COVID-19 and Remote Work: An Early Look at US Data*

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Abstract

We report the results of a survey on remote work for nationally-representative sample of the US population during the COVID-19 pandemic. The survey ran in three waves in April 2020, May 2020, and July 2020 covering a total of 75,000 respondents. Of those employed pre-COVID-19, we find that about half are now working from home, including 33.0% who report they had previously been commuting and recently switched to working from home. In addition, 10.1% report being laid-off or furloughed since the start of COVID-19. We find that the share of people switching to remote work can be predicted by the incidence of COVID-19 and that younger people were more likely to switch to remote work. Furthermore, states with a higher share of employment in information work including management, professional and related occupations were more likely to shift toward working from home and had fewer people continuing to commute. We find no substantial change in results between the first two waves, suggesting that most changes to remote work manifested by early April. However, by the third wave in July, employees started to return to workplaces, with 22 percent of those who had initially switched to remote work having switched back to commuting.

1 Introduction

The on-going COVID-19 pandemic is rapidly transforming how, and even whether, people work. Large numbers of people have remained in their homes to avoid the disease or due to shelter-in-place orders. Many businesses are closed and many people are not working remotely. There have been enormous and unprecedented increases in workers filing unemployment insurance claims (Goldsmith-Pinkham and Sojourner, 2020). These changes in work and employment have immediate implications for the economy, and may lead to permanent shifts that last beyond the pandemic.

*MIT's COUHES ruled this project exempt (project number E-2075). Code & Data: https://github.com/johnjosephhorton/remote_work/. Thanks to Sam Lord for helpful comments.

To get a real-time sense of how firms and workers are responding, we conducted three waves of surveys using Google Consumer Surveys (GCS), one each in April, May, and July 2020. [1] In the April version of the survey we asked a single question: ""Have you started to work from home in the last 4 weeks?" with the following response options:

1. "I continue to commute to work" [2]

2. "I have recently been furloughed or laid-off" [3]

3. "Used to commute, now work from home" [4]

4. "Used to work from home and still do" [5]

5. "Used to work from home, but now I commute" [6]

6. "None of the above / Not working for pay"

In the May version, we updated the question to: "Have you started to work from home in the last 2 months?". In the July version, we updated the question to: "Have you started to work from home since the start of COVID-19 (around February 2020)?"

We conducted the first wave of our survey from April 1, 2020 until April 6, 2020, for a total of 25,000 responses. We launched a second wave on May 2, 2020, collecting 25,001 responses until May 8, 2020. Finally, in our third wave, we collected a total of 16,278 responses from June 30 till August 8. The final wave took longer than the other ones because we ran a smaller national survey, which necessitated a parallel set of targeted state-level surveys in order to achieve sufficient statistical power for the smaller states. **All in all, we collected 66,279 responses and we find across the first two waves that over one third of workers have responded to the pandemic by shifting to remote work, while another 10% have been laid-off or furloughed.**

There is a great deal of variation across states in the share of people switching to remote work as well the share of people who continue to commute. These can each be predicted by incidence of COVID-19 as well as the industry composition of the state prior to the onset of the crisis. We also find that younger people were more likely than older people to switch from commuting to remote work. Responses did not meaningfully differ across the first two survey waves, suggesting that most changes to remote work had already manifested by early April. However, in the final wave, we start observing a move away from remote work and back to commuting as states loosen their "stay-at-home" policies.

[1] GCS is a relatively low-cost tool for rapidly collecting responses to simple questions Stephens-Davidowitz and Varian (2014), and response representativeness is often comparable to similar alternatives (Santoso et al., 2016; Brynjolfsson et al., 2019).

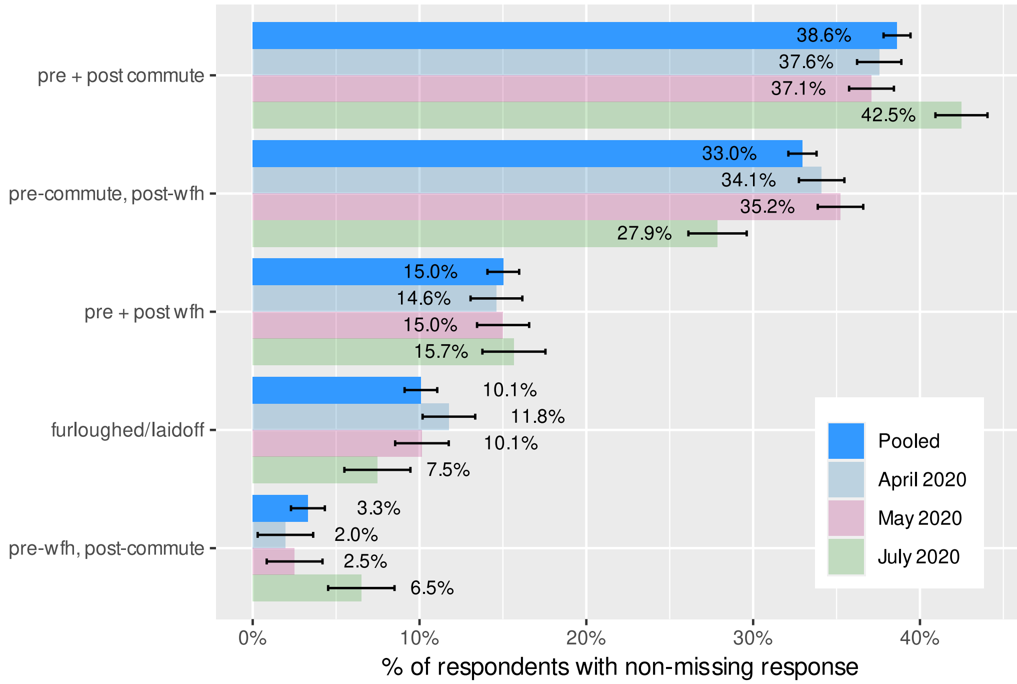
[2] shortened versions are used for plots and style: e.g. "I continue to commute to work" might be labelled as "pre + post commute"

[3] shortened version: "furloughed/laidoff"

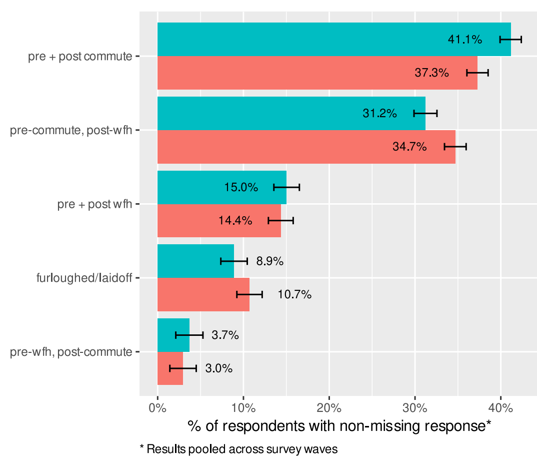
[4] shortened version: "pre-commute, post-wfh"

[5] shorthand version: "pre + post wfh"

