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

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

Abstract

This article documents the prevalence of work from home (WFH) using six nationally representative U.S. surveys. These surveys measure WFH using different questions, reference periods, samples, and survey collection methods. After constructing comparable samples and WFH measures across surveys, we find that the surveys show broadly similar trends in the trajectory of aggregate WFH since the COVID-19 outbreak. The most important source of disagreement in WFH levels across surveys is in WFH by self-employed workers; by contrast, WFH rates for employees are closely aligned across surveys. All surveys show that, in 2024, WFH remains substantially above pre-pandemic levels. We also highlight that while full-time WFH drove most of the increase in aggregate WFH during and after the pandemic, part-time WFH has become a more significant contributor since 2022. Finally, we validate the findings from the survey data by comparing self-reported commuting behavior to cell phone geolocation data from Google Workplace Visits.

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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] This literature relies on several surveys with information on commuting

[1] The WFH literature is too vast to summarize here. Two articles that carefully document the evolution of WFH following the COVID-19 outbreak are Barrero, Bloom, and Davis (2023b) and Bick, Blandin, and Mertens (2023).

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and WFH. These surveys measure WFH in different ways and use different reference periods, samples, and survey collection methods. As a result, they often exhibit very different WFH rates (Brynjolfsson, Horton, et al., 2023). This variation makes it difficult to understand exactly how much WFH increased and whether differences in WFH rates across surveys reflect concepts of WFH, different samples, or true disagreement between surveys.

This article aims to clarify the prevalence of WFH by systematically comparing the major nationally representative U.S. surveys that collect information on WFH. We study four surveys run by the U.S. Census Bureau and the Bureau of Labor Statistics: 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 online surveys: the Real-Time Population Survey (RPS) and the Survey of Working Arrangements and Attitudes (SWAA). Our goal is to construct comparable population samples and WFH measures across surveys and to investigate the extent of agreement or disagreement in key aggregate WFH patterns across surveys since the COVID-19 outbreak. In a companion article, we investigate whether different datasets show consistent patterns of heterogeneity in WFH across different types of workers and firms (Bick, Blandin, et al., 2025). Other research has compared WFH estimates in multiple surveys, including Abrahams (2023), Brynjolfsson, Horton, et al. (2023), Barrero, Bloom, and Davis (2023b), Glaeser (2023), and Barrero, Bloom, et al. (2024). However, our article involves more datasets over a longer time horizon.

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, SIPP, RPS, and SWAA and 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, CPS, SIPP, RPS, and SWAA, and it captures the prevalence of workers who never or rarely commute for work. It may be particularly useful for studying workers whose mobility is not restricted by the need to live close to a workplace (e.g., "work from anywhere workers").

We find broadly consistent aggregate trends across datasets for both WFH measures. All datasets show that WFH increased sharply following the COVID-19 outbreak, peaked in 2020, and gradually declined in subsequent years. In all datasets with information on pre-pandemic WFH, the most recent WFH estimates remain far above pre-pandemic rates. Two datasets, the ACS and ATUS, provide nearly two decades of pre-pandemic WFH data, enabling us to estimate the pre-COVID trend in WFH growth. If WFH had continued to grow at its pre-pandemic trend, in 2023 the WFH Only Rate in the ACS would have been between 5 and 6 percent, and the WFH Share in the ATUS would have been 20 percent. However, the actual figures in 2023 far exceed these predictions, with 14 percent in the ACS and 27 percent in the ATUS.

Although all datasets produce a similar trend in aggregate WFH over time, we 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 percent in the SIPP, 25 percent in the RPS, and 31 percent in the ATUS and SWAA. In the same year, the WFH Only Rate is 10 percent in the CPS, 13 percent in the RPS, 15 percent in the ACS, and 20 percent in the SWAA. We show that these differences are most pronounced for the self-employed. In contrast, WFH rates among employees show much closer alignment across surveys.

We conclude by incorporating cell phone geolocation data from Google Workplace visits (GWV) to study changes in commuting behavior over time. Unlike our survey-based sources of information on commuting behavior, 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 measure whether they commute to work on a particular day. We find that commuting volume in the GWV closely aligns with commuting volume in the RPS (the only one of the six surveys that allows us to track commuting volume relative to February 2020 at a high frequency).

Each of the datasets used in this article has its own advantages and disadvantages. First, the surveys allow researchers to collect individual-level demographic and labor market characteristics alongside WFH information, en-

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

abling deeper analysis into the causes and consequences of WFH. However, all the surveys suffer from recall error. Surveys are also potentially vulnerable to response-rate bias, especially online surveys that do not use probability-based sampling methods (Abrahams, 2023; Glaeser, 2023). Alternatively, while cell phone data do not suffer from recall and response-rate biases, they may not capture all work-related commuting and will not reflect the behavior of workers without cell phones. The fact that these diverse datasets provide similar estimates suggests that the stylized trends in aggregate WFH and commuting are robust to variations in data type, survey design, and sampling methods. At the same time, researchers should be aware of sizable differences in the level of WFH across some datasets, especially among the self-employed.

The remainder of the article 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, and Section 4 concludes.

2. MEASUREMENT AND DATA SOURCES

We begin this section by defining two distinct measures of WFH. We then discuss four government surveys and two independent surveys that 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.

Table 1
Survey Overview

Survey[a]	Organization	Sample Population	Sample Size[c]	Structure	WFH Share?	WFH Only Rate?
ACS	Census Bureau	U.S. Population	3 million	Cross-Section	—	✓
ATUS	Census Bureau	U.S. Population	11,500	Cross-Section	✓	—
SIPP	Census Bureau	U.S. Population	52,000	Rotating Panel	✓	✓
CPS	Census Bureau	U.S. Population	1 million	Rotating Panel	—	✓
HPS	Census Bureau	U.S. Population	1 million (varies)	Cross-Section	—	—
RPS	Bick and Blandin (2023)	U.S. Population, Age 18–64	20,000 (varies)	Quasi-Panel[d]	✓	✓
SWAA	Barrero et al. (2021)[b]	U.S. Population, Age 20–64	80,000	Cross-Section	✓	✓

[a] The surveys listed from top to bottom are, respectively, the American Community Survey (ACS), American Time Use Survey (ATUS), Survey of Income and Program Participation (SIPP), Current Population Survey (CPS), Household Pulse Survey (HPS), Real-Time Population Survey (RPS), and Survey of Working Arrangements and Attitudes (SWAA).
[b] Also cited as Barrero, Bloom, and Davis (2021).
[c] Approximate average annual sample size.
[d] The RPS is a repeated cross-sectional survey that collects both contemporaneous and retrospective information from respondents.

