Work from Home Before and After the COVID-19 Outbreak

Alexander Bick   Adam Blandin   Karel Mertens

ONLINE APPENDIX

Contents

A RPS: Measurement and Definitions

A.1 Sample Construction and Weighting

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

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

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

Month	Number of Observations	Number of Employed
02/20	66282	49901
05/20	4775	2567
06/20	9042	5212
07/20	7943	4917
08/20	6464	4107
09/20	8116	5272
10/20	3180	2136
11/20	3472	2321
12/20	3458	2241
01/21	3476	2312
02/21	3466	2325
03/21	3407	2266
04/21	3171	2168
05/21	3140	2095
06/21	3172	2213

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

condition on relationship status (spouse living in the same household, partner living in the same household, other). In addition, our sampling weights also replicate the employment rate in February 2020 in the CPS, as well as the employed-at-work rates, the employment rates and the labor force participation rates in each of the subsequent months.[1] We match these key labor market statistics not only in the aggregate, but also conditional on demographic characteristics. More specifically, we match the employed at work rate, the employment rate and the labor force participation rate in the current month rates by gender, age (18-24, 25-34, 35-44, 45-54, 55-64), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, all other racial and ethnic groups), education (high school or less, some college or associate degree, bachelor degree or more), marital status (married + spouse present, never married, other), relationship status (spouse living in the same household, partner living in the same household, other), presence of children in the household (yes or no), and region (Midwest, Northeast, South and West using the Census definition).

To give an impression how accurate the weighting scheme works, Figure A.1.1 compares employment rates in the CPS, which are included as a target in the construction of the RPS

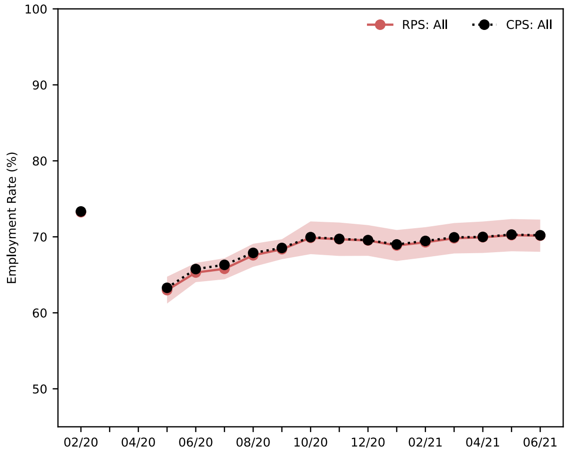
[1] Another use of the RPS, discussed in Bick and Blandin (2022), is to produce real-time labor market statistics in advance of the monthly CPS release. For this purpose, the current month CPS statistics are not yet available for targeting in the raking algorithm. The real-time forecasts of employment 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 weights, with the corresponding employment rates in the RPS in the aggregate and for selected demographic groups.

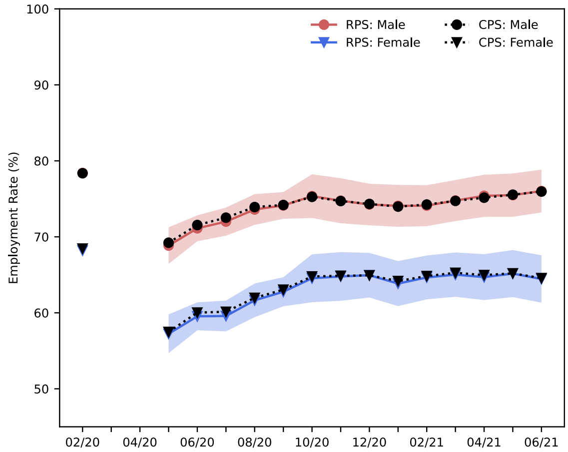
Another key dimension of interest in our analysis is the industry composition, which is however not included in our weighting procedure. Hence, the industry employment data is not mechanically replicated in the RPS by the sample weights. Figure A.1.3 compares the industry composition of employment in the CPS and RPS for all sample months, and shows that the two datasets align closely with the correlation between the two always being at least 0.7. The industries in which the RPS most undershoots the CPS are "professional and business services" (PBServ) and "health services" (Health); the largest RPS overshoot relative to the CPS is in "Other services" (other). We believe that these disparities may be attributable to some individuals in the service sector not knowing which industry to select, leading to undercounts in particular service industries and an over-count in the "other services" industry.

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

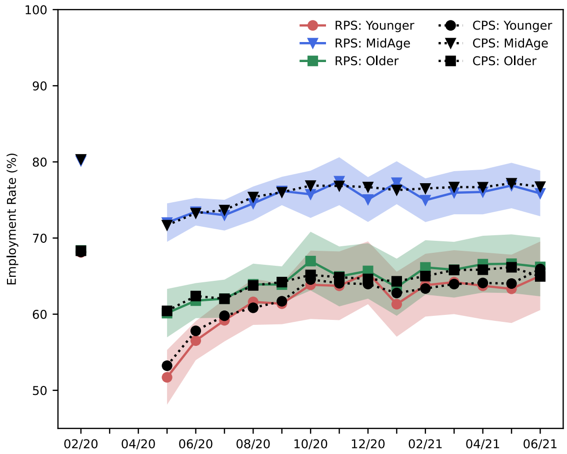
(a) Aggregate



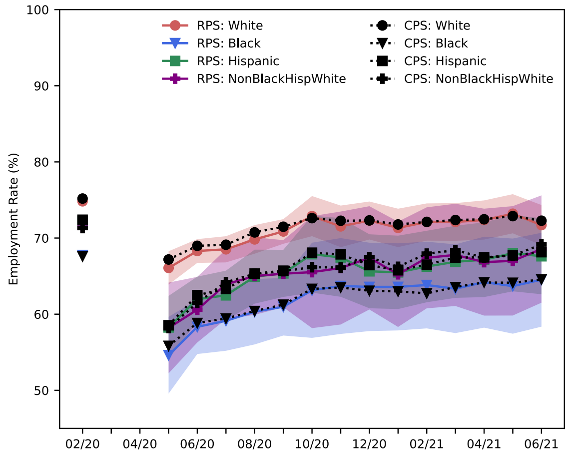
(b) By Sex



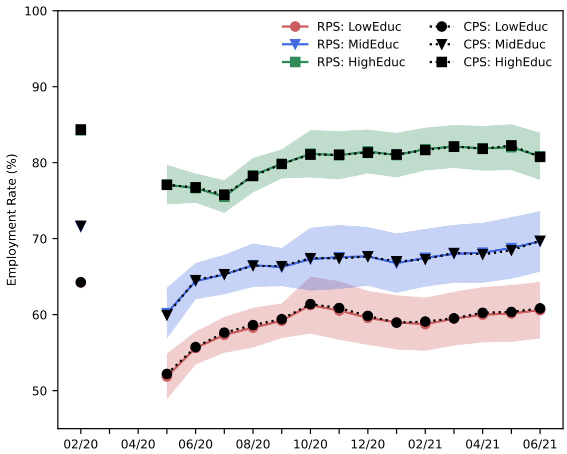
(c) By Age



(d) By Race



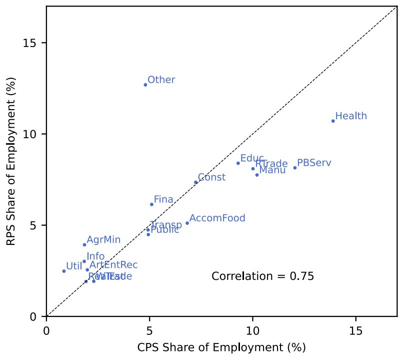
(e) By Education



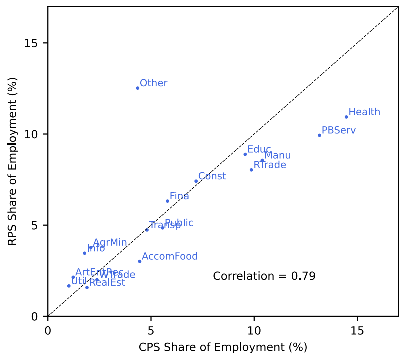
Source: Real-Time Population Survey, Current Population Survey, ages 18-64. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

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

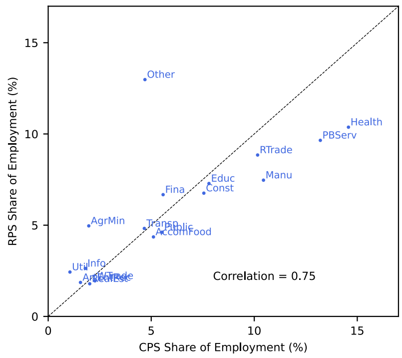
(a) February 2020



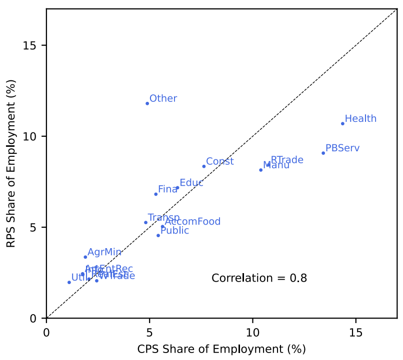
(b) May 2020



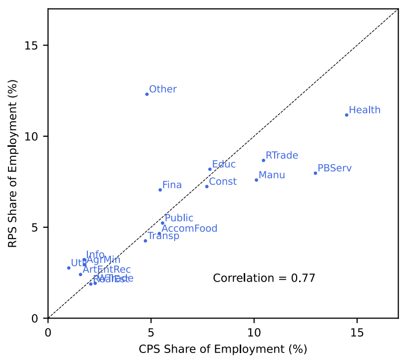
(c) June 2020



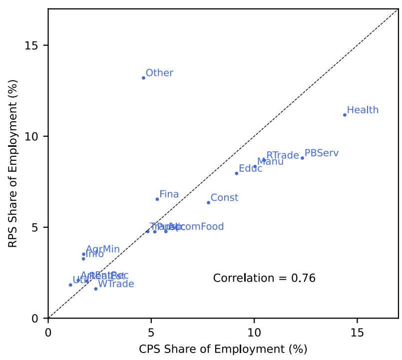
(d) July 2020



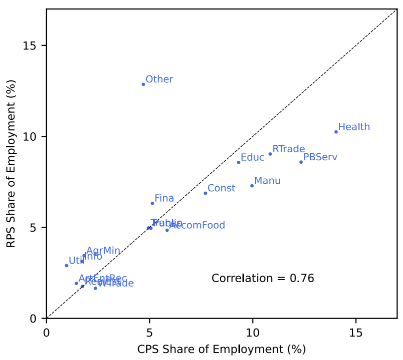
(e) August 2020



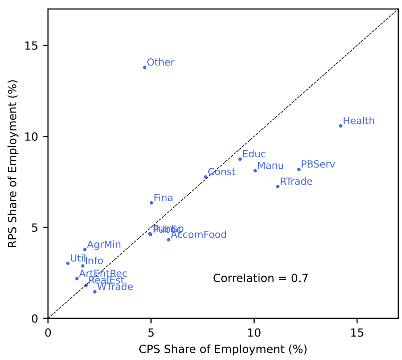
(f) September 2020



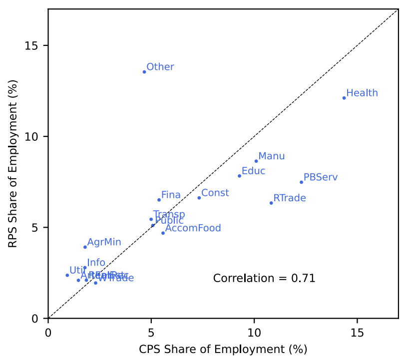
(g) October 2020



(h) November 2020



(i) December 2020

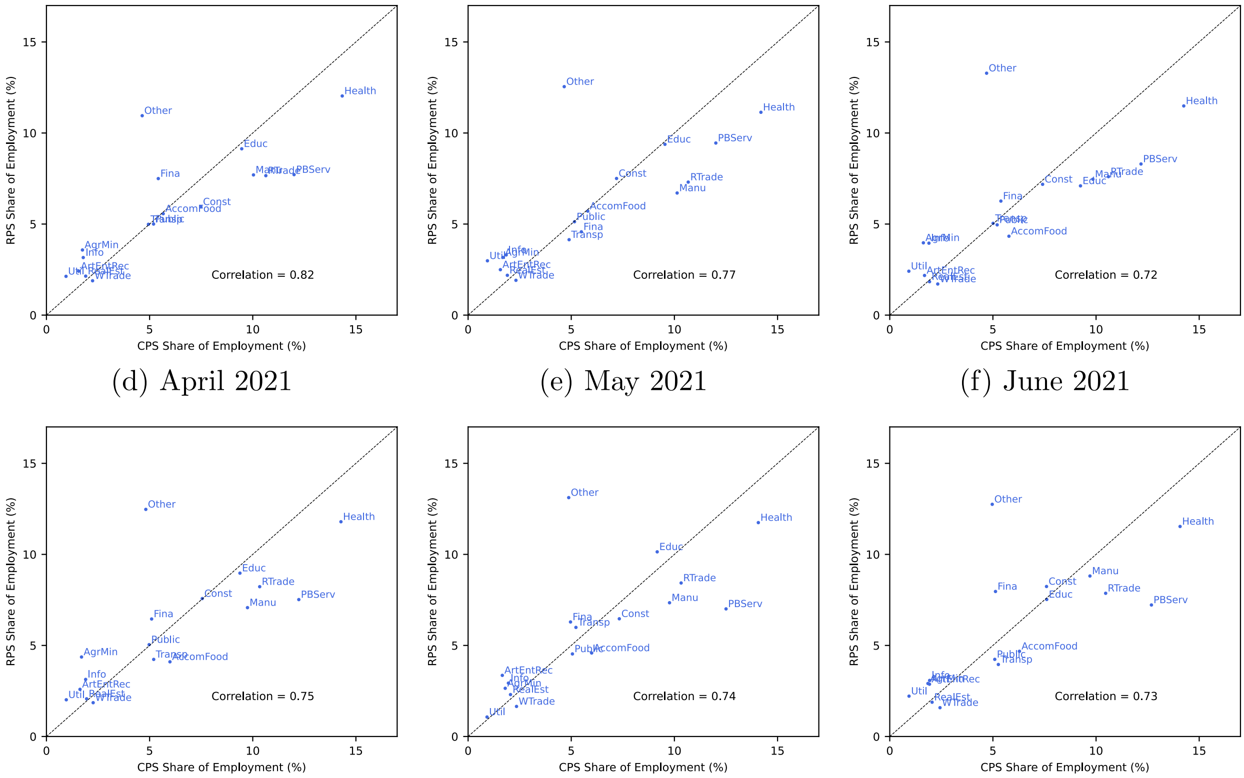


Source: Real-Time Population Survey, Current Population Survey, ages 18-64. The shaded region corresponds to two-standard-error bands. Appendix A.2 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month. Definitions of industry groups are provided in Appendix A.3.

