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

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Abstract

This paper documents the prevalence of work from home (WFH) in six U.S. data sets. These surveys measure WFH using different questions, reference periods, samples, and survey collection methods. Once we construct samples and WFH measures that are comparable across surveys, all surveys broadly agree about the trajectory of aggregate WFH since the Covid-19 outbreak. The 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. Finally, we highlight that an important source of quantitative differences in WFH across surveys is WFH by self-employed workers; by contrast, surveys closely agree on rates of WFH among employees.

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

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1 Introduction

Following the Covid-19 outbreak in March 2020, many U.S. workers stopped commuting and started to work from home (WFH). Almost immediately, a large literature emerged to document this trend and study its implications for the economy and society more broadly.[1] The literature relies on several surveys with information on commuting and WFH. These surveys measure WFH in different ways, with different reference periods, samples, and survey collection methods. As a result, they often exhibit very different rates of WFH (Brynjolfsson et al., 2023). This variation makes it difficult to understand exactly how much WFH increased and which workers and firms drove the increase in WFH. In particular, it is not immediately obvious whether differences in WFH rates across surveys reflect concepts of WFH, different samples, or true disagreement between surveys.

This paper aims to clarify the prevalence of WFH by systematically comparing the major nationally representative surveys with information on WFH in the U.S. 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).[2] We also study two privately-run surveys: the Real-Time Population Survey (RPS) and the Survey of Work Arrangements and Attitudes (SWAA). All of these surveys except the CPS and the SWAA include pre-pandemic information on WFH, allowing us to compare WFH rates to a pre-pandemic baseline. Our goal is to construct population samples and WFH measures that are comparable across surveys, and to investigate the extent of agreement or disagreement in key WFH patterns across surveys since the Covid-19 outbreak. Other papers have compared WFH estimates in multiple surveys, including Brynjolfsson et al. (2023), Barrero et al. (2023), and Barrero et al. (2024), but our paper involves more datasets, a longer time horizon, and more extensive analyses.

To facilitate comparisons across surveys, we show that each survey can be used to construct at least one of two WFH measures. The first measure is the *WFH Share of Workdays*, which we abbreviate as the *WFH Share*: the share of workdays within a given reference week that did not involve a commute. This measure is available in the ATUS, the SIPP, the RPS, and the SWAA. The WFH Share is informative about the overall prevalence of WFH in the economy. The second measure is the *WFH Only Rate*: the share of workers who did not commute for work at all in a given week. This measure is available in the ACS, the CPS, the SIPP, the RPS, and the SWAA. The WFH Only Rate captures the prevalence of workers who never or rarely commute for work; this measure may be particularly useful for studying workers whose mobility is not restricted by the

[1] The WFH literature too vast to summarize here. Two papers that carefully document the evolution of WFH following the Covid-19 outbreak are Barrero et al. (2023) and Bick et al. (2023).

[2] The Pulse is another survey run by the Census with information on WFH. However, as we discuss in Section 2, the Pulse's measure of WFH is difficult to compare to measures in other surveys.

need to live close to a workplace (e.g., "work from anywhere workers").

We find broad agreement across datasets in aggregate trends of both WFH measures. All datasets agree that WFH increased sharply following the Covid-19 outbreak, peaked in 2020, and gradually declined in the subsequent years. In all datasets, the most recent estimates indicate that WFH rates remain far above pre-pandemic rates. However, we do find notable differences across surveys in the level of WFH at a given point in time. For example, in 2022, the only year with available data for all surveys, the WFH Share is 23% in the SIPP, 25% in the RPS, and 31% in the ATUS and SWAA. In the same year, the WFH Only Rate is 10% in the CPS, 13% in the RPS, 15% in the ACS, and 20% in the SWAA. We explain that a portion of this disagreement is likely attributable to different ways of measuring WFH across datasets. We also show that disagreements in WFH rates are primarily concentrated among the self-employed. By contrast, the surveys exhibit much closer agreement over WFH rates among employees.

We also find that surveys broadly agree about demographic differences in WFH, with some exceptions. All surveys find 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. All surveys find that these disparities expanded after the Covid-19 outbreak. 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.

Finally, we compare firm-related differences in WFH across surveys. Because our surveys are household-based, we do not have firm-level data. However, three datasets have information on firm size (the 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. Moreover, the RPS and the SWAA 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 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. Using a measure of WFH potential from Dingel and Neiman (2020), we show that an industry's WFH potential almost perfectly predicts its WFH rate in 2020 and that in most industries actual WFH was close to potential. We end by showing that 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.

The remainder of the paper is structured as follows. Section 2 discusses our data sources and how we measure WFH. Section 3 compares aggregate trends in WFH across data sources. Section 4 analyzes demographic differences in WFH and Section 5 analyzes firm differences in WFH. Section 6 concludes.

2 Data Sources and Measurement

We begin this section by defining two distinct measures of WFH. We then discuss four government surveys and two independent surveys which all feature publicly available micro data on WFH, summarized in Table 1. For each survey, we describe the questions that provide WFH data, and state which of our key WFH measures can be constructed from this information.

2.1 Measuring Work from Home

The core concept of our WFH measures is a WFH workday. A WFH workday is a day in which some work was done for pay, but the worker did not commute for that work. This definition is distinct from but related to the concepts of telecommuting and remote work. For example, a self-employed person whose workplace was their own residence would be classified as WFH without working remotely, whereas an employee who worked neither at their residence nor at their workplace would be classified as working remotely without WFH. This definition also excludes days in which an individual commuted to work but also did some work at home. Finally, this definition excludes unpaid home production from our definition of work. Our focus on whether a commute takes place in a given day makes it well-suited to address questions related to transportation, congestion, pollution, and geographic mobility. However, this focus may be less relevant for questions related to how individuals spend their time at home.

Given our definition of a WFH workday, our first measure of WFH is the *WFH Share of Workdays*, which we abbreviate as the *WFH Share*. This is the ratio of workdays WFH to days worked within a given week.[3] The WFH Share will capture both full-time WFH workers and hybrid workers who WFH some days and commute on others.

Our second measure of WFH is the *WFH Only Rate*. This is the share of workers who

[3]For a given group of workers, this is the ratio of (i) all WFH workdays for that group to (ii) all workdays for that group; i.e., we do not compute a WFH share for each individual and then average them. The difference between our calculation and the latter is that workers who work more days receive a greater weight in the former calculation. Because the ATUS only contains information about a single day for each individual, we cannot compute the latter calculation in that dataset.

Table 1: Survey Overview

Survey	Organization	Sample Population	Approximate Average Annual Sample Size	Panel / Cross-Section	WFH Share?	WFH Only Rate?
American Community Survey (ACS)	Census Bureau	U.S. Population	3 million	Cross-Section		✓
American Time Use Survey (ATUS)	Census Bureau	U.S. Population	11.5 thousand	Cross-Section	✓	
Survey of Income and Program Participation (SIPP)	Census Bureau	U.S. Population	52 thousand	Rotating Panel	✓	✓
Current Population Survey (CPS)	Census Bureau	U.S. Population	1 million	Rotating Panel		✓
Household Pulse Survey (HPS)	Census Bureau	U.S. Population	1 million (varies)	Cross-Section		
Real Time Population Survey (RPS)	Bick and Blandin (2023)	U.S. Population, Aged 18-64	20 thousand (varies)	Current and Retrospective Cross-Sections	✓	✓
Survey of Working Arrangements and Attitudes (SWAA)	Barrero et al. (2021)	U.S. Population, Aged 20-64	60 thousand	Cross-Section	✓	✓

WFH every workday in a given week. This measure excludes hybrid workers who WFH some days and commute on others. The WFH Only Rate may be particularly relevant for studying the ability of workers to locate very long distances from their jobs, e.g. "work from anywhere" workers.

2.2 Government Surveys

We first discuss surveys run by U.S. government agencies (the U.S. Census Bureau and the Bureau of Labor Statistics).

2.2.1 American Community Survey (ACS)

Overview. The American Community Survey (ACS) is a nationally representative, cross-sectional survey of one percent of U.S. households, providing an annual sample size of over 3 million individuals. The survey is conducted throughout the year by the U.S. Census Bureau, but information on the survey week and month are not made publicly available and thus we can only construct annual estimates. The Census Bureau has consistently collected WFH data through the ACS since administration began in January 2000. We supplement our aggregate analysis with the decennial Census starting in 1960. The ACS provides both the longest-time coverage and the largest sample size among WFH datasets. We rely on the IPUMS version provided by Ruggles et al. (2024).

Measuring WFH. For each employed household member, the ACS and the decennial Census ask:

> "How did this person usually get to work LAST WEEK?"

The questionnaire provides a list of transportation methods, one of which is "Worked from home." The word "usually" suggests that the ACS measure of WFH captures workers who are mostly or fully WFH.[4] We identify respondents who reported that they usually "worked from home" in the previous week as WFH Only workers. The ACS does not contain information that would allow us to capture the WFH Share for partial WFH workers.

[4]The preceding question in the ACS asks "*At what location did this person work LAST WEEK? If this person worked at more than one location, print where he or she worked most last week.*" These directions also indicate that respondents should not be categorized as WFH unless they are primarily or fully WFH.

2.2.2 American Time Use Survey (ATUS)

Overview. The American Time Use Survey (ATUS) is a nationally representative, cross-sectional survey of U.S. households conducted by the Census Bureau. Participants in the ATUS are sampled from households who finished their eight interview in the Current Population Survey (CPS). The annual sample size started out with almost 21,000 respondents in 2003, but was significantly reduced to only 14,000 in 2004. Since then the sample size decreased gradually to only 8,500 in 2023. While the data is available at a monthly frequency, in this paper we pool data at the annual level due to small monthly sample sizes. The Census Bureau has administered the ATUS since January 2003, although data collection was paused during the second half of March 2020 and April 2020. We supplement our aggregate analysis with several years from the Multinational Time Use Study prior to 2003. We rely on the IPUMS versions provided by Flood et al. (2023) and Fisher et al. (2022).

Measuring WFH. The ATUS asks respondents to provide a complete account of the previous day's activities, including where and when they occurred. It is therefore possible to determine how much time individuals spent commuting to their job over the previous workday, and thereby construct the WFH Share as the total fraction of workdays without commutes. Because the ATUS only tracks individuals over the previous day, the survey does not contain information that would allow us to construct the WFH Only Rate.

2.2.3 Survey of Income and Program Participation (SIPP)

Overview. The Survey of Income and Program Participation (SIPP) is a nationally representative survey of U.S. households conducted by the Census Bureau. When the Census Bureau first administered the SIPP in 1984, the panels lasted approximately two and a half years while survey participants answered questions once every four months. In 1996, the Census redesigned the SIPP to make the panels last four years, and again in 2014 to make survey participants answer questions annually. In 2018, the SIPP switched to a rotating sample design, where each year a new cohort of individuals entered the SIPP and participated for four years. We rely on the version released by the U.S. Census Bureau (2024). Information on WFH is available on a regular basis since 2014, with average annual sample size corresponding to 52,000.

Measuring WFH. Information on WFH in the SIPP comes from the following three questions:

1. "During a typical week which days did/do/does [you/household member] work?"
2. "As part of [your/household member's] typical work schedule for [your/household member's] [job/business] are/were there any days when [you/household member]

work/works/worked only at home?"

3. "Which days did/do/does [you/household member] work only from home?"

Respondents are asked these question for each job they held since the previous year. They thus reflect typical work patterns rather than in the last week as in the ACS, relying on the respondent's interpretation of what constitutes a typical week. Moreover, during a job spell within a year there is no variation in either variable. For individuals holding multiple jobs in a given month, we use the information for the main job, which we define as the job with longest usual hours worked.

The first question allows us to estimate the usual number of days worked per week, and the third allows us to estimate the usual number of days WFH per week. Only individuals who respond yes to the second question are asked the third question. For individuals answering the second question with no, we set the number of days WFH to zero. Since there is no variation in WFH during the year for job-stayers, we only report statistics on the annual level. For the year 2020, we construct averages only over the post-Covid 19 outbreak months, i.e. April through December.

2.2.4 Current Population Survey (CPS)

Overview. The Current Population Survey (CPS) is a nationally representative survey of American households administered by the Census Bureau. The data follow a 4-8-4 panel structure: households are in the survey for 4 consecutive months, out for 8, and return for another 4 months before leaving permanently. Each sample is collected over a one week period, with questions referring to activities in the previous week. In recent years the typical annual sample size is roughly 1.3 million individuals. The CPS began in 1940, and the Census Bureau has conducted it since 1942. We rely on the IPUMS version provided by Flood et al. (2023), which has monthly data available since 1976.

Measuring WFH. From October 2022 through March 2024, the CPS asked respondents several questions related to WFH or telework, including:[5]

1. "At any time LAST WEEK, did (you/name) telework or work at home for pay?"

