset and State



Notes: 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 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. States are plotted as bubbles with areas directly proportional to their population share in the 2019 ACS release. The (rounded) population-weighted correlation of state-level WFH Only Rate in the ACS with state-level WFH-Only in another dataset is plotted in the upper-left hand corner of each panel. The 45-degree line is also plotted.

(0.91), followed by the SIPP (0.57), the RPS (0.53), and the SWAA (0.25). For 2023, the correlation with the ACS is the same for the CPS, lower for the RPS (0.23) and slightly higher for the SWAA (0.33), see Appendix Figure B.9.

These figures reveal three key takeaways. First, pre-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 agree about which states had a higher WFH Only Rate, but the strength of this agreement varies across datasets.

4 Firm-Level Differences in Work from Home

4.1 Firm Size

Barrero et al. (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, also focusing on employees, over time using the RPS, SWAA, SIPP, and CPS. Each panel corresponds to a different dataset and covers three distinct time periods: a pre-pandemic baseline, 2022/2023, and 2024. The SWAA and CPS do not measure pre-pandemic WFH, while information on both WFH and firm size in the RPS and CPS has only been available since 2023. 2024 data is not yet available in the SIPP. 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, 10/54/37 percent in the SWAA, 18/62/20 percent in the SIPP, and 11/35/54 percent in the CPS.

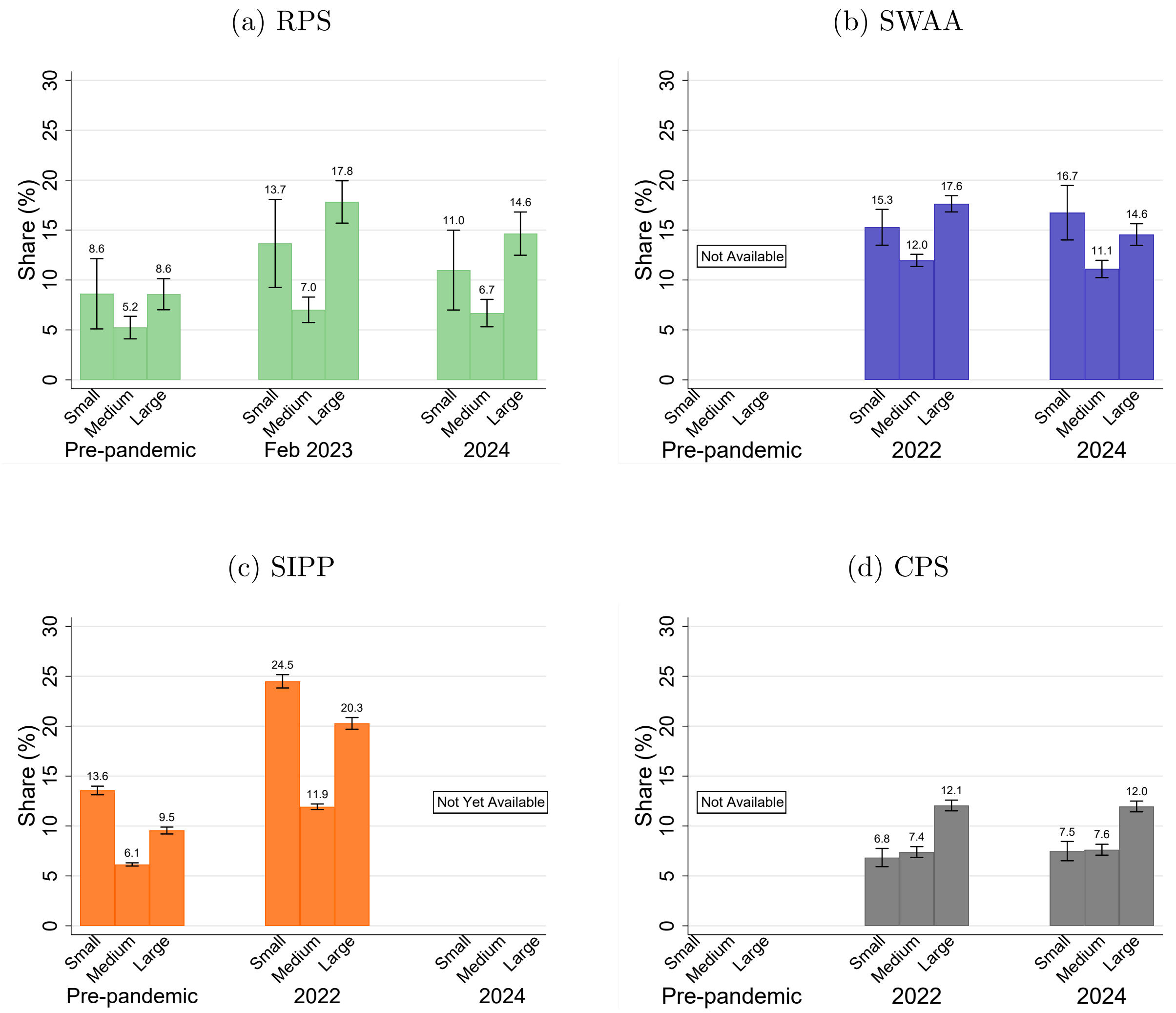
Figure 5 generally confirms the U-shaped relationship between firm size and the WFH Only Rate document by Barrero et al. (2023). In all datasets except the CPS, WFH is lowest for midsized firms in all time periods. WFH is most common among large firms in the RPS and CPS and among small firms in the SIPP.

The gradient between firm size and WFH increased after the Covid-19 outbreak in the RPS and the SIPP. The percentage point difference between small and midsized firms increased from 3.4 to 6.7 in the RPS and 7.5 to 12.6 in the SIPP. Similarly, the percentage point difference between large and midsize 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 signficant. The difference in WFH between small and midsize firms decreased slightly

5.3 to 4.9.

