How Many Americans Work Remotely?

PRELIMINARY AND INCOMPLETE

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Abstract

While there is widespread recognition that the remote work rate surged during the coronavirus pandemic, there is disagreement about the extent of this change. To address this limitation, we field a new, nationally-representative survey: the Remote Life Survey (RLS). After constraining the sample to working respondents who were employed before and during the pandemic, we find that in October, 2020, 31.6% of this continuously employed workforce always worked from home and 22.8% sometimes or rarely worked from home, totalling 53.6%. We compare our results with alternative measurement approaches, focusing on five factors: (a) differences in the selection of respondents among mail versus web-based surveys, (b) differences in the inclusion of self-employed workers, (c) ambiguity that arises from the classification of remote versus non-remote work into discrete categories, (d) the industry mix of the sample, and (e) the exclusion of people who were already remote pre-pandemic. We find that explanation (e) explains the bulk of the difference in estimates between the Current Population Survey and other measures of remote work, underestimating the remote work rate by up to 33 percentage points. Overall, we estimate that about half of the US workforce currently works remotely at least one day each week.

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1 Introduction

The COVID-19 pandemic and the associated federal and state quarantine policies led to a surge in the share of remote workers (Brynjolfsson et al., 2020).[1] While certain sectors were classified as essential, others were not and that, coupled with a supply-induced decline in demand (Guerrieri et al., 2020), led to substantial declines in employment (Cajner et al., 2021). The shift towards remote is expected to have significant effects on productivity based on the resulting impact on employee engagement and productivity (Barrero et al., 2021; Makridis and Schloetzer, 2022). Unfortunately, there remains wide disagreement and resulting uncertainty about aggregate remote work numbers. Our primary contribution is to document the wide dispersion in remote work measures and to explain how various survey decisions affect aggregate measurement differences.

Understanding the incidence of remote work is important for at least four reasons. First, there is a large literature documenting the link between coordination and firm performance (Bresnahan et al., 2002). Second, depending on how and which employees value remote work, the nature of the workplace and the supply chains of products and services may fundamentally change (Barrero et al., 2020; Bai et al., 2021). Third, the shift to remote work is having profound effects on migration and the composition & structure of cities (Coven et al., 2021; Delventhal et al., 2020; Althoff et al., 2020; Ramani and Bloom, 2021). Finally, remote work is a general purpose technology, meaning that a variety of spillovers beyond those enumerated here or anticipated today may occur throughout the economy. However, before these resulting effects can be quantified, we need proper measurement of remote workers and their intensity of remote work.

[1] There are many terms used to describe these non-traditional work arrangements, including “remote work,” “working-from-home,” and “working-from-anywhere,” but we find that these distinctions are practically minor. Future work should examine these differences, particularly as the workplace and composition of jobs changes.

The first part of the paper introduces a new survey instrument through from Gallup implemented between October and November 2020 with two main features. First, it is nationally-representative. Unlike many survey tools that focus on web responses, Gallup also covers respondents who prefer to reply to surveys through mail. Given the heterogeneous effects of the lockdowns on workers, distinguishing between these two sets of respondents matters.

The second part of our paper compares this new measure of remote work to five other measures of remote work. We find that most series are generally consistent over time, with relatively low dispersion in remote work incidence for similar periods of time. However, we find that the measure of remote work from the Current Population survey is an outlier compared to our new measure and four others.

The third part of our paper assesses potential explanations for the heterogeneity in estimates about the incidence of remote work. First, differences in the incidence of remote work among respondents who participate in web-only versus mail surveys can contribute a gap of 1.6 (pp) in our data. This suggests research should consider the effects of web-only surveys, however they are unlikely to explain a significant portion of measurement differences between surveys.

Second, we find that if a survey excludes the self-employed that can bias pre-pandemic remote work incidence by around -4-4.5 percentage points (interpretation: without self employment WFH incidence - with self employment WFH incidence = 4 to 4.5 pp). The bias on WFH intensity during the pandemic is less pronounced, from -0.2 to +0.2 percentage points. If self employed workers are taken into account, it can lead to a 3-4pp reduction in WFH adoption going from the pre-pandemic period to after the start of Covid-19 (interpretation: without self employment WFH gross adoption - with self employment WFH gross adoption = 3 to 4 pp). This is because self employed are more likely to already be teleworking before the pandemic started so their behavior would attenuate WFH adoption trends. As we show, this methodology choice can help account for differences in the extent of remote work from pre-pandemic periods. Specifically, relying on the American Time Use Survey biases measured remote work for the overall workforce down by excluding the self-employed. However, it is important to note that the CPS includes those who are self-employed. As a result, this cannot explain the discrepancy between the CPS and other surveys.

Third, differences can emerge due to the the how the survey question is designed relevant to remote work intensity. RLS data shows that limiting the responses to always remote only can reduce the share working remotely 21.9 to 15.3 percentage points compared the inclusion of those working remotely sometimes. However, looking at the BLS methodology shows that neither self-employment nor intensity of remote work can explain any of the gap between it and other measures.

Fourth, we examine whether industry mix is likely to explain any of the gap. Comparing our "sometimes WFH" metrics to the CPS under different industry composition weights we see that our adoption of "sometimes WFH" measure drops from 26% to 20%. This means that going from before to after the start of the Covid-19 pandemic, around a quarter of our working respondents have switched from not WFH to "sometimes WFH" using Gallup's industry composition. If we apply the CPS' industry mix, that number drops to 20%. Our measure of "sometimes WFH" stock levels during the pandemic (pre-pandemic stock + adoption) stands at 49% but drops to 41% with the application of CPS industry mix. Since the CPS number stands at 22%, we argue that the industry mix plays an important role in explaining the gap between our numbers and those of the CPS.

Finally, we show how inclusion or exclusion of pre-pandemic work can affect the measurement of remote work. If a survey only focuses on post-pandemic remote work, this can reduce the share working remotely by 25.3 to 6.7 percentage points, depending on whether the survey focuses on always remote versus remote sometimes. In addition to RLS evidence, we present consistent results from a Google Consumer Survey.

Altogether, we advise practitioners to consider carefully the measurement issues discussed in this paper. The most likely cause of the lower propensity of remote work observed in the CPS is exclusion of pre-pandemic remote work. When including those who are sometimes remote, this can reduce the estimated remote work share by up to 25.3 percentage points in our data. The consistency among other measures, including those longitudinal and non-web surveys, suggest that the CPS measure is indeed a substantial underestimate and has been for the duration of the pandemic. The bias appears to be 20 percentage points or more, which is an approximate magnitude of the bias expected by excluding pre-pandemic work from home.

Our paper is related with an emerging literature about the incidence of remote work. For example, the BLS approach to measuring remote work focuses on the ability to telework (Dey et al., 2020), which could produce an upwards biased estimate if the ability does not correspond with the actual implementation of it. Taking a similar approach with O*NET, Dingel and Neiman (2020) find that roughly 37% of jobs can be done remotely. Brynjolfsson et al. (2020) launch a survey of roughly 25,000 responses in April 2020 as well, finding upwards of a third of workers shifting to remote work. Moreover, Barrero et al. (2021) survey over 30,000 between May 2020 and March 2020, finding that 20% believe that full workdays will be supplied from home after the pandemic ends, relative to just 5% before. This is close to our survey responses: 9.5% say that all of their work will be remote after the pandemic and 20.8% say that most of their work will be.

