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

Alexander Bick
Arizona State University

Adam Blandin
Virginia Commonwealth University

Karel Mertens
Federal Reserve Bank of Dallas

First version: June 09, 2020
Current version: February 23, 2021

Abstract

Based on novel survey data, we document the evolution of commuting behavior in the U.S. over the course of the COVID-19 pandemic. Work from home (WFH) increased sharply and persistently after the outbreak, and much more so among some workers than others. Using theory and evidence, we argue that the observed heterogeneity in WFH transitions is consistent with potentially more permanent changes to work arrangements in some occupations, and not just temporary substitution in response to greater health risks. Consistent with increased WFH adoption, many more – especially higher-educated – workers expect to WFH in the future.

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

* *Contact*: alexander.bick@asu.edu; ajblandin@vcu.edu; mertens.karel@gmail.com. We thank the Center for the Advanced Study in Economic Efficiency at ASU, the Office of the Vice President for Research and Innovation at VCU, and the Federal Reserve Bank of Dallas for generous financial support. We also thank Minju Jeong, Abigail Kuchek, and Jonah Danziger for outstanding research assistance, and Yichen Su for helpful comments. The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Banks of Dallas or the Federal Reserve System. A previous version of this paper was titled "Work from Home After the COVID-19 Outbreak."

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 in the pandemic and capture some of its unique aspects. From May 2020 onward, the RPS included questions on the commuting habits of workers both before and during the pandemic. Based on a sample of more than 46,000 observations, we document a rich set of facts on how commuting behavior has evolved over the course of 2020. One of these facts is the large amount of heterogeneity in WFH transitions across different worker categories. To help understand the mechanisms behind this heterogeneity, we develop a stylized model of WFH employment in which commuting can decline because workers substitute on-site for home-based work within existing work arrangements with a WFH option, or because the pandemic accelerates the adoption of more flexible work arrangements and new WFH technology. We argue that the observed heterogeneity in WFH transitions is best explained by differences in WFH adoption during the pandemic, and we corroborate this claim with additional survey information on how many and which workers gained access to the option to WFH during the pandemic. The evidence for WFH adoption suggest the potential for longer-term welfare gains from increased WFH for certain workers. When asked directly about expected commuting behavior after the pandemic, many more respondents – especially women, older workers, and workers with high income/education – expect to WFH in the future relative before the pandemic.

One of the key objectives of this paper is to provide an accurate quantitative assessment of the surge in WFH during the pandemic. To do so, our methodology 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 an important distinction between WFH on a full- and part-time basis. Our survey also asks about commuting behavior before the pandemic, which allows us to analyze changes in commuting at the individual level. We further validate our measures with mobility data on commuting, as well as information available in the CPS since May 2020 on 'pandemic-related' telework.

Using the results from the RPS, we quantify the unprecedented decline in commuting following the initial outbreak. Commuting recovered substantially after the first U.S. wave of the

pandemic, but many workers continued to WFH at the end of 2020. This evidence complements that of other online surveys, such as by Brynjolfsson et al. (2020) and Barrero et al. (2021). Using the specific information available in the RPS, we find that the surge in WFH is driven almost entirely by increases in the share of 'WFH-Only' workers – defined as those workers that worked from home every workday in the reference week. The WFH-Only share of total employment quadrupled from 7.6 percent in February 2020 to 31.4 percent in May, fell to 24.3 percent in June, and declined more gradually afterwards. At the end of 2020, 20.4 percent of all employed still worked entirely from home. The share of workers that WFH on some workdays, on the other hand, dropped slightly in May relative to February, and returned fairly quickly to pre-pandemic levels in the rest of 2020.

The bulk of the transitions to WFH-Only are by workers that used to commute every workday. Moreover, the large increase in the WFH-Only rate is driven by workers that remained in their pre-pandemic jobs, not by reallocation towards new WFH-Only jobs: workers that started new jobs since February are considerably less likely to be WFH-Only than job stayers. There is also very little role for selection: workers that were already WFH-Only in February were almost as likely to lose their jobs during the pandemic as full-time commuters.

One of the most striking features of the data is the amount of heterogeneity in the adjustment in commuting across worker groups. In February, WFH-Only was relatively more common among older workers (ages 50 to 64), workers without children in the household, and workers with higher income and education. The pre-pandemic differences, however, are minor compared to those that emerged in the pandemic. For example, the share of highly educated WFH-Only workers (bachelor's degree or more) rose from 8.5 percent in February to nearly 50 percent in May, and remains at 33.2 percent at the end of 2020. In comparison, the share of low-education WFH-Only workers (high school or less) rose from 6.4 percent in February to 14.2 percent in May, and dropped back to 8.6 percent by the end of 2020. The WFH-Only shares of female, white, high-income and older workers also all rose substantially more than those of male, minority, low-income and younger workers.

To better understand the sources of the heterogeneity in WFH transitions and the relationship with job loss, we develop a stylized model of WFH employment that leads to a clear distinction between two main channels through which a pandemic can cause large numbers of commuters to start 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 working at home within working arrangements that already included the option to WFH 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 in the pandemic force changes to work arrangements through the adoption of a WFH option and/or of new technologies that enable WFH. A key aspect of this channel is that many of those that switched to WFH in the pandemic could in principle already have worked more productively from home before the start of the pandemic, for instance because of advances in information and communication technology. However, because of adoption lags, social norms or general inertia, employers did not provide the option to WFH until the pandemic.

The distributional and longer run implications of the surge in WFH depend importantly on the extent of WFH adoption in the pandemic. One possibility is that before the pandemic the option to WFH was widely available, but WFH was relatively uncommon because most workers are less productive at home. In this case, the rise in WFH would be mostly driven by temporary substitution, and would reverse in the longer run. The other possibility is that WFH was relatively uncommon because of low adoption. Once adopted in the pandemic, remote work can save time and costs also after the health crisis is over, such that some workers may continue to work remotely in the future. In this case, the pandemic potentially unlocked important welfare gains in the form of lower commuting costs, higher productivity, greater geographical mobility, etc.

While there is likely a role for both channels in explaining the aggregate rise in WFH, we argue that it is hard to rationalize the observed cross-sectional heterogeneity in WFH transitions without substantial WFH adoption in certain labor markets. Consistent with Bartik et al. (2020a) and Dingel and Neiman (2020), we find that WFH rates in the pandemic are strongly correlated with measures of the ability to WFH in different occupations. However, cross-sectional differences in WFH before the pandemic were comparatively much smaller, and not as elastic with respect to WFH ability. Relying on the substitution channel alone to explain why so many more high WFH-ability workers began to WFH in the pandemic – and were not doing so before – requires that these high WFH-ability workers experienced much larger increases in the cost of working on-site. If that were the case, sectors/demographic groups with more high WFH-ability workers should have also experienced larger job loss rates. In the data, however, job loss rates are strongly negatively correlated with WFH transitions. The alternative explanation for the heterogeneity in WFH transitions is that many more high WFH-ability workers started to WFH in the pandemic because WFH adoption was greater in sectors with the most unused capacity for WFH. The negative correlation between WFH transitions and job loss rates likely reflects that in some occupations WFH adoption helped maintain demand by enhancing consumer safety, for instance in the case of doctors switching to telemedicine or educators to remote learning. It could also simply reflect that the potential for WFH adoption

was greater in jobs were demand stayed relatively strong, e.g. in service sectors with low in-person contact with customers such as information or finance.

Additional survey information on the main reasons for commuting provides some direct evidence of WFH adoption in the pandemic. For instance, we find that a majority (63.6 percent) of workers that started WFH in the pandemic cite employer requirements as the main reason for commuting daily before the pandemic. We calculate that the total fraction of workers in work arrangements with a viable option to WFH at least some workdays – i.e. with both the nature of the job and the employer allowing WFH – increased from 33.3 percent in February to 43.8 percent in December 2020. The expansion in WFH access, however, is very unevenly distributed across worker groups, with high-income/high-education and older workers experiencing the largest increases in access.

Finally, we document that many workers expect to continue to WFH in the future. While during the pandemic workers mostly switched to WFH-Only, in the longer run more workers expect to WFH on a part-time basis instead. Overall, 12.5 percent of those employed in December expect to be WFH-Only in the future, while 24.5 percent expect to WFH on a part-time basis. There are large differences in expected changes in commuting behavior across worker groups: The share of highly educated workers who expect to WFH at least partially in the future increased by 19.5 percentage points compared to actual WFH behavior just before the pandemic. In contrast, the increase for low-education workers was only 3.3 percentage points. Workers that are female, over age 50, and high income also expect to WFH more in the long run than before the pandemic.

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 very 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. Our work also relates to a number of studies linking measures of WFH ability to job loss. While we focus primarily on the relationship between actual WFH behavior and job loss/WFH ability, in our dataset higher WFH ability is also associated with lower job loss. This confirms predictions by Alon et al. (2020), and is consistent with other evidence for this relationship in 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), among others.

2 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 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 that is more specifically relevant for analysis of the pandemic.

In this paper, we use information from the RPS on commuting behavior to track workers' WFH status in the health crisis. As in 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 on labor market status and commuting behavior during February of 2020, the month prior to the declaration of a global pandemic by the World Health Organization.[1] This unique retrospective 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 (2020).

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 partic-

[1] 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 year (2020). In February, which of the following best describes your work experience?* Appendix A shows that the results based on the retrospective questions remain overall consistent across the months in our sample.

[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).

ipate in exchange for 30 to 50 percent of the $5 paid per completed survey.[3] The Qualtrics panel 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.[4] 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. In addition, we interact all those categories with gender. Moreover, 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

[3]Qualtrics acts as a panel aggregator and distributes the survey to their partners' actively managed market research panels. All panel members opt-in to receive survey invitations after which they can choose to participate, see Qualtrics (2014). The panels used for the RPS include about 15 million people in the U.S. Surveys that are completed too quickly are dropped to eliminate respondents that did not answer questions carefully.

[4]More specifically, the targets were based on the following categories: Age: 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's degree or more; Marital status: married or not; Number of children in the household: 0, 1, 2, 3 or more; Census region: Midwest, Northeast, South and West; Annual household income in 2019: <$50k, $50k-100k, >$100k.

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 details all targeted categories.

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.[5] The resulting sample consist of 46,450 individual-level observations from online surveys completed between May and December 2020. 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 5,806 observations. Table A.1 in the Appendix 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 per week did you [your spouse/partner] work for this job?*
2. *Last week, how many days per week did you [your spouse/partner] commute to this job?*

For each of these questions, respondents are presented with a slider that provides a choice between integers from 0 to 7. 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

[5] 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.

three commuting categories just prior to the pandemic.

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 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 home-based

work. An additional advantage of the commuting focus is that it allows a validation of our survey results with non-survey-based evidence on commuting volume during the pandemic.

2.2 Aggregate Evolution of WFH Before and During the Pandemic

Before we describe the change in commuting patterns during the pandemic, we first provide some broader context regarding the prevalence of WFH before the pandemic. As documented by a number of studies, WFH was already gradually becoming more common prior to 2020, see for instance Oettinger (2011), Mateyka et al. (2012), Pabilonia and Vernon (2020) or Mas and Pallais (2020). The upward trend in WFH in recent decades, which is usually attributed to advances in information and communication technologies, is illustrated in Figure 1a. The figure plots measures of WFH rates since the early 2000s derived from the time use diary in the American Time Use Survey (ATUS) and from the American Community Survey (ACS). For comparison, Figure 1a also plots the closest RPS equivalents of the ACS and ATUS measures for February 2020.[6]

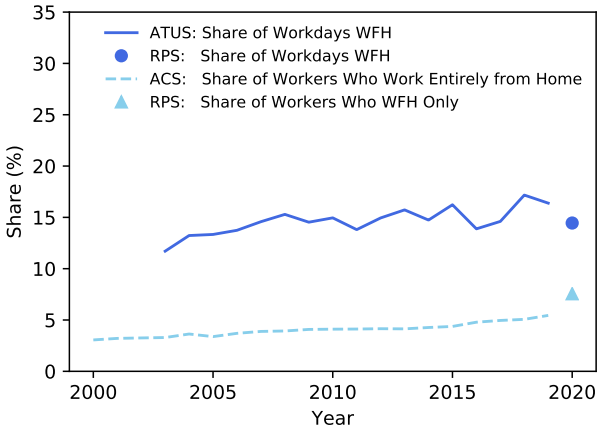
The ATUS time use diary asks about commuting only on the previous day, rather than for a full week, which means it is not possible to construct the same three WFH categories as for the RPS. Figure 1a therefore simply reports the share of all employed respondents without a daily commute in ATUS. This share has gradually increased from 11.7 percent in 2003 to 16.4 percent in 2019. In the RPS, the total fraction of workdays without commutes was 14.4 percent in February 2020, a slightly lower but nonetheless similar number. The other measure shown in Figure 1a is from the ACS, and is based on a question asking employed respondents how they usually got to work last week, with 'worked at home' as an answering option. Figure 1a shows that the fraction of people that reports usually working at home in the ACS increased from 3.1 percent in 2000 to 5.4 percent in 2019. The ACS number for 2019 is somewhat lower than the closest equivalent number in the RPS for February 2020 – the WFH-only fraction – which is 7.6 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.[7] The other main takeaway from the pre-pandemic ATUS and ACS measures is that,

[6] We work with the IPUMS version of the ACS, ATUS and CPS, see Ruggles et al. (2020), Hofferth et al. (2020), and Flood et al. (2020), respectively.

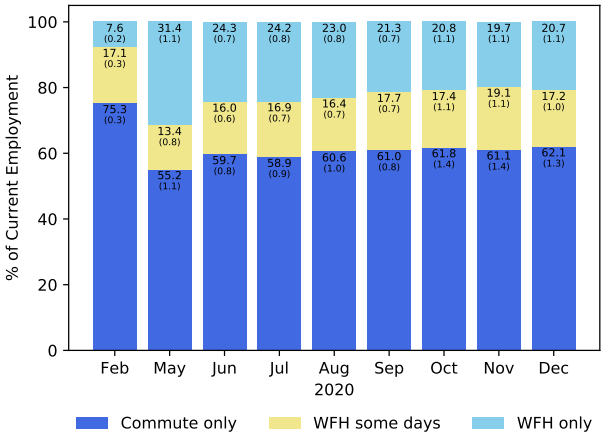
[7] There are several other sources of WFH estimates before the pandemic. The lowest estimate of the fraction of workers that 'usually' only WFH is 2.8 percent in the ATUS Leave and Job Flexibilities Module. In the Atlanta Fed's Survey of Business Uncertainty, US firms report that 3.4 percent of full-time 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

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); American Community Survey (left panel), 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 as described in Appendix A. The number of employed individuals in the sample is 34,867 for February, and 3,597 on average in the subsequent months. See Appendix A for sample sizes by month.

while WFH was rising at a slow and steady pace prior to 2020, it was still relatively uncommon at the start of the pandemic.

Figure 1b shows the extent of the change in commuting behavior during the pandemic in the RPS data. The figure plots the shares of all employed individuals in each of the three WFH categories defined above. Whereas 75.3 percent of all workers commuted every workday in February 2020, this share was only 55.2 percent by May, the first month our survey was conducted. In June 2020, the Commute-Only share recovered by 4.5 percentage points to 59.7 percent, and by another 2.4 percentage points in the rest of 2020, reaching 62.1 percent in December. The decline in the share of full-time commuters relative to February primarily reflects a rise in the share of WFH-Only workers. This share quadrupled from 7.6 percent in February to 31.4 percent in May. The WFH-Only share fell considerably, by 7.1 percentage points, in June. By the end of the year, the WFH-Only share declined by another 3.6 percentage points to 20.7 percent, which is still 13.1 percentage points larger than in February. The share of workers that WFH on some workdays dropped from 17.1 percent in February to 13.4 percent in May, but rose fairly quickly to levels that are comparable to before the pandemic.

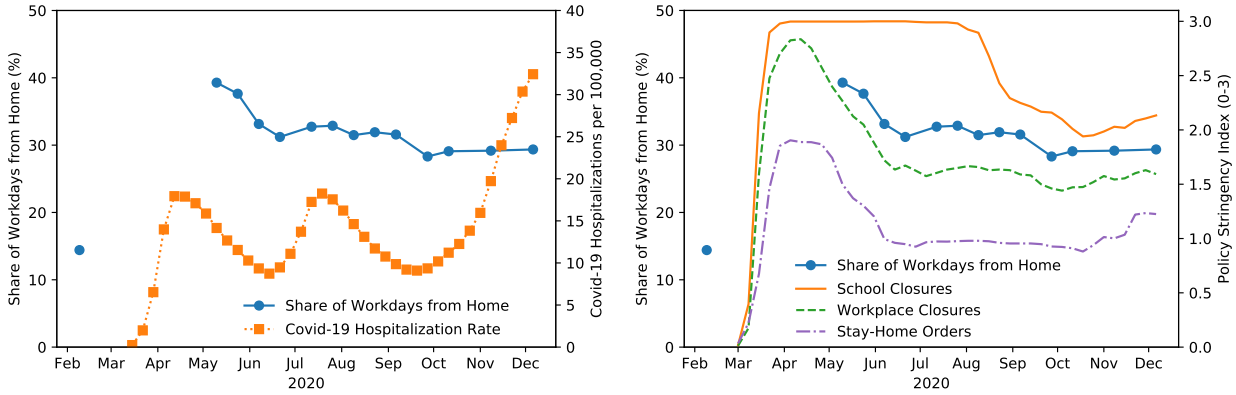
The initial shift towards WFH in response to the virus outbreak was very pronounced.

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 2: WFH, COVID-19 Hospitalizations, and Containment Policies

(a) WFH and Hospitalizations

(b) Containment Policies



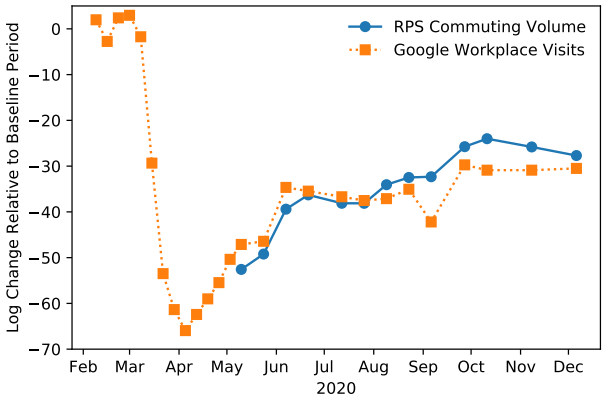
Source: Real-Time Population Survey (left panel), COVID Tracking Project (left panel), Oxford COVID-19 Government Response Tracker (OxCGRT) (right panel). *Left panel:* Share of workdays from home is the ratio of (weighted) total days WFH to total workdays in the RPS. See Appendix A for sample sizes 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.

However, WFH did not co-move nearly as strongly with the pandemic during the second half of 2020. Figure 2a displays the weekly 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 to 39.3 percent in May, the WFH share of workdays dropped to 31.2 percent during the May-June decline in hospitalizations after the first wave. During the second wave of the pandemic over the summer, 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 fourth quarter of 2020, the WFH share of workdays increased only moderately, to 29.4 percent in December.

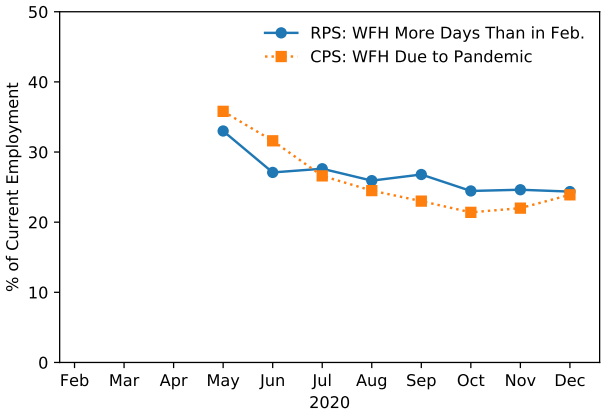
One possible reason for the larger initial rise in WFH is the greater stringency of virus containment policies in the first wave of the pandemic in the U.S. Figure 2b plots stringency indicators for the policies most directly relevant for WFH: stay-at-home-orders, workplace closures, and school closures. The series shown are population-weighted averages of state-level scores between 0 and 3 in the Oxford Government Response Tracker (Hale et al., 2020): 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. Figure 2b shows that containment policies were stricter and broader-based between late March and April than afterwards. After

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). *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. Those not working in February are included with zero commutes, but omitting them does not change the series meaningfully.

