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Work from Home Before and After the COVID-19 Outbreak*

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Abstract

Based on novel survey data, we document a persistent rise in work from home (WFH) over the course of the COVID-19 pandemic. Using theory and direct survey evidence, we argue that three quarters of this increase reflects adoption of new work arrangements that will likely be permanent for many workers. A quantitative model matched to survey data predicts that twice as many workers will WFH full-time post-pandemic compared to pre-pandemic, and that one in every five instead of seven workdays will be WFH. These model predictions are consistent with survey evidence on workers' own expectations about WFH in the future.

JEL Codes: J1, J2, J22, I18, R4
Keywords: working from home, telecommuting, telework, remote work, COVID-19

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1 Introduction

This paper uses novel data and theory to study the rise in work from home (WFH) during the COVID-19 pandemic. Our data source is the Real-Time Population Survey (RPS), an online nationwide survey we designed to track labor market developments during the pandemic.[1] From May 2020 through June 2021, the RPS included questions on the commuting behavior of workers both before and during the pandemic.

The first contribution of this paper is to provide an accurate quantitative assessment of the evolution of WFH during the pandemic. Based on a sample of more than 66,000 observations, we document that aggregate WFH increased sharply at the onset of the pandemic, from 14.4 percent of workdays in February 2020 to 39.6 percent in May 2020. This initial increase reflected rising WFH in every major demographic group and industry, but was primarily due to large changes by highly educated workers in a few key service industries with high WFH ability. A striking feature of the rise in WFH is its persistence: in June 2021, well over a year into the pandemic, the aggregate WFH share of workdays remained at 28.5 percent, roughly double the pre-pandemic level.

The second contribution of this paper is to investigate two basic explanations for the persistence in the rise of WFH which have different implications for WFH rates over the longer run. The first explanation is that, despite vaccine availability and expanded treatment options, concerns about the health risks of working away from the home have remained elevated. Workers and employers may therefore simply have continued to WFH due to ongoing fears of infection. The second explanation is that WFH has remained high because, after the initial forced adoption of WFH, the new work arrangements have brought benefits to workers and employers beyond the avoidance of health concerns. In this case, the pandemic may have permanently altered the commuting choices of workers. In this paper, we provide both model-based and direct survey evidence that the WFH increase during the pandemic was associated with a large expansion of access to the option to WFH. Our conclusion is that the pandemic has likely caused a sharp acceleration in a pre-existing secular trend towards more WFH in the U.S.

The measurement methodology in this paper addresses two main challenges: (1) obtaining nationally representative results from an online survey at reasonable cost; and (2) avoiding ambiguity in the interpretation of 'WFH' due to phrasing and context. Because the RPS adopts the same core questions as the Current Population Survey (CPS), we are able to benchmark our survey results to the CPS along a large number of dimensions, as well as follow its precise definition of 'employment'. Our WFH measures are based on questions regarding the frequency of commuting to the job in the reference week, which leads to a clear interpretation, and allows

[1] The RPS micro data is available at https://www.openicpsr.org/openicpsr/project/158081/version/V1/view and is free to use with appropriate citation.

us to distinguish between WFH on a full- and part-time basis. Our survey also asks about commuting behavior before the pandemic, which allows us to analyze transitions in commuting behavior at the individual level, a feature not available in any other dataset on WFH that we are aware of. Finally, we validate our estimates of WFH with mobility data on commuting from cell phones, and with information available in the CPS since May 2020 on 'pandemic-related' telework.

Our survey-based evidence on WFH contains several indications that rising WFH during the pandemic involved a large expansion in WFH access due to changing workplace policies by employers. The rise in WFH was not driven by composition effects of commuters losing their jobs at disproportionate rates, or by workers transitioning to new WFH-friendly jobs. Instead, the rise in WFH was driven by workers who commuted full-time before the pandemic, and who began to WFH full-time during the pandemic within their existing jobs. Moreover, almost two thirds of workers that started to WFH in the pandemic cite employer requirements as the main reason for commuting daily before the pandemic.

To provide a quantitative assessment of the role of increased access to WFH, we set up an equilibrium model of WFH employment with a clear distinction between two main channels through which a pandemic leads to more WFH. The first is an intuitive WFH substitution channel. Because of the increased health risks of working away from home, workers substitute on-site work for WFH within working arrangements that already included the option to do so before the pandemic. A key aspect of this channel is that, for those that switched to WFH in the pandemic, by revealed preference home-based work is less efficient than on-site work in a normal health situation; if it were not, those workers would have already worked from home before the pandemic. The second channel is a WFH adoption channel. In this channel, the increased health risks of on-site work forced widespread adoption of more flexible work arrangements that include the option to WFH. A key aspect of this channel is that many of those that switched to WFH could in principle already have worked more productively from home before the pandemic had they been allowed to do so.

We calibrate the model to industry-level data from the RPS, and perform a quantitative decomposition of the rise in the WFH Only share – the share of workers that WFH every workday – into substitution and adoption effects. Through the lens of the model, adoption effects were the dominant reason for the increase in WFH, explaining at least two thirds of the initial increase in the WFH Only share relative to before the pandemic. The exercise also suggests that the role of substitution declined somewhat over the course of the pandemic, especially in the spring of 2021 after vaccines became widely available, implying that adoption accounts for three quarters of the increase in WFH by the end of our sample in June 2021.

To provide an estimate of WFH in the longer run, we evaluate a counterfactual scenario in which access to WFH remains permanently elevated but the health situation returns to normal. The model predicts a WFH Only share of 14.6 percent, double the rate just before the pandemic. In an analogous exercise for the overall share of WFH workdays, the model predicts that 21.3 percent of all workdays will be supplied from home after the pandemic ends, compared to 14.4 percent just before the pandemic. We confront the model-based predictions for long run WFH with survey evidence on workers' expectations for WFH in the future. The data show that 12.1 percent of the employed respondents expect to be WFH Only in the future, and 23.4 percent of all workdays are expected to be WFH, broadly consistent with our model predictions. Importantly, in the future workers primarily expect to WFH on a part-time basis. The expectations data also reveal large differences in expected WFH between worker groups, especially by education. The expected increase in the share of highly educated workers, if realized, implies that almost half of all workers with a bachelor's degree or more would WFH at least partially. In contrast, relatively few low-education workers expect to WFH in the future. Any longer term gains from the permanent changes in work arrangements are therefore likely to be highly unequally distributed.

This paper is one of several recent studies using online household surveys to shed light on the impact of the COVID-19 pandemic on the labor market, see for example Adams-Prassl et al. (2020), Brynjolfsson et al. (2020), Barrero et al. (2021), or Foote et al. (2020). Barrero et al. (2021), in particular, share our focus on WFH. Despite several differences in methodology, they reach similar conclusions about the evolution of WFH in the pandemic. They also provide complementary survey evidence for WFH adoption, and for expectations of more WFH in the future, but do not feature information on the respondent's pre-pandemic commuting status. Our work also relates to a number of studies linking measures of WFH ability to job loss, such as Alon et al. (2020), Adams-Prassl et al. (2020), Mongey et al. (2020), and Papanikolaou and Schmidt (2020). Finally, this paper fits into a broader literature on longer-run trends in remote work, such as Gaspar and Glaeser (1998), Oettinger (2011), Mateyka et al. (2012), Mas and Pallais (2017, 2020), Pabilonia and Vernon (2020), Braun et al. (2021) among others. Braun et al. (2021), in particular, use a similar model to ours and American Time Use data for 2003-2019 to quantify the role of WFH productivity in driving the slow rise in WFH before the pandemic, relying on the assumption of perfect WFH adoption in all jobs before the pandemic. Finally, our model is also closely related to Delventhal et al. (2021) and Davis et al. (2021), who both embed WFH into a model of residential location choice. Delventhal et al. (2021) analyze the impact of the COVID-19 pandemic by imposing an exogenous increase in WFH, Davis et al. (2021) interpret the COVID-19 pandemic as temporary decrease in the productivity of working on-site. This induces an increase in the share of workers choosing to WFH, which in itself is assumed to increase the long-run productivity of WFH. As a consequence, WFH remains elevated after on-site productivity is assumed to return to the pre-pandemic level.

2 Measuring Work from Home During the COVID-19 Pandemic

2.1 Data Source and Measurement

Our data source is the Real-Time Population Survey (RPS), a national labor market survey of adults aged 18-64 which ran from April 2020 through June 2021. The RPS was designed by the authors and fielded online by Qualtrics, a large commercial survey provider. The RPS mirrors the Current Population Survey (CPS) along key dimensions. In particular, the survey follows questions on demographics and labor market outcomes in the basic CPS and CPS Outgoing Rotation Group as outlined in the CPS Interviewing Manual (US Census Bureau, 2015), using the same word-for-word phrasing when practical, and replicates the intricate sequence of questions necessary to assign labor market status. However, the survey also collects information not contained in the CPS that is more specifically relevant for analysis of the pandemic. The full micro data is publicly available via openICPSR.

In this paper, we use novel questions in the RPS on commuting behavior to track workers' WFH status throughout the pandemic. Like the CPS, the RPS asks respondents to report their labor market status in the week prior to the interview. Unlike the CPS, the RPS also consistently asks respondents to report retrospectively on labor market status during February of 2020, the month prior to the declaration of a global pandemic by the World Health Organization. We then ask about commuting behavior over both periods: "last week" and February 2020. This unique feature of the RPS allows us to measure individual-level changes in outcomes with respect to a pre-pandemic baseline.

In what follows, we provide a summary of the sampling procedures as well as a detailed description of the measurement of WFH status in the RPS. For additional discussion of the survey methodology as well as comparisons with official sources of labor market statistics, we refer to Bick and Blandin (2021).

2.1.1 Sample

Online panels such as Qualtrics are commonly used by academics for survey research as well as by federal agencies for survey pre-testing and evaluation.[2] In these online panels, respondents are not recruited by traditional probability-based sampling methods such as in the CPS panel. Instead panel members are recruited to the panel online and, in our case, can participate in exchange for 30 to 50 percent of the $5 paid per completed survey.

[2]See Yu et al. (2019) for an overview of online survey methods and their use for testing at U.S. Census Bureau and Bureau of Labor Statistics. The Qualtrics platform has been widely used in economic research in experimental settings, see e.g. Bursztyn et al. (2014), Kuziemko et al. (2015), Bhargava et al. (2017), and Zimmermann (2020), and more recently in the context of the COVID-19 pandemic, see e.g. Adams-Prassl et al. (2020), and Knotek II et al. (2020).

The Qualtrics panel includes about 15 million members and is not a random sample of the US population, even if one would condition on the 94 percent of individuals aged 18-64 living in households with internet access according to the 2019 American Community Survey. However, researchers can direct Qualtrics to target survey invitations to desired demographic groups. In the case of the RPS, the sample was targeted to be nationally representative for the U.S. along several broad demographic characteristics: gender, age, race and ethnicity, education, marital status, number of children in the household, Census region, and household income in 2019 (see Appendix A.1 for a detailed breakdown of the targets). Panel members are not allowed to take the survey twice in a row, but we are unable to verify whether respondents participate more than once in non-adjacent survey waves. According to Qualtrics staff, very few panel members did so.

From April through September 2020, the RPS typically collected 1,500 to 2,000 responses on the Qualtrics platform in interview waves fielded twice per month. In the first waves of June, July and September, the number of respondents was roughly twice as large. In October 2020, the RPS switched to a monthly frequency with approximately 2,200 respondents. As in the CPS, the RPS also asks respondents to answer the same questions on behalf of spouses or any unmarried partners in the same household. This additional information expands the number of individual-level observations by about 60 percent.

Even with the sampling targets, there remain some potential concerns about the representativeness of the sample for the population of US adults aged 18 to 64. First, the targets are not always met exactly. Second, the characteristics of live-in spouses and partners are not taken into account by the Qualtrics sampling procedure. Third, budget constraints limit our sample size, preventing even greater granularity in the sampling targets. To alleviate these concerns, we construct sample weights using the iterative proportional fitting (raking) algorithm of Deming and Stephan (1940). Our application of the raking algorithm ensures that the weighted sample proportions across key demographic characteristics match those in the CPS for the same month, using more disaggregated categories for education and marital status than those included in the Qualtrics sampling targets and interact categories with gender. In addition, our sampling weights also replicate the employment rate in February 2020 in the CPS, as well as the employed-at-work rates, the employment rates and the labor force participation rates in each of the subsequent months. We match these key labor market statistics not only in the aggregate, but also conditional on demographic characteristics. Appendix A.1 provides details on the categories targeted by our weighting scheme, and provides comparisons between the CPS and RPS for employment rates across demographic groups and industry composition.

We use RPS data since May 2020, which was the first month in which the questionnaire included the core questions on commuting behavior. We discard about 4.5 percent of all observations because of incomplete information.[3] The resulting sample consist of 66,282 individual-level observations from online surveys completed between May 2020 and June 2021. This is our total sample size for all information on employment and commuting in February 2020. For employment and WFH status over the course of the pandemic, we pool all results by month. This results in an average monthly sample size of 4,734 observations. Appendix A.1 provides the monthly sample sizes as well as more detail on sample construction.

2.1.2 Measurement of Commuting Behavior

Our main information on commuting behavior comes from the following survey questions regarding 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?*

For the first question, respondents are presented with a slider that provides a choice of integers from 1 to 7, since this question is only asked of individuals who worked in the previous week; for the second question, the integers span 0 to 7.[4] Based on the answers, we classify all employed individuals with nonzero workdays into one of three mutually exclusive categories:

1. **Commute Only**: Full-time commuters, or all employed respondents reporting an equal number of workdays and commuting days for the previous week.
2. **WFH Some Days**: Partial WFH workers, or all employed respondents reporting at least one commuting day but strictly fewer commuting days than workdays for the previous week.
3. **WFH Only**: Full-time WFH workers, or all employed respondents with nonzero workdays but zero commuting days for the previous week.

We also ask respondents to think back to February of 2020, and present them with the same questions for the main job in that month. These questions lead to the same classification into

[3] Among the excluded observations are all individuals who are employed but absent from work in the reference week; these individuals – which account of 2.5 percent of all observations–were not asked about their current WFH behavior.

[4] The default position for the slider is zero days commuted. The question is not recorded as "answered" until the respondent touches the slider (either with a mouse on a computer or a finger on a touchscreen). Individuals reporting that they commuted more days than worked were prompted with an error message, and asked to revise their answers.

three commuting categories just prior to the pandemic.[5]

As discussed in Mokhtarian et al. (2005) and Mas and Pallais (2020), variation in definitions and context can result in meaningful differences in survey-based measures of the prevalence of work from home, or of the related but separate concept of 'remote work'. We therefore emphasize a number of distinctive features of our WFH indicators.

First, our measures are conditioned on being 'employed' during the reference period according to the CPS definition, either as a paid employee or in a self-owned business, profession, trade, or farm. Since our questions about days worked and days commuted specifically refer to a job, our WFH indicators explicitly exclude any non-market home production that respondents may otherwise factor in when asked about 'work' in more general terms.

Second, our WFH indicators measure a broader concept than 'remote work' or 'telecommuting'. Self-employed individuals with a home-based business, for instance, may be working from home without working remotely. Since we observe in the RPS whether individuals have the same job before and during the pandemic, we will, however, occasionally refer to transitions to remote work, for instance when describing workers that changed from 'Commute Only' to 'WFH Only' on the same job.

Third, we intentionally ask about commuting 'to the job' rather than 'to the workplace', since some individuals – e.g. sales representatives visiting only customers on a given day – are not commuting to their workplace but still commute for their job.

Fourth, our definition of WFH includes everyone *not* commuting to the job on a workday. We believe the focus on commuting is important because it avoids possibly ambiguous interpretations of questions asking more directly whether respondents worked from home. Such questions may easily lead to an overestimation of the importance of home-based work, as it is likely that many workers often commute but also do some work from home on the same day, such as checking email or finishing work that could not be completed at the office. At the same time, 'not commuting' does not automatically equate to 'working at the primary residence'. Our WFH definition almost surely captures a range of other possible work locations, such as coffee shops, hotels, etc. and in that sense is closer to the working from anywhere (WFA) concept. With this clarification, we will continue to use the terminology 'work from home' or 'WFH' throughout this paper.

Finally, the fact that our WFH measures are derived from the reported fraction of weekly workdays with a commute allows a useful distinction between full- and part-time WFH. An additional advantage of the commuting focus is that it allows a validation of our survey results

[5]The retrospective questions do not ask about a specific week in February 2020. Instead, they are phrased as in the following: *For this question, we would like you to think back to February of this/last year (2020). In February 2020, which of the following best describes your work experience?* Appendix A.4 shows that the results based on the retrospective questions remain overall consistent across the months in our sample.

with non-survey-based evidence on commuting volume during the pandemic.

2.2 The Aggregate Evolution of WFH Before and During the Pandemic

Prior to 2020, WFH was already gradually becoming more common, as documented for instance in Oettinger (2011), Mateyka et al. (2012), Pabilonia and Vernon (2020) or Mas and Pallais (2020). This pre-existing upward trend in WFH is visible, for example, in measures from the American Community Survey (ACS) and the time use diary of the American Time Use Survey (ATUS). Figure 1a shows that the ATUS share of all employed respondents without a commute on the prior workday increased gradually from 11.7 percent in 2003 to 16.4 percent in 2019. In the ACS, the fraction of workers that report usually working at home increased from 3.1 percent in 2000 to 5.4 percent in 2019. Despite the upward trend in WFH, which is usually attributed to advances in information and communication technologies, the ATUS and ACS measures also reveal that WFH remained relatively uncommon at the onset of the pandemic.

A natural initial question is how the RPS information on pre-pandemic commuting choices compares to that of existing measures. Figure 1a plots the closest RPS equivalents of the ACS and ATUS measures for February 2020. The ATUS time use diary asks about commuting only on the previous day, rather than for a full week, which means it is not possible to construct exactly the same three WFH categories as for the RPS. The closest equivalent in our survey to the ATUS share of all employed respondents without a daily commute is the total fraction of workdays without commutes. This fraction was 14.4 percent in February 2020, only slightly lower than the corresponding fraction in the ATUS. The ACS measure is based on a question asking employed respondents how they 'usually' got to work last week, with 'worked at home' as an answering option. The ACS number of 5.4 percent for 2019 is somewhat lower than the closest equivalent number in the RPS for February 2020 – the WFH Only fraction – which is 7.5 percent. However, as we explained above, differences in phrasing lead to implicit changes in the precise meaning of WFH, which in the RPS is broader than work in one's primary residence. Taking into account the difficulties of comparing WFH measures across surveys, we are confident that the RPS paints a reliable picture of the prevalence of WFH just before the pandemic.[6]

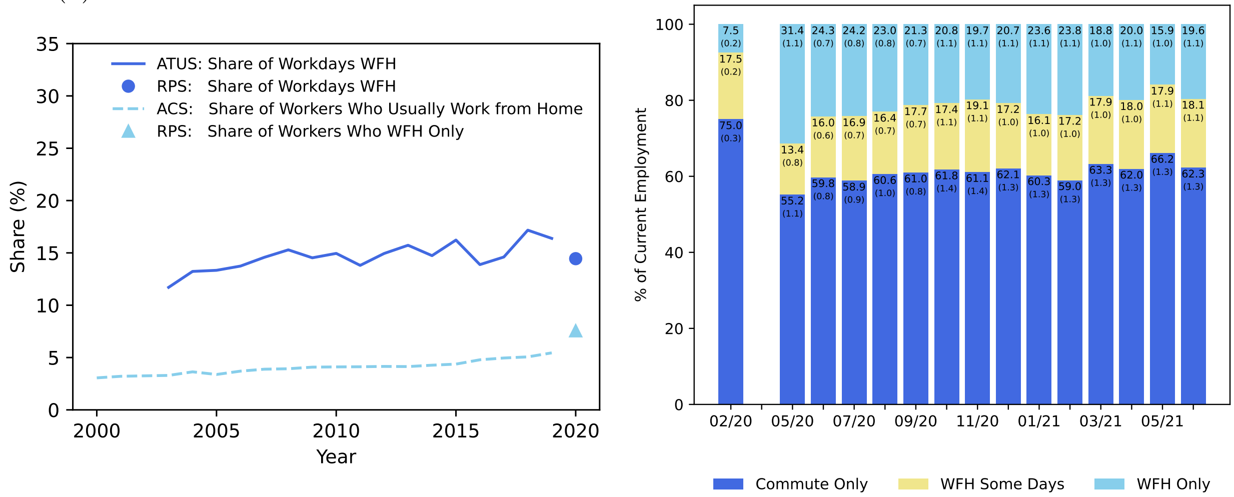
A key advantage of the RPS relative to existing surveys such as ACS and ATUS is that

[6]There are several other sources of WFH estimates before the pandemic. The lowest estimate of the fraction of workers that 'usually' only WFH is 2.8 percent in the ATUS Leave and Job Flexibilities Module. In the Atlanta Fed's Survey of Business Uncertainty, US firms report that 3.4 percent of full-time employees worked 5 full days per week at home in 2019 (Barrero et al., 2020). In the Survey of Income and Program Participation, Mateyka et al. (2012) calculate that 6.6 percent of all workers usually only WFH in 2010, and in the 2017 National Household Travel Survey 11.9 percent report doing so. Based on a Google Consumer Surveys question posted in April and May of 2020, Brynjolfsson et al. (2020) find that 15.0 percent of workers were already working from home prior to the pandemic. The range of estimates is therefore considerable, which in our view mostly reflects differences in context, phrasing and definitions, as also discussed in Mokhtarian et al. (2005).

Figure 1: WFH Before and During the COVID-19 Pandemic

(a) WFH Trends Before the Pandemic

(b) WFH During the Pandemic

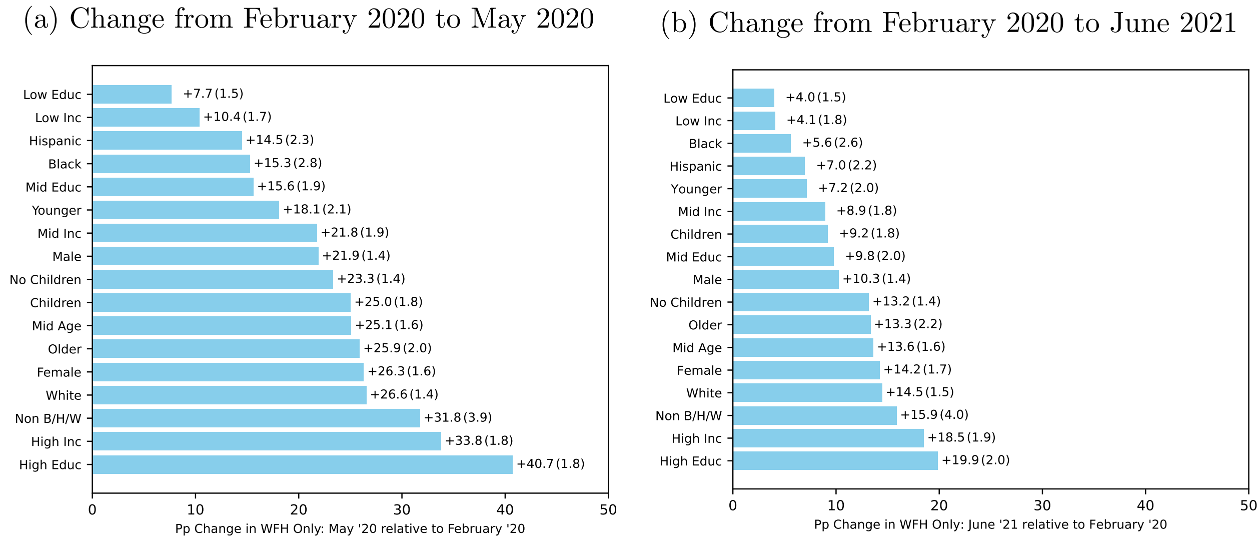


Sources: American Time Use Survey Time Diary (left panel; IPUMS version by Ruggles et al. (2020)) American Community Survey (left panel; IPUMS version by Hofferth et al. (2020)), and Real-Time Population Survey (left and right panels). All numbers in both panels are for the sample of adults aged 18-64. *Left panel:* RPS values correspond to February 2020. *Right panel:* Standard errors in parentheses, calculated as described in Appendix A.2. See Appendix A.1 for sample sizes by month.

its high frequency allows a detailed description of how commuting behavior changed as the pandemic unfolded. Figure 1b shows the shares of all employed individuals in each of the three WFH categories defined above. One key takeaway is that, after an early dramatic shift towards WFH in response to the virus outbreak, much of the increase in WFH has persisted throughout 2020 and 2021. The Commute Only share declined from 75.0 percent in February 2020 to 55.2 percent in May 2020, the first month containing our core commuting questions. It then partially recovered to 61.8 percent in October 2020, but then plateaued and temporarily fell again during the resurgence of the virus in early 2021. By June 2021, the Commute Only share was still just 62.4 percent, well below the level before the pandemic. Another key takeaway from Figure 1b is that the decline in the share of full-time commuters relative to February 2020 mostly reflects a (persistent) rise in the share of WFH Only workers. This share quadrupled from 7.5 percent in February 2020 to 31.4 percent in May 2020, and declined to 20.8 percent by October 2020. By June 2021 the share of workers working only from home was 19.6 percent, still more than 2.6 times the pre-pandemic level. In contrast, the share of workers that WFH on some workdays initially dropped from 17.5 percent in February 2020 to 13.4 percent in May 2020, but subsequently rose to levels that are comparable to before the pandemic.

The persistent rise in WFH Only behavior throughout our sample by itself does not lead to any firm conclusions about the long run change in commuting choices, since the pandemic

Figure 2: WFH Only Shares by Demographic Group



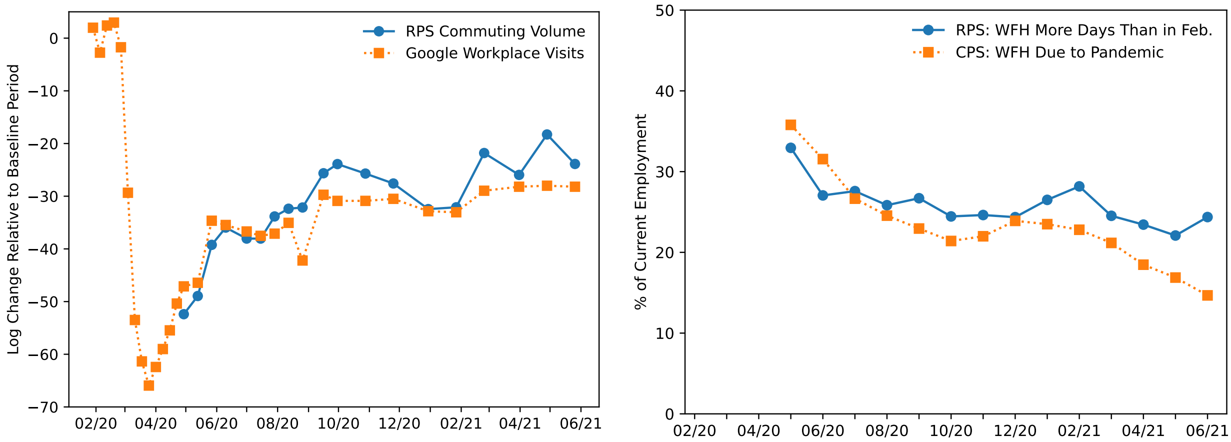
Source: Real-Time Population Survey. The sample is individuals (ages 18-64) employed in each month. *Panel (a):* displays the percentage point change in the share of WFH Only workers in May 2020 relative to February 2020. *Panel (b):* displays the percentage point change in the share of WFH Only workers in June 2021 relative to February 2020. Non B/H/W stands for not Black, White or Hispanic. Precise definitions of all demographic groups are provided in Appendix A.3. Standard errors in parentheses, calculated as described in Appendix A.2; see Appendix A.1 for sample sizes by month.

never fully receded over our sample. It is noteworthy, however, that WFH shares became much less responsive to changes in the health environment after the initial first wave of 2020. Appendix B.1 shows that the large spikes in COVID-19 hospitalizations in the late summer of 2020 and winter of 2020/2021 coincided with only modest increases in WFH, and that WFH remained well above pre-pandemic levels in June 2021 despite low levels of hospitalizations. Finally, the persistence in WFH was not due to continued government-imposed restrictions. Appendix B.1 documents that WFH remained high after the widespread elimination of most government-imposed social distance measures.