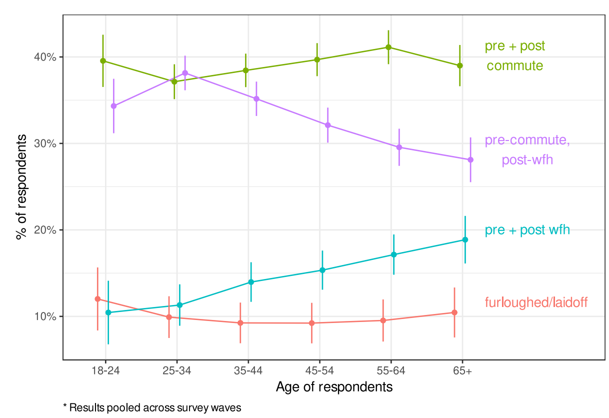
[6] shortened version: "pre-wfh, post-commute"



(a) Pooled Overall Results



(b) Pooled Results by Gender



(c) Pooled Results by Age

Figure 1

2 Results

We first report results pooled across all three survey waves (April, May, and Juy 2020) with breakdowns where indicated. We will further explore across-time differences in Section 2.5 below. Of the respondents, 37,555 reported something other than "None of the above..." This gives an implied employment rate of 57%, which is slightly lower than the BLS estimate of about 60%.[7] For the rest our analysis, we restrict our sample to those reporting being employed prior to the onset of COVID-19.

[7] `https://fred.stlouisfed.org/series/EMRATIO`

The distribution of answers pooled over all respondents is shown in Figure 1a. We can see that the most common response from workers was that they continue to commute, at 38.6% (95% CI is [37.8, 39.4]). But the next most common was that they have switched from commuting to working from home.

The fraction of workers who switched to working from home is about 33.0%. In addition, 15.0% reporting they were already working from home pre-COVID-19. This suggests about half the workforce is now working from home, significantly more than the Dingel and Neiman (2020) estimate of 37% of people working at home. [8]

Since April the BLS has released four monthly unemployment reports with the following estimates: 14.7% in April, 13.3% in May, 11.1% in June, and 10.2% in July. Our survey numbers suggest 11.8% , 10.1%, and 7.5% for April, May, and July, respectively. All of these estimates are lower than the BLS figures and we believe that the The difference may reflect the way respondents interpreted the phrase "furloughed or laid-off" or "None of the above / Not working for pay" in our survey, while the BLS reports a person as being unemployed if they have been out of a job for a month and searching for employment. [9]

2.1 By gender and age

In Figure 1b we report responses by inferred gender. Fractions are computed separately for males and females and across all survey waves. We detect statistically significant differences for 2 out of 5 responses (at a 95% confidence interval) — "I continue to commute to work" and "Used to commute, now work from home". In particular, within our sample, it appears that men were modestly more likely to continue to commute to work, and women were more likely to report switching from commuter to work from home status. Men were also slightly less likely to have been recently furloughed or laid-off and slightly more likely to report "Used to work from home and still do", but the differences in gender composition in these two cases are not statistically significant.

In Figure 1c we report responses by inferred age. A similar proportion of workers continue to commute to work across all age groups, as is also the case for the recently furloughed or laid-off worker contingent. On the other hand, the proportion of respondents that has recently converted from commuting to work to remote work steadily declines from the 25-34 age group to the 65 and older category. The differences between the 25-34 age group and the 65 and older group are

[8] Our estimates are broadly consistent with the broader literature, which includes a relatively wide range of estimates. Krantz-Kentkrantz (2019) uses 2013-2017 American Time Use Survey (ATUS) data to show 20.5% of workers working from home in some way on an average day. However, our question implies working from home all the time. The remote worker fraction in the ATUS is 11.4%. Our 14.2% estimate is also broadly consistent with the "Freelancing in America Survey" that reported 16.8% of workers report doing most or all of their work remotely, though this includes people working from co-working spaces, coffee shops, homes, etc (Ozimek, 2020). At the lowest end, the 2019 Census reports 5.3% of workers as "working from home." The wide range in answers suggests respondent uncertainty about the precise meaning of questions. Nevertheless, our results lie well within the existing estimates.

[9] `https://www.bls.gov/news.release/pdf/empsit.pdf`

statistically significant, and, the same can be said when comparing the 25-34 cohort to 45-54 as well as 55-64. As Figure 1c shows, younger workers (above age 25) are more likely to have switched from commuting to working from home.

Survey respondents in older age groups also reported *remaining* working remotely with greater propensities. These results are directionally consistent with the 2019 Census, though our estimates are larger. The differences may arise from a difference in the question asked. The Census asks about how workers get to work. The 2019 Upwork "Freelancing in America" study found younger workers were modestly *more* likely to work mostly or entirely from home Upwork (2019). It is possible that our survey is somewhere in between, grouping people who do some work at home with those who are fully committed remote labor. We will investigate this further in future work.