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

(a) January 2021 (b) February 2021 (c) March 2021

(d) April 2021 (e) May 2021 (f) June 2021



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

A.2 Sample Statistics

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

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

Sample proportions and their standard deviations are then calculated as

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

A.3 Definition of Demographic Groups and Industries

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

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

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

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

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

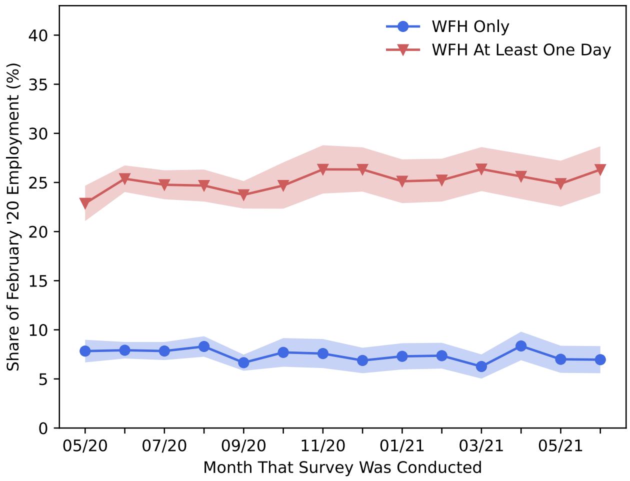
- **AgriMin**: NAICS = 11-21. Agriculture, Forestry, Fishing and Hunting and Mining, Quarrying, and Oil and Gas Extraction
- **Util**: NAICS = 22. Utilities
- **Const**: NAICS = 23. Construction
- **Manu**: NAICS = 31-33. Manufacturing
- **WTrade**: NAICS = 42. Wholesale Trade
- **RTrade**: NAICS = 44-45.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

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

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

A.4 February WFH Across Survey Months

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



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

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

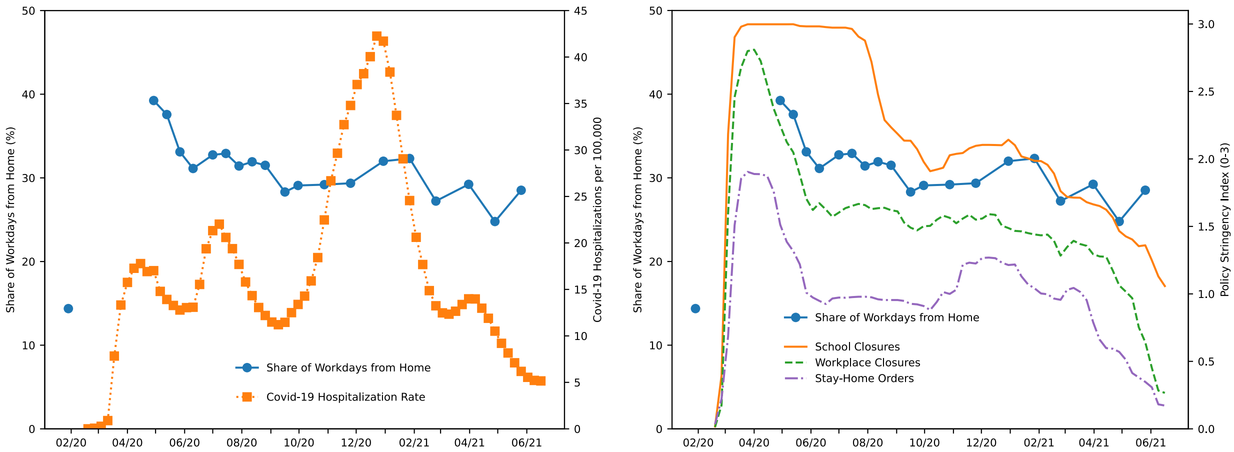
To examine whether this is the case, Figure A.4.4 displays rates of WFH in February separately for various months that the survey was conducted. Reassuringly, we find that reported WFH outcomes in February are fairly stable across survey months. For example, 7.9 percent of individuals surveyed in May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

B Additional WFH Facts

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

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

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



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

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

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

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

B.2 Change in Commuting Volume in the RPS

Figure B.2.1: Decomposition of Aggregate Change in Commuting

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

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

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

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

	Weekly Commuting Trips	Employment Rate	Days Worked / Week	Share of Work Days Commuted
05/20	-50.7	-15.1	-2.6	-33.0
	(4.3)	(0.9)	(2.9)	(6.0)
06/20	-38.2	-11.5	-3.0	-23.8
	(3.3)	(0.7)	(2.4)	(4.4)
07/20	-38.0	-10.7	-3.1	-24.3
	(3.5)	(0.7)	(2.8)	(4.9)
08/20	-33.1	-8.1	-2.5	-22.6
	(3.9)	(0.8)	(3.1)	(5.4)
09/20	-29.5	-6.9	-2.2	-20.5
	(3.5)	(0.7)	(2.6)	(4.6)
10/20	-23.9	-4.7	-0.3	-18.9
	(5.6)	(1.1)	(4.4)	(7.5)
11/20	-26.0	-5.0	-2.0	-19.0
	(5.6)	(1.1)	(4.4)	(7.5)
12/20	-27.6	-5.2	-3.1	-19.2
	(5.2)	(1.0)	(4.2)	(7.1)
01/21	-32.4	-6.2	-3.2	-23.0
	(5.2)	(1.0)	(4.2)	(7.1)
02/21	-32.1	-5.6	-3.0	-23.5
	(5.0)	(1.0)	(3.8)	(6.8)
03/21	-21.8	-4.8	-0.7	-16.3
	(5.2)	(1.0)	(4.2)	(7.0)
04/21	-26.0	-4.6	-2.3	-19.1
	(5.3)	(1.1)	(4.3)	(7.2)
05/21	-18.3	-4.2	-1.1	-13.0
	(5.5)	(1.1)	(4.3)	(7.2)
06/21	-23.9	-4.3	-1.5	-18.1
	(5.5)	(1.1)	(4.5)	(7.4)

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

B.3 WFH Across Demographic Groups

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

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

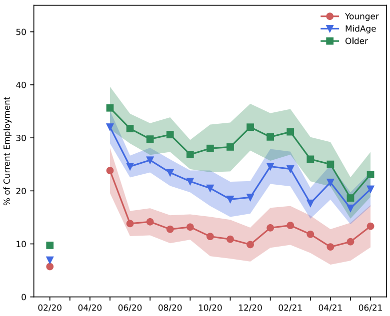
Next, we highlight the main takeaways from the figures showing the partial WFH rates (middle column). First, for every demographic group, partial WFH was more common than WFH Only prior to the pandemic. Second, for essentially all demographic groups, changes in the partial WFH rates during the pandemic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

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

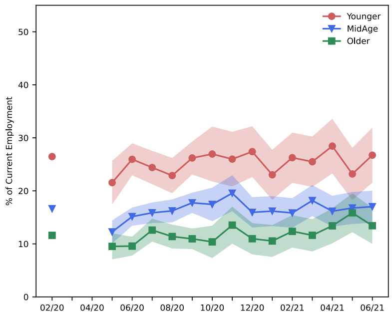
FIGURE B.3.1: Commuting Status by Selected Worker Characteristics - Part I