Our paper builds on a larger literature about the effects of remote work on productivity and workers. While there is a lot of descriptive evidence, causal estimates have been more difficult to obtain. In a pioneering randomized controlled trial (RCT) on China's largest online travel agency, (Bloom et al., 2015) finds that WFH led to a 13% performance increase and an overall increase in employee satisfaction. Moreover, using a natural experiment in the U.S. Patent and Trademark Office, Choudhury et al. (2021a) find a 4.4% increase in output as a result of their adoption of remote work arrangements for patent examiners. Using a more recent RCT in Bangladesh, Choudhury et al. (2021b) vary the number of days that employees come into the office, finding that additional days in the office are associated with more emails, particularly for hybrid work arrangements, and emails directed towards more diverse employees in the organization. Nonetheless, there has been much evidence of adverse and unintended effects, especially when remote work arrangements have been adopted poorly or in a rush (e.g., as in Gibbs et al. (2021)).

2 Data

2.1 Remote Life Survey

We launched the "Remote Life Survey (RLS)," consisting of 6,672 U.S. adults, ages 18 and older, and drawn from a nationally representative sample of Gallup's household panel. Of the 6,672 respondents, 6,049 completed the survey by web and 623 completed the survey by mail. Web interviews were completed between October 16-23 2020; mail surveys were sent on October 16 and responses were accepted through November 30. Gallup panelists are recruited through random selection methods, including through random-digit dial (RDD) telephone recruiting and addressed based sampling (ABS) mail recruiting.

One of the advantages of our survey instrument is that it also contains representation of adults without internet access, which could matter greatly for understanding the incidence of remote work and heterogeneity in its effects across the population. Among the mail respondents, we asked a subset of questions asked of the web respondents. All samples were drawn using a stratified sampling method to ensure our respondents are representative of the U.S. adult population. Furthermore, we included a small incentive of $2 to encourage participation in the study. The combined response rate for mail and web respondents was 28%, including 32% for web respondents and 26% for mail respondents.

To correct for non-response and ensure nationally representative samples according to gender, age, race, Hispanic ethnicity education, and census region, both the web-only and combined web/mail obtained samples were weighted. These weighting targets were computed using data from the most recent Current Population Survey. The margin of sampling error for the combined web and mail sample, and the web only sample of U.S. adults, is +/- 2 percentage points.

Table XX in the Online Appendix presents the full suite of questions. We focus on the responses to the following question: "In the past month, about how often did you work from home as part of your job? (1) 1 Never; (2) A few times a year; (3) About once a month; (4) About once a week; (5) 3-4 times a week; (6) I always worked from home." An advantage of our survey approach is that we provide respondents with the option of stating *how much* they work remotely, rather than a simple binary option, which is especially pertinent given recent evidence that varying interpretations of hybrid work will become the standard in the workplace (Barrero et al., 2021; Makridis and Schloetzer, 2022; Choudhury et al., 2021b). For our measurement of remote work, we focus on respondents who are employed and working around once a week, i.e. "sometimes remote."

In addition to these responses on remote work *during* the pandemic, we have information about remote work prior to the pandemic, which helps reconcile some of the disagreement that already exists in the literature and allows us to provide an estimate about the increase in remote work relative to the pre-pandemic baseline. In particular, we ask: "Prior to February 1, how often did you work from home as part of your job? (1) 1 Never; (2) A few times a year; (3) About once a month; (4) About once a week; (5) 3-4 times a week; (6) I always worked from home."

2.2 Other Measures of Remote Work During the Pandemic

There has been a flurry of interest in measuring the remote work economy since the onset of the pandemic. However, different surveys ask different questions to gauge the incidence of remote work at a given point of time, sometimes leading towards substantially different conclusions. Below, we consolidate several prominent examples of how remote work was measured during the pandemic.

1. *Barrero, Bloom, and Davis (2021)*

noitemsep Sample size: Approx 3,300

noitemsep Measurement time frame: 5/2020 - 3/2021

noitemsep Question asked: "How many full paid working days are you working from home this week?"

noitemsep Sample characteristics: U.S. residents, 20-64 years old, who earned at least $20,000 in 2019.

noitemsep Survey method: web surveys

2. BLS, Current Population Survey

noitemsep Sample size: 60,000 households

noitemsep Measurement time frame: 5/2020 - 12/2021

noitemsep Question asked: “At any time in the LAST 4 WEEKS, did (you/name) telework or work at home for pay because of the coronavirus pandemic?”

noitemsep Sample characteristics: all employed

3. Gallup

noitemsep Sample size: over 4,000 adults

noitemsep Measurement time frame: 4/2020 - 9/2021

noitemsep Question asked: “To what extent are you taking the following steps to avoid catching or spreading the coronavirus?” Working remotely always, working remotely sometimes, or never working remotely

noitemsep Sample characteristics: employed full-time or part-time

4. Brynjolffson, Horton, Ozimek, Rock, Sharma, TuYe (2020) - BHORST

noitemsep Sample size: 80,555

noitemsep Measurement time frame: April 2020 to January 2021

noitemsep Question asked: “Have you started to work from home in the last 4 weeks / 2 months?”

noitemsep Sample characteristics: U.S. adults 18-64, sampled through the Google Ad Publisher Network

5. Bick, Blandin, Mertens (2022) - BBM

noitemsep Sample size: 4,700 households per month

noitemsep Measurement time frame: 2/2020 - 6/2021

noitemsep Question asked: “Last week, how many days did you [your spouse/partner] commute to this job?”