2.1 Measuring WFH

The core concept of our WFH measures is a WFH workday. A WFH workday is a day on 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 is their own residence would be classified as WFH without working remotely, whereas an employee who works neither at their residence nor at their workplace would be classified as working remotely without WFH. This definition also excludes days on which an individual commuted to work but 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 WFH workdays to days worked within a given week.[3] The WFH Share captures 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*, the share of workers who 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 commute 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 Census Bureau and the Bureau of Labor Statistics). The two independent surveys—the RPS and the SWAA—collect data only for individuals aged 18–64 and 20–64, respectively. When analyzing the government surveys, we restrict our analysis to individuals aged 18–64, as in the RPS. Given the small share of 18- and 19-year-olds among the employed, further restricting the sample to those aged 20–64 would have a very modest impact on our results.

2.2.1 American Community Survey

Overview. The American Community Survey (ACS) is a nationally representative, cross-sectional survey of 1 percent of U.S. households, providing an annual sample size of over three million individuals. The survey is conducted throughout the year by the Census Bureau, but data on the survey week and month are not publicly available, and thus we can only construct annual estimates. The 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, Flood, 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.

2.2.2 American Time Use Survey

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 interviews in the CPS. The annual sample size began with almost 21,000 respondents in 2003 but was significantly reduced to only 14,000 in 2004. Since then, it decreased gradually to only 8,500 in 2023. While the data are available at a monthly frequency, in this article we pool data at the annual level due to small monthly sample sizes. The Bureau has administered the ATUS since January 2003, though 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 (MTUS) before 2003. We rely on the IPUMS versions provided by Flood, Sayer, et al. (2023) and Fisher, Gershuny, 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.

[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. Alternatively, one could average over the individual WFH shares. The difference between these two measures is that workers who work more days receive a greater weight in the former measure. However, we cannot compute the latter measure in the ATUS since it only contains information about a single day for each individual. In practice, because individual WFH shares do not vary much with the number of days worked (See Appendix Figure 2.3), the two measures yield similar estimates for the SIPP, RPS, and SWAA, as shown in Figure 1.2.

[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.

2.2.3 Survey of Income and Program Participation

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 so that participants would 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 (2019-2024). Information on WFH is available on a regular basis since 2014, with an average annual sample size of 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 questions for each job they held since the previous year. Thus, they reflect typical work patterns rather than conditions 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 the 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 WFH days per week. Only individuals who respond yes to the second question are asked the third question. For those answering "no" to the second question, we set the number of WFH days to zero. Since there is no variation in WFH during the year for job stayers, we only report statistics at 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

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 has been 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, King, et al. (2024), which has monthly data available since 1976.

Measuring WFH. Since October 2022, the CPS asks respondents several questions related to WFH or telework, including the following:[5]

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

For the first question, respondents report either "yes" or "no," and for the second question, they 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.

[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 respondents answer "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 option. We do not use this information as it does not allow us to construct either of our two variables of interest.

[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 article was written, the most recent year available for this dataset was for 2019 and thus did not cover the post-pandemic period.

2.2.5 Household Pulse Survey

The Household Pulse Survey (HPS) 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 HPS is a nationally representative, cross-sectional survey of American households administered by the Census Bureau since 2020. It 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 over time, with nearly two million observations in 2020 but under one million in 2023.

Measuring WFH. The most consistently available measure of telecommuting frequency in the HPS is available from September 2022 onward. The survey questionnaire asks all respondents, "In the past seven days, have any of the people in your household teleworked or worked from home?" For those who respond "yes" to this question, the HPS also asks, "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 therefore very expansive: A worker who worked from their home for an hour on a single workday would report working from home, even if they also commuted that day. The HPS also does not survey respondents about the number of workdays in the previous week. We therefore cannot 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 began using independent online surveys to collect national labor market data (Adams-Prassl, Boneva, et al., 2020; Belot, Choi, et al., 2021; Bell and Blanchflower, 2020; Coibion, Gorodnichenko, and Weber, 2020; Foote, Nordhaus, and Rivers, 2020). Several surveys collected data on WFH, including Foote, Nordhaus, and Rivers (2020), Brynjolfsson, Horton, et al. (2020), Brynjolfsson, Horton, et al. (2023), and Chen, Cortes, et al. (2023). In this article, we focus on two surveys that began collecting WFH data early in the COVID-19 pandemic and are still ongoing: the RPS and SWAA.

Relative to existing government surveys with WFH data, there are two primary advantages of independent online surveys. First, the RPS and SWAA published estimates sooner than several government surveys (both published their first WFH estimates in May 2020, compared with fall 2021 for the ACS and ATUS and summer 2022 for the SIPP). Second, rather than taking as given an existing set of questions, independent surveys can be designed to specifically address a given theory or research objective. For example, Bick, Blandin, and Mertens (2023) use information on employer-imposed commuting requirements in the RPS to understand changes in WFH throughout the pandemic and to predict the long-run rate of WFH after pandemic-related health concerns abated. Barrero, Bloom, and Davis (2023a) use attitudes toward social distancing among SWAA participants to assess the lingering impact of the pandemic on low labor force participation.

The advantages of independent online surveys also come with concerns over the representativeness and accuracy of the data they collect. By construction, online surveys do not sample individuals without internet access (in the 2022 ACS, 3.2 percent of individuals aged 18–64 report living in a household without access to the internet). Moreover, while researchers can ensure that online samples are representative in terms of observable demographic characteristics, they may suffer from selection based on unobservable characteristics (Abrahams, 2023). For example, participants of online surveys may be more comfortable with online applications, which may be a prerequisite for WFH and therefore lead to a biased sample (Glaeser, 2023).

Given concerns about the reliability of independent online surveys, it is especially important to compare estimates from the RPS and SWAA to the government surveys, which are not subject to the same concerns.

2.3.1 Real-Time Population Survey

Overview. The Real-Time Population Survey (RPS) is a nationally representative labor market survey of adults aged 18–64. It has been conducted 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. It fielded twice per month from April through September 2020 and 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) and Bick, Blandin, and Mertens (2023). To address concerns regarding representativeness, Bick and Blandin (2023) show that during the COVID-19 pandemic, the RPS closely aligns with the CPS along many dimensions neither targeted by the sampling procedure nor included in the weighting scheme, including the distribution of weekly hours worked, weekly earnings, and industries.[7]

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 those 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.[8] 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 Working Arrangements and Attitudes

Overview. The Survey of Working Arrangements and Attitudes (SWAA) is a monthly cross-sectional survey of Americans aged 20–64. From May 2020 to March 2021, it 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.[9] Because our goal is to estimate national-level WFH rates, we use SWAA data only since January 2022. The SWAA typically interviews 80,000 respondents annually.[10]

Measuring WFH. Since November 2021, the SWAA asks all respondents,[11] "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."[12] The SWAA's focus on "full workdays" of at least six hours will by construction not capture work and WFH on shorter workdays; we discuss the potential implications of this focus in Section 3.2.