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. The share of WFH workdays in Figure 2b closely tracks the stay-at-home and workplaces closure indicators, but we caution that the causality is not clear.[8]

2.3 Comparison with Other WFH Measures in the Pandemic

Before delving deeper into the RPS data to learn more about WFH during the pandemic, we pause to compare our WFH estimates to other available measures.

One valuable alternative source of high frequency information on commuting behavior is cellphone location data. Figure 3a plots the Google mobility metric for visits to the workplace in all 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

[8]We found only weak correlations between WFH and the policy indices across geographies. Studies of the behavioral responses in the pandemic in the U.S. typically find relatively small effects of policy, e.g. Kong and Prinz (2020), Baek et al. (2021) or Goolsbee and Syverson (2021). One exception is Coibion et al. (2020).

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 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, see Section 2.1.2, where we use zero as the answer for all individuals with zero workdays.

Even though the sources of information are very different, Figure 3a shows that our survey-based measure of commuting volume aligns well with the geolocation-based series. This gives us confidence in our measures. We emphasize, however, that mobility data from Google and similar sources do not reveal to what extent commuting declined because workers switched to WFH, or because they were not working. A decomposition of the RPS data shows that a substantial fraction (around a third) of the drop between May and February and the subsequent recovery in commuting can be explained by fluctuations in labor supply along both the intensive and extensive margins.[9] Mobility data is also not generally available at the individual level, and it is usually difficult for researchers to assess its precise origins and representativeness.

There are also several other survey-based sources of 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. This question differs from the RPS survey in a number of ways. It is explicitly conditioned on the pandemic being the reason for telework/WFH, it does not elicit any information about respondents' commuting behavior before the pandemic, it does not specify any particular quantity of tele- or home-based work, and it has a longer reference period (four weeks). At the same time, the CPS has a much larger sample than the RPS and uses more conventional survey methods. For these reasons, it provides another useful point of comparison for our measures.

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. To the extent the pandemic is the reason for the larger number of workdays without commutes, both fractions should be similar in magnitude. Figure 3b shows that both series indeed line up fairly closely. This concordance between the RPS and CPS provides some further validation of our measures, and also suggests that the pandemic remains the dominant reason

[9]Reductions in the length of the workweek account for 5.3 percent of the Feb-May decline in commuting volume in the RPS, whereas the drop in employment accounts for 29.9 percent. In December, commuting volume remained 27.7 log points below February levels, of which 11.2 percent of the shortfall is accounted for by a shorter average workweek, 19.5 percent by lower employment, and 69.3 percent by increased WFH. See Appendix B for full details.

for the reduction in commuting over the sample period. Going forward, however, our WFH measures should be better suited to measure any more permanent effects on commuting habits as the pandemic subsides.

Another useful source of information on WFH in the pandemic is Barrero et al. (2021), who present results from multiple waves of WFH surveys starting in May 2020 that were also administered by commercial online survey providers. Their survey results for May 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. For December, the proportions are 36.2 percent, 36.7 percent and 27.2 percent, respectively. As shares of current employment, these estimates imply WFH rates of 62.2 percent in May and 49.7 percent in December. These rates are substantially larger than those measured in the RPS or CPS in Figures 1b and 3b, which likely reflects differences in sample composition and survey methodology.[10] At the same time, they suggest a similar trajectory of WFH as the mobility data or the CPS and RPS measures since May. All available evidence therefore agrees that, despite a partial recovery in commuting, many workers have continued to WFH well beyond the initial months of the pandemic.[11]

2.4 Who Transitioned to WFH During the Pandemic?

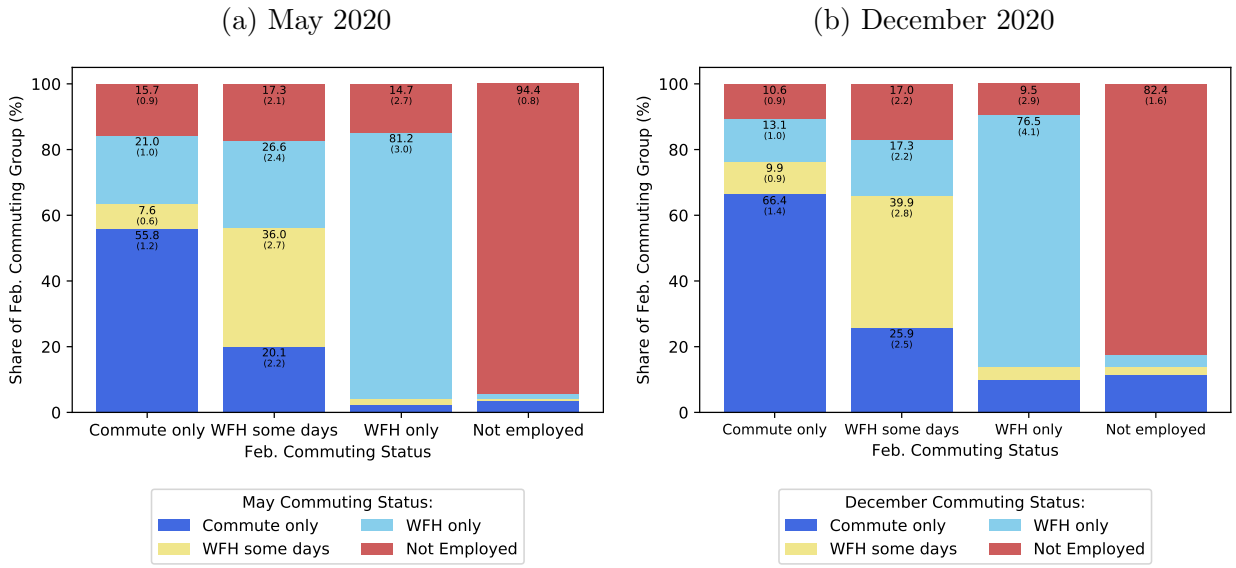
2.4.1 Individual-Level Transitions in WFH

As shown earlier in Figure 1b, the Commute-Only share of the workforce declined in the pandemic, while the WFH-Only share rose markedly. This suggests that the rise in WFH happened primarily because many workers that used to commute every workday stopped doing so entirely. To verify whether this is the case, Figure 4 depicts the transition rates across the WFH categories and non-employment between February and May in the left panel, and between February and December in the right panel (the other months are shown in Appendix C).

[10]The survey question to elicit respondents' combined WFH/employment status is: *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.* 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 ONET 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.

[11]Several other studies report survey estimates of WFH rates. Based on a Google Consumer Surveys question in early April and May, Brynjolfsson et al. (2020) find that about half of employed respondents in May worked from home. Based on data from the COVID Impact Survey conducted by NORC at the University of Chicago in April and May, Lyttelton et al. (2020) find that 55 percent of currently employed parents were telecommuting in April and May. In a survey of small business leaders, Bartik et al. (2020a) find that 45 percent of firms report having any workers switch to working remotely. In a Dallas-Fed survey of Texas-based employers, businesses report that on average 35 percent of employees were working remotely in August (Kerr, 2020).

Figure 4: 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 December 2020 for the right panel. The corresponding figures for all other sample months are in Appendix C. Standard errors in parentheses, calculated as as described in Appendix A; that section also contains sample sizes by month.

Figure 4a confirms that the February-May rise in WFH-Only is indeed primarily driven by a drastic change in the commuting habits of many daily commuters. As Figure 1b showed, over three quarters of all workers were full-time commuters in February 2020. Figure 4a shows that only 55.8 percent of those full-time commuters were still commuting every workday in May. More than a fifth (21.0 percent) switched to WFH-Only, and another 7.6 percent started working from home on a part-time basis. Only about a quarter of the February partial WFH workers switched to WFH-Only. Most continued to WFH partially, and about a fifth switched to Commute-Only. The vast majority of pre-pandemic WFH-Only workers remained WFH-Only in May. Together, the estimated transition rates imply that, among all those that were WFH-Only in May, about 60 percent were Commute-Only just before the pandemic, while most others were already WFH-Only in February (see Appendix C). The clear implication is that the overall decline in commuting happened because many workers switched from commuting 'all the time' to 'not at all', and less because of switches from full-time commuting to 'some WFH', or from 'some WFH' to 'only WFH'.

Figure 4b displays the same breakdown in WFH transitions between February and December. While there are increases in full-time commuting across all categories relative to May, we

still observe that only two thirds of February Commute-Only workers were commuting daily in December. The increase in Commute-Only relative to May reflects in part a decrease in the fraction that were not employed. However, a substantial share (13.1 percent) of February daily commuters remain WFH-Only at the end of 2020. The February-December transition rates imply that, among all those who WFH-Only in December, about half were Commute-Only in February (see Appendix C). At the same time, a slightly higher fraction of February Commute-Only workers was WFH on some workdays compared with May (9.9 percent vs 7.6 percent).

The other noteworthy feature in Figure 4 is that the rates at which workers transitioned out of employment are not markedly different by February WFH status. Specifically, individuals working from home daily before the pandemic lost employment at almost the same rates in May as daily commuters: 14.7 percent vs 15.7 percent, respectively. This means that there is little role for selection in driving the rise in the aggregate WFH share. It also indicates that being in a fully home-based job before the pandemic by itself was not sufficient to insulate workers from job loss during the pandemic, and suggests that reductions in demand affected some WFH-Only workers regardless.

Finally, Figure 4 shows that the vast majority of those not employed in February 2020 remained non-employed throughout the year.

2.4.2 The (Small) Role of Reallocation to New WFH Jobs

To what extent was the increase in WFH during the pandemic driven by workers who commuted in February but started new jobs at which they WFH? To assess the role of reallocation of workers towards WFH jobs in the pandemic, we rely on a question in the RPS that allows a distinction between workers that changed jobs since February, and workers that are still in the same job. Specifically, we ask:

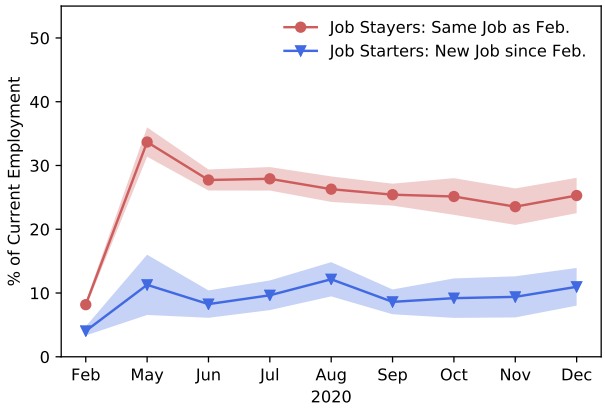
When did you [your spouse/partner] start working for this employer? (or for yourself [themself] if you [they] are self-employed)? If you [your spouse/partner] had any brief interruptions, like a temporary layoff or unpaid leave, please report when you [your spouse/partner] first started working for this employer.

The answering options are *(a) February 2020 or earlier*, *(b) March 2020*, *(c) April 2020*, and so on, until the month of the interview. We label all currently employed individuals that answer '*February 2020 or earlier*' as 'job stayers', and all others as 'job starters'.

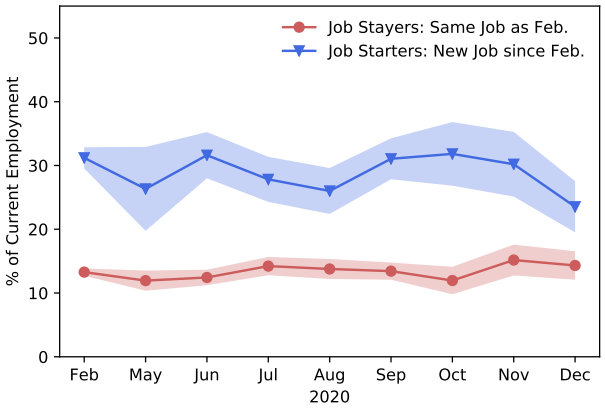
Figure 5 plots the WFH rates for job stayers and job starters since February. The left panel

Figure 5: WFH Among Job Stayers and Job Starters

(a) WFH-Only



(b) WFH Some Days



Source: Real-Time Population Survey. The sample is individuals (ages 18-64) employed in each month. The figure shows the share of WFH-Only workers (left panel) and partial-WFH workers (right panel). Job stayers are individuals who worked for the same employer in February and in the interview month. Job starters are individuals who did not work for the same employer in February and in the interview month; this includes both workers who switched employers and workers not employed in February. The shaded region corresponds to two-standard-error bands. Appendix A describes the calculation of standard errors and contains sample sizes by month.

shows the WFH-Only shares, while the right panel shows the shares of workers that WFH on some workdays. In both panels, the February WFH rates for the job starters are for those employed in their old February jobs. Job starters in subsequent months also include those that were not employed in February. Therefore, the changes relative to February reflect WFH differences between the old jobs of job starters that were employed in February, and the new jobs of all job starters. Appendix D shows that leaving out job starters not employed in February leads only to minor quantitative differences.

On the left, Figure 5a shows that there are substantial differences in WFH-Only rates between job stayers and job starters. 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). In May, WFH-Only rates are higher for both types of workers, but the rates rose far more for job stayers (to 33.6 percent vs 7.9 percent for job starters). Between June and December, WFH-Only rates average 25.9 percent for job stayers, whereas those for job starters were substantially lower (7.2 percent on average).

On the right, Figure 5b shows that job starters had substantially higher partial WFH rates than job stayers in February (31.2 percent vs 13.3 percent). These higher overall partial WFH rates reflect that job starters are more likely to be younger and have children in the household, both of which are associated with a greater propensity for working from home on a part-time

basis. While inevitably more variable because of the smaller number of observations, the partial WFH rates for job starters are relatively steady between May and December at a level that is similar to February (32.2 percent on average). The May-December partial WFH rate for job stayers is also relatively stable (averaging 13.4 percent). Combined with an increasing share of job starters in total employment (10.8 percent in May, growing to 31.8 percent in December), this leads to the modest increase in the total partial WFH share between June and December from 16 percent to 17.2 percent shown in Figure 1b.

The key implication of Figure 5 is that the change in commuting patterns during the pandemic was driven almost entirely by workers who switched to WFH-Only within the jobs they held at the start of the pandemic. Reallocation of workers towards new WFH jobs played a comparatively small part in the rise in the share of WFH-Only workers during the pandemic.

2.4.3 WFH by Demographic Group

It has been widely documented that the economic impact of the COVID-19 pandemic during the course of 2020 was highly unequally distributed across various demographic groups, see for instance, Adams-Prassl et al. (2020), Alon et al. (2020), Bartik et al. (2020b), Cajner et al. (2020), Couch et al. (2020), and Lee et al. (2021) among others. The same is also true for the changes in commuting, as is shown in Figure 6.

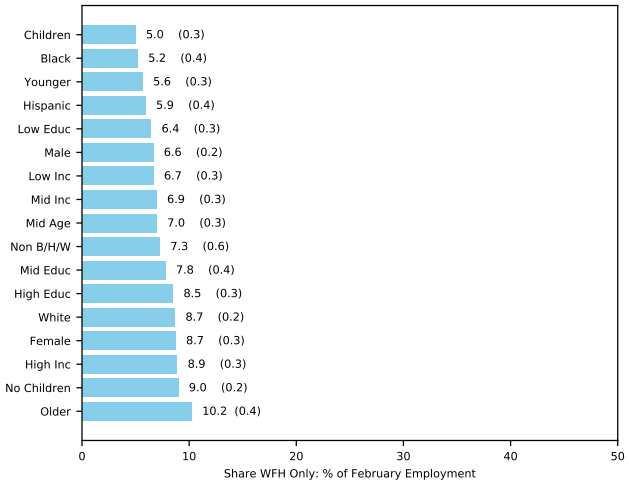
For brevity, Figure 6 focuses on the WFH-Only category (Appendix F provides results for partial WFH). Figure 6a shows the WFH-Only shares in February 2020 by age, race/ethnicity, education, 2019 household income levels, gender and the presence of children. Before the pandemic, WFH on a full-time basis was relatively more common among older workers (ages 50 to 64), workers without children present in the household, workers with higher levels of income or education, and among female and white workers. Younger and minority workers, as well as workers with children in the household were less likely to work exclusively at home. These cross-sectional differences in WFH before the pandemic are largely consistent with existing pre-pandemic evidence from ATUS and other sources (Mas and Pallais, 2020; Pabilonia and Vernon, 2020).

The pre-pandemic heterogeneity in the WFH-Only shares, however, is relatively small compared with the much larger differences arising during the pandemic. Figure 6b shows the percentage point changes in the WFH-Only shares of current employment in May relative to February among the various worker groups.[12] Whereas all worker categories saw substantial increases in WFH-Only shares, these increases were far larger for some groups than for others.

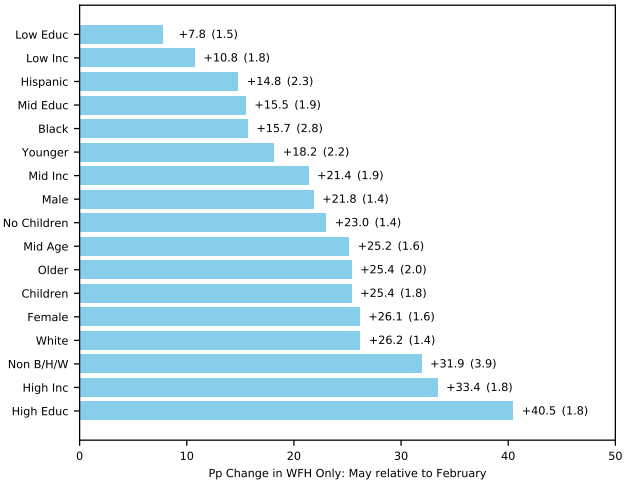
[12]In Appendix G, we show that the fraction of workers with increases in WFH in the RPS closely lines up with the shares of workers doing 'pandemic-related WFH' in the CPS for each worker category.

Figure 6: WFH-Only Shares by Demographic Group

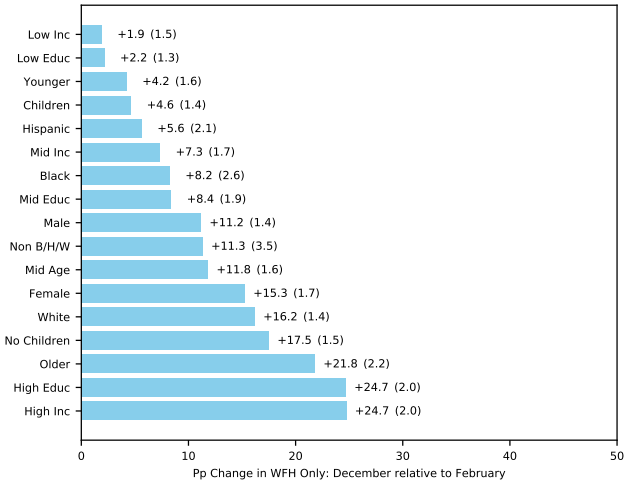
(a) Pre-Pandemic (February 2020)



(b) Change from Feb to May, 2020



(c) Change from Feb to Dec, 2020



Source: Real-Time Population Survey. The sample is individuals (ages 18-64) employed in each month. *Panel (a)* displays the share of WFH-Only workers in February 2020. *Panel (b):* displays the percentage point change in the share of WFH-Only workers in May relative to February 2020. *Panel (c):* displays the percentage point change in the WFH-Only share in December relative to February 2020. Definitions of demographic groups are provided in Appendix A.4. Standard errors in parentheses, calculated as as described in Appendix A; that section also contains sample sizes by month.

The share of highly educated workers (bachelor's degree or more), in particular, increased by 40.5 percentage points relative to February, up to the point where nearly half (49.0 percent) of all highly educated workers were WFH-Only. In contrast, the share of low-education workers (high school or less) increased by only 7.8 percent, and in total only 14.2 percent were WFH-Only in May. Large differences exist also for other worker categories. The increases in the WFH-Only shares of white, high-income and older workers, for example, were all significantly

larger than those for minority, low-income and younger workers respectively. The same heterogeneity patterns remain present after conditioning for other worker characteristics and industry of employment, see Appendix F.

The pronounced differences in WFH largely persist throughout 2020. Figure 6c shows the changes in WFH-Only shares in December relative to February 2020. Consistent with the partial recovery in aggregate commuting, the December WFH-Only shares are lower for all groups compared with earlier in May. High-income, high-education and older workers, in particular, continued to be fully home-based at much higher rates than low-income, low-education and younger workers. However, one group for which the increase in WFH was much less persistent are workers with children in the household. Whereas WFH increased similarly for workers with and without children early on in the pandemic, the share of working parents that were WFH-Only declined more rapidly in June and afterwards (see Appendix F for the full time series). In December, the WFH-Only share of workers with children was only 4.4 percent larger than before the pandemic, whereas it was 25.1 percent higher in May. In contrast, the WFH-Only share for workers without children was 23.5 percent higher in May than in February, but in December it was still 17.8 percent higher than before the pandemic. This suggests that the presence of children in the household is an important factor impeding on workers' ability to WFH for extended periods of time.