The increase in WFH varied substantially across demographic groups. Figure 2 displays the change in WFH Only by May 2020 and June 2021 relative to February 2020 (see Appendix B.3 for the full time series). The WFH Only share of highly educated workers (bachelor's degree or more) increased by 40.5 percentage points relative to February 2020, implying that nearly half (49.0 percent) were WFH Only in May 2020. In contrast, the share of low educated workers (high school or less) increased by only 7.8 percent, and in total only 14.2 percent were WFH Only in May 2020. Besides a very strong relationship with education, the share of WFH Only workers also rose more among high-income, older, female, White, and Non-Black/Hispanic/White (mostly Asians) workers. We continue to observe the same qualitative patterns through June 2021, and these patterns also remain very similar after conditioning for

Figure 3: Comparisons with Mobility Data and WFH in the CPS

(a) Commuting Volume (b) Pandemic-Related WFH



Sources: Real-Time Population Survey (left and right panels), Google COVID-19 Community Mobility Reports (left panel), Current Population Survey (right panel; IPUMS version by Flood et al. (2020)). *Left Panel*: Google data is expressed in log changes relative to a baseline period (Jan 3 to Feb 6, 2020). RPS commuting volume is the log change relative to February in the weighted average of the number of commuting trips reported by all RPS respondents, with a value of zero for those not working. *Right Panel*: CPS series shows the fraction of employed adults aged 18-64 answering yes to the WFH question in the CPS (see main text). RPS series is the (weighted) fraction of workers reporting more workdays without a commute last week compared with February 2020. Those not working in February 2020 are included with zero commutes, but omitting them does not change the series meaningfully.

other worker characteristics and industry of employment, see Appendix B.4.

2.3 Comparison with Other WFH Measures in the Pandemic

Before delving deeper into the RPS data to learn more about the evolution of WFH during the pandemic, we pause to compare measures of WFH in the RPS to other indicators of WFH behavior.

One valuable alternative source of high frequency information on commuting behavior is cellphone geolocation data. Figure 3a plots the Google mobility metric for visits to the workplace in the RPS reference weeks. This series is a measure of commuting volume based on products such as Google Maps, and in the figure is expressed as the log change relative to a baseline period from January 3 to February 6, 2020. We compare this measure to the log change in the number of commuting trips in the RPS relative to February 2020 in each of the reference weeks. The number of commuting trips in this case is the (weighted) average of the answers to the question how many days per week respondents commuted to their jobs, where we use zero as the answer for all individuals with zero workdays.

Although based on very different sources of information, Figure 3a shows that our survey-based measure of commuting volume aligns well with the geolocation-based series. The Google index shows a similar sharp initial decline in commuting volume, a substantial bounce back by the summer of 2020, but also a very persistent subsequent shortfall of around 30 log points relative to the pre-pandemic baseline. An obvious issue is that measures of commuting volume do not reveal to what extent commuting declined due to a rise in WFH or due to a decline in work. A decomposition based on the RPS data – which unlike mobility data allows us to disentangle these two components – shows that a substantial fraction of the drop in commuting volume during the pandemic is accounted for by a decline in days worked. For example, in June 2021, the last month of our sample, commuting volume remained 24.2 log points below February 2020 levels in the RPS. According to our decomposition, 4.1 percent of this shortfall is accounted for by a shorter average workweek and 21.5 percent by lower employment. Nevertheless, the majority (74.4 percent) of the June 2021 shortfall in commuting is due to higher levels of WFH (see Appendix B.2 for full details on this decomposition).

Two other surveys also provide information on WFH during the pandemic. Starting in May 2020, the CPS added the following question to the survey questionnaire: *"At any time in the last 4 weeks, did (you/name) telework or work at home for pay because of the coronavirus pandemic?"*, followed by a yes/no answering option. Clearly, the information in the CPS about WFH differs from the RPS in a number of ways. The newly added CPS questions is explicitly conditioned on the pandemic being the reason for telework/WFH, does not specify any particular quantity of tele- or home-based work, and has a longer reference period (four weeks). Moreover, there is no information about the respondents' commuting behavior before the pandemic. On the other hand, the CPS has a much larger sample than the RPS and uses more conventional survey methods, and thus provides another useful point of comparison.

Since the CPS specifically conditions on the pandemic and the RPS does not, we compare the fraction of workers answering 'yes' to the WFH question in the CPS with the fraction of workers in the RPS that report more workdays without a commute last week compared to February 2020. To the extent the pandemic was the reason for the larger number of workdays without commutes, both fractions should be similar in magnitude. Figure 3b shows that both aggregate series indeed line up fairly closely throughout 2020, and the same is true after disaggregating by industry or demographic group (see Appendix B.5). Beginning in January 2021, however, the RPS and CPS series paint a somewhat different picture: From December 2020 through June 2021 the CPS series declines from 23.9 percent to 14.7 percent, while the RPS measure remained essentially unchanged around 24 percent. The CPS data therefore suggests a gradual return to commuting choices that are more similar to before the pandemic. However, the decline in the CPS measure may simply mean that some workers stopped attributing commuting changes to the pandemic, possibly because workers see these ase more permanent. Because the RPS measures all WFH and not just WFH due to the pandemic, the CPS data are likely to understate the persistence of WFH relative to the RPS.

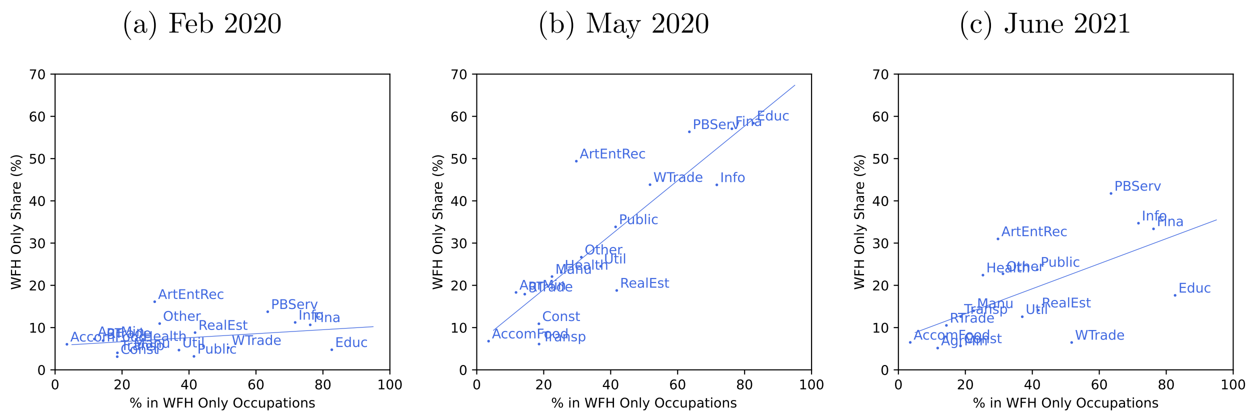
The staying power of WFH is also supported by the evidence in Barrero et al. (2021), who ran multiple waves of WFH surveys starting in May 2020 administered by commercial online survey providers. Their survey results for May 2020 show that 41.9 percent of respondents reported working from home, 25.6 percent were working on business premises, and 32.6 percent were not working. As shares of May 2020 employment, these estimates imply WFH rates of 62.2 percent. For June 2021, Barrero et al. (2021) report a still elevated WFH rate of 42.2 percent. The overall level the WFH rates measured by Barrero et al. (2021) are substantially larger than those implied by the Google mobility, RPS, and CPS data in Figures 1b and 3b, which likely reflects differences in sample composition and survey methodology.[7] At the same time, they suggest a similar trajectory of WFH as the Google mobility and RPS data since May 2020, confirming that many workers have continued to WFH well beyond the initial months of the pandemic.

2.4 Who Worked From Home During the Pandemic?

As we argued in the introduction, the scope for higher rates of WFH to persist after the pandemic likely hinges on the extent to which the pandemic led to the adoption of new WFH arrangements, which could entail net benefits even in normal health situations, rather than substitution within jobs that already offered a pre-existing WFH option. Before turning to our quantitative assessment of the roles of WFH substitution and adoption in explaining the persistent rise in WFH during the pandemic, we highlight several facts about which workers WFH during the pandemic. These facts, which rely importantly on the retrospective information in our survey that is not available in the CPS or Barrero et al. (2021) surveys, help justify our focus on the substitution and adoption channels in explaining the rise in WFH during the pandemic, and they will motivate a number of assumptions in our quantitative modeling framework.

[7]From May through October 2020 their survey question to elicit respondents' combined WFH/employment status was: *Currently (this week) what is your working status?*, with answering options: *(a) working on my business premises; (b) working from home; (c) still employed and paid, but not working; (d) unemployed; (e) not working and not looking for work.* In November 2020, they began asking a new set of questions: respondents who reported working in the previous week were asked how many full days they worked, and how many full paid working days they were worked from home, a sequence of questions closer to ours. Respondents were classified as WFH if full workdays at home account for at least 66 percent of all paid workdays. The higher estimates by Barrero et al. (2021) are somewhat at odds with available estimates of the maximum scope for home-based work. Dingel and Neiman (2020), for example, use O*NET data to classify the feasibility of WFH for all major occupations. Based on this classification, they conclude that at most 37 percent of all jobs in the U.S. could be performed entirely at home. Using a similar strategy, Su (2020) calculates that 39 percent of pre-pandemic jobs could potentially be exclusively done from home, at least in the short term.

Figure 4: Actual and Potential WFH Only Shares



Source: Real-Time Population Survey and Dingel and Neiman (2020). The x-axis is the share (percent) of February 2020 workers in potential WFH occupations based on the measures of Dingel and Neiman (2020). We plot the results for all months in Appendix B.6. The y-axis is the share (percent) of employed workers that are WFH Only. Definitions of industry groups are provided in Appendix A.3.

2.4.1 WFH Shares in the Pandemic Vary Strongly with Ability to WFH

A first important feature of the data is the large amount of heterogeneity in WFH transition rates across industries. Moreover, consistent with Bartik et al. (2020) and Dingel and Neiman (2020), we find that increases in WFH rates during the pandemic are strongly correlated with measures of the ability to WFH.

Figure 4 plots the WFH Only shares in different industries against estimates of the share of workers that were in potential WFH Only jobs in February 2020. To measure the fraction of workers in potential WFH Only occupations in each industry, we rely on Dingel and Neiman (2020), who use O*NET data to classify the feasibility of working entirely at home for all major occupations. The RPS does not collect information on occupation. Instead, we calculate the share of workers in potential WFH Only jobs based on the occupational composition of the worker's industry of employment in February 2020. The resulting fraction of jobs in which WFH Only is feasible varies greatly across economic sectors: in industries such as accommodation & food, retail trade, or arts & recreation, relatively few workers are in potential WFH Only occupations; in other sectors, such as the education, information or finance industries, a majority of workers are in potential WFH Only occupations.

Figure 4a shows that before the pandemic there was little relationship between WFH potential and WFH Only shares, possibly indicating low rates of WFH adoption. In sharp contrast, the relationship became strongly positive in May 2020, see Figure 4b. This positive relationship persists throughout the pandemic and remains present in the last month of our sample period June 2021, see Figure 4c. Whether workers in different industries were more or less likely to WFH throughout the pandemic was closely related to what fraction of those workers in potential WFH Only occupations before the pandemic. In Appendix B.7, we show that job losses during the pandemic were smaller in industries with higher WFH potential.

2.4.2 On-the-Job Transitions to WFH Are Most Important

A second important feature in the RPS data is that WFH increased primarily because workers switched to WFH within their existing jobs. In principle, job loss or fear of infection may have caused many more commuters to take on new WFH jobs or become non-employed. In that case, composition effects could be a meaningful driver of the increase in WFH rates. We find, however, that transitions by pre-pandemic commuters to new WFH jobs or non-employment are not important for explaining the overall rise in the WFH rate.

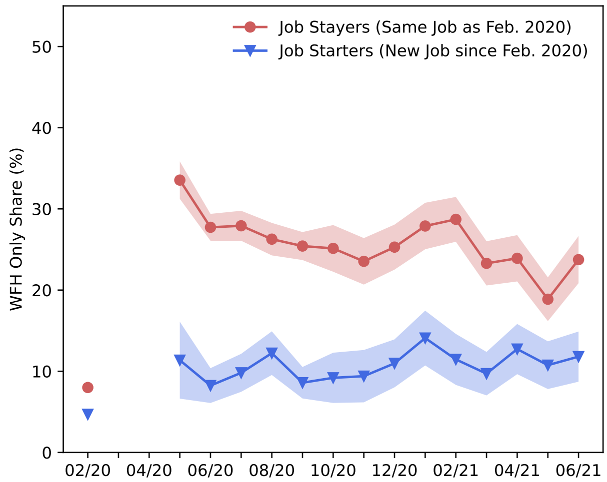
To assess the role of reallocation of workers towards WFH jobs, we rely on a question in the RPS that allows a distinction between workers that changed jobs since February 2020 ('job stayers') and workers that remained in the same job ('job starters').

Figure 5 plots the WFH rates for job stayers and job starters in February 2020 and during the pandemic. For job starters, changes relative to February 2020 reflect WFH differences between the old jobs of job starters that were employed in February, and the new jobs of all job starters (including those that were not employed in February 2020). Figure 5 shows that, before the pandemic, a larger fraction of job stayers were WFH Only compared with job starters in their old pre-pandemic jobs (8.2 percent vs 4.0 percent). WFH Only shares rose for both job stayers and job starters in May 2020, but they rose far more for job stayers, to 33.6 percent vs 11.8 percent for job starters; this gap largely persists over the entire sample. The much larger increase in the WFH Only share for job stayers indicates that the rise in the aggregate share of WFH Only workers was not driven by reallocation of workers towards new WFH jobs.[8]

We also do not find that pre-pandemic commuters disproportionately transitioned out of employment. Figure 6 depicts the transition rates across the WFH categories and non-employment between February and May 2020 in the left panel, and between February 2020 and June 2021 in the right panel (the other months are shown in Appendix B.9, and display similar qualitative patterns). From February to May 2020, workers who were WFH Only in February 2020 lost employment at almost the same rates in May 2020 as pre-pandemic daily commuters: 14.7 percent vs. 15.7 percent, respectively. The similar job loss rates imply that selection along pre-pandemic commuting status did not play a major role in the rise of WFH during the pandemic. Note that this finding is not inconsistent with the fact that industries with high potential WFH

[8]Throughout our sample, job starters were more likely to WFH some days than job stayers before the pandemic. The differences in the prevalence to WFH some days however mainly stem from compositional differences between job starters and stayers. See Appendix B.8 for a discussion.

Figure 5: WFH Only Among Job Stayers and Job Starters



Source: Real-Time Population Survey. The sample is individuals (ages 18-64) employed in the survey month. The figure shows the share of WFH Only workers that are 'job stayers', or individuals who worked for the same employer in February 2020 and in the interview month, and 'job starters', or individuals who did not work for the same employer in February 2020 and in the interview month; the latter category includes both workers who switched employers and workers not employed in February 2020. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

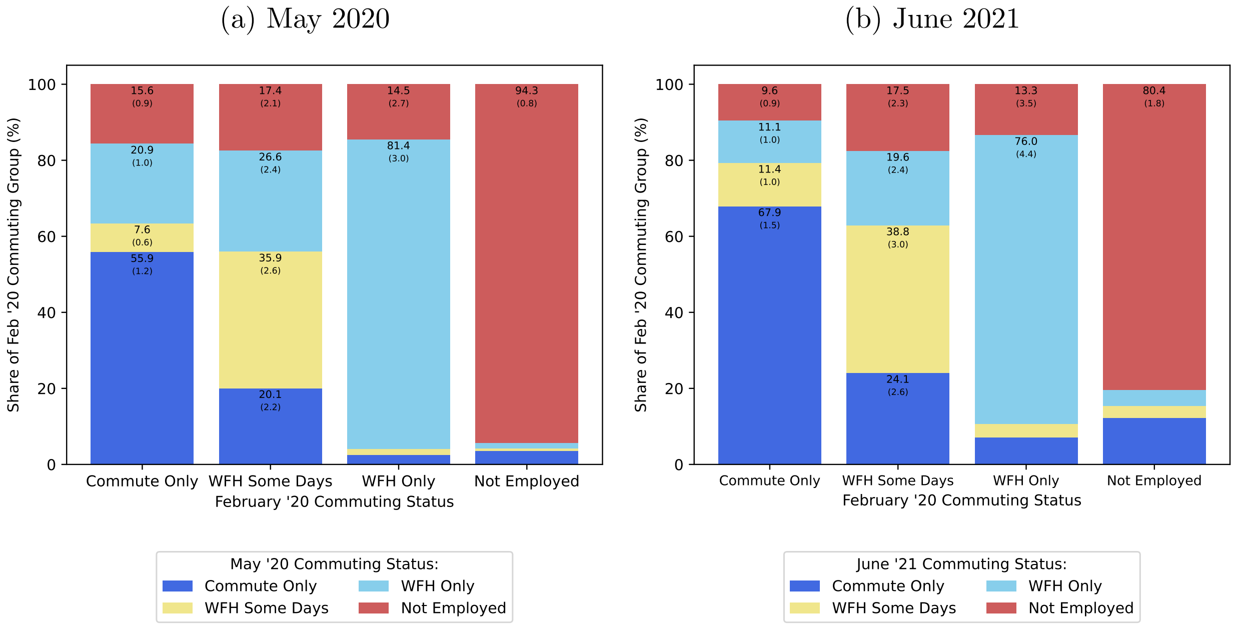
Only jobs experienced smaller job losses during the pandemic (see Appendix B.7). The latter fact relates primarily to workers' ability to switch to WFH during the pandemic, not to whether workers were already working from home before the pandemic. In June 2021, non-employment among pre-pandemic daily commuters were in fact lower (10.8 percent) than for WFH workers (17.1 and 16.7 percent). By mid 2021, therefore, pre-pandemic commuters were more likely to have returned to employment.

2.4.3 Most WFH Workers Used to Be Full-Time Commuters

A final important feature is that the rise in WFH was driven by a subset of workers who commuted every workday before the pandemic and who stopped doing so entirely during the pandemic. To see this, we turn again to Figure 6 and look at the transition rates across the WFH categories.

Figure 6a shows that only 55.9 percent of full-time commuters in February 2020 were still commuting every workday in May 2020. More than a fifth (20.9 percent) switched to WFH Only, and another 7.6 percent started working from home on a part-time basis. Given that over three quarters of all workers were full-time commuters in February 2020 (see Figure 1b), this means that much of the increase in WFH early in the pandemic reflects a drastic change in the commuting choices of many daily commuters. Over the same time period, many of those

Figure 6: WFH Transition Rates Relative to February 2020



Source: Real-Time Population Survey. The figure displays the composition of the population by WFH and employment status in the current month separately by workers' employment and WFH status in February 2020. Each bar corresponds to a February WFH/employment state: Commute Only, WFH Some Days, WFH Only, and Not Employed. Each color within a bar corresponds to a current WFH/employment state. The current month is May 2020 for the left panel and June 2021 for the right panel. The corresponding figures for all other sample months are in Appendix B.9. Standard errors in parentheses, calculated as described in Appendix A.2. See Appendix A.1 for sample sizes by month.

that did some WFH in February 2020 also switched to WFH Only, while pre-pandemic WFH Only workers mostly remained WFH Only.

The change in commuting behavior by pre-pandemic daily commuters shows a lot of persistence over the months in our sample. By mid 2021, still only two-thirds of pre-pandemic Commute Only workers were commuting daily, see Figure 6b. The increase from 55.9 percent in May 2020 to 67.9 percent in June 2021 reflects in part a decrease in the share of pre-pandemic daily commuters that were not employed, and in part that more were working from home on a part-time basis relative to earlier in the pandemic (11.4 percent in June 2021 compared with 7.6 percent in May 2020). Many pre-pandemic daily commuters (11.1 percent) were still WFH Only in June 2021.

3 WFH Transitions: Substitution, or Adoption?

Our analysis of the RPS data shows that the rise in WFH during the pandemic is first and foremost driven by workers that used to commute every workday switching to working entirely from home, and that the extent of the rise varies greatly depending on the feasibility of WFH in different jobs. These facts motivate a focus on the on-the-job choice to either WFH or not as function of workers' relative productivity of WFH and employers' WFH policies. In this Section, we lay out a theoretical model of that choice that leads to a precise description of the adoption and substitution channels for on-the-job transitions to WFH in a pandemic. We then present some additional qualitative survey facts pointing towards an important role of WFH adoption during the pandemic. Finally, we identify the model parameters from industry data, quantify the adoption and substitution effects through the lens of our model, and provide estimates of the longer-run WFH rates assuming that only the adoption effects persist.

3.1 A Model of Work from Home Employment

3.1.1 Environment

We consider an environment with a continuum of perfectly segmented labor markets, each populated by a continuum of individuals with size normalized to one. Individuals have linear preferences given by $u(w, l, h) = w – h - (1 + \chi)l$, where w is wages, h is time spent working at home, l is time spent working away from home, and χ is a cost of working on-site. The value of χ captures time spent commuting to work as well as any other costs (or benefits) associated with an equal amount of time worked on-site rather than at home, including both pandemic-related health risks of on-site work and any costs of complying with government workplace restrictions.

Each individual has at most one job. A job requires supplying one efficiency unit of labor regardless of the place of work. Individuals all have the same productivity in the workplace, which is normalized to one. However, they differ in WFH productivity z, where $1/z$ is the time required to complete the job at home. In each labor market, z has a Pareto distribution with cdf $\Phi(z) = 1 - \gamma z^{-\lambda}$ over the interval $[\gamma^{-1/\lambda}, \infty)$, where $\gamma \geq 0, \lambda > 0$ and $\gamma^{-1/\lambda}$ is the level of WFH productivity for the least productive individual. The value of γ will determine the average WFH productivity, and λ the labor supply elasticity of WFH. The workplace is always distinct from an individuals' home location, such that 'WFH' and 'remote work' are equivalent in the context of the model.

Each labor market features a monopolistic/monopsonistic firm that chooses the level of employment, E by setting wages flexibly. The firm operates a technology in which output equals employment, and the firm faces an inverse demand curve $p(E) = (\delta/E)^{1/\beta}/(1 - 1/\beta)$, where $\delta > 0$ determines the overall level of demand, and $\beta \geq 1$ is the elasticity of demand. The assumption of a single employer in a perfectly segmented labor market means that workers never change employer. This simplifying assumption is motivated by the finding earlier in Section 2.4.2 that the increase in WFH is largely about on-the-job transitions to WFH.

To model WFH adoption, we assume that in a fraction $1-\theta$ of labor markets firms exogenously do not allow WFH; in all other labor markets firms provide workers with the option to WFH. We also assume that firms that allow WFH can set separate wages for commuters and home workers, denoted by w_l and w_h respectively. In our setup, WFH employment only matters for firms because of the effect on the wage bill.[9]

3.1.2 Equilibrium

Each individual must choose whether to complete their job on-site ($h = 0$, $l = 1$), to complete the job from home ($h = 1/z$, $l = 0$), or to not work ($h = 0$, $l = 0$). For an individual with home productivity z, the utility of working on-site is $w_l - (1 + \chi)$, the utility of working from home is $w_h - 1/z$, and the utility from not working is 0. Individuals choose from these three options to maximize their utility, and choose to work and to commute if indifferent between the respective choices.

In equilibrium, the commuting wage w_l never exceeds $1 + \chi$, because the firm can always hire the same number of workers by paying $w_l = 1+\chi$ and earn more profits. For a commuting wage $w_l \leq 1 + \chi$, our assumptions about the distribution of WFH productivity imply that the supply of WFH labor is $e(w_h) = 1 - \Phi(1/w_h) = \gamma w_h^{\lambda}$. Hence, λ determines the elasticity of WFH labor supply, and γ determines its overall level. The supply of commuters is zero for $w_l < 1 + \chi$ and between 0 and $1 - e(w_h)$ when $w_l = 1 + \chi$.

Because the supply of commuters is infinitely elastic at $w_l = 1 + \chi$, firms that do not allow WFH choose E to maximize profits $p(E)E - (1 + \chi)E$. This results in firms choosing $E = \delta(1 + \chi)^{-\beta}$, where we assume that $\delta(1 + \chi)^{-\beta} < 1$ to ensure that $E < 1$ and firms never employ all individuals in their labor market. The profits of firms without WFH are given by $(\beta - 1)^{-1}\delta(1 + \chi)^{1-\beta}$.

The firms that provide a WFH option choose on-site employment E_l, WFH employment E_h and the WFH wage w_h to maximize the profits given by $p(E)E - (1 + \chi)E_l - w_h e(w_h)$, where $E = E_l + e(w_h)$. When the following condition holds

$$\gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda} < \delta(1+\chi)^{-\beta} \tag{1}$$

[9] Allowing for additional (linear) costs of on-site work incurred by firms would generate the same employment impact as a higher value of χ. Introducing an additional WFH cost for firms or workers is equivalent to changing the average value of WFH productivity γ.

the optimal decisions of the firm are given by

$$w_h = \frac{\lambda}{1+\lambda}(1+\chi) \ , \tag{2}$$

$$E_h = e\left(w_h\right) = \gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda} \ , \tag{3}$$

$$E_l = \delta(1+\chi)^{-\beta} - E_h. \tag{4}$$

Condition (1) ensures that WFH labor supply at the equilibrium wage is below the overall demand for labor, implying that the firm optimally employs a mix of commuters and WFH workers: $E_l > 0$, $E_h > 0$. When condition (1) is not satisfied, it is optimal for the firm to hire only WFH workers and pay a wage that is below $\lambda/(1+\lambda)(1+\chi)$. Because condition (1) is rarely violated in our quantitative analysis below, we relegate the details of this corner case to Appendix C.1.

The optimal wage (2) paid to the home worker is the firm's marginal revenue after a monopsonistic mark-down $\lambda/(1+\lambda)$. The firm hires commuters to the point where marginal revenue equals the commuter's wage $1+\chi$. The home worker's wage is therefore the marked down commuter's wage, and WFH employment in (3) is the WFH supply at that wage. An important feature of the firm's optimal decisions in (2)-(4) is that the productivity of WFH γ is irrelevant for the total level of employment $E_h + E_l = \delta(1+\chi)^{-\beta}$. The reason is that condition (1) guarantees that the commuter's wage $1+\chi$ is always the marginal wage that determines the overall level of employment. The commuter wage, however, is independent of WFH productivity γ. The level of WFH employment in (3) depends on the productivity of WFH γ, but it is independent of δ, the parameter determining the level of demand for the firm's output.