[5]For some months, a measure of pre-pandemic WFH is also available in the CPS. Respondents who report working in the previous week are asked whether they had WFH for pay before the start of the pandemic. If the respondent answers "yes" to both this question and question 1 above, they are then asked whether they worked more, less, or about as much from home for pay as in February 2020. From May 2020 to January 2021, the CPS also asked if "At any time in the last 4 weeks, did (you/name) telework or work at home for pay because of the coronavirus pandemic?", followed by a yes/no answering option." We do not use this information as it does not allow to construct either of our two variables of interest.

2. "LAST WEEK, (you/name) worked (# hours worked last week at all jobs) hours (total/at all jobs). How many of these hours did you telework or work at home for pay?"

To the first question respondents report either "yes" or "no": to the second question, respondents report an integer number of hours. We define the WFH Only Rate as the share of individuals for whom actual hours worked last week are identical to the hours teleworked / WFH for pay.[6] The CPS does not contain information that would allow us to capture the WFH Share for partial WFH workers.

2.2.5 Household Pulse Survey (HPS)

The Household Pulse Survey does not contain sufficient information to construct either the WFH Share or the WFH Only Rate. However, it does contain information on WFH, so we discuss it here for completeness.

Overview. The Household Pulse (HPS) is a nationally representative, cross-sectional survey of American households administered by the Census Bureau since 2020. The HPS is a relatively novel survey designed to provide high frequency information about American households. Each cross-sectional sample is collected over a period of one and a half to four weeks. Household members respond to the survey questions, which ask about both individual and household behavior. Samples sizes have been declining in time, with nearly 2 million observations in 2020 but under 1 million observations in 2023.

Measuring WFH. The most consistently available measure of telecommuting frequency in the HPS is available from September 2022 on. The survey questionnaire asks all respondents:

1. "In the past seven days, have any of the people in your household teleworked or worked from home?"

For those who responded "yes" to the above question, the HPS also asks:

2. "In the last seven days, have you teleworked or worked from home?"

For both questions, survey respondents answering "yes" also specify a categorical bin: one to two days, three to four days, and five or more days. The HPS measure of WFH is

[6] Since 1988, the National Longitudinal Study of Youth 1979 also collects the usual number of hours WFH and the usual number of hours worked. At the time this paper was written, the most recent year available for this data set was for 2019 and thus did not cover the post-pandemic period.

therefore very expansive: a worker who worked from their home for an hour on a single workday would report WFH, even if they also commuted that day. Tthe HPS also does not survey respondents about the number of workdays in the previous week. We therefore are not able to compute either the WFH Only Rate or the WFH Share using HPS data.

2.3 Independent Online Surveys

In response to rapidly evolving data demands amid the COVID-19 pandemic, economists have recently begun using independent online surveys to collect national labor market data (Adams-Prassl et al., 2020; Belot et al., 2021; Bell and Blanchflower, 2020; Coibion et al., 2020; Foote et al., 2020). Several surveys collected information on WFH, including Foote et al. (2020); Brynjolfsson et al. (2020, 2023). In this paper, we focus on two surveys which began collecting data on WFH early in the Covid-19 pandemic and are still ongoing.

2.3.1 Real-Time Population Survey (RPS)

Overview. The Real-Time Population Survey (RPS) is a nationally representative labor market survey of adults aged 18-64. It has run since April 2020, with WFH data currently available from May 2020 through June 2024. Survey collection is outsourced to Qualtrics, a large commercial survey provider. The RPS surveyed 53,756 individuals in 2020. The RPS fielded twice per month from April through September 2020, then switched to a monthly frequency in October 2020. The monthly surveys continued until June 2021, after which the survey fielded two to three times a year. Annual RPS sample sizes have averaged about 17,000 between 2021 and 2023. A more detailed explanation of the RPS can be found in Bick and Blandin (2023); Bick et al. (2023). The microdata through June 2021 are publicly available at `https://www.openicpsr.org/openicpsr/project/181641/version/V1/view` and for the remainder of the period covered will be made available upon publication.

Measuring WFH. Information on commuting behavior in the RPS comes from the survey questions below concerning the individual's main job:

1. "Last week, how many days did you [your spouse/partner] work for this job?"
2. "Last week, how many days did you [your spouse/partner] commute to this job?"

To answer the first question, respondents use a slider that provides a choice of integers between one and seven, since only individuals who worked in the previous week receive this prompt; for the second question, the integers range from zero to seven. The RPS also

asks analogous questions about usual days worked per week and usual days commuted per week in February 2020, just before the Covid-19 outbreak, providing a retrospective measure of pre-pandemic WFH.[7] The RPS allows us to construct both of our variables of interest, both before the pandemic and in the week preceding each survey wave.

2.3.2 Survey of Work Arrangements and Attitudes (SWAA)

Overview. The Survey of Working Arrangements and Attitudes (SWAA) is a monthly cross-sectional survey of Americans aged 20 to 64. 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.[8] Because our goal is to estimate WFH rates at the national level, we use SWAA data only since January 2022. The SWAA typically interviews 60,000 respondents annually and the data are publicly available at www.WFHresearch.com.

Measuring WFH. Since November 2021, the SWAA asks all respondents:[9]

"For each day last week, did you work a full day (6 or more hours), and if so where?"

Respondents are then asked to fill out a matrix with rows corresponding to each weekday and columns labeled "Did not work 6 or more hours", "Worked from home," and "Worked at employer or client site."[10] The SWAA's focus on "full workdays" of at least 6 hours will by construction not capture work and WFH on shorter workdays; we discuss the potential implications of this focus in Section 3.1.

[7] A potential concern with retrospective questions that ask about WFH behavior several months or years in the past is excessive measurement error. To address this, Figure A.3.1 plots the (retrospectively reported) February 2020 WFH Only Rate in the RPS separately for each survey wave. Reassuringly, while there is some fluctuation in this rate across survey waves, the variation is fairly mild and does not have a systematic trend.

[8] Since January 2022, two versions of the SWAA have been compiled: one that drops individuals who reported an income below $10,000 in the previous year and one with no earnings restriction.

[9] Between November 2020 and October 2021, the SWAA asked: "How many full days are you working this week (whether at home or on business premises)?" and "How many full paid working days are you working from home this week?" From May through October 2020, the only question related to WFH was: "Currently (this week) what is your working status?" where one of the possible answers was: "Working from home".

[10] This question is asked of all respondents, including those who previously reported that they did not work in the previous week. Following Barrero et al. (2021), we exclude individuals who give conflicting answers regarding work in the prior week.

3 Aggregate Trends in Work from Home

This section documents aggregate trends in WFH for the U.S. We first document longer term trends in WFH prior to the Covid-19 outbreak. We then analyze the evolution of WFH since the pandemic. Next, we quantify the roles of full-time WFH versus partial WFH for trends in the overall level of WFH. The section concludes with a comparison of commuting rates in survey data with commuting rates based on cell phone geolocation data.

3.1 Longer Term and Recent Trends

Figure 1a displays rates of WFH over the half century from 1960-2019. The WFH Only Rate is available in the Decennial Census (hollow pink squares, 1960-2000) and in the ACS (pink squares, 2000-2019). Over this time period, the WFH Only Rate displays a mild U-shaped pattern: it peaks at 6% in 1960, declines to a low of 3% in 1980, and then gradually increases, reaching 5% in 2019. While the gradual increase in WFH in recent decades is well-documented (Oettinger, 2011; Mateyka et al., 2012; Pabilonia and Vernon, 2020; Mas and Pallais, 2020), to our knowledge we are the first to point out the declining WFH Only Rate prior to 1980.

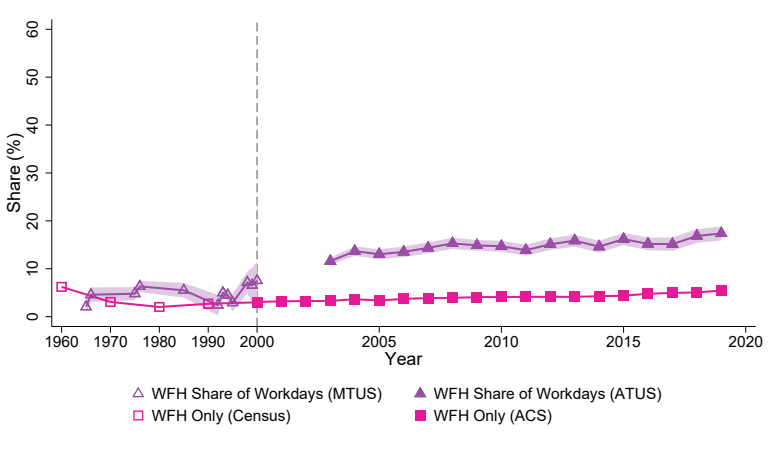
The WFH Share is available in the MTUS (hollow pink triangles, 1965-2000) and in the ATUS (pink triangles, 2003-2019). Prior to 2000 the WFH Share is volatile due to small sample sizes, but all years show a WFH Share below 10%. From 2003-2019, the WFH Share in the ATUS gradually increases from 12% in 2003 to 16% percent in 2019.

Figure 1b shows that the WFH Share increased sharply after the Covid-19 outbreak in early 2020, then declined slowly in the ensuing years. Just before the pandemic the WFH Share ranges from 13% in the SIPP to 17% in the ATUS. In 2020 the WFH Share ranges from 26% in the SIPP to 38% in the ATUS, roughly double pre-pandemic values. All datasets show a gradual and roughly parallel decline since mid-2020. The most recent estimate from the ATUS, in 2023, is 27%, about 1.5 times higher than its pre-pandemic value. The most recent estimate for the RPS and SWAA are from June 2024: the RPS estimate is 23% (about 1.6 times higher than its pre-pandemic value) and the SWAA estimate is 30%.

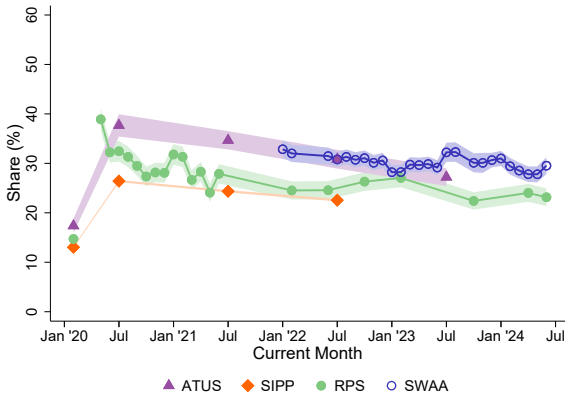
Figure 1c displays the WFH Only Rate over time. The evolution of the WFH Only Rate is qualitatively similar to the evolution of the WFH Share in Figure 1b. Just before the pandemic the WFH Only Rate ranges from 5% in the ACS to 11% in the SIPP. In May 2020 the WFH Only Rate rises to 32% in the RPS, then gradually declines to 19% by December 2020. The average WFH Only Rate in the SIPP for the months May - December is 24%. The ACS, SIPP, and RPS then show a gradual and roughly parallel decline from 2020 through mid-2022; since mid-2022, the WFH Only Rate in the SWAA,

Figure 1: Aggregate Rates of Work from Home

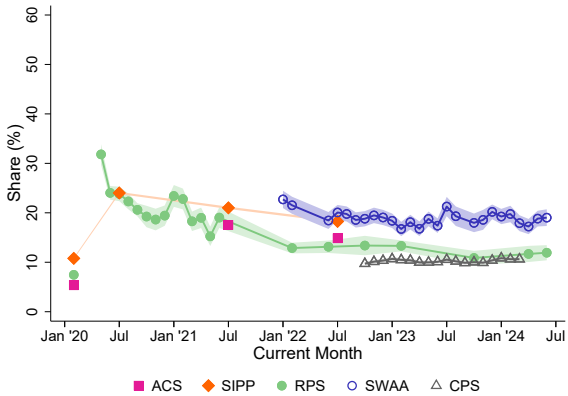
(a) Pre-Covid Trends in WFH



(b) WFH Share



(c) WFH Only



Notes: Figure 1 displays both recent and longer-run trends in WFH. Figure 1a compares pre-pandemic trends in WFH, plotting both the WFH Share in the ATUS and the WFH Only Rate in the ACS on an annual basis. Figure 1b compares more recent trends in the WFH Share across datasets, while Figure 1c uses the WFH Only measure instead. 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.

RPS, and CPS has been relatively flat. The most recent estimate from the CPS, in March 2024, was 11%. The June 2024 estimate in the SWAA is higher, at 19%. The June 2024 estimate in the RPS lies in between at 12%, about 1.6 times its pre-pandemic value.

While all datasets in Figures 1b and 1c display remarkably similar trends in WFH since the Covid-19 outbreak, there is some disagreement about the level of WFH at any given point in time. For the WFH Share, the SWAA displays the highest estimates, followed by the ATUS, then the RPS, then the SIPP. For the WFH Only Rate, the SWAA displays the highest estimates, followed by the SIPP, then the ACS and RPS, then the CPS.