3 WFH Transitions: Substitution or Adoption?

In this section, we take a closer look at the nature of the WFH transitions during the pandemic, focusing specifically on explanations for the large differences in WFH across workers that emerged during the pandemic. We first lay out a theoretical model that describes more precisely the WFH substitution and WFH adoption channels discussed in the introduction. We then document cross-sectional empirical relationships between WFH transitions, job loss, and WFH ability, and we argue that the evidence points to WFH adoption playing an important role in explaining the observed heterogeneity in WFH transitions.

3.1 A Model of WFH Employment

3.1.1 Environment

We consider an environment with a continuum of geographically perfectly segmented labor markets, each populated by a continuum of workers with size normalized to one. Workers 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. This cost captures time spent commuting to work, but also any other costs (or benefits) associated with

an equal amount of time worked away from the home rather than at home. These may include the pandemic-related health risks of on-site work that can be avoided by working remotely, or any costs of non compliance with government restrictions on working on-site.

Each worker has at most one job. A job requires supplying one efficiency unit of labor regardless of the place of work. Workers 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 worker. The value of γ captures workers' overall ability to WFH. The workplace is always distinct from a workers' home location, such that 'WFH' and 'remote work' are equivalent in the context of the model.

Each local labor market features a monopolistic/monopsonistic firm that chooses the level of employment, E. 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 $\beta > 1$ 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 allows us to abstract entirely from job reallocation, which is not very important in driving the rise in WFH in our sample period, see Section 2.4.2.

In a fraction $1 - \theta$ of labor markets, firms do not allow WFH. In the other labor markets the firms provide workers with the option to WFH. We assume that firms that allow WFH can set separate wages for commuters and home workers, denoted by w_l and w_h respectively. For firms, WFH employment only matters because of the effect on the wage bill.[13]

3.1.2 Equilibrium

A utility-maximizing worker with home productivity z is willing to complete the job on-site, i.e. commute, $(h = 0, l = 1)$ as long as the pay-off is at least as great as not working, $w_l - (1+\chi) \geq 0$, and at least as great as completing the job from home, $w_l - (1+\chi) \geq w_h - 1/z$. If $w_h - 1/z > w_l - (1 + \chi)$ and $w_h \geq 1/z$, the worker instead prefers to complete the job at home $(h = 1/z,\ l = 0)$. Else, the worker prefers not to work. Note that any work done by a given worker is either entirely on-site or entirely from home. We therefore abstract from partial WFH, which is motivated by the evidence in Section 2.4.1 showing the dominating role of switches from full-time commuting to full-time WFH in the pandemic.

[13]For employment outcomes, allowing for additional (linear) costs of on-site work for firms is equivalent to changing the value of χ, while introducing an additional WFH cost for firms is equivalent to changing the value of WFH productivity γ.

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 increase 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 $w_l = 1+\chi$.

Next, we introduce the following assumptions on the parameters of the model:

$$\delta(1+\chi)^{-\beta} < 1 \tag{1}$$

$$\gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda} < 1 \tag{2}$$

As will be clear momentarily, (1)-(2) guarantee that firms never employ all workers in their labor market, allowing us to focus on interior solutions to the firms' profit maximization problems.

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 assumption (1) ensures that $E < 1$. 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 $E = E_l + e(w_h)$. Depending on parameter values, these firms may choose to employ a mix of commuters and home workers, or they may choose to employ only home workers. We discuss each case in turn.

Case 1: WFH firms employ both commuters and home workers. When the following condition holds

$$\gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda} < \delta(1+\chi)^{-\beta} \tag{3}$$

the optimal decisions of the firm are given by

$$w_h = \frac{\lambda}{1+\lambda}(1+\chi) \ , \tag{4}$$

$$E_h = e\left(w_h\right) = \gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda} \ , \tag{5}$$

$$E_l = \delta(1+\chi)^{-\beta} - E_h. \tag{6}$$

Condition (3) ensures that WFH labor supply at the equilibrium wage is below the overall demand for labor, such that $E_l > 0$, $E_h > 0$, and the firm optimally employs a mix of commuters and WFH workers.

The optimal wage (4) 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 (5) is the WFH supply at that wage. An important feature of the firm's optimal decisions in (4)-(6) is that the ability to WFH is irrelevant for the total level of employment $E_h + E_l = \delta(1+\chi)^{-\beta}$. The reason is that condition (3) 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 the workers' WFH productivity. The level of WFH employment in (5) depends on the ability to WFH, but it is independent of the 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

$$(1+\chi)/(1+\lambda)E_h \geq 0 \tag{7}$$

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.[14]

[14]If wage discrimination is not possible, the firm pays all workers $w = 1+\chi$ and sets $E_h = e(1+\chi)$. Without wage discrimination, the entire WFH surplus goes to the WFH workers and firm profits are the same with or without WFH option.

Case 2: Firms employ only home workers. If the parameters are such that

$$\delta(1+\chi)^{-\beta} < \gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda}, \tag{8}$$

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 (8) holds, the optimal decisions of the firm are given by

$$w_h = \frac{\lambda}{1+\lambda}\delta^{1/\beta}e(w_h)^{-1/\beta} = \left(\frac{\lambda}{1+\lambda}\right)^{\frac{\beta}{\beta+\lambda}}(\delta/\gamma)^{\frac{1}{\beta+\lambda}}, \tag{9}$$

$$E_h = e(w_h) = \delta^{\frac{\lambda}{\beta+\lambda}}\gamma^{\frac{\beta}{\beta+\lambda}}\left(\frac{\lambda}{1+\lambda}\right)^{\frac{\beta\lambda}{\beta+\lambda}}, \tag{10}$$

$$E_l = 0. \tag{11}$$

Because the firm sets a wage that is lower than $(1+\chi)\lambda/(1+\lambda)$, it is the case that $E_h < \gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda}$. Assumption (2) therefore guarantees that $E_h < 1$.

The optimal wage (9) still equals the firm's marginal revenue after the monopsonistic markdown. However, under condition (8) 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

$$\left(\frac{1}{\beta-1}+\frac{1}{1+\lambda}\right)\delta\left(\left(\frac{\delta}{\gamma}\right)^{\frac{1}{\beta+\lambda}}\left(\frac{\lambda}{1+\lambda}\right)^{-\frac{\lambda}{\beta+\lambda}}\right)^{1-\beta} - \frac{\delta\,(1+\chi)^{1-\beta}}{\beta-1} > 0 \tag{12}$$

where the inequality is guaranteed by (8). The firm unambiguously prefers to provide the WFH option. As in Case 1, 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.

3.1.3 WFH Substitution and Adoption in a Pandemic

In the model, there are several reasons why a pandemic can cause commuters to switch to working from home. First, increased health risks are likely to increase the cost of working on-site, χ. We think of increases in χ as potentially arising both directly from the higher health risks

as well as indirectly from any government restrictions imposed. Strictly enforced government-mandated workplace closures can be thought of as large increases in χ that make any on-site work prohibitive, as in Case 2 above. Note that a rise in χ amounts to an adverse shock to the supply of on-site labor. Second, any pandemic-related changes in χ increase firms' profit incentives for providing the WFH option, and may therefore lead to increases in the fraction θ of firms that allow WFH. Such an increase in θ amounts to an increase in the demand for WFH labor. Finally, the pandemic may lead to the use of new WFH technologies that change the overall WFH productivity, γ. Any such increase in γ amounts to an increase in the supply of WFH labor.

Let $\varepsilon_\theta = \Delta \ln \theta$, $\varepsilon_\gamma = \Delta \ln \gamma$, $\varepsilon_\chi = \Delta \ln(1+\chi)$, and $\varepsilon_\delta = \Delta \ln \delta$ denote the changes in the model parameters during the pandemic. How these changes impact WFH employment depends on whether WFH firms employ commuters before the pandemic, and if so whether they decide to switch all workers to WFH or not.

First, suppose that all firms employing home workers also employ commuters both before and during the pandemic. In other words, condition (3) holds at all times, and firms' decisions are always as in Case 1 above. The log change in average WFH employment E_h^a across all firms is then given by

$$\Delta \ln E_h^a = \varepsilon_\theta + \varepsilon_\gamma + \lambda \varepsilon_\chi \tag{13}$$

WFH employment in (13) rises after increases in WFH labor demand ($\varepsilon_\theta > 0$) and supply ($\varepsilon_\gamma > 0$), or after an increase in the cost of on-site labor $\varepsilon_\chi > 0$. However, WFH employment does not depend on changes in overall demand, ε_δ, as the firms' marginal cost of labor depends on the commuters' wage only.

Next, suppose that all WFH firms only employ home workers both before and during the pandemic. This means condition (8) holds at all times, and firms' decisions are always as in Case 2 above. The log change in average WFH employment in this case is given by

$$\Delta \ln E_h^a = \varepsilon_\theta + \frac{\beta}{\beta+\lambda}\varepsilon_\gamma + \frac{\lambda}{\beta+\lambda}\varepsilon_\delta \tag{14}$$

As above, WFH employment increases after increases in WFH labor demand and supply, $\varepsilon_\theta > 0$ and $\varepsilon_\gamma > 0$. However, the change in WFH employment in (14) no longer depends on changes in the cost of working on-site ε_χ, as all workers are always home workers. In contrast to (13), WFH employment is increasing in the change in demand, ε_δ.

The last case we consider is when all firms with a WFH option employed a mix of home workers and commuters before the pandemic, but in the pandemic all workers are home workers. In other words, condition (3) holds before the pandemic, but the increase in the cost of on-site work $\varepsilon_\chi > 0$ or the drop in demand $\varepsilon_\delta < 0$ are large enough such that condition (8) starts to hold in the pandemic. In that case, the log change in average WFH employment is

$$\begin{aligned} \Delta \ln E_h^a &= \varepsilon_\theta + \frac{\beta}{\beta+\lambda}\varepsilon_\gamma + \frac{\lambda}{\beta+\lambda}\varepsilon_\delta - \frac{\lambda}{\beta+\lambda}\ln\sigma \ , \\ \text{where} \quad \sigma &\equiv (\gamma/\delta)(1+\chi)^{\lambda+\beta}\left(\lambda/(1+\lambda)\right)^{\lambda} < 1 \ . \end{aligned} \tag{15}$$

In (15), σ is the pre-pandemic share of WFH employment in total employment at firms that have the WFH option. The first three terms in (15) are the same as in (14). However, the change in WFH employment in (15) additionally depends negatively on the pre-pandemic share of WFH employment, σ. The reason is that a high-γ firm with one percent more WFH employees than a low-γ firm in (5) will have only $\beta/(\beta+\lambda) < 1$ percent more WFH employees in (10). Ceteris paribus, a higher ability to WFH implies that a smaller fraction of workers are laid off in the pandemic. However, if the firm allowed WFH before the pandemic, it also means that a smaller fraction of workers need to switch from commuting to WFH. In other words, WFH employment growth is decreasing in the pre-pandemic WFH share because high-γ firms already employ a larger share of the optimal number of WFH employees in the pandemic as home workers before the pandemic.

A key feature of the model is that reductions in the demand for firms' goods or services, $\varepsilon_\delta < 0$, never create any reason for commuting workers to switch to WFH. In (13), the change in WFH employment is independent of ε_δ, while in (14) and (15) lower demand leads to job loss for WFH workers. This is important, because it means the model can explain why WFH transitions are not a feature of more typical recessions.[15] At the same time, the model can also explain why demand-driven recessions can lead to job loss for home workers. This will be the case when negative demand shocks hit occupations that are mostly home-based, see (14), or in labor markets that experience large enough drops in demand (15). In Section 2.4.1, we documented significant rates of job loss for workers that worked from home before the pandemic. In the model, this can only be explained by adverse shocks to demand. When any of the other shocks raise WFH employment, pre-pandemic WFH employees are always retained by the firms, as they were already more productive at home before the pandemic.

In the model, all transitions from commuting to WFH must be driven by higher costs of supplying labor on-site, $\varepsilon_\chi > 0$, by more employers allowing WFH, $\varepsilon_\theta > 0$, or by improvements

[15] There is for example no evidence of any meaningful rise in WFH in the 2008-09 recession, see Figure 1a.

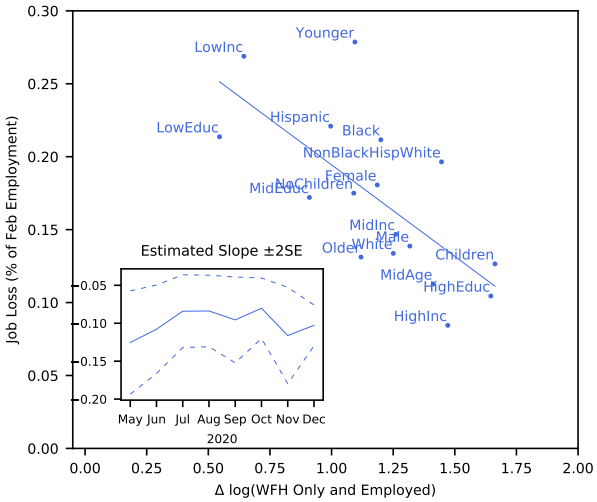
in WFH productivity, $\varepsilon_\gamma > 0$. We refer to WFH transitions that are the result of either of the last two drivers, i.e. $\varepsilon_\theta > 0$ or $\varepsilon_\gamma > 0$, as the *WFH adoption channel*. The *WFH substitution channel* instead refers to all WFH transitions caused by cost increases $\varepsilon_\chi > 0$ conditional on $\varepsilon_\theta = 0$ and $\varepsilon_\gamma = 0$. The key distinction between channels is that, all else equal, WFH adoption reduces costs and raises worker productivity. Many of the WFH transitions driven by adoption may therefore persist in the longer-run. In contrast, the WFH substitution channel can only occur at firms that already provided the WFH option before the pandemic. For this reason, they are necessarily associated with lower worker productivity and lower profits relative to before the pandemic, such that we would expect these WFH transitions to reverse once the health crisis ends.

Possible Reasons for Low WFH Adoption before the Pandemic In the model, providing the WFH option to workers is always profitable because firms are able to pay lower wages to home-based workers. Several empirical studies support the real-world potential for firms to lower wage costs by allowing WFH. 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. Using French administrative data, Le Barbanchon et al. (2020) find that gender differences in commute valuation can account for a .5 log point hourly wage deficit for women.

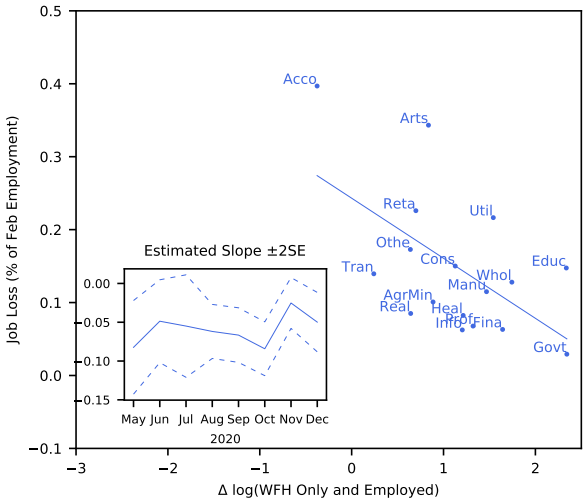
The WFH adoption channel requires that adoption was relatively low before the pandemic despite the potential benefits for firms and workers. Of course, one is that in many occupations WFH is infeasible, see e.g. Dingel and Neiman (2020) or Su (2020). But even when WFH is a viable option, many firms may not have sufficient profit incentives to allow WFH in normal circumstances. One reason could be that wage discrimination based on WFH status is difficult because of fairness concerns. There may be various fixed costs of WFH adoption, for example in terms of new equipment and communication technologies, that do not justify the increase in variable profits. There could also be problems of adverse selection if remote work attracts unobservably less productive workers. Using data from a call center, Harrington and Emanuel (2020) document 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. Another possibility is that WFH was still relatively uncommon prior to pandemic because of inertia and slow adjustment to sociotechnical innovations. Employers and employees may underestimate the viability of WFH without any actual experience. Bloom et al. (2014) document, for example, how a temporary experiment showing meaningful productivity gains lead to the permanent adoption of WFH by a Chinese call center.

Figure 7: Job Loss vs. Changes in WFH-Only Employment

(a) By Demographic Group



(b) By Industry



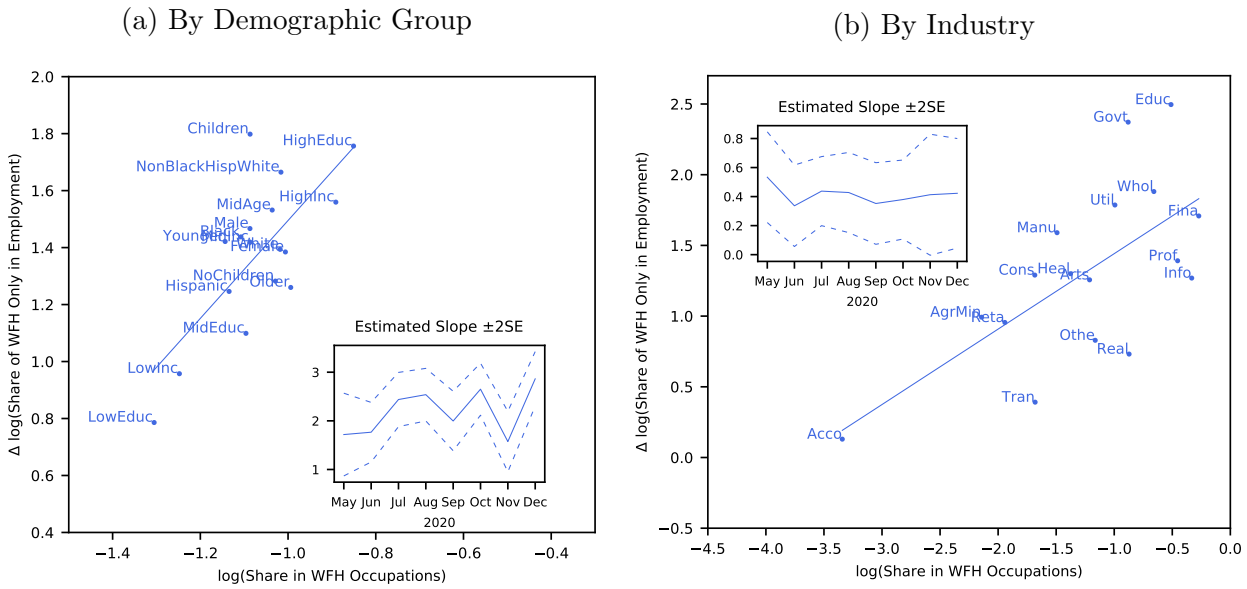
Source: Real-Time Population Survey. Scatters show May data. The inset plot shows the regression slope for each month with two-standard-error bands. In both panels, the sample is individuals (ages 18-64) employed in February 2020. The x-axis is the log change from February to May in WFH-Only employment among February workers. The y-axis is the percent decline in employment among February workers from February to May. Definitions of demographic and industry groups are provided in Appendix A.4. Industry classification is by industry of employment in February.

3.2 Cross-Sectional Facts About WFH Transitions, Job Loss and WFH Ability

With the theory in hand, we next present two cross-sectional empirical facts about WFH transitions in the pandemic that will be informative for the role of the WFH adoption channel in explaining the large heterogeneity in WFH transitions. For brevity, here we report these facts only for the WFH-Only category. Appendix H shows the same qualitative facts hold if we also include workers that transitioned to partial WFH in the pandemic.

Fact 1: WFH transitions and job loss are negatively correlated across demographic groups and industries. Figure 7 plots the log change in WFH-Only employment among February workers against the fraction of February workers that was no longer employed that month. The left panel conditions on a range of worker characteristics, including gender, age, ethnicity, the presence of children, education and 2019 income. The right panel conditions on the industry of employment in February. Both panels show that groups with higher growth in WFH-Only employment among those with a job in February also experienced lower rates of job loss in May. This negative relationship between WFH transitions and rates of job loss persists also in the later months. This is shown in the inset plots in Figure 7, which report the regression slopes of the relationship for each month. Across both demographic groups and industries, the two-standard-error bands around the slope estimates exclude zero in all months.