3. AGGREGATE TRENDS IN WFH

This section documents aggregate trends in WFH for the U.S. We first document longer-term trends in WFH before the COVID-19 outbreak and then analyze the evolution of WFH since the pandemic. Next, we quantify the roles of full-time 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.

[7] 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.

[8] 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 1.1 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.

[9] 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.

[10] The SWAA data can be accessed at www.WFHresearch.com.

[11] 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 SWAA asked, "Currently (this week) what is your working status?," where one of the possible answers was "Working from home".

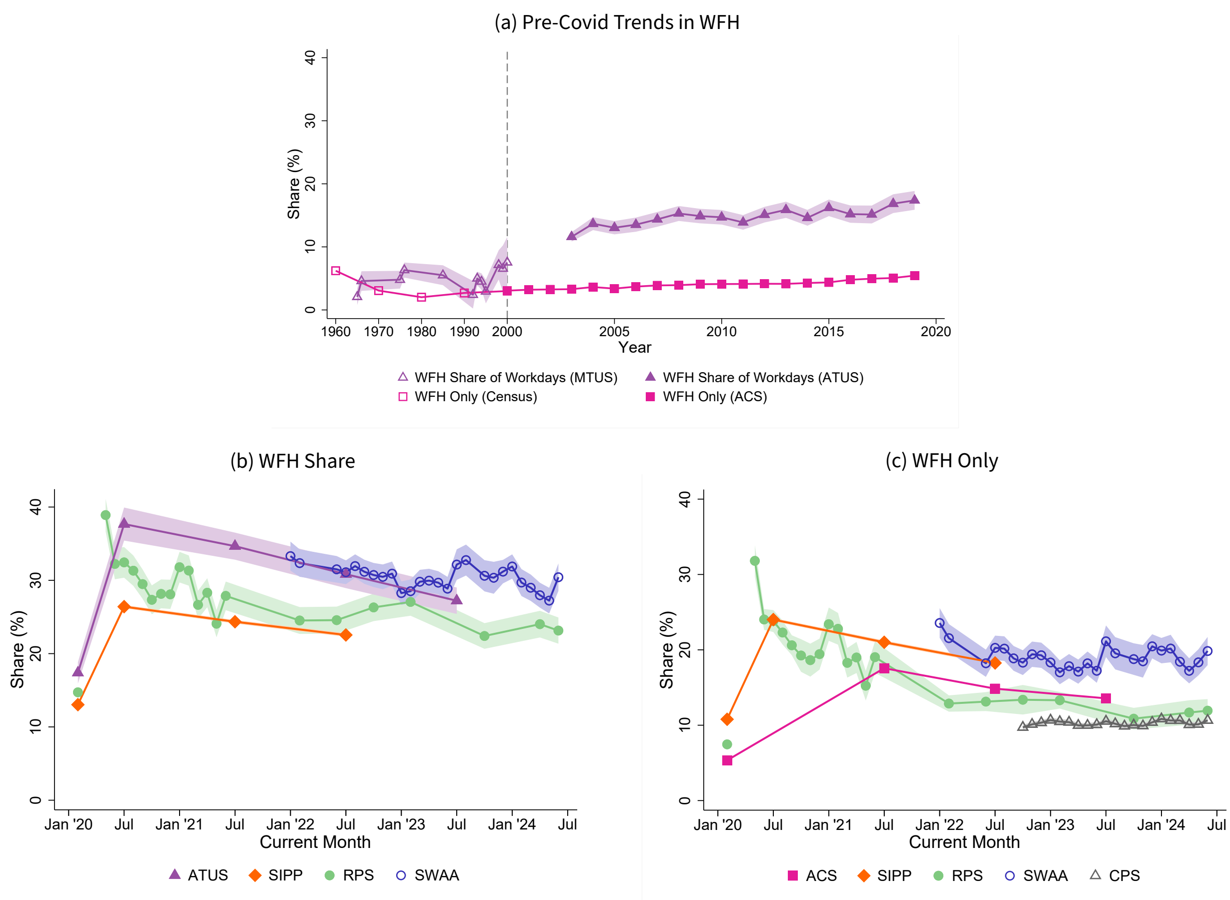
[12] This question is asked of all respondents, including those who previously reported that they did not work in the previous week. Following Barrero, Bloom, and Davis (2021), we exclude individuals who give conflicting answers regarding work in the prior week.

3.1 The Evolution of WFH over Time

Figure 1 displays aggregate trends in WFH using data from the six surveys discussed in Section 2. To provide a longer-term perspective, Figure 1a also incorporates data from the decennial census and the MTUS. Each marker symbol represents a different dataset, and the shaded regions around each series represent a 95 percent confidence interval. We plot these intervals for all surveys, but they are not visible for the ACS and SIPP.

Figure 1

Aggregate Rates of WFH



NOTE: 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. The shaded regions represent 95 percent confidence intervals. We compute moments at the annual level in the ACS, SIPP, and ATUS and plot these in July of the corresponding year. We plot data from the 2019 releases of the ACS, SIPP, and ATUS in February 2020. We omit the 2020 ACS release because we cannot distinguish pre-pandemic months from post-pandemic months. The 2020 ATUS data only use responses from May through December 2020, while the 2020 SIPP data use responses from April through December 2020. We drop low-quality observations and those who fail attention-check questions in the SWAA.

Figure 1a displays WFH rates from 1960 to 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 percent in 1960, declines to a low of 3 percent in 1980, and then gradually increases, reaching 5 percent in 2019. While the gradual increase in WFH in recent decades is well-documented (Oettinger, 2011; Mateyka, Rapino, and Landivar, 2012; Pabilonia and Vernon, 2020; Mas and Pallais, 2020), to our knowledge, we are the first to point out the declining WFH Only Rate before 1980.

The WFH Share is available in the MTUS (hollow pink triangles, 1965–2000) and the ATUS (pink triangles, 2003–2019). Before 2000, the WFH Share is volatile due to small sample sizes, but all years show the WFH Share below 10 percent. From 2003 to 2019, the WFH Share in the ATUS gradually increases from 12 percent in 2003 to 17 percent in 2019.