These disparities could be partially explained by differences in survey design and question phrasing. One specific instance where surveys may disagree is in the treatment of an irregular workday, for example if a respondent only occasionally works on a Saturday. The ATUS, RPS, and SWAA all measure WFH in the previous day or week, and so should capture these days of work; in contrast, the SIPP asks about usual days worked, and so may not capture these days. If irregular workdays are disproportionately WFH workdays, then this will be reflected in a lower WFH rate for the SIPP.

A second instance where surveys may disagree is in the treatment of marginal workdays in which a small amount of work is done, such as answering a few work calls or emails. The ATUS is based on single-day time diaries and we classify a workday as any day in which the respondent reports doing any work for their main job. Our ATUS-based measure should therefore capture most marginal workdays. The RPS asks individuals to report the days in the previous week that they worked for their main job, so respondents may exclude some marginal workdays. The SIPP asks about usual workdays, so again respondents may exclude some marginal workdays. The SWAA only asks about "full" workdays of at least 6 hours of work, so by construction excludes marginal workdays. To the extent that marginal workdays are disproportionately WFH (which is intuitive since these days are the least likely to justify a fixed commuting cost), this would tend to produce higher WFH rates in the ATUS and lower WFH rates in the SWAA. To summarize, different treatment of irregular and marginal workdays may explain why the SIPP's WFH Share is at the lower end and the ATUS' WFH Share is at the higher end, it likely does not explain the relatively high estimates in the SWAA.

A final source of disagreement among datasets is the measurement of WFH for self-employed workers, which we detail in Section 5. There we show that most of the disagreement in WFH rates across datasets is driven by self-employed workers.

3.2 What Drove the Rise in WFH: WFH Only or Hybrid Work?

Figures 1b and 1c reveal qualitatively similar trends in the WFH Share and the WFH Only Rate. Since the two variables are intimiately linked, a natural question is the extent to which changes in the WFH Only Rate account for changes in the WFH Share, as opposed to changes in partial or hybrid WFH behavior. To investigate this, first note that the overall WFH Share can be decomposed as follows.

$$\begin{aligned}(1) \qquad \text{WFH Share} =& (\text{WFH Only Rate}) \times \frac{(\text{WD} \mid \text{WFH Only})}{\text{WD}} \times 1 \\ &+ (\text{WFH-SD Rate}) \quad \times \frac{(\text{WD} \mid \text{WFH-SD})}{\text{WD}} \times (\text{WFH Share} \mid \text{WFH-SD})\end{aligned}$$

where "WD" denotes average workdays among a particular group of workers, the "WFH-SD Rate" denotes the share of workers who WFH some but not all workdays, and "WFH Share | WFH-SD" denotes the WFH Share among workers who WFH some but not all workdays. The aggregate WFH Share is the sum of two terms. The first summand is the WFH Only Rate weighted by the average workdays of these workers relative to the employed population overall. The second summand is the WFH Some Days share weighted by the average workdays of these workers relative to the employed population overall, multiplied by the WFH Share among these workers.

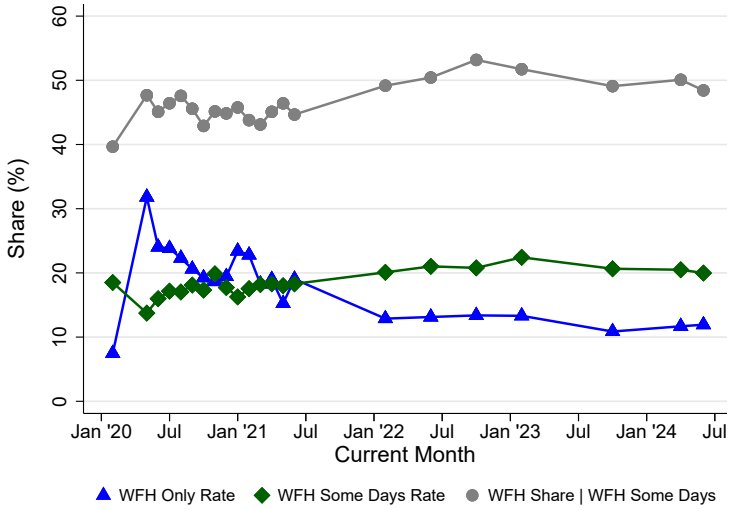
Figure 2a plots the WFH Only Rate, the WFH Some Days rate, and the WFH Share conditional on WFH Some Days in the RPS. (This information is also contained in the SIPP, but at a lower frequency and with data available only through 2022; we discuss these estimates in Appendix C). An immediate takeaway is that percent changes in the WFH Only Rate relative to its pre-pandemic baseline are much larger than changes in the other components. From February 2020 to May 2020, the WFH Only Rate increased by a factor of four, while no other component changed by more than 26%. By June 2024, the WFH Only Rate was still 1.6 times its pre-pandemic value, more than twice as large as the deviations of any other component. Importantly, however, as the WFH Only Rate declined from 2020-2024, the overall WFH Share and the WFH Share among WFH Some Days workers both increased, suggesting that fully remote work was partially being replaced by hybrid WFH. Appendix Figure C.3.1 shows the evolution of the two remaining components, i.e. the ratio of average days worked of WFH Only workers and WFH Some Days workers relative to average days worked by all workers, respectively. These components are nearly static over time, never deviating by more than 12% from their pre-pandemic values.

To quantify the relative contributions of these five components for the overall WFH Share, we conduct a counterfactual calculation that changes each of these components one at a time. To simplify notation it is helpful to first abbreviate all terms in Equation (1) by a single letter:

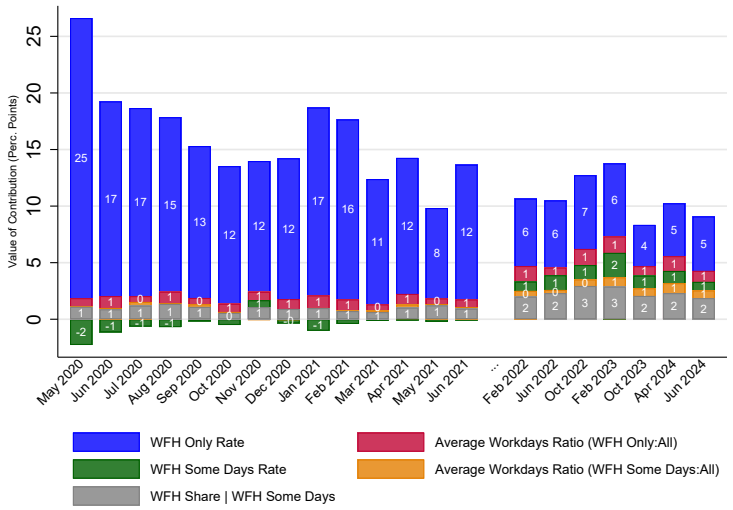
$$(2) \qquad W_t = A_t \times B_t + C_t \times D_t \times E_t,$$

Figure 2: Decomposition of the Work from Home Share of Workdays

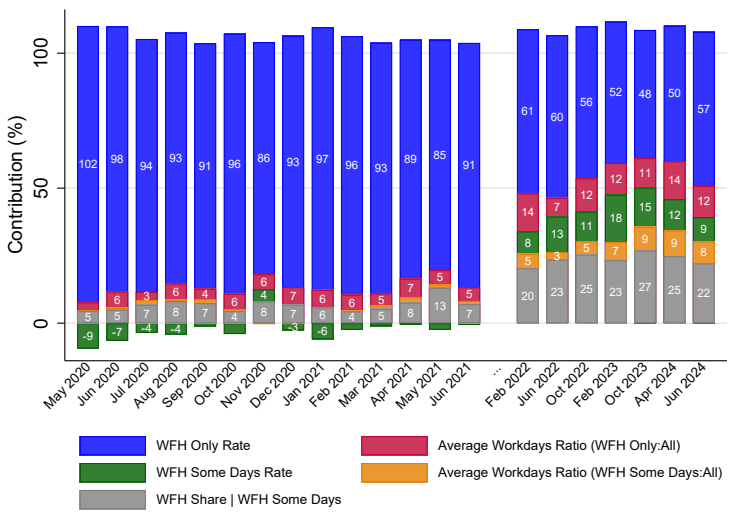
(a) Components Relative to February 2020



(b) $W_t - \widehat{W_t}$



(c) Contributions of Each Component



with W_t denoting "WFH Share", A_t denoting "WFH Only Rate", B_t denoting "$\frac{\text{WD} \mid \text{WFH Only}}{\text{WD}}$", and so on. For each component $i \in \{A, \ldots, E\}$, we calculate a counterfactual WFH Share $\widehat{W}_{i,t}$ where we set $i_t = i_0$ equal to its pre-pandemic value and set all other components to their actual values. We then compute the difference between W_t and $\widehat{W}_{i,t}$, which shows the impact of a change in component i on the overall WFH Share:

$$\delta_{i,t} = W_t - \widehat{W}_{i,t} \tag{3}$$

If component i remained unchanged from its pre-pandemic value, then $\delta_{i,t} = 0$. Note that the sum of these $\delta_{i,t}$ over all components need not necessarily equal the actual WFH Share because there can be interactions between them.

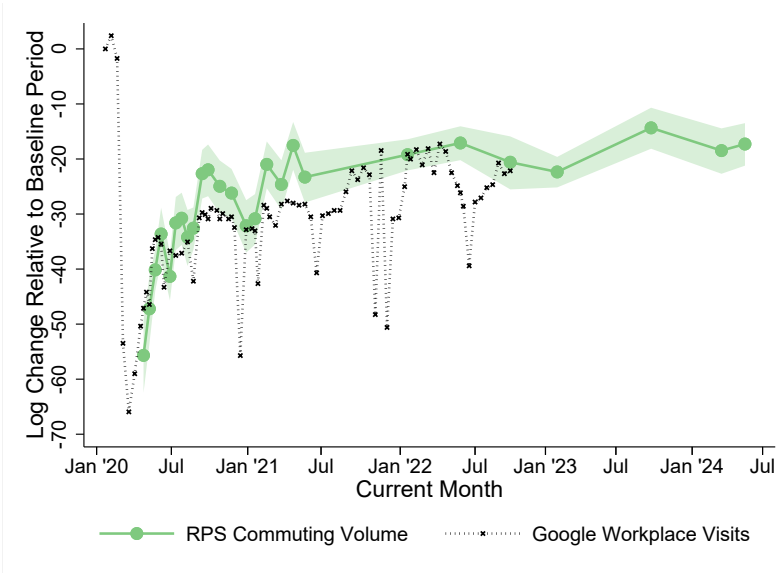
Figure 2b displays the results of this decomposition. Figure 2c expresses $\delta_{i,t}$ as a percentage of the aggregate increase in WFH $W_t - W_{2019}$. Unsurprisingly, changes in the WFH Only Rate explain a large majority of changes in the WFH Share. This is particularly true in 2020 and the first half of 2021. By the first half of 2024, the relative contribution of the WFH Only Rate is smaller, but still accounts for roughly half of the increase in the aggregate WFH Share relative to before the pandemic. The next most important component is the "WFH Share | WFH SD", the WFH Share of workers who WFH some but not all days. In June 2024, this component accounts for 22% of the increase in the aggregate WFH Share, compared to 57% for the WFH Only Rate. The remaining three components each explain around 10% of the aggregate increase in the WFH Share. The interaction effects between the terms are modestly positive, which is why the sum of all terms add up to slightly more than 100%.

We conclude that the WFH Only Rate accounts for a majority of the evolution of the aggregate WFH Share since the start of 2020. The effect of the WFH Only Rate was particularly pronounced in the first year of the pandemic: in every month from May 2020 through June 2021 at least 85% of the increase in the WFH Share is accounted for by the increase in the WFH Only Rate. However, since 2022 both the WFH Some Days rate and the WFH Share conditional on WFH Some Days have a positive contribution to the overall WFH Share, and by June 2024 nearly one third of the rise in the WFH Share was accounted for by these components.

3.3 Commuting Trips

Section 3.1 compared estimates of WFH across multiple surveys. In this Section, we incorporate an entirely different source of information based on cellphone geolocation data from Google Workplace Visits (GWV). GWV tracks cell phone locations over time and uses visitation histories to designate particular locations as a home or workplace. Once GWV has identified an individual's home and workplace, it can then measure whether the individual commutes to work on a particular day. From February 2020 through October 2022 GWV made daily commuting volumes for the U.S. publicly available, which we

Figure 3: Commuting Volume



Notes: Figure 3 displays the log change in commuting volume relative to a comparable baseline period across two different data sources: Google Workplace Visits (GWV) and the RPS. The baseline period is the week of February 3rd-9th, 2020 for the Google Workplace visits series and the entire month of February 2020 for the RPS series.

aggregate to weekly volumes. The volumes are expressed as log changes relative to a baseline of February 2020.