While WFH productivity does not affect the marginal wage, it affects the average wage because firms discriminate wages based on WFH status. As a result, firms pay lower wages to the inframarginal WFH employees. Providing the WFH option to the workers increases firm profits by

$$(1+\chi)/(1+\lambda)E_h \geq 0 \tag{5}$$

which is strictly positive unless $\gamma = E_h = 0$ and there are no home workers. The additional profits from providing the WFH option are increasing in the cost of on-site work χ and in the overall WFH productivity γ. Despite the lower wage, WFH workers are also better off with the WFH option as they enjoy more leisure time. Therefore, providing a WFH option is preferable to firms and workers with sufficiently high WFH productivity, while workers who always choose to commute are indifferent about having the WFH option.[10]

[10] If wage discrimination is not possible, the firm pays all workers $w = 1+\chi$ and sets $E_h = e(1+\chi)$. Without

An important potential indicator of the real-world potential benefits of WFH is whether, ceteris paribus, wages are indeed lower for WFH workers than for commuters. Based on a discrete choice experiment conducted within the application process of a national call center, Mas and Pallais (2017) find that job applicants are willing to take on average 8 percent lower wages in exchange for the WFH option. Based on the American Working Conditions Survey, Maestas et al. (2018) find a stated preference for WFH implying a willingness-to-pay of 4.1 percent of wages on average. Finally, using French administrative data, Le Barbanchon et al. (2020) find that gender differences in commute valuation can account for a .5 log point lower hourly wage for women compared to men.

3.1.3 WFH Substitution and Adoption in a Pandemic

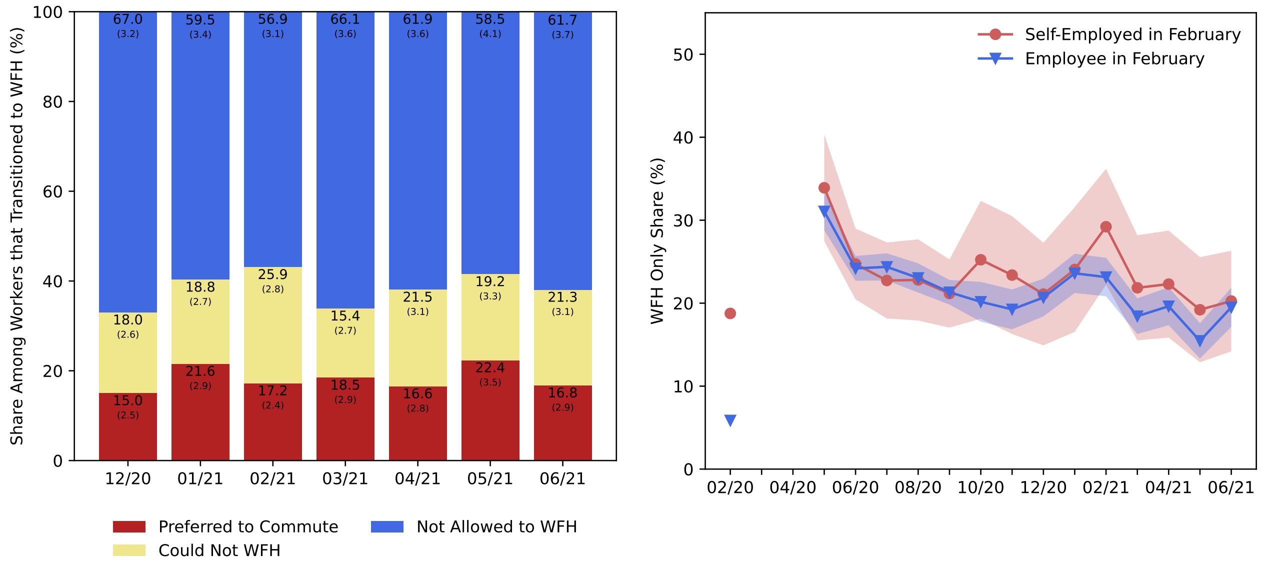
Aggregating across firms, total WFH employment is $\bar{E}^h = \theta E_h$ where E_h is given by Equation (3) and θ is the share of firms allowing WFH. In the model, a pandemic may increase total WFH employment $\bar{E}^h$ for several reasons. First, greater health risks are likely to raise the cost of working on-site, χ, which increases WFH employment at firms with a WFH option, E_h. We think of increases in χ as potentially arising both directly from higher health risks as well as indirectly from government regulations related to social distancing or workplace closures. Second, any pandemic-related changes in χ create greater profit incentives for firms to provide the WFH option, see Equation (5), and may therefore lead to increases in the fraction θ of firms that allow WFH. Finally, the pandemic may lead to the use of new WFH technologies that change overall WFH productivity, γ, increasing E_h. Note that reductions in δ, or the demand for firms' goods or services, never create any reason for commuting workers to switch to WFH, which can explain why WFH transitions are not a feature of more typical recessions.

We refer to all WFH transitions caused by increases in the costs of on-site work χ at a given level of θ as the WFH substitution channel. The WFH adoption channel instead refers to all transitions that are the result of either increases in the adoption of WFH arrangements (higher θ) or WFH technologies (higher γ). The central distinction between these two channels is that, all else equal, WFH adoption (weakly) reduces the disutility and wage costs of providing the labor necessary to complete a job. This is why WFH transitions driven by adoption are more likely persist in the longer-run. In contrast, the WFH substitution channel always implies an increase in the disutility and wage costs of providing labor. For this reason, WFH transitions driven by WFH substitution should reverse once the health crisis fades and χ decreases to its pre-pandemic level.

wage discrimination, the entire WFH surplus goes to the WFH workers and firm profits are the same with or without WFH option.

Figure 7: Access to WFH Before and After the COVID-19 Outbreak

(a) Reason for Commuting in Feb. '20 (b) WFH Only: Employees vs. the Self-Employed



Source: Real-Time Population Survey. The sample in the left panel is all workers that commuted every workday in February 2020, WFH at least some days in the survey month, and were still working for the same employer as in February 2020. Standard errors are in parentheses. The sample in the right panel is individuals employed both in February 2020 and last week. Class of worker (self-employed or not) is assigned based on the February 2020 status. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

3.2 Some Survey-Based Evidence on WFH Adoption

A natural way to assess the potential role of adoption is to simply ask workers directly about their employers' WFH policies. Beginning in December 2020, we asked respondents in the RPS the following question: *Which of the following best explains why you [your spouse/partner] commuted to work every workday in February 2020?*

a) *My [spouse/partner's] job could not be done from home*

b) *Some or all of my [spouse/partner's] job could have been done from home, but my [spouse/-partner's] employer required me [them] to commute each day*

c) *Some or all of my [spouse/partner's] job could have been done from home, but I [my spouse/partner's] preferred to commute each day*

Figure 7a shows a breakdown of the reasons given by job stayers that switched to at least one day of WFH for why the were commuting daily in February 2020. The main takeaway is that a clear majority cited employer requirements as the main reason for commuting before the pandemic (62.9 percent after averaging across all months), implying that most workers who transitioned to WFH on-the-job did not have the option to WFH before the pandemic. In terms of our model, this points to a substantial increase in adoption, θ. In contrast, only 18.3 percent (averaged across months) cited personal preferences as the main reason for commuting daily in February 2020. Even if we assume that all these workers indeed had the option to WFH before the pandemic, this relatively small fraction suggests a more limited role for substitution effects. A meaningful fraction of respondents in Figure 7a stated that they did not WFH because their job could not be done from home before the pandemic (18.8 percent across all available months). Apart from possible measurement error, this could reflect changes in the nature of the job for some workers. Another explanation is that for some workers WFH became feasible after the adoption of new WFH technologies in the pandemic (an increase in γ in our model), for example doctors switching to telemedicine, or educators to remote learning.

Another potential source of direct evidence of changes in employers' WFH policies during the pandemic is to look at differences in the WFH transitions of employees and self-employed workers. Whereas WFH decisions by payroll workers are potentially constrained by whether employers allow WFH or not, this should be less relevant for workers that are self-employed. Figure 7b shows that self-employed workers were about three times as likely to be WFH Only before the pandemic as employees. However, gaps in WFH Only shares between employees and the self-employed essentially disappeared during the pandemic. Moreover, by June 2021, WFH Only shares for the self-employed were not statistically different from pre-pandemic levels, while WFH Only shares for employees remained well above pre-pandemic levels. The large 'difference-in-difference' in WFH between payroll workers and the self-employed is consistent with employers removing commuting requirements for employees in the pandemic.[11]

Both pieces of evidence in Figure 7 suggest that many workers indeed gained access to the option to WFH in the pandemic, and therefore that adoption effects are likely important in understanding the extent and persistence of the rise in WFH during the pandemic. However, this evidence for WFH adoption does not allow any firm quantitative conclusions about how many more workers would WFH absent the higher costs of working on-site induced by the pandemic. In what follows, we use the RPS data and structure of our theoretical model to address this counterfactual question.

3.3 Model Parameters and Identification

The first step in the quantitative analysis is to obtain values for all model parameters. Because the health risks as well as the potential for WFH vary greatly by economic sector (see Section 2.4.1), we set the model parameters to target employment and wages at the industry level. In

[11] In February 2020, the self-employed also had rates of WFH Some Days that were slightly higher than for employees, and these differences have narrowed somewhat since May 2020, see Appendix B.10. The patterns for self-employed and employed are similar if we condition on *current* class of worker (self-employed or not) as opposed to pre-pandemic class of worker.

addition, we allow the key model parameters to vary by month in order to capture the variation in the employment and health dynamics over the course of our sample period. We present monthly estimates of the substitution and adoption effects on the economy wide WFH rate by aggregating the results across all industries. Our baseline analysis focuses on a decomposition of the adjustment in the share of WFH Only workers in employment, which is the key dimension along which WFH increased during the pandemic, see Section 2.2. In Appendix C.3, we present an alternative decomposition of the share of all workdays without a commute to also capture partial commuting behavior.

Within each industry and time period, the endogenous variables (E_h, E_l, w_h and w_l) depend on six parameters: $\lambda, \beta, \gamma, \chi, \delta, \theta$. Our dataset spans 17 different industries and 15 time periods (February 2020, and May 2020 through June 2021). To reduce the total number of free parameters, we make a few simplifying assumptions. First, we assume that the elasticity of demand, β, and the elasticity of WFH labor supply, λ, are both constant across time and across industries. Large differences in λ across industries seem implausible as they would arguably have resulted in much greater variation in WFH rates before the pandemic following decades of advances in information and communication technologies. Second, we assume that the WFH productivity γ differs across industries, but does not change over time. Imposing that γ is time invariant is an important assumption in the context of our analysis, because it means that variation in the fraction of employers that allow WFH, θ, is the only form of WFH adoption that affects the WFH Only share. There is unfortunately little information available that is useful for identifying the change in the productivity of WFH over the course of the pandemic, in particular at a monthly frequently or at the industry level. That said, our direct survey evidence of the extent of WFH adoption in the previous section gives us confidence that changes in employer's WFH policies are likely the most important form of WFH adoption in the pandemic.

We begin by assigning the following values to λ and β, the two parameters that are both time-invariant and common across industries. We set the elasticity of WFH labor supply $\lambda = 9$ such that the wage of a WFH worker is a fraction $\lambda/(1+\lambda) = 0.9$ of the commuter wage. This value is roughly in line with experimental evidence on willingness to pay to WFH, see for instance Mas and Pallais (2017). We set the demand elasticity $\beta = 2$ as a baseline value. As we will discuss later, the results of the decomposition of the WFH Only share are not very sensitive to alternative values for either λ or β.

Next, we assign the remaining parameter values for the pre-pandemic baseline period, February 2020. For each industry, we obtain a value for the pre-pandemic adoption rate θ directly from an industry-specific estimate of the share of workers with access to WFH Only, using the survey question in Section 3.2. Specifically, we add the fraction of daily commuters that cite personal preference as the main reason for commuting to the fraction of workers that are WFH

Only before the pandemic. That is, we exclude all workers that are in jobs that cannot be done from home, or that are working for employers that do not allow WFH. In the aggregate, this results in an estimated 15.2 percent of workers in jobs where WFH Only is allowed before the pandemic, among which about half (7.5 percentage points) chose to WFH. The pre-pandemic values of χ are normalized to equal zero in each industry. The two remaining parameters, δ and γ are set to perfectly match the level of industry WFH employment, $\bar{E}_h$, as well as total industry employment, $\bar{E}$, in February 2020 in the RPS data. The values of δ and γ are pinned down by conditions (3) and (4), and by the definitions of total industry employment $\bar{E} = \theta(E_h + E_l) + (1 - \theta)E = E$ and total industry WFH employment $\bar{E}_h = \theta E_h$.

The remaining 14 periods cover the months from May 2020 to June 2021. As mentioned earlier, we assume that the WFH productivity parameter γ does not change over time, and for each industry we therefore set its value equal to the value obtained in the pre-pandemic period. The monthly values of the remaining three time-varying parameters, χ, δ, θ, are set to perfectly match the monthly observations of total industry employment, WFH employment in each industry, and the industry-specific wage. For each industry/month, the values for χ, δ and θ can be solved recursively from

$$\chi = \frac{\bar{w}(1+\lambda)}{(1 - \bar{E}_h/\bar{E}) + \lambda} - 1 \tag{6}$$

$$\delta = \bar{E}(1+\chi)^{\beta} \tag{7}$$

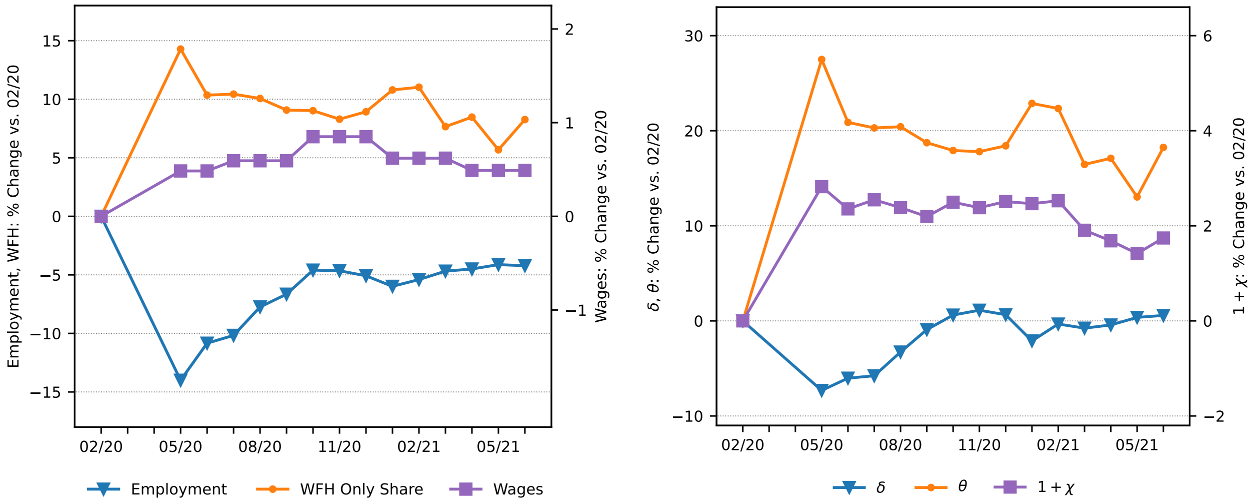
$$\theta = \frac{\bar{E}_h}{(1+\chi)^{\lambda}} \left(\frac{1+\lambda}{\lambda}\right)^{\lambda} \gamma^{-1} \tag{8}$$

where the average wage $\bar{w}$, total employment $\bar{E}$, and total WFH employment $\bar{E}_h$ are the observables and the values for β, λ and γ are given. Equation (6) follows directly from the definition of $\bar{w}$ as the average of the commuters' and remote workers' equilibrium wages, given by $1 + \chi$, and $(1 + \chi)\lambda/(1 + \lambda)$, respectively. Equation (7) follows from condition (4) and $\bar{E} = \theta(E_h + E_l) + (1 - \theta)E = E$, while (8) follows from $\bar{E}_h = \theta E_h$ and condition (3).

To identify our model parameters, we use industry data on total employment $\bar{E}$ and WFH employment $\bar{E}_h$ from the RPS and construct industry wages $\bar{w}$ based on the Employment Cost Indices (ECIs). In particular, we use detrended real measures of the ECIs for total compensation from the Bureau of Labor Statistics' National Compensation Survey. The ECI captures wages and salaries as well most non-wage benefits (including hazard pay and other bonuses related to increased health risks), and are also free from the influence of large changes in the occupational composition, making them better measures of changes in compensation for work than the earnings measures in the CPS or RPS. One drawback is that the ECI is only available at a quarterly frequency. For each industry-month, we use the non-seasonally adjusted level of the ECI for private industry workers. Our model assumes flexible wages, and since in

Figure 8: Evolution of Empirical Moments and Identified Parameters

(a) Evolution of Aggregate Empirical Moments (b) Evolution of Aggregate Identified Parameters



Source: Left Panel: Employment and WFH Only shares are from the Real-Time Population Survey (RPS). Wages are from the Employment Cost Indices (ECIs). Employment and WFH Only shares correspond to the left vertical axis; wages correspond to the right vertical axis. The displayed values are a weighted average of industry-level moments, where the weights correspond to employment in February 2020. *Right Panel*: Industry-level parameters are identified using industry-level moments on employment, WFH, and wages and Equilibrium conditions (6) - (8). The displayed values are a weighted average of industry-level parameters, where the weights correspond to employment in February 2020.

practice wages may take some time to adjust to shocks, we use the subsequent quarter value. We deflate by a four quarter backward moving-average of the CPI-U price index, and measure the change in the resulting real wage relative to the 2020 Q1 value after detrending by the average real growth in the 10 years prior to 2020Q1. For two of the 17 industries we consider, the ECI is not available: For agriculture and mining, we therefore use the index for workers in construction, extraction, farming, fishing, and forestry occupations; for arts and recreation, we use the index for its supersector, leisure and hospitality. Finally, for the finance and real estate industries, we use ECIs that exclude incentive pay workers to remove the influence of large fluctuations in asset prices during the pandemic.

To provide intuition on how the identification strategy works, Figure 8a shows the aggregates of the industry data fed into conditions (6) - (8). Figure 8b shows the identified model parameters, aggregated across industries using February 2020 employment weights. Viewed through the lens of the model, the WFH, employment and wage data imply broad-based increases in both the costs of on-site work as well as adoption rates during the pandemic. Based on condition (6), the increases in χ were driven by the higher WFH rates, but also by real wages above levels implied by the pre-pandemic trend. Based on the identified distribution of WFH productivities γ and our baseline value of λ, the increases in χ overall do not suffice to quantitatively explain the extent of the increases in WFH rates during the pandemic. Doing so also requires persistent increases in adoption rates θ, as determined by condition (8). Even with the increases in χ, condition (7) requires substantial reductions in demand to explain the employment drops in the earlier months of the pandemic. In the aggregate, however, demand recovers roughly to pre-pandemic levels by the end of 2020, and dips only slightly during the 2021 winter surge of the virus. The costs of on-site work remain elevated throughout the pandemic months in 2020, but – coinciding with the vaccine roll-out – decreased following the 2021 winter surge.

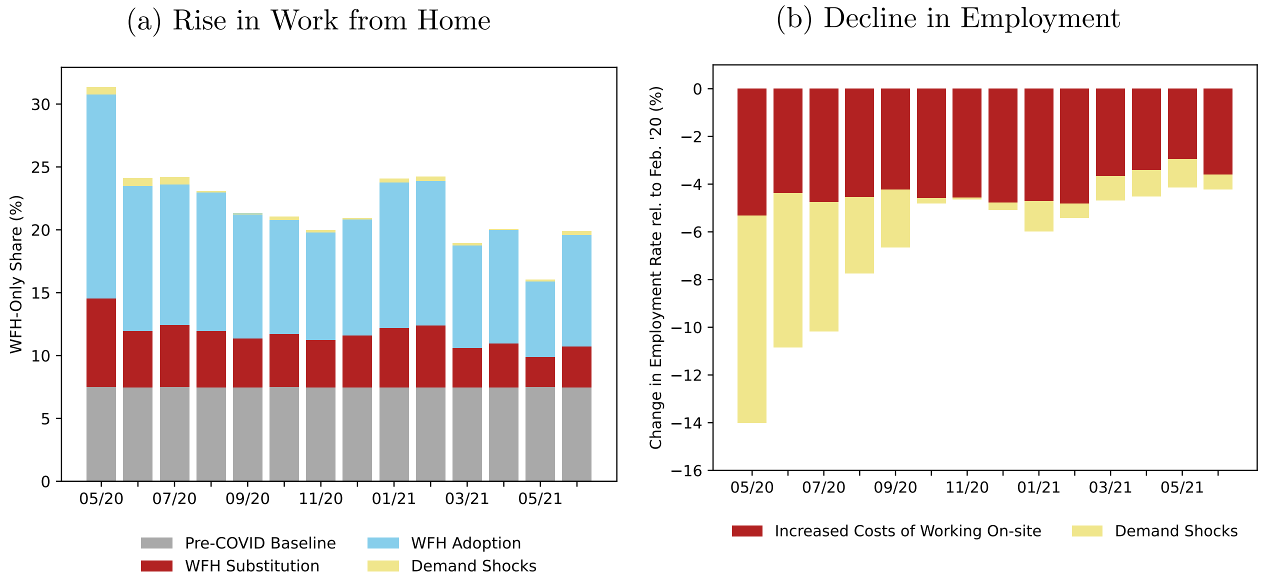
Finally, we note that in fifteen of the 17×15 industry-month pairs, condition (1) is violated, meaning that our identification strategy results in sufficiently low demand and high on-site costs such that firms hire only WFH workers. Appendix C.1 details how we change our identification strategy in these rare corner solutions, which have no meaningful impact on the results.

3.4 Decomposition Results

Having set parameter values for each industry and time period, we now proceed to quantify the contribution of various drivers to the aggregate change in WFH during the pandemic. To quantify the WFH substitution effect, we compare the outcomes in the model under the identified monthly sequences of χ for all industries with a counterfactual path in which the values of χ remain unchanged from the baseline pre-pandemic period for all industries. We repeat the same exercise for θ and δ to obtain the effects of changes in adoption rates θ and demand δ in every industry. Because of the nonlinearities in the model, the numerical results for one parameter in general depend on whether we assume that the sequences of the other parameters are kept fixed at pre-pandemic values or follow the trajectories identified by the data. To present a single set of results, we evaluate all possible combinations of counterfactual trajectories and calculate the average contributions over all these combinations. After aggregating across all industries, this results in a decomposition of the aggregate WFH Only share into substitution, adoption and demand effects for each month in our sample. This decomposition is shown in Figure 9a.

Figure 9a shows that the adoption effects (increases in θ) were the quantitatively dominant reason for the increase in the WFH Only share. In May 2020, the first pandemic month with RPS data available, WFH adoption effects account for 16.2 percentage points of the 23.9 percentage points increase in the aggregate WFH Only share, or 67.8 percent of the total increase relative to the pre-pandemic level. Figure 9a also shows that the aggregate adoption effects were fairly persistent, and explain an even larger share of the increase in WFH in the last few months of our sample. In June 2021, for example, increases in θ accounted for a 9.2 percentage point increase in the WFH Only share, or three quarters of the total 12.1 percentage point increase relative to February 2020.

Figure 9: Decomposition Results



Source: Real-Time Population Survey (RPS) and model simulations. The aggregate results in each figure are a weighted average of these industry-level decompositions. *Left Panel:* The y-axis is the share of workers who are WFH Only in each month May 2020 - June 2021. The pre-COVID baseline level of WFH Only (gray) is based on RPS data. The effects of WFH substitution (red), WFH adoption (light blue), and demand (tan) on the WFH Only share are based on industry-level decompositions which compare WFH Only shares under the identified monthly sequences of parameters with a counterfactual path that changes a single parameter at a time (χ for substitution, θ for adoption, and δ for demand). *Right Panel:* The sum of the stacked bars in each month is the percent change in employment relative to February 2020 in the RPS. The effects of WFH substitution (red) and demand (tan) on the WFH Only share are based on industry-level decompositions which compare employment under the identified monthly sequences of parameters with a counterfactual path that changes a single parameter at a time (χ for substitution and δ for demand).

The bulk of the remaining increase in WFH is explained by substitution effects, i.e. by the direct reaction to the identified increases in the cost of on-site work χ by workers with the option to WFH. In May 2020, WFH substitution increased the WFH Only share by 7.1 percentage points, explaining 29.6 percent of the increase in the WFH Only share. Substitution effects declined somewhat in June 2020, were relatively stable throughout the rest of 2020, and then – coinciding with the vaccine rollout – declined in the first half of 2021. By June 2021, substitution effects account for a 3.2 percentage point rise in the WFH Only share, about a quarter of the total increase relative to February 2020.[12] Finally, changes in industry demand δ had a relatively minor effect on WFH in all months. As we explained in Section 3.1, changes in δ do not affect WFH employment as long as the marginal worker remains a commuter. In our decomposition, they generate only relatively small effects that arise because of the impact on the denominator of the WFH Only share.

While our identification strategy results in adoption effects explaining most of the increase

[12] Our model abstracts from the more generous UI benefits over our sample period. Adding distortionary effects of these benefits on labor supply would lead to smaller identified increases in χ, and reduce the role of substitution effects.

in WFH, this does not imply that the increases in the cost of working on-site had little economic impact. Figure 9b shows the contributions of changes in χ to total aggregate employment in percent of its February 2020 level, along with the contributions of changes in industry demand δ (changes in θ have no impact on total employment in our model). Between May 2020 and February 2021, increase in χ account for a 5 percent reduction in employment, only decreasing somewhat in the last four month of our sample to between 3 and 4 percent. These job losses alone exceed those in each US postwar recession apart from the Great Recession. In the early months of the pandemic, the role of demand in generating job loss is very large, with reductions in δ contributing substantially more than the increases in χ. The demand effects on employment fade gradually over the course of 2020, are no longer a driver of the employment shortfall by year end, but re-emerge in part during the winter surge of the virus and in the months thereafter.

3.5 Robustness

The result that the rise in WFH is mostly driven by WFH adoption is robust to various alternative assumptions, which we discuss in detail in Appendix Sections C.2-C.3. Here, we summarize the conclusions of several robustness exercises.

Different values for λ. Appendix C.2 reports results for different values of the elasticity of WFH labor supply λ. One could expect that higher values of the elasticity of WFH labor supply λ necessarily make the substitution effects more important for a given set of empirical moments. The results of the decomposition are, however, not overly sensitive to changes in the value of λ because of two opposing effects on the contribution of the substitution effects in the decomposition. On the one hand, a higher λ means that more workers switch to WFH for a given increase in χ. On the other hand, a higher λ also reduces the increase in the identified values for χ implied by the observed increase in the WFH Only share $\bar{E}_h/\bar{E}$, see equation (6). Even for very large values of λ, increased costs of on-site work χ continue to contribute at most half of the increase in the WFH Only share even in the early months of the pandemic.

Different values for β. The value of β does not affect the decomposition of the WFH rate, see Appendix C.2, because neither the identified values of χ and θ in equations (6) and (8), nor the level of WFH employment in the model depend on β.