Figure 1b shows that the WFH Share increased sharply after the COVID-19 outbreak in early 2020 and then declined slowly in the ensuing years. In 2020 the WFH Share ranges from 26 percent in the SIPP to 38 percent in the ATUS, roughly double the pre-pandemic values of 13 percent and 17 percent, respectively. All datasets show a gradual and roughly parallel decline since mid-2020. The most recent estimate from the ATUS, in 2023, is 27 percent—about 1.6 times higher than its pre-pandemic value of 17 percent and 1.3 times higher than what would have been predicted based on pre-pandemic trends.[13] The most recent estimate for the RPS and SWAA are from June 2024: The RPS estimate is 23 percent (about 1.6 times higher than its pre-pandemic value), and the SWAA estimate is 30 percent.

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 percent in the ACS to 11 percent in the SIPP. In May 2020 the WFH Only Rate rises to 32 percent in the RPS and then gradually declines to 19 percent by December 2020. The average WFH Only Rate in the SIPP for April through December 2020 is 24 percent. The ACS, SIPP, and RPS then show a gradual and roughly parallel decline from 2020 to mid-2022; since mid-2022, the WFH Only Rate in the SWAA, RPS, and CPS has been relatively flat. The most recent ACS estimate for 2023 is 14 percent, about 2.5 times larger than what a continuation of pre-pandemic trends in the ACS would have predicted for 2023.[14] The most recent estimate from the CPS, in March 2024, was 11 percent. The June 2024 estimate in the SWAA is higher, at 20 percent, and the June 2024 estimate in the RPS lies in between at 12 percent, about 1.6 times its pre-pandemic value.

3.2 *Why Do Datasets Disagree About Levels of WFH?*

While all datasets in Figures 1b and 1c display remarkably similar trends in WFH since the COVID-19 outbreak, there is nontrivial disagreement about the level of WFH at any given point in time. For the WFH Share, the SIPP consistently exhibits the lowest estimates, while the ATUS and SWAA exhibit the highest. For instance, in 2022 the WFH Share ranges from 23 percent in the SIPP to 31 percent in the SWAA and ATUS. The WFH Only Rate is the lowest in the CPS and highest in the SWAA and SIPP. In 2022, the implied WFH Only Rate ranges from 10 percent in the CPS to 20 percent in the SWAA.

3.2.1 Conceptual Differences in WFH Measures

Section 2 described in detail how information on WFH is collected in each survey. We now highlight how differences in WFH measures between surveys may contribute to the observed differences in our WFH measures between datasets.

One specific instance where survey results may differ 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 they should capture these days of work. In contrast, the SIPP asks about usual days worked, and so it 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 six hours of work, so by construction, it excludes marginal workdays. To the extent that marginal workdays are disproportionately WFH (which is intuitive since these days are the least likely to justify

[13] We obtain this estimate from running a regression of the WFH Share in the ATUS on a linear time trend between 2003 and 2019. Based on this regression, we predict a WFH Share of 20 percent for 2023.

[14] We obtain this estimate from running a regression of the WFH Only Rate in the ACS on a linear time trend between 2000 and 2019 and then predict a WFH Only Rate of 5.5 percent for 2023.

a fixed commuting cost), this would tend to produce higher WFH rates in the ATUS and lower WFH rates in the SWAA. To summarize, although different treatment of irregular and marginal workdays may explain why the SIPP's WFH Share is at the lower end and the ATUS's WFH Share is at the higher end, it likely does not explain the relatively high estimates in the SWAA.

Finally, we classify individuals in the ACS as WFH Only if they usually worked from home during the previous week, which includes those who worked from home every day or on the majority of workdays. In contrast, the RPS and SWAA provide daily data for the prior week and classify only those who worked from home every single workday as WFH Only. Individuals who worked from home on most days but commuted on at least one day are not categorized as WFH Only in these datasets. This difference may explain why the WFH Only Rate is slightly higher in the ACS than in the RPS, but not why it exceeds the ACS rate in the SWAA.

3.2.2 WFH for the Self-Employed Versus Employees

These conceptual differences across surveys may be more important for particular groups of workers. Figure 2 documents greater variation in WFH rates across datasets for the self-employed than for employees across surveys.[15] The pre-pandemic WFH Share among the self-employed ranges from 29 percent in the RPS to 36 percent in the SIPP. By 2022, this estimate was 35 percent in the RPS, 39 percent in the SIPP, 44 percent in the ATUS, and 62 percent in the SWAA. In contrast, Figure 2b shows that the WFH Share among employees is much more similar across datasets, ranging from 10 to 15 percent before the pandemic and from 20 to 30 percent in 2022. These numbers reflect the close agreement for the WFH Share among employees, in contrast to the wide disparity for the WFH Share among the self-employed. Figures 2c and 2d display qualitatively similar patterns for the WFH Only Rate. The disparate WFH estimates for the self-employed across surveys could reflect different definitions of employment and self-employment or different sample compositions.

In a companion article, we investigate how levels and trends in WFH have differed across demographic groups (sex, age, education), firm characteristics, and geography since the pandemic (Bick, Blandin, et al., 2025). We find no comparably dramatic differences across datasets along any of these dimensions.

3.2.3 Taking Stock

The six diverse datasets considered in this article provide similar stylized trends in aggregate WFH and commuting that are robust to variations in data type, survey design, and sampling methods. Notably, this includes online surveys where participants may be more comfortable with online applications. At the same time, researchers should be aware of sizable differences in the level of WFH between some datasets, especially among the self-employed.