By Age

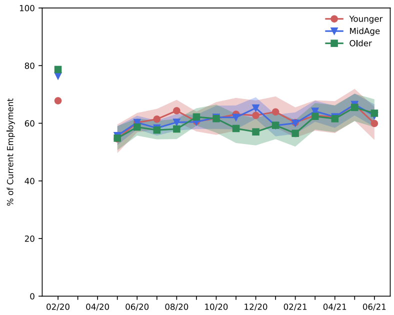
(a) WFH Only



(b) WFH Some Days

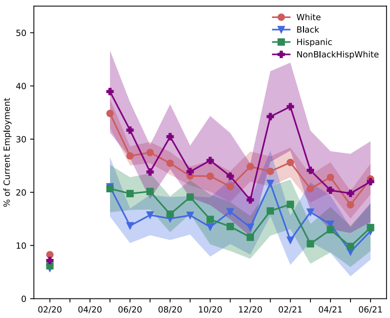


(c) Commute Only

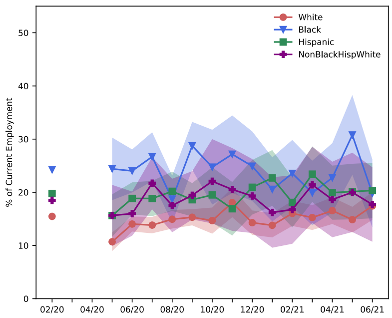


By Race/Ethnicity

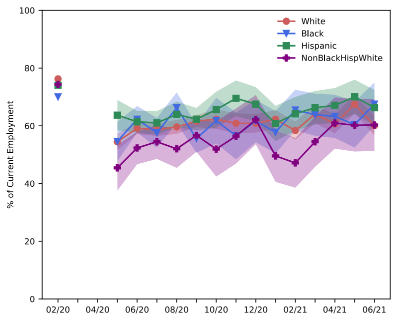
(d) WFH Only



(e) WFH Some Days

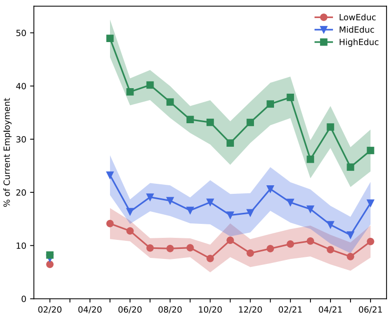


(f) Commute Only

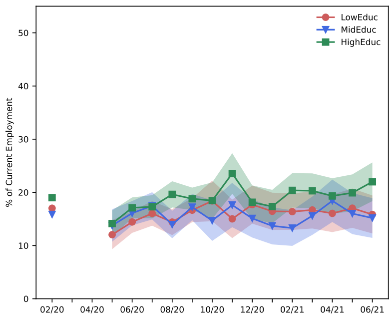


By Education

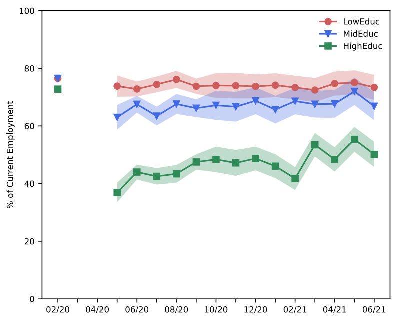
(g) WFH Only



(h) WFH Some Days

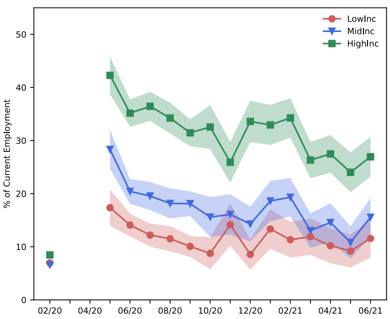


(i) Commute Only

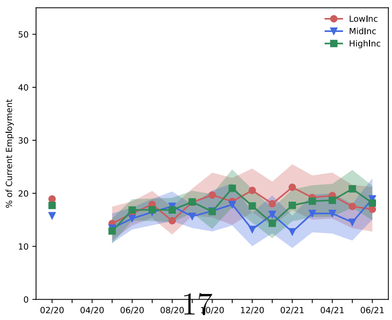


By Household Income

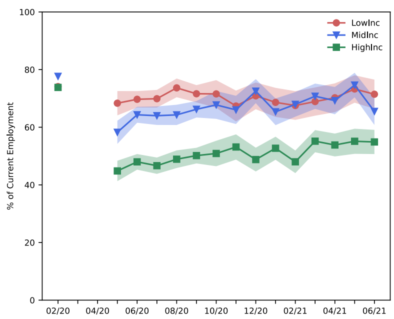
(j) WFH Only



(k) WFH Some Days

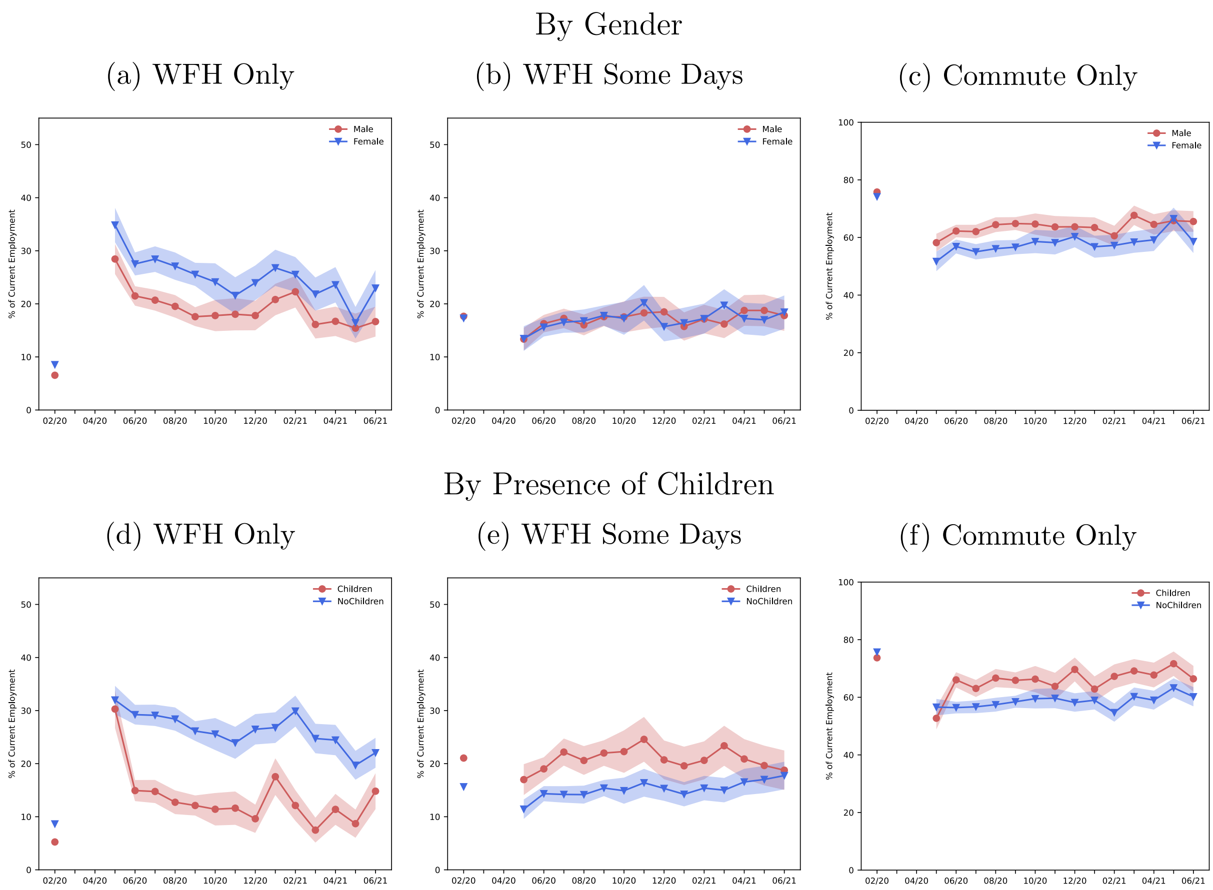


(l) Commute Only



Source: Real-Time Population Survey, ages 18-64. The sample is individuals employed in the relevant month. The figure shows the share of WFH Only workers (left panels), partial-WFH workers (middle panels) and Commute Only workers (right panels) each month. The shaded region corresponds to two-standard-error bands. Appendix A.3 describes the calculation of standard errors. See Appendix A.1 for sample sizes by month.

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



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

B.4 Conditional WFH Probabilities

Section 1.2 in the main text documents substantial differences in the increases in WFH Only shares between demographic groups. Table B.4 presents results from linear probability model for WFH Only that conditions on all worker characteristics for February 2020, May 2020, and June 2020. As in Figure 2, we restrict the samples in May 2020 and June 2021 to those who were also employed in February 2020. Overall, the results from the regression analysis are qualitatively consistent with to the unconditional group comparisons discussed in the main text.

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

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

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

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

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

	02/20	05/20	06/21
	(1)	(2)	(3)
Constant	0.032***	0.225***	0.197***
	(0.006)	(0.045)	(0.046)
Female	0.021***	0.014	0.046***
	(0.002)	(0.017)	(0.018)
Age 18-29	-0.013***	-0.053**	-0.073***
	(0.003)	(0.023)	(0.023)
Age 50-64	0.019***	0.046**	-0.017
	(0.003)	(0.021)	(0.021)
Black	-0.012***	-0.073***	-0.035
	(0.004)	(0.028)	(0.028)
Hispanic	-0.005	-0.047**	-0.035
	(0.003)	(0.023)	(0.024)
Non-Black/Hispanic/White	-0.004	-0.000	0.005
	(0.004)	(0.031)	(0.031)
High school or less	-0.005	-0.037*	-0.033
	(0.003)	(0.022)	(0.023)
Bachelors or more	-0.001	0.187***	0.053**
	(0.003)	(0.022)	(0.022)
2019 HH income: \$0-\$50k	0.010***	-0.037	0.018
	(0.003)	(0.023)	(0.024)
2019 HH income: \$100k +	0.002	0.045**	0.041**
	(0.003)	(0.020)	(0.021)
Children	-0.025***	-0.055***	-0.066***
	(0.003)	(0.019)	(0.019)
Observations	49,901	2,530	2,083
R^2	0.025	0.216	0.102
Note:			*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.3. The regressions are weighted based on sample weights, see Appendix A.1.

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

	WFH Only		WFH Some Days	
	(1)	(2)	(3)	(4)
Constant	0.032***	0.077***	0.084***	0.208***
	(0.006)	(0.014)	(0.009)	(0.018)
Female	0.021***	0.034***	0.002	0.014*
	(0.002)	(0.006)	(0.003)	(0.007)
Age 18-29	-0.013***	-0.018**	0.098***	0.090***
	(0.003)	(0.007)	(0.004)	(0.010)
Age 50-64	0.019***	0.001	-0.031***	-0.036***
	(0.003)	(0.007)	(0.004)	(0.009)
Black	-0.012***	-0.014	0.060***	0.074***
	(0.004)	(0.009)	(0.005)	(0.012)
Hispanic	-0.005	-0.012	0.013***	0.010
	(0.003)	(0.008)	(0.005)	(0.010)
Non-Black/Hispanic/White	-0.004	0.004	0.004	0.070***
	(0.004)	(0.010)	(0.006)	(0.013)
High school or less	-0.005	-0.017**	0.002	-0.042***
	(0.003)	(0.007)	(0.005)	(0.010)
Bachelors or more	-0.001	-0.002	0.038***	0.075***
	(0.003)	(0.007)	(0.004)	(0.009)
2019 HH income: $0-$50k	0.010***	0.030***	0.013***	0.002
	(0.003)	(0.008)	(0.005)	(0.010)
2019 HH income: $100k +	0.002	0.011*	0.028***	0.036***
	(0.003)	(0.007)	(0.004)	(0.009)
Children	-0.025***	-0.029***	0.033***	-0.015*
	(0.003)	(0.006)	(0.004)	(0.008)
Observations	49,901	14,602	49,901	14,602
R^2	0.025	0.032	0.043	0.055
Note:	*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 and in the reference week. Definitions of demographic and industry groups are provided in Appendix A.3. The regressions are weighted based on sample weights, see Appendix A.1.

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

Sex: Before the pandemic, the WFH Only coefficient for women was positive, and this coefficient increases slightly in the year ahead expectations. The coefficient for WFH Some Days is small and less significant. These estimates are qualitatively consistent with slightly higher unconditional WFH rates for women in Figure 11b.

Age: Before the pandemic, the WFH Only coefficient for workers under 30 was negative and the coefficient for workers over 50 was positive. For year ahead expectations, the coefficient for young workers remains similar, but the coefficient for older workers becomes insignificant. Conversely, in the WFH Some Days regression, the coefficient on young workers is strongly positive and the coefficient on older workers is strongly negative, both before the pandemic and in year ahead expectations. Together, these estimates paint a somewhat different picture from Figure 11b, which shows that on average older workers expect larger WFH increases relative to before the pandemic. The regression results therefore indicate that the differences in expected WFH changes by age are likely accounted for by other variables correlated with age.

Race and ethnicity: Before the pandemic, the WFH Only coefficients for Black, Hispanic, and Non-Black/Hispanic/White were all negative and small in magnitude, with only the Black coefficient being significant. These estimates are similar in year ahead expectations. In the WFH Some Days regression, all three coefficients are positive before the pandemic. The coefficients for Black and Hispanic are fairly similar in the year ahead expectations. The notable change is that the Non-Black/Hispanic/White coefficient becomes large and significant. Overall, these results are qualitatively consistent with the results in Figure 11b, which shows similar average expected changes in WFH for White, Black, and Hispanic workers, but much larger changes for Non-Black/White/Hispanic workers.

Education: Before the pandemic, the WFH Only coefficients for education were small, and they remain so in the year ahead expectations. In the WFH Some Days regression, the coefficient on High school degree or less was close to zero, while Bachelor's degree or more was positive and significant. In the year ahead expectations, the coefficient on High school degree or less becomes significantly negative and the coefficient on Bachelor's degree or more becomes more positive. Overall, these result are qualitatively consistent with the results in Figure 11b, which shows expanding gaps in WFH by education, primarily coming from WFH Some Days.

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

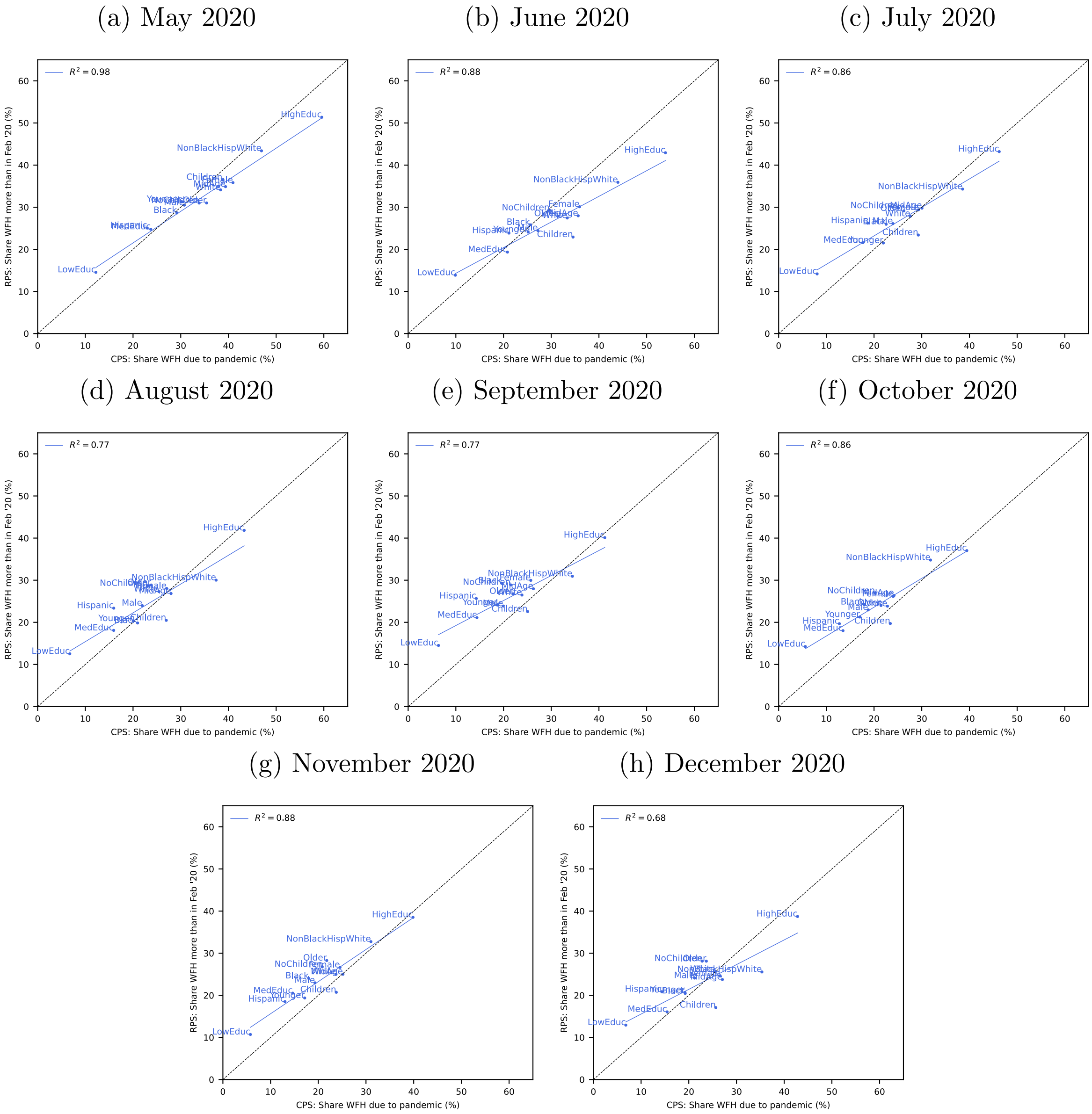
Presence of children: Before the pandemic, the WFH Only coefficient for the presence of children was significantly negative, and this coefficient is fairly stable in the year ahead expectations. In the WFH Some Days regression, the coefficient on presence of children was significantly positive before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

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

Section 1.2 documents large differences in the increases in WFH Only shares between demographic groups during the pandemic in the RPS. Here, we assess the extent to which heterogeneity in WFH in the RPS is consistent with heterogeneity in WFH in the CPS. Starting in May 2020, the CPS added the following question to the survey questionnaire: *"At any time in the last 4 weeks, did (you/name) telework or work at home for pay because of the coronavirus pandemic?"*, followed by a yes/no answering option. Data based on this question is not directly comparable to WFH data in the RPS for several reasons (see Section 1.3 for a discussion of the WFH question asked by the CPS and how it compares to WFH information in the RPS). However, the RPS does provide information on whether individuals worked a higher fraction of days from home last week compared to a typical week in February 2020, just prior to the pandemic. Figures B.5.1, B.5.2, B.5.3, and B.5.4 compare these measures in the RPS and CPS by demographic group and industry.