Figure 5: WFH Only Rate By Firm Size, Employees Only



Notes: 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, so we plot data from the February 2023 RPS wave and March 2023 CPS wave instead. 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 classify firms into one of three mutually exclusive categories: small (1-9 employees), medium (10-499 employees), and large (500 or more employees). See Figure B.6 for the WFH Share by firm size among employees. See Figure B.7 and Figure B.8 for the time series of the WFH Only Rate and WFH Share by firm size.

in the RPS (from 6.7 to 4.3) and increased slightly in the SIPP (from 3.3 to 5.6). Over the same time period, the difference in WFH between large and midsize firms decreased slightly in both the RPS (from 10.8 to 7.9) and the SWAA (from 5.6 to 3.5). Despite the flattening from 2023-2024, the gradient between firm size and WFH in the RPS is steeper in 2024 than pre-pandemic.

Figure 5d 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 is still evident. As in the RPS, WFH in small and midsize firms converged between 2023 and 2024. The difference in WFH between midsize and small firms decreased slightly (from 0.6 to 0.1 percentage points), as did the difference in WFH between large and midsize firms (from 4.7 to 4.4 percentage points).

4.2 Industries

Figure 6 displays variation in WFH by industry. Each panel plots 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, the CPS, the RPS, and the 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.

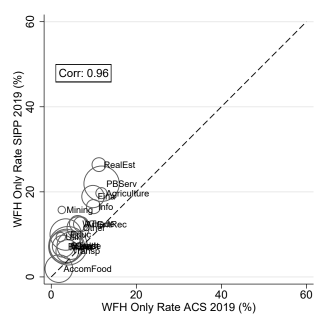
Figures 6a and 6g display WFH by industry before the pandemic in the ACS, SIPP, and RPS. SIPP estimates are higher and more dispersed than in the ACS and RPS. The correlation of industry-level WFH with the ACS is 0.79 in the RPS and 0.96 in the SIPP, indicating close agreement regarding industry-level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

Figures 6b and 6h show that in 2021 the mean and dispersion of industry-level WFH increased considerably across all datasets. The population-weighted standard deviation increased from 3.3 to 12.0 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 agreement between datasets in 2021: the correlation of industry-level WFH with the ACS rises to 0.91 in the RPS and 0.99 in the SIPP. Although WFH rose in nearly every industry, all datasets agree that WFH increased most in the Professional/Business Services, Finance, and Information industries.

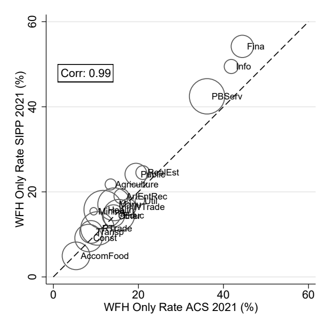
Figures 6c, 6f, 6i, and 6l display results for 2022. From 2021 to 2022, the population-weighted standard deviation decreased from 12.0 to 7.7 percentage points in the RPS, from 11.4 to 10.0 in the ACS, and from 13.9 to 11.3 in the SIPP. However, this still far exceeds the pre-pandemic variation in WFH by industry. In particular, in all of these datasets the 2022 WFH Only Rate in 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). In 2022 we also have industry-level information for the CPS and the SWAA. 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