Including Partial WFH. In Appendix C.3 we discuss the results of a decomposition of the share of workdays WFH instead of the WFH Only share of employment. A reasonable conjecture is that the role of substitution effects would increase after also taking into account partial commuting behavior. Incorporating partial WFH leads to a contribution of adoption effects of 54.6 percent to the overall increase in the share of workdays WFH in May 2020. This is indeed somewhat less than the 67.8 percent contribution of adoption effects to the WFH Only share in our baseline analysis, suggesting that in certain jobs only substitution to WFH on a part-time basis is possible. By June 2021, the adoption effects contribute 64.4 percent to the increase in the share of WFH workdays. Incorporating part-time WFH, therefore, does not change our finding that the persistence in the rise in WFH is primarily driven by adoption.

3.6 Adoption Effects by Industry

The aggregate impact of WFH adoption shown in Figure 9a masks considerable heterogeneity across industries. This heterogeneity is, in itself, informative about the likely longer run level of access to WFH arrangements in many industries. In general, the cross-industry variability in the identified WFH adoption effects is closely related to the variability in WFH ability across industries discussed earlier in Section 2.4.1. Figure 10 shows the relationship between the adoption-driven component of the WFH Only increases as identified in the model, and the share of jobs in potential WFH Only occupations based on the classification of Dingel and Neiman (2020). In May 2020 (left panel), the relationship was strongly positive, and aligns closely with the relationship between potential WFH shares and observed WFH Only shares shown earlier in Figure 4. This means our decomposition explains the weak relationship before the pandemic by the fact that WFH arrangements were relatively uncommon even in sectors with relatively large potential for remote work.

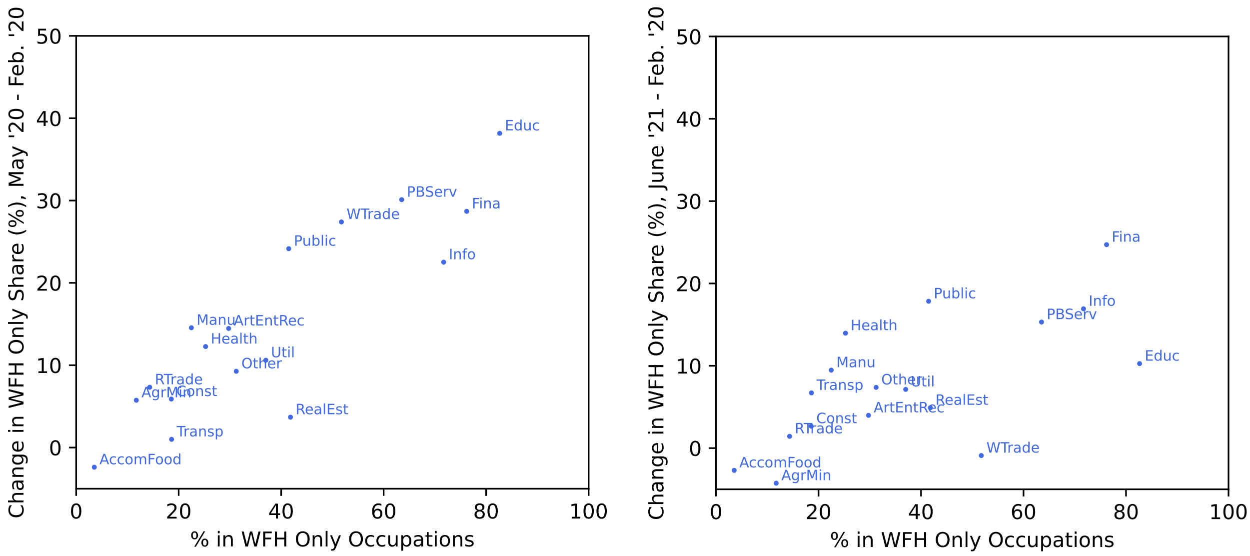
The right panel of Figure 10 shows that the relationship remained positive in the last month of our sample, June 2021, but with two notable differences. In the wholesale trade and education sectors, the adoption effect on the increase in WFH was large early in the pandemic, but was much smaller by mid 2021. The education sector, in particular, stands out in that it had both the largest early-pandemic adoption effect and the highest share of jobs in which WFH is feasible (83 percent). However, following a widespread return to in-person learning in the fall of 2020, the adoption effect in education fell to only 11.9 percentage points by mid 2021, down from 38.1 percentage points in May 2020. This reversal in WFH adoption suggests that full-time WFH arrangements are not viable in the longer run in much of the education sector. In other high-WFH potential sectors such as information, finance or professional and business services, the estimated adoption effects in mid 2021 were instead highly persistent, and were only modestly below those in May 2020. The staying power of WFH arrangements suggests that the rise in WFH in these sectors is much more likely to persist even with a full return to a pre-pandemic health environment.

3.7 How Much WFH After the Pandemic?

Recall that the key theoretical distinction between WFH substitution and adoption is that WFH substitution entails reductions in worker welfare and higher production costs for firms,

Figure 10: Change in WFH Due to Adoption Across Industries

(a) May 2020 (b) June 2021



Source: Real-Time Population Survey and Dingel and Neiman (2020). The x-axis is the share (percent) of February 2020 workers in potential WFH occupations based on the measures of Dingel and Neiman (2020). The y-axis is the change in the WFH Only share of employed workers (percent) due to adoption relative to February 2020. The left panel corresponds to May 2020, and the right panel corresponds to June 2021. Definitions of industry groups are provided in Appendix A.3.

while WFH adoption entails potential improvements in worker welfare and lower labor costs for firms. This distinction can explain why the adoption effects on WFH persisted over our sample in most (though not all) industries. In this section, we explore the potential longer run prevalence of WFH by making the assumption that the level of WFH adoption observed towards the end of our sample is in fact permanent. Specifically, we assume that the adoption rate θ in each industry remains at the average of the last four months of our sample (after the winter surge), while all other parameters instead are at their pre-pandemic values. In our model, these assumptions imply that output and employment in each industry return to exactly the same levels as in February 2020. This assumption therefore abstracts from any longer term effects of more WFH on the composition of employment. With this caveat in mind, we assume that the only difference relative to February 2020 is that 31.4 percent of the workforce has the option to WFH, compared with 15.2 percent before the pandemic.

In the scenario of a permanently higher WFH adoption rate, our model predicts a WFH Only share of 14.6 percent, or about one in seven workers. This would roughly double the WFH Only share from the 7.5 percent observed just before the pandemic, and would constitute an increase far exceeding the cumulative rise in WFH Only over the last two decades, see Figure 1a. Repeating the same counterfactual exercise in the alternative model that allows for partial WFH (see Appendix C.3), we find that 51.3 percent of the workforce has the option to work at least partly from home in the new regime, and 21.3 percent of all work days are WFH. This is a substantial increase relative to just before the pandemic, when 33.4 percent of the workforce had at an option to work at least partially WFH, and 14.4 percent of all workdays were effectively worked from home. Both model predictions, therefore, imply that the pandemic caused a sharp acceleration in the pre-existing upward secular trend in WFH shown in Figure 1a.

If WFH adoption during the pandemic indeed unlocked new permanent benefits for many firms and workers, a natural question is why these benefits were not taken advantage of earlier. One possible answer is that, even if WFH was in principle already viable in many jobs before the pandemic, in practice many employers may not have had sufficient profit incentives to allow WFH. One potential reason is that employers and employees may have underestimated the benefits of WFH without any actual experience. This possibility is supported by evidence in Bloom et al. (2014), which documents how a temporary experiment showing meaningful productivity gains lead to the permanent adoption of WFH by a Chinese call center. There may also be various sunk costs of WFH adoption, for example in terms of new management practices or communication technologies, that did not justify the increase in variable profits at lower costs of on-site work before the pandemic. This is a version of countercyclical restructuring that has been well documented empirically in the context of labor reallocation, see e.g. Davis and Haltiwanger (1990), or capital replacement, see for instance Cooper and Haltiwanger (1993) or Hershbein and Kahn (2018).[13] Another potential reason for low levels of adoption of WFH arrangments prior to the pandemic is that an individual firm potentially faces problems of adverse selection if remote work attracts unobservably less productive workers. Using data from a call center, Harrington and Emanuel (2020) document for example that, while the productivity of previously on-site workers rose by 7 percent after switching to remote work in 2018-2019, the opportunities to go remote also attracted less productive applicants. Such problems of adverse selection may be of less concern with more broad-based adoption of WFH arrangements within a labor market. Relatedly, complementarities may imply that the relative productivity of WFH is higher when more workers WFH.

4 Survey Expectations for WFH in the Future

In this section, we confront the model-based predictions for WFH in the long run with survey evidence from the RPS on workers' own expectations for WFH in the future. We also assess which demographic groups are more likely to experience the benefits of more flexible work arrangements in the future.

[13]For theories of lower adjustment costs in bad times leading to restructuring, see e.g. Aghion and Saint-Paul (1998), Koenders and Rogerson (2005), or Berger (2018).

4.1 Model Predictions versus Survey Expectations for WFH

Under the assumption that access to WFH remains similar to the later months in our sample, the model-based analysis of the previous section predicts that about one out of every seven workers will choose to work full remotely in the longer run, and that just over a fifth of all workdays will not involve a commute. We find that these model-based predictions are broadly consistent with workers' own expectations.

Beginning with the December 2020 wave of the RPS, we asked all respondents with a job the following question:

We would like to know a little about what you expect for commuting in the future. Please think ahead to a year from now. In a year from now, how many days do you expect [your spouse/partner] to commute to work?[14]

a) *I expect [my spouse/partner] to commute to work every workday*

b) *I expect [my spouse/partner] to commute to work at least once per week*

c) *I do not expect [my spouse/partner] to commute to work at all*

d) *I do not expect [my spouse/partner] to a year from now*

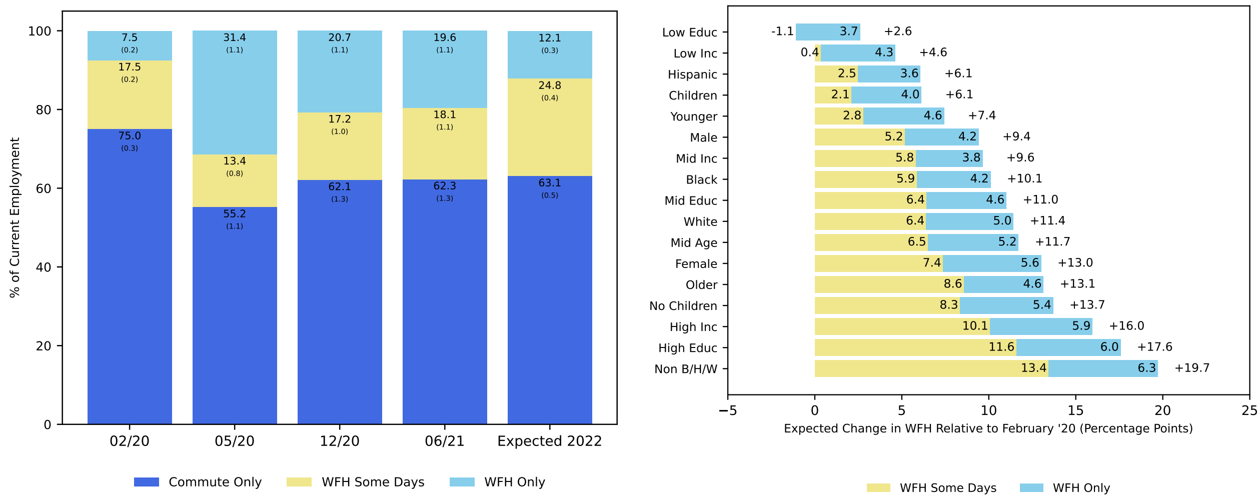
We classify all respondents answering a, b or c to the question above as workers that in the future will be 'Commute Only', 'WFH Some Days' and 'WFH Only' respectively, and compute the shares in the total number of workers that expected to work (i.e. all workers not answering d). Figure 11a shows the breakdown for the commuting expectations, pooling the results for all months December 2020 through June 2021. For comparison, the figure also repeats the actual shares for selected months in 2020 and 2021 from Figure 1b.

Figure 11a shows that, overall, 36.9 percent of workers expected to WFH at least one day per week one year ahead. This is a much higher share than before the pandemic (25.0 percent), and only slightly lower than the actual WFH share in June 2021 (37.7 percent). However, there is a meaningful difference in the frequency with which workers expected to WFH conditional on doing so at least partially. Only 12.1 percent of workers expected to WFH Only one year ahead, compared to 19.6 percent in June 2021. The decline in expected WFH Only was primarily offset by an expected rise in WFH Some Days, from 18.1 percent in June 2021 to 24.8 percent one year ahead. This shift towards more hybrid work might point to the importance of informal interactions and firm-specific social capital requiring physical presence at the workplace on at least some workdays. We can also estimate the overall share of workdays respondents expected to WFH by assuming that partial commuters will WFH on 40 percent of workdays, which was

[14] In December 2020, we referred to 2022 instead of 'a year from now'.

Figure 11: Expectations for WFH One Year Ahead

(a) Aggregate (Levels) (b) By Demographic Group (Changes)



Source: Real-Time Population Survey. *Left Panel:* The 2020-2021 bars display the workers shares by commuting status. The "Expected 2022" bar displays the worker shares by expected commuting status in 2022. Expectations data were collected from December 2020 through June 2021, and are pooled across months. Standard errors in parentheses, calculated as described in Appendix A.2. *Right Panel*: The sample is individuals (ages 18-64) employed both in February 2020 and in the months December 2020 - June 2021, for which expectations data is available. The figure displays the difference between expected WFH rates for 2022 and actual WFH rates in February 2020 by demographic group. Non B/H/W stands for not Black, White or Hispanic. Precise definitions of all demographic groups are provided in Appendix A.3.

that group's frequency of WFH in the sample months since December 2020 when we began asking the expectations question. This assumption implies that workers expected 23.4 percent of workdays to be from home one year ahead, compared with 28.5 percent in June 2021 and 14.4 percent just before the pandemic.

The year ahead expectations of WFH can be compared to the model's predictions for WFH after the pandemic, see Section 3.7. Given progress on vaccination in the months that we elicited WFH expectations, we think it is reasonable to assume that most survey respondents expected the pandemic would have largely subsided within a year of their survey date.[15] Consistent with that interpretation, Appendix B.11 shows that WFH expectations remained fairly stable across between December 2020 and June 2021. The analysis of WFH over the long-run in our model predicted that 14.6 percent of workers would be WFH Only, fairly close to the 12.1 percent expected share in Figure 11a. The alternative exercise based on the share of workdays from home predicted that 21.3 percent of workdays would be from home, again fairly close to the 23.4 percent expected share in the RPS data.

The evidence from the RPS on expectations for more WFH in the future is consistent with

[15] We fielded the expectations question for the first time in between December 14-17, 2020, just after the Pfizer–BioNTech COVID-19 vaccine had been granted Emergency Use Authorization (EUA) by the U.S. Food and Drug Administration on December 11, 2020.

that from other surveys. Based on a similar question in their online household survey, Barrero et al. (2021) conclude that 22 percent of all full workdays will be supplied from home, which is close to our RPS-based estimate of 23.4 percent and our model-based prediction of 21.3 percent. Several surveys of businesses indicate that many employers also project permanent increases in their home-based workforce as a result of the pandemic.[16]

Earlier, we documented substantial heterogeneity in WFH increases during the pandemic across various demographic groups (Section 2.2). The evidence for WFH adoption in this paper suggests that the pandemic may have unlocked important longer-term welfare gains in the form of lower commuting costs, higher productivity, and greater geographical mobility. In this Section, we show that many of these differences between demographic groups are also present in expectations of future WFH. Any such long-run welfare gains are therefore likely to be highly unequally distributed.

Figure 11b highlights some of the key differences in WFH expectations across demographic groups, which largely echo the differences in actual WFH transitions observed during the pandemic. For each category, the figure plots the expected percentage point increase in the expected fraction of WFH workers one year ahead relative to February 2020. In general, workers in all categories expected more WFH in the future. However, the extent of the anticipated increase varies greatly across different groups, driven primarily by expected changes in WFH Some Days. Overall, many more Non-Black/Hispanic/White (mostly Asian) workers and workers with high income/education, in particular, expected to do more WFH relative to before the pandemic. On the other hand, low income/education, Hispanic, and younger workers, and workers with children expected smaller increases in WFH. Most of the unconditional patterns across demographics groups also remain present after conditioning for other worker characteristics and industry of employment, see Appendix B.4 for a discussion.

The expected increases in WFH for some groups were quite large in magnitude. For example, Figure 11b shows that the fraction of highly educated workers (bachelor's degree or more) who expected to WFH on a part- or full-time basis was 17.6 percentage points higher than before the pandemic. If realized, this would imply almost half of all highly educated workers would WFH at least partially. By contrast, less educated workers (high school degree or less) expected only a 2.5 percentage point increase in WFH relative to before the pandemic. These expectations, if accurate, suggest that the longer term gains from increased WFH are likely to be highly unequally distributed, and disproportionately benefit high-education/income workers.

[16] In a survey of 1,800 small business leaders, Bartik et al. (2020) find that one-third of firms with WFH employees in the pandemic believe that remote work will remain more common. A Dallas Fed survey of 390 Texas-based employers shows that businesses expect 20.6 percent of employees to work remotely on average, compared to 8.3 percent before the pandemic, see FRB Dallas (2020). An Atlanta Fed survey of 280 employers shows that business expect that 10.3 percent (27.1 percent) of employees will WFH Only (WFH at least one day) after the pandemic, compared to 3.4 percent (9.7 percent) in 2019, see Barrero et al. (2020).

5 Concluding Remarks

This paper uses a sample of more than 66,000 observations from a novel national survey to document the evolution of WFH in the US over the course of the COVID-19 pandemic. WFH increased sharply and persistently in the pandemic, primarily driven by a large number of pre-pandemic daily commuters who stopped commuting entirely while remaining in the same jobs. Based on a quantitative model of WFH we argue that most of the increase in WFH can be attributed to the adoption of new WFH arrangements during the pandemic. Because more flexible work arrangements create new benefits for workers and employers also in a normal health environment, we argue that the work arrangements of many workers were likely permanently changed by the pandemic. Assuming that access to WFH remains at similar levels as at the end of our sample period, our model predicts that about one in every seven workers will choose to work WFH Only after the end of the pandemic, and that just over one fifth of all workdays will be WFH. We find that these model predictions are consistent with the survey respondents' actual expectations for WFH in the future.

If the work arrangements of many workers were indeed permanently changed by the pandemic, this is likely to have a wide range of important economic consequences. The unequal expansion of flexible working arrangements could amplify pre-existing inequities across workers, as well as redraw the boundaries of labor markets in many occupations. A permanent rise in remote work would create incentives for people to change where they live and work (Davis et al., 2021; Delventhal et al., 2021). Residential relocation by remote workers farther from their workplace could negatively impact rental prices and municipal finances in urban areas where many firms are located and have the opposite effect in more distant suburbs. Reductions in spending on non-tradable services in city centers is likely to disproportionately affect lower-income and less-educated workers (Althoff et al., 2022). Remote work may also induce larger-scale geographic reallocation across metro areas and states, especially if reduced in-person interactions weaken agglomeration and innovation externalities in the most productive, but also most expensive cities (Ahlfeldt et al., 2015; Delventhal et al., 2021; Liu and Su, 2020; Moretti, 2021).

A rise in WFH may also impact market activity and home production within couples (Alon et al., 2020). It is well known that women typically spend more time on home production and childcare than men. This differential leads women to systematically work fewer hours in the market, and to select into occupations where lower hours are more common. Because short hours are often associated with low hourly wages (also known as a "part-time wage penalty"), this channel can lead to lower hourly wages and annual earnings (Erosa et al., 2022; Goldin, 2014). Related research has shown that women also tend to commute shorter distances than men, which results in a smaller sample of potential job opportunities and a lower average hourly wage rate (Le Barbanchon et al., 2020). WFH, which is more common among women, has the potential to either unwind or exacerbate these disparities. On the one hand, WFH can reduce the commuting costs of a given job, which could allow women to work longer hours or accept jobs located farther away. On the other hand, complementarities between WFH and home production could incentivize couples to specialize, with a larger share of home production falling on the spouse that works remotely. The relative magnitudes of these channels could therefore have implications both for aggregate labor supply and for differences in labor market outcomes across genders.

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APPENDIX FOR ONLINE PUBLICATION ONLY

Contents

A RPS: Measurement and Definitions

A.1 Sample Construction and Weighting

The full RPS dataset from May 2020 - June 2021 include 69,608 individuals. We have two observations per individual: one corresponding to February 2020, and one corresponding to the survey month. From this, we delete (i) observations without the necessary demographic information to create sample weights, (ii) observations with missing employment data, and (iii) observations who are employed but who have missing WFH data. We then drop any individual who had one of their observations (either February or the current month) deleted in either of the steps above. These selection criteria mean that 4.8 percent of individuals in the original sample are dropped, yielding a final sample of 66,282 individuals. Among the observations that were dropped, the most common category was individuals who were employed but absent from work in the current month according to the CPS definition: 1,840 individuals fell into this group across all survey waves. These individuals were not asked the questions on days worked and commuting. Table A.1.1 displays the breakdown of the sample sizes across survey months.

Table A.1.1: Sample Sizes by Month in the RPS

Month	Number of Observations	Number of Employed
02/20	66282	49901
05/20	4775	2567
06/20	9042	5212
07/20	7943	4917
08/20	6464	4107
09/20	8116	5272
10/20	3180	2136
11/20	3472	2321
12/20	3458	2241
01/21	3476	2312
02/21	3466	2325
03/21	3407	2266
04/21	3171	2168
05/21	3140	2095
06/21	3170	2213

Source: Real-Time Population Survey, ages 18-64. Sample sizes are unweighted.

As described in the body of the paper, we asked Qualtrics to administer the survey to a sample of respondents who match the US population along a few broad demographic characteristics: gender, five age bins (18-24, 25-34, 35-44, 45-54, 55-64), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, other), education (high school or less, some college or associate degree, bachelor degree or more), married or not, number of children in the household (0, 1, 2, 3 or more), three 2019 annual household income bins (<$50k, $50k-100k, >$100k) and four census regions. Using the iterative proportional fitting (raking) algorithm of Deming and Stephan (1940) we construct sampling weights to ensure the RPS matches the CPS sample proportions for the same set of demographic characteristics as those included in the Qualtrics sampling targets. We do however use more disaggregated categories for education and marital status, and interact all categories with gender. In particular, for education we distinguish between less than high school, high school graduate or equivalent, some college but no degree, associate's degree in college, bachelor's degree, and graduate degree. For marital status we distinguish between married + spouse present, divorced, never married, and 'other'. We also condition on relationship status (spouse living in the same household, partner living in the same household, other). In addition, our sampling weights also replicate the employment rate in February 2020 in the CPS, as well as the employed-at-work rates, the employment rates and the labor force participation rates in each of the subsequent months.[1] We match these key labor market statistics not only in the aggregate, but also conditional on demographic characteristics. More specifically, we match the employed at work rate, the employment rate and the labor force participation rate in the current month rates by gender, age (18-24, 25-34, 35-44, 45-54, 55-64), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, all other racial and ethnic groups), education (high school or less, some college or associate degree, bachelor degree or more), marital status (married + spouse present, never married, other), relationship status (spouse living in the same household, partner living in the same household, other), presence of children in the household (yes or no), and region (Midwest, Northeast, South and West using the Census definition).

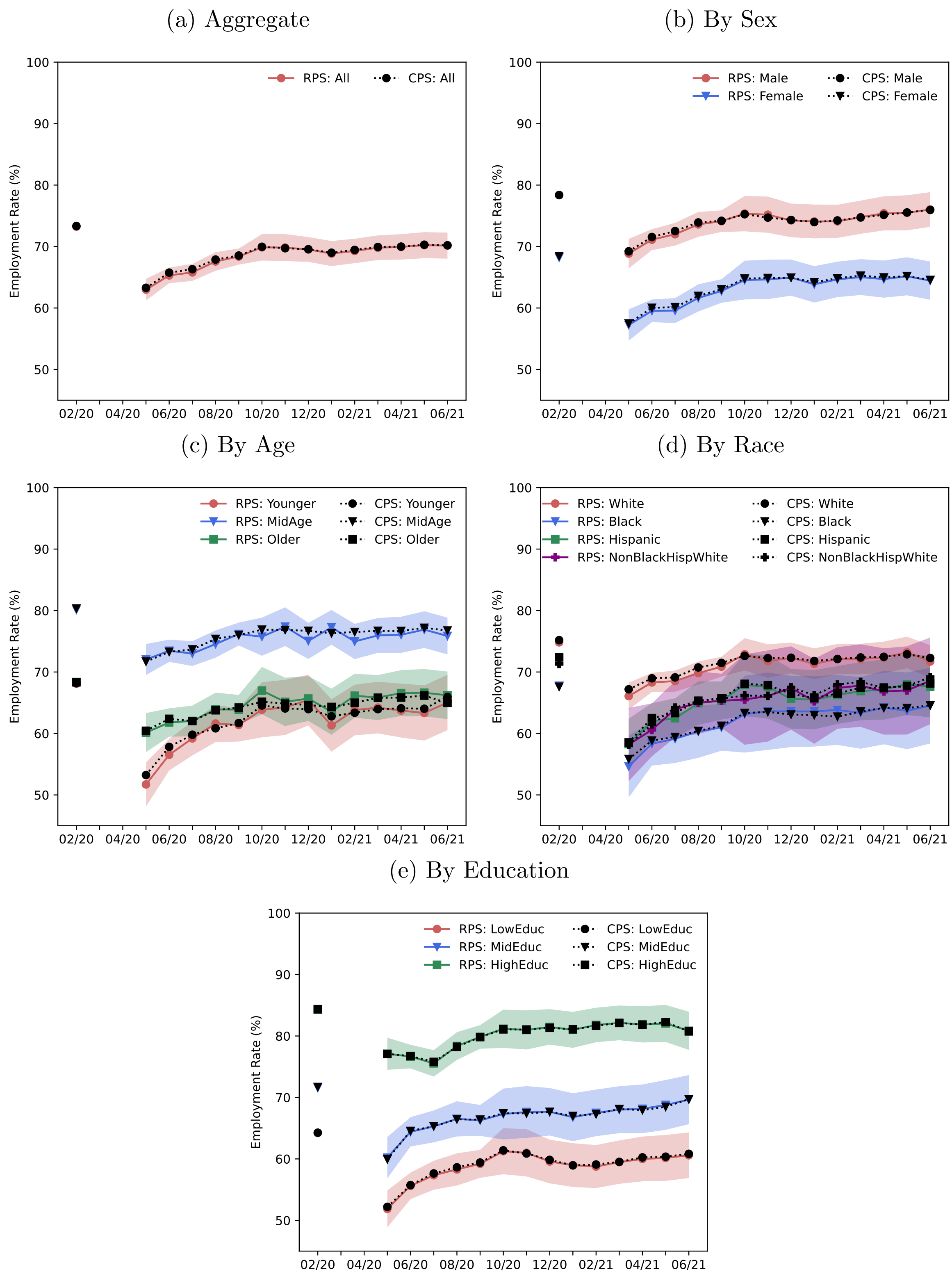
To give an impression how accurate the weighting scheme works, Figure A.1.1 compares employment rates in the CPS, which are included as a target in the construction of the RPS sample weights, with the corresponding employment rates in the RPS in the aggregate and for selected demographic groups.