Weekly commuting volume, CV is linked to the WFH Share, W, according to the following equation:

$$CV = EMP \cdot WD \cdot (1 - W) \tag{4}$$

where EMP is employment and WD is the average number of days worked per week. While we cannot use GWV to directly estimate WFH, we can estimate commuting volume from a data source that has information on EMP, WD, and W. The data set also must have information for February 2020 because the GWV volumes are expressed as changes relative to that time period. Of the surveys used in this article, only the RPS has the necessary information and frequency for a precise comparison with GWV. Using 2019 as a pre-pandemic baseline, the SIPP could also provide estimates of changes in commuting volume, but only at an annual frequency.

Figure 3 plots the log change in weekly GWV relative to February 2020 alongside the log change in commuting volume in the RPS. Despite completely different data sources, the RPS and GWV estimates of commuting volume are quite similar. Workplace visits and commuting volume both exhibited the greatest decline during the initial weeks of the pandemic. A slow recovery began between fall 2020 and summer 2021, leveling off at roughly 30 log points below the pre-pandemic baselines. Another upwards shift began during late summer 2021, leveling off again at about 25 log points below the pre-pandemic baselines. Both data sources find that commuting remained 15-25 log points below pre-pandemic levels even as late as October 2022. Except for a temporary increase in October

2023, RPS commuting volume has remained relatively stable since GWV data availability ended.

To recap, a key objective of this paper is to compare measures of WFH across a wide array of data sources. Section 3.1 found broadly similar estimates of WFH across six different surveys. This section incorporated a completely different data source based on cellphone geolocation data. We found that the commuting volume in this dataset closely matched commuting volume in the RPS. Each of these datasets have their own advantages and disadvantages. For example, all surveys will suffer from some amount of recall error. Alternatively, cellphone data may not capture all work-related commuting and will not reflect the behavior of workers without cellphones. However, the fact that these datasets provide broadly consistent estimates suggests that the stylized trends in aggregate WFH and commuting are robust to variations in data type, survey design, and sampling methods.

4 Demographic Differences in Work from Home

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% 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.

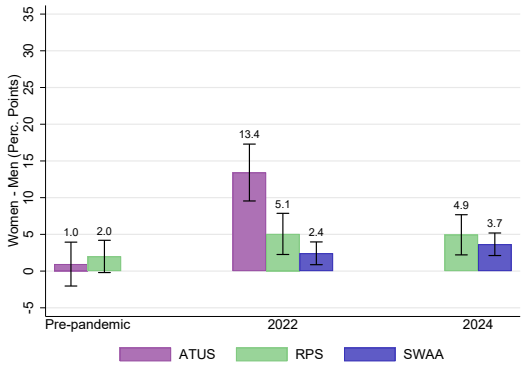
Most existing work documenting variation in WFH focuses on a cross section from one particular time period and dataset. This section provides estimates of how demographic variation in WFH has evolved over time in different datasets, considering cross-sections from before, during, and after the Covid-19 pandemic.

4.1 Sex

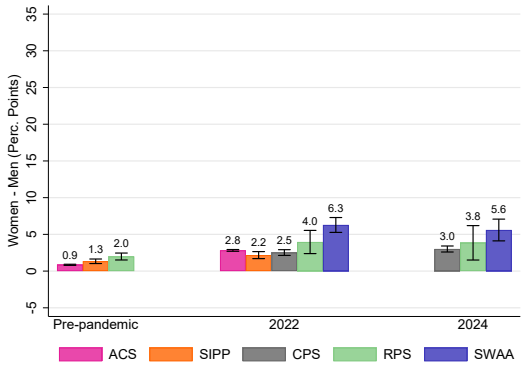
Figure 4 displays differences in WFH between women and men. Figure 4a plots the percentage point difference in the WFH Share and Figure 4b plots the percentage point difference in the WFH Only Rate. We display differences from three time periods: pre-pandemic, 2022 (the most recent year for which the 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% 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

Figure 4: WFH By Sex: Women-Men

(a) WFH Share



(b) WFH Only Rate



Notes: Figure 4 displays differences in WFH between men and women. Figure 4a plots the percentage point difference in the WFH Share and Figure 4 plots the percentage point difference in the WFH Only Rate. The whiskers correspond to 95% 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 point only uses responses from May through December 2020. See Figure B.1.1 for a time series of WFH by sex.

hybrid WFH is very uncommon in that dataset (see Figures 2c and C.2.1c).

Figure 4a 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.

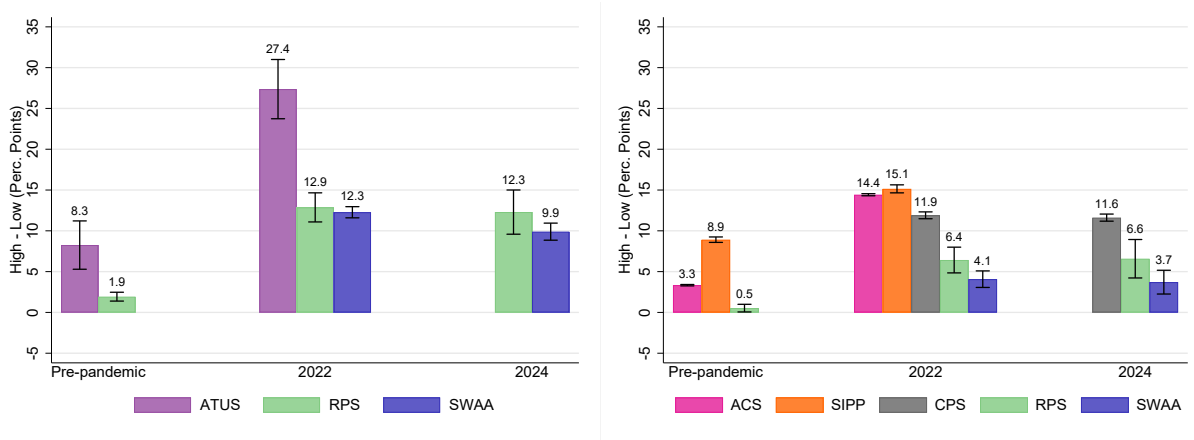
Figure 4b reveals broadly similar patterns for differences in the WFH Only Rate between women and men. Prior to the pandemic, the female WFH Only Rate was between 0.9-2.0 percentage points higher than the male rate in the ACS, SIPP, and RPS. In 2022 this gap expanded in all three datasets and was largest 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.

4.2 Education

Figure 5: WFH By Education: High-Low

(a) WFH Share (b) WFH Only



Notes: See the notes for Figure 4. 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.2.1 for a time series of WFH by educational attainment.

Figure 5 displays differences in WFH by educational attainment. The structure is identical to Figure 4, 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 5a 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 5b 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.

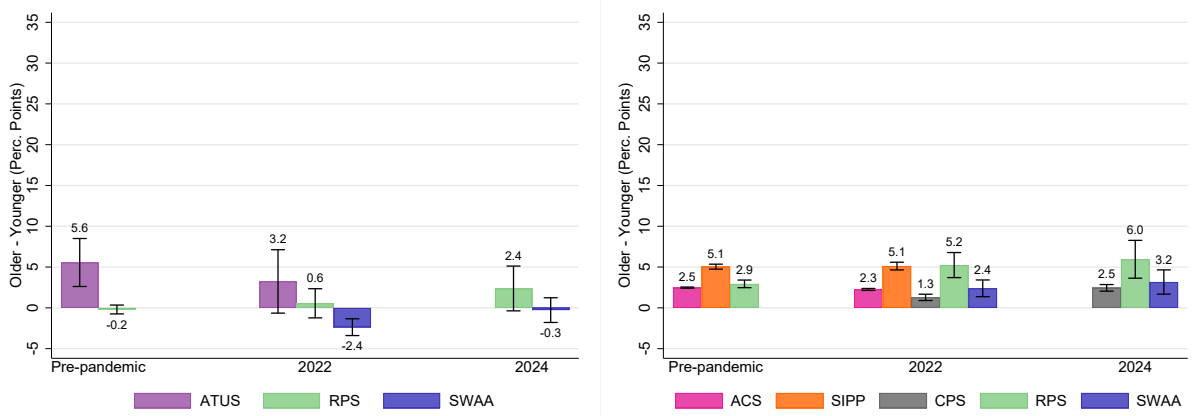
These figures reveal three key takeaways. First, before the pandemic workers with a four-year college degree already WFH more than workers without a four-year degree.

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.

4.3 Age

Figure 6: WFH By Age: Older-Younger

(a) WFH Share (b) WFH Only



Notes: See the notes for Figure 4. 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.3.1 for a time series of WFH by age.

Figure 6 displays differences in WFH between Older workers (aged 40-64) and Younger workers (aged 18-39). Figure 6a 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 rate among older workers in the ATUS before the pandemic.

By contrast, Figure 6b 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.

4.4 States

Figure 7 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. 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 states. 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.

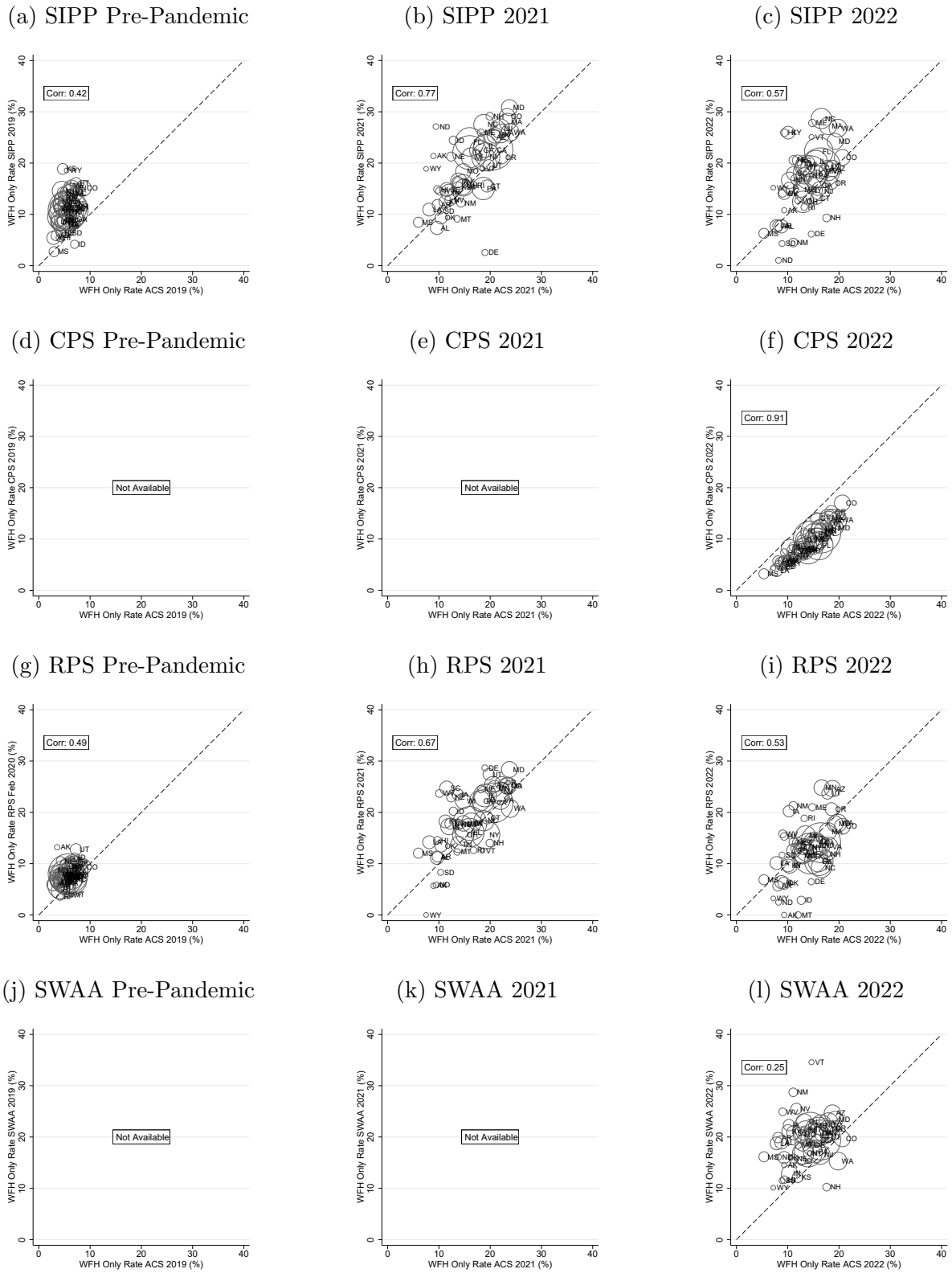
Figures 7a and 7g display pre-pandemic WFH by state in the ACS, SIPP, and RPS. SIPP estimates of WFH across states are higher and more dispersed than in the the RPS and ACS. Figures 7b and 7h show a large increase in both the mean and dispersion of state-level WFH.[11] The correlation of state-level 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 7c, 7f, 7i, and 7l 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.[12] The CPS displays the highest correlation with the ACS (0.91), followed by the SIPP (0.57), the RPS (0.53), and the SWAA (0.25).