Figure 6: WFH Only Rate By Dataset and Industry

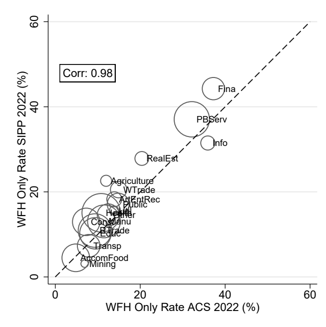
(a) SIPP Pre-Pandemic



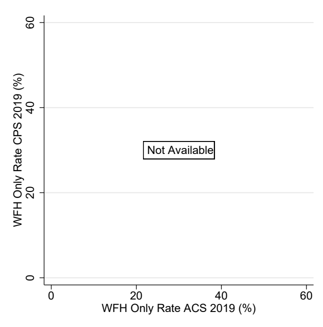
(b) SIPP 2021



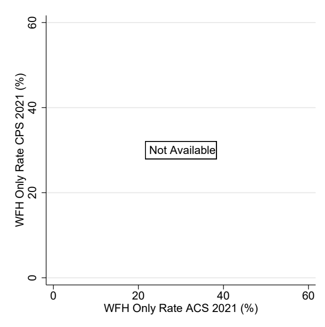
(c) SIPP 2022



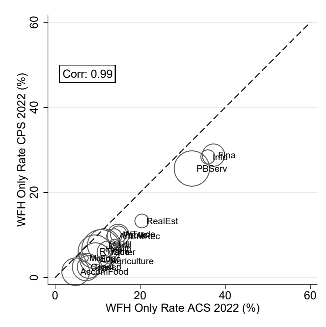
(d) CPS Pre-Pandemic



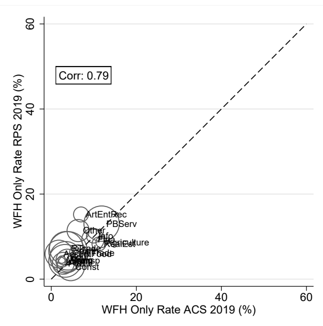
(e) CPS 2021



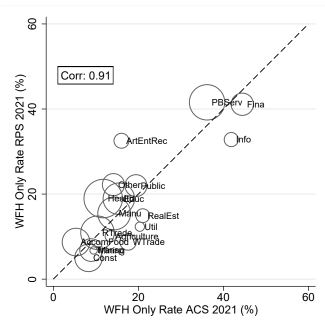
(f) CPS 2022



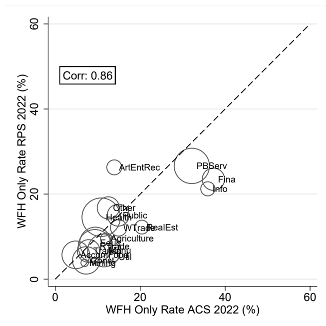
(g) RPS Pre-Pandemic



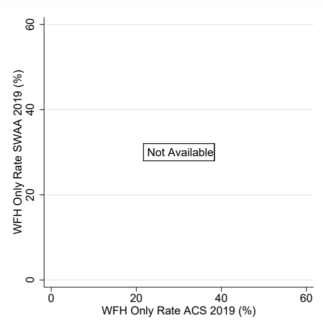
(h) RPS 2021



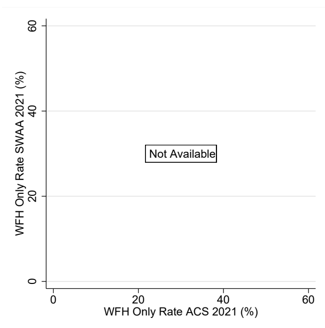
(i) RPS 2022



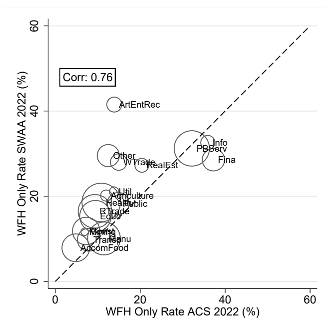
(j) SWAA Pre-Pandemic



(k) SWAA 2021



(l) SWAA 2022



Notes: 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. Industries are plotted as bubbles with areas directly proportional to their share of employment in the 2019 ACS release. The (rounded) population-weighted correlation of industry-level WFH Only Rate in the ACS with industry-level WFH Only Rate in another dataset is plotted in the upper-left hand corner of each panel. The 45-degree line is also plotted.

qualitatively and quantitatively similar the CPS, RPS, and SWAAfor 2023, see Appendix Figure B.10.

4.2.1 The Changing Role of Industry WFH Potential

In an influential paper, 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 Only 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 agreement across all datasets on the WFH Only Rate by industry. Second, only the RPS contains estimates of WFH Only spanning from pre-pandemic through to the present year.

Figure 7a shows that the Dingel-Neiman measure of WFH potential was weakly predictive of actual WFH pre-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 changes in May of 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 is 0.94. Most industries are close to the 45-degree line, suggesting that in the months after the Covid-19 outbreak most industries 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 is associated with a 0.17 percentage point increase in actual WFH, compared with 0.70 in May of 2020. In particular, while some industries with high WFH potential continue to exhibit elevated levels of WFH (such as Professional and Business Services, Information Services, and Financial Services), by 2022 WFH rates had fallen dramatically in other high-potential industries (such as Education). Figures 7d, 7f, and 7e show that this pattern remains present as late as 2024, when the coefficient of WFH potential for actual WFH is 0.12 in the RPS, 0.18 in the SWAA, and 0.22 in the CPS. In all three datasets most industries