noitemsep Sample characteristics: all employed

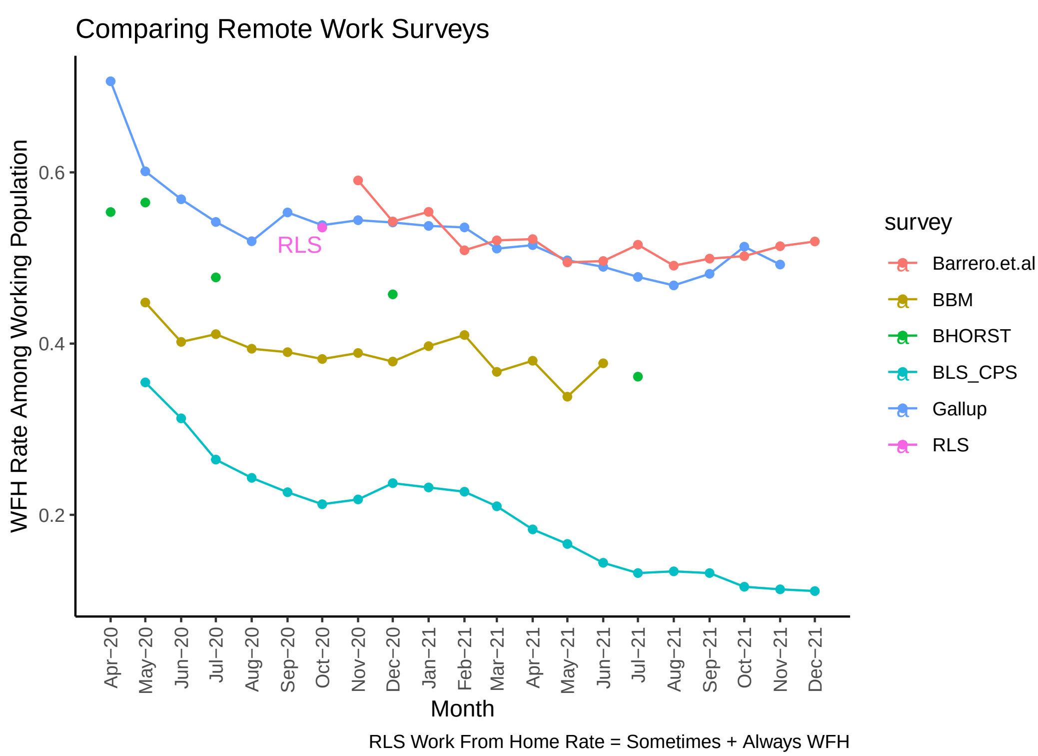

Figure 1: Remote work defined generously as either sometimes or always WFH

Four of the six measures are substantially consistent, while BBM is generally below those measures, but CPS is a clear outlier compared to the rest of them. If we focus on the average from 12/2020 through 6/2021, when we have estimates for five of the six series, we can see that the BLS is nearly half the next closest number. From November 2020 through November 2021, the longest period when we have three consistent measures, we can see that BLS is 17.3%, again less than half of Gallup and Barrero et al, which both show just over half of workers remote. The BLS is different in not only levels, but also trends. From 5/2020 to 11/2021, the BLS measure declines a cumulative 24 percentage points while the Gallup measure only declines 11 percentage point.

Survey	11/2020 through 6/2021 average	11/2020 through 11/2021 average
BLS CPS	20.0%	17.3%
Gallup	51.8%	50.8%
BHORST	45.7%	NA
Barrero et al	52.0%	51.9%
BBM	37.8%	NA%

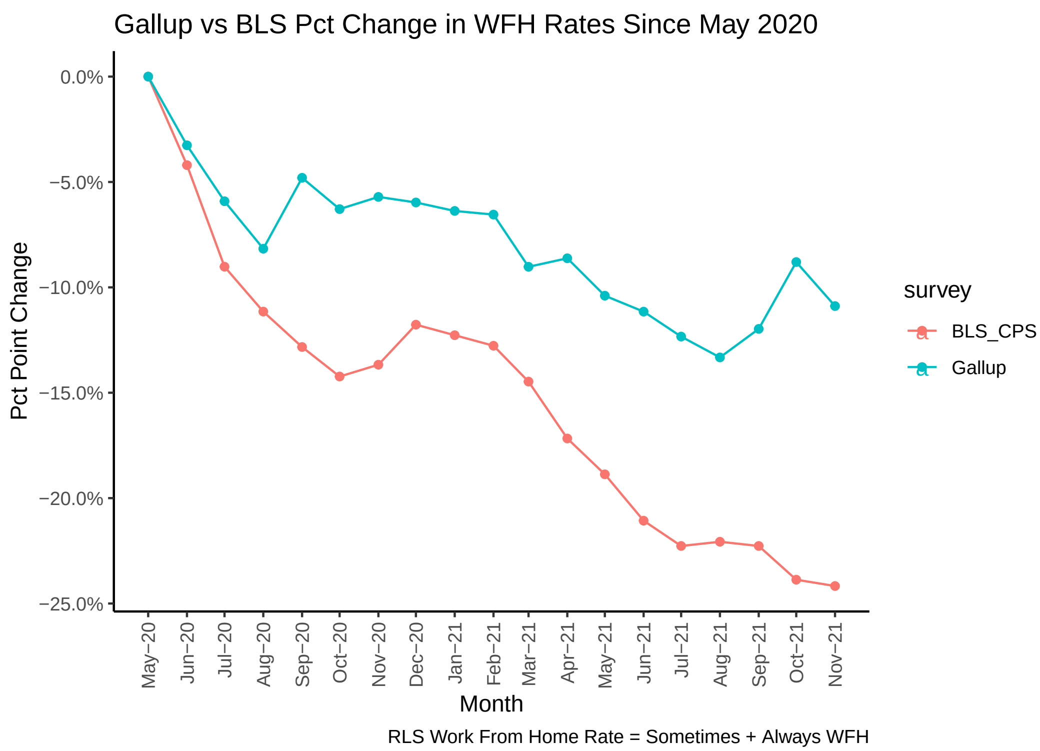

Figure 2: Cumulative percentage point change in share working from home at all

2.3 NLSY Comparison

An additional measure of remote working is available from the BLS using the National Longitudinal Survey 1997 (NLSY97). This measure is useful for additional comparison to the CPS because it is a longitudinal dataset that has tracked individuals over time since 1997. The sample includes 8,984 individuals who born between 1980 and 1984, who were interviewed in a supplement from Feb 2021 to May 2021 about the effects of the COVID-19 pandemic on work and life Auginbaugh and Rothstein (2022). To create a demographically similar comparison group, we utilized CPS microdata from IPUMS over these months focusing on individuals born in the same time-period as the NSLY sample.

The results show a significant discrepancy, with the CPS showing 23% of workers remote at all, compared to 46.7% in the NLSY97. These results are consistent with the time-series evidence, with the CPS generally being half the level of other surveys. In this case, compared to a representative and long-standing survey produced by the BLS itself.

Survey	CPS	NLSY97
None	77.0%	53.3%
Some remote	.	21.3%
All remote	.	25.4%
All + some remote	23.0%	46.7%

2.4 Remote Work by Industry: Comparing CPS to Gallup

We now compare our remote work shares across industries between the RLS and CPS data during the October 2020 - December 2020 Gallup survey period. The distribution of occupations between Gallup and CPS is different for several job areas. Based on the 95% confidence intervals, we see that there are several categories with significant differences. Most notably, CPS does not include "Military" occupations. While it is just a small portion of our Gallup data, military-related jobs appear to have higher WFH adoption than average, which could help explain some of the gap between CPS and Gallup. Transportation, service and sales workers have lower remote work intensities, but are more represented in the CPS data, which exacerbates the gap between CPS and Gallup. However, CPS seems to have more workers in professional services like finance and consulting, which are highly remotable. That might be offset by Gallup's heavier representation of other remote work intensive groups like "computer and mathematical professions", "designers", and "engineers".