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

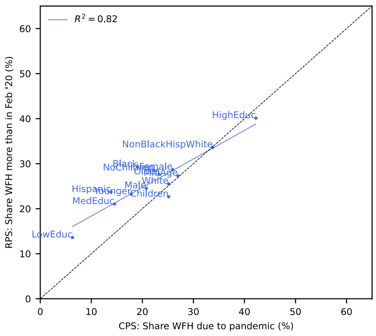
FIGURE B.5.1: Work from Home by Individual Characteristics in 2020: RPS vs. CPS



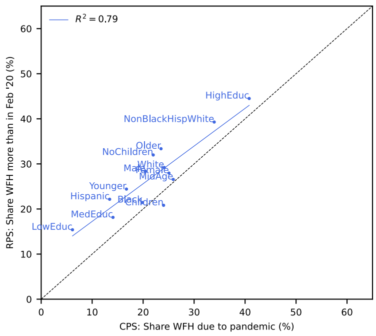
Sources: Real-Time Population Survey and Current Population Survey, ages 18-64. The graphs compare WFH rates in the RPS and CPS by demographic group. Both the RPS and CPS samples are individuals employed in a given month. The CPS values show the sample share answering yes to the WFH question in the CPS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

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

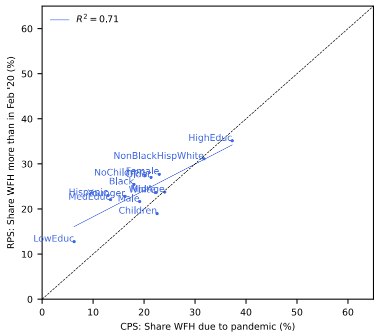
(a) January 2021



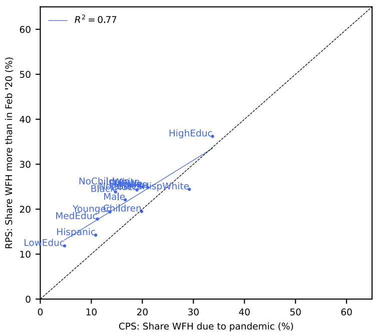
(b) February 2021



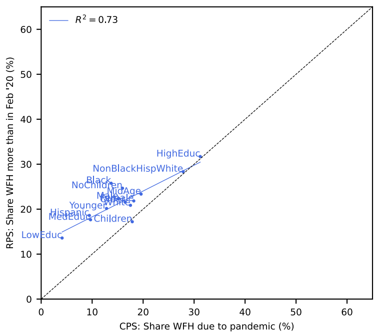
(c) March 2021



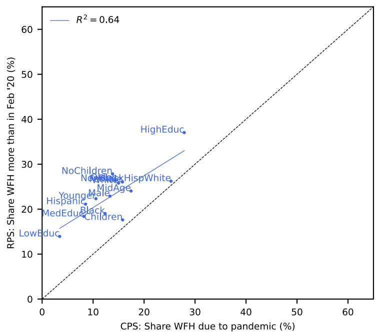
(d) April 2021



(e) May 2021



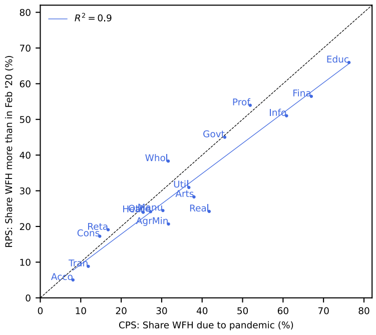
(f) June 2021



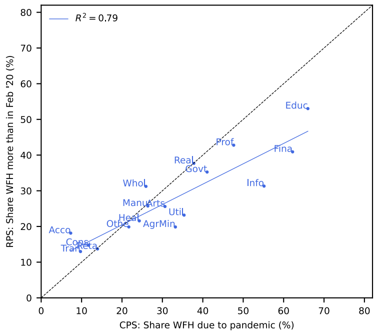
Sources: Real-Time Population Survey and Current Population Survey, ages 18-64. The graphs compare WFH rates in the RPS and CPS by demographic group. Both the RPS and CPS samples are individuals employed in a given month. The CPS values show the sample share answering yes to the WFH question in the CPS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