Figure 7: WFH Potential and Actual WFH By Industry

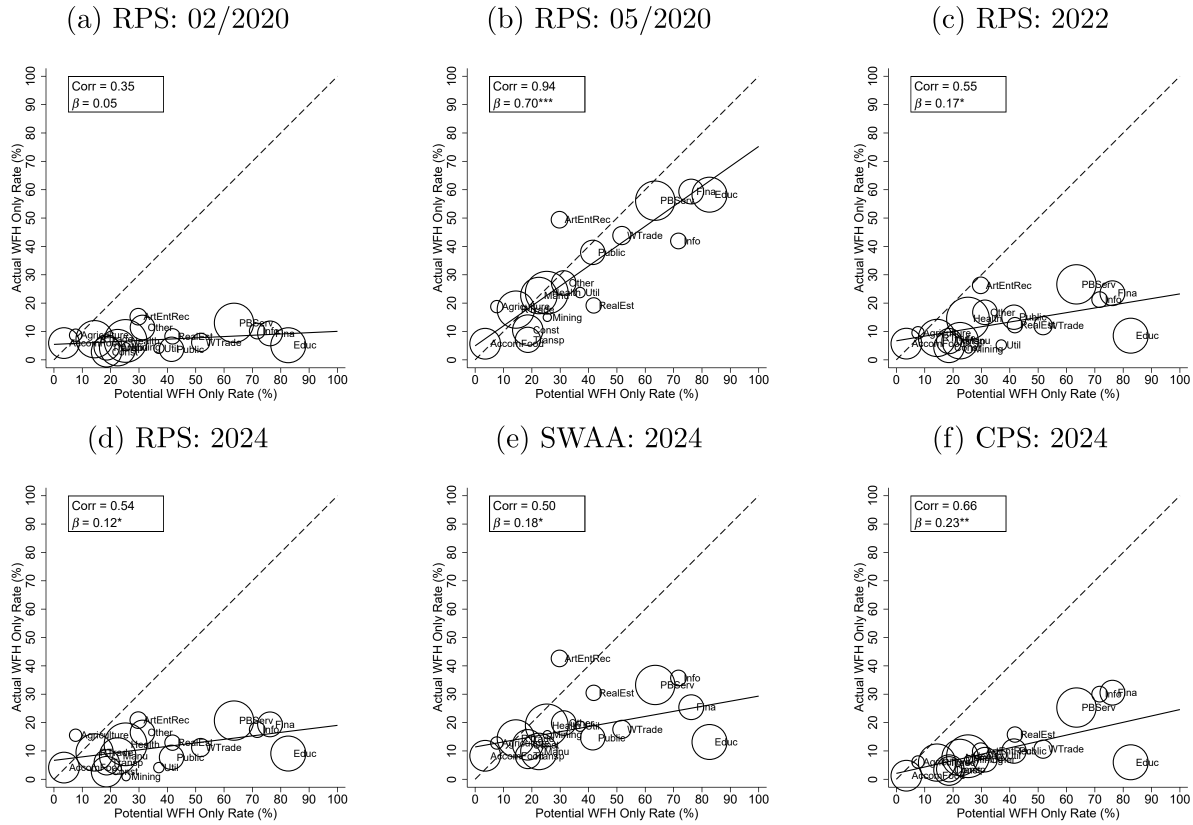


Figure 7 plots the measure of WFH potential by industry from Dingel and Neiman (2020) on the horizontal axis against the actual WFH Only Rate in the RPS by industry on the vertical axis. Industries are categorized according to NAICS classifications and are plotted as bubbles with areas directly proportional 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 2024 as a post-pandemic baseline to best distinguish the short-run impact of the pandemic on the WFH Only Rate from longer-run trends.

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 rates of WFH, regardless of the circumstances. Alternatively, industries with high WFH potential may exhibit high or low rates of WFH 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 et al., 2021; Maldonado and De Witte, 2022).

5 Conclusion

The prevalence of WFH varies greatly across groups. In this paper, we show that different surveys generally estimate similar differences in WFH rates by sex, education, state of residence, firm size, and industry. We also document agreement among surveys 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 disagree quantitatively about WFH disparities, such as differences between education groups or the self-employed versus employees.

The results in this paper regarding persistent disparities in WFH by demographic and firm characteristics may offer some helpful clues for future researchers investigating why aggregate rates of WFH have declined from their pandemic peaks while remaining above their pre-pandemic levels (Bick et al., 2024). Another important topic for future research concerns the consequences of persistently higher rates of WFH. One example is higher rates of WFH by 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 et al., 2020). In the other direction, WFH may increase labor force participation among marginal workers (Bick et al., 2022; Tito, 2024); this could disproportionately impact women, especially those with young children. If WFH makes it easier to juggle work and childcare, greater access to WFH could also potentially increase fertility (Kurowska et al., 2023).

Another example is higher rates of WFH 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 et al., 2024), which could impact local or state tax revenues, housing prices, and emissions.

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A Datasets and Definitions

A.1 Sample Statistics

We use the iterative proportional fitting (raking) algorithm of Stephan et al. (1940) to construct sampling weights. Before pooling survey data from different interview waves within the same month in the RPS, we adjust the weights from this raking algorithm as suggested in Potthoff et al. (1992).

$$N^{adj} = \left(\sum w\right)^2 / \sum w^2$$
$$w^{adj} = N^{adj} \times w / \sum w$$

In other datasets, the person-weighting w is such that $w = w^{adj}$ because survey data are less frequently available. We there calculate sample proportions (including the WFH Only Rate) and their standard deviations as

$$\hat{p} = \left(\sum w^{adj} x\right) / \sum w^{adj}$$
$$Std(\hat{p}) = \left(\sum_x \left((x - \hat{p})^2 w^{adj} / \sum w^{adj}\right) / \sum w^{adj}\right)^{\frac{1}{2}}$$

Let W denote workdays and C denote commute days. We compute the WFH Share of Workdays as:

$$\hat{r} = 1 - \frac{\sum C w^{adj}}{\sum W w^{adj}}$$

See the replication code for how we compute the standard error of this estimate.

A.2 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 which correspond to the bar graphs in section 4 and also report results by race and ethnicity. Demographic groups are defined as follows:

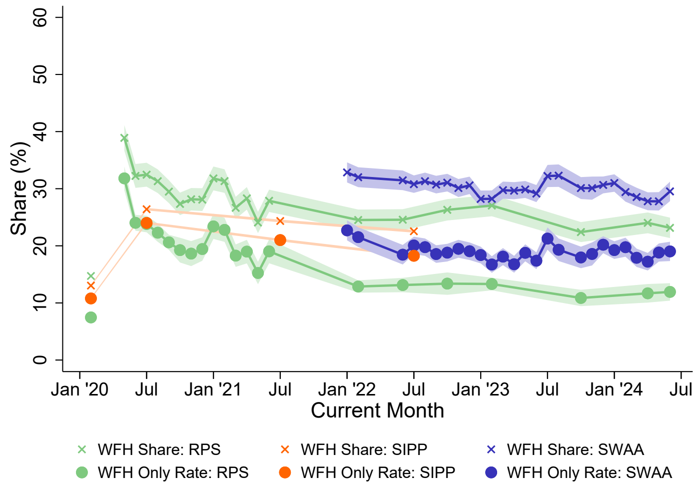
- Age
  - **Younger**: 18-39
  - **Older**: 40-64
- Education

- **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 $= 72$. Accomodation 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)