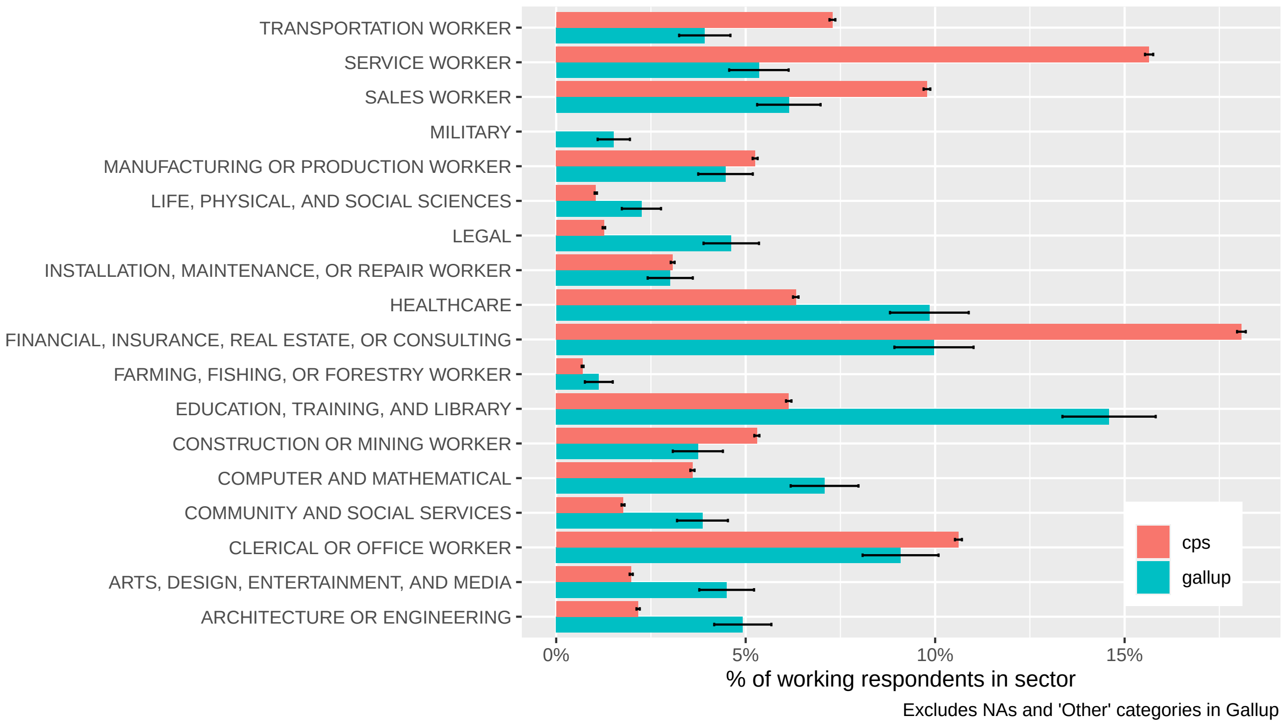

Figure 3: Occupation Distribution Across CPS and Gallup

Interestingly, a significant swath (around 10%) of Gallup respondents classified themselves as “Other” under job categories and these individuals had a WFH rate of 40-50% since the start of the pandemic depending on whether one is interested in the sometimes or always WFH group. These rates are certainly higher than the CPS average. [Insert comment on how correlated folks who answer “Other” correlate with self-employment indicators]

To aggregate all of these potential effects coming from compositional differences we apply CPS industry weights to Gallup data (and exclude categories that CPS does not include, like the military) to see how overall remote work intensities change. We see that using the CPS industry weights reduces our WFH intensities across the board and narrows the gap between CPS and Gallup work from home statistics:

- `wt_mean_adopt_alwaysWFH_gallup`: weighted mean rate of working respondents who adopted

WeightedMean_stat	no reweighting	with CPS reweighting
wt_mean_adopt_alwaysWFH_gallup	0.23	0.19
wt_mean_adopt_sometimesWFH_gallup	0.26	0.20
wt_mean_post_always_gallup	0.32	0.28
wt_mean_post_sometimes_always_gallup	0.49	0.41
wt_mean_wfh_cps	0.22	0.22

always WFH since the pandemic

- `wt_mean_adopt_sometimesWFH_gallup`: weighted mean rate of working respondents who adopted sometimes WFH since the pandemic. Superset of always WFH respondents.
- `wt_mean_post_always_gallup`: weighted mean rate of working respondents who are always WFH since the pandemic. Includes switchers due to pandemic and non-switchers.
- `wt_mean_post_sometimes_always_gallup`: weighted mean rate of working respondents who are sometimes WFH since the pandemic. Includes switchers due to pandemic and non-switchers.
- `wt_mean_wfh_cps`: weighted mean rate of working respondents who adopted WFH since the pandemic. Uses CPS data and CPS question wording.

The "post" designation in variables refers to the period since the start of the pandemic in February 2020. In this sense, it can be considered a "during the pandemic" measurement. Since the CPS survey did not obtain WFH frequency information, we consider our "sometimes WFH" segment the most comparable sub-population to the CPS-defined remote working population. In particular, anyone who reported working from home at least once a week is considered as part of this classification. This excludes those who responded "About once a month", "Once or twice", or "A few times a year". We strip out employment effects by filtering for working respondents who remained employed in both the pre and post periods.

Comparing our "sometimes WFH" metrics to the CPS under different industry composition weights we see that our adoption of "sometimes WFH" measure drops from 26% to 20% among the working respondents population with matched occupations plus the "military". This means that going from before to after the start of the Covid-19 pandemic in February 2020, around a quarter of our respondents have switched from not WFH to "sometimes WFH" using Gallup's industry composition. If we apply the CPS' industry mix, that number drops to 20%. Our measure of "sometimes WFH" stock levels during the pandemic (pre-pandemic stock + adoption) stands at 49% but drops to 41% with the application of CPS industry mix. Since the CPS number stands at 22%, we argue that the industry mix plays an important role in explaining the gap between our numbers and those of the CPS.

3 Sources of Measurement Differences

3.1 Survey Responses from Web and Mail

Many surveys on remote work are conducted through web-based surveys, which could attract a systematically different type of individual—that is, individuals who are more likely to engage in remote work. Three of the four of the surveys described in Section 2.2 are web only, only the CPS includes in-person surveying. One advantage of our approach, therefore, is that we include responses from individuals who are more likely respond to surveys through web, as well as those who are more likely respond through mail, thereby producing a more representative sample.

We begin by exploring whether mail versus web respondents are systemically different in their propensity to work from home and whether these differences are explained by demographics.

First, we regress indicators for always and mostly WFH on an indicator for being a Web-only respondent, controlling for demographics and other state and zipcode characteristics. Second, we regress an indicator for being a Web-only respondent on the aforementioned set of controls. Our controls include: indicators for race (African American, Hispanic—normalized to White), indicators for education (high school, technical/associates, some college, some post-graduate, and post-graduate—normalized to college), an indicator for full-time employment status before and after February 1, 2021, zipcode log download speeds for fixed and mobile internet, state log median household income, and state industry employment shares (manufacturing, wholesale and retail trade, professional, and finance, insurance, and real estate). These results are documented in Table 4.

Columns 1 and 3 present the raw differences, demonstrating that web only respondents are 23.6pp more likely to always WFH and 14.5pp more likely to mostly WFH, relative to their mail respondent counterparts. This demonstrates selection effects into how respondents take the survey. However, it is an open question whether these selection effects can be mitigated through the inclusion of standard demographics.

Columns 2 and 4 introduce a individual demographic characteristics (race, education, and employment status) and various state-specific controls, such as the median household income and employment shares in different industries. While the raw differences in WFH decline to by roughly a half, suggesting that many, but not all, of the differences in responses are absorbed by these controls, there are still substantial differences in selection: web only respondents are 9.4pp more likely to always WFH and 7.4pp more likely to sometimes WFH, relative to mail respondents.[2]

[2]The location-specific controls also helps reduce the presence of selection effects considerably. For example, excluding the location-specific measures leads to a coefficient in column 2 of roughly 0.11, rather than 0.094.

Importantly, we find null associations between race and always WFH, but we do find slightly negative effects of African Americans and Hispanics for mostly WFH, suggesting they are slightly less likely to participate in intermediate WFH. Similarly, those with a post-graduate education are more likely to always or sometimes WFH, relative to those with a college education, and those with only a technical/associates or some college degree are fairly less likely to WFH. Finally, while faster mobile internet speeds is negatively associated with mostly WFH, it is more strongly associated with always WFH, reflecting the greater demand for fast internet among people whose enter labor market fortunes require remote work.

Given that we have documented important differences in WFH among those who respond via the web versus mail, we now examine the correlates of web-based responses. In short, African Americans are roughly 14.2pp less likely to respond via the web. Moreover, education is highly correlated with web responses. College-educated workers are 53.8pp more likely to respond by web, relative to those without a high school degree. Other educational brackets, including high school graduates, are also all more likely to respond by web. We subsequently add geographic information too. For example, we find an economically and statistically weak association between fixed and mobile download speed and selection into responding through the web. Higher state median household income is also strongly correlated with selection into web responses. Finally, we find strong negative associations between web responses and the share of manufacturing in a state and positive responses between web responses and both retail and professional employment shares.