Another key dimension of interest in our analysis is the industry composition, which is however not included in our weighting procedure. Hence, the industry employment data is not mechanically replicated in the RPS by the sample weights. Figure A.1.3 compares the industry composition of employment in the CPS and RPS for all sample months, and shows that the two datasets align closely with the correlation between the two always being at least 0.7. The industries in which the RPS most undershoots the CPS are "professional and business

[1] Another use of the RPS, discussed in Bick and Blandin (2021), is to produce real-time labor market statistics in advance of the monthly CPS release. For this purpose, the current month CPS statistics are not yet available for targeting in the raking algorithm. The real-time forecasts of employment and other labor market statistics are therefore based on alternative weights that use information from the CPS for the preceding month. Our goal in this paper is to provide the most accurate ex-post measurement of commuting behavior in the pandemic, which is why we prefer to target CPS labor market statistics for the same month.

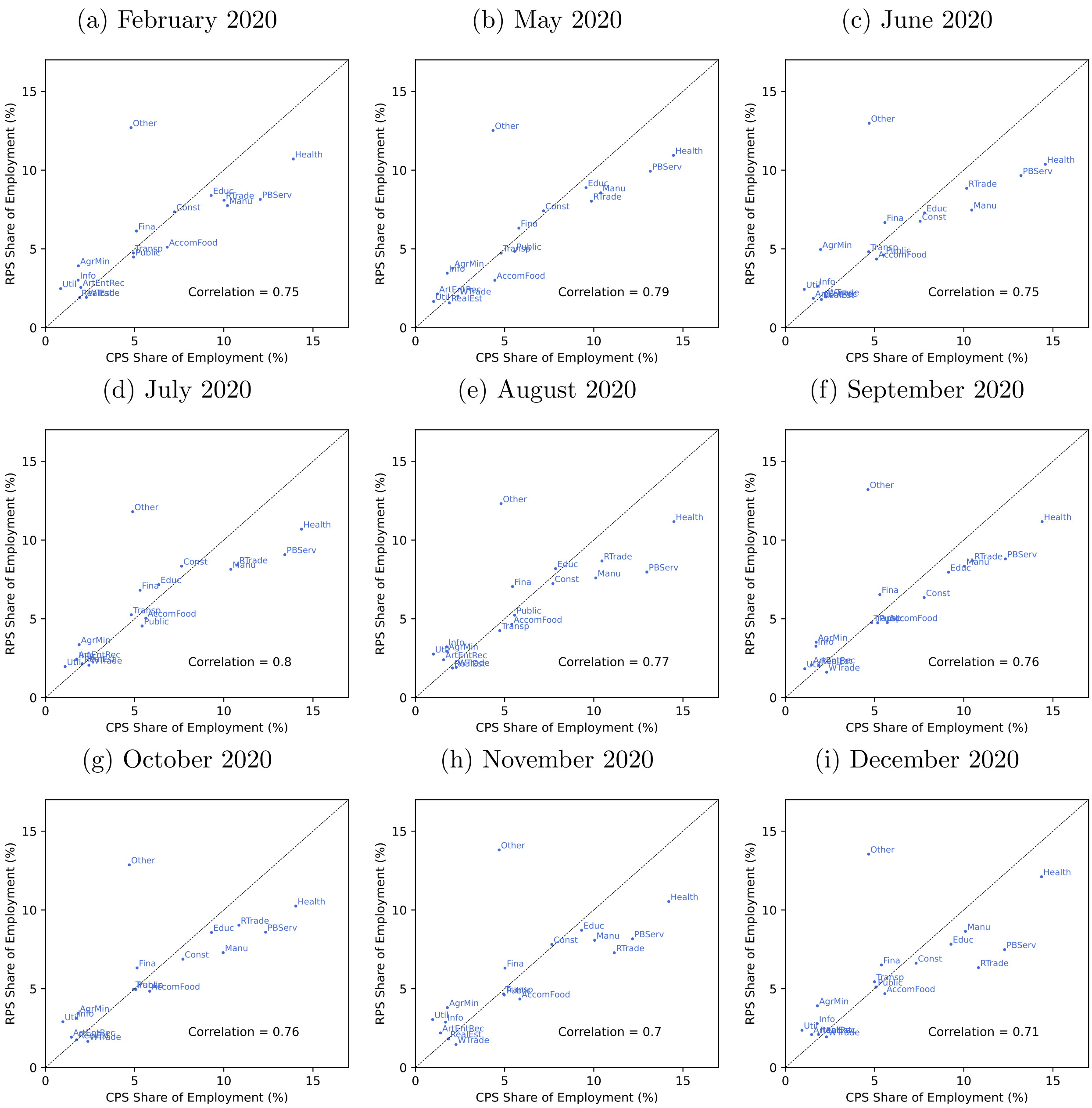
services" (PBServ) and "health services" (Health); the largest RPS overshoot relative to the CPS is in "Other services" (other). We believe that these disparities may be attributable to some individuals in the service sector not knowing which industry to select, leading to under-counts in particular service industries and an over-count in the "other services" industry.

Figure A.1.1: Employment Rates in the CPS and RPS



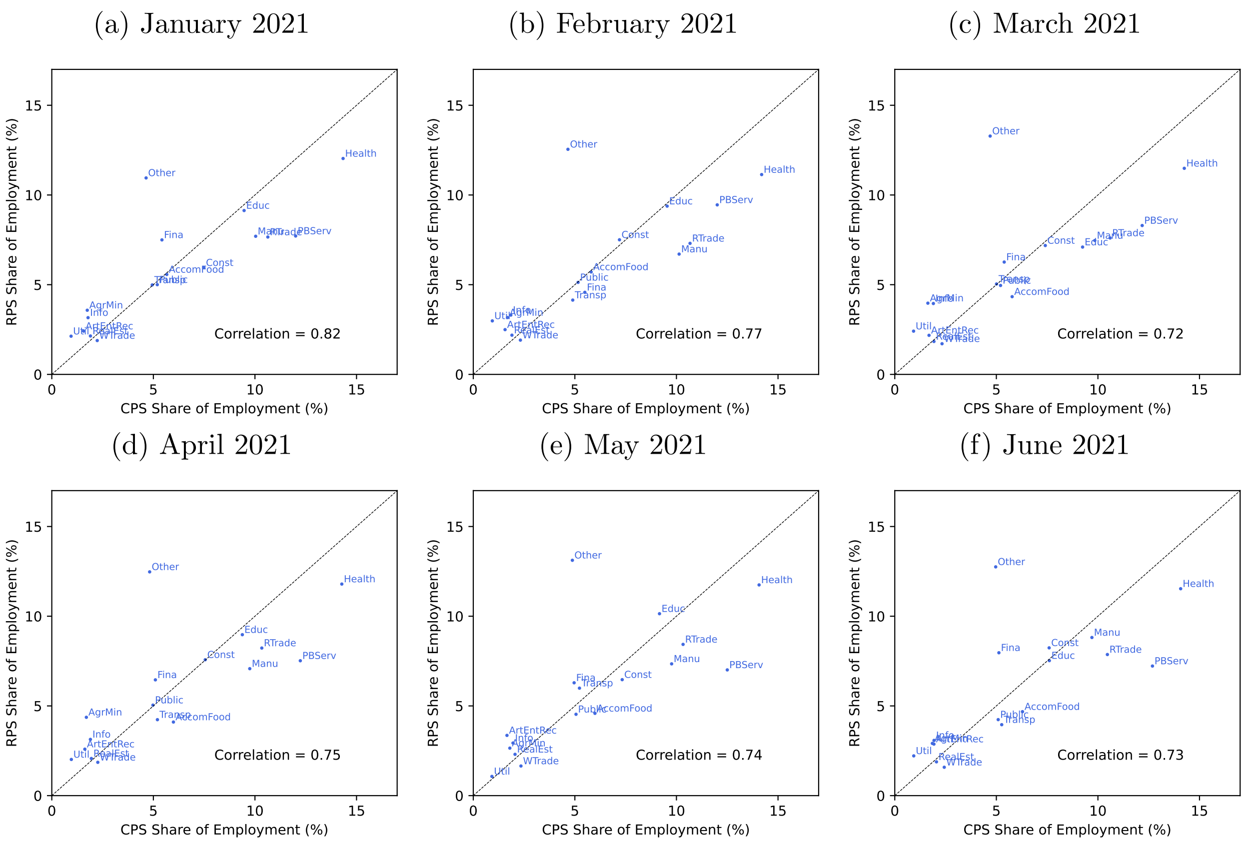
Source: Real-Time Population Survey, Current Population Survey, ages 18-64. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

FIGURE A.1.2: Industry Composition in the CPS and RPS in 2020



Source: Real-Time Population Survey, Current Population Survey, ages 18-64. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month. Definitions of industry groups are provided in Appendix A.3.

Figure A.1.3: Industry Composition in the CPS and RPS in 2021



Source: Real-Time Population Survey, Current Population Survey, ages 18-64. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month. Definitions of industry groups are provided in Appendix A.3.

A.2 Sample Statistics

Before pooling survey data from different interviews waves within the same month, we adjust the weights from the raking algorithm described above as suggested in Potthoff et al. (1992):

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

Sample proportions and their standard deviations are then calculated as

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

A.3 Definition of Demographic Groups and Industries

Several figures in the paper report results separately for different demographic groups and industries. Demographic groups are defined as follows:

- Age
  - **Younger**: Ages 18-29
  - **Mid Age**: Ages 30-49
  - **Older**: Ages 50-64
- Race and Ethnicity
  - **Black**: Identify as Black and not Hispanic
  - **Hispanic**: Identify as Hispanic
  - **White**: Identify as White and not Hispanic
  - **NonBlackHispWhite** or **Non B/H/W**: All other racial and ethnic groups
- Education
  - **Low Educ**: High School degree or less
  - **Mid Educ**: Some college or associates degree, but no Bachelor's degree
  - **High Educ**: Bachelor's degree or more
- 2019 Household Income

- **Low Inc**: \$0 – \$49,999
- **Mid Inc**: \$50,000 – \$100,000
- **High Inc**: \$100,000 or more

- Children
  - **Children**: Child under age 18 lives in household
  - **No Children**: No child under age 18 lives in household

Industries correspond to the 18 major industries in the NAICS, except that we combine Agriculture (NAICS=11) and Mining (NAICS=21) due to small sample sizes. The resulting 17 industries are defined as follows:

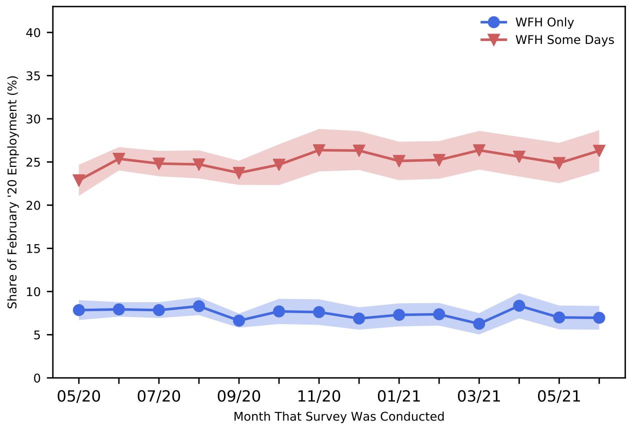
- **AgriMin**: NAICS = 11-21. Agriculture, Forestry, Fishing and Hunting and Mining, Quarrying, and Oil and Gas Extraction
- **Util**: NAICS = 22. Utilities
- **Const**: NAICS = 23. Construction
- **Manu**: NAICS = 31-33. Manufacturing
- **WTrade**: NAICS = 42. Wholesale Trade
- **RTrade**: NAICS = 44-45. Retail Trade
- **Transp**: NAICS = 48-49. Transportation and Warehousing
- **Info**: NAICS = 51. Information
- **Fina**: NAICS = 52. Finance and Insurance
- **RealEst**: NAICS = 53. Real Estate and Rental and Leasing
- **PBServ**: NAICS = 54-56. Professional, Scientific, and Technical Services and Management of Companies and Enterprises and Administrative and Support and Waste Management and Remediation Services
- **Educ**: NAICS = 61. Educational Services
- **Health**: NAICS = 62. Health Care and Social Assistance
- **ArtEntRec**: NAICS = 71. Arts, Entertainment, and Recreation
- **AccomFood**: NAICS = 72. Accommodation and Food Services

- **Other**: NAICS = 81. Other Services (except Public Administration)
- **Public**: NAICS = 99. Federal, State, and Local Government, excluding state and local schools and hospitals and the U.S. Postal Service (OES Designation)

Finally, for about 11 percent of those employed in February 2020 in the early May wave information is missing. In that wave we did not collect industry for those employed in February 2020 but who had a new job in the reference week or were not employed in the reference week. The exception are those who were on layoff in the reference week from their February job. Starting with the late May wave, industry in for February 2020 is available for everyone employed in February 2020.

A.4 February WFH Across Survey Months

FIGURE A.4.4: February WFH Rates By Month the Survey Was Conducted



Source: Real-Time Population Survey, ages 18-64, February 2020 observations. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

The RPS asks individuals about employment and WFH outcomes in February 2020, just prior to the COVID-19 pandemic. A potential concern is whether respondents are able to accurately answer such retrospective questions, particularly for later months in the survey. One indication of recall difficulties would be if February statistics varied widely or systematically across months that the survey was conducted.

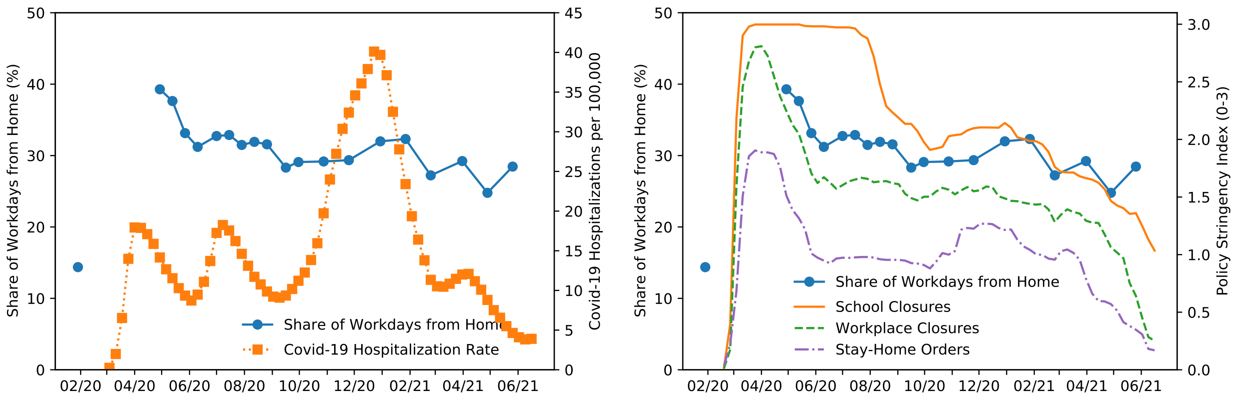
To examine whether this is the case, Figure A.4.4 displays rates of WFH in February separately for various months that the survey was conducted. Reassuringly, we find that reported WFH outcomes in February are fairly stable across survey months. For example, 7.9 percent of individuals surveyed in May 2020 reported to be WFH Only in February 2020, compared with 7.0 percent of individuals surveyed in June 2021. These differences are not statistically significant at the 5 percent level; neither are differences between any two other months in the survey. The share of partial WFH workers are also fairly stable across months, though there is a bit more variation with this variable. For example, 22.9 percent of individuals surveyed in May 2020 reported to be partial WFH in February 2020, compared with 26.4 percent of individuals surveyed in June 2021. This difference is significant at the 5 percent level. Overall, the share of workers that are partial WFH is lower in May 2021 than other months; no two months from June-onward are statistically different from one another at the 5 percent level.

B Additional WFH Facts

B.1 The Evolution of WFH and the COVID-19 Pandemic

FIGURE B.1.1: The Evolution of WFH and the COVID-19 Pandemic

(a) WFH and Hospitalizations (b) WFH and Containment Policies



Source: Real-Time Population Survey (left panel), COVID Tracking Project (left panel), Oxford COVID-19 Government Response Tracker (OxCGRT) (right panel). *Left panel:* Share of workdays from home is the ratio of (weighted) total days WFH to total workdays in the RPS. See Appendix A.1 for sample sizes by month. COVID-19 Hospitalization Rate is the number of individuals currently hospitalized with COVID-19 per 100,000. *Right panel*: Population-weighted weekly averages of U.S. state-level OxCGRT stringency scores between 0 and 3. School Closures; [1], recommended; [2], required at some levels (e.g., high school or public schools); [3], required at all levels. Workplace Closures: [1], recommended; [2], required for some sectors; [3], required for all non-essential workplaces. Stay-Home Orders: [1], recommendation to stay at home; [2], requirement with some exceptions (daily exercise, essential trips); [3], requirement with minimal exceptions.

The initial shift towards WFH in response to the virus outbreak was very pronounced. However, WFH did not co-move nearly as strongly with the pandemic during the second half of 2020. Figure B.1.1a displays the weekly COVID-19 hospitalization rate for the U.S., together with the share of all workdays in which workers worked from home in each of the RPS waves. After rising from 14.4 percent in February 2020 to 39.3 percent in May 2020, the WFH share of workdays dropped to 31.2 percent during the May-June 2020 decline in hospitalizations after the first wave. During the second wave of the pandemic in the late summer of 2020, the WFH share of workdays rose only modestly to 32.9 percent, falling back to 28.3 percent in mid-September. During the more severe third wave in the winter of 2020/2021, the WFH share of workdays again increased only moderately, to a local peak of 32.3 percent in February 2021. In June 2021, COVID-19 hospitalizations had declined to their lowest level since March 2020, yet the WFH share of workdays remained at 28.5 percent, double the pre-pandemic rate from February 2020 and essentially unchanged relative to Fall 2020.

One possible reason for the larger initial rise in WFH is the greater stringency of virus containment policies in the first wave of the pandemic in the U.S. Figure B.1.1b plots stringency indicators for the policies most directly relevant for WFH: stay-at-home-orders, workplace closures, and school closures. The series shown are population-weighted averages of state-level scores between 0 and 3 in the Oxford Government Response Tracker : 0 means no policies are in place; '1' means there is a recommendation to stay at home or close schools/workplaces; '2' means government restrictions are in place but with broad exceptions; and '3' means restrictions with only minimal exceptions.[2] Figure B.1.1b shows that containment policies were stricter and broader-based between late March and April than afterwards. After reopening the economy in May and June, local governments relied mainly on recommendations to stay at home, while workplace closures were more limited and more targeted. Schools in the U.S. remained closed throughout the summer vacation, with many reopening only virtually in the fall. The third wave saw the return of stricter containment measures in some parts of the U.S., but there was no broad-based return to the stricter policies of the first months of the pandemic. Social distancing policies were largely eliminated in the spring and summer of 2021, yet in June 2021 WFH remained essentially unchanged relative to Fall 2020 levels.

[2] See Hale, T., T. Atav, L. Hallas, B. Kira, Phillips, A. Petherick, and A. Pot (2020). *Variation in US states' responses to COVID-19.* BSG-WP-2020/034. Blavatnik School of Government.

B.2 Change in Commuting Volume in the RPS

FIGURE B.2.1: Decomposition of Aggregate Change in Commuting

Source: Real-Time Population Survey, ages 18-64. All series are expressed as log changes relative to February 2020. The sample for the Employment Rate series is all individuals age 18-64. The sample for the Days Worked per Week and the Share of Work Days Commuted series are employed individuals age 18-64. The numbers corresponding to the graph are also given in Table B.2.1.

Figure 3a in the main text displays the log change in aggregate weekly commuting trips relative to February 2020 in the RPS. Aggregate weekly commuting trips are the product of the number of workers, the average days worked per week per worker, and the average share of workdays commuted. Table B.2.1 displays the log changes in each of these components of aggregate commuting trips, which are also shown in Figure B.2.1.

In May 2020, aggregate commuting fell by 50.9 log points relative to February 2020. Of this, 15.2 log points (29.9 percent) was due to lower employment, while 2.7 log points (5.3 percent) was due to fewer days worked per worker per week. The remaining 33.0 log points (64.8 percent) was due to a reduction in the share of work days commuted relative to February, i.e. an increase in WFH. By June 2021, aggregate commuting had recovered relative to May 2020, but was still 24.2 log points lower than just before the pandemic. Of this, 5.2 log points (21.5 percent) was due to lower employment, and 1.0 log points (4.1 percent) was due to fewer days worked per worker per week. The remaining 18.0 log points (74.4 percent) was due to a reduction in the share of work days commuted relative to February 2020.

Table B.2.1: Change in Log of Aggregate Commuting Trips

	Weekly Commuting Trips	Employment Rate	Days Worked / Week	Share of Work Days Commuted
05/20	-50.9	-15.3	-2.6	-33.0
	(4.3)	(0.9)	(2.9)	(6.0)
06/20	-38.4	-11.7	-2.9	-23.8
	(3.3)	(0.7)	(2.4)	(4.4)
07/20	-38.2	-10.9	-3.0	-24.2
	(3.5)	(0.7)	(2.7)	(4.9)
08/20	-33.3	-8.3	-2.4	-22.6
	(3.9)	(0.8)	(3.1)	(5.4)
09/20	-29.7	-7.1	-2.1	-20.5
	(3.5)	(0.7)	(2.6)	(4.6)
10/20	-24.0	-4.9	-0.3	-18.9
	(5.6)	(1.1)	(4.4)	(7.5)
11/20	-25.8	-5.0	-1.9	-19.0
	(5.6)	(1.1)	(4.4)	(7.5)
12/20	-27.7	-5.4	-3.1	-19.2
	(5.2)	(1.0)	(4.2)	(7.1)
01/21	-32.6	-6.4	-3.2	-23.0
	(5.2)	(1.0)	(4.2)	(7.1)
02/21	-32.2	-5.8	-3.0	-23.5
	(5.0)	(1.0)	(3.8)	(6.8)
03/21	-21.9	-5.0	-0.7	-16.3
	(5.2)	(1.0)	(4.2)	(7.0)
04/21	-26.1	-4.8	-2.2	-19.1
	(5.3)	(1.1)	(4.3)	(7.2)
05/21	-18.4	-4.4	-1.1	-13.0
	(5.5)	(1.1)	(4.3)	(7.2)
06/21	-24.2	-5.2	-1.0	-18.0
	(5.5)	(1.1)	(4.4)	(7.3)

Source: Real-Time Population Survey, ages 18-64. All series are expressed as log changes relative to February 2020. The sample for the Employment Rate series is all individuals age 18-64. The sample for the Days Worked per Week and the Share of Work Days Commuted series are employed individuals age 18-64.

B.3 WFH Across Demographic Groups

Figures B.3.1 and B.3.2 display results for all months in the RPS sample, and for all three WFH statuses: WFH Only, WFH Some Days, and Commute Only.

We highlight a few takeaways from the figures showing WFH Only shares (first column). First, for every demographic group, WFH Only increased from February to May 2020. Second, every demographic group saw a decline in WFH Only from May 2020 to June 2021. Third, although there were some differences in WFH Only shares before the pandemic, the differences are much larger in the pandemic.

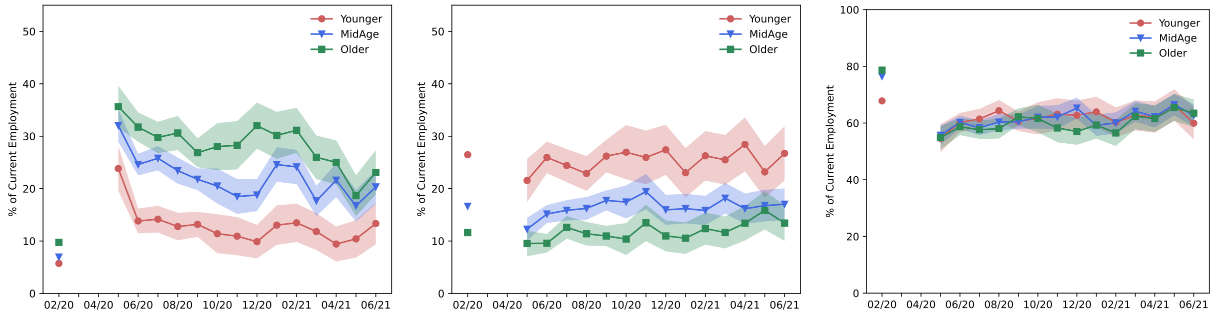
Next, we highlight the main takeaways from the figures showing the partial WFH rates (middle column). First, for every demographic group, partial WFH was more common than WFH Only prior to the pandemic. Second, for essentially all demographic groups, changes in the partial WFH rates during the pandemic were modest relative to changes in the WFH Only shares.

Finally, we emphasize the key takeaways from figures showing the Commute Only rates (last column). First, for every demographic group a large majority of workers commuted every workday prior to the pandemic. There was little heterogeneity in Commute Only rates across demographic groups; the largest exception to this was that younger workers (aged 18-29) had a Commute Only rate that was about 10 percentage points (13 percent) lower than workers aged 30 and over. Second, for every demographic group the share of workers who commuted only fell from February to May 2020, although there was sizable heterogeneity in this change across demographic groups. Third, by June 2021 Commute Only rates had recovered almost completely to February 2020 levels for some groups – low education (high school degree or less), low or medium income (2019 household income less than $100k) – but had only recovered slightly for others – high education (bachelor's degree or more), high income (2019 household income exceeding $100k), and individuals with no children under age 18 in the household.