A.3 WFH Only Versus WFH Share

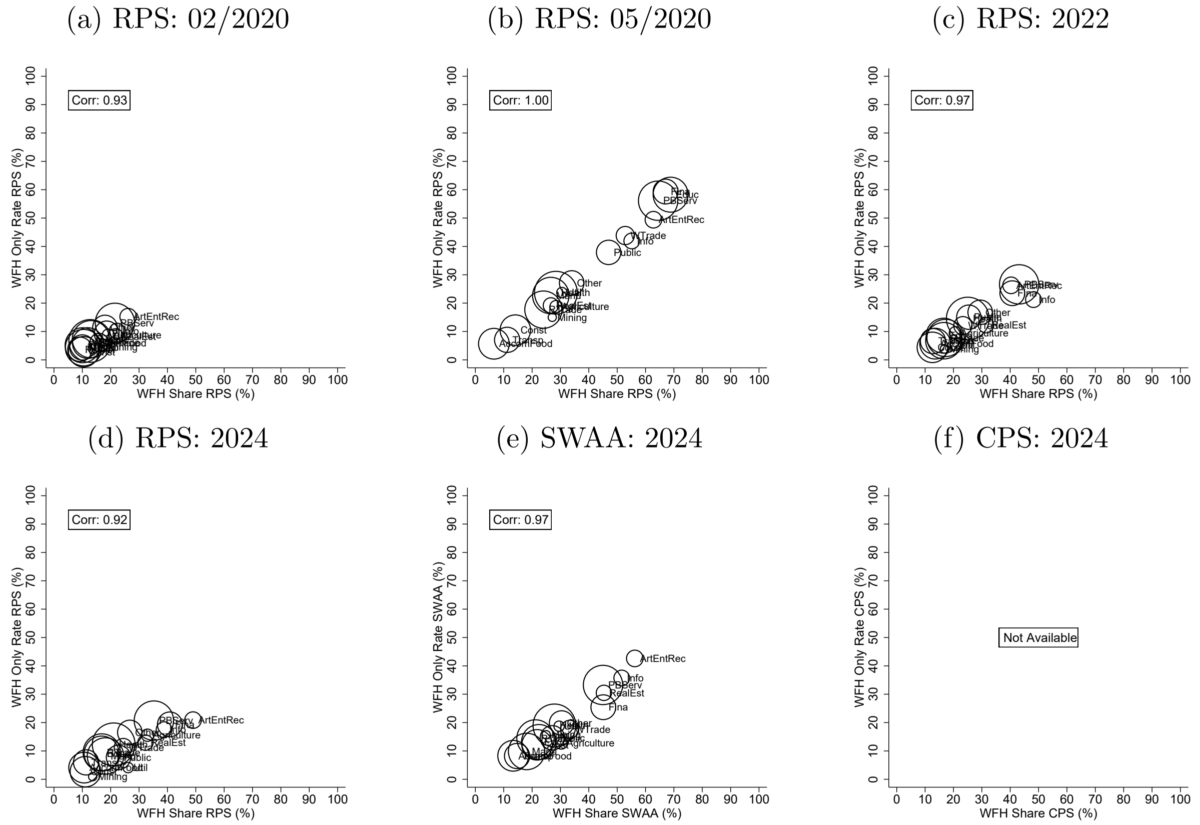
FIGURE A.1: WFH Only Rate and WFH Share in the RPS, SWAA, and SIPP



Notes: Figure A.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 uses responses from April through December 2020.

Figure A.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 deal exclusively with the WFH Only Rate. Agreement between our two WFH measures is especially pronounced in the SIPP. Therefore, with rare exceptions, this paper does not report the WFH Share when analyzing the SIPP. The SIPP WFH Share is reported in other appendix figures.

Figure A.2: WFH Only Rate Against WFH Share By Dataset



Notes: Figure A.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.

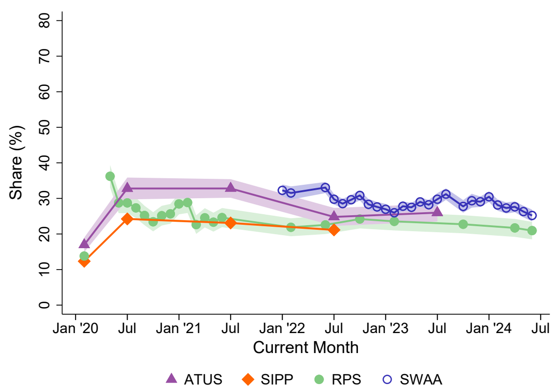
Figure 7 showed that WFH potential as estimated by Dingel and Neiman (2020) was somewhat predictive of the WFH Only Rate in the RPS, CPS, and SWAA. Figure A.2 shows that the WFH Share is highly correlated with the WFH Only Rate in the RPS and SWAA, suggesting that this relationship is robust to changing the WFH measure.