Figure 8: Changes in WFH-Only Share of Employment vs. Share in WFH Occupations



Source: Real-Time Population Survey and Dingel and Neiman (2020). Scatters show May data. The inset plot shows the regression slope for each available month with two-standard-error bands. The x-axis is the log share of February workers in potential WFH occupations based on the measures of Dingel and Neiman (2020). The y-axis is the log change from February to May in the share of employed workers that are WFH-Only. Industry classification is by industry of employment in February. Definitions of demographic and industry groups are provided in Appendix A.4.

Fact 2: Changes in the share of WFH-Only workers are positively correlated with differences in WFH ability across occupations. Figure 8 plots the log change in WFH employment shares against the log share of workers that were in potential WFH jobs in February. To measure the fraction of workers in potential WFH occupations, 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 jobs based on the occupational composition of the worker's industry of employment in February. For each demographic group, we take the average of the industry shares in WFH occupations weighted by the group's employment share in each industry. Figure 8 shows that the relationship between these occupation-based measures of WFH potential and actual changes in WFH-Only employment shares from February to May is strongly positive. The relationship is also very persistent. The inset plots in Figure 8 provide the regression slopes in each month. The estimates are positive and highly statistically significant in all months, both across demographic groups and industries. Averaging the R-squared statistics across months, the share of workers in WFH occupations in February accounts for 82.8 percent of the variation in WFH transitions across demographic groups, and for 33.5 percent of the variation across industries. This means that whether workers in different groups/industries experienced more or fewer WFH transitions is closely related to what frac-

tion of those workers were in potential WFH occupations before the pandemic. Bartik et al. (2020a) document a similar fact based on U.S. business surveys, and Dingel and Neiman (2020) document a close relationship between levels of WFH rates and the share of potential WFH workers in a cross-section of countries in the pandemic.[16] Fact 1 and 2 together also suggest that larger pre-pandemic shares in WFH occupations are associated with lower job loss rates during the pandemic. Appendix H documents that this is indeed the case.[17]

3.3 Why WFH Substitution Alone Cannot Explain the Facts

Explanations for the large heterogeneity in WFH transitions in the pandemic must be consistent with each of the two facts above. At first glance, the negative relationship between WFH transitions and job loss (Fact 1) seems most consistent with the WFH substitution channel. In the context of the model, whenever the cost of on-site work increases ($\varepsilon_\chi > 0$), pre-pandemic commuters are the first in line to lose employment, while workers with relatively higher WFH productivity z are more likely to remain employed as they substitute on-site work with WFH. However, differences in WFH productivity *within* labor markets are not the relevant dimension for explaining the relationship between WFH transitions and job loss. Fact 2 shows that the variation in WFH transitions across worker groups is first and foremost related to differences in occupational composition.[18] For that reason, the observed heterogeneity in WFH transitions needs to be explained in terms of differences in WFH ability across different labor markets rather than within labor markets. Given this requirement, we argue next that the theoretical model implies that the WFH substitution channel is either directly at odds with Fact 1, or consistent with Fact 1 but not with Fact 2.

To focus on heterogeneity across different labor markets, we henceforth let $\Delta \ln E_h^{a,j}$ denote the change in WFH employment in labor market j, and think of the model equations as determining nationwide aggregates of segmented labor markets for separate occupations. We allow all parameters in the model to potentially differ across labor markets both before and during the pandemic. The only exceptions are the elasticity of demand, β, and the elasticity of WFH labor supply, λ, which we assume are both constant and identical across labor markets. In principle, large differences in the elasticity of WFH labor supply across labor markets could explain why many more workers transitioned to WFH in some labor markets than in others. We rule this out ex ante, since large differences in λ would have resulted in much more variation in WFH rates before the pandemic as a result of decades of advances in information and

[16] Gottlieb et al. (2020) also find a strong relationship between WFH ability and actual WFH in the pandemic in Costa Rica and Brazil.

[17] This is in line with the predictions by Alon et al. (2020), and also consistent with the evidence for this relationship in Adams-Prassl et al. (2020), Mongey et al. (2020), and Papanikolaou and Schmidt (2020).

[18] One possible exception is the presence of children in the household, which may have become more important in terms of the ability to WFH for extended periods of time, see Section 2.4.3.

communication technologies. The heterogeneity in WFH ability across labor markets is instead captured by differences in the level of overall WFH productivity, γ_j. To make our argument as sharply as possible, we impose in this section that none of the WFH transitions in the pandemic are driven by WFH adoption, i.e. $\varepsilon_\theta^j = \varepsilon_\gamma^j = 0$ in each labor market j. This leaves us with only two possible scenarios in which job losses and WFH transitions occur simultaneously.[19]

The first scenario is one in which all firms always employ both commuters and home workers. With an increase in the costs of on-site work, $\varepsilon_\chi^j > 0$ average employment growth $\Delta \ln E^{a,j}$ in occupation j is given by

$$\Delta \ln E^{a,j} \quad = \quad \varepsilon_\delta^j - \beta \varepsilon_\chi^j \ ,$$

which apart from ε_χ^j also depends on the demand ε_δ^j for the goods and services produced by workers in that occupation. Using (13), the log change in WFH employment when $\varepsilon_\theta^j = \epsilon_\gamma^j = 0$ is $\Delta \ln E_h^{a,j} = \lambda \varepsilon_\chi^j$. This means that all heterogeneity in WFH transitions $\Delta \ln E_h^{a,j}$ caused by the pandemic must be due to differential increases in the cost of on-site work across labor markets. However, the problem with this scenario is that labor markets with larger $\varepsilon_\chi^j > 0$ should also experience greater job loss rates, which makes it difficult to explain Fact 1.

To see this more formally, the covariance between log WFH employment growth and job loss rates in this scenario is

$$Cov(\Delta \ln E_h^{a,j}, -\Delta \ln E^{a,j}) \quad = \quad \beta \lambda Var(\varepsilon_\chi^j) - \lambda Cov(\varepsilon_\delta^j, \varepsilon_\chi^j) \ . \tag{16}$$

The first term on the right hand side of (16) is always positive, as larger increases in the cost of working on-site always generate larger job losses and more WFH transitions. A negative covariance as in Fact 1 then requires that $Cov(\varepsilon_\delta^j, \varepsilon_\chi^j) > \beta Var(\varepsilon_\chi^j) \geq 0$, or in other words, that labor markets with larger increases in the cost of working on-site also experience relatively higher levels of demand. This seems improbable. Any correlation between ε_δ^j and ε_χ^j is almost surely negative, for instance because in jobs with more person-to-person contact health risks tend to be higher for both workers and consumers. This scenario therefore does not allow a plausible explanation for Fact 1. The key model restriction that leads to this conclusion is the fact that WFH transitions are independent of the changes in demand ε_δ^j as long as there are also workers that continue to commute.

The second possible scenario in which job losses and WFH transitions occur simultaneously is when the increases in costs of on-site work $\varepsilon_\chi^j > 0$ are large enough such that only WFH

[19]The case where all WFH firms employ only home workers prior to the pandemic is immediately ruled out. All job losses lead to declines in WFH employment, and with $\epsilon_\theta^j = \epsilon_\gamma^j = 0$ no worker transitions to WFH.

workers are employed in the pandemic, and all workers that were previously commuting either switch to home-based work or are laid off. In this case, average employment growth is, up to a first-order log-linear approximation,

$$\Delta \ln E^{a,j} = \theta^j \left(\frac{\lambda}{\beta + \lambda} \varepsilon_\delta^j + \frac{\beta}{\beta + \lambda} \ln \sigma^j \right) + (1 - \theta^j)(\varepsilon_\delta^j - \beta \varepsilon_\chi^j) \ , \tag{17}$$

where $0 \leq \sigma^j < 1$ is the pre-pandemic share of WFH employment in labor market j at employers that allow WFH. Since σ^j is proportional to WFH ability γ^j, see (15), job loss rates in this scenario are naturally larger in labor markets with lower WFH ability, as is the case in the data (see Appendix H). Using (15), the change in WFH employment when $\epsilon_\theta^j = \epsilon_\gamma^j = 0$ is $\Delta \ln E_h^{a,j} = \frac{\lambda}{\beta+\lambda}(\varepsilon_\delta^j - \ln \sigma^j)$. The key difference with the first scenario is that WFH transitions now depend on changes in demand ε_δ^j. Since both WFH and total employment depend on the level of demand in the pandemic, heterogeneity in the extent of the decline in demand across labor markets generates a negative relationship between WFH transitions and job loss rates, as in Fact 1.[20]

The problem with this second scenario is that it is particularly hard to reconcile with the observed WFH patterns before the pandemic, and therefore with Fact 2. To see this, consider that the average share of WFH employment before the pandemic in labor market j is given by $\theta^j \sigma^j$. If all WFH firms employ only home-based workers in the pandemic, the WFH employment share in the pandemic is approximately θ^j, i.e. the fraction of employers that allow WFH. Therefore, without changes in θ^j in the pandemic, the log ratio of the pandemic to pre-pandemic WFH employment share is, approximately, $-\ln \sigma^j$. The change in WFH employment shares relative to February should therefore be negatively related to WFH ability γ^j. The reason is simply that in firms with a workforce that is relatively more productive at home, a smaller share of the workforce needs to switch to WFH after work on-site becomes prohibitively costly. However, this is inconsistent with Fact 2, which shows that in practice a larger share of the workforce started to WFH in groups with a larger share of workers in high-WFH-ability occupations.[21] In this case, the key discrepancy with the theory is that, without additional WFH

[20] Note that WFH employment can still increase even when demand and total employment are both lower than before the pandemic. This will be the case as long as $0 < \Delta \ln E_h^{a,j} < -\ln \sigma^j$, or equivalently $\ln \sigma^j < \varepsilon_\delta^j < -\frac{\beta}{\lambda} \ln \sigma^j$. The first inequality states that the drop in demand cannot be so large that all commuters are laid off and none switch to working remotely. The second inequality ensures that the level of demand in the pandemic is low enough to cause job loss.

[21] An exact expression for the log change in the WFH share is $\Delta \ln(E_h^{a,j}/E^{a,j}) = -\ln \sigma^j + (1 - \theta^j)(-\beta/\lambda \Delta \ln E_h^{a,j} + \beta \varepsilon_\chi^j)$ where the last term arises because pandemic employment levels generally differ across WFH and non-WFH firms. The exact expression in principle does allow for two ways of explaining the positive relationship in Figure 8, but neither is realistic. One way is a large negative covariance between $(1-\theta^j)\Delta \ln E_h^{a,j}$ and WFH ability γ^j, the other is a large positive covariance between ε_χ^j and γ^j. The first is very unlikely given that there is also a strong positive relationship between $\Delta \ln E_h^{a,j}$ and γ^j in the data, while the second would require implausibly that $\varepsilon_\chi^j > 0$ at non-WFH firms is systematically much larger in labor markets with higher

adoption, WFH employment shares should already have been far greater in high-WFH-ability labor markets before the pandemic than they are in the data.

In sum, it is hard for the substitution channel to rationalize why so many more workers in high-WFH-ability labor markets transitioned to WFH in the pandemic if they already had the option to WFH before. Large numbers of WFH transitions are not a feature of non-pandemic recessions. If in most labor markets WFH employment remained relatively insulated from demand conditions also in the pandemic recession, it is difficult to explain why WFH transitions correlated so strongly with job loss across labor markets. If WFH employment instead became much more dependent on demand conditions because the pandemic forced most work off-site at many firms, it is hard to explain why the larger WFH capacity in the higher WFH-ability occupations was not already used before the pandemic.

3.4 WFH Adoption in the Pandemic

Since the empirical facts are hard to explain with the substitution channel alone, the more likely explanation involves WFH adoption. The most straightforward explanation for the two facts in Section 3.2 is that WFH adoption in the pandemic was concentrated in (a) occupations with relatively stronger demand during the pandemic, and in (b) occupations with high WFH ability before the pandemic.

As documented earlier, WFH employment was relatively uncommon before the pandemic despite advances in information technology over recent decades. It seems reasonable that the pandemic lead to a sudden acceleration in the adoption of flexible work arrangements and WFH technology precisely in those occupations where the unused capacity for WFH was the greatest. In the model, a pandemic-related rise in the cost of on-site work $\varepsilon_\chi > 0$ always makes the WFH option relatively more attractive to workers and employers, and the profit impact of providing the WFH option in (7) is greater in a pandemic when workers' WFH productivity γ is larger. Greater WFH adoption in high-WFH-ability occupations naturally explain why the changes in WFH shares are increasing in WFH ability, as in Fact 2.

To explain Fact 1, i.e. the negative relationship between job loss and WFH transitions in Figure 7, WFH adoption in the pandemic must be greater in occupations where demand during the pandemic was relatively stronger. One likely reason is that switching to remote work in contact-intensive occupations by itself improves consumer safety – online education or telemedicine are examples – and therefore helps sustain demand. Also, many of the white collar service occupations that already did not require much physical contact with customers

WFH ability.

before the pandemic – such as in the information or financial sectors – are also the occupations with the greatest WFH potential, and therefore likely also experienced greater jumps in WFH adoption in the pandemic. Regardless of the precise reasons, a positive cross-sectional correlation between WFH adoption and demand conditions easily explains the negative relationship between job loss and WFH transitions in Fact 1.

One possible test of the role of changes in employers' WFH policies 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. In the RPS data, we find that self-employed workers were about three times as likely to be WFH-Only before the pandemic as employees. The WFH-Only rate for the self-employed was higher in May compared to February, but declined to pre-pandemic levels fairly quickly. In sharp contrast to payroll workers, self-employed workers were just as likely to work entirely from home throughout the second half of 2020 as in February, see Appendix E. The large 'difference-in-difference' in WFH between payroll workers and self-employed is consistent with employers removing commuting requirements for employees in the pandemic.

Additional survey information available in the RPS allows us to measure more directly how many workers gained the option to WFH in the pandemic. In a survey question included in the December wave, we asked respondents about the main reasons for commuting to work:

Which of the following best explains why you [your spouse/partner] commuted to work every workday last week?

a) *My [spouse/partner's] job cannot 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 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*

We also asked respondents to think back to February of 2020, and presented them with the same questions for the main job in that month. The answers allow us to asses directly what fraction of the WFH transitions in the pandemic are by workers that were required to commute by their employers before the pandemic.

In the December survey, 1,904 respondents said they commuted every workday in February, just before the pandemic. Among these, referencing outcomes in February, 60.2 percent stated

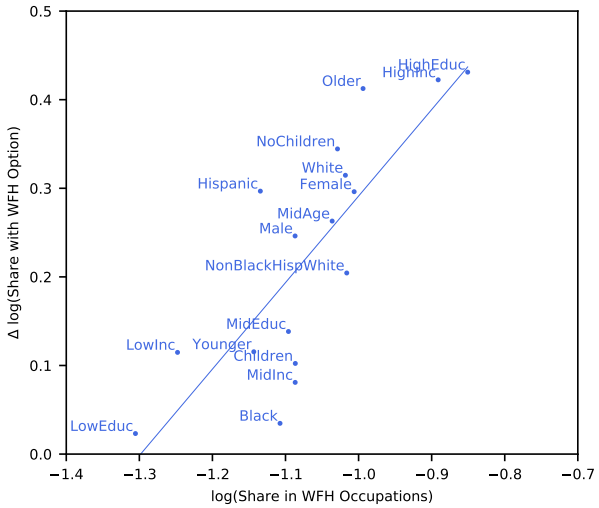
their jobs could not be done from home, 30.4 percent stated their employers required daily commuting, and 9.4 percent said they preferred to commute every day. Figure 4 shows that 23.0 percent of those February daily commuters WFH at least one workday in December, which is far more than the 9.4 percent who commuted daily in February due to personal preference. This suggests that many that switched to WFH did so after their employers no longer required them to commute every workday. Indeed, among the 418 respondents that switched to WFH at least one workday per week, 63.6 percent cite employer requirements as the main reason for commuting on a daily basis in February. Another 23.5 percent say their jobs could not be done from home in February, while only 12.9 percent cite preferences as the main reason. Most of those that transitioned to WFH (79.0 percent) report working in the same job as prior to the pandemic. Therefore, a large majority of the transitions from daily commuting to WFH between February and December involved employers lifting the commuting requirement.

The role of WFH adoption is also evident in the reasons given by workers for commuting during the pandemic. In the substitution channel, there would be a shift in the composition of reasons given for commuting. A greater proportion of workers in a pandemic would commute because they need to, either because their jobs cannot be done at home or because their employers do not allow remote work, while a smaller fraction would commute because of personal preference. In the sample of 1374 workers commuting daily to their December jobs (i.e. during the pandemic), 68.4 percent stated their current jobs could not be done from home, 22.2 percent of respondents stated their employers required daily commuting, while 9.4 percent stated they preferred to commute every day. Compared to before the pandemic, a smaller fraction of workers cites employer requirements, while a similar fraction of daily commuters states personal preference as the main reason for commuting in December. This suggests that many more workers gained access to the WFH option.

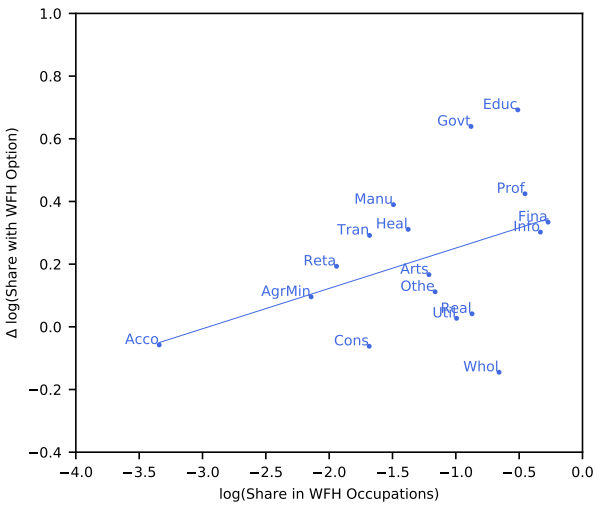
In addition, we can compare estimates of the total number of workers with access to a viable WFH option before and during the pandemic. To obtain such estimates, we add the number of daily commuters that cite personal preference as the main reason for commuting to the number of workers that WFH at least one workday. To be clear, by 'access to a viable WFH option' here we mean workers that could in principle WFH at least one workday per week. That is, we exclude all workers that are in jobs that cannot be done from home (not viable), or that are working for employers that do not allow WFH (no access). Based on this calculation, we find that 43.8 percent of the workforce had access to a viable WFH option in December, compared to 33.3 percent in February. The February-to-December increase from 24.9 to 37.9 percent in the fraction that worked from home at least one workday is mostly (80.8 percent) accounted for by workers gaining access to WFH. Very little of the increase in WFH (19.2 percent) originates with decreases in the fraction of workers commuting because of personal preference, as would

Figure 9: Change in Share with WFH Option vs. Feb Share in WFH Occupations

(a) By Demographic Group



(b) By Industry



Source: Real-Time Population Survey and Dingel and Neiman (2020). Scatters show December data. The x-axis is the log share of February workers in potential WFH occupations based on the measures of Dingel and Neiman (2020). The y-axis is the log change from February to December in the share of employed workers with a WFH option. A worker has a WFH option if they WFH at least one day, or if they commuted only but cited personal preference as the main reason why they did not WFH (see main text for details). Information on why individuals commuted to work was not collected prior to December 2020. Industry classification is by industry of employment in February. Definitions of demographic and industry groups are provided in Appendix A.4.

be the case under the substitution channel.