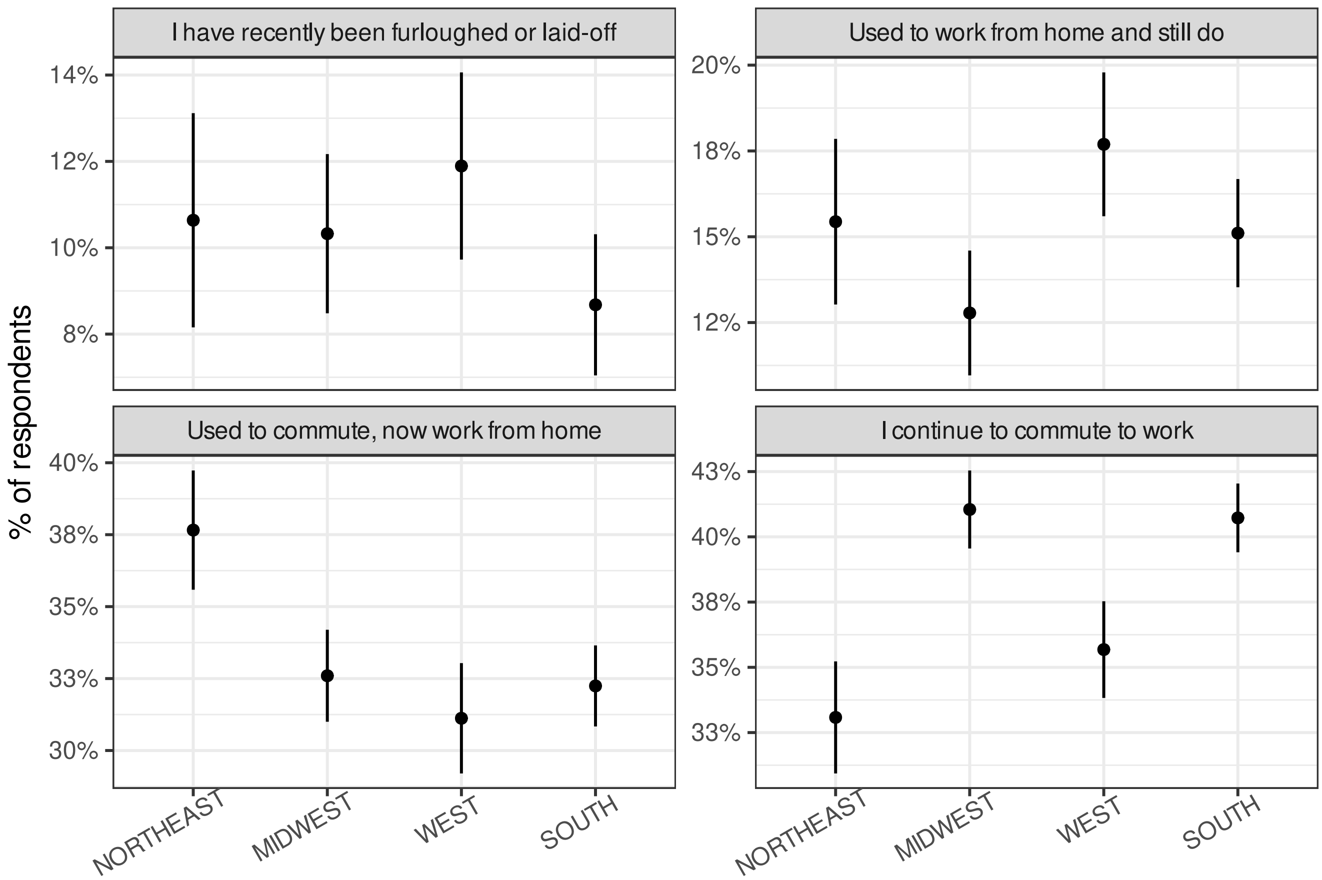
2.2 Geographic variation

COVID-19 has affected various parts of the US differently, and that heterogeneity has also changed across time. For example, the main epicenter back in April and May was located in the Northeast but that has shifted during the summer as Florida, Texas, and California become the new hotpots while the Northeast made significant progress in "flattening the curve" and saw its case numbers decline.

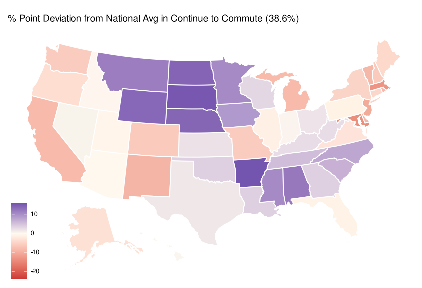
In Figure 2a, we plot the fraction of respondents choosing each answer by region, pooled across all surveys. GCS captures a respondent's city and state, which are then mapped to the regions "Northeast", "Midwest", "West", and "South."

In the bottom right facet, we can see that the South and the Midwest have the highest fractions still commuting to work and the Northeast has the lowest. In contrast, we can see in the bottom left facet, that the Northeast has the highest fraction of respondents switching to working from home. The fraction of respondents answering "used to work from home and still do" can be interpreted as a rough estimate of much remote work existed before the start of the pandemic, assuming that the effect of the pandemic on furloughs within the pre-existing remote working population is relatively uniform across the country. Under this interpretation we note how the West Coast had the largest remote working fraction to begin with while the Midwest had the lowest rates. Combining both "used to commute, now work from home" and "used to work from home and still do" can produce a rough estimate of the total fraction of employed respondents working from home and the Northeast has the highest, with over half the working respondents working from home.

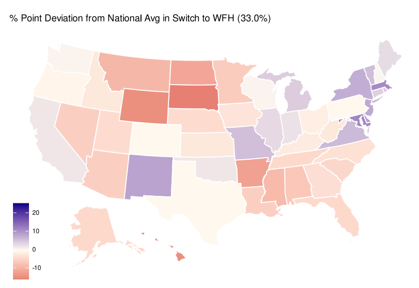
For a finer-grained look, we also map the responses across states. Across the three maps we take the national average for the response of interest and calculate the state-level deviation from that average. Blue indicates a positive percentage point deviation from the national average while red represents a negative percentage point deviation. White is used to represent 0 percentage point deviation and national averages are indicated in the figure captions. As we saw in Figure 2a, the highest fraction switching to working from home are in the Northeast. The map also visually



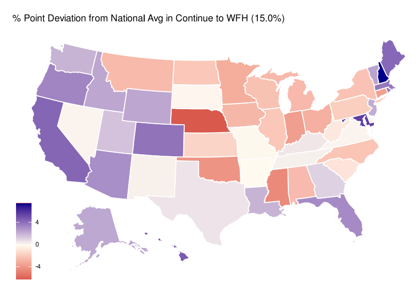
(a) Pooled Results by Region



(b) Continue commuting
Avg: ≈ 39 %



(c) Switch to WFH
Avg: ≈ 33 %

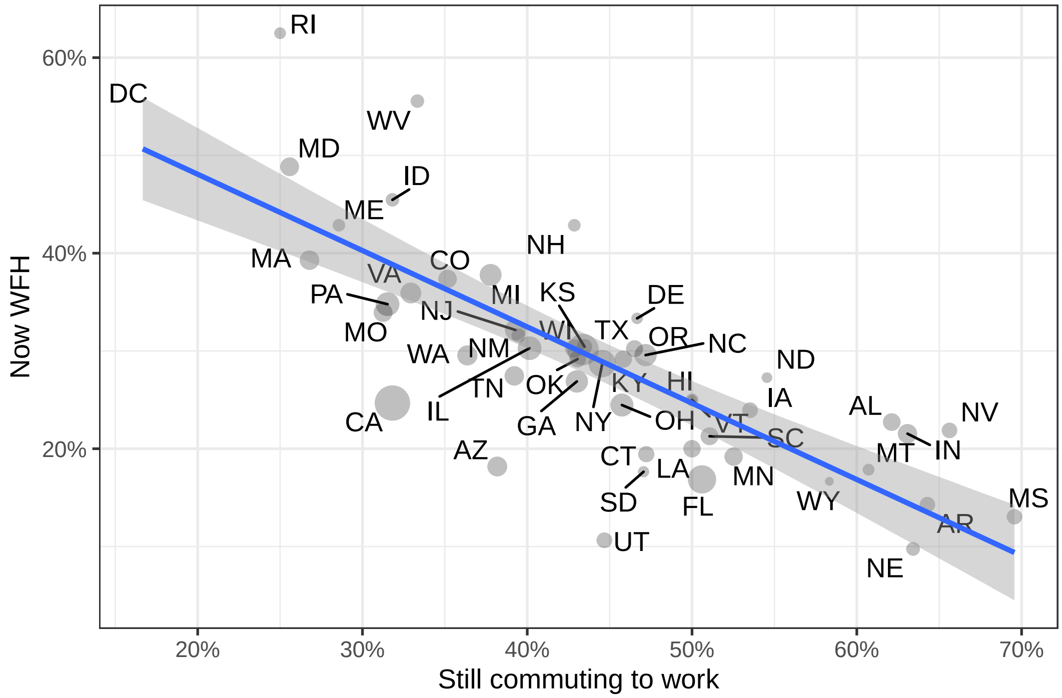


(d) Continue WFH
Avg: ≈ 15 %

Figure 2: All results are pooled across survey waves

confirms how most of the South and parts of the Midwest show substantially less switching to remote work. One stark takeaway from these maps is how the "continuing to commute" map (Figure 2b) is an almost mirror image of the "switching from commute to work from home" map (Figure 2c).