B Additional WFH Graphs

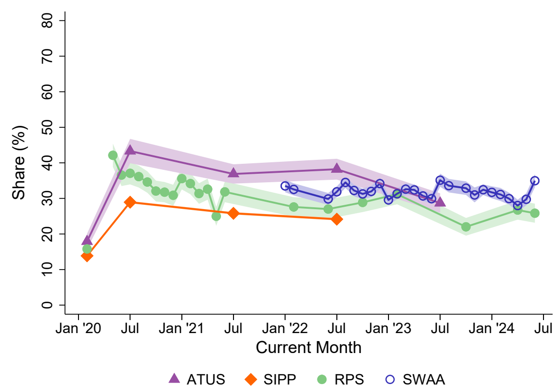
B.1 Sex

FIGURE B.3: WFH By Sex

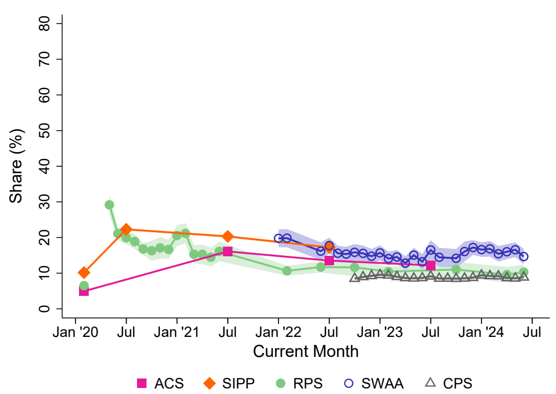
(a) WFH Share: Men



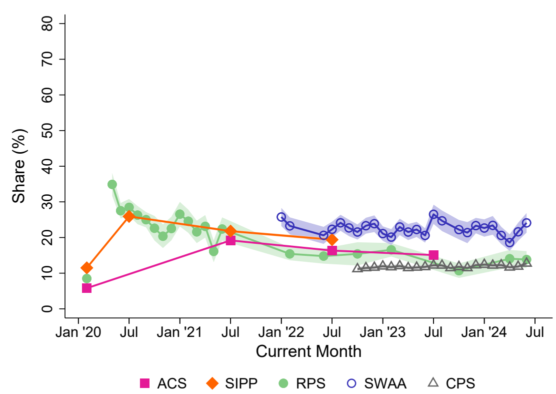
(b) WFH Share: Women



(c) WFH Only Rate: Men



(d) WFH Only Rate: Women



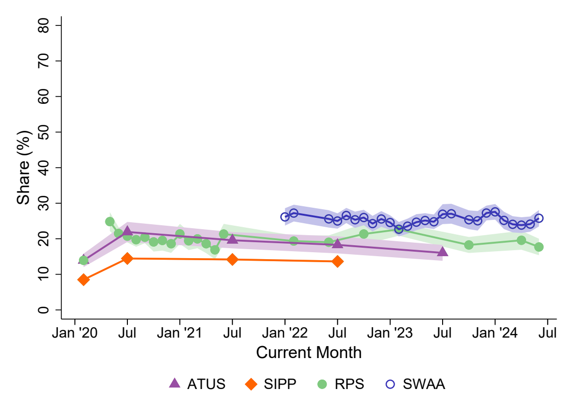
Notes: Figure B.3 compares the prevalence of WFH between men and women over time. Figures B.3a and B.3b plot the WFH Share, while figures B.3c and B.3d plot the WFH Only Rate. The shaded regions represent 95 percent confidence intervals. We compute moments on the annual level in the ACS, SIPP, and ATUS 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 point only uses responses from May through December 2020, while the 2020 SIPP data uses responses from April through December 2020.

Figure 1 displayed gaps in WFH rates between men and women across three distinct time periods. Figure B.3 displays the full time series and plots WFH rates for men and women separately. As suggested by Figure 1, men consistently have lower rates of WFH than women.

B.2 Education

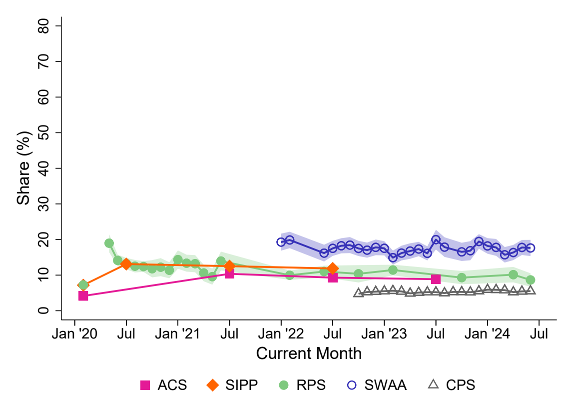
Figure B.4: WFH By Education

(a) WFH Share: No BA

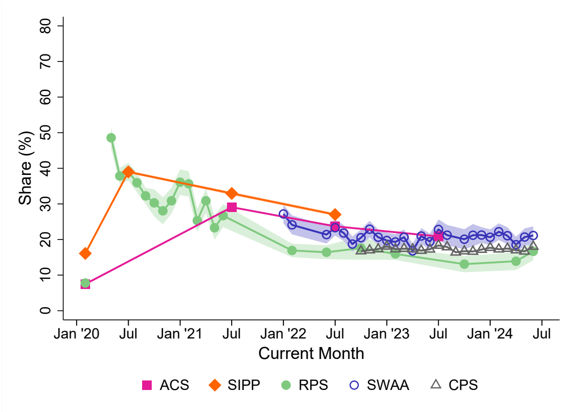


(b) WFH Share: BA

(c) WFH Only Rate: No BA



(d) WFH Only Rate: BA



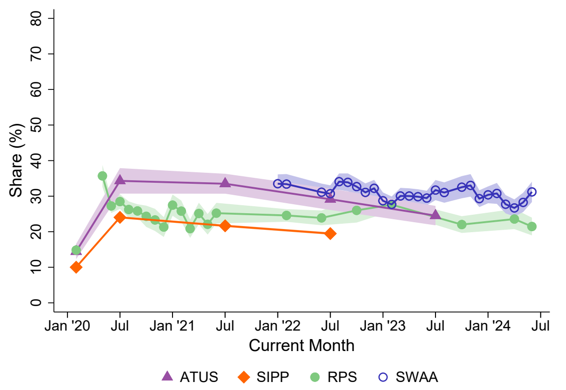
Notes: Figure B.4 compares the prevalence of WFH between Low and High education workers over time. Figures B.4a and B.4b plot the WFH Share, while figures B.4d and B.4c plot the WFH Only Rate. The shaded regions represent 95 percent confidence intervals. We compute moments on the annual level in the 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 point only uses responses from May through December 2020 ,while the 2020 SIPP data uses responses from April through December 2020.

Figure 2 displayed gaps in WFH rates between High and Low education workers across three distinct time periods. Figure B.4 displays the full time series and plots WFH rates for High and Low education workers separately. As suggested by Figure 2, High education workers consistently have higher rates of WFH than Low education workers.