FIGURE B.3.1: Commuting Status by Selected Worker Characteristics - Part I

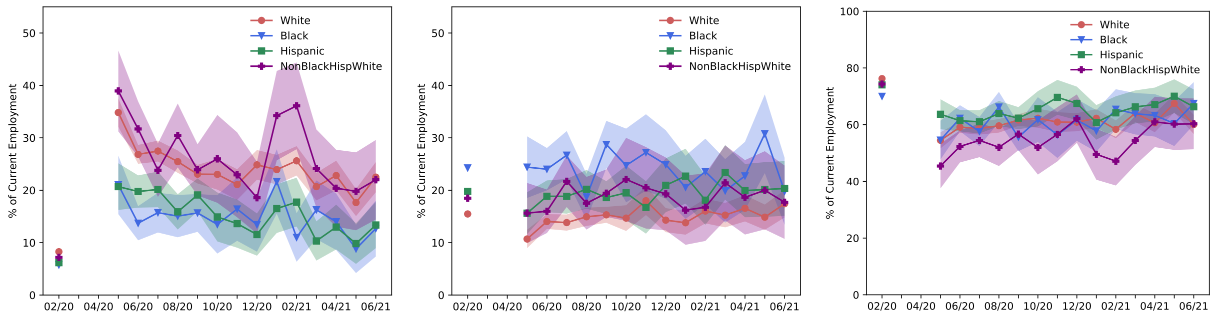
By Age

(a) WFH Only (b) WFH Some Days (c) Commute Only



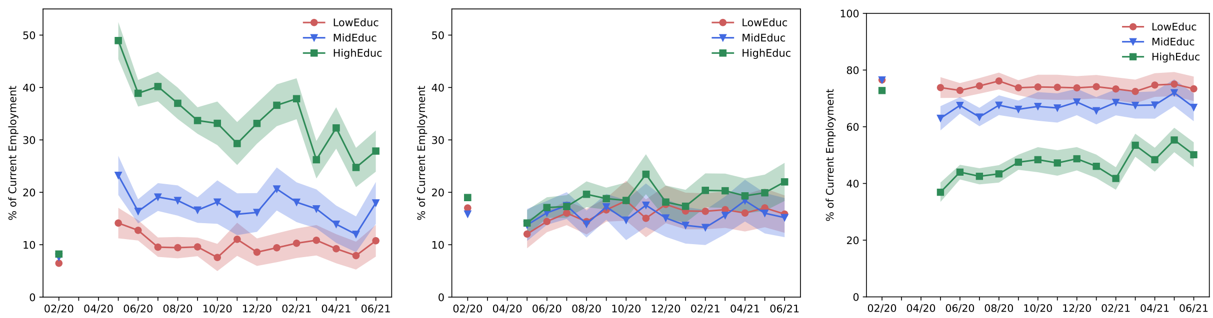
By Race/Ethnicity

(d) WFH Only (e) WFH Some Days (f) Commute Only



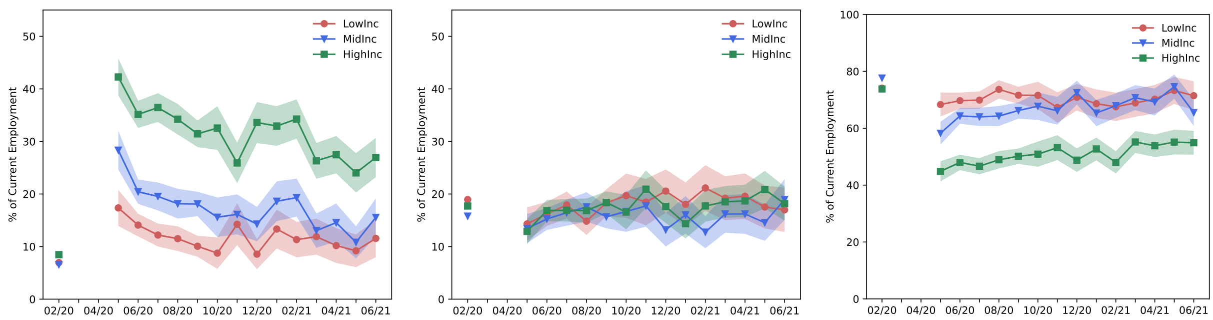
By Education

(g) WFH Only (h) WFH Some Days (i) Commute Only



By Household Income

(j) WFH Only (k) WFH Some Days (l) Commute Only

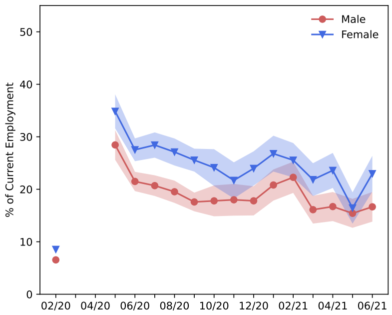


Source: Real-Time Population Survey, ages 18-64. The sample is individuals employed in the relevant month. The figure shows the share of WFH Only workers (left panels), partial-WFH workers (middle panels) and Commute Only workers (right panels) each month. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

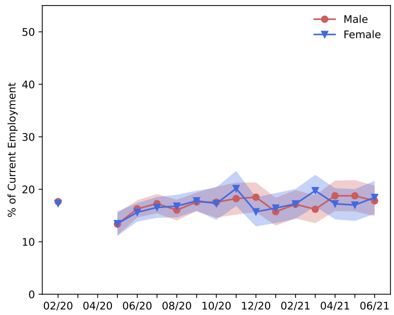
Figure B.3.2: Commuting Status by Selected Worker Characteristics - Part II

By Gender

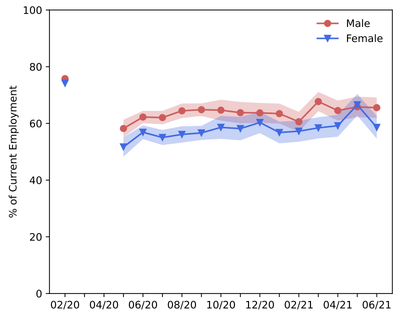
(a) WFH Only



(b) WFH Some Days

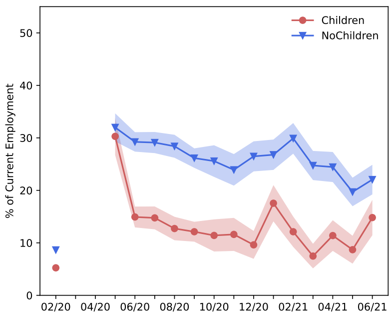


(c) Commute Only

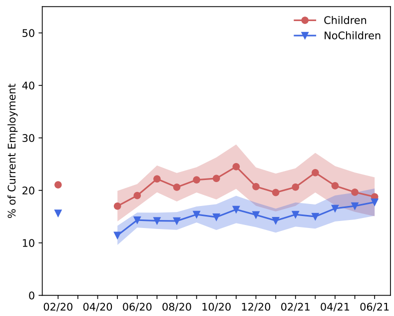


By Presence of Children

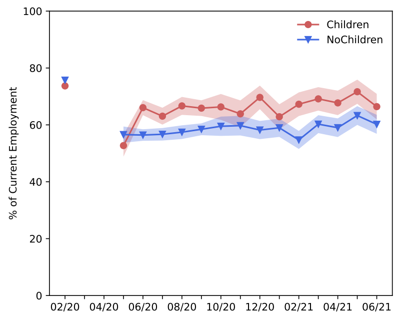
(d) WFH Only



(e) WFH Some Days



(f) Commute Only



Source: Real-Time Population Survey, ages 18-64. The sample is individuals employed in the relevant month. The figure shows the share of WFH Only workers (left panels), partial-WFH workers (middle panel) and Commute Only workers (right panels) each month. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

B.4 Conditional WFH Probabilities

Section 2.2 in the main text documents substantial differences in the increases in WFH Only shares between demographic groups. Table B.4 presents results from linear probability model for WFH Only that conditions on all worker characteristics for February 2020, May 2020, and June 2020. As in Figure 2, we restrict the samples in May 2020 and June 2021 to those who were also employed in February 2020. Overall, the results from the regression analysis are qualitatively consistent with to the unconditional group comparisons discussed in the main text.

Column (1) predicts WFH Only status in February 2020 using information on gender, age, race and ethnicity, education, household income, the presence of children, and industry. Workers who were female, older, white, had lower household income, and had no children in the home were more likely to WFH Only in February 2020. However, the size of the coefficients tend to be fairly small and the R^2 is only 0.025, indicating that demographics and industry are poor predictors of WFH prior to the pandemic.

Column (2) predicts WFH Only status in May 2020, near the onset of the pandemic. There is no change in the signs on the coefficients related to gender, age, race and ethnicity, and children, but the magnitudes increase markedly for all these variables except sex. Education becomes a much stronger predictor of WFH in May 2020: in particular, the probability of WFH only for workers with a Bachelor's degree or more is 18.7 percentage points higher than for workers with some college (the reference group), and 22.4 percentage points higher than for those with a high school degree or less, all else equal. The magnitude of the coefficients on household income also become larger in May 2020 compared to before the pandemic, though these estimates are only marginally significant. The R^2 increases from 0.025 in February 2020 to 0.216 in May 2020, indicating that a larger share of the variance in WFH Only is accounted for by demographics and industries.

Column (3) predicts WFH Only status for June 2021, the final month of our sample. Between May 2020 and June 2021, the intercept term declines in magnitude, though it remains elevated compared to before the pandemic. Most of the coefficients decline in magnitude; notably, the coefficient on Bachlor's degree or more declines from 0.187 in May 2020 to 0.053 in June 2021. One exception to this pattern is the coefficient on females, which increases in magnitude and becomes strongly significant.

Figure 11b in the main text documents substantial differences between demographic groups in expected WFH one year ahead relative to pre-pandemic WFH rates. Table B.4.2 presents results from linear probability model for WFH before the pandemic and expected WFH after the pandemic that conditions on all worker characteristics and industries. Overall, most of the results from the regression analysis are qualitatively consistent with the unconditional group

Table B.4.1: Predictors of WFH Only: Linear Probability Model

	02/20	05/20	06/21
Constant	0.032***	0.225***	0.197***
	(0.006)	(0.045)	(0.046)
Female	0.021***	0.014	0.046***
	(0.002)	(0.017)	(0.018)
Age 18-29	-0.013***	-0.053**	-0.073***
	(0.003)	(0.023)	(0.023)
Age 50-64	0.019***	0.046**	-0.017
	(0.003)	(0.021)	(0.021)
Black	-0.012***	-0.073***	-0.035
	(0.004)	(0.028)	(0.028)
Hispanic	-0.005	-0.047**	-0.035
	(0.003)	(0.023)	(0.024)
Non-Black/Hispanic/White	-0.004	-0.000	0.005
	(0.004)	(0.031)	(0.031)
High school or less	-0.005	-0.037*	-0.033
	(0.003)	(0.022)	(0.023)
Bachelors or more	-0.001	0.187***	0.053**
	(0.003)	(0.022)	(0.022)
2019 HH income: \$0-\$50k	0.010***	-0.037	0.018
	(0.003)	(0.023)	(0.024)
2019 HH income: \$100k +	0.002	0.045**	0.041**
	(0.003)	(0.020)	(0.021)
Children	-0.025***	-0.055***	-0.066***
	(0.003)	(0.019)	(0.019)
Industry dummies	Yes	Yes	Yes
Observations	49,901	2,530	2,083
R^2	0.025	0.216	0.102

Source: Real-Time Population Survey, ages 18-64. Estimates from a linear probability model. The sample is all individuals employed in February 2020. Definitions of demographic and industry groups are provided in Appendix A.3. The regressions are weighted based on sample weights, see Appendix A.1.

Table B.4.2: Predictors of WFH: Linear Probability Model

	WFH Only		WFH Some Days	
	02/20	Expected	02/20	Expected
Constant	0.032***	0.077***	0.084***	0.208***
	(0.006)	(0.014)	(0.009)	(0.018)
Female	0.021***	0.034***	0.002	0.014*
	(0.002)	(0.006)	(0.003)	(0.007)
Age 18-29	-0.013***	-0.018**	0.098***	0.090***
	(0.003)	(0.007)	(0.004)	(0.010)
Age 50-64	0.019***	0.001	-0.031***	-0.036***
	(0.003)	(0.007)	(0.004)	(0.009)
Black	-0.012***	-0.014	0.060***	0.074***
	(0.004)	(0.009)	(0.005)	(0.012)
Hispanic	-0.005	-0.012	0.013***	0.010
	(0.003)	(0.008)	(0.005)	(0.010)
Non-Black/Hispanic/White	-0.004	0.004	0.004	0.070***
	(0.004)	(0.010)	(0.006)	(0.013)
High school or less	-0.005	-0.017**	0.002	-0.042***
	(0.003)	(0.007)	(0.005)	(0.010)
Bachelors or more	-0.001	-0.002	0.038***	0.075***
	(0.003)	(0.007)	(0.004)	(0.009)
2019 HH income: \$0-\$50k	0.010***	0.030***	0.013***	0.002
	(0.003)	(0.008)	(0.005)	(0.010)
2019 HH income: \$100k +	0.002	0.011*	0.028***	0.036***
	(0.003)	(0.007)	(0.004)	(0.009)
Children	-0.025***	-0.029***	0.033***	-0.015*
	(0.003)	(0.006)	(0.004)	(0.008)
Industry dummies	Yes	Yes	Yes	Yes
Observations	49,901	14,602	49,901	14,602
R^2	0.025	0.032	0.043	0.055

Source: Real-Time Population Survey, ages 18-64. Estimates from a linear probability model. The sample is all individuals employed in February 2020 and in the reference week. Definitions of demographic and industry groups are provided in Appendix A.3. The regressions are weighted based on sample weights, see Appendix A.1.

comparisons discussed in the main text, but we also highlight a few notable differences. Our most important takeaways from the unconditional averages in Figure 11b are that most workers expect larger increases in WFH Some Days than WFH Only, and that expected changes in WFH Some Days vary more across demographic groups than expected changes in WFH Only; the regression results in this section confirm that these takeaways are also reflected in conditional averages.

> *Sex:* Before the pandemic, the WFH Only coefficient for women was positive, and this coefficient increases slightly in the year ahead expectations. The coefficient for WFH Some Days is small and less significant. These estimates are qualitatively consistent with slightly higher unconditional WFH rates for women in Figure 11b.
>
> *Age:* Before the pandemic, the WFH Only coefficient for workers under 30 was negative and the coefficient for workers over 50 was positive. For year ahead expectations, the coefficient for young workers remains similar, but the coefficient for older workers becomes insignificant. Conversely, in the WFH Some Days regression, the coefficient on young workers is strongly positive and the coefficient on older workers is strongly negative, both before the pandemic and in year ahead expectations. Together, these estimates paint a somewhat different picture from Figure 11b, which shows that on average older workers expect larger WFH increases relative to before the pandemic. The regression results therefore indicate that the differences in expected WFH changes by age are likely accounted for by other variables correlated with age.
>
> *Race and ethnicity:* Before the pandemic, the WFH Only coefficients for Black, Hispanic, and Non-Black/Hispanic/White were all negative and small in magnitude, with only the Black coefficient being significant. These estimates are similar in year ahead expectations. In the WFH Some Days regression, all three coefficients are positive before the pandemic. The coefficients for Black and Hispanic are fairly similar in the year ahead expectations. The notable change is that the Non-Black/Hispanic/White coefficient becomes large and significant. Overall, these results are qualitatively consistent with the results in Figure 11b, which shows similar average expected changes in WFH for White, Black, and Hispanic workers, but much larger changes for Non-Black/White/Hispanic workers.
>
> *Education:* Before the pandemic, the WFH Only coefficients for education were small, and they remain so in the year ahead expectations. In the WFH Some Days regression, the coefficient on High school degree or less was close to zero, while Bachelor's degree or more was positive and significant. In the year ahead expectations, the coefficient on High school degree or less becomes significantly negative and the coefficient on Bachelor's degree or more becomes more positive. Overall, these result are qualitatively consistent with the

results in Figure 11b, which shows expanding gaps in WFH by education, primarily coming from WFH Some Days.

Household income: Before the pandemic, the WFH Only coefficients for lower income and higher income households were both small but positive. In the year ahead expectations, these coefficients remain positive but increase in magnitude. In the WFH Some Days regression, the coefficients on lower and higher income households were also positive and were larger than the pre-pandemic coefficients from the WFH Only regression. In the year ahead expectations for WFH Some Days, the coefficient for lower income households falls to near zero, while the coefficient for high income households remains fairly stable. These results diverge somewhat from the results in Figure 11b, which shows expanding gaps in WFH by household income driven largely by WFH Some Days. The regression results therefore indicate that the differences in expected WFH changes by household income are likely accounted for by other variables correlated with houseohld income.

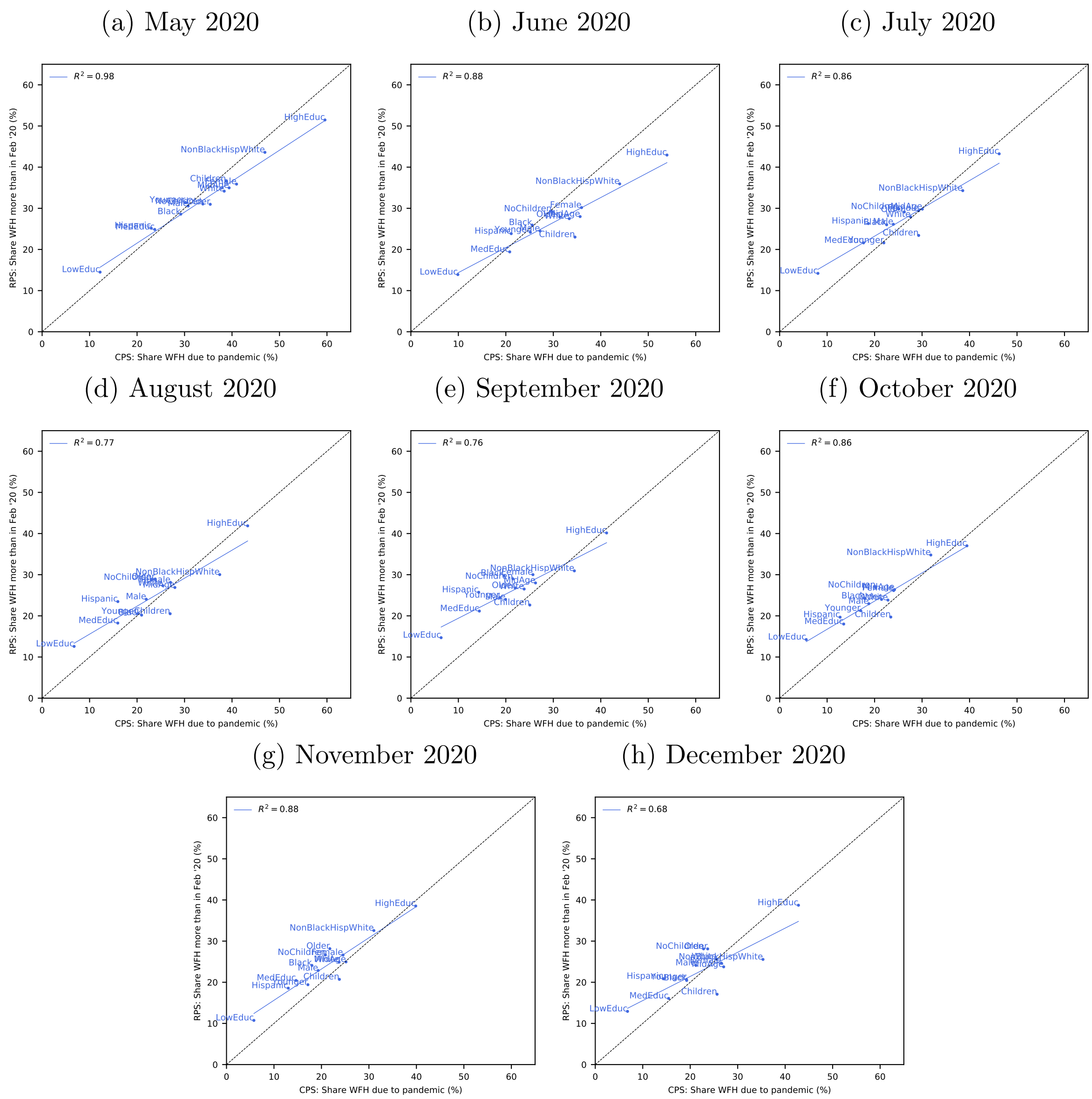
Presence of children: Before the pandemic, the WFH Only coefficient for the presence of children was significantly negative, and this coefficient is fairly stable in the year ahead expectations. In the WFH Some Days regression, the coefficient on presence of children was significantly positive before the pandemic, but becomes negative in year ahead expectations. These estimates are qualitatively consistent with the results in Figure 11b, which shows expanding gaps in WFH by presence of children, driven primarily by differences in WFH Some Days.

B.5 Work from Home Comparisons in the RPS and CPS

Section 2.2 documents large differences in the increases in WFH Only shares between demographic groups during the pandemic in the RPS. Here, we assess the extent to which heterogeneity in WFH in the RPS is consistent with heterogeneity in WFH in the CPS. Starting in May 2020, the CPS added the following question to the survey questionnaire: *"At any time in the last 4 weeks, did (you/name) telework or work at home for pay because of the coronavirus pandemic?"*, followed by a yes/no answering option. Data based on this question is not directly comparable to WFH data in the RPS for several reasons (see Section 2.3 for a discussion of the WFH question asked by the CPS and how it compares to WFH information in the RPS). However, the RPS does provide information on whether individuals worked a higher fraction of days from home last week compared to a typical week in February 2020, just prior to the pandemic. Figures B.5.1, B.5.2, B.5.3, and B.5.4 compare these measures in the RPS and CPS by demographic group and industry.

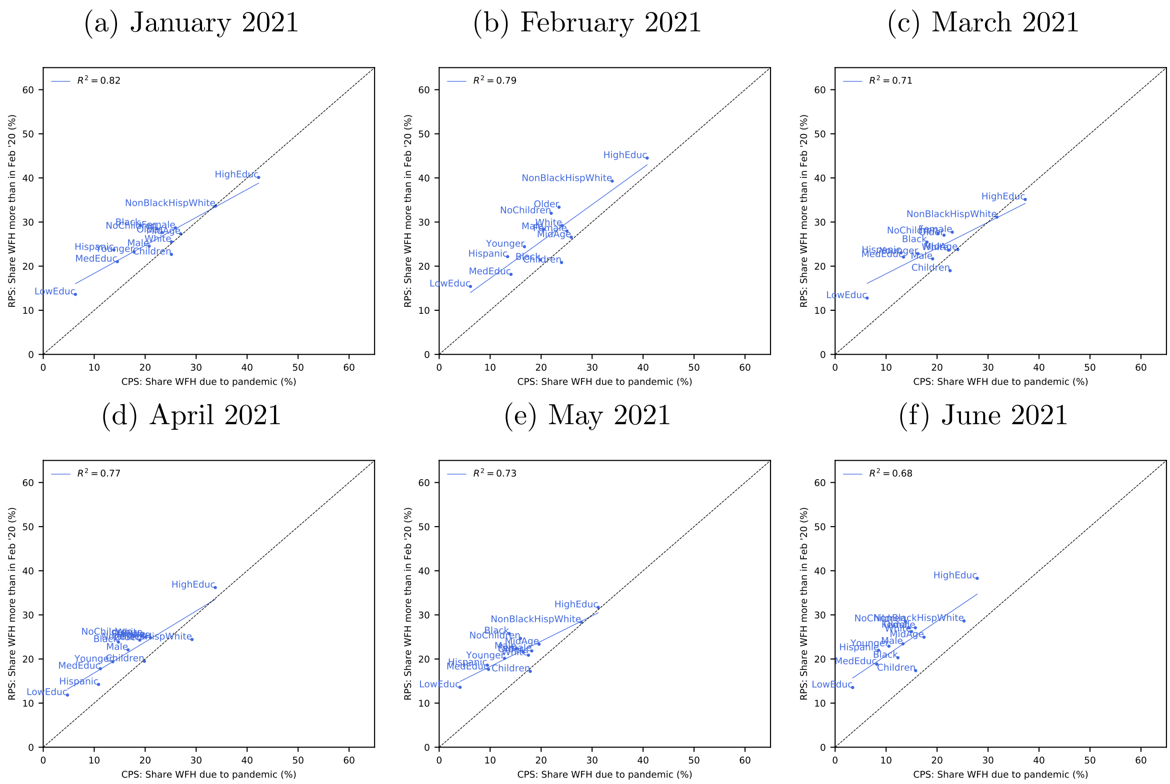
We emphasize three primary takeaways from these figures. First, the best-fit lines through the scatterplots feature a high R^2 value (it is above 0.6 in every figure but one, and is above 0.7 in a large majority of months). This implies that both surveys feature a similar ranking of WFH rates across worker groups. Second, the slope of the best-fit lines is slightly below one, indicating that the variation in pandemic-related WFH in the CPS is somewhat larger than variation in additional WFH in the RPS. Third, the scattered data lie fairly close to the 45 degree line throughout 2020, indicating that both survey measures yield fairly similar levels, despite representing somewhat different WFH concepts. Fourth, beginning in 2021, the level of WFH begins to decline more in the CPS than in the RPS, consistent with the aggregate results displayed in Figure 3b.

Figure B.5.1: Work from Home by Individual Characteristics in 2020: RPS vs. CPS



Sources: Real-Time Population Survey and Current Population Survey, ages 18-64. The graphs compare WFH rates in the RPS and CPS by demographic group. Both the RPS and CPS samples are individuals employed in a given month. The CPS values show the sample share answering yes to the WFH question in the CPS (see main text). The RPS values show the sample share reporting more workdays without a commute last week compared to February 2020. Those not employed in February 2020 are included with zero commutes before the pandemic. Definitions of demographic groups are provided in Appendix A.3. We do not include the income categories because the CPS does not contain information on 2019 household income for the months of interest.

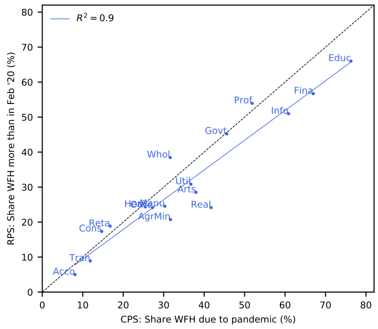
Figure B.5.2: Work from Home by Individual Characteristics in 2021: RPS vs. CPS



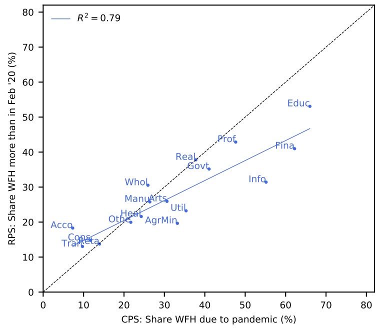
Sources: Real-Time Population Survey and Current Population Survey, ages 18-64. The graphs compare WFH rates in the RPS and CPS by demographic group. Both the RPS and CPS samples are individuals employed in a given month. The CPS values show the sample share answering yes to the WFH question in the CPS (see main text). The RPS values show the sample share reporting more workdays without a commute last week compared to February 2020. Those not employed in February 2020 are included with zero commutes before the pandemic. Definitions of demographic groups are provided in Appendix A.3. We do not include the income categories because the CPS does not contain information on 2019 household income for the months of interest.