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.

[11] 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.

[12] 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 7: WFH Only Rate By Dataset and State



Notes: Figure 7 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.

5 Firm-Level Differences in Work from Home

In addition to a worker's own characteristics, WFH opportunities may also depend on the characteristics of a worker's firm, such as the number of coworkers they interact with and the type of product or service the firm produces. This section explores the relationship between WFH and these firm characteristics. As in prior sections, our primary contribution is to produce comparable estimates for multiple datasets to highlight instances of agreement or disagreement, and to document how these patterns have evolved since the Covid-19 outbreak.

5.1 The Self-Employed versus Employees

Because self-employed workers may have more autonomy in their WFH choice, we begin this section by comparing WFH among self-employed workers and employees. Consistent with this intuition, we find large differences in both WFH levels and trends between self-employed workers and employees.Figure 8 plot WFH rates separately for the self-employed and employees. Figures 8a and 8b plot the WFH Share in the ATUS, the SIPP, the RPS, and the SWAA, while Figures 8c and 8d plot the WFH Only Rate in the ACS, the SIPP, the CPS, the RPS, and the SWAA.

Figure 8a shows that the ATUS, SIPP, and RPS exhibit similar pre-pandemic estimates of the WFH Share for the self-employed, ranging from 29%-36%. Following the Covid-19 outbreak, all three datasets display modest changes in the WFH Share, in sharp contrast to trends in the overall WFH rate. Notably, the SWAA displays higher rates of WFH among the self-employed.[13] For example, in 2022 the average WFH rate by self-employed in the SWAA is 61%, compared with 39% in the SIPP, 44% in the ATUS, and 35% in the RPS. Despite the disagreement in levels, the SWAA also displays a fairly flat WFH trajectory over time.

Figure 8b shows that the WFH Share among employees displays much greater variation over time, driving the pattern for the overall WFH Share. Just before the pandemic, the WFH Share ranged from 10%-15% in the ATUS, SIPP, and RPS. In 2020 the WFH Share in each dataset more than doubles relative to before the pandemic. After 2020, the WFH Share declines in parallel across all datasets. Compared with the self-employed, there is less disagreement in the WFH Share for employees across datasets. For example, in 2022 the average WFH rate by employees is 30% in the ATUS, 26% in the SWAA,

[13] In each dataset we rely on the self-reported status of being an employee or self-employed. The SWAA offers two self-employment options: (i) "I am self-employed and run my own business" and (ii) "I earn most of my income as an independent contractor, freelancer, or gig worker." We classifiy anyone in the SWAA choosing either option as self-employed. Classifying (ii) as employees would increase the WFH Share and WFH Only Rate among the self-employed further in the SWAA as WFH is more prevalent for group (i) than for group (ii).

Figure 8: WFH By Employment Type

Notes: Figure 8 displays time series of WFH rates for employees and the self-employed using two different measures of WFH. Figures 8a and 8b plot the WFH Share, while figures 8c and 8d plot the WFH Only Rate. Figures 8a and 8c correspond to the self-employed, while figures 8b and 8d correspond to employees. Prepandemic baselines are plotted in February 2020, and vary by dataset: 2019 in the ATUS, ACS, and SIPP, and February 2020 in the RPS. Datasets with annual frequencies (the ATUS, ACS, and SIPP) are plotted in July of the corresponding year. 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.

23% in the RPS, and 20% in the SIPP. In June 2024, the WFH rate is 21% in the RPS (1.6 times its pre-pandemic value) and 24% in the SWAA.

Figures 8c and 8d display qualitatively similar patterns to those documented for the WFH Share. In particular, the WFH Only Rate for the self-employed is relatively flat over time and exhibits greater variation across datasets, while the WFH Only Rate for employees varies more over time and exhibits little variation across datasets.

To summarize, this section established three key findings. First, in every time period and dataset, the self-employed have higher WFH rates than employees. This is consistent

with findings by Gottlieb et al. (2020); Barrero et al. (2023) and Bick et al. (2023), but here we show that this pattern is consistent across multiple datasets. Second, WFH varied more over time among employees than among the self-employed. Third, there is more disagreement between datasets over the rate of WFH for the self-employed and less disagreement over the rate of WFH for employees. This is especially true for the WFH Only Rate among employees, which exhibits minimal differences across datasets.

In the remainder of this section, we will focus on the WFH Only Rate as our key measure of WFH. We do this for several reasons. First, focusing on one measure reduces the number of figures, which helps simplify the analysis. Second, much of our analysis will leverage the large sample size in the ACS, which only contains a measure of the WFH Only Rate. Third, in datasets where we can observe both the WFH Share and the WFH Only Rate, we generally find similar patterns with both measures of WFH (see Figure A.4.1).

5.2 Firm Size

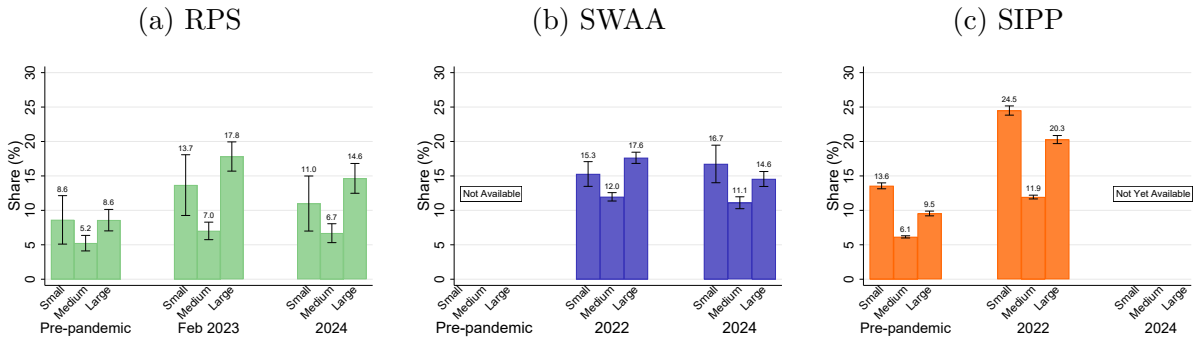
Barrero et al. (2023) document a U-shaped relationship between firm size and fully remote work using pooled SWAA data from 2020-2023. Figure 9 documents this relationship over time using the RPS, SIPP, and SWAA. Each panel corresponds to a different dataset and covers three distinct time periods: a pre-pandemic baseline, 2022/2023, and 2024. (The 2024 data is not yet available from the SIPP, and the SWAA does not measure pre-pandemic WFH.) 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% of employees in the RPS, 10%/54%/37% in the SWAA, and 18%/62%/20% in the SIPP.

Figure 9a confirms the U-shaped relationship between firm size and the WFH Only Rate suggested by Barrero et al. (2023). In all datasets and time periods, WFH is lowest for midsized firms. The WFH Only Rate is highest for large firms in the RPS and the 2022 SWAA, while in the SIPP and the 2024 SWAA it is highest for small firms.

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.

From 2022/2023 to 2024 the difference in WFH between small and midsize firms decreased slightly 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

Figure 9: 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 in 2022, so we plot data from February 2023 RPS 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.4.1 for the WFH Share by firm size among employees. See Figure B.4.2 and Figure B.4.3 for the time series of the WFH Only Rate and WFH Share by firm size.

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.

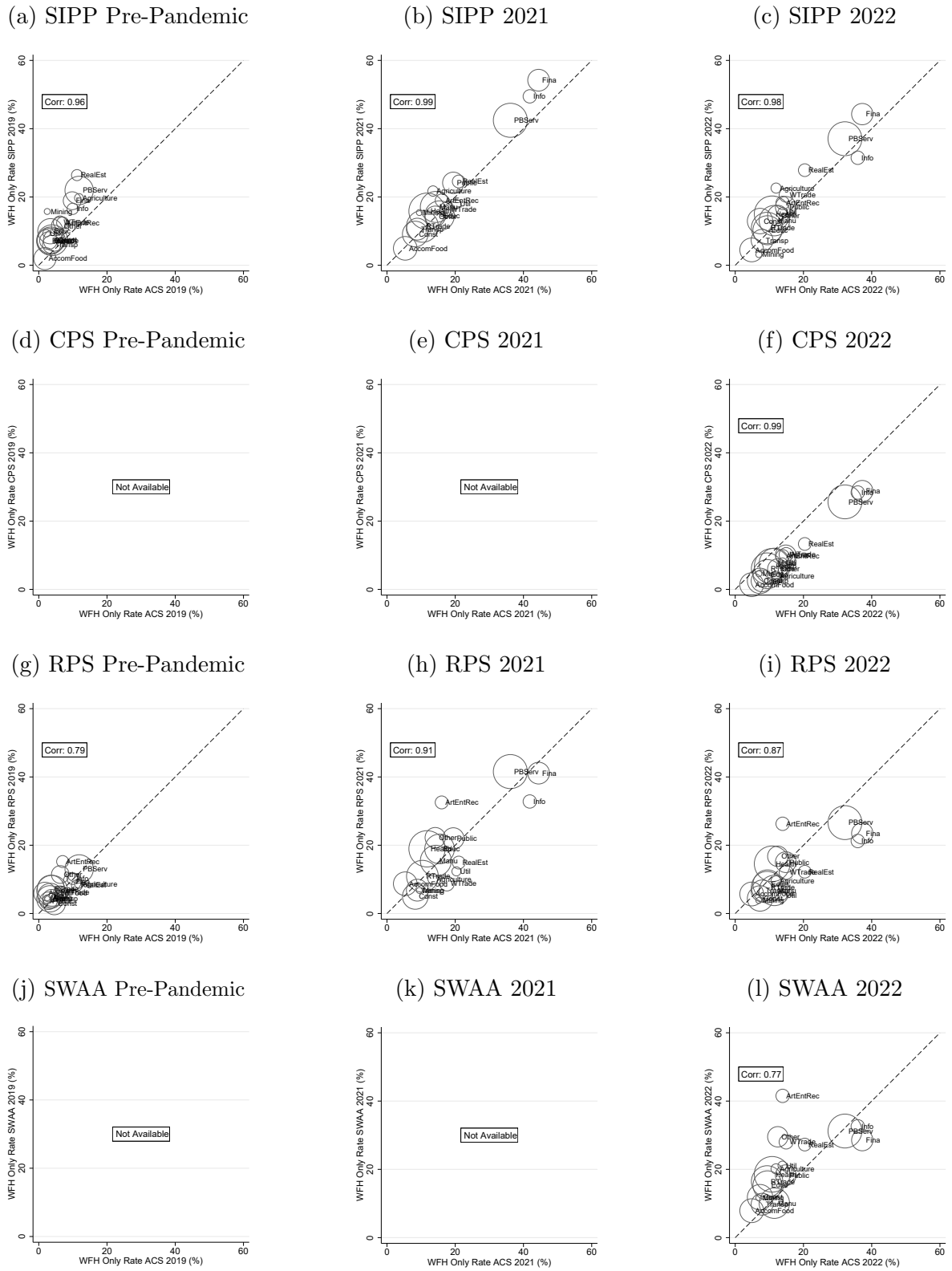
5.3 Industries

Figure 10 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 10a and 10g 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 10b and 10h 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

Figure 10: WFH Only Rate By Dataset and Industry



Notes: Figure 10 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.

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 10c, 10f, 10i, and 10l 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 10f 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 10i and 10l exhibit a slightly lower correlation with the ACS for the RPS and SWAA.