[INSERT TABLE 4 HERE]

What are the aggregate implications of differential selection into these two types of survey instruments? Since Mail-only respondents are less likely to WFH, failing to include them may overestimate the share. Restricting our sample to those who are employed in both periods, we find 31.4% of Web-only respondents who always WFH, whereas only 6.3% of Mail-only respondents always WFH. The differences are slightly smaller for mostly WFH: 22.4% for Web-only and 8.1% for Mail-only. Given that 93.5% of the employed respondents are Web-only, ignoring the Mail-only respondents is likely to overstate WFH by 1.6% for always WFH ($= (0.314 - 0.063) \times 0.065$) and 0.92% for mostly WFH ($= (0.224 - 0.081) \times 0.065$). In sum, while including Web-only respondents has its limitations, it is not a significant enough factor to distort the overall share and it clearly cannot explain why the BLS estimates are much lower than the Gallup estimates.

3.2 Self-Employment

The best evidence for the impact of self-employment on remote work measures, comes from differences in measures of pre-pandemic extent of remote work. Specifically, we observe a large gap between in BLS-ATUS survey data and Brynjolfsson et al - Gallup in the pre-pandemic period.

The Bureau of Labor Statistics (BLS) produces the American Time Use Survey (ATUS) annually and it is conducted via telephone interviews. Respondents need to record in a 24-hour diary all of their activities and are interviewed about how those 24 hours were spent. The ATUS periodically adds special, topical questions at the end of the ATUS interview, and they are referred to as a module. One of the modules of interest to us is the 2017-18 Leave and Job Flexibilities Module. According to the BLS, the purpose of this module was to "obtain information about workers' access to and use of leave, job flexibilities, and work schedules" [3]. There were about

[3]See BLS Description of Results: https://www.bls.gov/news.release/flex2.htm

10,000 respondents in the 2017-2018 iteration of the survey. The BLS also highlights that this data excludes all self-employed workers and that is why we are interested in comparing our results to those of the BLS.

A few comments on how our numbers compares to those of the BLS. First, we note that Figure 4 below only contains comparisons between ATUS and Gallup for those who responded with some degree of WFH during the pre-pandemic period. Secondly, we see that the "never WFH" category for ATUS is 85.3% and for Gallup is 64.5%, which implies a 20 percentage point difference between Gallup and ATUS in terms of WFH pre-pandemic adoption.

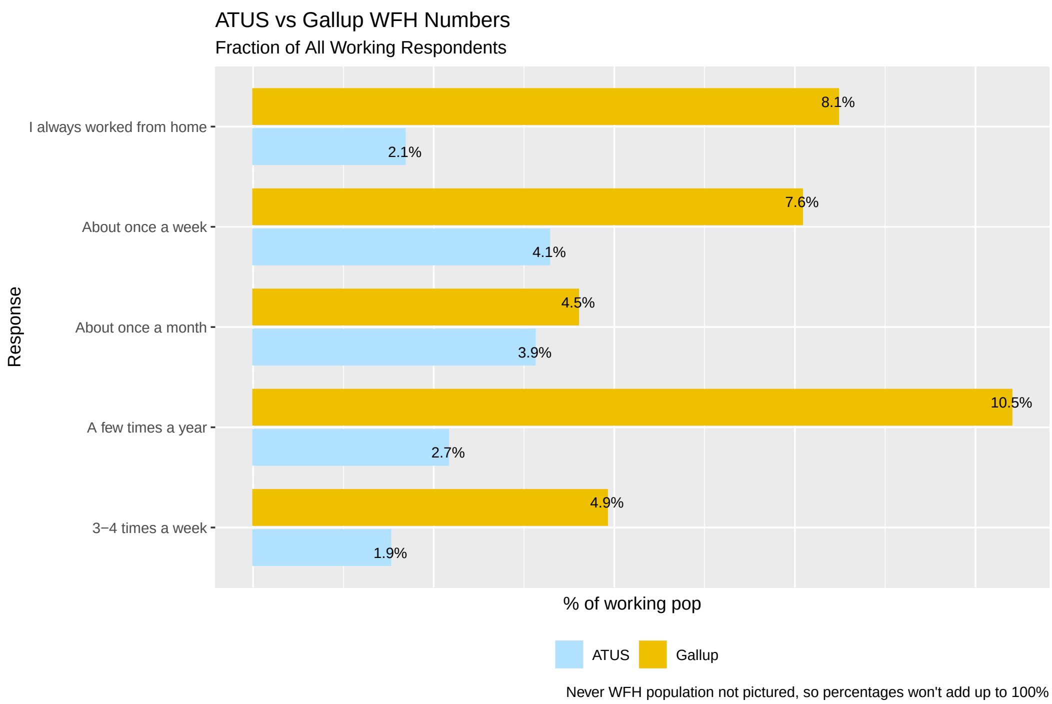

Figure 4: ATUS vs Gallup Response Rates Excluding "Never WFH"

Given the differences between our numbers when compared to ATUS and knowing that ATUS does not include self-employment, we want to dive deeper into how self-employment relates to remote work. We begin by defining various proxy variables for capturing the self-employed population. Two such variables are "sole proprietorship" and "home based business":

- **"Sole proprietorship"**: the population of **currently** employed workers (they answered either "employed full time" or "employed part time" in the current employment question in our survey) who report "None/I am the sole proprietor" to Q25 in our survey.[4]

- **"Home based business"**: the population of workers who, in the **pre-pandemic period**, worked from home and justified their WFH choice by answering "I had a home-based business" to Q4.[5]

Both of these flags were constructed using responses from the Gallup questionnaire. We also combine the two to create the intersection and union of these measures. Table 1 summarizes respondent frequencies in each of these categories. One reason for using the union of sole proprietorship and home based business is that it captures all individuals with work environments that approach self-employment both before the onset of the pandemic and during the pandemic. It is considered the most generous definition of self-employment in our survey and we use it as the main self-employment variable since it provides a conservative upper bound on self-employment rates. Finally, Gallup provides us with a 2017 demographic panel variable that reflects the state of self-employment in its 2017 survey population and we can use that to sanity check our results. We avoid using it as the primary measure of self-employment because 2017 is too distant from our period of interest.

Figure 5 shows how the combined variable using the intersection of "sole proprietorship" and "home-based business" relates to teleworking intensity before, during, and after the pandemic. The latter is simply a projection or a set of expectations that respondents have.

[4] Q25 asks "Approximately how many people, other than yourself, work at your company or organization? If you have more than one job, answer in terms of your primary job."

[5] Q4 asks "Thinking about the times you worked from home prior to February 1, which of the following best describes your remote work situation?"