Figure 3: Still commuting versus work from home fractions by US State



2.3 Predictors of across-state variation

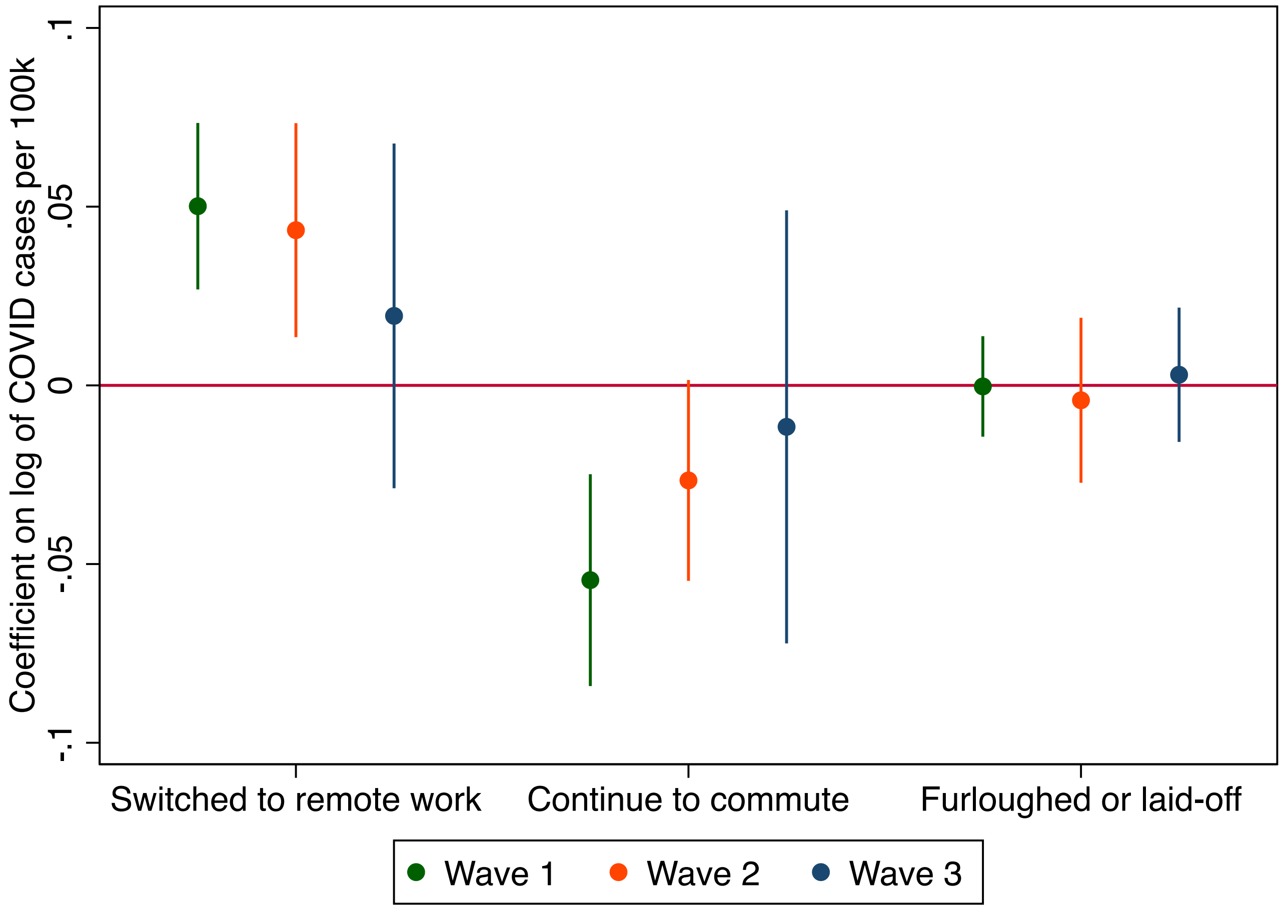
In Figure 3 we plot the fraction of respondents working from home versus the fraction still commuting by US state. There is a clear negative relationship, suggesting a fraction of current commuters could potentially transition to work-from-home status. Each 10 percentage point increase in the fraction still commuting is associated with about a 6 percentage point decline in the fraction of workers now working from home.

2.3.1 COVID-19 infection rates

Figure 4 documents how heterogeneity in COVID-19 infection rates (measured as the log of cases per 100,000 individuals[10]) affects switching to remote work or continuing to work from home. We report results from the April (wave 1), May (wave 2), as well as July (wave 3) waves of the survey. COVID incidence is measured at the time of the survey. The first panel shows that a doubling of COVID-19 cases per 100k individuals is associated with a 5% rise in the fraction of workers who switch to working from home in wave 1 and a 4.3% rise in wave 2. This effect is more muted by the July wave, suggesting either a move back to the pre-COVID status quo or declining state-wise variation in COVID incidence. We discuss evidence in favor of the former interpretation below. However, the latter is also true: while mean log cases per 100k population double between waves 2 and 3, the variance falls by 16%.

[10]Data accessed on July 6, 2020 from The New York Times: https://github.com/nytimes/covid-19-data