3.3 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 intimately 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:

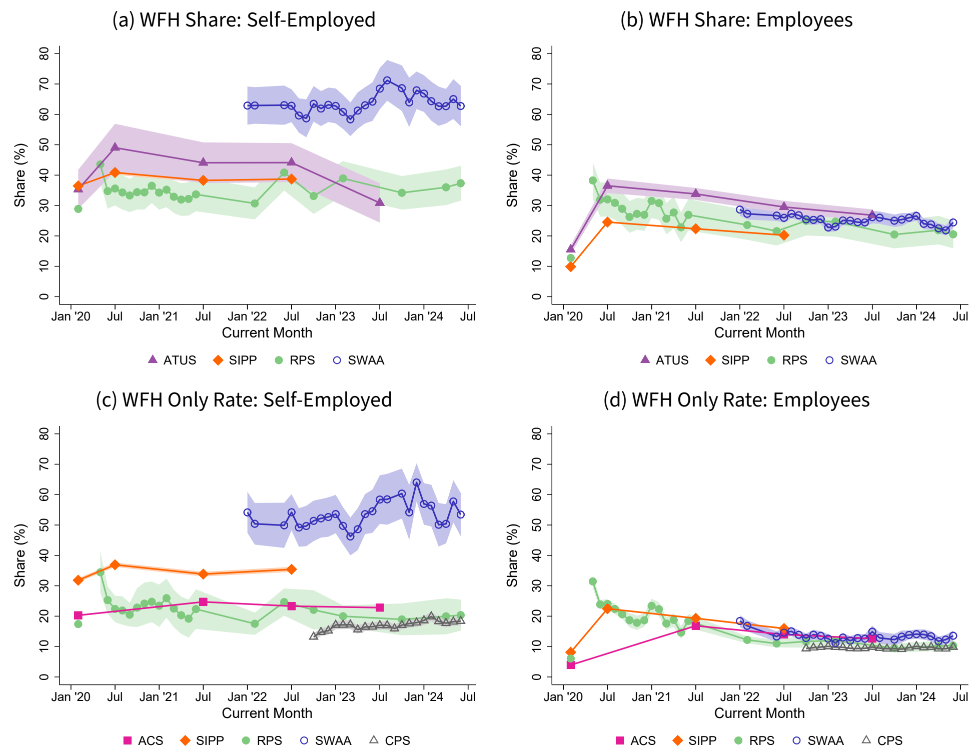
$$\begin{aligned}(1)\qquad \text{WFH Share} =& (\text{WFH Only Rate}) \times \frac{(\text{WD} \mid \text{WFH Only})}{\text{WD}} \times 1 \\ &+ (\text{WFH-SD Rate}) \quad \times \frac{(\text{WD} \mid \text{WFH-SD})}{\text{WD}} \times (\text{WFH Share} \mid \text{WFH-SD}),\end{aligned}$$

where "WD" denotes the average number of workdays among a particular group of workers, "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 number of workdays among these

[15] 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 classify 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 in the SWAA, as WFH is more prevalent for group (i) than for group (ii).

Figure 2

WFH by Employment Type



NOTE: Figure 2 displays time series of WFH rates for employees and the self-employed using two different measures of WFH. Figures 2a and 2b plot the WFH Share, while Figures 2c and 2d plot the WFH Only Rate. Figures 2a and 2c correspond to the self-employed, while figures 2b and 2d correspond to employees. The shaded regions represent 95 percent confidence intervals. Pre-pandemic 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 only use responses from May through December 2020, while the 2020 SIPP data use responses from April through December 2020. We drop low-quality observations and those who fail attention-check questions in the SWAA.

workers relative to the employed population overall. The second is the WFH Some Days Share, similarly weighted, and multiplied by the WFH Share among these workers.

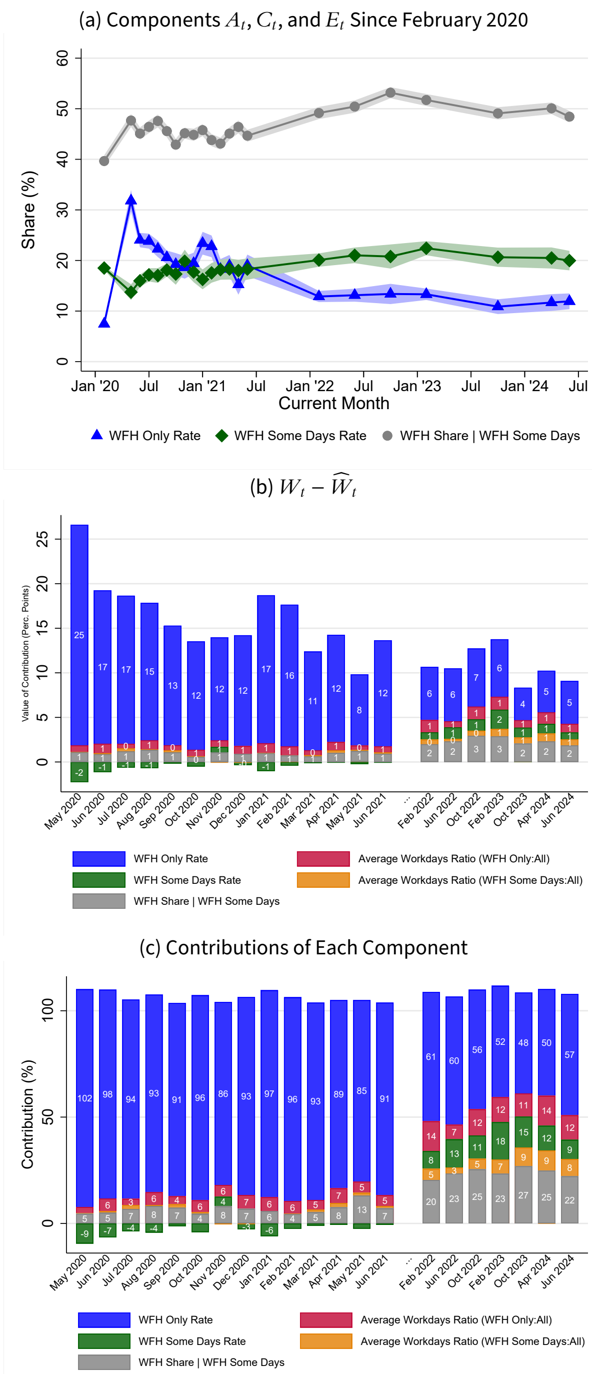
Figure 3 plots the WFH Only Rate, the WFH Some Days Rate, and the WFH Share conditional on WFH Some Days in the RPS. (This information is also contained in the SIPP but at a lower frequency and with data available only through 2022; we discuss these estimates in Appendix 2.) An immediate takeaway is that percentage 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 one-fourth. 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 to 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 2.3 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 percent 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:

$$W_t = A_t \times B_t + C_t \times D_t \times E_t, \tag{2}$$

Figure 3

Decomposition of the WFH Share



NOTE: Figure 3 displays the results of the decomposition procedure outlined in Section 3.3. Figure 3a plots components A_t, C_t, and E_t (respectively, the WFH Only Rate, the WFH Some Days Rate, and the WFH Share conditional on WFH Some Days) over time. The shaded regions represent 95 percent confidence intervals. Because they occasionally exceed 100 percent, components B_t and D_t are plotted separately in Figure 2.3. Figure 3b plots the $\delta_{i,t}$ estimator for each RPS survey month, quantifying the absolute impact of each decomposition component on the rise in the WFH Share. The point estimate for this effect is shown inside of the corresponding bar when it is sufficiently large. Figure 3c plots $\delta_{i,t}$ as a share of the overall increase in WFH ($W_t - W_{2019}$), quantifying the relative importance of each component on the rise in the WFH Share. The point estimate for this effect is also shown inside of the corresponding bar when it is sufficiently large.