Variable	**Levels**	**n**	%	∑ %
HomeBased	No	1155	87.1	87.1
	Yes	171	12.9	100.0
	all	1326	100.0	
firm_size	1-5 other people	270	8.8	8.8
	101-500 other people	538	17.4	26.2
	21-100 other people	511	16.6	42.8
	6-20 other people	396	12.8	55.6
	No answer	8	0.3	55.9
	None/I am the sole proprietor	180	5.8	61.7
	Over 500 other people	1180	38.3	100.0
	all	3083	100.0	
HomeBased_OR_SoleProprietor	No	2823	91.6	91.6
	Yes	260	8.4	100.0
	all	3083	100.0	
HomeBased_AND_SoleProprietor	No	2992	97.0	97.0
	Yes	91	3.0	100.0
	all	3083	100.0	
demo2017_emp_anySelf	No	2461	79.8	79.8
	Yes	622	20.2	100.0
	all	3083	100.0	

Table 1: Summary Table of Self-Employment Variables

It is clear how, even before the pandemic, who those were self-employed were already more likely to engage in WFH. The pandemic prompted a larger increase in WFH among the non self-employed vis-a-vis the self-employed. Finally, those who are self-employed expect a smaller reduction in WFH rates than those who are not in a hypothetical post-pandemic world.

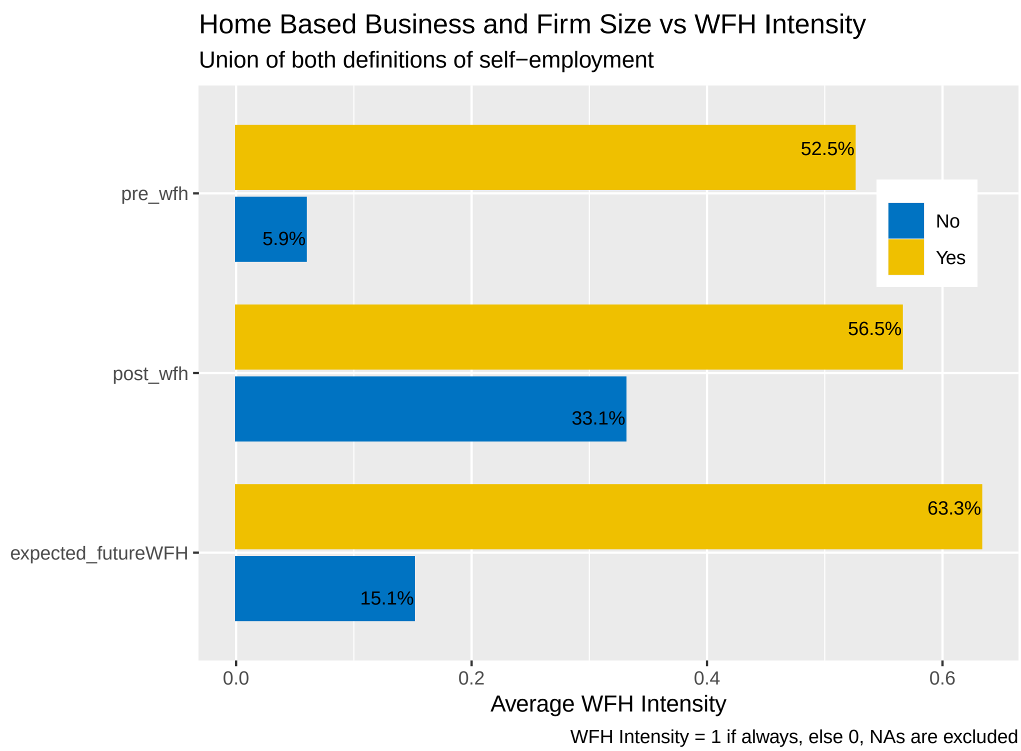

Figure 5: Combined Measure of Self-Employment vs. WFH

3.2.1 Self Employment Regressions

We believe that one of the key drivers behind the the WFH measuring discrepancies between our data and that of ATUS is the self-employment population. Therefore, we need to establish that self-employment is predictive of pre-pandemic WFH holding all else equal.

We believe that one of the key drivers behind the the WFH measuring discrepancies between our data and that of ATUS is the self-employment population. Therefore, we need to establish that self-employment is predictive of pre-pandemic WFH holding all else equal. Our two baseline models try to isolate the link between self-employment status, as defined by the intersection of the home-based business and sole proprietorship flags, and two work from home variables – one for the fraction of people always working from home and another

Table 2: Probit Model

	Probability of Always WFH in Different Periods:					
	Pre	-	During	-	Post	-
	(1)	(2)	(3)	(4)	(5)	(6)
College		0.153^{**}		0.580^{***}		-0.308^{***}
		(0.072)		(0.050)		(0.077)
Age		0.006^{*}		-0.006^{***}		0.006^{**}
		(0.003)		(0.002)		(0.003)
Female		0.132^{*}		0.298^{***}		0.072
		(0.069)		(0.048)		(0.072)
Self-Employed	1.626^{***}	1.623^{***}	0.603^{***}	0.717^{***}	1.372^{***}	1.289^{***}
	(0.087)	(0.088)	(0.082)	(0.085)	(0.097)	(0.099)
Constant	-1.562^{***}	-1.985^{***}	-0.438^{***}	-0.627^{***}	-1.032^{***}	-1.163^{***}
	(0.038)	(0.160)	(0.024)	(0.109)	(0.039)	(0.169)
Observations	3,065	3,035	3,076	3,046	1,777	1,764
Log Likelihood	-808.291	-792.417	-1,965.052	-1,834.722	-802.336	-782.211
Akaike Inf. Crit.	1,620.583	1,594.834	3,934.103	3,679.444	1,608.672	1,574.421

Note: *p<0.1; **p<0.05; ***p<0.01
Self-Employed defined as HomeBased/SoleProp

Table 3: Baseline Probit with Sometimes WFH

	Probability of Always WFH in Different Periods:					
	Pre	-	During	-	Post	-
	(1)	(2)	(3)	(4)	(5)	(6)
College		0.420^{***}		0.460^{***}		0.190^{***}
		(0.059)		(0.057)		(0.068)
Age		0.006^{***}		-0.0002		-0.003
		(0.002)		(0.002)		(0.003)
Female		-0.007		-0.034		-0.066
		(0.056)		(0.054)		(0.060)
Self-Employed	0.208^{**}	0.219^{**}	0.119	0.160^{*}	-0.500^{***}	-0.451^{***}
	(0.093)	(0.095)	(0.093)	(0.094)	(0.096)	(0.099)
Constant	-1.041^{***}	-1.588^{***}	-0.947^{***}	-1.194^{***}	0.002	0.035
	(0.029)	(0.130)	(0.028)	(0.123)	(0.032)	(0.142)
Observations	3,065	3,035	3,076	3,046	1,777	1,764
Log Likelihood	-1,310.833	-1,274.160	-1,423.592	-1,380.189	-1,216.257	-1,201.362
Akaike Inf. Crit.	2,625.666	2,558.320	2,851.183	2,770.378	2,436.515	2,412.725

Note: *p<0.1; **p<0.05; ***p<0.01
Self-Employed defined as intersection of HomeBased and SoleProp

for the fraction of people sometimes working from home. Sometimes working from home is defined as those who responded with "3-4 times a week" or "About once a week". The two regressions are run with and without demographic controls and across three distinct periods — before the start of the Covid-19 pandemic in February 2020, during the Covid-19 pandemic, and expectations for a future post-Covid world.

We find that increased self-employment is associated with higher rates of "always work from home" before, during and after the pandemic, with the additional demographic controls having no notable effects on either direction of magnitude. Both college educated and female workers are more likely to adopt "always work from home" during the pandemic. There are two slightly surprising observations:

- College educated workers expect a decline in "always WFH" after the pandemic when compared to non-college workers but that is somewhat offset by an expectation increased "sometimes WFH" in the same period. This could be a sign that hybrid workplaces are more prevalent in fields dominated by college-educated workers.https://www.overleaf.cor
- The self-employed population expect a shift from "sometimes WFH" to "always WFH" in the post pandemic world

As such, we can use these results to confirm that capturing a larger self-employed population will upward bias our work from home rates. However, it is important to note that the CPS includes those who are self-employed. As a result, this cannot explain the discrepancy between the CPS and other surveys.