5.3.1 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 11 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 11 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 10 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 11a 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 11b. A 1

Figure 11: WFH Potential and Actual WFH By Industry

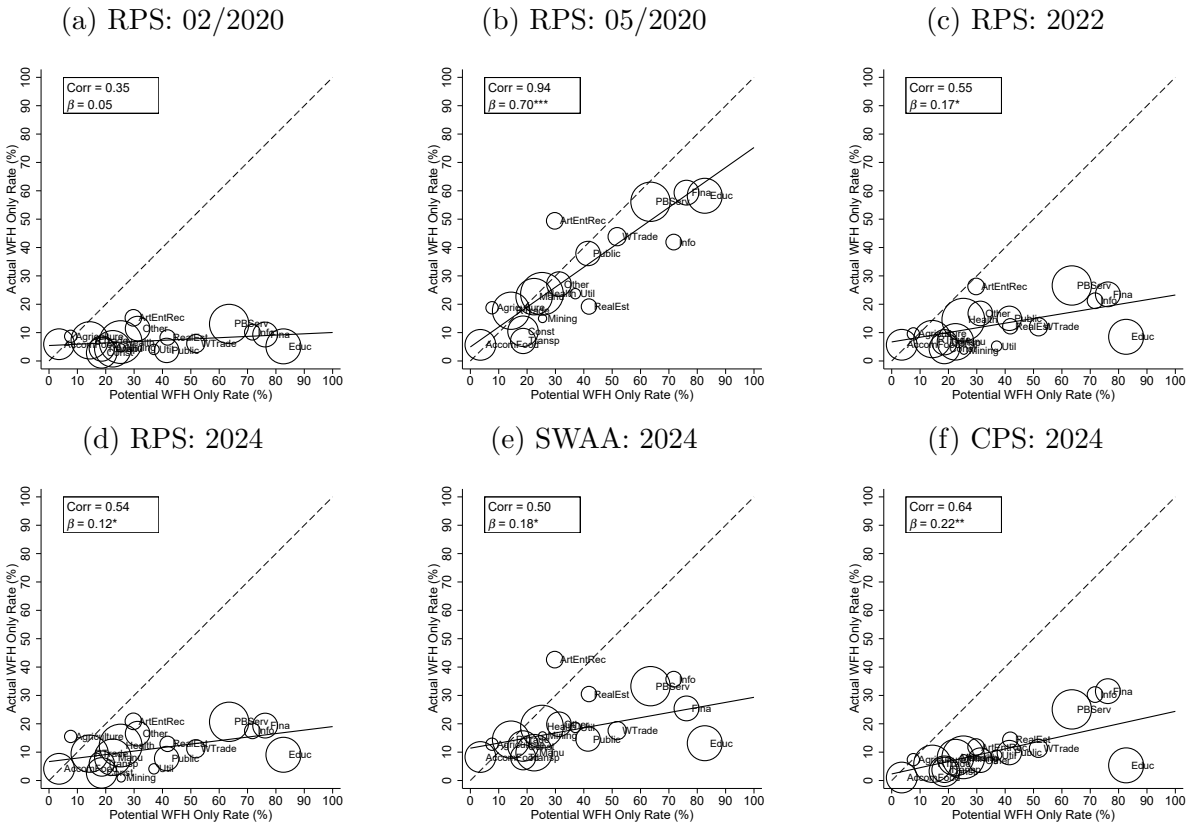


Figure 11 plots the measure of WFH potential by industry from Dingel and Neiman (2020) on the horizontal axis against the actual WFH Only Rate in the RPS by industry on the vertical axis. Industries are categorized according to NAICS classifications and are plotted as bubbles with areas directly proportional 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.

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 11c 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 11d, 11f, and 11e 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 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).

6 Conclusion

The prevalence of work from home (WFH) varies greatly across surveys. But these surveys measure WFH using different questions, reference periods, samples, and survey collection methods. In this paper, we try to understand the extent to which different rates of WFH reflect true disagreement between surveys. To do so, we conduct a systematic comparison of six major national surveys with information on WFH for the U.S. We define two measures of WFH and show that each of the surveys we study can be used to construct at least one of these measures. When we use comparable samples and comparable WFH measures, we find that all surveys broadly agree on the aggregate trajectory of WFH following the Covid-19 outbreak. The surveys agree that pre-pandemic differences in WFH rates by sex, education, and state of residence expanded following the Covid-19 outbreak and show similar post-pandemic trends in WFH by firm size and industry. We note some instances in which surveys disagree quantitatively about WFH rates. In particular, we highlight that an important source of quantitative differences in WFH across surveys is WFH by self-employed workers; by contrast, surveys closely agree on rates of WFH among employees.

In surveys with estimates through 2024, we find that aggregate WFH rates in 2024 remain roughly 60% higher than pre-pandemic levels and appear to have stabilized, suggesting that elevated rates of WFH will persist in the coming years. These predictions are also supported by the quantitative structural model developed in Bick et al. (2023). In that model, a pandemic can cause an increase in WFH through two channels. The first channel is a temporary increase in workers' demand for WFH due to acute health concerns from in-person work, which fades as the pandemic subsides. The second channel is that the increased health risk may induce employers to adopt more flexible work arrangements, including the ability to WFH. If these new arrangements turn out to be

more productive or more desirable ex-post, higher rates of WFH can persist beyond the pandemic. The model is calibrated using RPS data from February 2020 through June 2021 and used to predict the long-run rate of WFH after pandemic-related health concerns have abated. The model predictions for the long-run, a 21% WFH Share and 15% WFH Only rate, line up closely with actual WFH data from the RPS in June 2024, a 23% WFH Share and a 12% WFH Only rate. The notion that WFH will remain permanently elevated is also supported by elevated shares of job ads featuring a hybrid or full remote option, which by nature feature a persistent component going into the future (Hansen et al. (2023); see Appendix Figure B.5.1).

Despite higher rates of WFH relative to before the Covid-19 pandemic, WFH rates have fallen considerably since the spring and summer of 2020. This implies that some workers who can WFH are no longer doing so. Understanding why some workers continue to WFH when they did not before the pandemic, and why others have resumed commuting, is an important question for future research. The results in this paper regarding persistent disparities in WFH by demographic and firm characteristics may offer some helpful clues for this literature.

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.

A final example concerns geographic variation in WFH. For instance, WFH could raise the demand for housing if WFH workers require more space in which to work (Mondragon and Wieland, 2022), which might disproportionately increase housing prices in locations with high WFH. 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:

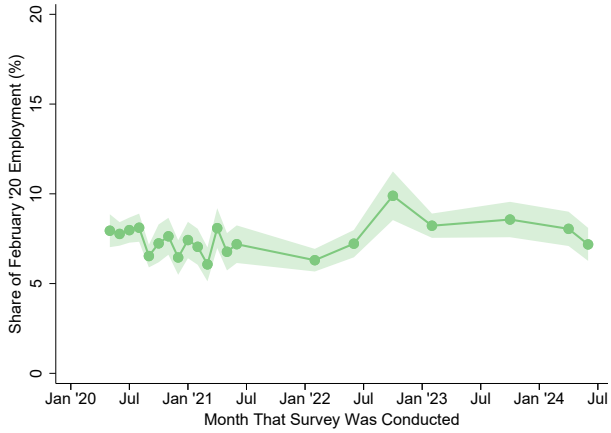
- Age
  - **Younger**: 18-39
  - **Older**: 40-64
- Education

  - **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 February WFH in RPS Across Survey Months

Figure A.3.1: RPS February 2020 WFH Only Rate By Survey Month

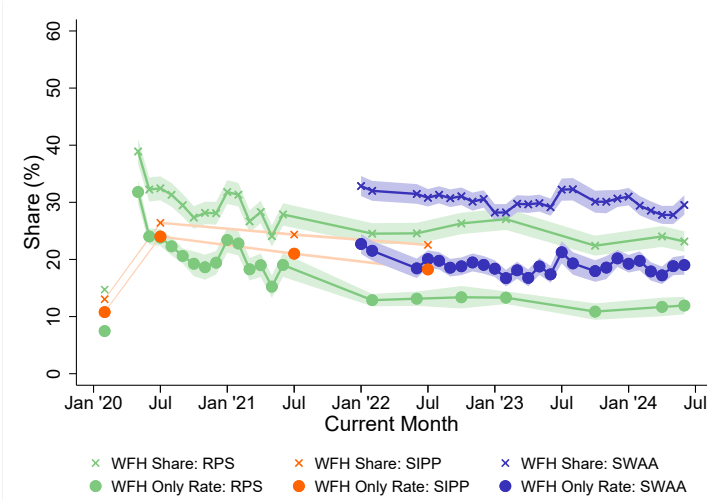


Notes: Figure A.3.1 displays the share of workers in the RPS who were WFH Only in February 2020 in every survey wave.

Section 2.3.1 explained that the RPS is a retrospective survey which asks respondents about their WFH status in February 2020. Figure A.3.1 shows that the share of respondents who identified as WFH Only workers in February 2020 was fairly constant over time, suggesting that the retrospective question phrasing produces reliable estimates of pre-pandemic WFH.

A.4 WFH Only Versus WFH Share

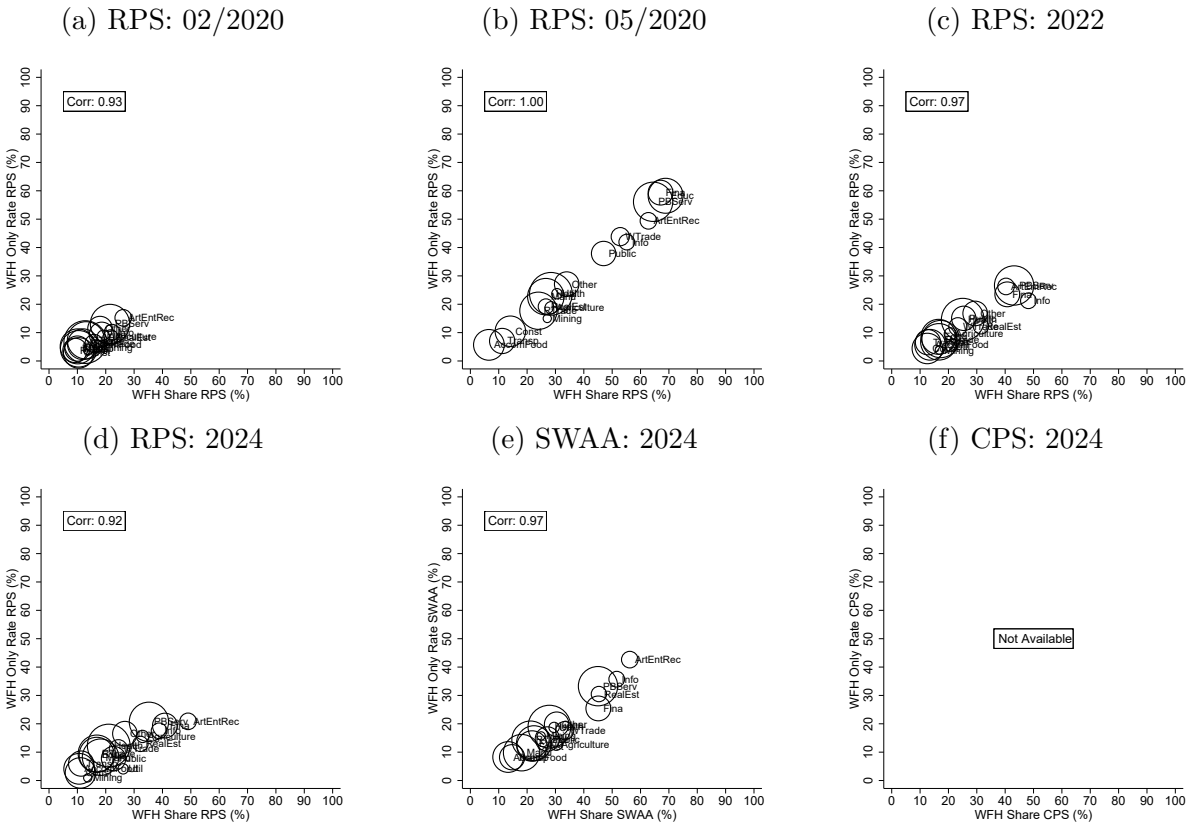
FIGURE A.4.1: WFH Only Rate and WFH Share in the RPS, SWAA, and SIPP



Notes: Figure A.4.1 shows the evolution of the WFH Only Rate and the WFH Share in the RPS, SWAA, and SIPP over time. We plot data from the 2019 release of the SIPP in February 2020. 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 A.4.1 illustrates that the WFH Only Rate and WFH Share follow broadly similar trends across datasets where they are both available. Consequently, Sections 5.1-5.3 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.4.2: WFH Only Rate Against WFH Share By Dataset



Notes: Figure A.4.2 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.

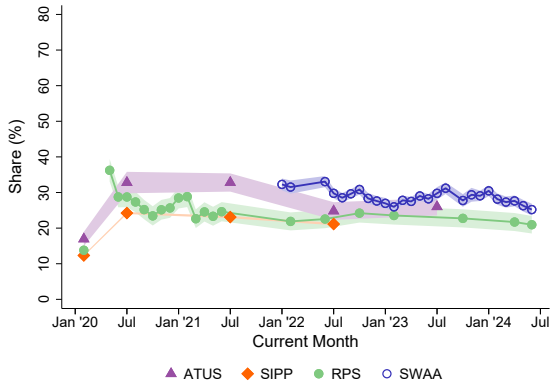
Figure 11 showed that WFH potential as estimated by Dingel and Neiman (2020) was somewhat predictive of the WFH Only Rate in the RPS, CPS, and SWAA. Figure A.4.2 shows that the WFH Share is highly correlated with the WFH Only Rate in the RPS and SWAA, suggesting that this relationship is robust to changing the WFH measure.