Figure 4: Predicting remote work over time by COVID-19 incidence

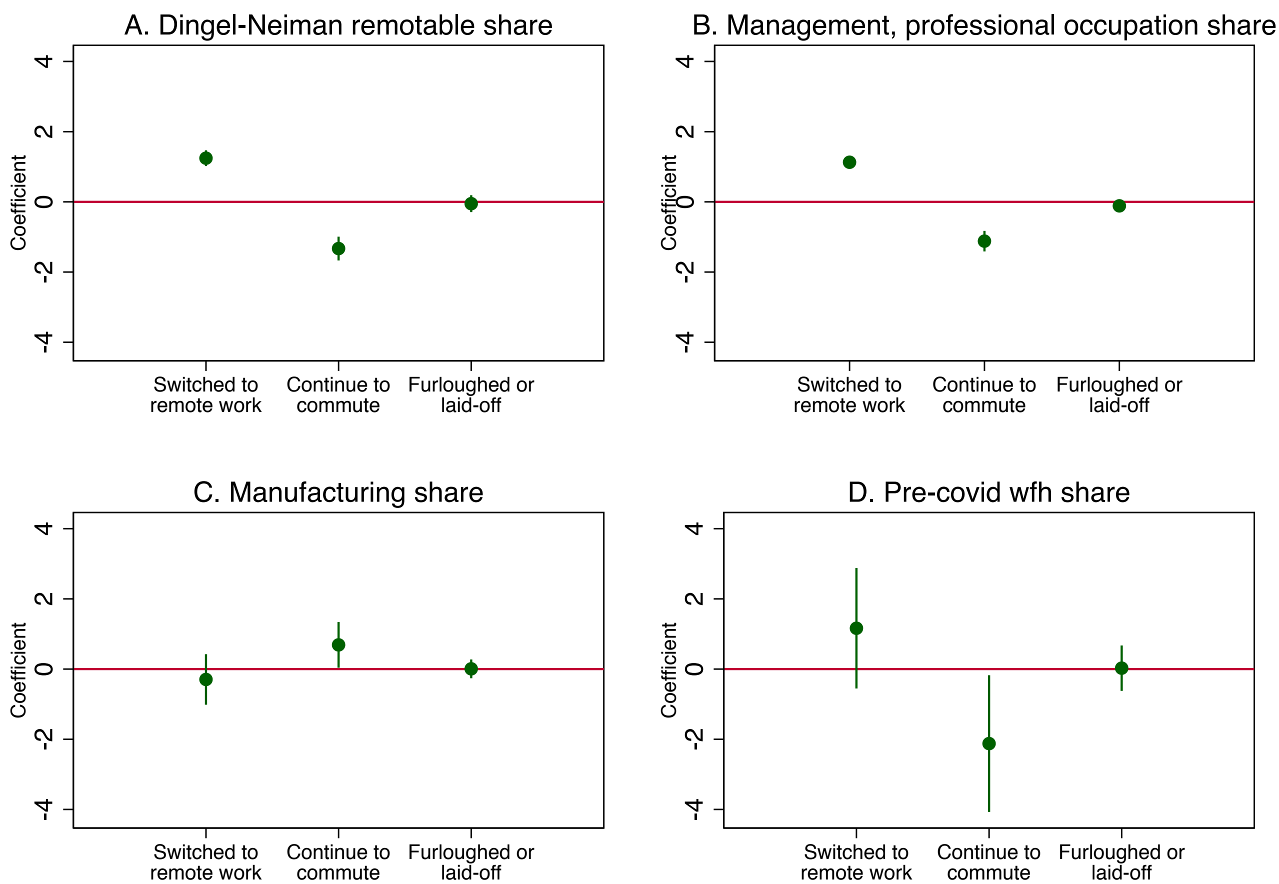


The second panel of Figure 4 reports results for continuing to commute. Doubling the COVID-19 cases per 100k individuals predicts a 5.4% fall in the fraction of those continuing to commute in wave 1, and a 2.7% fall in wave 2. Just as with switching to remote work, this result is muted by wave 3 (July).

Surprisingly, as shown in the third panel, we do not find a strong or statistically significant relationship between our measure of incidence and survey reports of being furloughed or laid-off.

Waves 1 and 2 show substantial consistency, supporting the conclusion that most short-term changes to remote work occurred by April. We would expect these relationships if higher spread is associated with higher responsiveness of government or individuals. By July, however, employees seem to have switched back towards the pre-COVID status quo, being more likely to continue to commute and less likely to be still working remotely relative to pre-COVID times. These associations are not to be interpreted as causal and future work will explore the causal effect of the pandemic on switches into remote work.

Figure 5: Predicting remote work by pre-COVID distribution of occupations



2.3.2 Pre-COVID distribution of economic activity

To explore how the pre-COVID distribution of occupations across states predicts shifts into remote work, we regress our survey outcomes on three different measures of the ease of making an occupation remote. The first is the state's pre-COVID share of "management, professional and related" (MPR) occupations. These include predominantly information work and other white collar jobs in management, consulting and related fields. The Bureau of Labor Statistics classifies them as having high potential for working from home (Krantz-Kentkrantz (2019)). The second is the state's share of jobs classified by Dingel-Neiman as being feasible to do from home Dingel and Neiman (2020). This classification is based on O*NET surveys that ask workers to describe various aspects of their jobs such as how much time they spent walking, whether they send emails, and whether they work outdoors. Dingel and Neiman (2020) provides a detailed description of how these questions are translated into a classification of whether the job can be done from home. The third measure we use is the pre-COVID share of manufacturing jobs in a state; one would expect these to be less easily done from home. Finally, we also regress survey responses on the share of jobs that were already remote in a state.

We pool data from the three waves for our main analysis and include time fixed-effects. [11].

Figure 5 shows that not all occupations have been affected equally. In particular, states with a larger share of employment in information work as well as other jobs that can more easily be done at home were more likely to have large shifts into remote work. Panel A shows that states with a larger share of workers in MPR occupations (Krantz-Kentkrantz (2019)) were more likely to have large shifts into remote work. A 1% rise in the share of workers in MPR occupations is associated with a 1.1% rise in those reporting now working from home and 1.1% decline in those reporting that they continue to commute to work.

Panel B of Figure 5 shows that states with a larger share of employment that could be feasibly done from home per the Dingel-Neiman measure are more likely to experience switches into remote work (a 1.24% rise in the latter for a 1% rise in the former). They are also less likely to see workers continuing to commute to work (a 1.3% fall in the latter for a 1% rise in the DN feasibly remote share).

Panel C shows prior share in manufacturing employment as not being a statistically significant predictor of switches into remote work. However, as expected, the sign of the coefficient is negative. Pre-COVID-19 manufacturing share positively predicts continuing to commute in a statistically significant way: a 1% increase the pre-COVID-19 share of employment in manufacturing is associated with a 0.69% increase in continuing to commute to work.

In the final panel (D) we look at how the pre-COVID share of workers working from home (measured in the 2017 ACS) influences survey responses. Interestingly, pre-COVID work from home share is not strongly predictive of COVID-induced shares of people switching into work from home,

[11] Appendix tables 3, 2, 4, and 5 show that the observed patterns remain consistent across survey waves.

although the sign is positive. It is, as would be mechanically expected, less likely to be associated with workers reporting that they continue to commute to work (with a 1% rise in pre-COVID work from home predicting a 2.1% fall in those continuing to commute).

None of the measures of the ability to switch into remote work is a particularly strong predictor of surveyed individuals reporting being furloughed or laid-off in a state. Appendix table 1 reports numerical values of all coefficients.

Taken together, these results suggest that places with greater capacity for increasing the amount of working from home are not necessarily places where workers are already working from home. Instead, the occupation mix is more predictive than prior remote work of the "remote-ability" of the marginal job that is not yet remote. Of course, these estimates are especially relevant for short-run adjustments that workers and their employers can make. The longer term capacity to rely on remote work and associated hysteresis in employment patterns will take months to years to make accurate measurement possible.