3.3 Intensity of Remote Work

Another potential source of discrepancy among measurement approaches for remote work stems from the heterogeneity in the intensity of remote work. If, for example, a survey only allows respondents to answer "yes" or "no," then some may answer "no" simply because they assume that "yes" refers to "always" or "mostly" working-from-home. The RLS survey data, however, allows us to explicitly measure the intensity of remote work.

The following reported average rates are weighted using demographic variables provided to us by Gallup to make sure our panel is representative U.S. population. We also only calculated over the employed population, which constrains the working population further by imposing the condition that respondents need to be employed before and during the pandemic. We find that 31.6% of the (employed) sample reports that they always WFH, 9.56% does WFH 3-4 times/week, and 5.69% does WFH once a week. Roughly 46.4% never WFH, leaving only 6.69% that do WFH rarely (e.g., once or twice during the last four weeks). Taking a broader definition of WFH that includes those who WFH once a week, then 46.85% of respondents do WFH at the time of our sample in October 2020. Furthermore, if we broaden even more the definition of WFH to include those who worked from home once or twice during the last month, then 53.6% of respondents are engaged in remote work at the time of our sample in October 2020. If we only treated those who always WFH as remote workers, then we would be underestimating the overall share by up to 22% under the assumption that all those who are hybrid remote workers labeled themselves as non-remote workers.

Frequency of remote work	Percent
Never	46.4%
Once or twice	6.69%
About once a week	5.69%
3-4 times a week	9.56%
Always	31.6%
Sometimes v.1	53.6%
Sometimes v.2	46.9%

In short, a measure that only included those who always work from home would reduce the share working remotely by between 22 to 15.25 percentage points, making this a first-order important decision when it comes to measuring remote work. This is a plausible source of measurement disagreement between some surveys. However, the CPS question the BLS uses to measure remote work is as follow: "At any time in the last 4 weeks, did you telework or work at home for pay *because of the coronavirus pandemic*?" That means respondents are not limited to those working exclusively at home, but those doing so at any time in the last four weeks. Nonetheless, the intensity of remote work is evidently not a first-order factor behind the discrepancy between the BLS - CPS estimates.

3.4 Inclusion or Exclusion of Pre-Pandemic Working

We now examine a final factor behind the discrepancy. The CPS remote work question explicitly refers to working at home "because of the coronavirus pandemic." The exclusion of people working remotely to various degrees because of the pandemic raises potential measurement issues with other surveys by excluding two potential groups of people.

First, the CPS survey excludes those who worked entirely remotely pre-pandemic. In the instructions provided to surveyors, it states "Enter No if person worked entirely from home before the Coronavirus pandemic." Second, there is gray area for those who are now working remotely permanently, but are no longer doing so as a temporary pandemic adaptation.

Fortunately, because of our RLS survey design, we can measure the effect of excluding pre-pandemic workers two ways. As a reminder, in our RLS wording for measuring remote work (either pre or during the pandemic), we asked: "In the past month, about how often did you work from home as part of your job?". So there is no explicit qualifier that ties remote work to the pandemic. First, the RLS survey allows us to see the effect of focusing only on new working from home. Excluding those who were working from home sometimes pre pandemic reduces the share working from home sometimes during the pandemic from 53.6% to 28.3%. If we are interested in the effects on those always working from home, excluding those doing so pre-pandemic reduces measured always working from home from 31.6% to 24.9% . In short, excluding those previously working from home reduces pandemic work from home rates by 25.3 to 6.7 percentage points.

As a robustness test and more up-to-date estimate, we ran an additional set of Google Consumer Surveys from December 28,2021 till January 17, 2022. It captured a sample of 3,500 respondents and explicitly asked whether someone was working from home now or pre-pandemic. The results show that excluding those remote before the pandemic reduces the share remote from 46.3% to 35.8%, a decline of 10.5 percentage points.

In short, the exclusion of those working remotely pre-pandemic can generate double-digit changes in the percent working remotely. When carefully measuring pre and post extent and then removing people with the RLS, we find that the percent working from home can be reduced by 25.3 percentage points if we focus on those who were sometimes remote pre-pandemic. Ignoring the extent of pre-pandemic remoteness in the survey question, the GCS results suggest a decline of 10.5 percentage points. Both results suggest that how BLS CPS surveyors are framing the question can result in either single digit or double digit changes in measurement. Excluding only those who were always remote pre-pandemic will result in smaller (but still significant) changes, while excluding those who were sometimes remote can cut measured remote working in half. Asking questions that do not include extensive margins likely results somewhere in between.

Remote work status	Percent
Yes, but I was remote before the pandemic	10.5%
Yes, I'm now permanently remote	12.7%
Yes, I'm now temporarily remote	13.4%
Yes, but unsure whether permanent or not	9.7%
No, I am back at my workplace (in person)	53.8%
Sum: remote at all	46.3%
Sum: remote post-pandemic only	35.8%

3.5 The Effect of Adding a Covid-19 Condition in Remote Work Surveys (Robustness Check)

One question that arises from the consideration of pre-pandemic remote work is, why doesn't Gallup also have a lower estimated share? Their survey question asks:

"To what extent are you taking the following steps to avoid catching or spreading the coronavirus?"

The answer likely lies in the nature of the survey method. CPS surveyors code the answers themselves as a result of an interview with respondents. In comparison, the Gallup survey is self-reported answers to a digital survey on a phone or computer. As a result Gallup respondents are interpreting the questions, whereas BLS surveyors interpret the respondent's answer.

As a robustness test and a more up-to-date estimate, we ran a series of additional Google Consumer Surveys between July 8, 2021 and July 13, 2021 that explicitly asked whether someone was working from home now because of the pandemic's onset. This allows us to test whether our earlier GCS wave and RLS questionnaire design could have replicated the results of the CPS-BLS.

We ran two experiments, each with a pair of two different surveys. Across a pair of surveys we were interested in the effect of adding the qualifier "because of the coronavirus pandemic" to our headline question since that's is one distinguishing feature between the CPS-BLS survey and ours (both RLS and earlier GCS waves) As such, here are the two questions we were comparing:

1. Original Question in GCS waves: At any time in the **last 4 weeks**, did you telework or work at home for pay?

2. Modified Question to Approach CPS-BLS wording: At any time in the **last 4 weeks**, did you telework or work at home for pay **because of the coronavirus pandemic**?

In addition, we had two different experimental set ups: one pair of surveys had their answer choice order randomized and the other pair had its choice order fixed. It turned out that the randomization of order had minimal impact (likely because the choices were short and there were only three) but we will continue discussing these as separate experiments in order to maximize transparency and comparability.

Under random choice order we sampled a total of 4,971 people and yielded 2,774 respondents with imputed demographic characteristics to construct a representative sample:

- Without Covid-19 Qualifier: “No” (60.3%), “Yes” (23.3%), “Currently not working” (16.5%)
- With Covid-19 Qualifier: “No” (61.5%), “Yes” (21.3%), “Currently not working” (17.2%)

Under fixed choice order we sampled a total of 4,953 people and yield 2,995 respondents with imputed demographic characteristics to construct a representative sample:

- Without Covid-19 Qualifier: “No” (62.3%), “Yes” (27.1%), “Currently not working” (10.5%)

- With Covid-19 Qualifier: "No" (63.9%), "Yes" (24.5%), "Currently not working" (11.6%)

Therefore, we find that inclusion of the condition only reduced the percent reporting they worked remotely by around 2%. This suggests that self-reported conditioning can have limited impact, and helps explain why Gallup's survey does not appear downward biased by the conditional phrasing.