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 3b displays the results of this decomposition. Figure 3c 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 percent of the increase in the aggregate WFH Share, compared with 57 percent for the WFH Only Rate. The remaining three components each explain around 10 percent 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 adds up to slightly more than 100 percent.

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 percent 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.

3.4 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 cell phone geolocation data from 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, and we aggregate them 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:

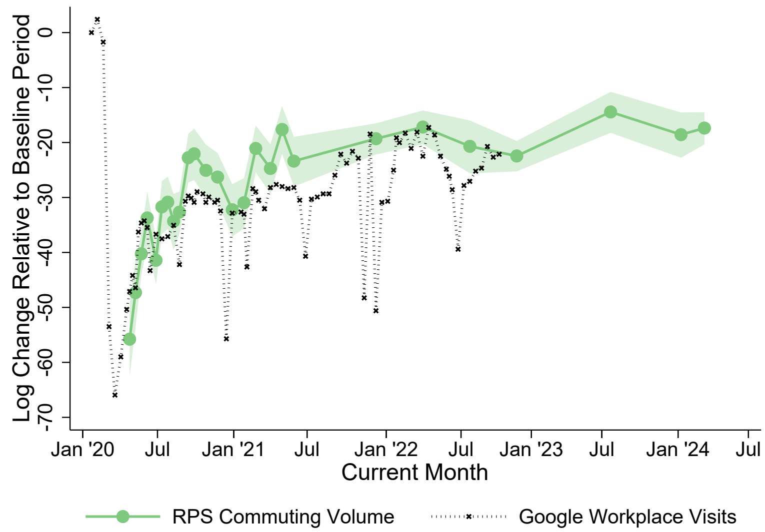
$$CV = EMP \cdot WD \cdot (1 - W), \tag{4}$$

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 dataset must also 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.[16] 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 4 plots the log change in weekly workplace visits from 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

[16] For an earlier comparison of the GWV and the RPS, see Bick, Blandin, and Mertens (2023). Glaeser (2023) uses the GWV in his discussion of the SWAA estimates but also cautions against the representativeness of the GWV because the devices used to measure mobility may be held by a non-random sample of the population and the prevalence of devices in the population may change over time.

Figure 4
Commuting Volume



NOTE: The figure 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 shaded green region represents a 95 percent confidence interval. The baseline period is the week of February 3–9, 2020 for the GWV series and the entire month of February 2020 for the RPS series.

off at roughly 30 log points below the pre-pandemic baselines. Another upward shift began in late summer 2021, again leveling off 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 article is to compare measures of WFH across a wide array of data sources. In Section 3.1, we found broadly similar estimates of WFH across six major surveys. In this section, we expanded the analysis by incorporating an entirely different data source based on cell phone geolocation data. We found that the commuting volume in this dataset closely matched commuting volume in the RPS. Each of these datasets has its own advantages and disadvantages. For example, all surveys will suffer from some amount of recall error. Alternatively, cell phone data may not capture all work-related commuting and will not reflect the behavior of workers without cell phones. 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. CONCLUSION

While the prevalence of WFH varies greatly across surveys, they measure WFH using different questions, reference periods, samples, and collection methods. In this article, we examine the extent to which different WFH rates 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 show broadly consistent trends in the aggregate trajectory of WFH following the COVID-19 outbreak.

Although all datasets show a consistent qualitative trend in aggregate WFH over time, we continue to observe substantial differences in the level of WFH across surveys. We find that these discrepancies are smaller for employees and larger for self-employed workers. Further research is needed to determine whether the large differences among the self-employed are driven by different sample composition or different definitions of self-employment, workdays, or WFH.

A central question for policymakers and researchers is the extent to which elevated levels of WFH will persist going forward. In surveys with estimates through 2024, we find that aggregate WFH rates in 2024 remain roughly 60 percent higher than pre-pandemic levels and have stabilized in the last two years. While these estimates do not indicate what will happen in the future, Bick, Blandin, and Mertens (2023) develop a quantitative structural model that predicts persistently elevated WFH. In the 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 is a shift in employer practice: 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 WFH rates 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 percent WFH Share and a 15 percent WFH Only Rate—align closely with actual WFH data from the RPS in June 2024—a 23 percent WFH Share and a 12 percent WFH Only Rate. The notion that WFH will remain permanently elevated is also supported by the high share of job ads offering a hybrid or fully remote option, suggesting a persistent shift in work arrangements (Hansen, Lambert, et al., 2023; also see Appendix Figure 1.3).

Finally, despite higher WFH rates 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.

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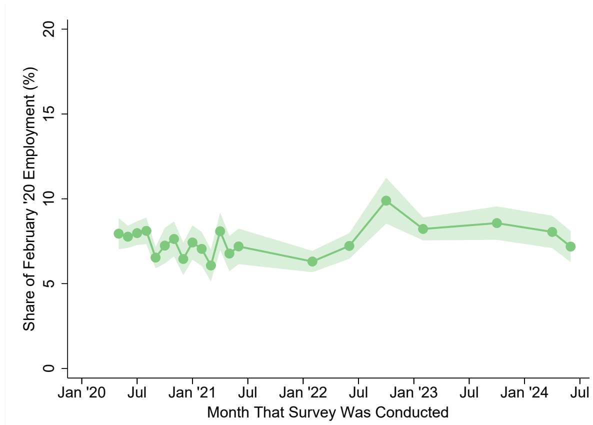
APPENDIX 1. DATASETS AND DEFINITIONS

Appendix Figure 1.1

RPS February 2020 WFH Only Rate by Survey Month

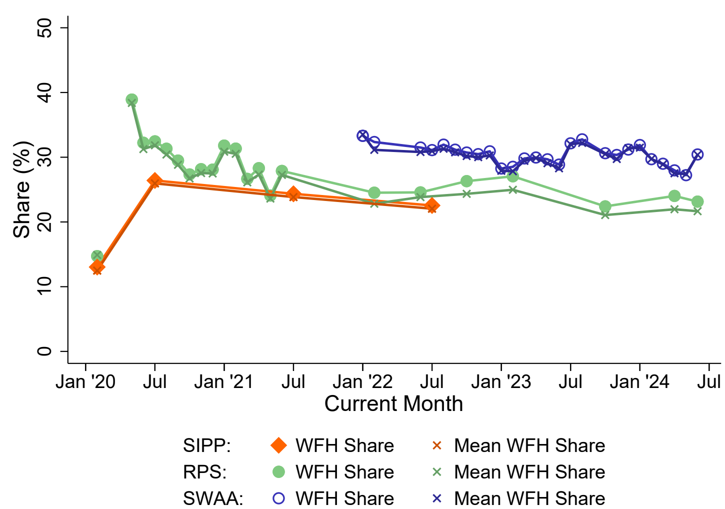


NOTE: Figure 1.1 displays the share of workers in the RPS who were WFH Only in February 2020 in every survey wave. The shaded green region represents a 95 percent confidence interval.