B Additional WFH Graphs

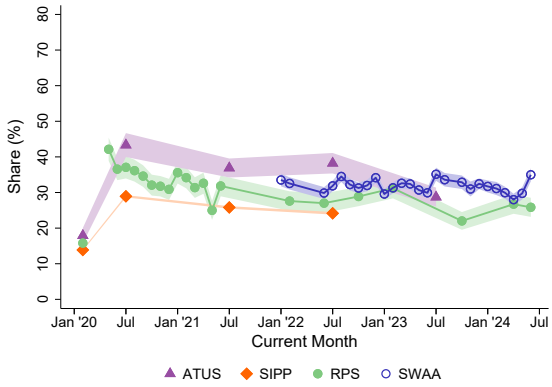
B.1 Sex

Figure B.1.1: WFH By Sex

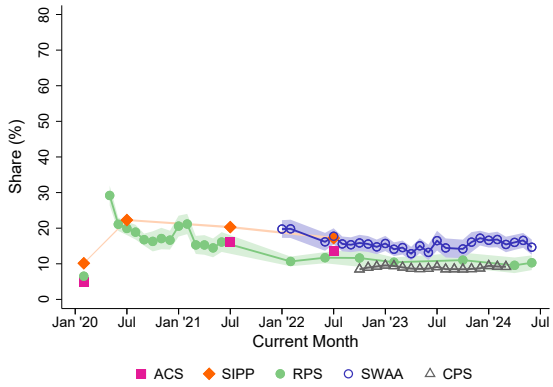
(a) WFH Share: Men



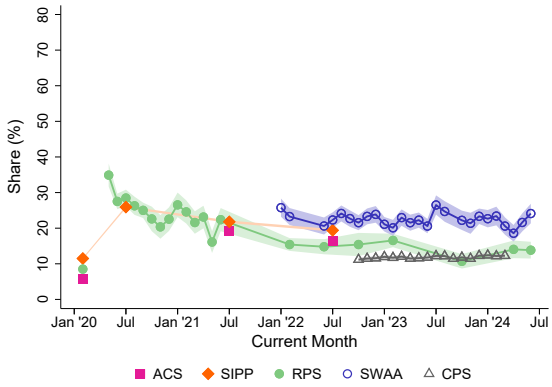
(b) WFH Share: Women



(c) WFH Only Rate: Men



(d) WFH Only Rate: Women



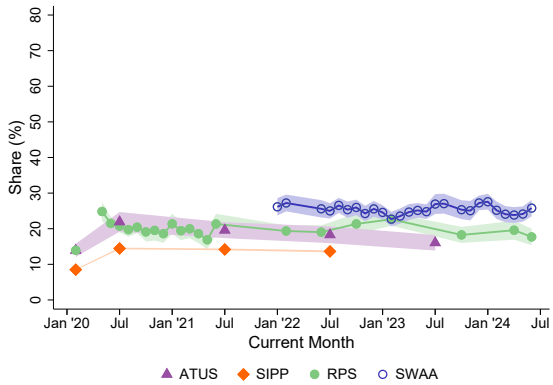
Notes: Figure B.1.1 compares the prevalence of WFH between men and women over time. Figures B.1.1a and B.1.1b plot the WFH Share, while figures B.1.1c and B.1.1d plot the WFH Only Rate. We compute moments on the annual level in the ACS, SIPP, and ATUS and plot these in July of the corresponding year. 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 4 displayed gaps in WFH rates between men and women across three distinct time periods. Figure B.1.1 displays the full time series and plots WFH rates for men and women separately. As suggested by Figure 4, men consistently have lower rates of WFH than women.

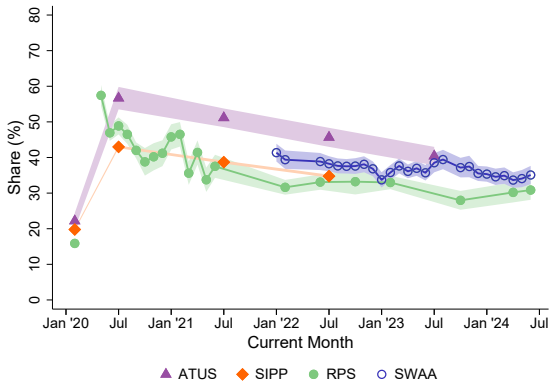
B.2 Education

Figure B.2.1: WFH By Education

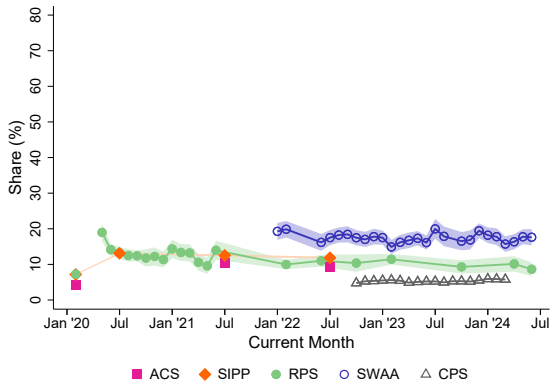
(a) WFH Share: No BA



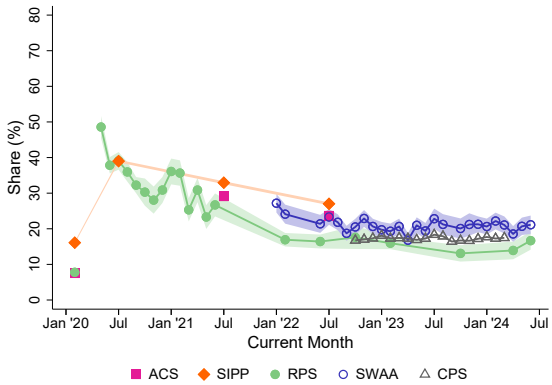
(b) WFH Share: BA



(c) WFH Only Rate: No BA



(d) WFH Only Rate: BA



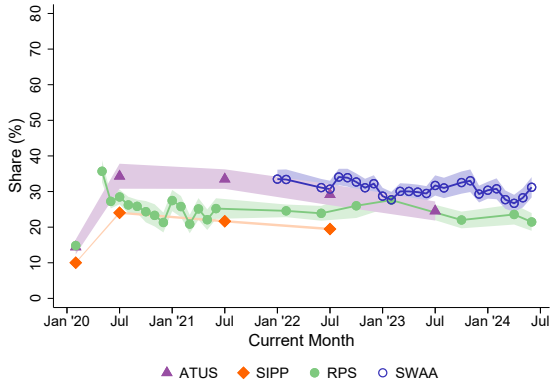
Notes: Figure B.2.1 compares the prevalence of WFH between Low and High education workers over time. Figures B.2.1a and B.2.1b plot the WFH Share, while figures B.2.1d and B.2.1c plot the WFH Only Rate. We compute moments on the annual level in the ACS, SIPP, and ATUS and plot these in July of the corresponding 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 5 displayed gaps in WFH rates between High and Low education workers across three distinct time periods. Figure B.2.1 displays the full time series and plots WFH rates for High and Low education workers separately. As suggested by Figure 5, High education workers consistently have higher rates of WFH than Low education workers.

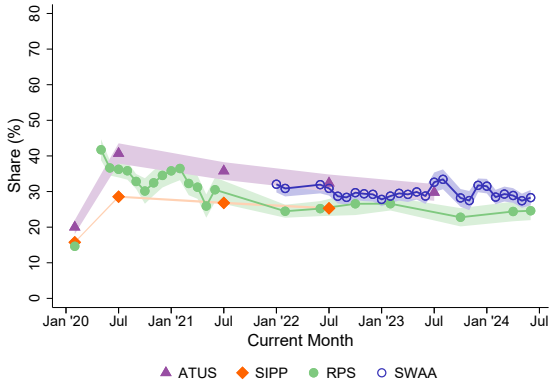
B.3 Age

Figure B.3.1: WFH By Age

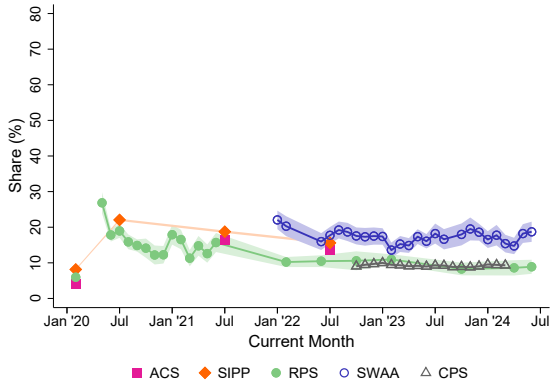
(a) WFH Share: 18-39



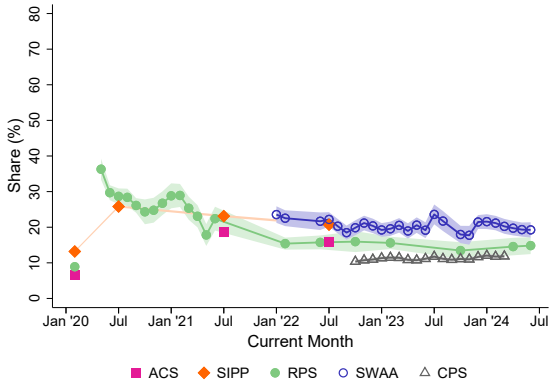
(b) WFH Share: 40-64



(c) WFH Only Rate: 18-39



(d) WFH Only Rate: 40-64

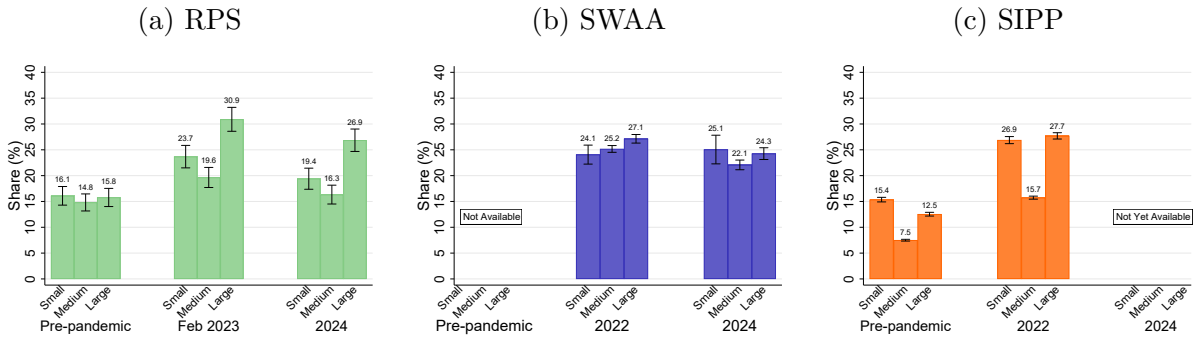


Notes: Figure B.3.1 compares the prevalence of WFH between Younger and Older workers over time. Figures B.3.1a and B.3.1b plot the WFH Share, while figures B.3.1c and B.3.1d plot the WFH Only Rate. We compute moments on the annual level in the ACS, SIPP, and ATUS and plot these in July of the corresponding 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 6 displayed gaps in WFH rates between Older and Younger workers across three distinct time periods. Figure B.3.1 displays the full time series and plots WFH rates for Older and Younger education workers separately. As suggested by Figure 6, the series are fairly close together.

B.4 Firm Size

FIGURE B.4.1: WFH Share By Firm Size, Employees Only



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.4.3 for the time series of WFH Share by firm size among employees.

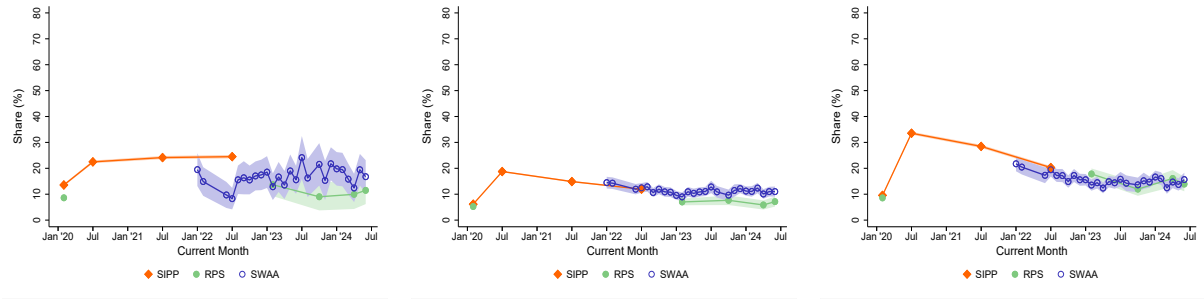
Figure 9 plotted the WFH-Only rate by firm size among employees only across the RPS, SWAA, and SIPP. Figure B.4.1 plots the WFH Share by firm size among employees.