4 Conclusion

Remote work represents a massive, fast moving shift in how we work. But how massive is the move, and how fast moving? The timing and incidence of remote work is a crucial issue for economists and policymakers, yet there are significant discrepancies between surveys. In this paper we have documented a variety of measurement issues that practitioners should consider. While web versus mail-in can affect results, the effects appear quite modest. Self-employment can have a more substantial impact, as self-employed workers are significantly more likely to be remote and also are a non-trivial share of the workforce. Questionaire design and the intensity of remote work can also have substantial impacts, and can increase remote work share by double-digit percentages. Finally, whether a survey is designed to capture all remote working or simply post-pandemic remote working is of first-order importance as well.

By comparing a variety of remote work surveys and looking closely at the methodology, we believe that the last issue is a substantial one for the CPS measure of remote work. This measure is consistently half that of other measures, which are otherwise broadly consistent.

The gap between the CPS and other Gallup and Barrero et al has averaged 33 percentage points. This gap is trending up and is in the most recent data, approximately 38 percentage points.

One measure, the CPS, being an outlier would normally not be a serious issues given the variety of measures available. However, the disparity is potentially consequential because the CPS measure is influential as an official government measure of remote work. For example, in September 2021, Elaine Godfrey wrote in the Atlantic that media perceptions of remote work were biased up [6]. She guessed that in March, 2021 40% of workers were remote, but argues the CPS shows the real number was half that. In contrast, Figure X shows that most estimates were around 50%, meaning her estimate was underestimating if the consensus is correct. The Atlantic also surveyed the public about remote work perceptions in August, 2021 and the median respondent believed between 40% and 50% were working remotely. Barrero et al and Gallup estimate between 46% and 49% working remotely in August, making the public perception a good estimate. However, the author argued "In reality, only 13.4 percent worked from home in the final month of summer.", citing the CPS.

We cannot hope to understand how much remote work will affect the economy and society if we do not know how many people are working remotely. Taking measurement issues careful will help ensure we do that.

[6]: https://www.theatlantic.com/politics/archive/2021/09/work-from-home-numbers/620107/

Tables and Figures

Table 4: Understanding Differences in Remote Work and Selection into Web-only Responses

Dep. var. =	Always WFH		Mostly WFH		Web-based Respondent				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Web-only Respondent	.235***	.134***	.145***	.101***					
	[.023]	[.026]	[.019]	[.022]					
Black		.001		-.027	-.154***	-.165***	-.160***	-.166***	-.166***
		[.027]		[.026]	[.018]	[.018]	[.017]	[.017]	[.017]
Hispanic		.007		-.017	-.024**	-.030***	-.032***	-.045***	-.045***
		[.024]		[.021]	[.011]	[.011]	[.011]	[.011]	[.011]
High School		-.163***		-.138***	-.041***	-.031**	-.029**	-.028**	-.028**
		[.023]		[.020]	[.014]	[.014]	[.014]	[.014]	[.014]
Technical/Associates		-.095***		-.078***	.115***	.121***	.120***	.121***	.121***
		[.029]		[.025]	[.012]	[.012]	[.012]	[.012]	[.012]
Some College		-.150***		-.066***	.117***	.118***	.119***	.118***	.118***
		[.027]		[.025]	[.012]	[.012]	[.012]	[.012]	[.012]
Some Post-graduate		-.034		.094**	.130***	.127***	.126***	.126***	.126***
		[.045]		[.043]	[.012]	[.012]	[.012]	[.012]	[.012]
Post-graduate		.094***		.074***	.130***	.125***	.125***	.126***	.126***
		[.026]		[.025]	[.011]	[.011]	[.011]	[.011]	[.011]
Employed before and after Feb 1		-.083		.009	.058***	.056***	.057***	.058***	.058***
		[.055]		[.047]	[.008]	[.008]	[.008]	[.008]	[.008]
log(Fixed Download Speed)		.030		.003		.041***	.032***	.024**	.024**
		[.019]		[.020]		[.011]	[.011]	[.011]	[.011]
log(Mobile Download Speed)		.102***		-.042**		.036***	.029***	.035***	.035***
		[.019]		[.016]		[.010]	[.010]	[.010]	[.010]
log(Median Household Income)		.195**		.001			.144***	.066*	.066*
		[.089]		[.079]			[.027]	[.040]	[.040]
Manufacturing Employment, %		-.183		-.116				-.333**	-.333**
		[.287]		[.270]				[.159]	[.159]
Wholesale Employment, %		2.780		-2.662				2.363*	2.363*
		[2.607]		[2.420]				[1.218]	[1.218]
Retail Employment, %		1.026		-.491				1.584***	1.584***
		[1.200]		[1.060]				[.566]	[.566]
Professional Employment, %		.900		-.205				.934***	.934***
		[.587]		[.521]				[.295]	[.295]
FIRE Employment, %		-.755		-.801				.200	.200
		[.857]		[.756]				[.415]	[.415]
R-squared	.02	.10	.01	.04	.10	.12	.12	.13	.13
Sample Size	4699	4683	4699	4683	8313	8309	8309	8309	8309

Notes.—Sources: Gallup, American Community Survey (ACS), and Ookla. The table reports the coefficients associated with regressions of working from home (WFH) in columns 1-4 and an indicator whether the respondent answered the survey through the web versus through the mail in columns 5-9 on a vector of individual demographic characteristics (race, education, and employment status) and other regional controls, including: 2020 Q1 zipcode log download speeds in mbps for fixed and mobile connections, and a vector of state income and employment shares from the 2019 ACS. Columns 1-2 measure WFH using an indicator for whether the respondent always works from home and columns 3-4 for mostly working at home. Standard errors are heteroskedastic-robust and Gallup sample weights are used.

Table 5: Probit Model

	Probability of Always WFH in Different Periods:					
	Pre	-	During	-	Post	-
	(1)	(2)	(3)	(4)	(5)	(6)
College		0.153^{**}		0.580^{***}		-0.308^{***}
		(0.072)		(0.050)		(0.077)
Age		0.006^{*}		-0.006^{***}		0.006^{**}
		(0.003)		(0.002)		(0.003)
Female		0.132^{*}		0.298^{***}		0.072
		(0.069)		(0.048)		(0.072)
Self-Employed	1.626^{***}	1.623^{***}	0.603^{***}	0.717^{***}	1.372^{***}	1.289^{***}
	(0.087)	(0.088)	(0.082)	(0.085)	(0.097)	(0.099)
Constant	-1.562^{***}	-1.985^{***}	-0.438^{***}	-0.627^{***}	-1.032^{***}	-1.163^{***}
	(0.038)	(0.160)	(0.024)	(0.109)	(0.039)	(0.169)
Observations	3,065	3,035	3,076	3,046	1,777	1,764
Log Likelihood	-808.291	-792.417	-1,965.052	-1,834.722	-802.336	-782.211
Akaike Inf. Crit.	1,620.583	1,594.834	3,934.103	3,679.444	1,608.672	1,574.421

Note: *p<0.1; **p<0.05; ***p<0.01
Self-Employed defined as HomeBased/SoleProp

A Online Appendix

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