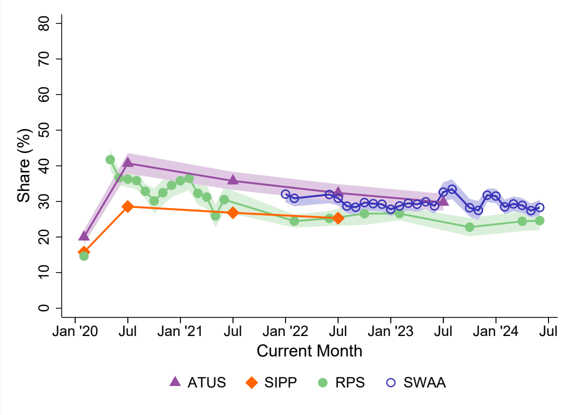
B.3 Age

Figure B.5: WFH By Age

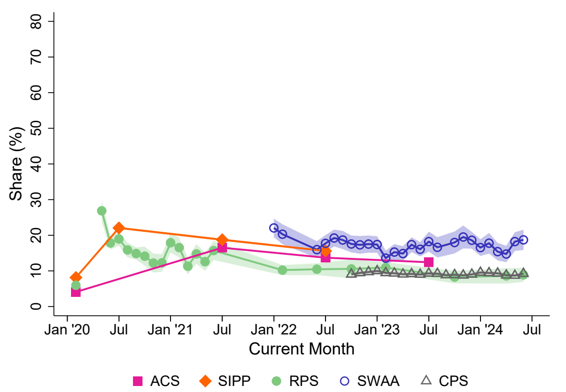
(a) WFH Share: 18-39



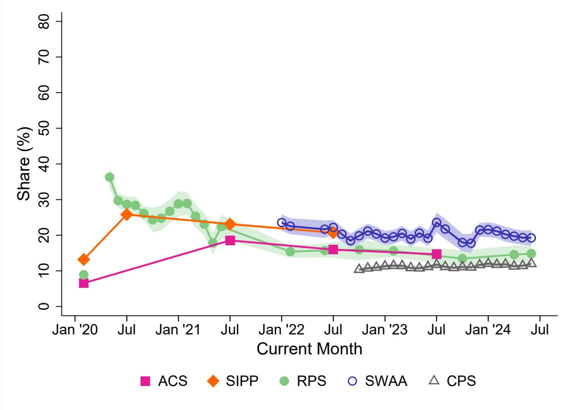
(b) WFH Share: 40-64



(c) WFH Only Rate: 18-39



(d) WFH Only Rate: 40-64



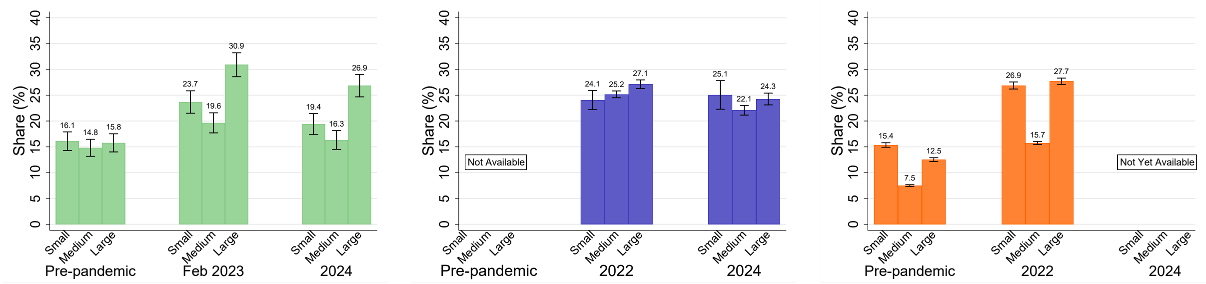
Notes: Figure B.5 compares the prevalence of WFH between Younger and Older workers over time. Figures B.5a and B.5b plot the WFH Share, while figures B.5c and B.5d plot the WFH Only Rate. The shaded regions represent 95 percent confidence intervals. We compute moments on the annual level in the ACS, 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 point only uses responses from May through December 2020, while the 2020 SIPP data uses responses from April through December 2020.

Figure 3 displayed gaps in WFH rates between Older and Younger workers across three distinct time periods. Figure B.5 displays the full time series and plots WFH rates for Older and Younger education workers separately. As suggested by Figure 3, the series are fairly close together.

B.4 Firm Size

Figure B.6: WFH Share By Firm Size, Employees Only

(a) RPS (b) SWAA (c) SIPP



Notes: 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. 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 Figure B.8 for the time series of WFH Share by firm size among employees.

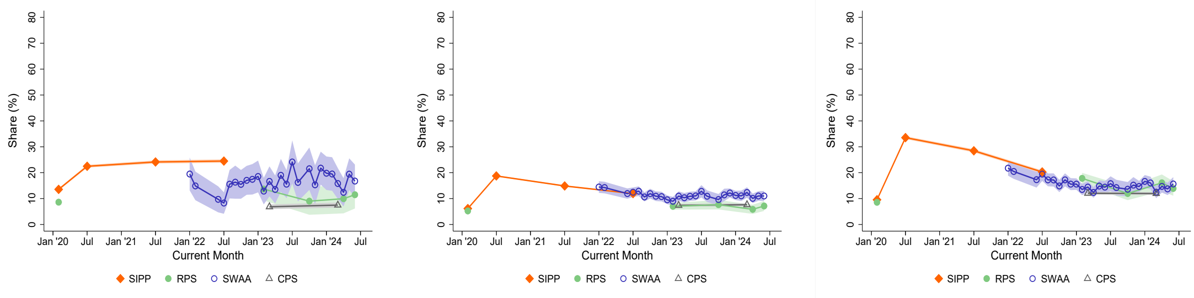
Figure 5 plotted the WFH-Only rate by firm size among employees only across the RPS, SWAA, and SIPP. Figure B.6 plots the WFH Share by firm size among employees.

Figure 5 displayed the WFH Only Rate by firm size across three distinct time periods. Figure B.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.

Figure B.6 displayed the WFH Share by firm size across three distinct time periods. Figure B.8 displays the full time series and plots the WFH Share for small, medium, and large firms separately. As suggested by Figure B.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.