Figure B.5.3: Work from Home by Industry in 2020: RPS vs. CPS

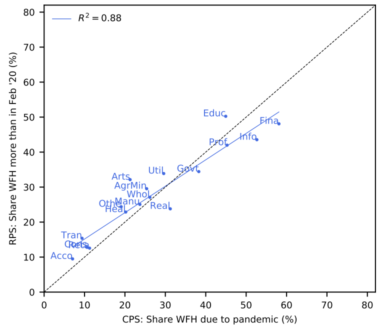
(a) May 2020



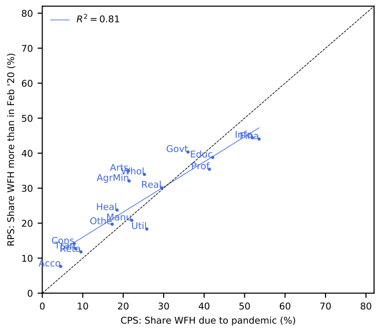
(b) June 2020



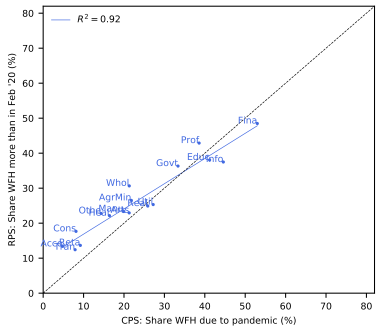
(c) July 2020



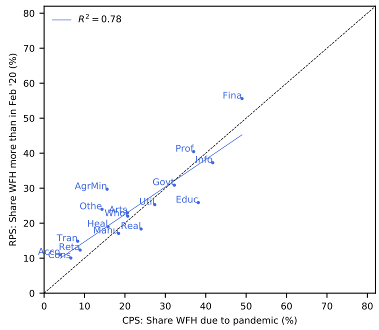
(d) August 2020



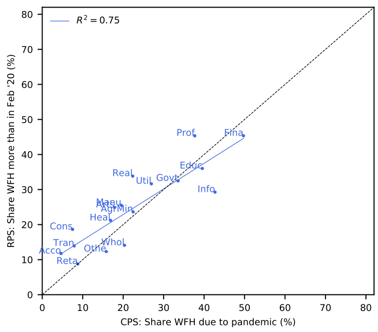
(e) September 2020



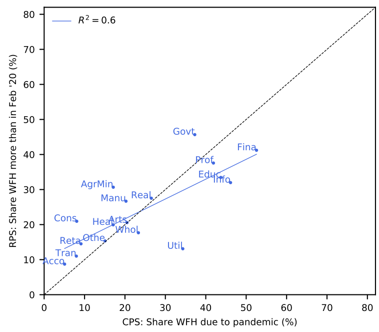
(f) October 2020



(g) November 2020

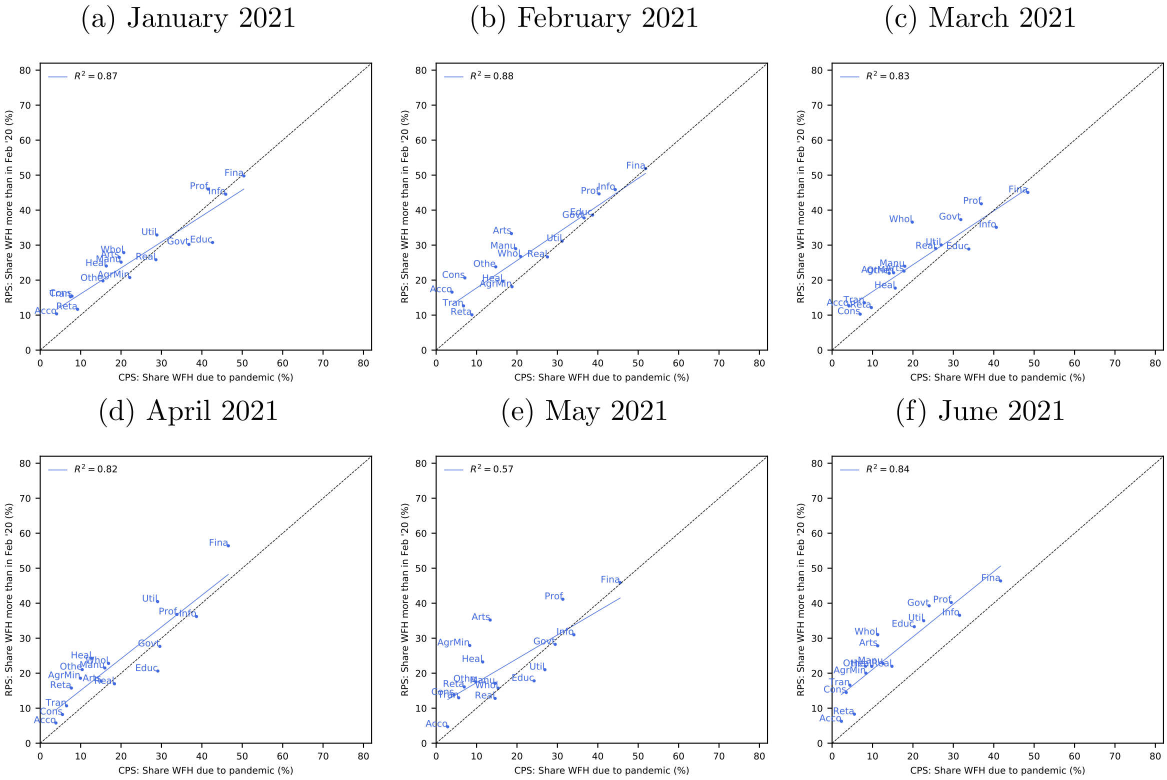


(h) December 2020



Sources: Real-Time Population Survey and Current Population Survey, ages 18-64. The graphs compare WFH rates in the RPS and CPS by demographic group. Both the RPS and CPS samples are individuals employed in a given month. The CPS values show the sample share answering yes to the WFH question in the CPS (see main text). The RPS values show the sample share reporting more workdays without a commute last week compared to February 2020. Those not employed in February 2020 are included with zero commutes before the pandemic. Industry classification is by industry of employment in the current month. Definitions of industry groups are provided in Appendix A.3.

Figure B.5.4: Work from Home by Industry in 2021: RPS vs. CPS



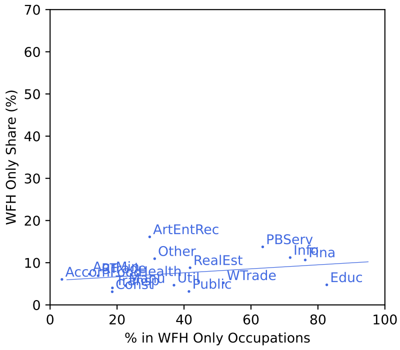
Sources: Real-Time Population Survey and Current Population Survey, ages 18-64. The graphs compare WFH rates in the RPS and CPS by demographic group. Both the RPS and CPS samples are individuals employed in a given month. The CPS values show the sample share answering yes to the WFH question in the CPS (see main text). The RPS values show the sample share reporting more workdays without a commute last week compared to February 2020. Those not employed in February 2020 are included with zero commutes before the pandemic. Industry classification is by industry of employment in the current month. Definitions of industry groups are provided in Appendix A.3.

B.6 WFH Only Shares versus WFH Potential

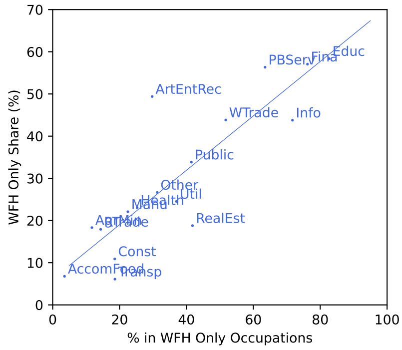
Figure 4 plots the WFH Only shares in different industries against estimates of the share of workers that were in potential WFH Only jobs in February 2020 for February 2020, May 2020, and June 2021. Figures B.6.5 and B.6.6 repeats the plots for these three months and shows them as well for all other sample months. While there was little relationship between WFH potential and WFH Only shares before the pandemic in February 2020, the relationship became strongly positive in May 2020. This positive relationship persisted throughout the pandemic, although it weakens somewhat by June 20201 at the end of our sample period.

Figure B.6.5: WFH Only Shares versus WFH Potential in 2020

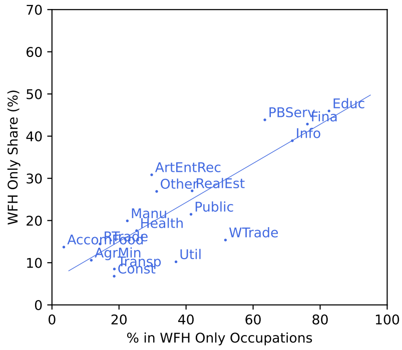
(a) February 2020



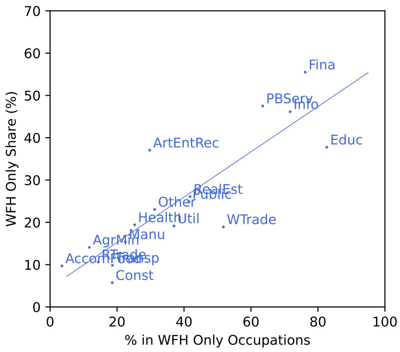
(b) May 2020



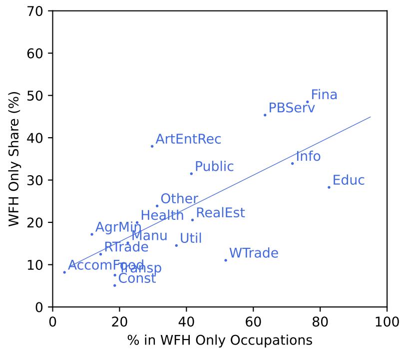
(c) June 2020



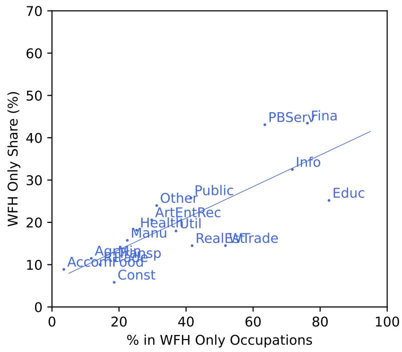
(d) July 2020



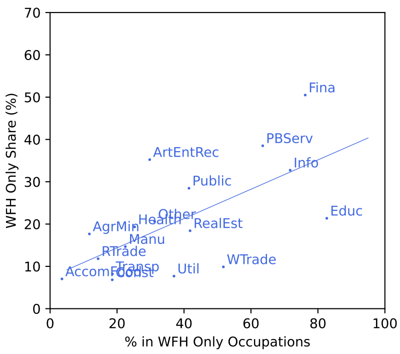
(e) August 2020



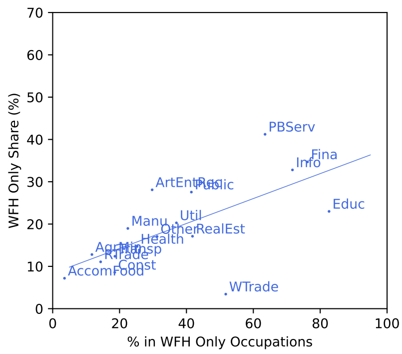
(f) September 2020



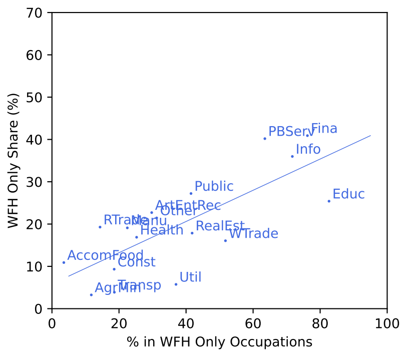
(g) October 2020



(h) November 2020

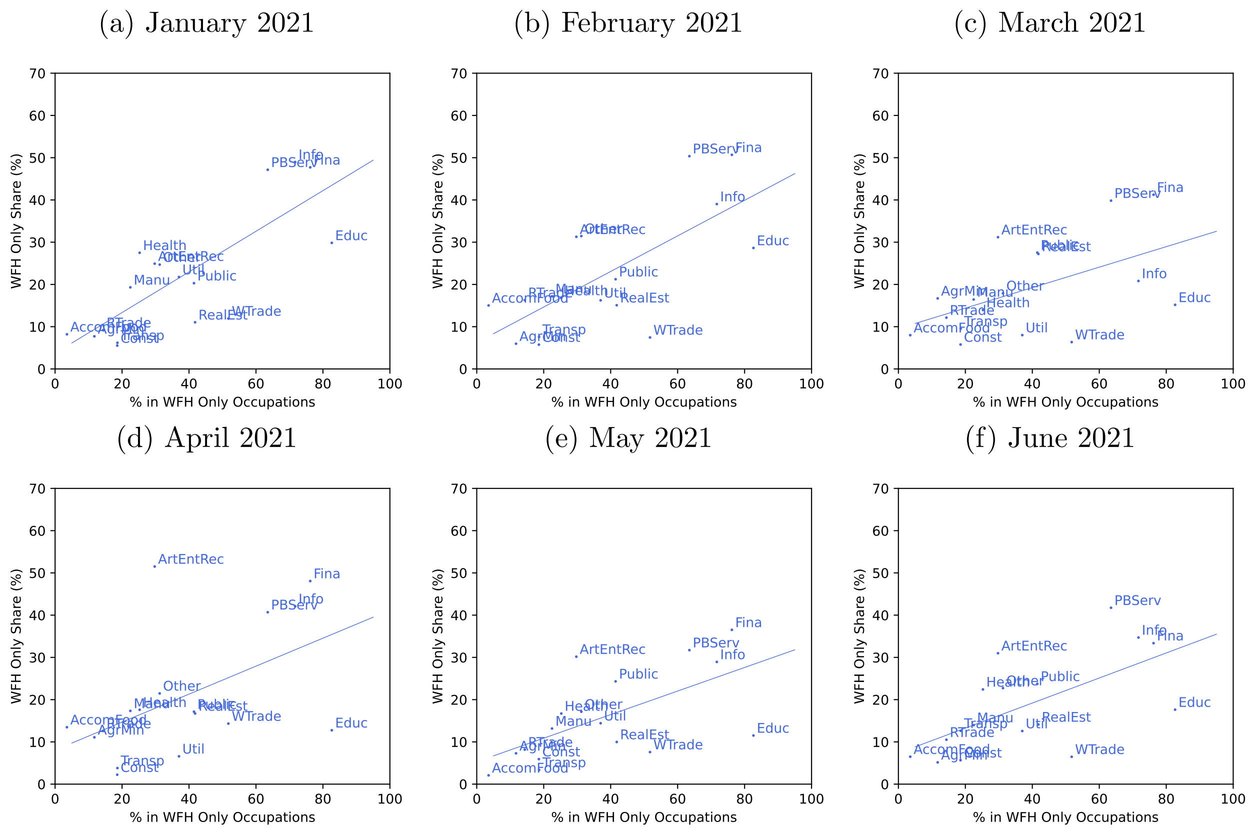


(i) December 2020



Source: Real-Time Population Survey and Dingel and Neiman (2020). The x-axis is the share (percent) of February 2020 workers in potential WFH occupations based on the measures of Dingel and Neiman (2020). The y-axis is the share (percent) of employed workers that are WFH Only. Definitions of industry groups are provided in Appendix A.3.

Figure B.6.6: WFH Only Shares versus WFH Potential in 2021

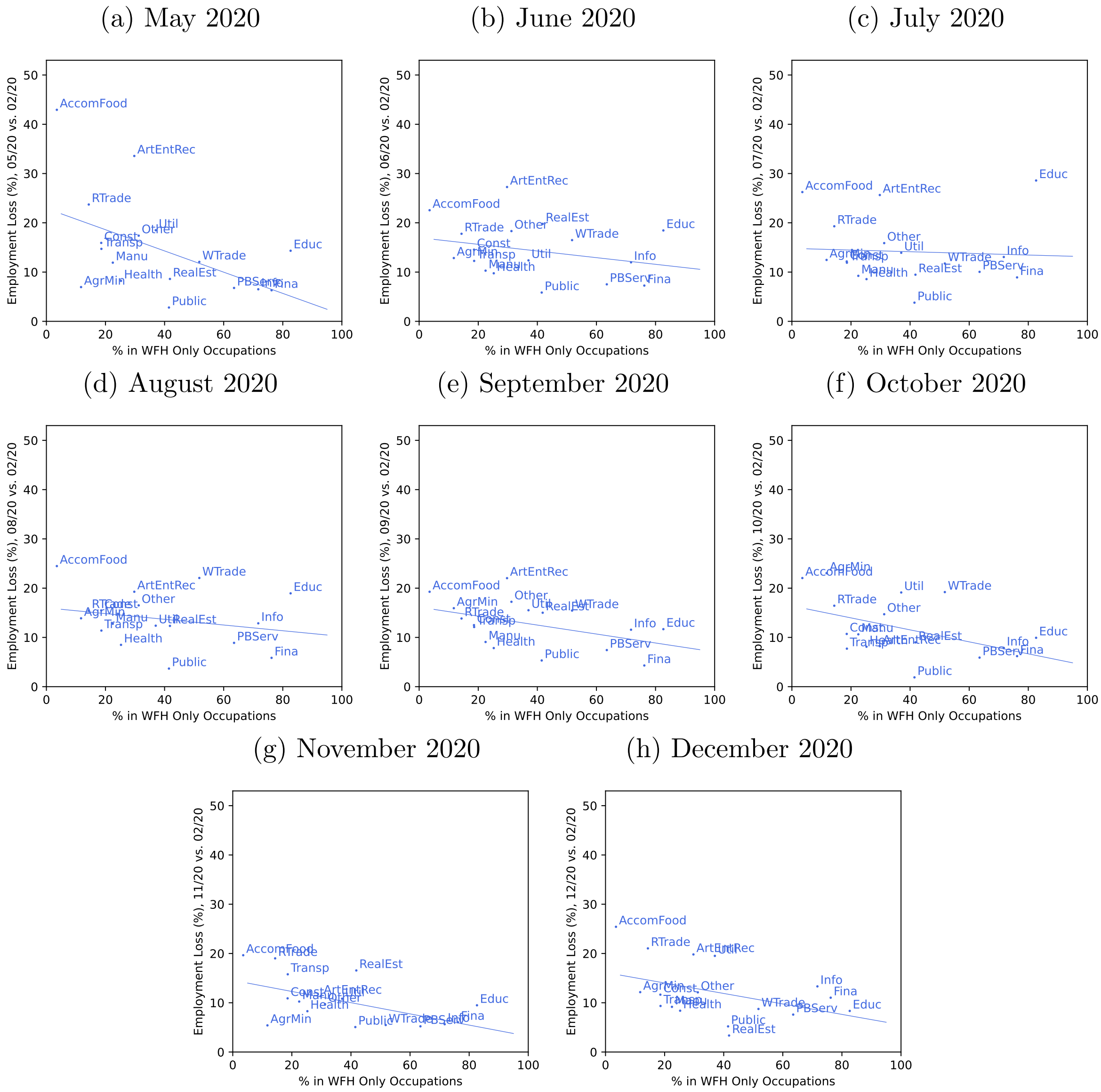


Source: Real-Time Population Survey and Dingel and Neiman (2020). The x-axis is the share (percent) of February 2020 workers in potential WFH occupations based on the measures of Dingel and Neiman (2020). The y-axis is the share (percent) of employed workers that are WFH Only. Definitions of industry groups are provided in Appendix A.3.

B.7 Employment Loss and Potential WFH Potential

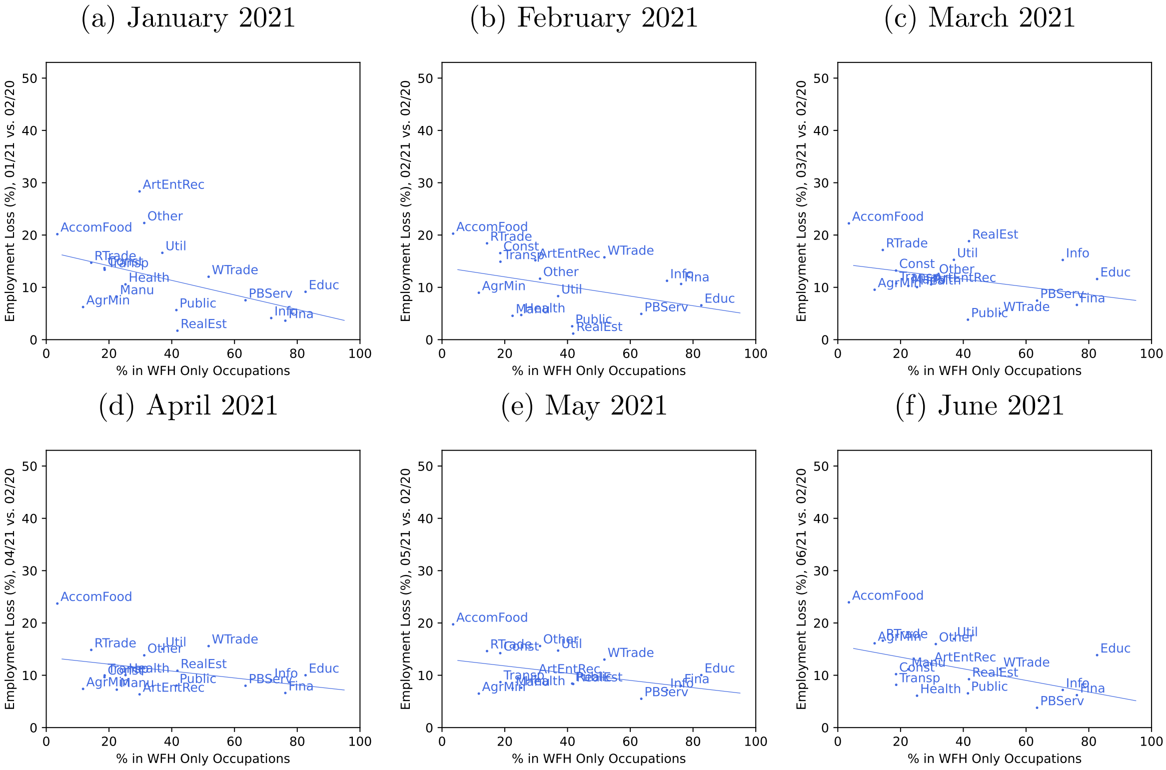
Figure 4 shows that WFH Only Shares and potential WFH Only Shares were strongly positively correlated in May 2020 and June 2021 (Appendix B.6 shows these results hold all true in all months during the pandemic). Figures B.7.1 and B.7.2 show that at the same time a strong negative correlation between employment losses and potential WFH Only Shares. This negative correlation was particularly strong in May 2020, and weakest in the summer 2020 (June-August), when employment losses were particularly large in education, the industry with the largest potential WFH Only share.

Figure B.7.1: Employment Losses and Potential WFH Only Shares in 2020



Sources: Real-Time Population Survey and Dingel and Neiman (2020). The x-axis is the share (percent) of February 2020 workers in potential WFH occupations based on the measures of Dingel and Neiman (2020). We plot the results for all months in Appendix B.6. The y-axis is the employment loss (percent) in the survey months relative to February 2020. Definitions of industry groups are provided in Appendix A.3.

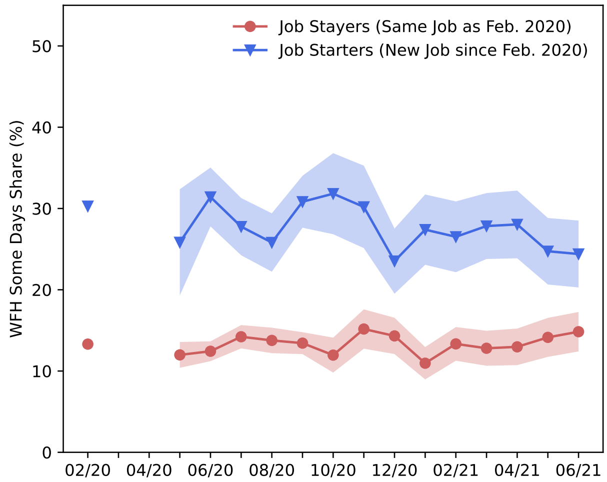
FIGURE B.7.2: Employment Losses and Potential WFH Only Shares in 2020



Sources: Real-Time Population Survey and Dingel and Neiman (2020). The x-axis is the share (percent) of February 2020 workers in potential WFH occupations based on the measures of Dingel and Neiman (2020). We plot the results for all months in Appendix B.6. The y-axis is the employment loss (percent) in the survey months relative to February 2020. Definitions of industry groups are provided in Appendix A.3.

B.8 WFH by Job Tenure

FIGURE B.8.1: WFH Some Days Among Job Stayers and Job Starters



Source: Real-Time Population Survey. The sample is individuals (ages 18-64) employed in the survey month. The figure shows the share of WFH Some Days workers that are 'job stayers', or individuals who worked for the same employer in February 2020 and in the interview month, and 'job starters', or individuals who did not work for the same employer in February 2020 and in the interview month; the latter category includes both workers who switched employers and workers not employed in February 2020. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

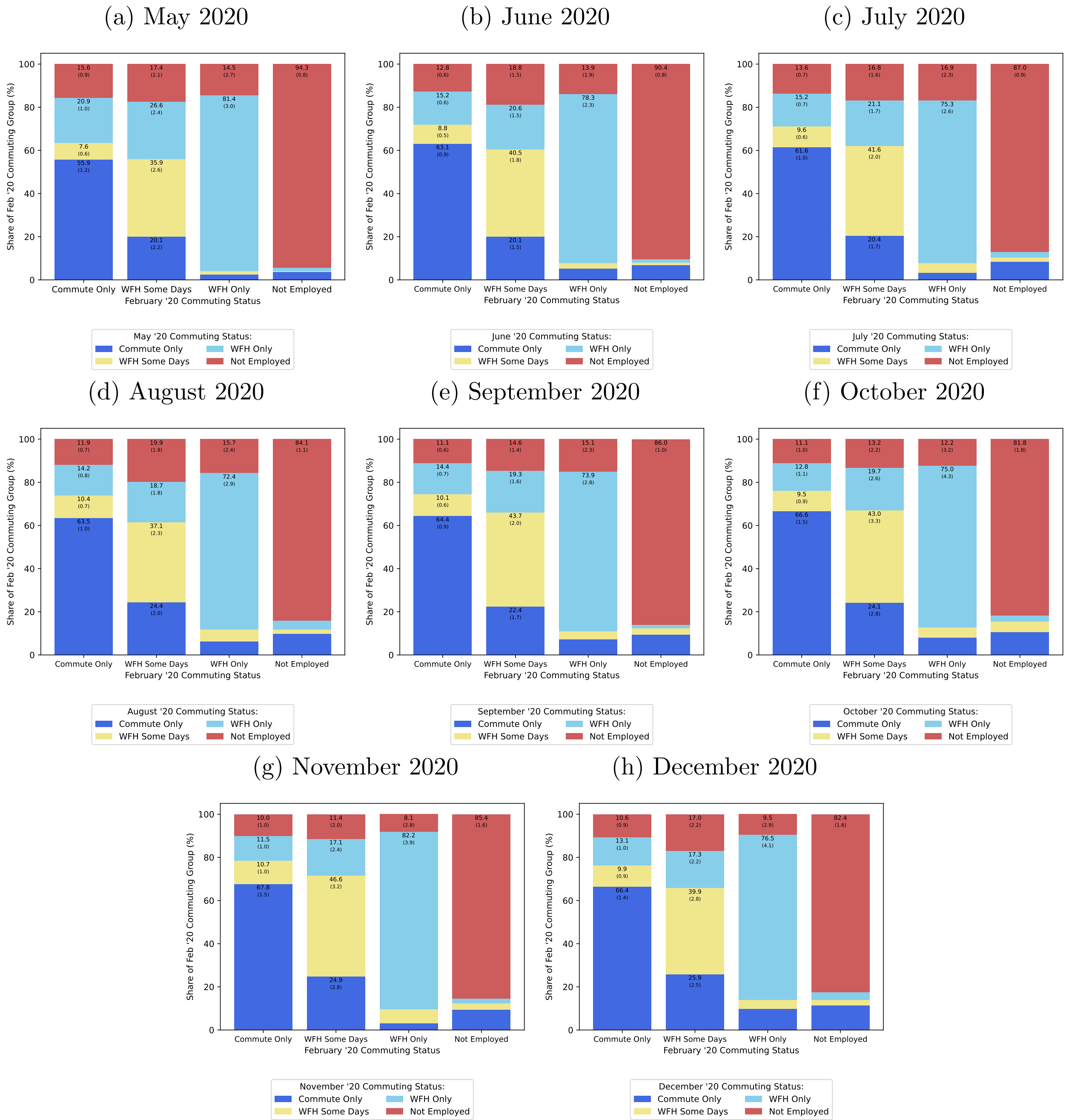
Figure 5 in the main text plots WFH Only shares for job stayers and job starters since February 2020. Figure B.8.1 shows that job starters in the pandemic do have higher partial WFH rates than job stayers. The partial WFH rates for both job starters and stayers remain overall relatively close to the rates in workers' February 2020 jobs. The generally higher partial WFH rates reflect that recent job starters are more likely to be younger and have children, both of which are associated with a greater propensity for part-time WFH. The increasing share of job starters since February 2020 induces some gradual increase in the partial WFH rate following the initial drop in partial WFH in May 2020, but overall contributes little to the rise in WFH over our sample period. Although not shown, we also find very similar patterns for the shares WFH Only and WFH Some Days if we considers a more narrow definition of job starters, by excluding individuals who were not employed in February 2020.