2.4 Impact on unemployment

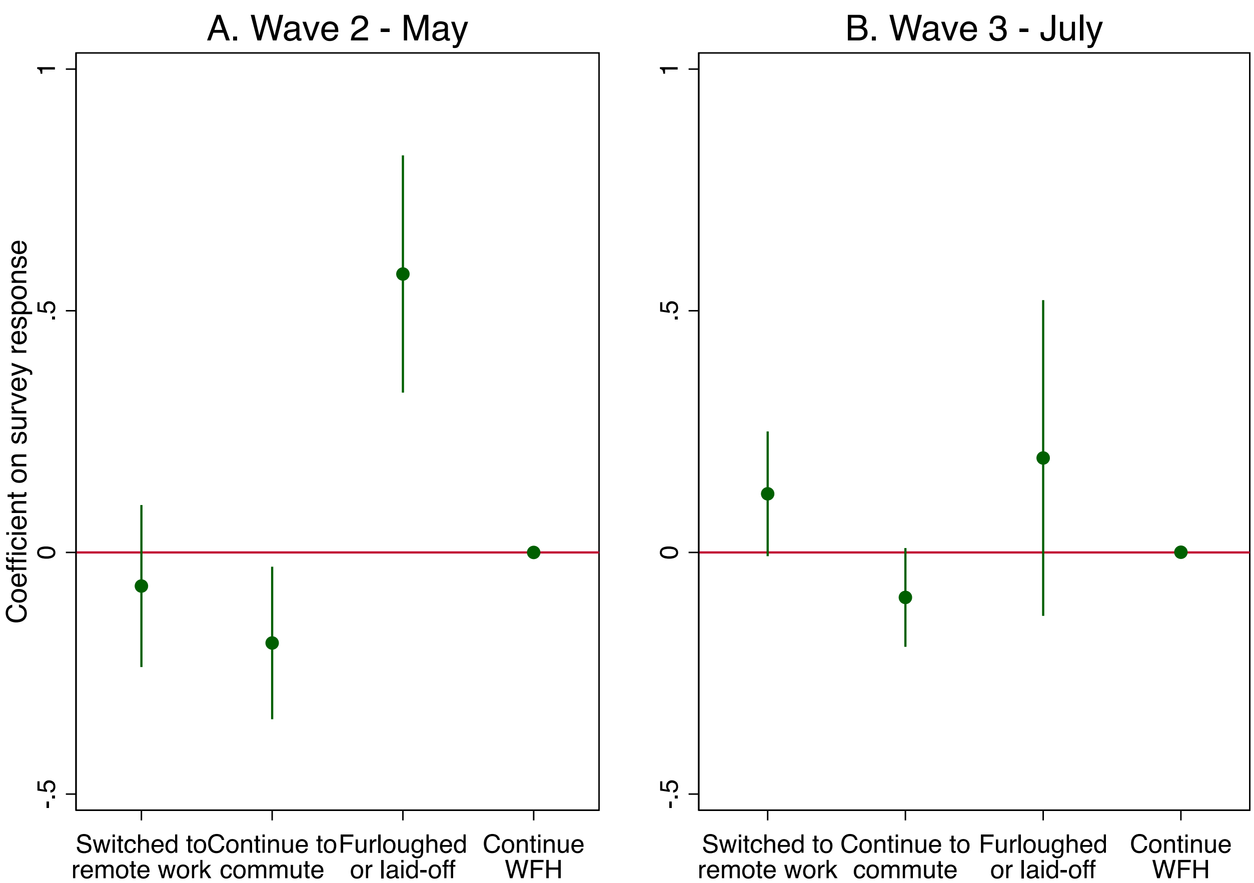
A natural question is how these various measures vary with unemployment and UI claims by state. In Figure 6, we combine our data with that on the April and June unemployment rate from the Bureau of Labor Statistics [12]. BLS classifies an individual as unemployed if they were out of work and searching for at least four weeks. Our goal is to gauge the extent to which our survey measures predict changes in unemployment between February and the survey date. We perform this analysis for waves 2 (May) and 3 (July), since the BLS definition of 4 weeks of searching would first pick up those who become unemployed at the onset of COVID (March) as unemployed only in the April survey. We control for levels of the unemployment rate in February.

Panel A reports results for Wave 2 and Panel B for wave 3. As of May switching into remote work is not predictive of the unemployment rate in a statistically significant manner, albeit the coefficient is positive. By July this coefficient becomes statistically significant: a 1% rise in those switching into remote work is associated with a 0.12% increase in the unemployment rate. Continuing to commute is negatively associated with the unemployment rate during both waves: a 1% rise in continuing to commute is associated with a 0.18% fall in the unemployment rate in May and a 0.9% fall in July. As one might expect, survey reports of being unemployed are predictive of the actual unemployment rate in a state. Continuing to work from home is uncorrelated with the state's unemployment rate.

At face value, the positive association between switches into remote work and unemployment rate seems puzzling–one might instead expect a negative relationship if remote work serves as a buffer against unemployment. One way to reconcile this puzzle is to observe that, taken together, the findings above suggest that workers who would otherwise be continuing to commute to work

[12] Accessed August 9, 2020 from https://www.bls.gov/web/laus/laumstcm.htm

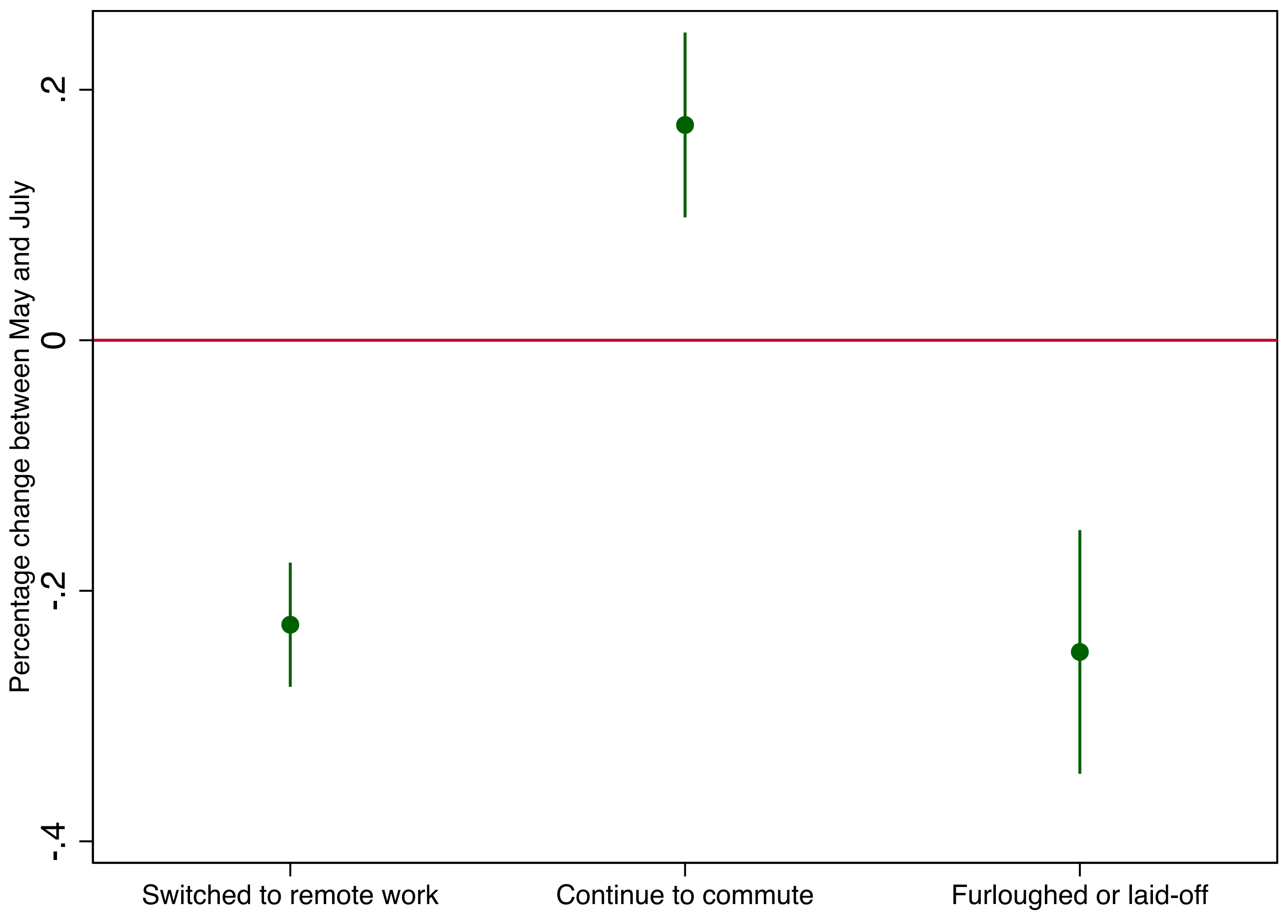
Figure 6: Predicting state unemployment rate by survey responses



are splitting into (a) work-from-home or (b) becoming unemployed.