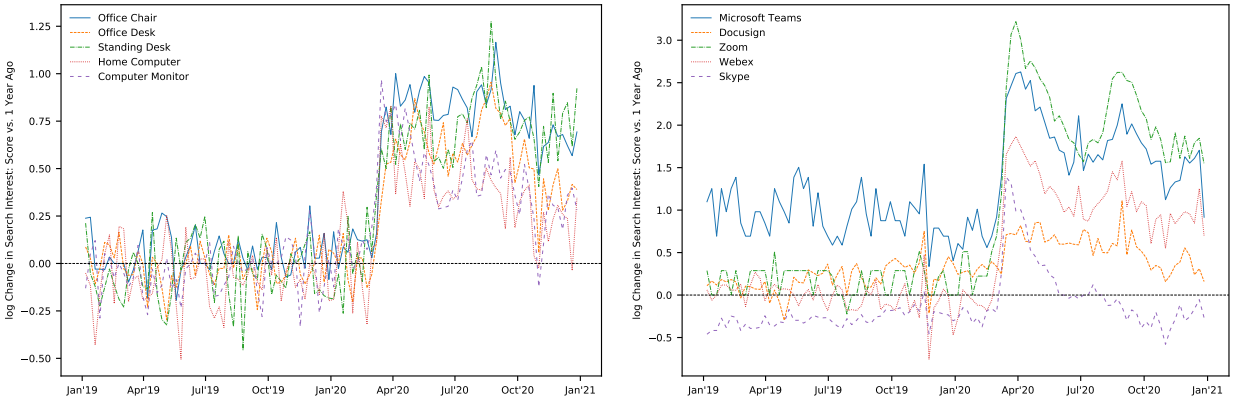
The increases in WFH access are unevenly distributed across workers. Figure 9 depicts the growth in WFH access among workers that were employed in both February and December across different demographic groups and industries. Specifically, the figure plots the log changes in the number of workers with access to a viable WFH option relative to February against the estimated share of workers in WFH occupations in February. The left panel of Figure 9 shows that the fraction of workers with a WFH option increased for all demographic groups, while the right panel shows increases for all industries except accommodation and food, construction and wholesale trade. Moreover, the expansions in WFH access were systematically larger in the categories with more workers in high WFH occupations. In particular, high-income, high-education and older workers experienced the largest log point increases, as did workers in the education, public and professional business services sectors. The positive relationship between the expansion in WFH access and the share of workers in WFH occupations is fully consistent with heterogeneity in WFH adoption being the key reason for the negative relationship between WFH and job loss, and it is also consistent with the empirical facts documented in Section 3.2.

Our definition of WFH adoption includes not only expanded access to WFH (higher θ), but

Figure 10: Google Searches for WFH Equipment and Software

(a) WFH Equipment

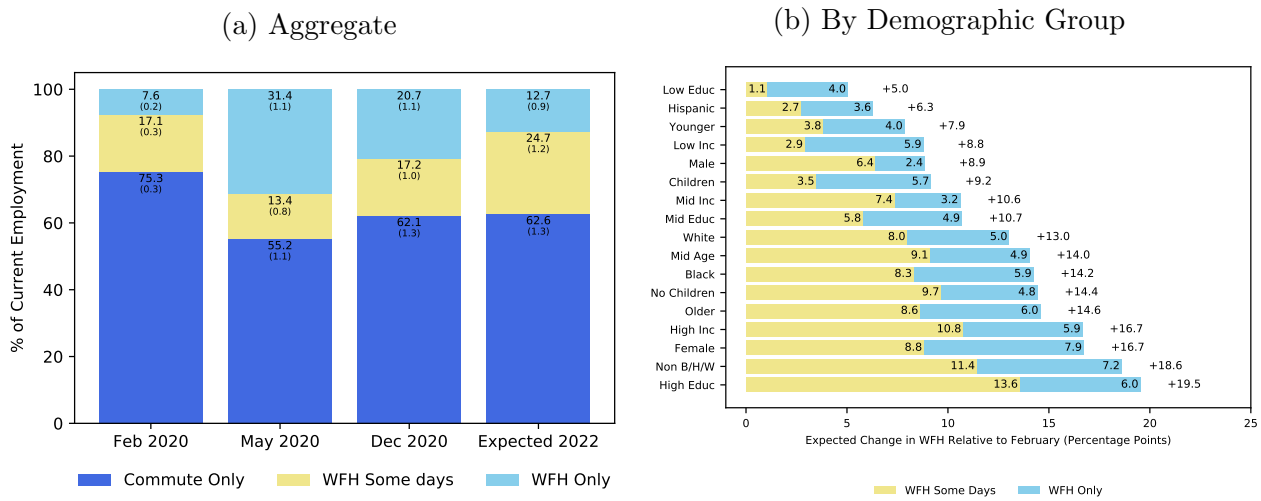
(b) WFH Software



Source: Google Trends, accessed 1/11/2021. Series are log changes in the weekly search interest score relative to 52 weeks ago.

also improvements in WFH productivity (higher γ). It is more difficult to directly measure increases in WFH productivity. However, there are signs of an acceleration in investments aimed at improving WFH productivity. According to the Bureau of Economic Analysis, for example, investment spending by private businesses on computers and peripheral equipment in the second and third quarter of 2020 increased by 9.3 and 23.6 percent relative to the previous year, compared to an average increase of 1.9 percent in 2019. Workers almost certainly also made similar investments. Figure 10 shows weekly internet search scores from Google trends for a variety of WFH-related terms. The left panel shows searches related to office and computer hardware. The right panel shows search results for various WFH-related software. Both panels show sharp increases in searches for WFH equipment and software in late March and early April relative to one year prior, exactly at the time of the pandemic-related wave of WFH transitions. The Google search results are also consistent with recent survey evidence in Barrero et al. (2021), finding that workers on average invested over 14.2 hours and about $604 dollars in equipment and infrastructure to facilitate WFH. There are also some signs of an increase in the pace of innovation in WFH-related technologies. Bloom et al. (2020), for example, document that patent applications since the pandemic have meaningfully shifted in the direction of information and communication technologies that can support WFH. Based on a survey on technology adoption by UK businesses, Riom and Valero (2020) find a positive relationship between the share of the potential WFH workforce before the crisis and the adoption of digital technologies. If a similar relationship exists for US firms, it would further reinforce the positive relationship between WFH ability and WFH adoption.

Figure 11: Expectations for WFH in the Future



Source: Real-Time Population Survey. *Left panel:* February, May, and December 2020 bars display the workers shares by commuting status. The "Expected 2022" bar displays the worker shares in December 2020 by expected commuting status in 2022. *Right panel:* The sample is individuals (ages 18-64) employed both in February and December 2020. The figure displays the difference between expected WFH rates for 2022 and actual WFH rates in February 2020 by demographic group. Definitions of demographic groups are provided in Appendix A.4. Standard errors in parentheses, calculated as as described in Appendix A. WFH expectations are based on a sample of 2,163 respondents in December.

4 Expectations for WFH in the Future

Section 2.2 showed that commuting recovered substantially in the second half of 2020 after the sharp decline in the first wave of the pandemic. This suggests that at least part of the WFH surge in the pandemic is the result of more temporary substitution. At the same time, the evidence for WFH adoption in the previous section 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. Given that many more high-education/income workers switched to WFH in the pandemic, any such gains are likely to be highly unequally distributed. If the non-wage benefits of WFH are indeed significant, employers in high WFH sectors are likely to save on labor costs, which could lead to further reallocation towards high-skill sectors. More remote work may also reduce spending in large cities, which would likely impact many lower-skill service workers, see also Althoff et al. (2020) and Barrero et al. (2021).

On the other hand, it is possible that the experimentation with WFH necessitated by the health crisis in many cases proves relatively unsuccessful in the longer run. The benefits of WFH may not outweigh the costs under more normal health conditions, and many employers may therefore not continue to allow the same extent of WFH after the pandemic ends. Moreover, certain disadvantages of WFH may become more apparent in the longer run, and some existing evidence suggests that information and communication technologies are ultimately not

a substitute for face-to-face interactions, see Gaspar and Glaeser (1998).

It is too early to know precisely how much more pervasive WFH will be in the future as a result of the COVID-19 pandemic. To have some indication nonetheless, we present survey results on households' expectations for WFH in the future. In the December wave of the RPS, we asked all respondents with a job the following question:

In 2022 and later, how many days do you expect [your spouse/partner] to commute to work?

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 be working in 2022*

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 expect to work (i.e. all workers not answering d). Figure 11a displays the resulting estimates, which are based on a sample of 2,163 observations. For comparison, the figure also repeats the actual shares in each commuting category in February, May and December.

Overall, 37.4 percent of workers expect to WFH on a part- or full-time basis in 2022 and beyond, which is almost as many as were actually doing so in December (37.9 percent). If realized, this would be a substantial increase compared with February, when 24.7 percent WFH at least one day per week. At the same time, there is a meaningful difference in how frequently workers expect to WFH in the future relative to December. Whereas in December 20.7 percent are WFH-Only, only 12.7 percent expect to WFH-Only in 2022 and beyond. Almost a quarter of all workers (24.7 percent) expect to WFH on part-time basis, compared with 17.2 percent in December. The expected shift towards more part-time WFH relative to December 2020 would mean a further recovery in commuting as the pandemic wanes, although not to pre-pandemic levels on a per capita basis.

Our finding that WFH is expected to persist after the pandemic is consistent with other survey evidence. Based on a similar question in their online household survey, Barrero et al. (2021) find that 22 percent of all full workdays will be supplied from home, compared with 5 percent before the pandemic. Several surveys of businesses indicate that workers' expectations are consistent with those of employers, many of which project permanent increases in their

home-based workforce as a result of the pandemic.[22]

The expectations for more WFH in the future suggest that the adoption of WFH spurred by the pandemic has proven beneficial to at least some workers and employers, and that these benefits are expected to persist after the health crisis ends. Our survey data, however, also clearly shows that any longer-lasting benefits from WFH are unlikely to be shared equally. Figure 11b documents the differences in WFH expectations across demographic groups. For each category, the figure plots the expected increase in the fraction of WFH workers relative to February. Whereas in all categories more workers expect to WFH, the extent of the anticipated increase varies greatly in ways that reflect the large differences in WFH adjustment during the pandemic.

Highly educated workers (bachelor's degree or more), in particular, see the largest expected change in commuting behavior. Figure 11b shows an expected increase of 19.5 percent in the share of highly educated workers that expect to WFH on a part- or full-time basis. If realized, this would mean that almost half of all workers with a bachelor's degree or more would WFH at least partially, and almost 15 percent would not commute to their jobs at all. Many more women anticipate a persistent change in commuting behavior than men. The expected increase in the share of women doing at least some WFH is 18.7 percentage points, compared with 8.9 percentage points for men. Mid-age (30 to 49) and older workers (50 to 64) expect to WFH more than younger workers, and workers with higher incomes in 2019 expect to do more WFH than lower income workers. In Section 2.4.3, we documented that workers with children in the household returned to commuting in greater numbers in the second half of 2020 than workers without children. Figure 11b suggest that the presence of children will remain an important factor in WFH decisions going forward. Finally, Hispanic workers expectations of long run WFH among Hispanics increased less than for other ethnicities and races.

5 Concluding Remarks

This paper uses data 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 in the pandemic, primarily driven by a large number of pre-pandemic daily commuters who stopped commuting entirely while remaining in the same jobs. There were very large differences in the extent of the increases in WFH across demographic groups and industries. Using theory and evidence, we argued that the observed heterogeneity in WFH transitions is consistent with potentially

[22]In a survey of 1,800 small business leaders, Bartik et al. (2020a) 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 Kerr (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).

more permanent changes to the work arrangements for certain groups of workers, in particular those with high levels of education. The survey data on WFH presented in this paper is useful for studying a wide range of other questions related to the COVID-19 pandemic, such as the trade-offs between health and economic opportunity (Kaplan et al., 2020), the extent of supply chain disruptions across sectors (Bonadio et al., 2020), the impact on educational outcomes (Agostinelli et al., 2020), gender imbalances (Alon et al., 2020), or the location decisions of firms and workers (Althoff et al., 2020; Liu and Su, 2020).

References

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh (2020). "Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys". In: *Journal of Public Economics* 189. ISSN: 0047-2727. DOI: 10.1016/j.jpubeco.2020.104245.

Agostinelli, F., M. Doepke, G. Sorrenti, and F. Zilibotti (2020). *When the Great Equalizer Shuts Down: Schools, Peers, and Parents in Pandemic Times*. Tech. rep. National Bureau of Economic Research.

Alon, T. M., M. Doepke, J. Olmstead-Rumsey, and M. Tertilt (Apr. 2020). "The Impact of Covid-19 on Gender Inequality". In: *Covid Economics: Vetted and Real-Time Paper* 4, pp. 62–85.

Althoff, L., F. Eckert, S. Ganapati, and C. Walsh (2020). *The City Paradox: Skilled Services and Remote Work*. Unpublished Manuscript. DOI: http://dx.doi.org/10.2139/ssrn.3737652.

Baek, C., P. B. McCrory, T. Messer, and P. Mui (2021). "Unemployment Effects of Stay-at-Home Orders: Evidence from High Frequency Claims Data". In: *The Review of Economics and Statistics* forthcoming. DOI: 10.1162/rest_a_00996.

Barrero, J. M., N. Bloom, and S. J. Davis (2021). *Why Working From Home Will Stick*. Unpublished Manuscript.

Barrero, J. M., N. Bloom, and S. J. Davis (June 2020). "COVID-19 Is Also a Reallocation Shock". In: *Brookings Papers on Economic Activity* forthcoming.

Bartik, A. W., Z. B. Cullen, E. L. Glaeser, M. Luca, and C. T. Stanton (2020a). *What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys*. Working Paper 27422. National Bureau of Economic Research. DOI: 10.3386/w27422.

Bartik, A. W., M. Bertrand, F. Lin, J. Rothstein, and M. Unrath (2020b). "Measuring the labor market at the onset of the COVID-19 crisis". In: *Brookings Papers on Economic Activity* forthcoming.

Bhargava, S., G. Loewenstein, and J. Sydnor (Apr. 2017). "Choose to Lose: Health Plan Choices from a Menu with Dominated Option*". In: *The Quarterly Journal of Economics* 132.3. DOI: 10.1093/qje/qjx011.

Bick, A. and A. Blandin (2020). *The Labor Market Impact of a Pandemic: Validation and Application of a Do-It-Yourself CPS*. Federal Reserve Bank of Dallas Working Paper. DOI: 10.24149/wp2031.

Bloom, N., S. J. Davis, and Y. Zhestkova (2020). *COVID-19 Shifted Patent Applications toward Technologies that Support Working from Home*. Becker Friedman Institute Working Paper 2020-133. DOI: 10.2139/ssrn.3695191.

Bloom, N., J. Liang, J. Roberts, and Z. J. Ying (2014). "Does Working from Home Work? Evidence from a Chinese Experiment". In: *The Quarterly Journal of Economics* 130.1, pp. 165–218. DOI: 10.1093/qje/qju032.

Bonadio, B., Z. Huo, A. A. Levchenko, and N. Pandalai-Nayar (May 2020). *Global Supply Chains in the Pandemic*. Working Paper 27224. National Bureau of Economic Research. DOI: 10.3386/w27224.

Brynjolfsson, E., J. Horton, A. Ozimek, D. Rock, G. Sharma, and H. Y. T. Ye (2020). *Covid-19 and remote work: An early look at U.S. data*. NBER Working Paper 27344. DOI: 10.3386/w27344.

Bursztyn, L., F. Ederer, B. Ferman, and N. Yuchtman (2014). "Understanding Mechanisms Underlying Peer Effects: Evidence From a Field Experiment on Financial Decisions". In: *Econometrica* 82.4. DOI: https://doi.org/10.3982/ECTA11991.

Cajner, T., L. D. Crane, R. A. Decker, J. Grigsby, A. Hamins-Puertolas, E. Hurst, C. Kurz, and A. Yildirmaz (July 2020). "The U.S. Labor Market during the Beginning of the Pandemic Recession". In: *Brookings Paper on Economic Activity* forthcoming.

Coibion, O., Y. Gorodnichenko, and M. Weber (2020). *The Cost of the Covid-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending*. NBER Working Paper 27141. DOI: 10.3386/w27141.

Couch, K. A., R. W. Fairlie, and H. Xu (2020). "Early evidence of the impacts of COVID-19 on minority unemployment". In: *Journal of Public Economics* 192, p. 104287. ISSN: 0047-2727. DOI: https://doi.org/10.1016/j.jpubeco.2020.104287.

Deming, W. E. and F. F. Stephan (1940). "On a Least Squares Adjustment of a Sampled Frequency Table When the Expected Marginal Totals are Known". In: *The Annals of Mathematical Statistics* 11.4, pp. 427–444.

Dingel, J. I. and B. Neiman (2020). "How many jobs can be done at home?" In: *Journal of Public Economics* 189, p. 104235. ISSN: 0047-2727. DOI: 10.1016/j.jpubeco.2020.104235.

Flood, S., M. King, R. Rodgers, S. Ruggles, and J. R. Warren (2020). *Integrated Public Use Microdata Series, Current Population Survey: Version 8.0*. [dataset]. Minneapolis, MN: IPUMS. DOI: https://doi.org/10.18128/D030.V8.0.

Foote, C., W. D. Nordhaus, and D. Rivers (2020). *The US Employment Situation Using the Yale Labor Survey*. Cowles Foundation Discussion Papers 2243. Cowles Foundation for Research in Economics, Yale University.

Gaspar, J. and E. L. Glaeser (Jan. 1998). "Information Technology and the Future of Cities". In: *Journal of Urban Economics* 43.1, pp. 136–156. DOI: 10.1006/juec.1996.2031.

Goolsbee, A. and C. Syverson (2021). "Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020". In: *Journal of Public Economics* 193. DOI: 10.1016/j.jpubeco.2020.104311.

Gottlieb, C., J. Grobovšek, M. Poschke, and F. Saltiel (Sept. 2020). *Working from Home in Developing Countries*. IZA Working Paper 13737.

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.

Harrington, E. and N. Emanuel (2020). *Working Remotely? Selection, Treatment, and Market Provision of Remote Work*. Unpublished Manuscript. Harvard University. DOI: 10.2139/ssrn.3601959.

Hofferth, S. L., S. Flood, M. Sobek, and D. Backman (2020). *American Time Use Survey Data Extract Builder: Version 2.8*. [dataset]. Minneapolis, MN: IPUMS. DOI: https://doi.org/10.18128/D010.V10.0.

Kaplan, G., B. Moll, and G. Violante (2020). *The Great Lockdown and the Big Stimulus:Tracing the Pandemic Possibility Frontier for the U.S.* Working Paper.

Kerr, E. (2020). *Texas Business Outlook Surveys, August Special Questions*. URL: https://www.dallasfed.org/research/surveys/tbos/2020/2008q.aspx.

Knotek II, E. S., R. S. Schoenle, A. M. Dietrich, K. Kuester, G. J. Müller, K. O. R. Myrseth, and M. Weber (2020). *Consumers and COVID-19: A Real-Time Survey*. Economic Commentary 2020-08. Federal Reserve Bank of Cleveland. DOI: 10.26509/frbc-ec-202008.

Kong, E. and D. Prinz (2020). "Disentangling policy effects using proxy data: Which shutdown policies affected unemployment during the COVID-19 pandemic?" In: *Journal of Public Economics* 189. DOI: 10.1016/j.jpubeco.2020.104257.

Kuziemko, I., M. I. Norton, E. Saez, and S. Stantcheva (2015). "How Elastic Are Preferences for Redistribution? Evidence from Randomized Survey Experiments". In: *American Economic Review* 105.4, pp. 1478–1508. DOI: 10.1257/aer.20130360.

Le Barbanchon, T., R. Rathelot, and A. Roulet (2020). "Gender Differences in Job Search: Trading off Commute Against Wage*". In: *The Quarterly Journal of Economics*. DOI: 10.1093/qje/qjaa033.

Lee, S. Y., M. Park, and Y. Shin (Jan. 2021). *Hit Harder, Recover Slower? Unequal Employment Effects of the Covid-19 Shock*. NBER Working Paper 28354. DOI: 10.3386/w28354.

Liu, S. and Y. Su (2020). "The impact of the Covid-19 pandemic on the demand for density: Evidence from the US housing market". In: *Available at SSRN 3661052*.

Lyttelton, T., E. Zang, and K. Musick (2020). *Gender Differences in Telecommuting and Implications for Inequality at Home and Work*. Unpublished Manuscript. Yale University. DOI: 10.2139/ssrn.3645561.

Maestas, N., K. J. Mullen, D. Powell, T. von Wachter, and J. B. Wenger (2018). *The Value of Working Conditions in the United States and Implications for the Structure of Wages*. NBER Working Paper 25204. DOI: 10.3386/w25204.

Mas, A. and A. Pallais (2017). "Valuing Alternative Work Arrangements". In: *American Economic Review* 107.12, pp. 3722–59. DOI: 10.1257/aer.20161500.

Mas, A. and A. Pallais (2020). "Alternative Work Arrangements". In: *Annual Review of Economics* 12.1, pp. 631–658. DOI: 10.1146/annurev-economics-022020-032512.

Mateyka, P. J., M. A. Rapino, and L. C. Landivar (2012). *Home-Based Workers in the United States: 2010*. Current Population Reports P70-132. U.S. Census Bureau.

Mokhtarian, P., I. Salomon, and S. Choo (2005). "Measuring the Measurable: Why can't we Agree on the Number of Telecommuters in the U.S.?" In: *Quality & Quantity: International Journal of Methodology* 39.4, pp. 423–452. DOI: 10.1007/s11135-004-6790-z.

Mongey, S., L. Pilossoph, and A. Weinberg (May 2020). *Which Workers Bear the Burden of Social Distancing Policies?* NBER Working Paper 27085. DOI: 10.3386/w27085.