B.9 WFH Transitions Relative to February

Figure 6 in the main text displays the transition rates in WFH and employment status between February 2020 and the first RPS survey month (May 2020) and between February 2020 and June 2021. Figures B.9.1 and B.9.2 display the corresponding transition rates for all months in between. The results indicate that many workers who commuted only or WFH partially in February transitioned to WFH Only during the COVID-19 pandemic. The reverse was not true: conditional on remaining employed, the vast majority of workers who were WFH Only in February continued to do so during the pandemic. The results also indicate that employment losses during the pandemic did not differ strongly by pre-pandemic WFH status.

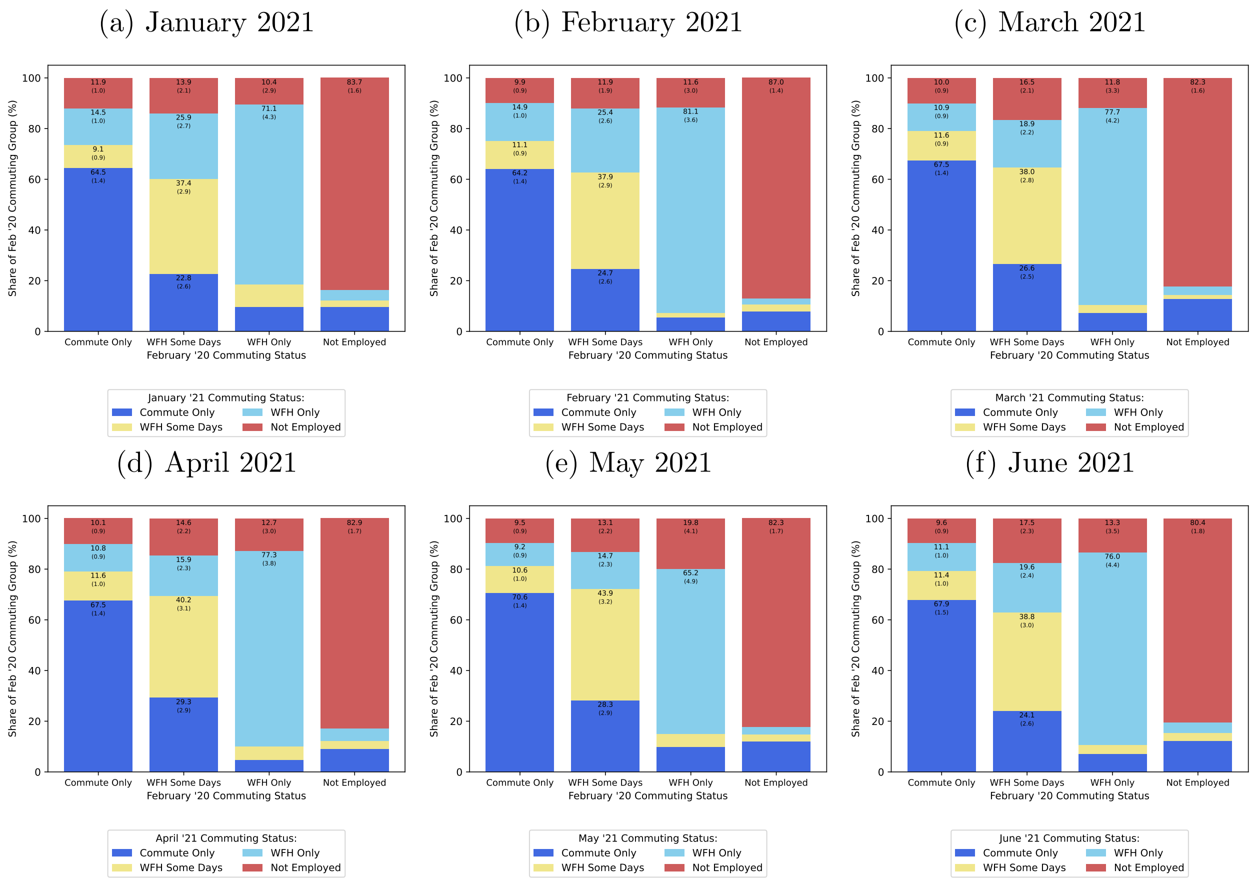
Figures B.9.3 and B.9.4 display figures analogous to Figures B.9.1 and B.9.2, except that now transitions are conditioned on current WFH/employment status rather than on the status from February. The results indicate that the vast majority of workers who commuted only during the COVID-19 pandemic already commuted early in February. Conversely, roughly half of individuals who WFH partially or were WFH Only during the pandemic reported that they commuted only just before the pandemic.

Figure B.9.1: WFH Transition Rates in 2020 By February 2020 WFH Status



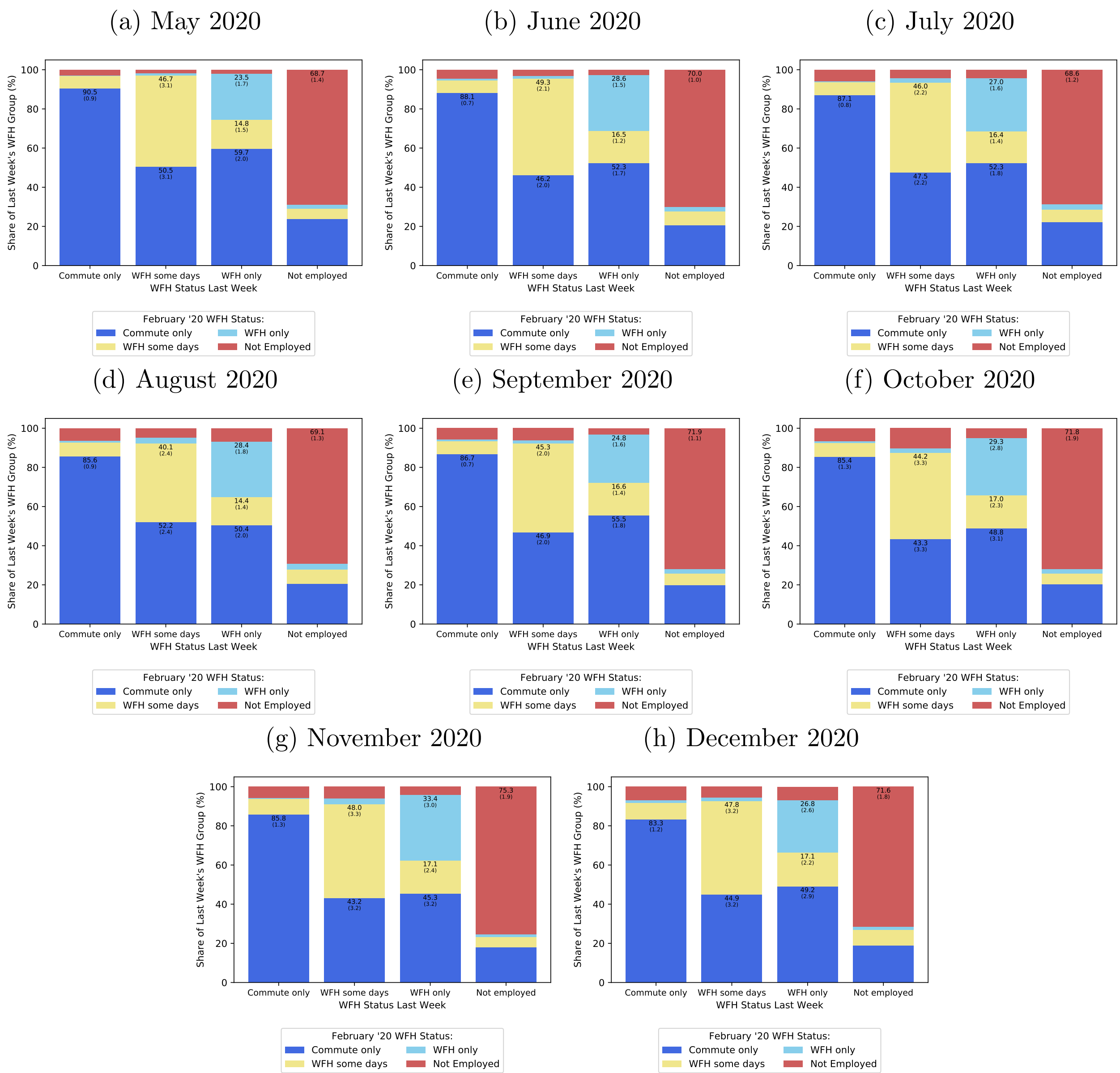
Source: Real-Time Population Survey, ages 18-64. The figure displays the composition of the population by WFH and employment status in the current month separately by workers' employment and WFH status in February 2020. Each bar corresponds to a February WFH/employment state: Commute Only, WFH Some Days, WFH Only, and Not Employed. Each color within a bar corresponds to a current WFH/employment state. Standard errors in parentheses, calculated as described in Appendix A.2. See Appendix A.1 for sample sizes by month.

FIGURE B.9.2: WFH Transition Rates in 2021 By February 2020 WFH Status



Notes: See Figure B.9.1.

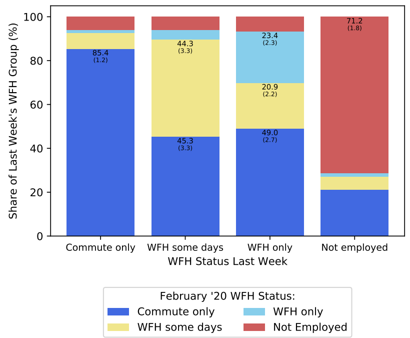
Figure B.9.3: WFH Transition Rates in 2020 By Current WFH Status



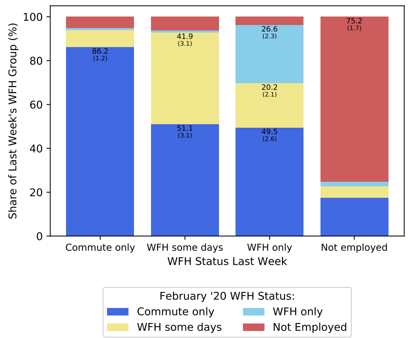
Source: Real-Time Population Survey, ages 18-64. The figure displays the composition of the population by WFH and employment status in February 2020 separately by workers' employment and WFH status in the current month. Each bar corresponds to a current WFH/employment state: Commute Only, WFH Some Days, WFH Only, and Not Employed. Each color within a bar corresponds to a February 2020 WFH/employment state. Standard errors in parentheses, calculated as described in Appendix A.2. See Appendix A.1 for sample sizes by month.

Figure B.9.4: WFH Transition Rates in 2021 By Current WFH Status in 2021

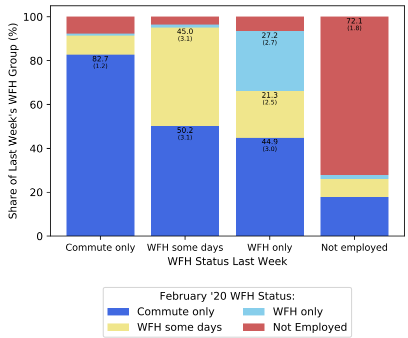
(a) January 2021



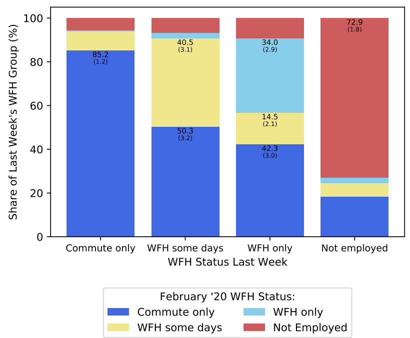
(b) February 2021



(c) March 2021

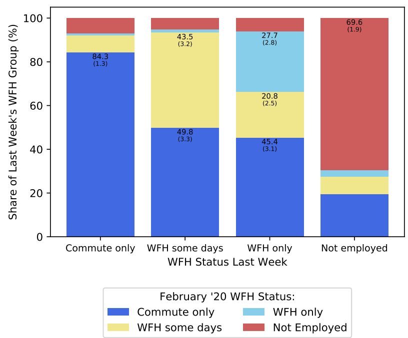


(d) April 2021



(e) May 2021

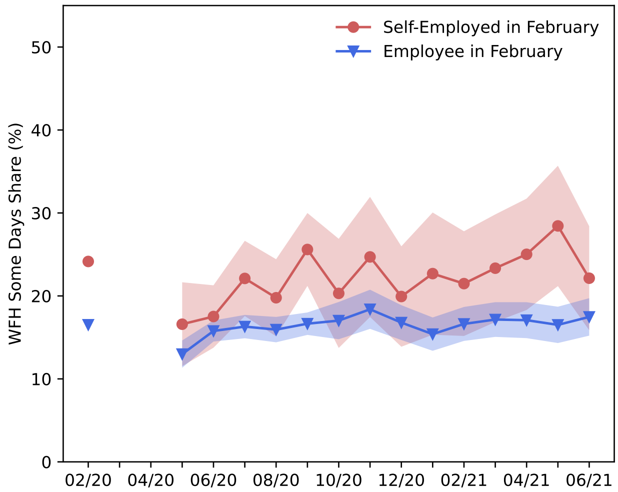
(f) June 2021



Notes: See Figure B.9.3.

B.10 WFH Among Employees vs. the Self-Employed

Figure B.10.1: WFH Some Days

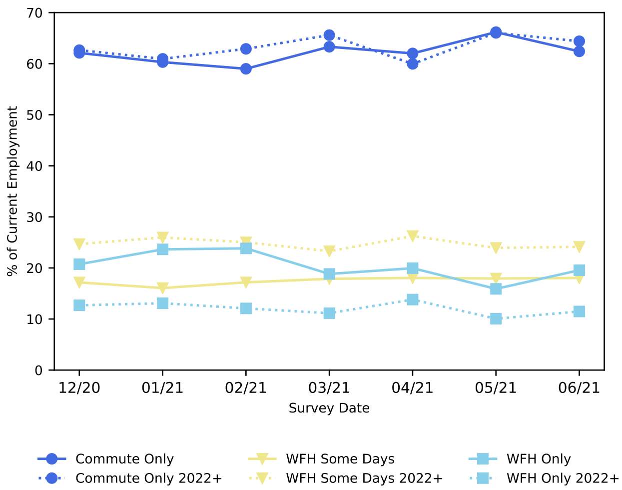


Source: Real-Time Population Survey, ages 18-64. The sample is individuals employed both in February 2020 and last week. The figure shows the share of WFH Only workers (left panel) and the share of partial-WFH workers (right panel) each month. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

Figure 7b in the main text plots WFH Only shares since February 2020 separately for workers who were employees in February 2020 and for workers who were self-employed in February 2020. In February 2020, the self-employed were over three times more likely to WFH Only compared with employees. Since May 2020, however, the two groups of workers have nearly identical rates of WFH Only. Figure B.10.1 shows that in February 2020, the self-employed also had rates of WFH Some Days that were slightly higher than for employees. These differences narrowed early in the pandemic, but increased again somewhat over the following months. Although not shown, we also find very similar patterns for the shares WFH Only and WFH Some Days if we condition on current class of worker (self-employed or not) as opposed to pre-pandemic class of worker.

B.11 Future WFH Expectations Across Survey Months

FIGURE B.11.2: Current WFH and Future Expectations, By Month the Survey Was Conducted



Source: Real-Time Population Survey, ages 18-64, months December 2020 through June 2021. Solid lines correspond to actual WFH in the interview month. Dashed lines correspond to expected WFH rates for 2022 and beyond.

From December 2020-onward, the RPS asked individuals about expectations of WFH for 2022 and beyond (see the phrasing in Section 4). Figure B.11.2 displays expected WFH rates by interview month (dashed lines). For reference, it also plots actual WFH rates by interview month (solid lines). We highlight four main takeaways from this figure. First, expected commuting patterns are fairly stable across interview months: the max of each series is within seven percentage points of the corresponding min, and there is no clear systematic change over time. Second, expected future rates of Commute Only are very close to current rates of Commute Only. Third, expected future rates of WFH Some Days are above current rates of WFH Some Days. Fourth, expected future rates of WFH Only are below current rates of WFH Only. Together, the latter three points suggest that few people who WFH expect to return to Commute Only in the future, but that some people who currently WFH Only expect to transition to a hybrid commuting regimen in the future.

C Appendix Materials For Model-Based Decomposition

C.1 Equilibrium and Identification When Firms Hire Only WFH Workers

If the parameters are such that

$$\delta(1+\chi)^{-\beta} < \gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda} < 1\ , \tag{C.1.1}$$

the supply of WFH labor exceeds the firms' overall labor demand at the marked-down commuter wage. In this case it is optimal for the firm to pay a wage that is below $(1+\chi)\lambda/(1+\lambda)$ and hire only WFH workers. This arises when the overall WFH productivity γ is relatively high, or when the cost of working on-site χ – and therefore the commuters' wage – is relatively high. When (C.1.1) holds, the optimal decisions of the firm are given by

$$w_h = \frac{\lambda}{1+\lambda}\delta^{1/\beta}e(w_h)^{-1/\beta} = \left(\frac{\lambda}{1+\lambda}\right)^{\frac{\beta}{\beta+\lambda}}(\delta/\gamma)^{\frac{1}{\beta+\lambda}}\ , \tag{C.1.2}$$

$$E_h = e(w_h) = \delta^{\frac{\lambda}{\beta+\lambda}}\gamma^{\frac{\beta}{\beta+\lambda}}\left(\frac{\lambda}{1+\lambda}\right)^{\frac{\beta\lambda}{\beta+\lambda}}\ , \tag{C.1.3}$$

$$E_l = 0. \tag{C.1.4}$$

Because the firm sets a wage that is lower than $(1+\chi)\lambda/(1+\lambda)$, it is the case that $E_h < \gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda}$. The second inequality in Assumption (C.1.1) therefore guarantees that $E_h < 1$, such that the firm does not hire all workers in its labor market.

The optimal wage (C.1.2) still equals the firm's marginal revenue after the monopsonistic mark-down. However, under condition (C.1.1) it is optimal to set the marginal revenue strictly lower than $1+\chi$ and employ only home workers. In this case, the overall level of employment is independent of the cost of on-site work χ, but depends on the overall WFH productivity. Unlike the case where firms also hire commuters, WFH employment now also depends on the level of demand δ.

By allowing WFH, the firm increases profits by

$$\left(\frac{1}{\beta-1}+\frac{1}{1+\lambda}\right)\delta\left(\left(\frac{\delta}{\gamma}\right)^{\frac{1}{\beta+\lambda}}\left(\frac{\lambda}{1+\lambda}\right)^{-\frac{\lambda}{\beta+\lambda}}\right)^{1-\beta} - \frac{\delta\,(1+\chi)^{1-\beta}}{\beta-1} > 0 \tag{C.1.5}$$

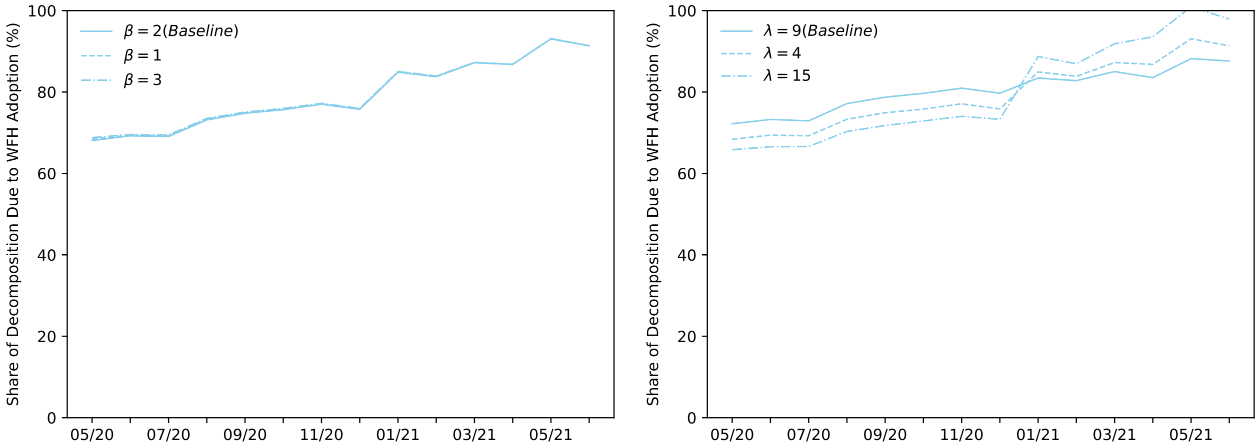
where the inequality is guaranteed by (C.1.1). The firm unambiguously prefers to provide the WFH option. The additional profits from providing the WFH option are increasing in the cost of on-site work χ and in the workers' WFH productivity γ.

As mentioned in the main text, in seven of the 17×15 industry-month pairs of the baseline decomposition, the condition in (1) is violated, meaning that our calibration strategy results in sufficiently low demand and high on-site costs such that firms hire only WFH workers. In those cases, we first calculate the δ as in the main text and derive the critical value of χ such that, given that value of δ, employment and WFH and non-WFH firms would be exactly identical. Next we set the actual level of χ to that critical value, and obtain $\theta = \bar{E}_h/\bar{E}$.

C.2 Sensitivity of the Decomposition to different values of β and λ

Figure C.2.1: Aggregate Adoption Effect for Different Values of β and λ

(a) Sensitivity to β (b) Sensitivity to λ



Source: Real-Time Population Survey (RPS) and model simulations.

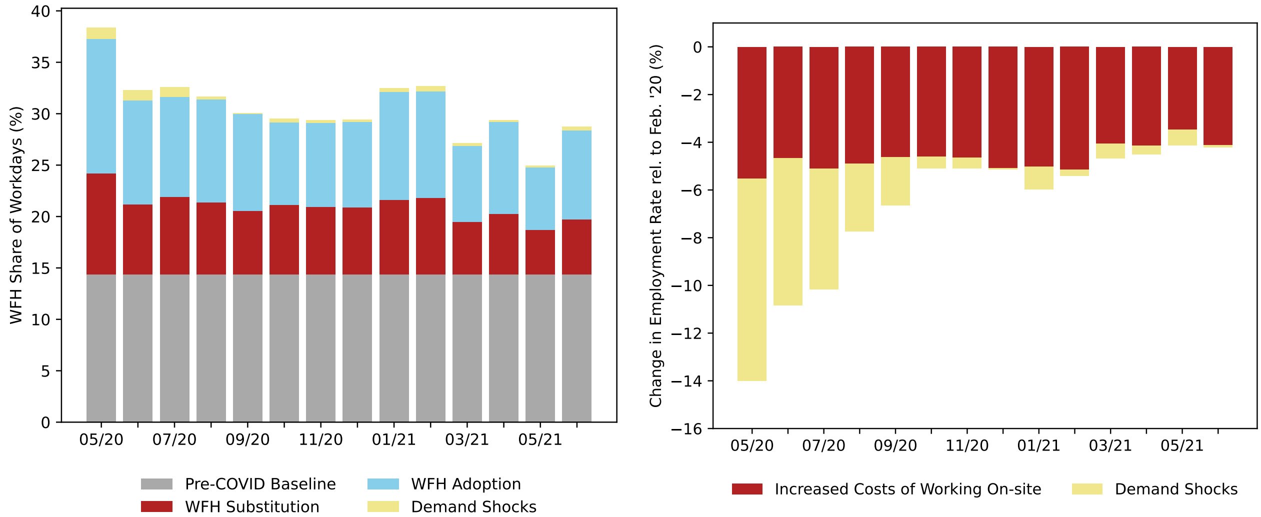
Figure C.2.1 plots the share of the increase in WFH attributed to WFH adoption for our baseline parameters of the demand elasticity β and the WFH labor supply elasticity γ along with a lower and higher value of each parameter, respectively. Figure C.2.1a shows that the choice of β has no impact on the role of adoption, because neither the identified values of χ and θ in (6) and (8), nor the level of WFH employment in the model depend on β. Figure C.2.1b reveals some modest impact of the choice of λ, although there is no systematic pattern. Early on in the pandemic, both a lower and higher value of λ than in the benchmark results in a smaller share of the increases in WFH being attributed to adoption, while the opposite is true towards the end of the sample. The reason for the relatively small and non-systematic effect because of two opposing effects on the contribution of the substitution effects in the decomposition. Imposing say a higher λ means that more workers switch to WFH for a given increase in χ, but at the same time a higher λ also reduces the increase in the identified values for χ implied by the observed increase in the WFH Only share $\bar{E}_h/\bar{E}$, see equation (6).

C.3 Model-Based Decompositions Using the WFH Share of Workdays

FIGURE C.3.2: Model-Based Decompositions Using WFH Share of Workdays

(a) WFH Share of Workdays

(b) Employment



Source: Real-Time Population Survey (RPS) and model simulations. Left panel: The y-axis is the WFH share of workdays in each month May 2020 - June 2021. The pre-COVID baseline level of WFH Only (gray) is based on RPS data. The effects of WFH substitution (red), WFH adoption (light blue), and demand (tan) on the WFH Only share are based on decompositions which compare WFH Only shares under the identified monthly sequences of parameters with a counterfactual path that changes a single parameter at a time (χ for substitution, θ for adoption, and δ for demand). Right panel: The aggregate results in the figure are a weighted average of these industry-level decompositions. The sum of the stacked bars in each month is the change in log employment relative to February 2020 in the RPS. The effects of WFH substitution (red) and demand (tan) on the WFH Only share are based on industry-level decompositions which compare employment under the identified monthly sequences of parameters with a counterfactual path that changes a single parameter at a time (χ for substitution and δ for demand). Both panels: aggregate results in the figure are a weighted average of these industry-level decompositions.

Figure C.3.2 documents the results of our decomposition exercise when the model is identified using the share of days WFH rather than the WFH Only share, allowing also for an intensive margin of WFH. In this case, our model setup can be interpreted such that every worker draws different WFH productivities z for each work day, inducing some workers to commute every day, some to WFH on some days and to commute on others, and some to WFH Only. The identification follows the same steps as the baseline, except that we replace $\bar{E}_h$ with the share of WFH workdays in each industry multiplied by total industry employment. The only other difference is in the calibration of the adoption rates in the pre-pandemic period: we add the fraction of daily commuters that cite personal preference as the main reason for commuting to the fraction of workers that are either WFH Only of WFH Some Days before the pandemic.

Figure C.3.2a shows that incorporating partial WFH leads to a contribution of adoption effects of 55.4 percent to the overall increase in the share of workdays worked from home in

May 2020 as opposed to 68.4 percent in our baseline analysis. By June 2021, the adoption effects contribute 86.2 percent to the increase in the share of WFH workdays, which is almost as much as the contribution of adoption to the WFH Only share in Figure 9a. Incorporating part-time WFH, therefore, does not substantially change the main result that the persistence in the rise in WFH is driven by adoption effects.

Figure C.3.2b shows that incorporating partial WFH only minimally increases the share of employment losses explained by the increased cost of on-site work vis-a-vis our baseline model (compare Figure 9b).