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

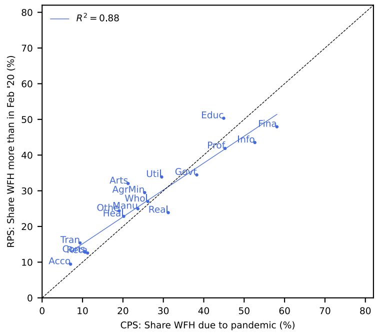
(a) May 2020



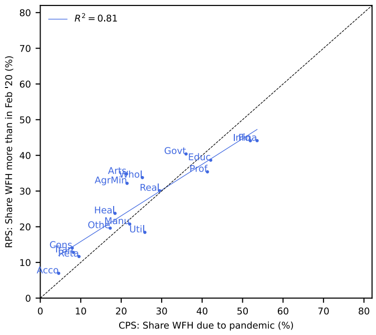
(b) June 2020



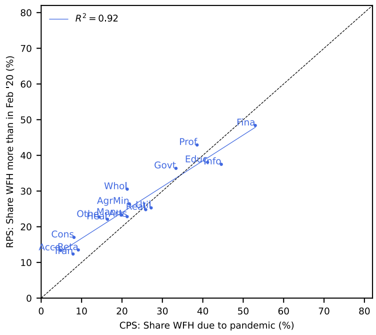
(c) July 2020



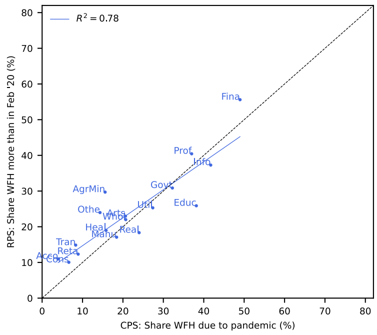
(d) August 2020



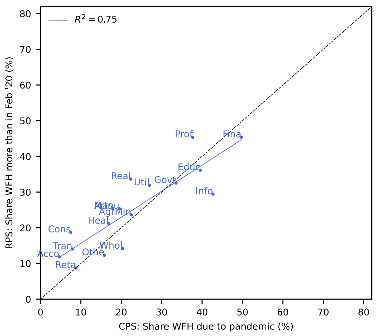
(e) September 2020



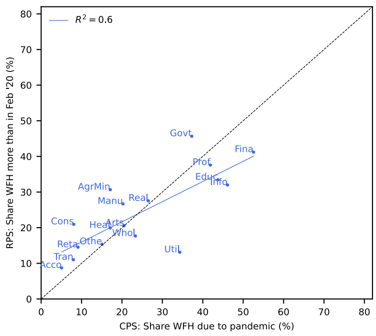
(f) October 2020



(g) November 2020

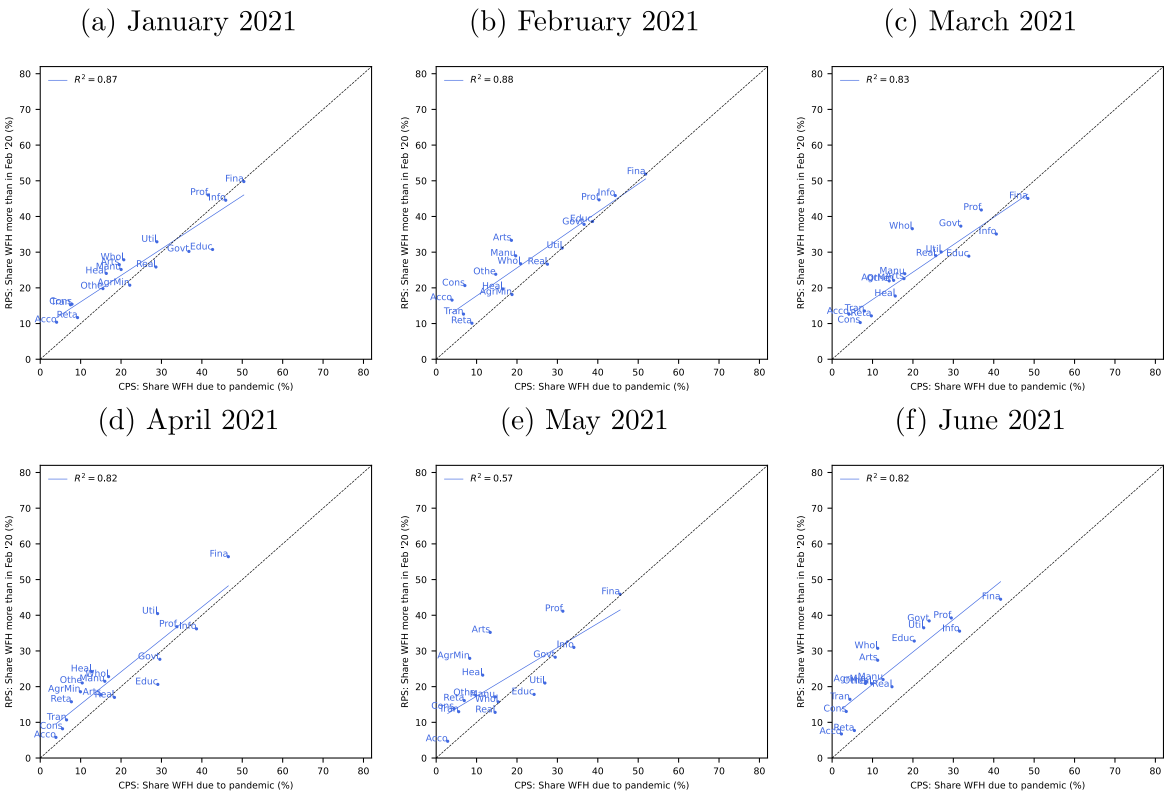


(h) December 2020



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

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

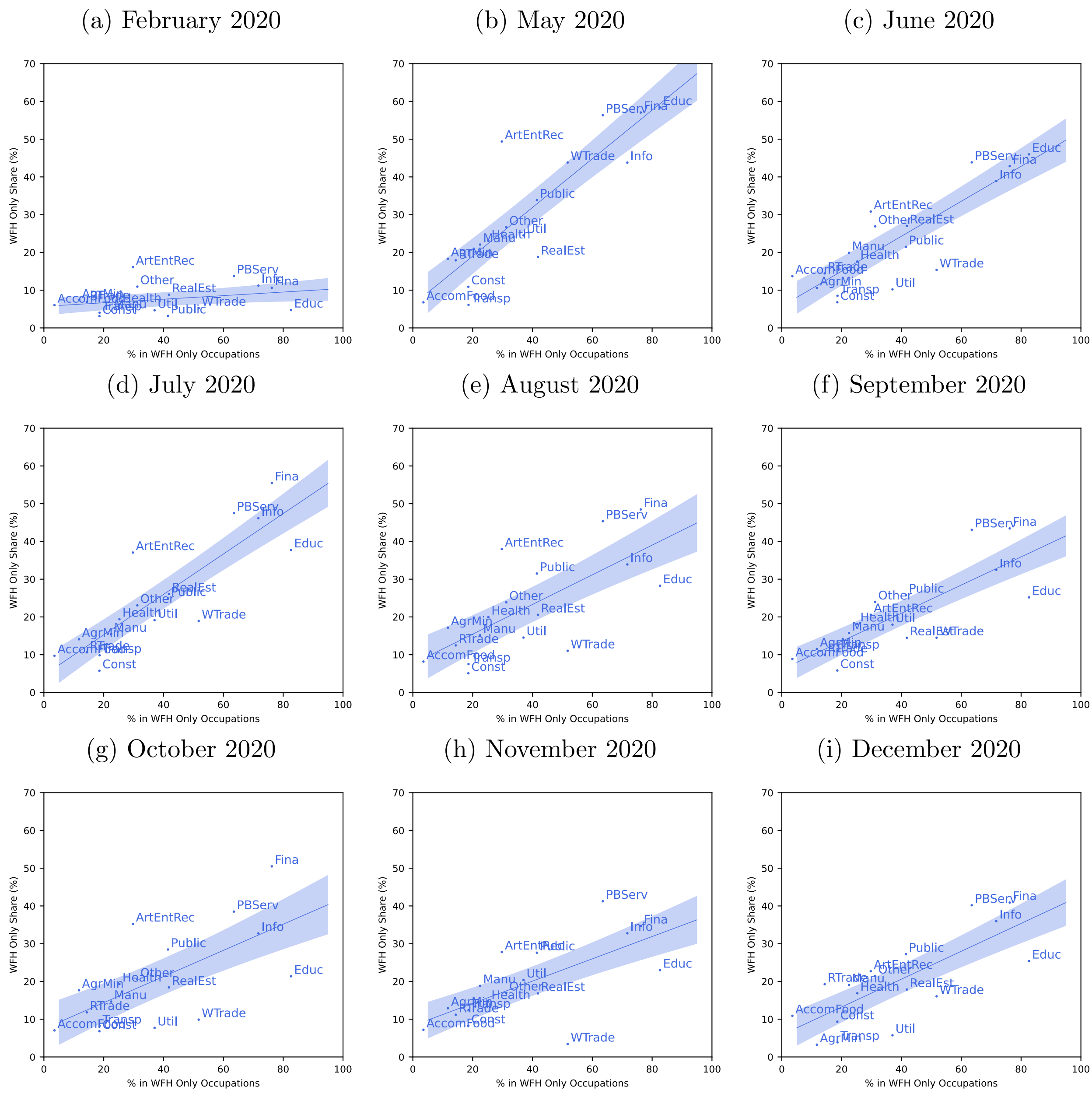


Sources: Real-Time Population Survey and Current Population Survey, ages 18-64. The graphs compare WFH rates in the RPS and CPS by demographic group. Both the RPS and CPS samples are individuals employed in a given month. The CPS values show the sample share answering yes to the WFH question in the CPS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

B.6 WFH Only Shares versus WFH Potential

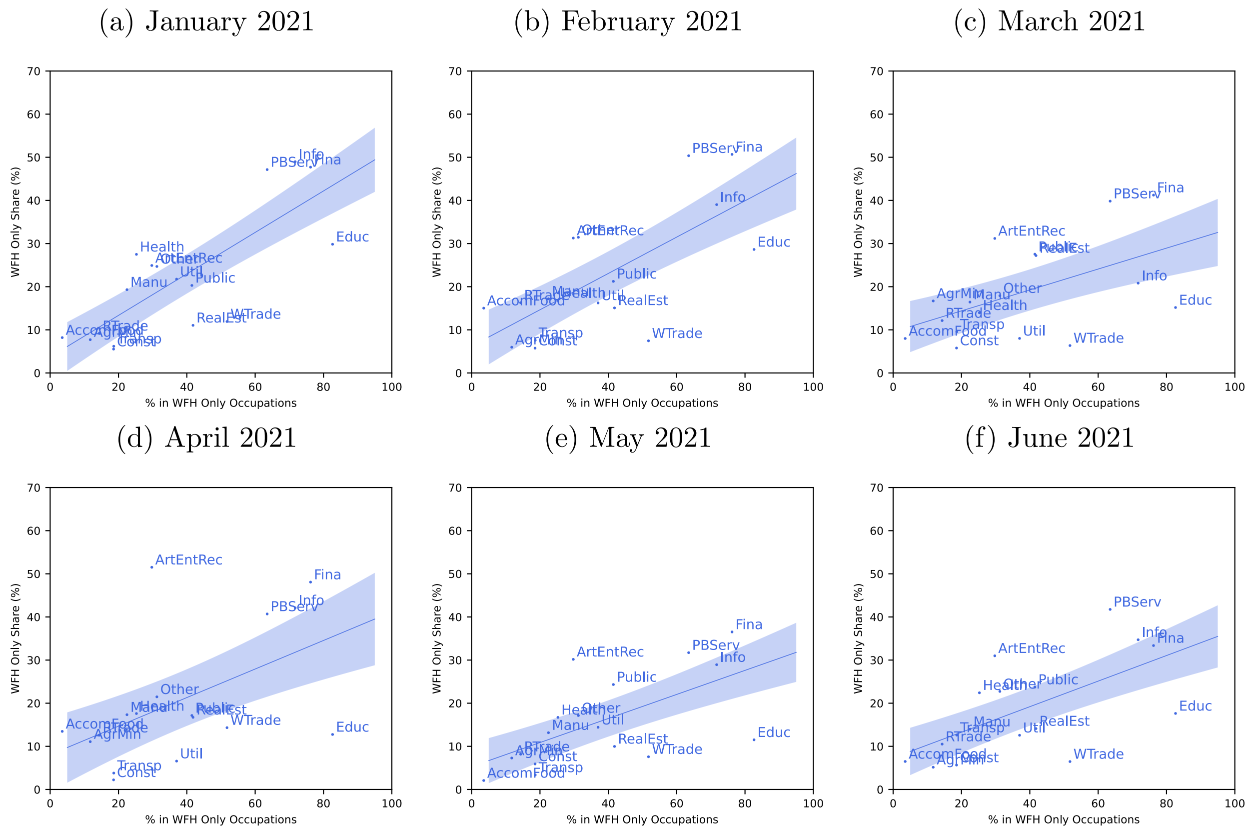
Figure 4 plots the WFH Only shares in different industries against estimates of the share of workers that were in potential WFH Only jobs in February 2020 for February 2020, May 2020, and June 2021. Figures B.6.5 and B.6.6 repeats the plots for these three months and shows them as well for all other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

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



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

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

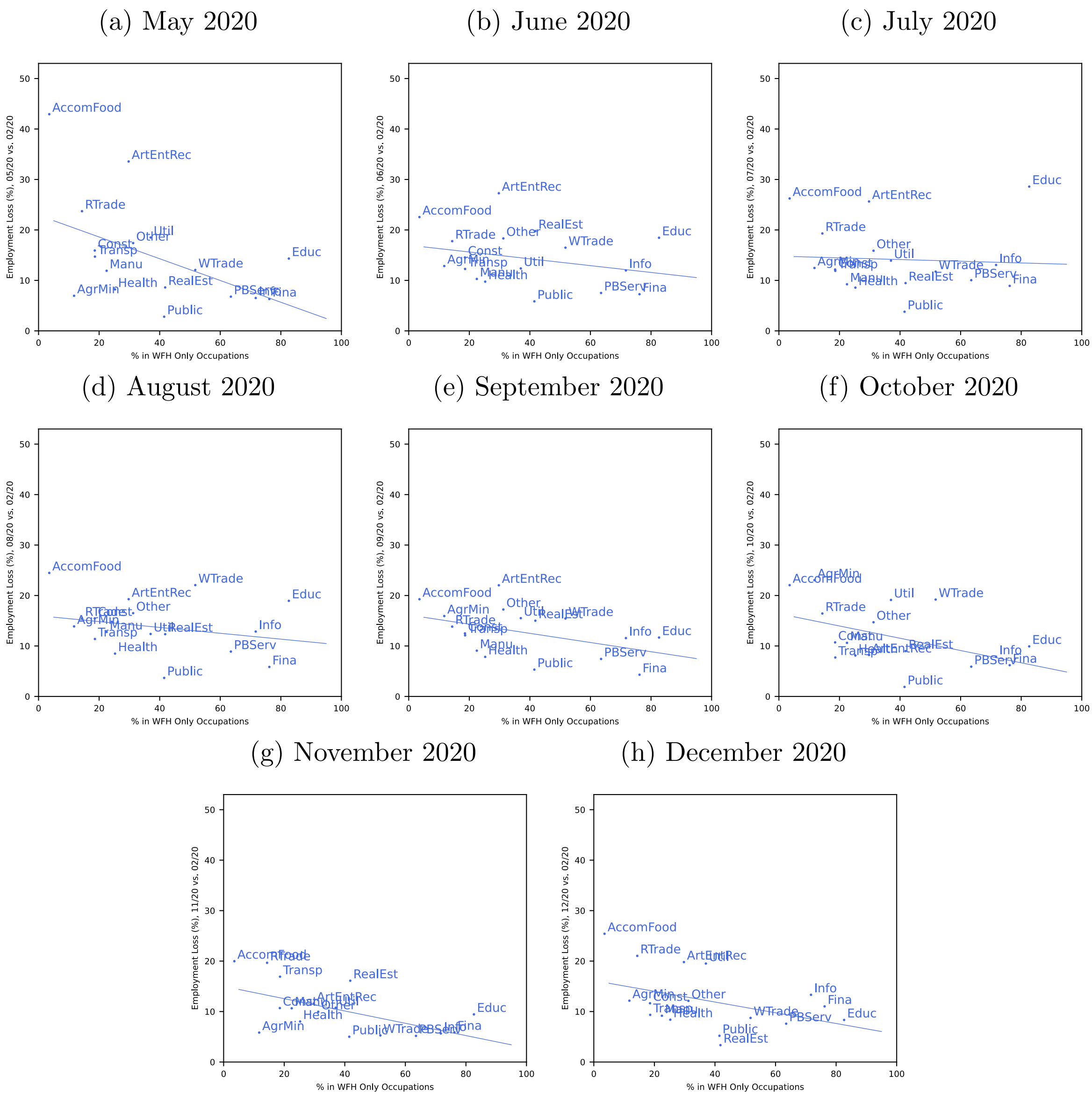


Source: Real-Time Population Survey and Dingel and Neiman (2020). The x-axis is the share (percent) of February 2020 workers in potential WFH occupations based on the measures of Dingel and Neiman (2020). The y-axis is the share (percent) of employed workers that are WFH Only. Definitions of industry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

B.7 Employment Loss and Potential WFH Potential

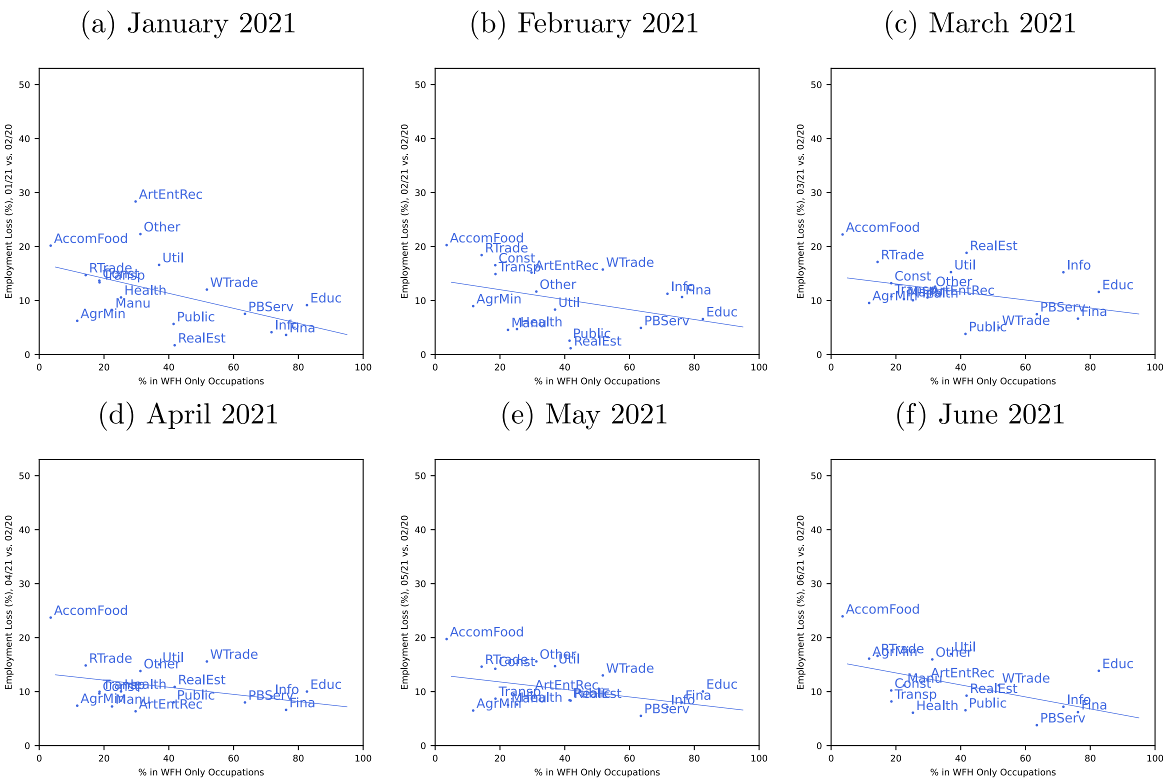
Figure 4 shows that WFH Only Shares and potential WFH Only Shares were strongly positively correlated in May 2020 and June 2021 (Appendix B.6 shows these results hold all true in all months during the pandemic). Figures B.7.1 and B.7.2 show that at the same time a strong negative correlation between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

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



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

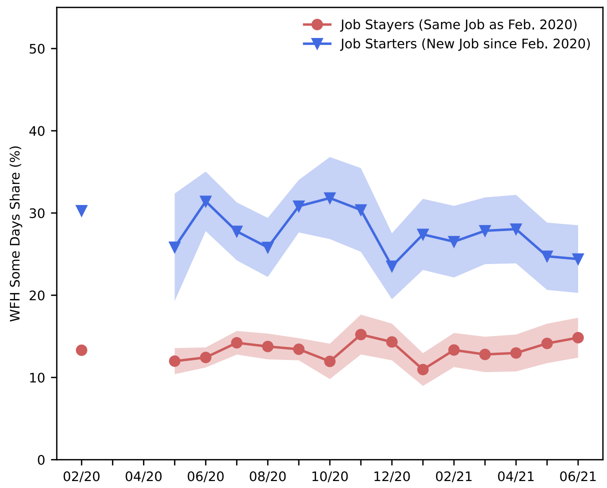
Figure B.7.2: Employment Losses and Potential WFH Only Shares in 2020



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

B.8 WFH by Job Tenure

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



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

Figure 6 in the main text plots WFH Only shares for job stayers and job starters since February 2020. Figure B.8.1 shows that job starters in the pandemic do have higher partial WFH rates than job stayers. The partial WFH rates for both job starters and stayers remain overall relatively close to the rates in workers' February 2020 jobs. The generally higher partial WFH rates reflect that recent job starters are more likely to be younger and have children, both of which are associated with a greater propensity for part-time WFH. The increasing share of job starters since February 2020 induces some gradual increase in the partial WFH rate following the initial drop in partial WFH in May 2020, but overall contributes little to the rise in WFH over our sample period. Although not shown, we also find very similar patterns for the shares WFH Only and WFH Some Days if we considers a more narrow definition of job starters, by excluding individuals who were not employed in February 2020.