Section 2.3.1 explained that the RPS is a retrospective survey that asks respondents about their WFH status in February 2020. Figure 1.1 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.

Appendix Figure 1.2

WFH Share of Workdays and Mean WFH Share by Survey

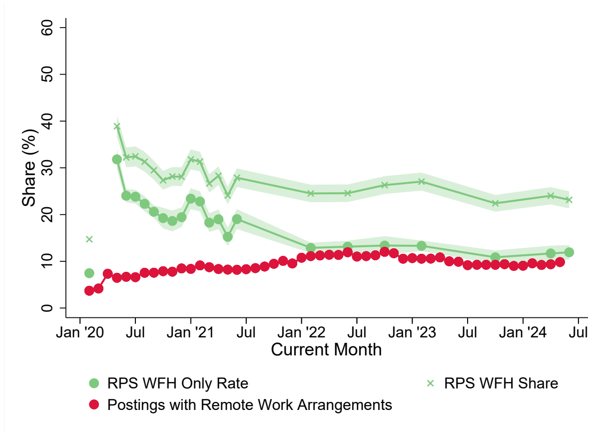


NOTE: Figure 1.2 displays the WFH Share and Mean WFH Share in the SIPP, RPS, and SWAA since 2020. For the SIPP, we plot data from the 2019 release, fielded in February 2020. We compute annual-level moments and plot them in July of the corresponding data. The 2020 SIPP uses responses from April through December 2020. In the SWAA, we drop low-quality observations and those who fail attention-check questions.

Section 2.1 discussed two alternatives for measuring the overall prevalence of WFH: WFH Share and Mean WFH Share. The former measure assigns greater weight to workers with more workdays and is available for the SIPP, RPS, SWAA, and ATUS, while the latter measure is available in all of these except the ATUS. Figure 1.2 shows that these two measures align quite closely in practice.

Appendix 1.1 Job Postings

Appendix Figure 1.3
Job Postings with Remote Work Arrangements and WFH in the RPS



NOTE: Figure 1.3 shows the evolution of the share of job postings advertising remote work arrangements, as well as the WFH Only Rate and the WFH Share in the RPS over time. The shaded regions represent 95 percent confidence intervals. The job postings data come from Hansen, Lambert, et al. (2023).

Figure 1.3 shows that the share of job postings advertising remote work arrangements has risen considerably since the start of the pandemic. As mentioned in Section 4, this supports the notion that WFH will remain elevated above pre-pandemic levels well into the future.

APPENDIX 2. DECOMPOSITION PROCEDURE

Appendix 2.1 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

$$
\begin{aligned}
W &= \frac{\sum H_i}{\sum D_i} \\
&= \frac{\sum \mathbb{I}(H_i = D_i) \times H_i + \sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum D_i} \\
&= \frac{\sum \mathbb{I}(H_i = D_i) \times H_i}{\sum D_i} + \frac{\sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum D_i} \\
&= \frac{P}{P} \times \frac{\sum \mathbb{I}(H_i = D_i)}{\sum \mathbb{I}(H_i = D_i)} \times \frac{\sum \mathbb{I}(H_i = D_i) \times H_i}{\sum D_i} + \frac{P}{P} \times \frac{\sum \mathbb{I}(0 < H_i < D_i)}{\sum \mathbb{I}(0 < H_i < D_i)} \times \frac{\sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum D_i} \\
&= \frac{1}{P} \sum \mathbb{I}(H_i = D_i) \frac{\frac{\sum \mathbb{I}(H_i = D_i) \times H_i}{\sum \mathbb{I}(H_i = D_i)}}{\frac{1}{P} \sum D_i} + \frac{1}{P} \sum \mathbb{I}(0 < H_i < D_i) \frac{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum \mathbb{I}(0 < H_i < D_i)}}{\frac{1}{P} \sum D_i}.
\end{aligned}
$$

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

$$
\begin{aligned}
&\frac{1}{P} \sum \mathbb{I}(0 < H_i < D_i) \frac{\frac{1}{\sum \mathbb{I}(0 < H_i < D_i)} \sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\frac{1}{P} \sum D_i} \times \frac{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\sum \mathbb{I}(0 < H_i < D_i)}}{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\sum \mathbb{I}(0 < H_i < D_i)}} \\
&= \frac{1}{P} \sum \mathbb{I}(0 < H_i < D_i) \frac{\frac{1}{\sum \mathbb{I}(0 < H_i < D_i)} \sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\sum \mathbb{I}(0 < H_i < D_i)}} \times \frac{\frac{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\sum \mathbb{I}(0 < H_i < D_i)}}{\frac{1}{P} \sum D_i} \\
&= \frac{1}{P} \sum \mathbb{I}(0 < H_i < D_i) \frac{\frac{1}{\sum \mathbb{I}(0 < H_i < D_i)} \sum \mathbb{I}(0 < H_i < D_i) \times D_i}{\frac{1}{P} \sum D_i} \times \frac{\sum \mathbb{I}(0 < H_i < D_i) \times H_i}{\sum \mathbb{I}(0 < H_i < D_i) \times D_i}.
\end{aligned}
$$

This is the WFH Some Days Rate weighted by (the average number of days worked by WFH Some Days workers divided by the average number of 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 the ratio of average workdays by WFH Only workers to average workdays, C the WFH Some Days Rate, D the ratio of average workdays by WFH Some Days workers to average workdays, and E 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.