Oettinger, G. S. (2011). "The Incidence and Wage Consequences of Home-Based Work in the United States, 1980-2000". In: *The Journal of Human Resources* 46.2, pp. 237–260.

Pabilonia, S. W. and V. Vernon (2020). *Telework and Time Use in the United States*. Unpublished Manuscript. U.S. Bureau of Labor Statistics. DOI: 10.2139/ssrn.3601959.

Papanikolaou, D. and L. D. Schmidt (Nov. 2020). *Working Remotely and the Supply-side Impact of Covid-19*. Unpublished Manuscript. Northwestern University and MIT.

Potthoff, R. F., M. A. Woodbury, and K. G. Manton (1992). ""Equivalent Sample Size" and "Equivalent Degrees of Freedom" Refinements for Inference Using Survey Weights under Superpopulation Models". In: *Journal of the American Statistical Association* 87.418. DOI: 10.1080/01621459.1992.10475218.

Qualtrics (2014). *ESOMAR 28 - 28 Questions to help Research Buyers of Online Samples*. URL: https://success.qualtrics.com/rs/qualtrics/images/ESOMAR%5C%2028%5C%202014.pdf.

Riom, C. and A. Valero (2020). *The Business Response to Covid-19: The CEP-CBI Survey on Technology Adoption*. CEP Discussion Paper 009. London School of Economics.

Ruggles, S., S. Flood, R. Goeken, J. Grover, E. Meyer, J. Pacas, and M. Sobek (2020). *IPUMS USA: Version 10.0*. [dataset]. Minneapolis, MN: IPUMS. DOI: https://doi.org/10.18128/D010.V10.0.

Su, Y. (2020). *Working from Home During a Pandemic: It's Not for Everyone*. URL: https://www.dallasfed.org/research/economics/2020/0407.

US Census Bureau (2015). *Current Population Survey Interviewing Material*. URL: https://www2.census.gov/programs-surveys/cps/methodology/intman/CPS_Manual_April2015.pdf.

Yu, E., A. C. Fobia, J. Graber, J. Holzberg, R. Kaplan, B. Kopp, K. Kubzdela, B. Mockovak, R. Morrison, and P. Scanlon (2019). *White Paper: Experiences Using Online Testing to Support Survey-Methods Research and Pre-Testing in the Federal Government*. Census Working Papers RSM2019-06. U.S. Census Bureau.

Zimmermann, F. (Feb. 2020). "The Dynamics of Motivated Beliefs". In: *American Economic Review* 110.2, pp. 337–61. DOI: 10.1257/aer.20180728.

APPENDIX FOR ONLINE PUBLICATION ONLY

A Work From Home in the RPS

A.1 Details on Sample Construction

The full RPS dataset from May - December include 48,645 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 4.5 percent of individuals in the original sample are dropped, yielding a final sample of 46,450 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: 1,174 individuals fell into this group across all survey waves. These individuals were not asked the questions on days worked and commuting. Table A.1 displays the breakdown of the sample sizes across survey months.

Table A.1: Sample Sizes by Month in the RPS

Month	Number of Observations	Number of Employed
Feb	46450	34867
May	4775	2567
Jun	9042	5212
Jul	7943	4917
Aug	6464	4107
Sep	8116	5272
Oct	3180	2136
Nov	3472	2321
Dec	3458	2241

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

A.2 Weighting

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.[23] 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).

A.3 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):

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

[23] Another use of the RPS, discussed in Bick and Blandin (2020), 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.

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.4 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

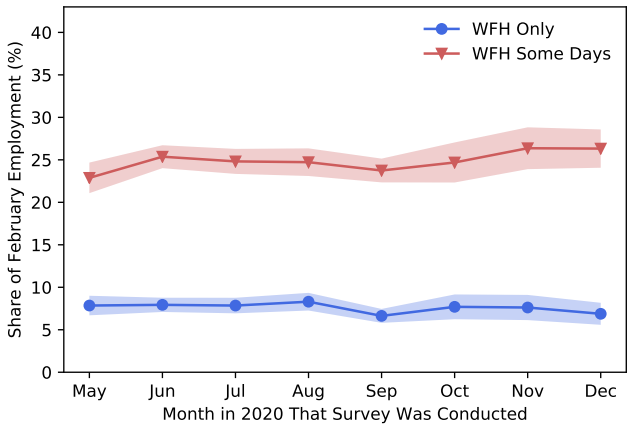
Industries correspond to the 18 major industries in the NAICS, except that we combine Agriculture (NAICS=11) and Mining (NAICS=21) due to small sample sizes. The resulting 17 industries are defined as follows:

- **AgriMin**: NAICS = 11-21. Agriculture, Forestry, Fishing and Hunting and Mining, Quarrying, and Oil and Gas Extraction
- **Util**: NAICS = 22. Utilities
- **Cons**: NAICS = 23. Construction
- **Manu**: NAICS = 31-33. Manufacturing
- **Whol**: NAICS = 42. Wholesale Trade
- **Reta**: NAICS = 44-45. Retail Trade
- **Tran**: NAICS = 48-49. Transportation and Warehousing
- **Info**: NAICS = 51. Information
- **Fina**: NAICS = 52. Finance and Insurance
- **Real**: NAICS = 53. Real Estate and Rental and Leasing
- **Prof**: 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
- **Heal**: NAICS = 62. Health Care and Social Assistance
- **Arts**: NAICS = 71. Arts, Entertainment, and Recreation
- **Acco**: NAICS = 72. Accommodation and Food Services
- **Othe**: NAICS = 81. Other Services (except Public Administration)
- **Govt**: 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% 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.5 February WFH Across Survey Months

FIGURE A.1: February WFH Rates By Month the Survey Was Conducted



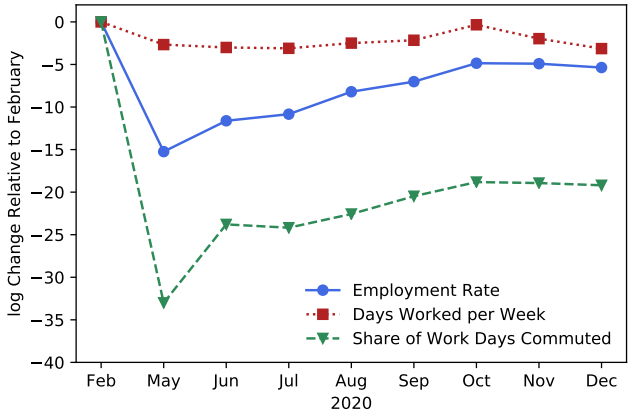
Source: Real-Time Population Survey, ages 18-64, February observations. The shaded region corresponds to two-standard-error bands. Appendix A describes the calculation of standard errors and contains sample sizes by month.

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.1 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% of individuals surveyed in May reported to be WFH-Only in February, compared with 6.9% of individuals surveyed in December. These differences are not statistically significant at the 5% 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% of individuals surveyed in May reported to be partial WFH in February, compared with 26.3% of individuals surveyed in December. This difference is significant at the 5% level. Overall, the share of workers that are partial WFH is lower in May than other months; no two months from June-onward are statistically different from one another at the 5% level.

B Change in Commuting Volume in the RPS

FIGURE B.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.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.1 displays the log changes in each of these components of aggregate commuting trips, which are also shown in Figure B.1.

In May 2020, aggregate commuting fell by 50.9 log points relative to February. Of this, 15.2 log points (29.9%) was due to lower employment, while 2.7 log points (5.3%) was due to fewer days worked per worker per week. The remaining 33.0 log points (64.8%) was due to a reduction in the share of work days commuted relative to February, i.e. an increase in WFH. By December, aggregate commuting had recovered relative to May, but was still 27.7 log points lower than in February. Of this, 5.4 log points (19.5%) was due to lower employment, and 3.1 log points (11.2%) was due to fewer days worked per worker per week. The remaining 19.2 log points (69.3%) was due to a reduction in the share of work days commuted relative to February.

Table B.1: Change in Log of Aggregate Commuting Trips

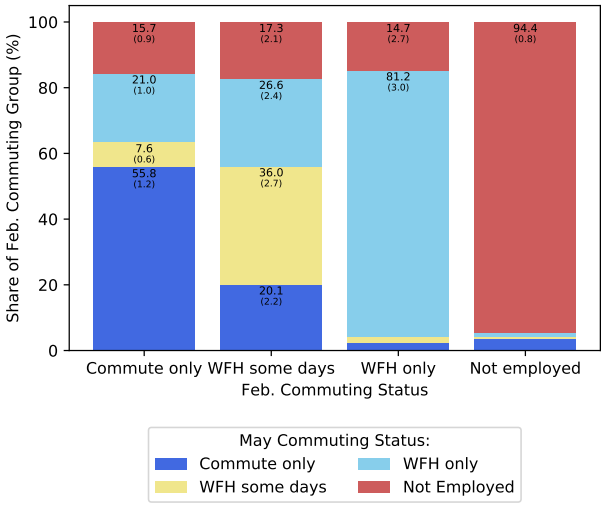
	Weekly Commuting Trips	Employment Rate	Days Worked / Week	Share of Work Days Commuted
May	-50.9	-15.2	-2.7	-33.0
	(4.3)	(0.9)	(2.9)	(6.1)
Jun	-38.4	-11.6	-3.0	-23.8
	(3.3)	(0.7)	(2.4)	(4.5)
Jul	-38.1	-10.8	-3.1	-24.2
	(3.6)	(0.7)	(2.8)	(4.9)
Aug	-33.3	-8.2	-2.5	-22.6
	(4.0)	(0.8)	(3.2)	(5.5)
Sep	-29.7	-7.0	-2.2	-20.5
	(3.5)	(0.7)	(2.6)	(4.7)
Oct	-24.0	-4.9	-0.3	-18.8
	(5.7)	(1.1)	(4.5)	(7.6)
Nov	-25.8	-4.9	-2.0	-18.9
	(5.7)	(1.1)	(4.4)	(7.6)
Dec	-27.7	-5.4	-3.1	-19.2
	(5.2)	(1.0)	(4.2)	(7.1)

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.

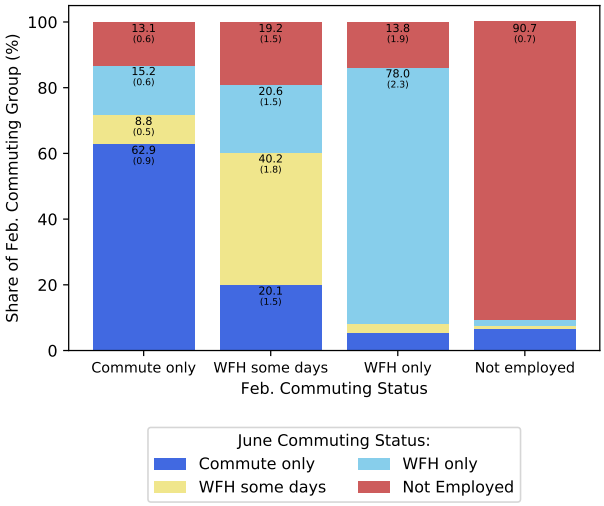
C WFH Transitions Relative to February

FIGURE C.1: WFH Transition Rates, By Current Month WFH Status - Part I

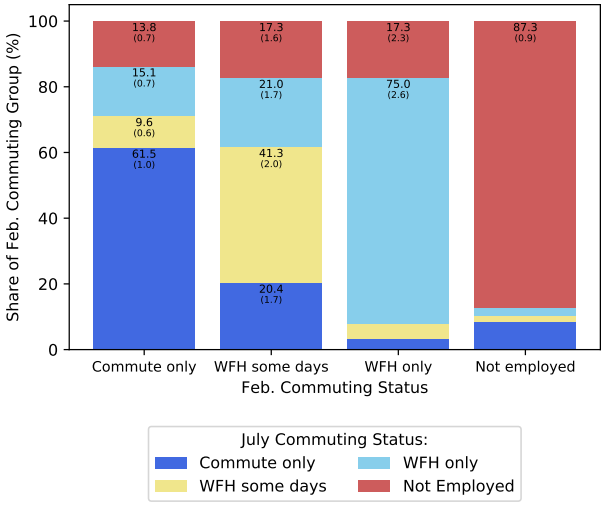
(a) May 2020



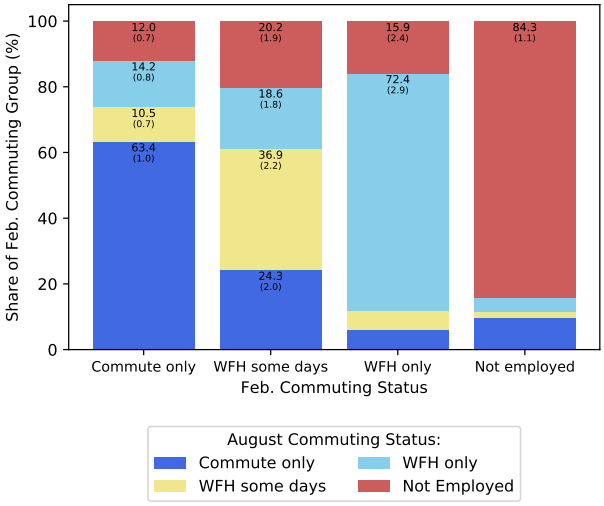
(b) June 2020



(c) July 2020

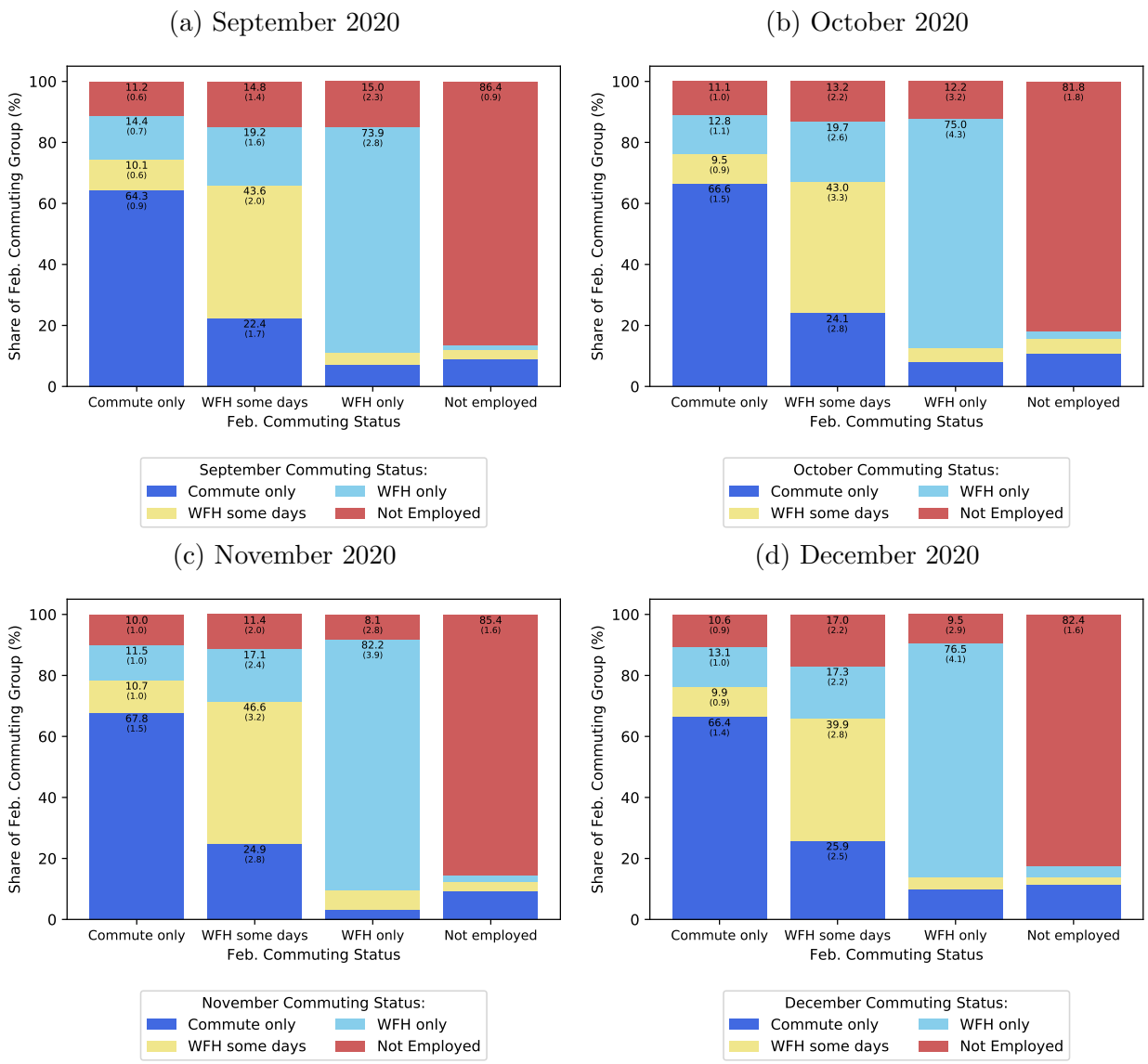


(d) August 2020



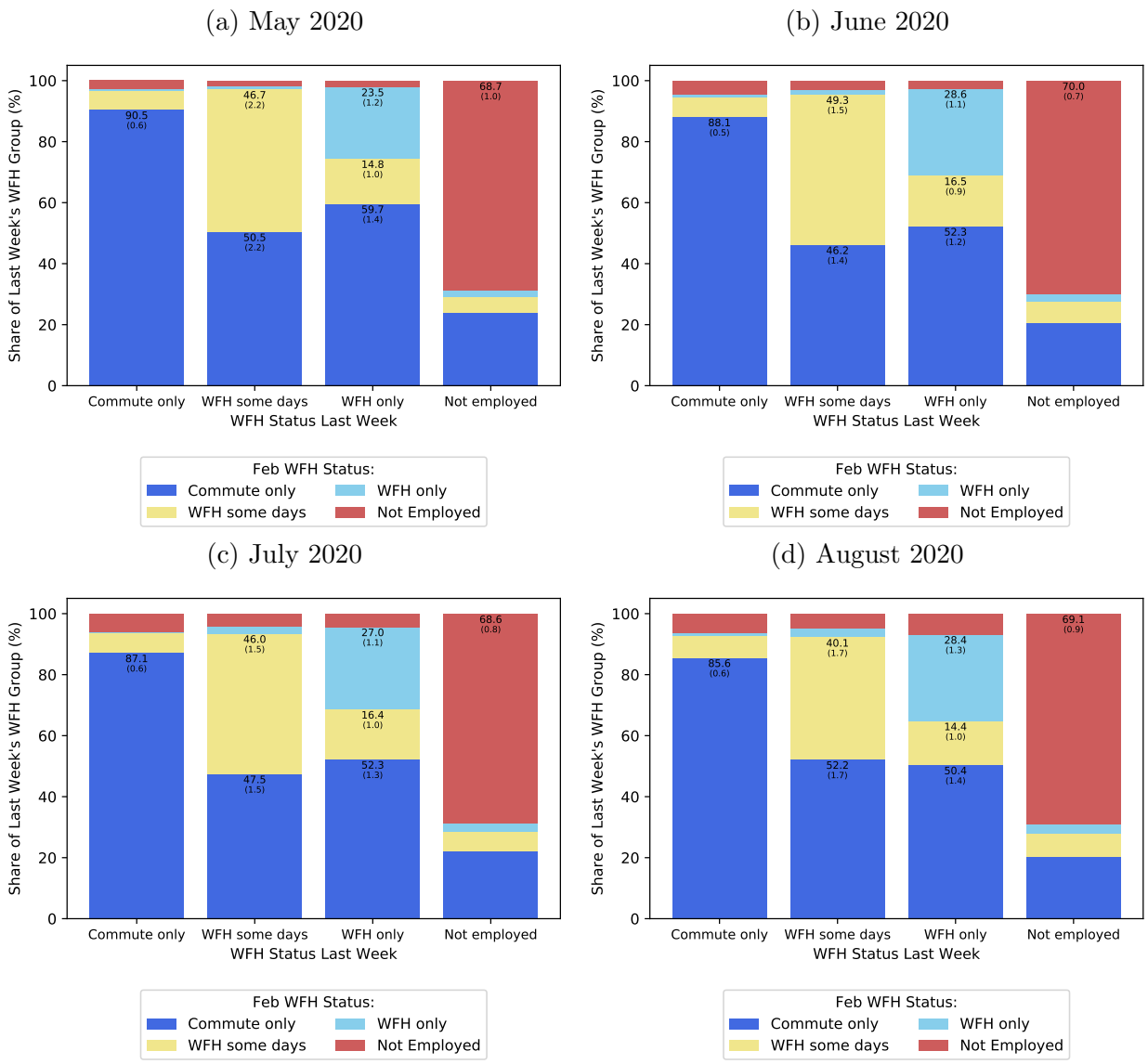
Source: Real-Time Population Survey, ages 18-64. The figure displays the composition of the population by WFH and employment status in the current month separately by workers' employment and WFH status in February 2020. Each bar corresponds to a February WFH/employment state: Commute-Only, WFH Some Days,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

FIGURE C.2: WFH Transition Rates, By Current Month WFH Status - Part II



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 as described in Appendix A; that section also provides sample sizes by month.