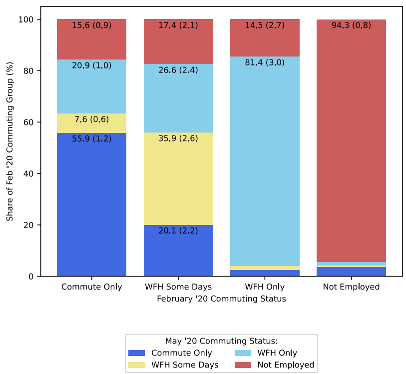
B.9 WFH Transitions Relative to February

Figure 5 in the main text displays the transition rates in WFH and employment status between February 2020 and the first RPS survey month (May 2020) and between February 2020 and June 2021. Figures B.9.1 and B.9.2 display the corresponding transition rates for all months in between. The results indicate that many workers who commuted only or WFH partially in February transitioned to WFH Only during the COVID-19 pandemic. The reverse was not true: conditional on remaining employed, the vast majority of workers who were WFH Only in February continued to do so during the pandemic. The results also indicate that employment losses during the pandemic did not differ strongly by pre-pandemic WFH status.

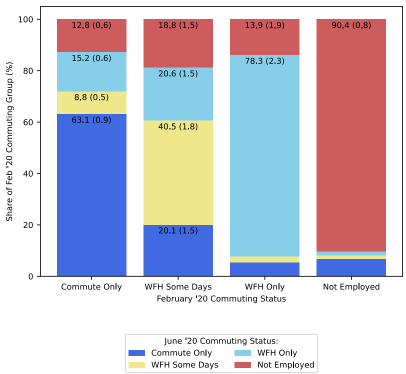
Figures B.9.3 and B.9.4 display figures analogous to Figures B.9.1 and B.9.2, except that now transitions are conditioned on current WFH/employment status rather than on the status from February. The results indicate that the vast majority of workers who commuted only during the COVID-19 pandemic already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

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

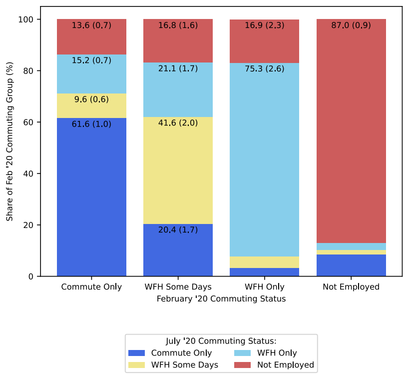
(a) May 2020



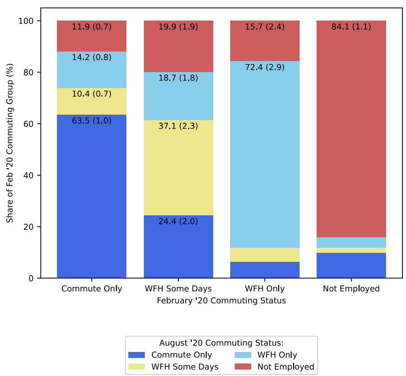
(b) June 2020



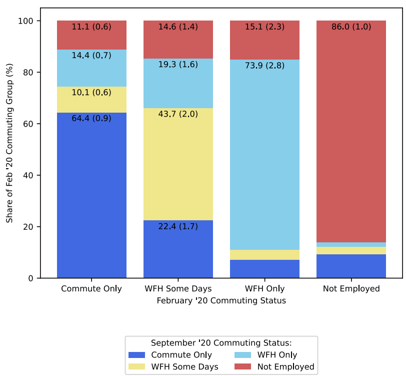
(c) July 2020



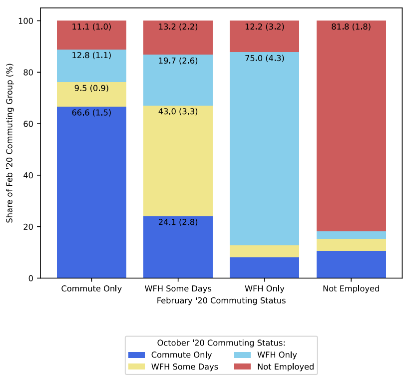
(d) August 2020



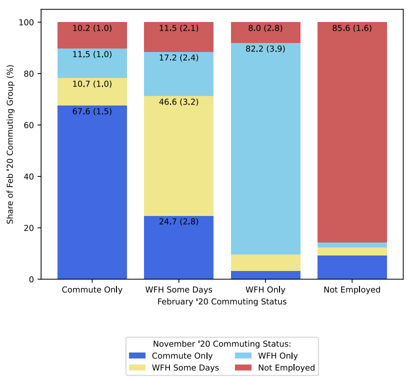
(e) September 2020



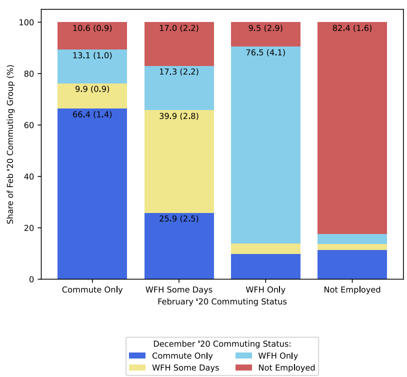
(f) October 2020



(g) November 2020

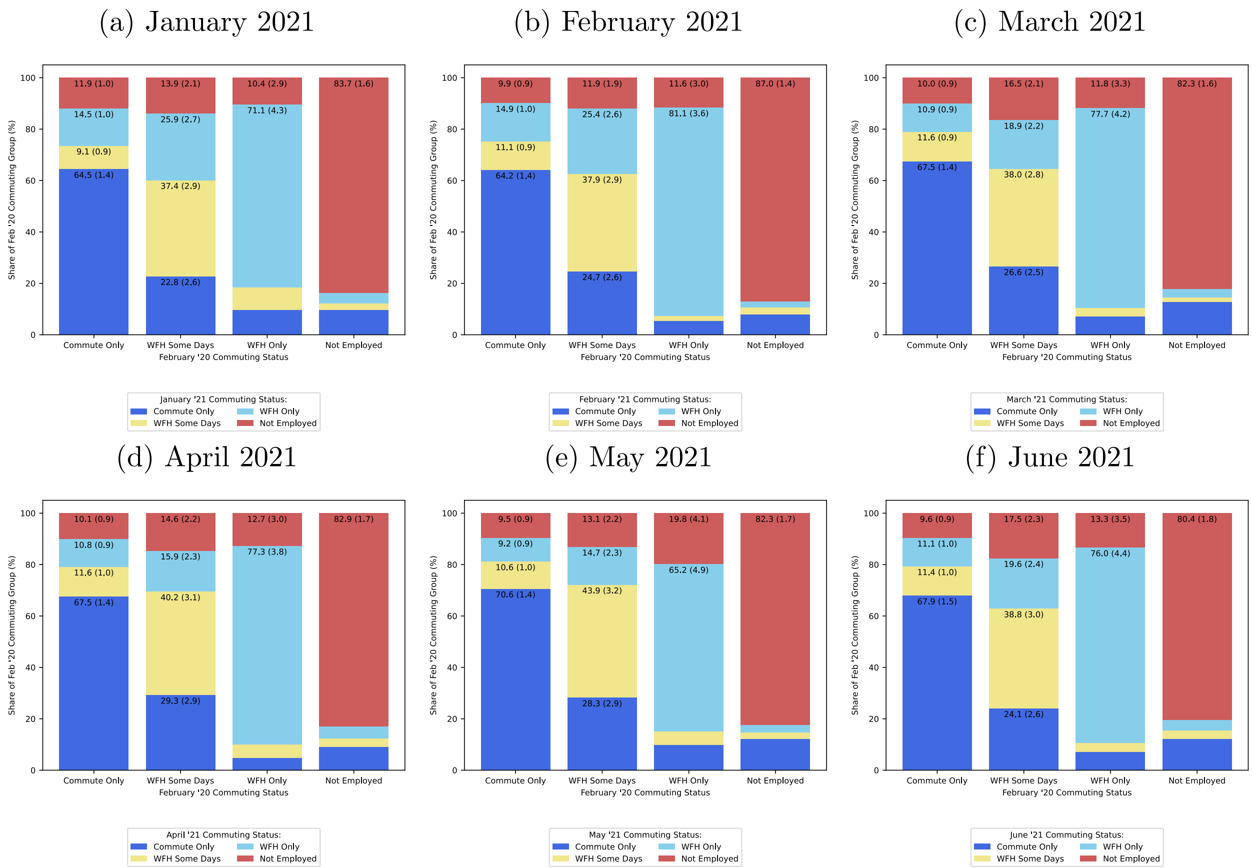


(h) December 2020



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 described in Appendix A.2. See Appendix A.1 for sample sizes by month.

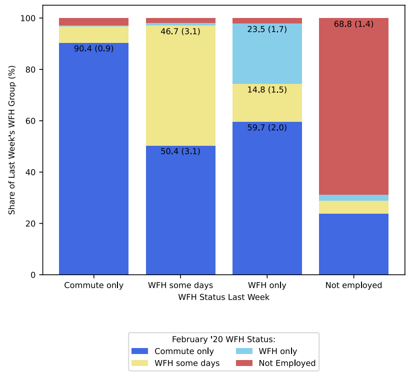
Figure B.9.2: WFH Transition Rates in 2021 By February 2020 WFH Status



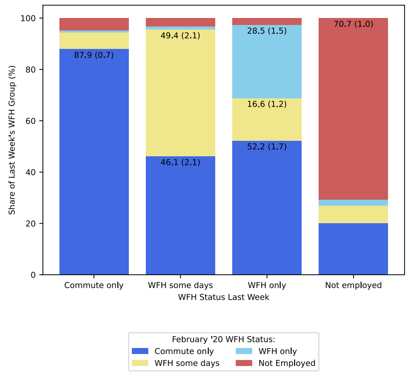
Notes: See Figure B.9.1.