Figure 9 displayed the WFH Only Rate by firm size across three distinct time periods. Figure B.4.2 displays the full time series and plots WFH rates for small, medium, and large firms separately. As suggested by Figure 9, 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.4.1 displayed the WFH Share by firm size across three distinct time periods. Figure B.4.3 displays the full time series and plots the WFH Share for small, medium, and large firms separately. As suggested by Figure B.4.1, 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.4.2: WFH Only By Firm Size, Employees

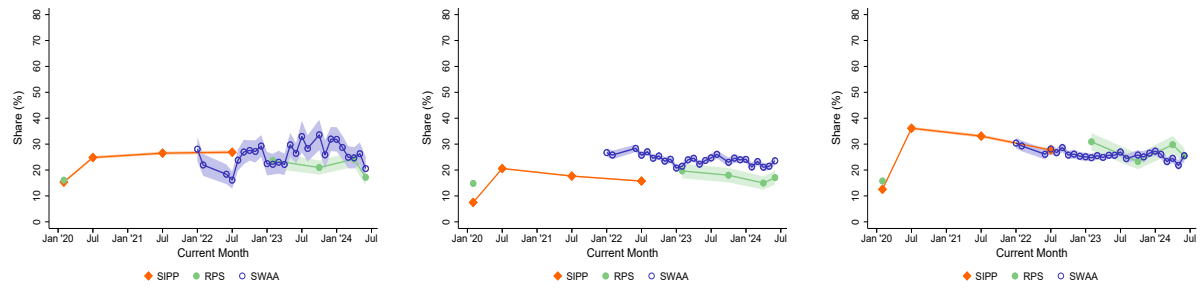
(a) Small Firms (b) Medium Firms (c) Large Firms



Notes: Figure B.4.2 compares the prevalence of WFH Only by firm size over time. Figures B.4.2a, B.4.2b, and B.4.2c plot the WFH-Only rate among workers in small, medium, and large firms respectively. 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.4.3: WFH Share By Firm Size, Employees

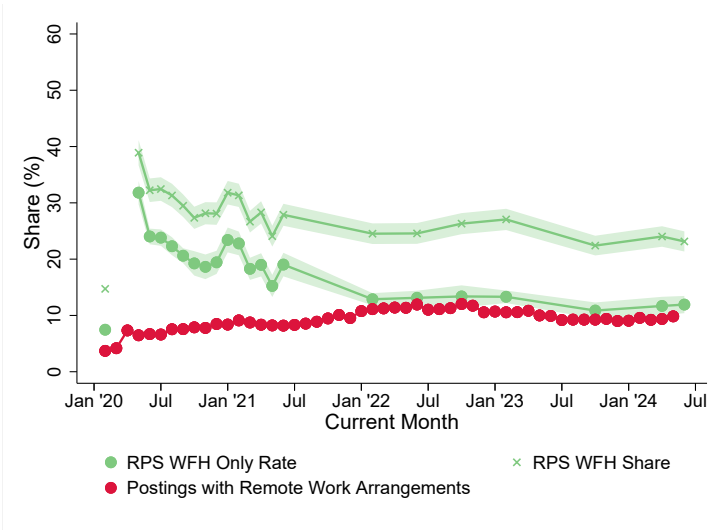
(a) Small Firms (b) Medium Firms (c) Large Firms



Notes: Figure B.4.2 compares the WFH Share by firm size over time. Figures B.4.3a, B.4.3b, and B.4.3c plot the WFH Share among workers in small, medium, and large firms respectively. 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 Job Postings

Figure B.5.1: Job Postings With Remote Work Arrangements and WFH in the RPS



Notes: Figure B.5.1 shows the evolution of the share of job postings advertising remote work arrangements and the WFH Only Rate and the WFH Share in the RPS over time. The job postings data comes from Hansen et al. (2023).

Figure B.5.1 shows that the share of job postings advertising remote work arrangements has risen considerably since the start of the pandemic. As mentioned in Section 6, this supports the notion that WFH will remain elevated above pre-pandemic levels well into the future.

C Decomposition Procedure

C.1 Derivation

Let $\mathbb{I}(\cdot)$ be an indicator function equal to unity if $(\cdot)$ is true. Then the WFH Share of Workdays W is related to days WFH H, workdays D, and the employed population P according to:

$$W = \frac{\sum H_i}{\sum D_i}$$

$$= \frac{\sum \mathbb{I}(H_i = D_i) \times H_i + \sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum D_i}$$

$$= \frac{\sum \mathbb{I}(H_i = D_i) \times H_i}{\sum D_i} + \frac{\sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum D_i}$$

$$= \frac{P}{P} \times \frac{\sum \mathbb{I}(H_i = D_i)}{\sum \mathbb{I}(H_i = D_i)} \times \frac{\sum \mathbb{I}(H_i = D_i) \times H_i}{\sum D_i} + \frac{P}{P} \times \frac{\sum \mathbb{I}(0 < H_i < D_i)}{\sum \mathbb{I}(0 < H_i < D_i)} \times \frac{\sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum D_i}$$

$$= \frac{1}{P} \sum \mathbb{I}(H_i = D_i) \frac{\frac{\sum \mathbb{I}(H_i = D_i) \times H_i}{\sum \mathbb{I}(H_i = D_i)}}{\frac{1}{P} \sum D_i} + \frac{1}{P} \sum \mathbb{I}(0 < H_i < D_i) \frac{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum \mathbb{I}(0 < H_i < D_i)}}{\frac{1}{P} \sum D_i}$$

The first term is the WFH Only Rate times the average days worked by WFH Only workers divided by average aggregate workdays. The second term is the WFH Some Days Rate times the average days WFH by WFH Some Days workers divided by average aggregate workdays. This latter term can be decomposed further:

$$\frac{1}{P} \sum \mathbb{I}(0 < H_i < D_i) \frac{\frac{1}{\sum \mathbb{I}(0 < H_i < D_i)} \sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\frac{1}{P} \sum D_i} \times \frac{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\sum \mathbb{I}(0 < H_i < D_i)}}{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\sum \mathbb{I}(0 < H_i < D_i)}}$$

$$= \frac{1}{P} \sum \mathbb{I}(0 < H_i < D_i) \frac{\frac{1}{\sum \mathbb{I}(0 < H_i < D_i)} \sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\sum \mathbb{I}(0 < H_i < D_i)}} \times \frac{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\sum \mathbb{I}(0 < H_i < D_i)}}{\frac{1}{P} \sum D_i}$$

$$= \frac{1}{P} \sum \mathbb{I}(0 < H_i < D_i) \frac{\frac{1}{\sum \mathbb{I}(0 < H_i < D_i)} \sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\frac{1}{P} \sum D_i} \times \frac{\sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}$$

This is the WFH Some Days Rate weighted by (the average days worked by WFH Some Days workers divided by average aggregate workdays). The second term is the WFH Share conditional on WFH Some Days.

We can now simplify our notation. Let A be the WFH Only Rate, B be the ratio of average workdays by WFH Only workers to average workdays, C be the WFH Some Days rate, D be the ratio of average workdays by WFH Some Days workers to average workdays, and E be the WFH Share conditional on WFH Some Days. We have that

$$W = AB + CDE$$

Switching to a dynamic model setting, this becomes:

$$W_t = A_t \times B_t + C_t \times D_t \times E_t$$

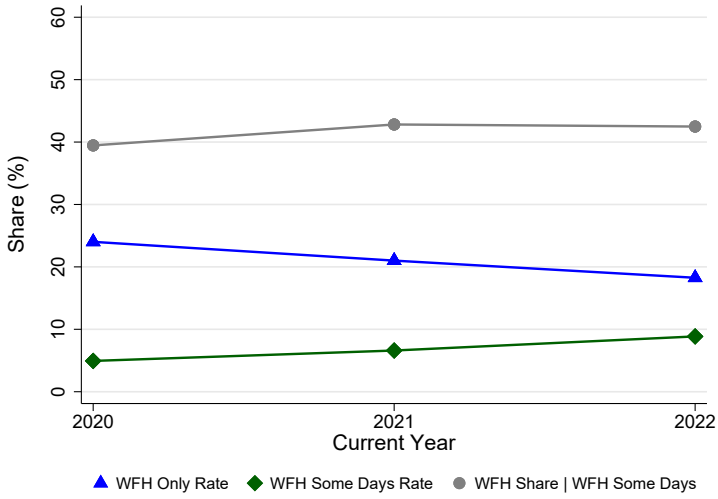
As seen in Equation 2.

C.2 Decomposition in the SIPP

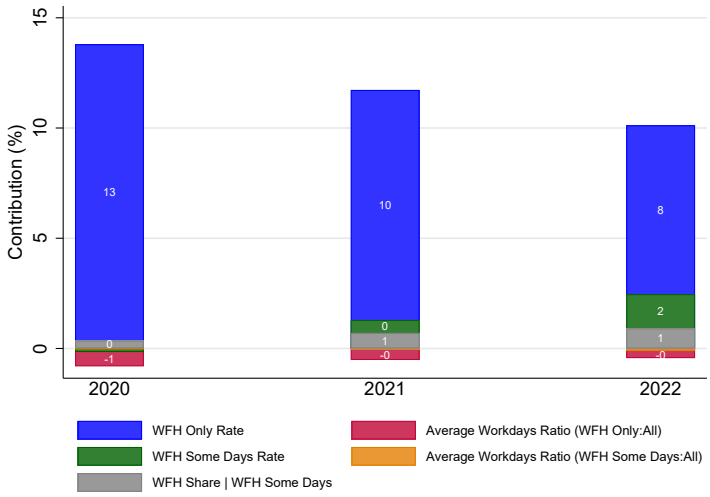
Figure 2 showed the results for the decomposition discussed in Section 3.2 using RPS data. Figure C.2.1 shows the results for the same decomposition using SIPP data. The RPS and SIPP agree that the WFH Only Rate drove nearly all the increase in WFH in 2020 and 2021. However, by 2022, the WFH Only Rate was a much larger contributor to overall WFH in the SIPP. Aggregating RPS observations to an annual level, 62% of the rise in WFH in 2022 was due to the WFH Only Rate in the RPS as compared to 81% in the SIPP. A likely explanation is that the SIPP underestimates hybrid work; see Section 2.2.3.

Figure C.2.1: WFH Decomposition

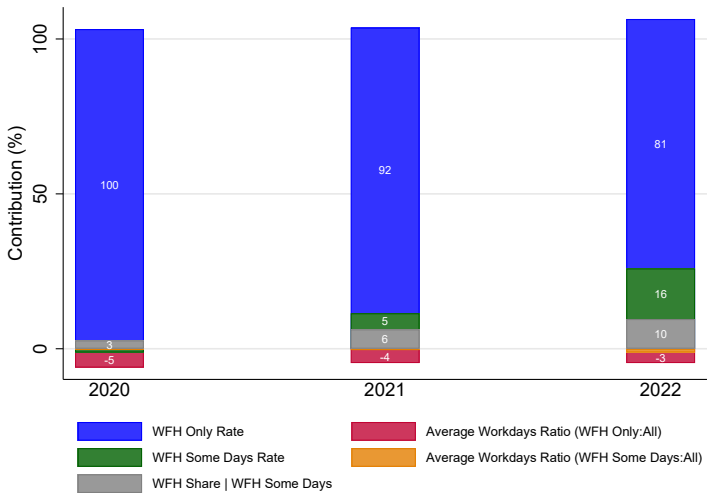
(a) Components Relative to 2019



(b) SIPP $W_t - \widehat{W}_t$



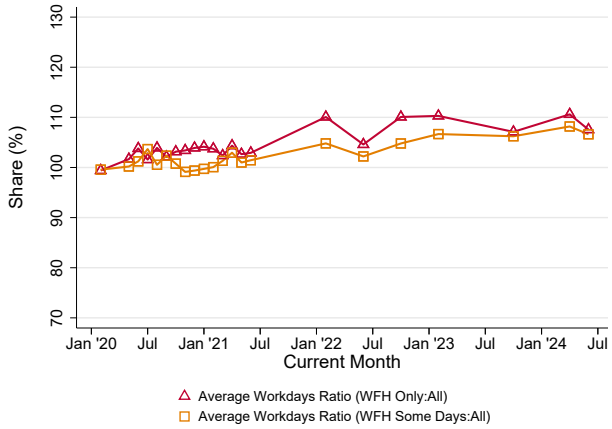
(c) SIPP Contributions of Each Component



Notes: Figure C.2.1 shows the WFH decomposition results discussed in Section 3.2 using SIPP data. We use the 2019 SIPP release as the pre-pandemic baseline. The 2020 SIPP data uses responses from April through December 2020.

C.3 Average Workdays in the RPS

FIGURE C.3.1: Average Workdays Ratio RPS



Notes: Figure C.3.1 plots two average workdays ratios. The first is the ratio of average workdays among WFH Only workers to average workdays among all workers and the second is the ratio of average workdays among WFH Some Days workers to average workdays among all workers.

Figure 2a plotted three of the five components of our decomposition in the RPS. Because the other two components exceeded 100%, they are not displayed in Figure 2a. Figure C.3.1 plots both of these components. As suggested by Figure 2c, these components are nearly static over time, never deviating by more than 12% from their pre-pandemic values.