Figure B.7: WFH Only By Firm Size, Employees

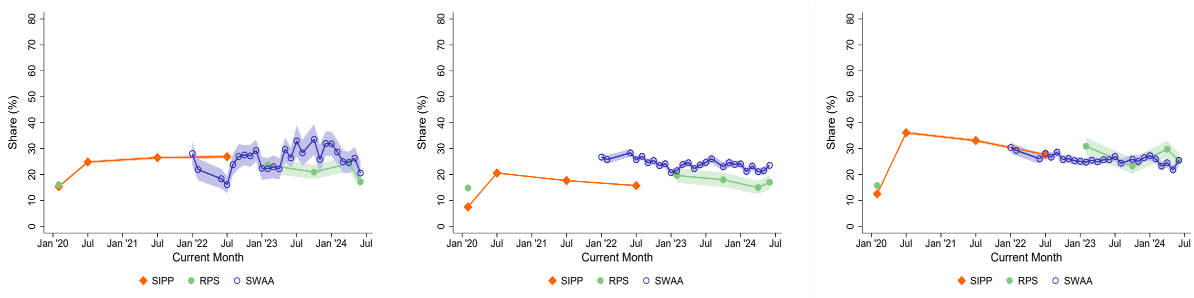
(a) Small Firms (b) Medium Firms (c) Large Firms



Notes: Figure B.7 compares the prevalence of WFH Only by firm size over time. Figures B.7a, B.7b, and B.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 on 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 uses responses from April through December 2020.

Figure B.8: WFH Share By Firm Size, Employees

(a) Small Firms (b) Medium Firms (c) Large Firms



Notes: Figure B.7 compares the WFH Share by firm size over time. Figures B.8a, B.8b, and B.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 on 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 uses responses from April through December 2020.

B.5 WFH By State and Industry

Figure B.9: WFH Only Rate By Dataset and State, 2023

(a) CPS (b) RPS (c) SWAA

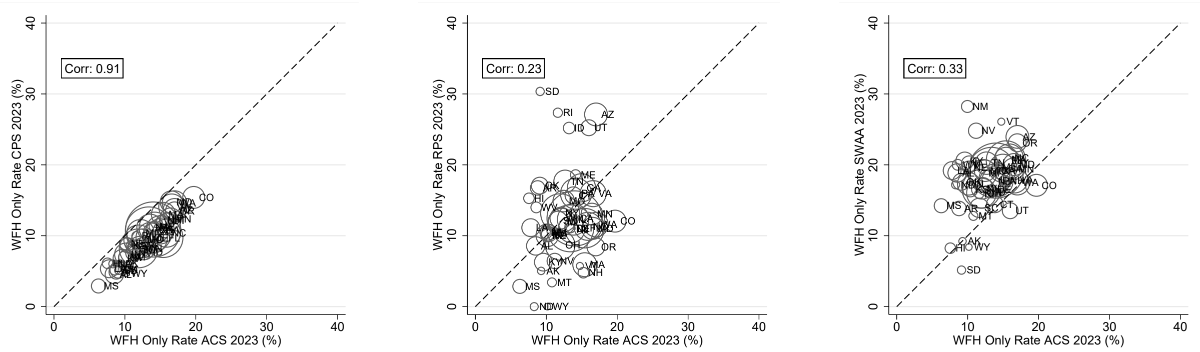


Figure B.9 displays heterogeneity in WFH by state. Each figure plots the WFH Only Rate by state in the ACS in 2023 on the horizontal axis against the WFH Only Rate by state in either the CPS, RPS, or SWAA in 2023. States are plotted as bubbles with areas directly proportional to their population share in the 2019 ACS release. The (rounded) population-weighted correlation of state-level WFH Only Rate in the ACS with state-level WFH-Only in another dataset is plotted in the upper-left hand corner of each panel. The 45-degree line is also plotted.

Figure B.10: WFH Only Rate By Dataset and Industry, 2023

(a) CPS (b) RPS (c) SWAA

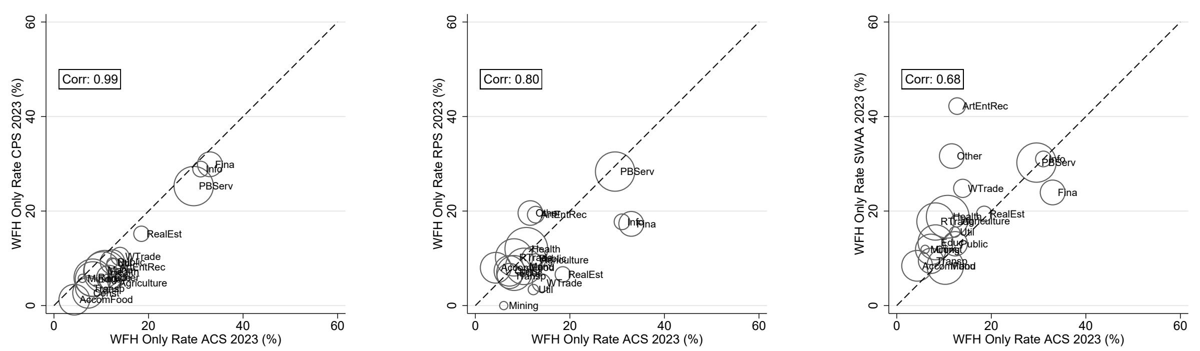


Figure B.10 displays heterogeneity in WFH by industry. Each figure plots the WFH Only Rate by industry in the ACS in 2023 on the horizontal axis against the WFH Only Rate by industry in either the CPS, RPS, or SWAA in 2023. Industries are plotted as bubbles with areas directly proportional to their population share in the 2019 ACS release. The (rounded) population-weighted correlation of industry-level WFH Only Rate in the ACS with industry-level WFH-Only in another dataset is plotted in the upper-left hand corner of each panel. The 45-degree line is also plotted.