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

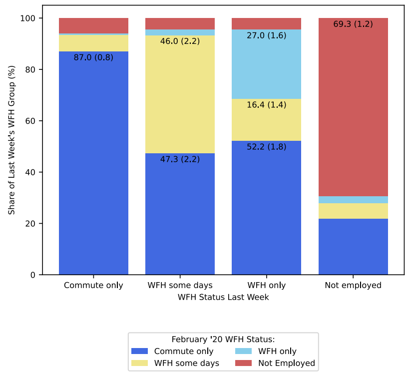
(a) May 2020



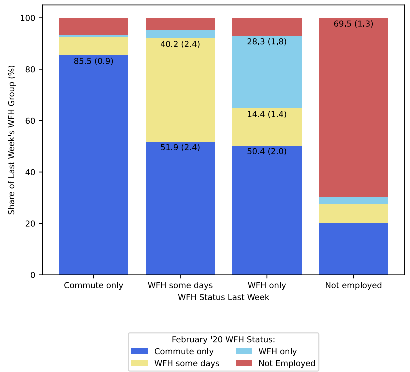
(b) June 2020



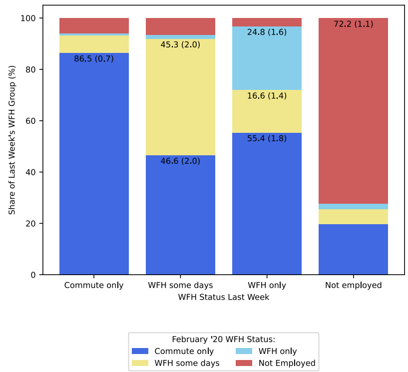
(c) July 2020



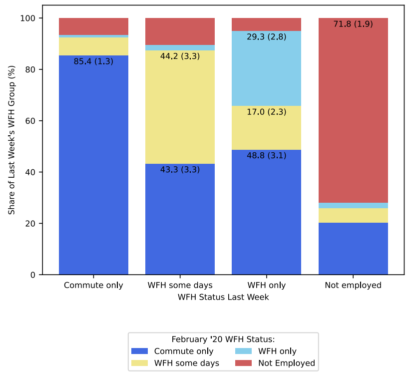
(d) August 2020



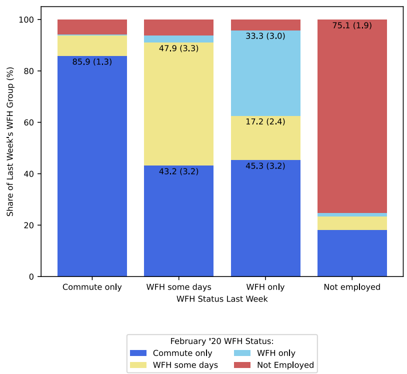
(e) September 2020



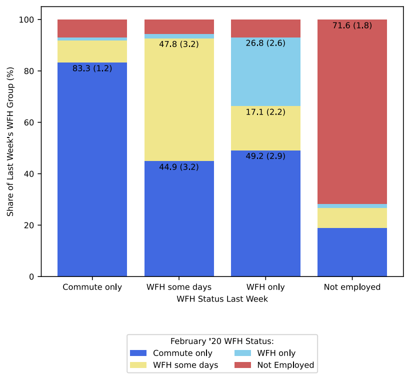
(f) October 2020



(g) November 2020



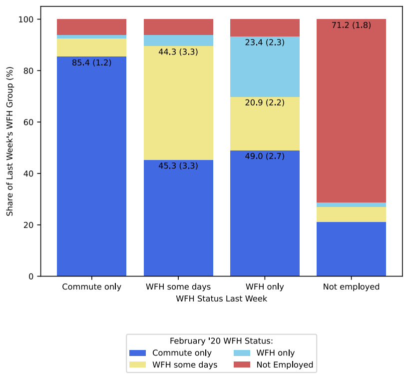
(h) December 2020



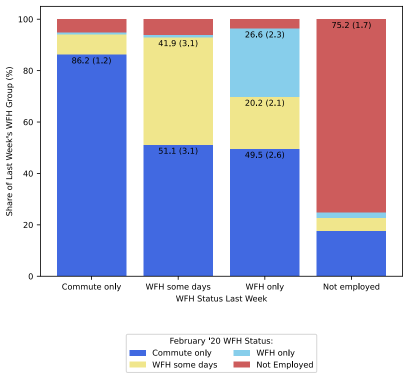
Source: Real-Time Population Survey, ages 18-64. The figure displays the composition of the population by WFH and employment status in February 2020 separately by workers' employment and WFH status in the current month. Each bar corresponds to a current WFH/employment state: Commute Only, WFH Some Days,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

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

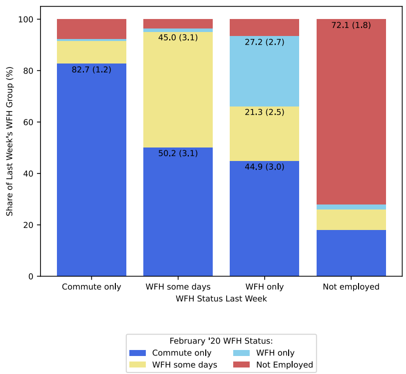
(a) January 2021



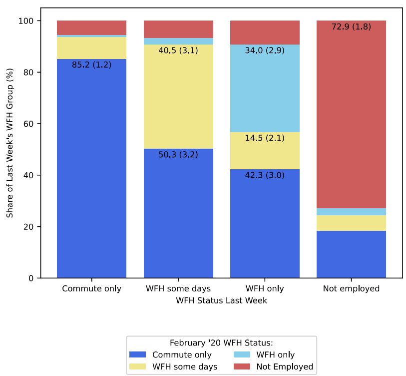
(b) February 2021



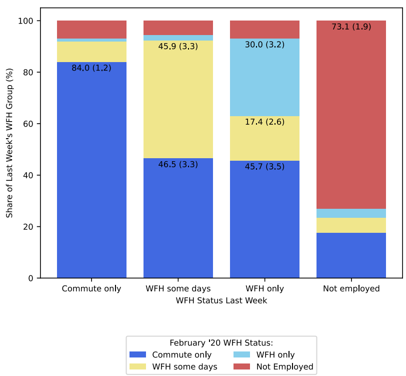
(c) March 2021



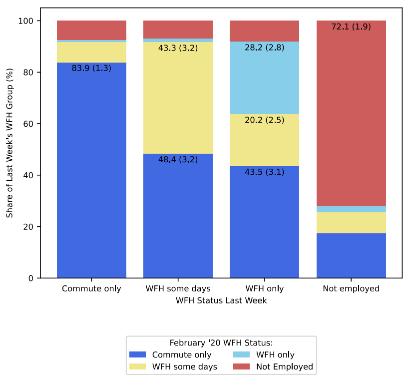
(d) April 2021



(e) May 2021



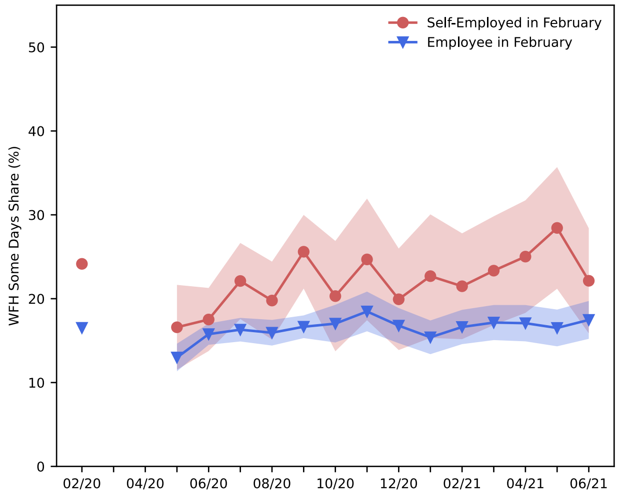
(f) June 2021



Notes: See Figure B.9.3.

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

FIGURE B.10.1: WFH Some Days

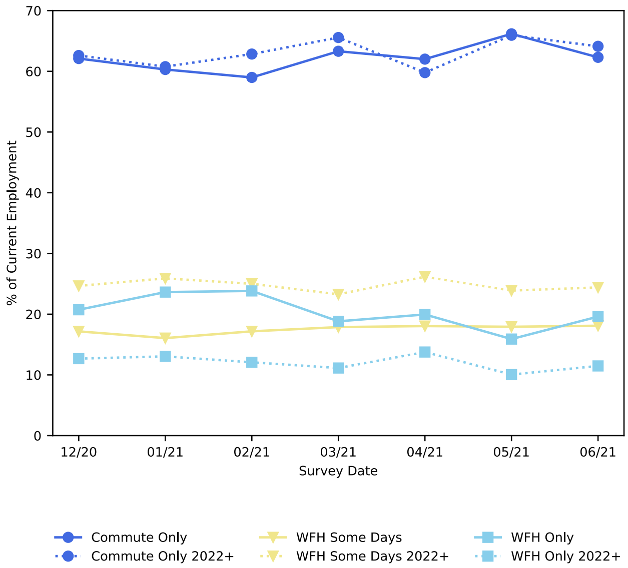


Source: Real-Time Population Survey, ages 18-64. The sample is individuals employed both in February 2020 and last week. The figure shows the share of WFH Only workers (left panel) and the share of partial-WFH workers (right panel) each month. The shaded region corresponds to two-standard-error bands.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

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

B.11 Future WFH Expectations Across Survey Months

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



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

From December 2020-onward, the RPS asked individuals about expectations of WFH for 2022 and beyond (see the phrasing in Section 3). Figure B.11.2 displays expected WFH rates by interview month (dashed lines). For reference, it also plots actual WFH rates by interview month (solid lines). We highlight four main takeaways from this figure. First, expected commuting patterns are fairly stable across interview months: the max of each series is within seven percentage points of the corresponding min, and there is no clear systematic change over time. Second, expected future rates of Commute Only are very close to current rates of Commute Only. Third, expected future rates of WFH Some Days are above current rates of WFH Some Days. Fourth, expected future rates of WFH Only are below current rates of WFH Only. Together, the latter three points suggest that few people who WFH expect to return to Commute Only in the future, but that some people who currently WFH Only expect to transition to a hybrid commuting regimen in the future.

C Appendix Materials For Model-Based Decomposition

C.1 Derivation of Equations in Section 2.1.2

Using $E = E_l + E_h$ and $E_h = e(w_h)$, profits can be written as $p(E)E - (1+\chi)(E - e(w_h)) - w_h e(w_h)$. The first order condition with respect to w_h is

$$(1+\chi)e'(w_h) - w_h e'(w_h) - e(w_h) \quad = \quad 0,$$

where $e'(w_h)$ denotes the first derivative of $e(w_h) = \gamma w_h^{\lambda}$. Since $w_h e'(w_h)/e(w_h) = \lambda$, this condition can be rewritten as

$$(1+\chi)/w_h\lambda - (1+\lambda) = 0 \quad \Rightarrow \quad w_h = \frac{\lambda}{1+\lambda}(1+\chi),$$

which corresponds to equation (2). Substituting into $E_h = e(w_h)$ yields equation (3). The first order condition with respect to E is

$$p'(E)E + p(E) - (1+\chi) \quad = \quad 0,$$

where $p'(E)$ denotes the first derivative of $p(E) = (\delta/E)^{1/\beta}/(1-1/\beta)$. Since $Ep'(E)/p(E) = -\frac{1}{\beta}$, this condition can be rewritten as

$$(1-1/\beta)p(E) - (1+\chi) = 0 \quad \Rightarrow \quad E = \delta(1+\chi)^{-\beta}.$$

Since $E_l = E - E_h$, this leads to equation (4). Since $E_h = \gamma(\lambda/(1+\lambda)(1+\chi))^{\lambda}$, the condition in equation (1) ensures that WFH employment does not exceed total employment $E = \delta(1+\chi)^{-\beta}$. Substituting the solutions above into the profit objective yields

Substituting the solutions above into the profit objective yields

$$\begin{aligned}
& p(E)E - (1+\chi)(E - E_h) - w_h E_h, \\
& = p(E)E - (1+\chi)E - (w_h - (1+\chi))E_h, \\
& = \frac{\delta(1+\chi)^{1-\beta}}{1-1/\beta} - (1+\chi)\delta(1+\chi)^{-\beta} + \frac{1+\chi}{1+\lambda}E_h, \\
& = \delta(1+\chi)^{1-\beta} + \frac{1+\chi}{1+\lambda}E_h.
\end{aligned}$$

Since firm profits are $\delta(1+\chi)^{1-\beta}$ without the WFH option, this means that $\frac{1+\chi}{1+\lambda}E_h$ is the increase in profits by providing WFH, as in equation (5).

C.2 Equilibrium and Identification When Firms Hire Only WFH Workers

If the parameters are such that

$$\delta(1+\chi)^{-\beta} < \gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda} < 1\ , \tag{C.2.1}$$

the supply of WFH labor exceeds the firms' overall labor demand at the marked-down commuter wage. In this case it is optimal for the firm to pay a wage that is below $(1+\chi)\lambda/(1+\lambda)$ and hire only WFH workers. This arises when the overall WFH productivity γ is relatively high, or when the cost of working on-site χ—and therefore the commuters' wage—is relatively high. When (C.2.1) holds, the optimal decisions of the firm are given by

$$w_h = \frac{\lambda}{1+\lambda}\delta^{1/\beta}e(w_h)^{-1/\beta} = \left(\frac{\lambda}{1+\lambda}\right)^{\frac{\beta}{\beta+\lambda}}(\delta/\gamma)^{\frac{1}{\beta+\lambda}}\ , \tag{C.2.2}$$

$$E_h = e(w_h) = \delta^{\frac{\lambda}{\beta+\lambda}}\gamma^{\frac{\beta}{\beta+\lambda}}\left(\frac{\lambda}{1+\lambda}\right)^{\frac{\beta\lambda}{\beta+\lambda}}\ , \tag{C.2.3}$$

$$E_l = 0. \tag{C.2.4}$$

Because the firm sets a wage that is lower than $(1+\chi)\lambda/(1+\lambda)$, it is the case that $E_h < \gamma\left(\frac{\lambda}{1+\lambda}(1+\chi)\right)^{\lambda}$. The second inequality in Assumption (C.2.1) therefore guarantees that $E_h < 1$, such that the firm does not hire all workers in its labor market.

The optimal wage (C.2.2) still equals the firm's marginal revenue after the monopsonistic mark-down. However, under condition (C.2.1) it is optimal to set the marginal revenue strictly lower than $1+\chi$ and employ only home workers. In this case, the overall level of employment is independent of the cost of on-site work χ, but depends on the overall WFH productivity. Unlike the case where firms also hire commuters, WFH employment now also depends on the level of demand δ.