Appendix 2.2 Decomposition in the SIPP

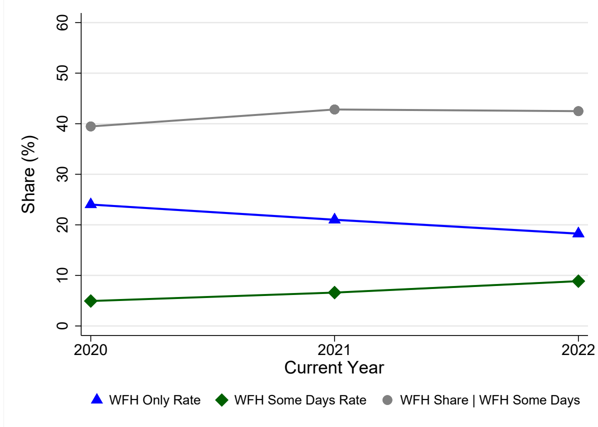
Figure 3 showed the results for the decomposition discussed in Section 3.3 using RPS data. Figure 2.1 shows the results for the same decomposition using SIPP data. Figure 2.1a plots three of the five components of our decomposition in the SIPP. Because the other two components exceeded 100 percent, they are not displayed in Figure 2.1a, and shown separately in Figure 2.2.

The RPS and SIPP both suggest 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 percent of the rise in WFH in 2022 was due to the WFH Only Rate in the RPS, compared to 81 percent in the SIPP. A likely explanation is that the SIPP underestimates hybrid work; see Section 2.2.3.

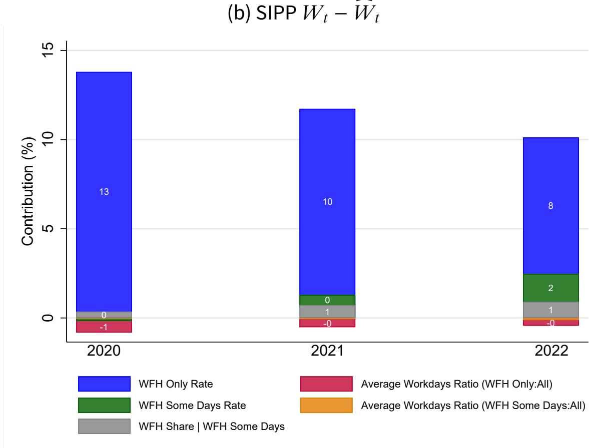
Appendix Figure 2.1

SIPP Decomposition of the WFH Share of Workdays

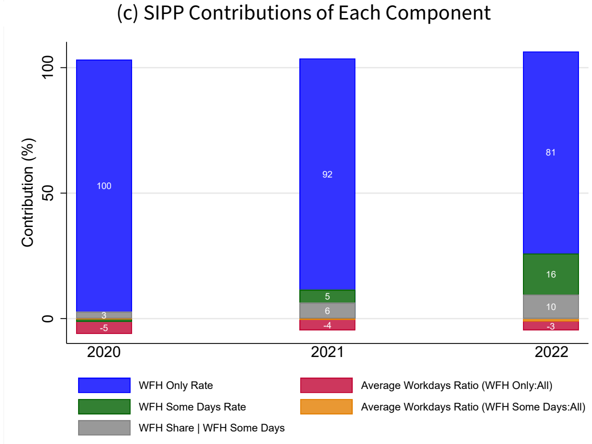
(a) SIPP Components A_t, C_t, and E_t Since February 2020



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



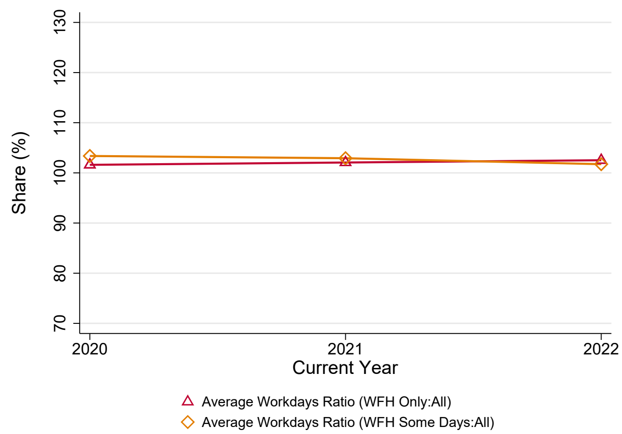
(c) SIPP Contributions of Each Component



NOTE: Figure 2.1 shows the WFH decomposition results discussed in Section 3.3 using SIPP data. We use the 2019 SIPP release as the pre-pandemic baseline. The 2020 SIPP data use responses from April through December 2020. Figure 2.1a plots components A_t, C_t, and E_t (respectively, the WFH Only Rate, the WFH Some Days Rate, and the WFH Share of Workdays conditional on WFH Some Days) over time. We plot 95 percent confidence intervals, but they are too narrow to be visible. Because they occasionally exceed 100 percent, components B_t and D_t are plotted separately in Figure 2.2. Figure 2.1b plots the $\delta_{i,t}$ estimator for each SIPP survey year, quantifying the absolute impact of each decomposition component on the rise in the WFH Share. The point estimate for this effect is shown inside of the corresponding bar when it is sufficiently large. Figure 2.1c plots $\delta_{i,t}$ as a share of the overall increase in WFH ($W_t - W_{2019}$), quantifying the relative importance of each component on the rise in the WFH Share. The point estimate for this effect is also shown inside of the corresponding bar when it is sufficiently large.

Appendix Figure 2.2

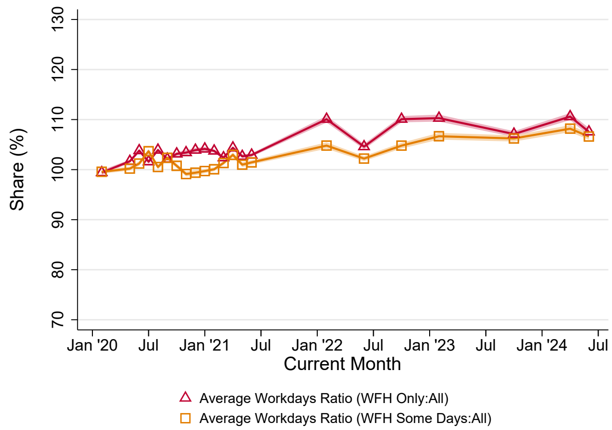
Average Workday Ratio in the SIPP



NOTE: Figure 2.2 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.

Appendix 2.3 Average Workdays in the RPS

Appendix Figure 2.3
Average Workday Ratio in the RPS



NOTE: Figure 2.3 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 3 plotted three of the five components of our decomposition in the RPS. Because the other two components exceeded 100 percent, they are not displayed in Figure 3. Figure 2.3 plots both of these components. As suggested by Figure 3, these components are nearly static over time, never deviating by more than 12 percent from their pre-pandemic values.