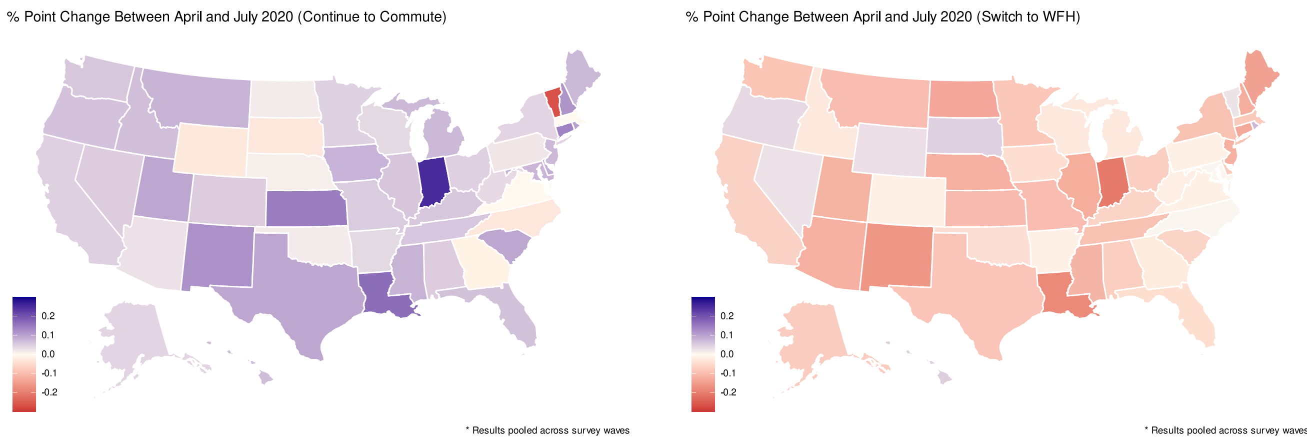
2.5 Changes over time

Figure 7: Changes in work from May to July



Survey responses between the first wave (April) and second wave (May) of the survey do not demonstrate significantly different patterns, driven largely by strong positive correlations in responses. For example, when looking within states, the correlation in reports of workers having switched into remote work is 0.79; for continuing to commute to work, the correlation is 0.73, and for being laid off or furloughed it is 0.63. This suggests that most short-term changes to remote work and commuting had already occurred by the first week of April.

By July, however, employees seemed to be returning back to commuting to work and away from remote work. To illustrate this shift, we calculate the percentage point changes in response rates for "I continue to commute to work" and "Used to commute, now work from home" and map them out in Figure 8a and Figure 8b, respectively. We use blue to denote increases from April to July,



(a) Continue to commute

(b) Switched to remote work

Figure 8: Percentage point changes between April and July 2020
(Blue = increases, Red = declines)

white to denote 0 percent point change, and red to denote declines from April to July. It is clear from these maps that workers reverted back to old commuting habits in most of the states.

Figure 7 and appendix Table 6 explores the statistical significance of this retreat by pooling state-level data from the May and July waves and regressing each of the survey outcomes on an indicator equal to 1 for July. Figure 7 reports the percentage change in a response between May and July, with May as the baseline value; Table 6 reports the percentage point change, i.e., the coefficient on July. The share of respondents reporting having switched to remote work declines by 8% points in July relative to a May rate of 35%, signifying a 22% decline. These individuals are switching back to commuting, with those reporting that they continue to commute (relative to pre-COVID times) rising by 6.3% points over a base of 37%, i.e. a 17% rise. Respondents are also 2.5% points less likely to report being furloughed or laid off in July than in May relative to a base of 10%.

Appendix Table 6 also explores the extent to which the pre-COVID distribution of economic activity predicts patterns of continuing to commute. A greater share of pre-COVID employment in information work, such as management, professional and related occupations is associated with smaller returns to commuting. One would expect this since these types of jobs are more easily done at home. However, the MPR share is not a statistically significant predictor of the time pattern in switches into remote work, likely because of low power (the coefficient is positive).

While long-term hysteresis remains a topic of future research, early results from July indicate some shifts back to the pre-COVID status quo.

2.6 Implications and suggestions for future work

These are a set of preliminary analyses of a rapidly-evolving crisis. We have documented some early shifts in the economy, and it remains to be seen if some of these changes are last beyond the end of the pandemic. For instance, once businesses and individuals invest in the fixed costs of remote work, including technology but perhaps more importantly in developing the necessary human capital and organizational processes, then they may decide to stay with the new methods. Furthermore, the crisis has forced people to try out new approaches, some of which may be unexpectedly efficient or effective. In either case, lasting changes from the crisis would be expected. Long term changes may involve not only remote work, but also the structure of industries and international trade. For example, tasks that can be done by remote workers may be more likely to be off-shored, as distance becomes less relevant. The tasks that comprise many occupations may be unbundled and re-bundled to separate those that require in-person presence at a business from those that can be done remotely. Remote work is one way in which employers can protect both the health and job security of their employees. Additional work to understand these changes is needed.

3 Conclusion

We document some early facts about how the US labor force is responding to COVID-19 pandemic. In particular, we find that since between February and May 2020 over one third of the labor force switched to remote work, resulting in about half of American workers working from home three months into the pandemic. The state-level COVID-19 infection rates predict these switches. Furthermore, states with more people in management, professional and related occupations were more likely to see large shifts toward working from home and had fewer people laid off or furloughed.

If there is hysteresis as people learn new ways to work remotely and businesses reorganize, the pandemic-driven changes may portend more lasting effects on the organization of work. We will continue to track changes to the nature of remote work, asking how pandemic-induced changes transform workplaces in the short and long-term.

The code and data for this project are here: https://github.com/johnjosephhorton/remote_work/.

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4 Appendix

Table 1: Predicting remote work by pre-COVID distribution of occupations

	Dependent variable:		
	Switch to work from home	Continue to commute	Furloughed or laid-off
	(1)	(2)	(3)
	Panel A: Management, Professional, and Related occupation share		
MPR share	1.128***	-1.120***	-0.114
	(0.089)	(0.145)	(0.080)
Constant	-0.096**	0.803***	0.141***
	(0.036)	(0.056)	(0.031)
Observations	153	153	153
R^2	0.56	0.41	0.19
	(1)	(2)	(3)
	Panel B: Dingel-Neiman remotable share		
Dingel-neiman	1.244***	-1.331***	-0.052
remotable share	(0.112)	(0.169)	(0.120)
Constant	-0.094**	0.834***	0.116***
	(0.039)	(0.058)	(0.040)
Observations	153	153	153
R^2	0.54	0.43	0.18
	(1)	(2)	(3)
	Panel C: Manufacturing share		
Manufacturing share	-0.295	0.689**	0.006
	(0.358)	(0.324)	(0.133)
Constant	0.349***	0.323***	0.099***
	(0.043)	(0.037)	(0.015)
Observations	153	153	153
R^2	0.17	0.17	0.18
	(1)	(2)	(3)
	Panel D: Prior remote work share		
Pre-COVID fraction	1.163	-2.123**	0.026
working from home	(0.855)	(0.969)	(0.322)
Constant	0.265***	0.490***	0.098***
	(0.037)	(0.044)	(0.016)
Observations	153	153	153
R^2	0.17	0.13	0.18