By allowing WFH, the firm increases profits by

$$\left(\frac{1}{\beta-1}+\frac{1}{1+\lambda}\right)\delta\left(\left(\frac{\delta}{\gamma}\right)^{\frac{1}{\beta+\lambda}}\left(\frac{\lambda}{1+\lambda}\right)^{-\frac{\lambda}{\beta+\lambda}}\right)^{1-\beta} - \frac{\delta\,(1+\chi)^{1-\beta}}{\beta-1} > 0 \tag{C.2.5}$$

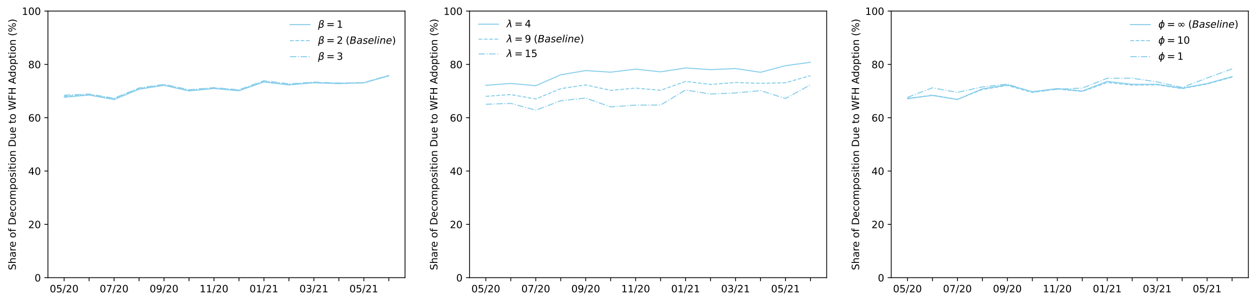
where the inequality is guaranteed by (C.2.1). The firm unambiguously prefers to provide the WFH option. The additional profits from providing the WFH option are increasing in the cost of on-site work χ and in the workers' WFH productivity γ.

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

C.3 Sensitivity of the Decomposition to Values of Demand and Supply Elasticities

FIGURE C.3.1: Sensitivity of the Decomposition to Values of Demand and Supply Elasticities

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



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

Panels (a) and (b) in Figure C.3.1 plots the increase in WFH attributed to WFH adoption for our baseline parameters of the demand elasticity β, the WFH labor supply elasticity λ along with a lower and higher value of each parameter, respectively. In our baseline model, the labor supply of commuters is infinitely elastic. Panel (c) in Figure C.3.1 plots the increase in WFH attributed to WFH adoption for lower values of this elasticy, which we parametrize by ϕ.

Figure C.3.1a shows that the choice of β has no impact on the role of adoption, because neither the identified values of χ and θ in (7) and (9), nor the level of WFH employment in the model depend on β. Figure C.3.1b shows the relatively modest impact of the choice of λ. Specifically, lower values of λ result in a larger share of the increases in WFH being attributed to adoption. The reason for the quantitatively relatively small effect is that there are two opposing effects on the contribution of the substitution effects in the decomposition. Imposing a higher λ means that more workers switch to WFH for a given increase in χ, but at the same time a higher λ also reduces the increase in the identified values for χ implied by the observed increase in the WFH Only share $\bar{E}_h/\bar{E}$, see equation (7).

In our baseline model, the labor supply of commuting workers is infinitely elastic, as we assume that all workers are equally productive when working on-site. Here, we relax this assumption and let workers also differ in productivity when working on-site such that the labor supply of commuters becomes finitely elastic. For simplicity, we assume that on-site productivity is proportional to $z^{\lambda/\phi}$ such that the marginal worker always remains a commuter in equilibrium and the resulting total supply of labor in equilibrium is given by $E = (w_l/(1+\chi))^{\phi}$, where ϕ is the labor supply elasticity. In our baseline model, $\phi = \infty$ such that $w_l = 1 + \chi$ in equilibrium. In the generalized model, the firm continues to set the WFH wage by marking down the commuter wage w_l by $\lambda/(1 + \lambda)$, while the commuter's wage w_l is a markdown $\phi/(1 + \phi)$ of marginal revenue, resulting in $w_l = \delta^{\frac{1}{\phi+\beta}}(1 + \chi)^{\frac{\phi}{\phi+\beta}} (\phi/(1 + \phi))^{\frac{\beta}{\phi+\beta}}$ in equilibrium. The key difference with the baseline model is that w_l becomes an increasing function of the level of demand, δ.

Figure C.3.1c shows the contributions of adoption effects to the WFH Only Share when assuming values of $\phi = 10$ or $\phi = 1$ in each industry. The calibration of the other parameters follows exactly the same strategy as in the baseline model, requiring χ, δ and θ to match employment, average wages and the WFH share in each industry. The elasticity ϕ is assumed constant during the pandemic in all industries. Figure C.3.1c shows that varying the value of ϕ has relatively small quantitative effects on the implied contribution of adoption effects to the WFH Only Share in our decomposition. Lower values of ϕ generally lead to larger implied increases in the costs of on-site work χ, which leads to larger increases in the WFH wage and more substitution towards WFH. However, when ϕ is finite, the WFH wage also becomes decreasing in the level of demand δ, and the drop in demand during the pandemic therefore lowers WFH wages and reduces the supply of WFH labor. The net effect of the different values of χ and δ on the wage of WFH workers is relatively muted. Instead, lowering ϕ primarily changes the relative importance of increases in costs of on-site work χ and reductions in demand δ in explaining total employment losses, with increases in χ becoming relatively more important in driving job loss when the elasticity ϕ is lower.

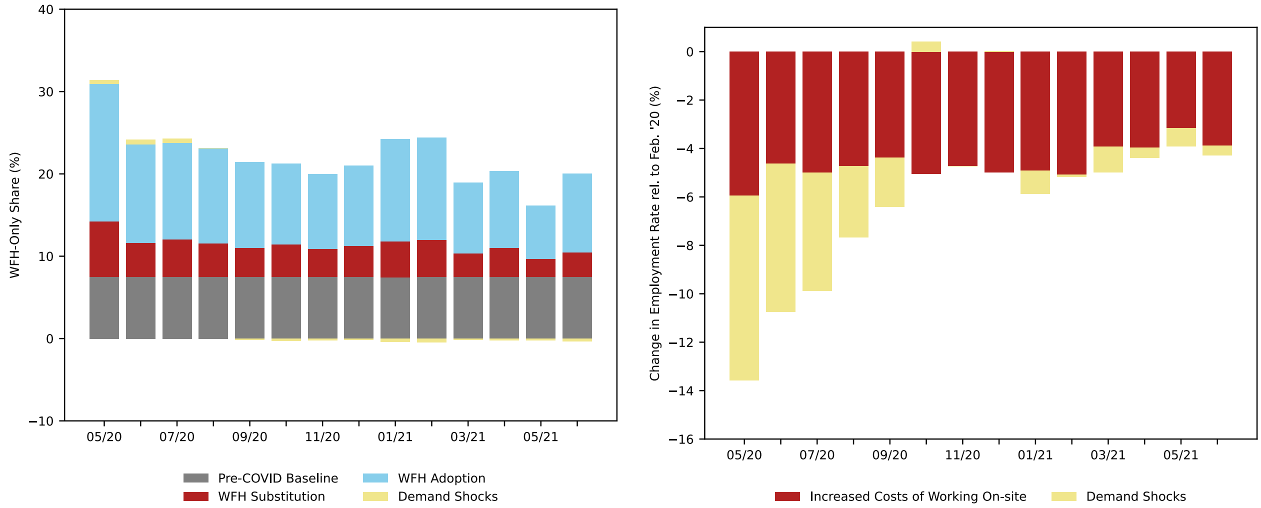
C.4 Log-Normal Distribution of WFH Productivity

Our baseline model assumes that WFH productivity is distributed according to a Pareto distribution. This assumption implies that the elasticity of WFH labor supply is constant, which permits straightforward analytical solutions to the model. In this section, we instead consider a log-normal distribution for WFH productivity, $log(z) \sim N(\mu, \sigma^2)$. In that case, the WFH labor supply function is $E_h = e(w_h) = \Phi\big(-(\ln(w_h) + \mu)/\sigma\big)$, where Φ is the cdf of $N(\mu, \sigma^2)$, and the elasticity of WFH labor supply is $\lambda(w_h) = \varphi\big(-(\ln(w_h) + \mu)/\sigma\big)/\big(\sigma e(w_h)\big)$, which is decreasing in w_h. Analogous to our baseline model, we set industry-specific values of μ and σ to match (1) the observed WFH Only Share before the pandemic, and (2) a wage for the WFH worker that is a fraction $\lambda(w_h)/(1+\lambda(w_h))$=0.9 of the commuter wage before the pandemic in every industry. As in the baseline identification strategy, we assume that the productivity distribution remains constant during the pandemic, i.e. the industry-specific values of μ and σ do not change over

FIGURE C.4.1: Model Decompositions with a Log-Normal Distribution of WFH Productivity

(a) WFH Only Share

(b) Employment



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

time. The remaining parameters are calibrated as in the baseline quantitative analysis, but solved numerically rather analytically.

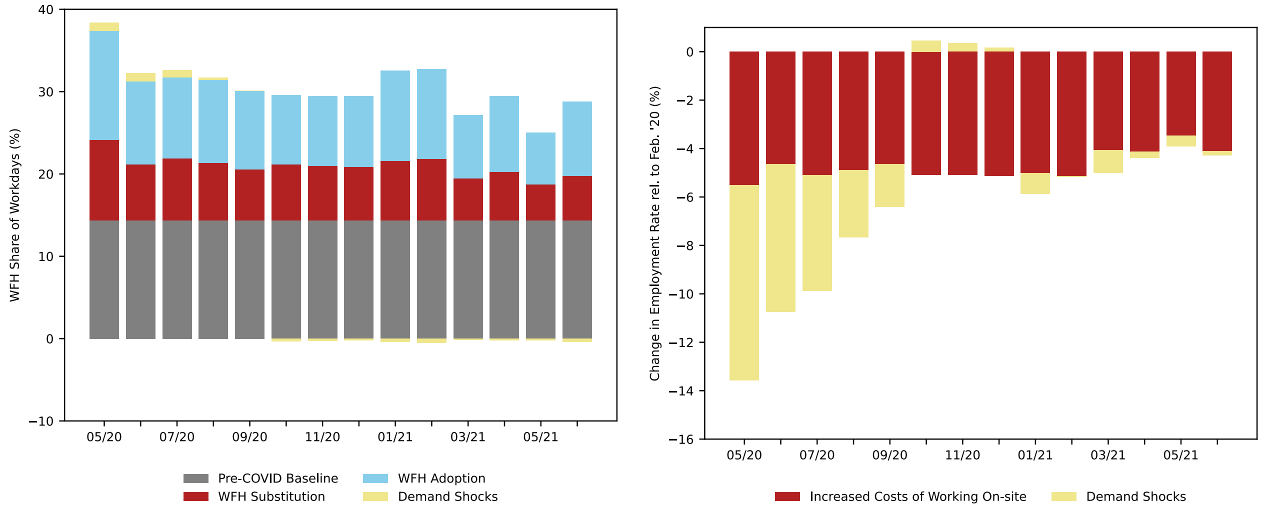
Figures C.4.1a and C.4.1b show the results of the decompositions of the aggregate WFH Only share and employment based on a log-normal distribution for workers' WFH productivity. These decompositions can be compared to those based on the Pareto distribution in Figures 9a and 9b of the main text. The main finding is that the quantitative results are little changed by switching to a log-normal distribution. Figure C.4.1a shows that adoption effects remain the dominant reason for the increase in the WFH Only share. In May 2020, WFH adoption effects account for 16.6 percentage points of the 23.9 percentage points increase in the aggregate WFH Only share, compared with 16.2 percentage points in our baseline analysis. In June 2021, adoption effects account for 9.5 percentage points of the total 12.1 percentage points increase in the WFH Only share, compared with 9.2 percentage points in the baseline analysis. The employment decomposition results in Figure C.4.1b are also quantitatively close to the baseline. Finally, the predicted long run level of the WFH Only share based on the model with a log-normal distribution is 14.9 percent, very similar to the 14.6 percent predicted in the baseline model.

C.5 Model-Based Decompositions Using the WFH Share of Workdays

FIGURE C.5.1: Model-Based Decompositions Using WFH Share of Workdays

(a) WFH Share of Workdays

(b) Employment



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

Figure C.5.1 documents the results of our decomposition exercise when the model is identified using the share of days WFH rather than the WFH Only share, allowing also for an intensive margin of WFH. In this case, our model setup can be interpreted such that every worker draws different WFH productivities z for each work day, inducing some workers to commute every day, some to WFH on some days and to commute on others, and some to WFH Only. The identification follows the same steps as the baseline, except that we replace $\bar{E}_h$ with the share of WFH workdays in each industry multiplied by total industry employment. The only other difference is in the calibration of the adoption rates in the pre-pandemic period: we add the fraction of daily commuters that cite personal preference as the main reason for commuting to the fraction of workers that are either WFH Only of WFH Some Days before the pandemic.

Figure C.5.1a shows that incorporating partial WFH leads to a contribution of adoption effects of 55.4 percent to the overall increase in the share of workdays worked from home in May 2020 as opposed to 68.4 percent in our baseline analysis. By June 2021, the adoption effects contribute 86.2 percent to the increase in the share of WFH workdays, which is almost as much as the contribution of adoption to the WFH Only share in Figure 9a. Incorporating part-time WFH, therefore, does not substantially change the main result that the persistence in the rise in WFH is driven by adoption effects.

Figure C.5.1b shows that incorporating partial WFH only minimally increases the share of employment losses explained by the increased cost of on-site work vis-a-vis our baseline model (compare Figure 9b).