FIGURE C.3: WFH Transition Rates, By Current WFH Status - Part I

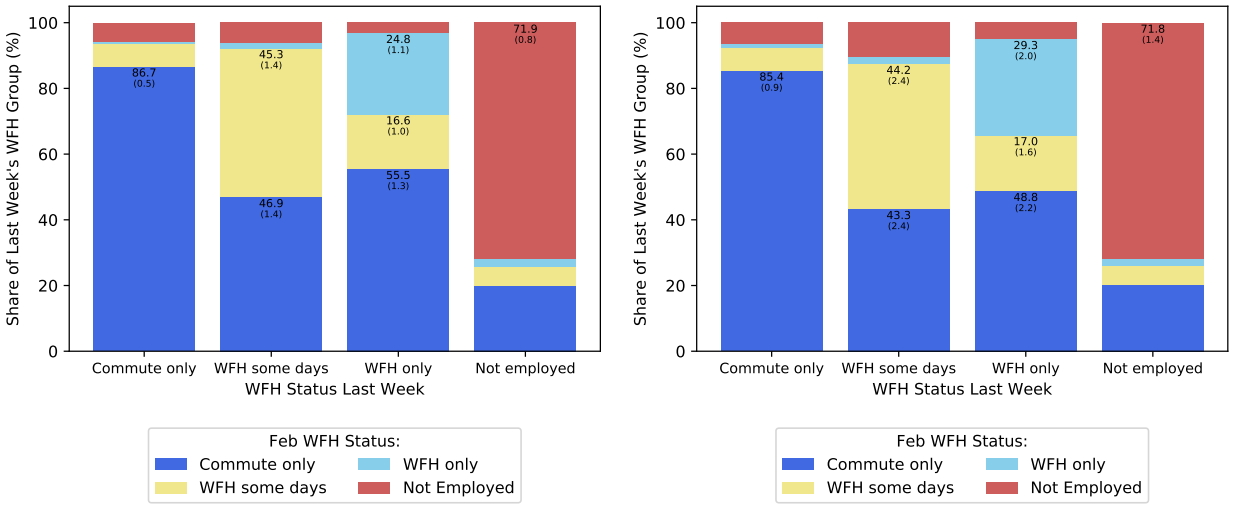


Source: Real-Time Population Survey, ages 18-64. The figure displays the composition of the population by WFH and employment status in February 2020 separately by workers' employment and WFH status in the current month. Each bar corresponds to a current WFH/employment state: Commute-Only, WFH Some Days,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

FIGURE C.4: WFH Transition Rates, By Current WFH Status - Part II

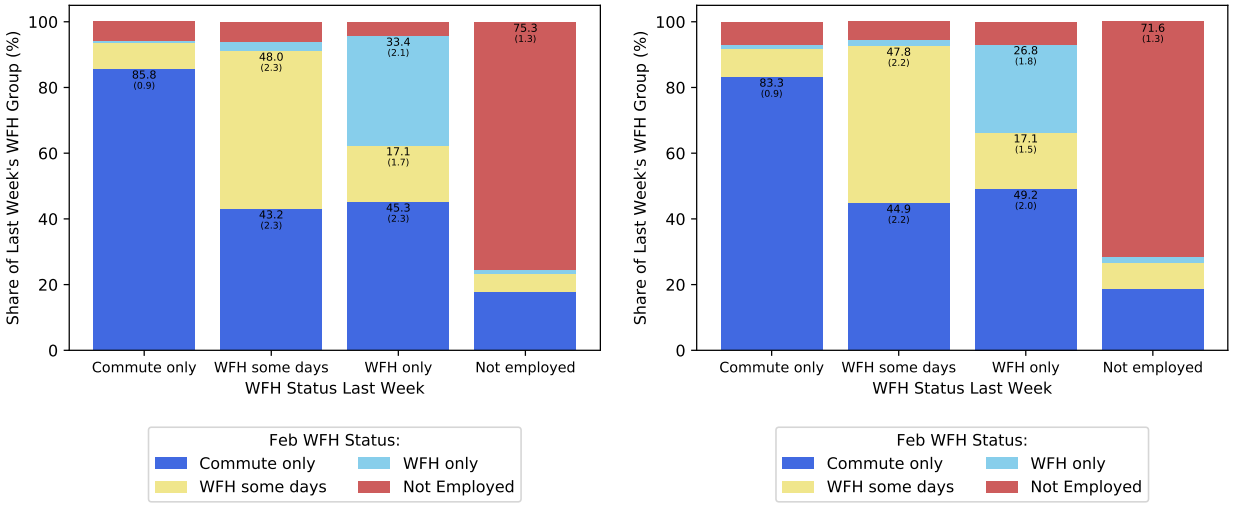
(a) September 2020

(b) October 2020



(c) November 2020

(d) December 2020



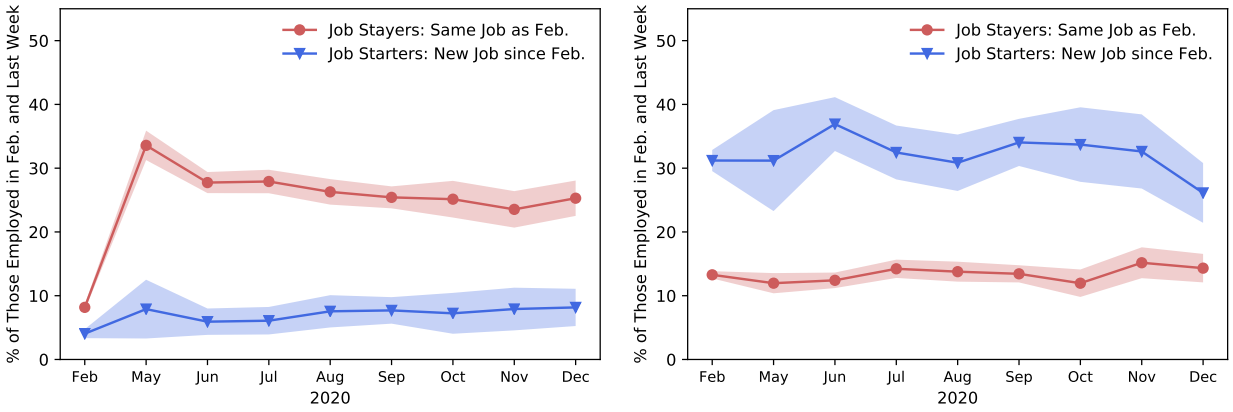
Source: Real-Time Population Survey, ages 18-64. The figure displays the composition of the population by WFH and employment status in February 2020 separately by workers' employment and WFH status in the current month. Each bar corresponds to a current WFH/employment state: Commute-Only, WFH Some Days,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

Figure 4 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 December 2020. Figures C.1 and C.2 displays 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 February WFH status.

Figures C.3 and C.4 display figures analogous to Figures C.1 and C.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 in February.

D WFH by Job Tenure: Alternative Sample

FIGURE D.1: WFH Among Job Stayers and Job Starters, Employed in February and Last Week



(a) WFH-Only

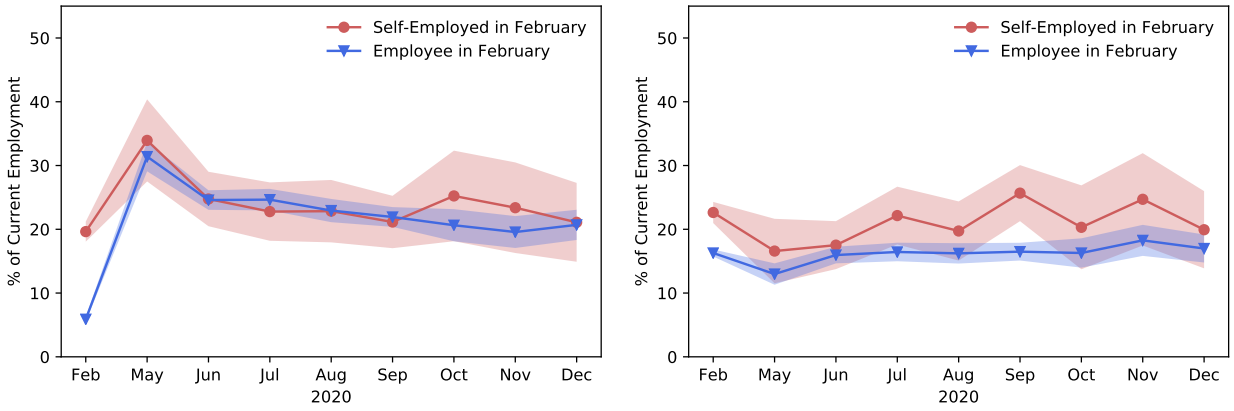
(b) WFH Some Days

Source: Real-Time Population Survey, ages 18-64. The sample is individuals employed both in February 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. Job stayers are individuals who worked for the same employer in February and in the interview month; by construction these individuals were all employed in February. Job starters refer to individuals who were employed in February, but who did not work for the current employer in February. The shaded region corresponds to two-standard-error bands. Appendix A describes the calculation of standard errors and contains sample sizes by month.

Figure 5 in the main text plots WFH rates for job stayers and job starters since February 2020. In that figure, job stayers refer to individuals employed in the current month who report working for the same employer as in February, while job starters refer to all individuals who were not working for their current employer in February. This includes individuals who had switched employer since February, as well as individuals who were not employed in February. Here, Figure D.1 considers a more narrow definition of job starters, by excluding individuals who were not employed in February. Similar to Figure 5, the present plots show that the increase in WFH-Only that occurred during the COVID-19 pandemic was concentrated among job stayers, rather than job starters. The plot also shows that there was little change in partial WFH rates, either among job stayers or job starters. The similar results in Figures 5 and D.1 confirm that the results are not sensitive to including or excluding workers who were not employed in February.

E WFH Among Employees vs. the Self-Employed

FIGURE E.1: WFH Among Employees vs. the Self-Employed



(a) WFH-Only

(b) WFH Some Days

Source: Real-Time Population Survey, ages 18-64. The sample is individuals employed both in February 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 describes the calculation of standard errors and contains sample sizes by month.

Figure E.1 plots WFH rates since February 2020 separately for workers who were employees in February and for workers who were self-employed in February. In February, the self-employed were over three times more likely to WFH-Only compared with employees. Since May, however, the two groups of workers have nearly identical rates of WFH-Only. In February, the self-employed also had rates of WFH Some Days that were slightly higher than for employees, and these differences may also have narrowed somewhat since May. Overall, since July WFH rates for the self-employed have returned to pre-pandemic levels, while WFH rates for employees remain elevated well above their pre-pandemic levels. Although not shown, we also find very similar patterns if we condition on *current* class of worker (self-employed or not) as opposed to February class of worker.

F Heterogeneity in Work from Home

F.1 Time Series of Commuting Status by Worker Characteristic

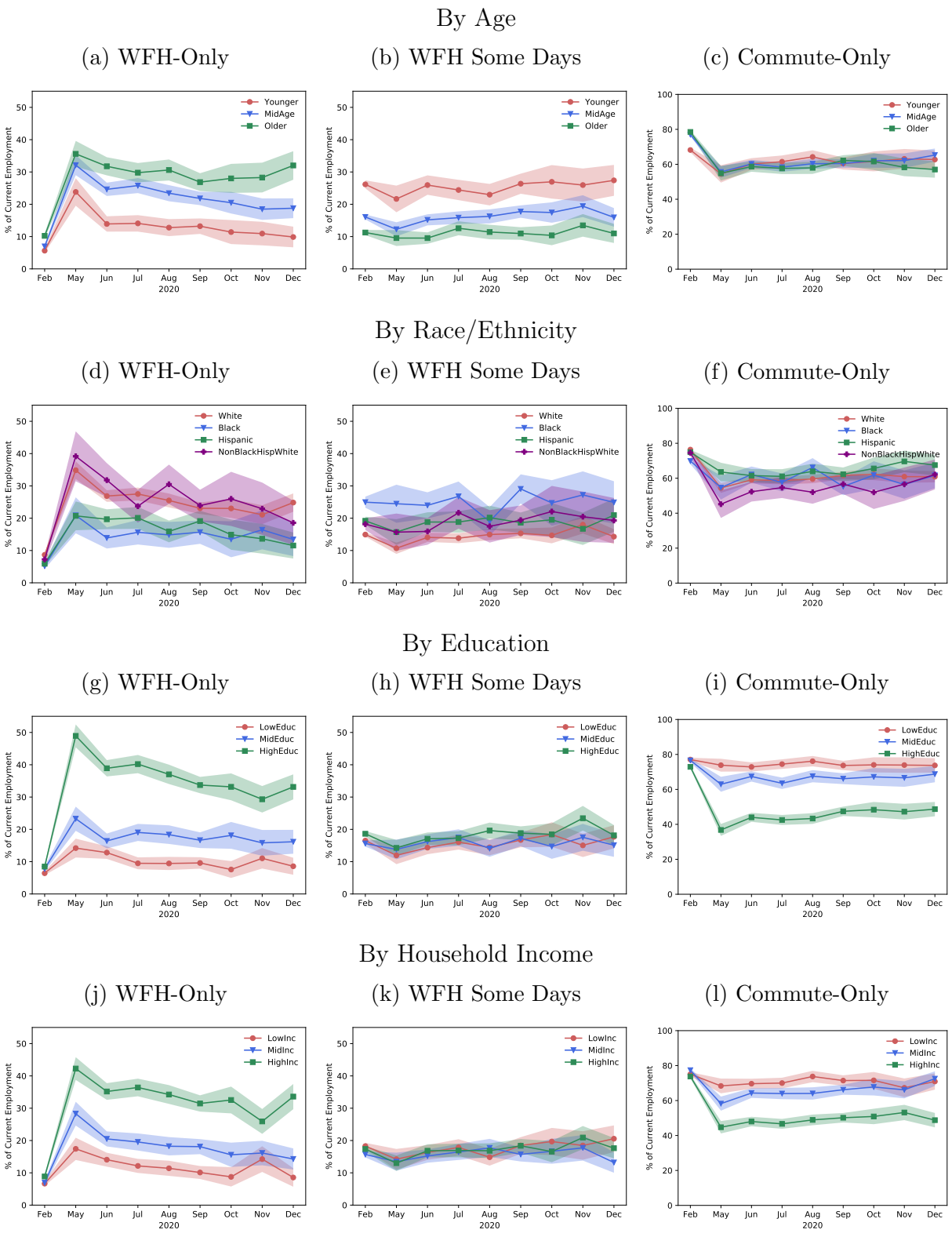
Figure 6a in the main text compares WFH before and during the COVID-19 pandemic across demographic groups. In the interest of space, that figure only showed results for WFH-Only and for three months: February, May, and December 2020. Here, Figures F.1 and F.2 display results for all months in the RPS 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 rates (first column). First, for every demographic group, WFH-Only increased from February to May. Second, every demographic group saw a decline in WFH-Only from May to December. Third, although there were some differences in WFH-Only rates 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 rates.

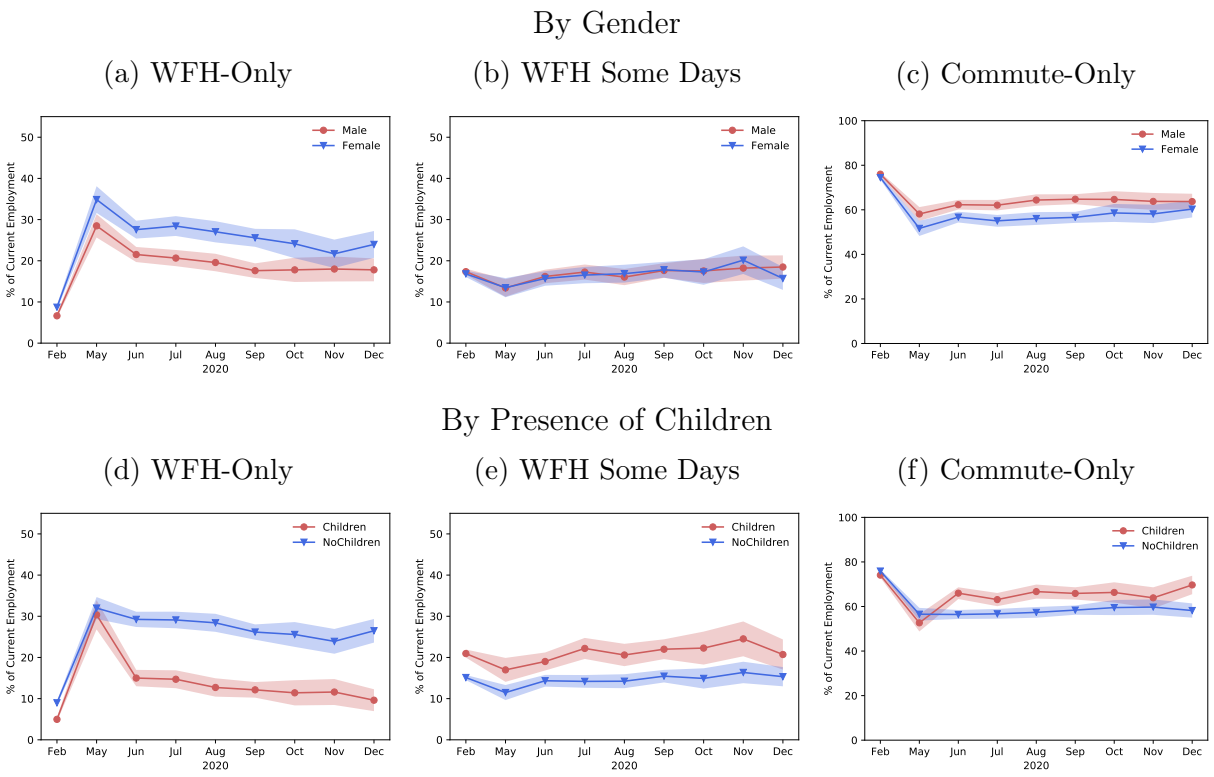
Finally, we emphasize the key takeaways from figures showing the Commute-Only rates (last column). First, for every demographic group a large majority of workers commuted every workday prior to the pandemic. There was little heterogeneity in Commute-Only rates across demographic groups; the largest exception to this was that younger workers (aged 18-29) had a Commute-Only rate that was about 10 percentage points (13%) lower than workers aged 30 and over. Second, for every demographic group the share of workers who commuted only fell from February to May, although there was sizable heterogeneity in this change across demographic groups. Third, by December Commute-Only rates had recovered completely to February 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 F.1: Commuting Status by Selected Worker Characteristics - Part I



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 describes the calculation of standard errors and contains sample sizes by month.

FIGURE F.2: Commuting Status by Selected Worker Characteristics - Part II



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 describes the calculation of standard errors and contains sample sizes by month.