Notes: Significance indicators: $p \leq 0.1 : *$, $p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 2: Predicting remote work by MPR share

	Dependent variable:		
	Switch to work from home	Continue to commute	Furloughed or laid-off
	(1)	(2)	(3)
		Panel A: Wave 1	
MPR share	1.152***	-1.100***	-0.229**
	(0.122)	(0.170)	(0.092)
Constant	-0.092*	0.781***	0.205***
	(0.049)	(0.064)	(0.035)
Observations	51	51	51
R^2	0.47	0.30	0.07
	(1)	(2)	(3)
		Panel B: Wave 2	
MPR share	1.076***	-0.889***	-0.143
	(0.126)	(0.164)	(0.119)
Constant	-0.043	0.694***	0.153***
	(0.050)	(0.066)	(0.048)
Observations	51	51	51
R^2	0.45	0.28	0.02
	(1)	(2)	(3)
		Panel C: Wave 3	
MPR share	1.157***	-1.371***	0.028
	(0.119)	(0.183)	(0.083)
Constant	-0.152***	0.934***	0.065**
	(0.046)	(0.068)	(0.031)
Observations	51	51	51
R^2	0.53	0.50	0.00

Notes: Significance indicators: $p \leq 0.1 : *$, $p \leq 0.05 : **$ and $p \leq .01 : * * *$.

Table 3: Predicting remote work by Dingel-Neiman share of feasibly remote jobs

	Dependent variable:		
	Switch to work from home	Continue to commute	Furloughed or laid-off
	(1)	(2)	(3)
		Panel A: Wave 1	
Dingel-neiman remotable share	1.319***	-1.366***	-0.199
	(0.168)	(0.217)	(0.132)
Constant	-0.106*	0.831***	0.187***
	(0.060)	(0.074)	(0.044)
Observations	51	51	51
R^2	0.47	0.35	0.04
	(1)	(2)	(3)
		Panel B: Wave 2	
Dingel-neiman remotable share	1.168***	-1.059***	-0.043
	(0.169)	(0.168)	(0.157)
Constant	-0.035	0.719***	0.115**
	(0.059)	(0.061)	(0.055)
Observations	51	51	51
R^2	0.41	0.31	0.00
	(1)	(2)	(3)
		Panel C: Wave 3	
Dingel-neiman remotable share	1.245***	-1.568***	0.087
	(0.121)	(0.200)	(0.111)
Constant	-0.141***	0.951***	0.047
	(0.040)	(0.067)	(0.036)
Observations	51	51	51
R^2	0.47	0.50	0.02

Notes: Significance indicators: $p \leq 0.1 : *$, $p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 4: Predicting remote work by manufacturing share

	Dependent variable:		
	Switch to work from home	Continue to commute	Furloughed or laid-off
	(1)	(2)	(3)
	Panel A: Wave 1		
Manufacturing Occupations	-0.151	0.549	0.070
	(0.385)	(0.363)	(0.185)
Constant	0.347***	0.322***	0.114***
	(0.046)	(0.040)	(0.021)
Observations	51	51	51
R^2	0.01	0.05	0.00
	(1)	(2)	(3)
	Panel B: Wave 2		
Manufacturing Occupations	-0.346	0.838***	-0.113
	(0.404)	(0.308)	(0.236)
Constant	0.387***	0.284***	0.112***
	(0.049)	(0.034)	(0.029)
Observations	51	51	51
R^2	0.03	0.17	0.01
	(1)	(2)	(3)
	Panel C: Wave 3		
Manufacturing Occupations	-0.390	0.680*	0.063
	(0.356)	(0.392)	(0.103)
Constant	0.312***	0.363***	0.070***
	(0.041)	(0.044)	(0.012)
Observations	51	51	51
R^2	0.04	0.08	0.01

Notes: Significance indicators: $p \leq 0.1 : *$, $p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 5: Predicting remote work by pre COVID-19 work from home

	Dependent variable:		
	Switch to work from home	Continue to commute	Furloughed or laid-off
	(1)	(2)	(3)
		Panel A: Wave 1	
Pre-COVID fraction working from home	1.161	-1.464	-0.325
	(0.915)	(1.357)	(0.524)
Constant	0.278***	0.445***	0.136***
	(0.040)	(0.061)	(0.026)
Observations	51	51	51
R^2	0.02	0.02	0.01
	(1)	(2)	(3)
		Panel B: Wave 2	
Pre-COVID fraction working from home	0.337	-1.057	-0.038
	(0.974)	(1.006)	(0.441)
Constant	0.337***	0.416***	0.103***
	(0.044)	(0.047)	(0.023)
Observations	51	51	51
R^2	0.00	0.02	0.00
	(1)	(2)	(3)
		Panel C: Wave 3	
Pre-COVID fraction working from home	1.991**	-3.848***	0.440
	(0.984)	(1.130)	(0.339)
Constant	0.181***	0.609***	0.055***
	(0.044)	(0.050)	(0.015)
Observations	51	51	51
R^2	0.07	0.18	0.02

Notes: Significance indicators: $p \leq 0.1 : *$, $p \leq 0.05 : **$ and $p \leq .01 : ***$.

Table 6: Changes in remote work between May and July

	Dependent variable:		
	Switch to WFH	Continue to commute	Furloughed or laid-off
	(1)	(2)	(3)
	Panel A: Indicator for July		
July	-0.080***	0.063***	-0.025***
	(0.016)	(0.018)	(0.008)
Constant	0.353***	0.367***	0.101***
	(0.011)	(0.012)	(0.007)
Observations	102	102	102
R^2	0.21	0.11	0.10
	(1)	(2)	(3)
	Panel B: Dingel-Neiman remotable share		
DN	1.168***	-1.059***	-0.043
	(0.169)	(0.168)	(0.157)
July	-0.106	0.232**	-0.068
	(0.071)	(0.090)	(0.066)
DN*July	0.077	-0.508*	0.130
	(0.208)	(0.261)	(0.192)
Constant	-0.035	0.719***	0.115**
	(0.059)	(0.061)	(0.055)
Observations	102	102	102
R^2	0.56	0.48	0.10
	(1)	(2)	(3)
	Panel B: Management, Professional, and Related occupation share		
MPR	1.076***	-0.889***	-0.143
	(0.126)	(0.164)	(0.119)
July	-0.110	0.240**	-0.088
	(0.068)	(0.095)	(0.057)
MPR*July	0.081	-0.482*	0.171
	(0.174)	(0.246)	(0.145)
Constant	-0.043	0.694***	0.153***
	(0.050)	(0.066)	(0.048)
Observations	102	102	102
R^2	0.60	0.47	0.11
	(1)	(2)	(3)
	Panel D: Manufacturing share		
Mfg	-0.346	0.838***	-0.113
	(0.404)	(0.308)	(0.236)
July	-0.076	0.079	-0.043
	(0.064)	(0.056)	(0.031)
Mfg*July	-0.044	-0.158	0.175
	(0.538)	(0.498)	(0.257)
Constant	0.387***	0.284***	0.112***
	(0.049)	(0.034)	(0.029)
Observations	102	102	102
R^2	0.24	0.22	0.10

Notes: Significance indicators: $p \leq 0.1 : *$, $p \leq 0.05 : **$ and $p \leq .01 : ***$.