F.2 Conditional WFH Probabilities

Table F.1: Conditional WFH-Only Probabilities

	February		May		December	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.077***	0.025***	0.243***	0.236***	0.156***	0.125***
	(0.004)	(0.008)	(0.026)	(0.046)	(0.025)	(0.043)
Female	0.022***	0.023***	0.034*	0.014	0.029*	0.028
	(0.003)	(0.003)	(0.017)	(0.017)	(0.017)	(0.017)
Age 18-29	-0.011***	-0.013***	-0.049**	-0.054**	-0.052**	-0.047**
	(0.004)	(0.004)	(0.024)	(0.023)	(0.022)	(0.022)
Age 50-64	0.019***	0.022***	0.048**	0.046**	0.046**	0.050**
	(0.004)	(0.004)	(0.021)	(0.021)	(0.021)	(0.021)
Black	-0.021***	-0.019***	-0.065**	-0.075***	0.001	0.002
	(0.005)	(0.005)	(0.029)	(0.028)	(0.028)	(0.028)
Hispanic	-0.010**	-0.008**	-0.056**	-0.049**	-0.034	-0.024
	(0.004)	(0.004)	(0.024)	(0.023)	(0.024)	(0.024)
Non-Black/Hispanic/White	-0.007	-0.007	-0.006	-0.000	-0.031	-0.037
	(0.005)	(0.005)	(0.032)	(0.031)	(0.031)	(0.031)
High school or less	-0.009**	-0.006*	-0.076***	-0.037*	-0.032	-0.027
	(0.004)	(0.004)	(0.023)	(0.022)	(0.023)	(0.023)
Bachelors or more	0.002	-0.001	0.236***	0.186***	0.132***	0.120***
	(0.004)	(0.004)	(0.022)	(0.022)	(0.021)	(0.021)
2019 HH income: $0-$50k	0.005	0.004	-0.042*	-0.037	-0.020	-0.013
	(0.004)	(0.004)	(0.023)	(0.023)	(0.023)	(0.023)
2019 HH income: $100k +	0.006	0.003	0.055***	0.044**	0.079***	0.072***
	(0.004)	(0.004)	(0.021)	(0.020)	(0.022)	(0.021)
Children	-0.031***	-0.029***	-0.057***	-0.053***	-0.096***	-0.096***
	(0.003)	(0.003)	(0.020)	(0.019)	(0.020)	(0.019)
Industry		X		X		X
Observations	34,556	34,556	2,521	2,521	2,124	2,124
R^2	0.011	0.028	0.138	0.216	0.125	0.159

*p<0.1; **p<0.05; ***p<0.01

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. The regressions are weighted based on sample weights, see Appendix A.

Section 2.4.3 in the main text documents substantial differences in WFH-only rates between demographic groups and industries. Table F.1 presents results from linear probability model for WFH-Only that conditions on all worker characteristics. 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, and the presence of children. Column (2) displays results of a regression with all the same right-hand variables plus controls for industry. By construction, the sample for column (2) is restricted to individuals who were employed in February; to maintain comparability, column (1) is also restricted to those employed in February. Workers who were female, older, white, and had no children in the home were more likely to be WFH-Only in February; this remains true whether or not one controls for industry. However, the size of the coefficients is small, and the R^2 is very low, below 0.03 in both columns (1) and (2), indicating that demographics and industry are poor predictors of WFH prior to the pandemic.

Columns (3)-(4) predict 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 in all cases the magnitudes increase markedly. Further, education and household income become quite strong predictors of WFH-Only in May, while these variables were insignificant for February. The R^2 is higher for May as well, at 0.138 without industry controls and 0.217 with industry controls.

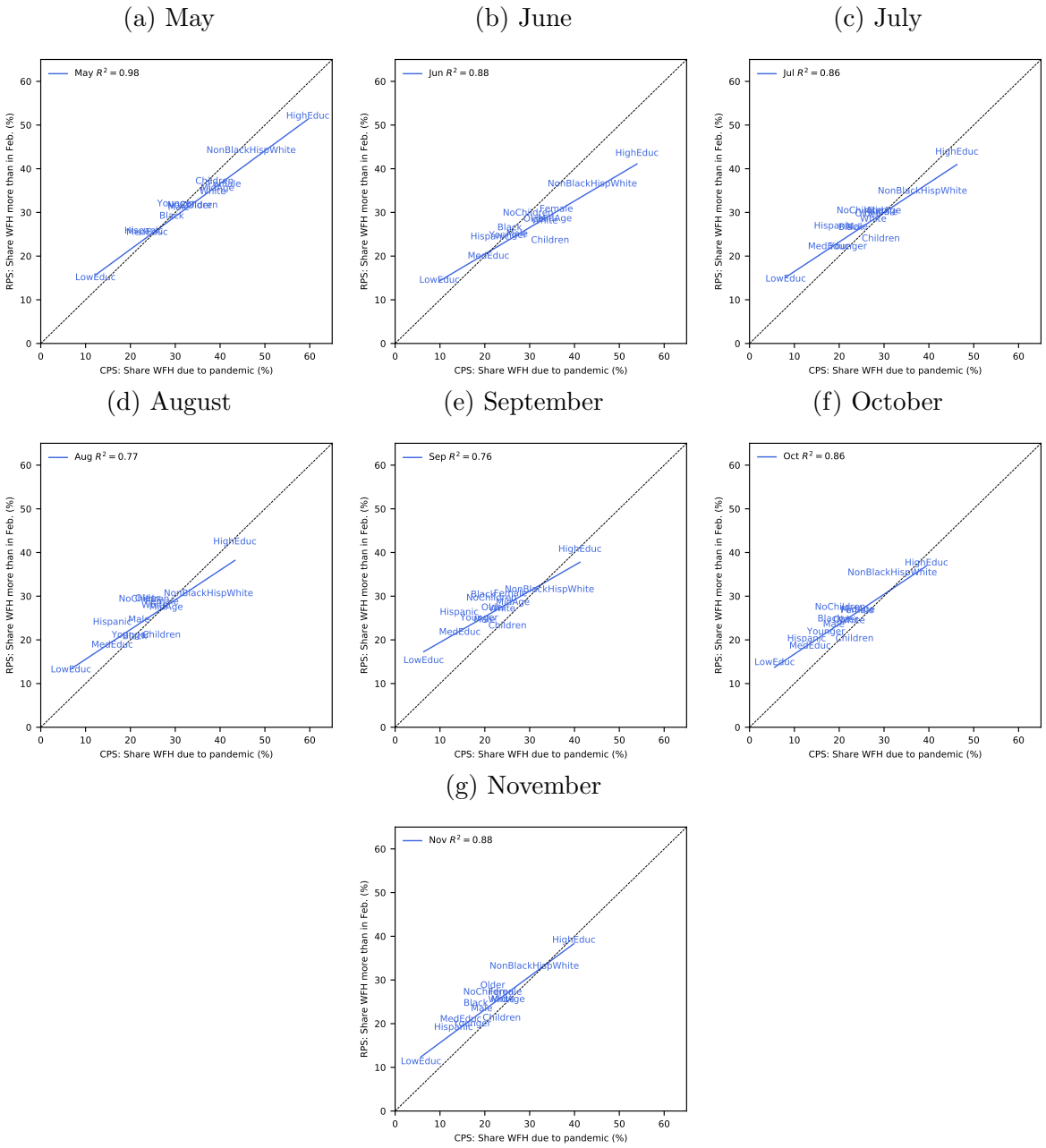
Columns (5)-(6) predict WFH-Only status for December 2020. Between May and December, the intercept term declines in magnitude. In several cases the estimated coefficients remain stable from May to December, including for females and younger and older workers. Several coefficients decline in magnitude and become insignificant from May to December, including for Black and Hispanic, low education, and low income. Interestingly, from May to December the magnitude of the coefficient for high education declines somewhat, while the magnitudes of the coefficients for high income and children increase.

G Work from Home Comparisons in the RPS and CPS

Section 2.4.3 in the main text documents that, in the RPS, differences in WFH between demographic groups increased substantially during the pandemic. 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 G.1 and G.2 compare these measures in the RPS and CPS by demographic group and industry.

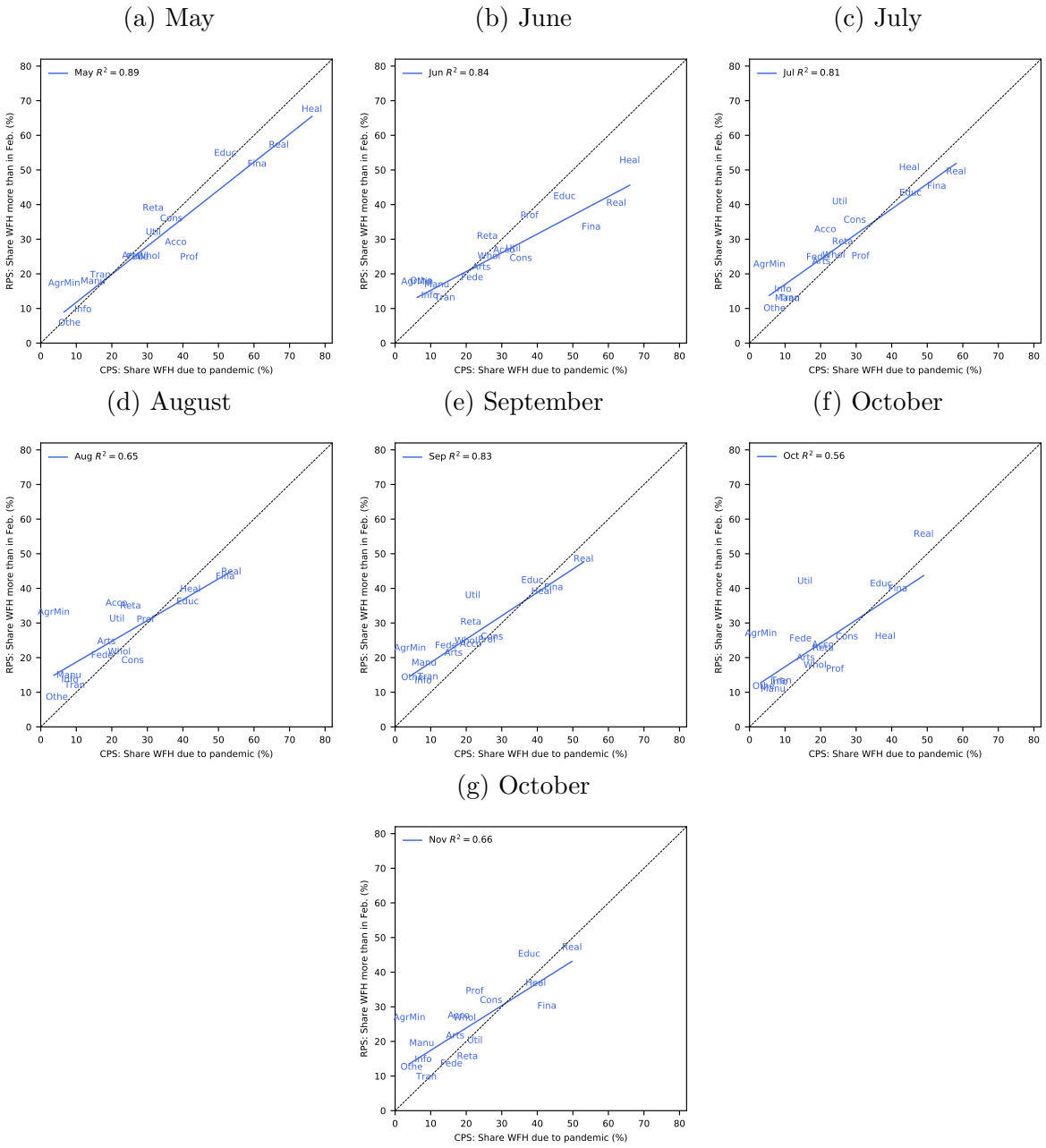
We emphasize three primary takeaways from these figures. First, the best-fit lines through the scatterplots feature a high R^2 value (it is above 0.6 in every month but one, and is above 0.7 in a majority of months). This implies that both surveys feature a similar ranking of WFH rates across worker groups. Second, the scattered data lie fairly close to the 45 degree line, indicating that both survey measures yield fairly similar levels, despite representing somewhat different WFH concepts. Third, 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.

FIGURE G.1: Work from Home by Individual Characteristics: 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. Those not employed in February are included with zero commutes before the pandemic. Definitions of demographic groups are provided in Appendix A.4. We do not include the income categories because the CPS does not contain information on 2019 household income for the months of interest.

FIGURE G.2: Work from Home by Industry: 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. Those not employed in February 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.4.

H Additional Facts On WFH, Job Loss and WFH ability

H.1 Job Loss and WFH Ability

(a) By Demographic Group

(b) By Industry

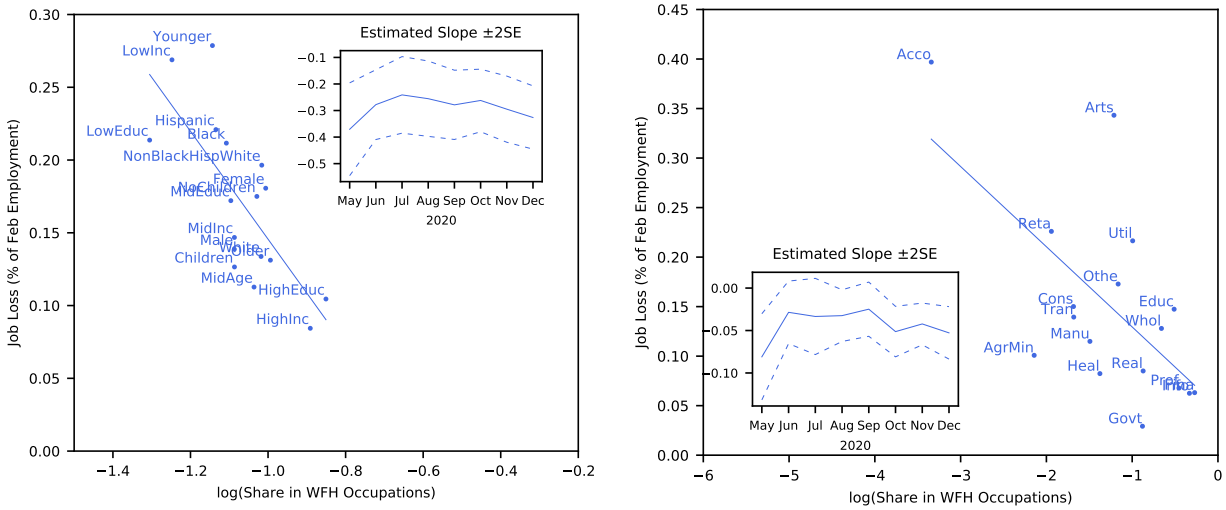


FIGURE H.1: Job Loss in the Pandemic vs. Share in WFH Occupations

Source: Real-Time Population Survey, ages 18-64. Scatters show data from May. The inset plot shows the regression slope for each available month with two-standard-error bands. In both panels, the sample is individuals who were employed in February 2020. The x-axis is the sample share of potential WFH workers based on the measures of Dingel and Neiman (2020). The y-axis is the percent decline in employment from February to May. *Left panel:* Outcomes by demographic group. *Right panel:* Industry classification is by industry of employment in February. Definitions of demographic and industry groups are provided in Appendix A.4.

Larger pre-pandemic shares in WFH occupations are associated with lower job loss rates during the pandemic. Figure H.1 plots the log change in the number of February workers that were WFH-Only in May against the log share of workers that were in WFH jobs in February, based on the measures of Dingel and Neiman (2020). The regression slopes are negative in all months of our sample and across both demographic groups and industries. Across both demographic groups and industries, the relationship is statistically significant in all months. Job loss rates in different groups/industries were therefore clearly negatively related to WFH ability across occupations.

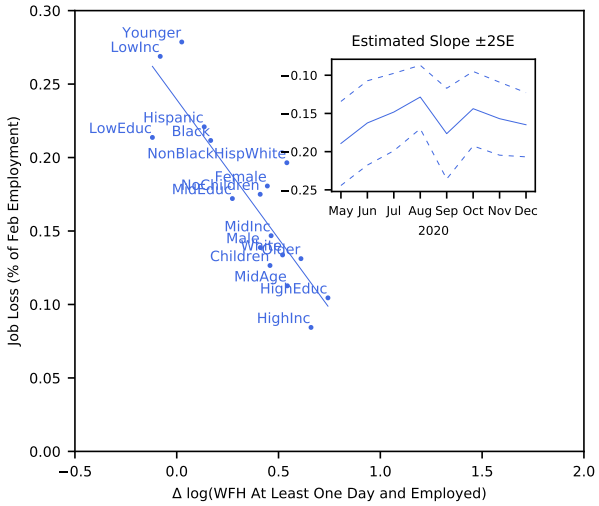
H.2 Partial WFH, Job Loss, and WFH Ability

Figure 7 in the main text showed larger job losses during the pandemic are associated with smaller growth in WFH-Only employment during the pandemic. Here, Figure H.2 documents the relationship for a broader definition of WFH: WFH at least one day. With this broader definition of WFH, we continue to find a negative relationship between job losses and growth in WFH employment across demographic groups and industries.

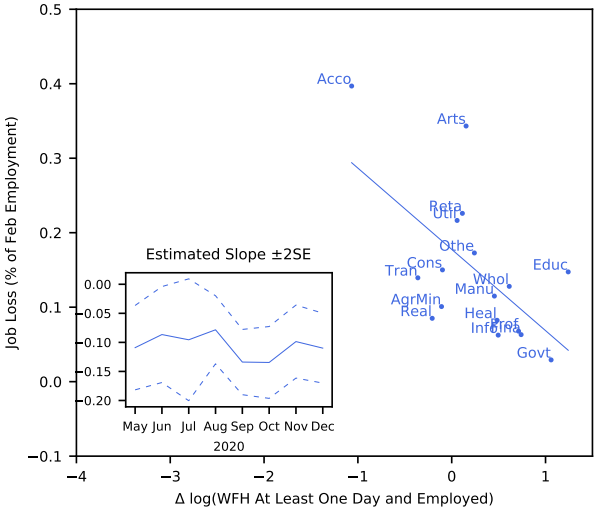
Figure 8 in the main text showed that larger shares of WFH occupations were associated with stronger growth in the WFH-only share of employment. Here, Figure H.3 documents this relationship for WFH at least one day. With this broader definition of WFH, we continue to find a positive relationship between WFH occupation share and the size and WFH growth during the pandemic. The relationship remains statistically significant for all months when comparing demographic groups and industries.

FIGURE H.2: Job Loss vs. Changes in WFH Employment

(a) By Demographic Group



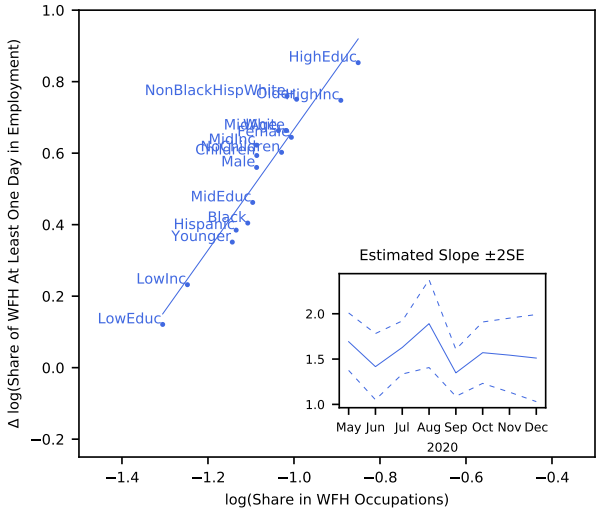
(b) By Industry



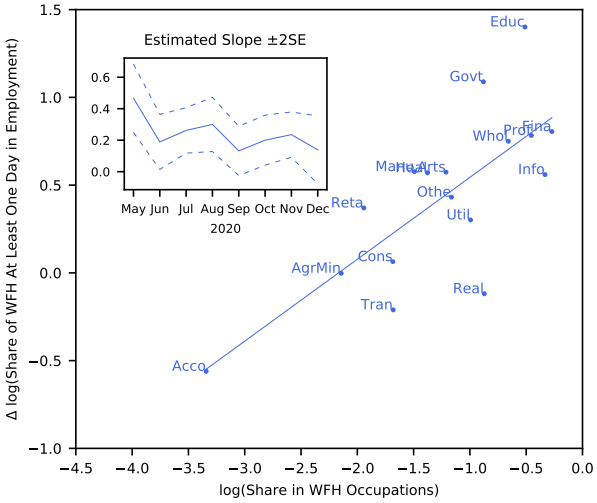
Source: Real-Time Population Survey, ages 18-64. Scatters show data from May. The inset plot shows the regression slope for each available month with two-standard-error bands. In both panels, the sample is individuals who were employed in February 2020. The x-axis is the log change from February to May in the sample share who was employed and WFH at least one day. The y-axis is the percent decline in employment from February to May. *Left panel:* Outcomes by demographic group. *Right panel:* Industry classification is by industry of employment in February. Definitions of demographic and industry groups are provided in Appendix A.4.

FIGURE H.3: Changes in Full- and Part-Time WFH Share of Employment vs. Share in WFH Occupations

(a) By Demographic Group



(b) By Industry



Source: Real-Time Population Survey (ages 18-64) and Dingel and Neiman (2020). Scatters show data from May. The inset plot shows the regression slope for each available month with two-standard-error bands. The x-axis is the February sample share of potential WFH workers based on the measures of Dingel and Neiman (2020). The y-axis is the log change from February to May in the share of employed workers who WFH at least one day. *Left panel:* Outcomes by demographic group. *Right panel:* Industry classification is by industry of employment in February. Definitions of demographic and industry groups are provided in Appendix A.4.