

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

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Abstract

We report the results of a nationally-representative sample of the US population on how they are adapting to the COVID-19 pandemic. The survey ran from April 1-5, 2020. Of those employed four weeks earlier, 34.1% report they were commuting and are now working from home. In addition, 11.8% report being laid-off or furloughed in the last 4 weeks. There is a strong negative relationship between the fraction in a state still commuting to work and the fraction working from home which suggests that many workers currently commuting could be converted to remote workers. 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, using data on state unemployment insurance (UI) claims, we find that states with higher fractions of remote workers have higher-than-expected UI claims.

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1 Introduction

The on-going COVID-19 pandemic has confined large numbers of people to their homes via quarantines and shelter-in-place orders. Large numbers of businesses are closed and many people are not working remotely. There have already been enormous and unprecedented increases in workers filing unemployment insurance claims ([Goldsmith-Pinkham and Sojourner, 2020](#)).

To get a real-time sense of how firms and workers are responding, we conducted a survey using Google Consumer Surveys (GCS).¹ 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. “I have recently been furloughed or laid-off”
3. “Used to commute, now work from home”
4. “Used to work from home and still do”
5. “Used to work from home, but now I commute”
6. “None of the above / Not working for pay”

We launched our survey on April 1, 2020 and collected responses until April 5, collecting a total of 25,000 responses. We find that over one third of workers have responded to the pandemic by shifting to remote work, while another 11% 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. We find that these can each be predicted by incidence of COVID-19. We also find that younger people were more likely than older people to switch from commuting to remote work.

¹GCS 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 Results

Of the respondents, 14,173 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%.² For the rest of our analysis, we restrict our sample to those reporting being employed four weeks prior.

The distribution of answers pooled over all respondents is shown in Figure 1. We can see that the most common response from workers was that they continue to commute, at 37.6% (95% CI is [36.3,38.9]). 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 34.1%. In addition, 14.6% reporting they were already working from home pre-COVID-19. This suggests nearly half the workforce is now working from home, significantly more than the [Dingel and Neiman \(2020\)](#) estimate of 34% of people working at home.³

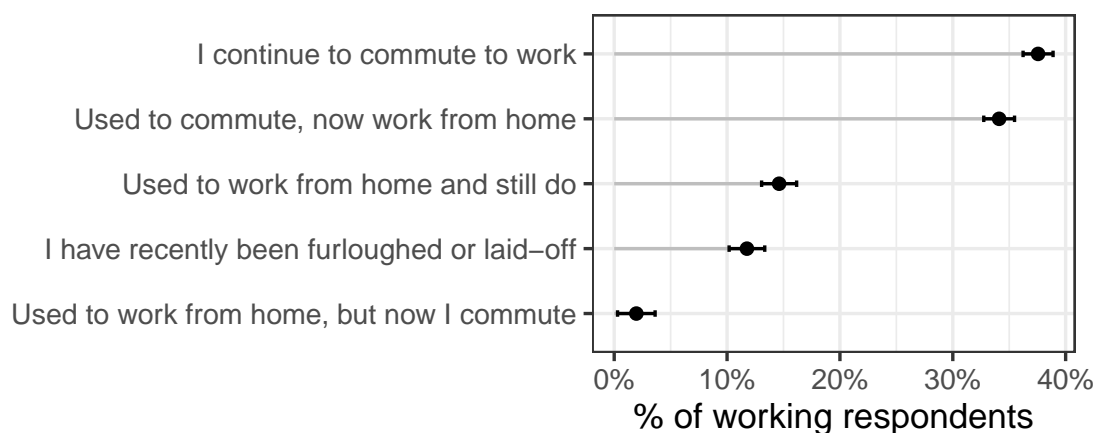
We find that 11.8% of workers report recently being laid off or furloughed. If we take the US labor force at about 165 million, this implies that about 16 million Americans are recently out of work. The total UI filings for the last two weeks adds up to 9.9 million.⁴ However, not all unemployed have yet filed for unemployment. Given the decline in hiring, [Wolfers \(2020\)](#) estimates we

²<https://fred.stlouisfed.org/series/EMRATIO>

³Our estimates are broadly consistent with the literature, however there is 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.

⁴<https://www.dol.gov/ui/data.pdf>

Figure 1: Answers to the question “Have you started to work from home in the last 4 weeks?”, conditional upon being in the labor force from a US sample



are dealing with about 16 million unemployed, matching our point estimate.⁵

GCS also infers respondent gender. We analyzed responses by gender but did not find any notable differences.

2.1 Geographic variation

COVID-19 has affected various parts of the US differently, with the main epicenter in New York City. In Figure 2, we plot the fraction of respondents choosing each answer by region. GCS captures a respondent’s city and state, which are then mapped to the regions “Northeast”, “Midwest”, “West”, and “South.”

In the first facet from the left, we can see that the South has the highest fraction still commuting to work and the Northeast has the lowest. In the second facet from the right, we can see that the Northeast has the highest fraction of respondents switching to working from home, and the South has

⁵<https://www.nytimes.com/2020/04/03/upshot/coronavirus-jobless-rate-great-depression.html>

the fewest. The Northeast started from the lowest fraction working from home, though these fractions are imprecisely estimated and are all fairly similar to each other. The Northeast fraction now working from home is over 40%.

For a finer-grained look, we plot responses by state. In Figure 5 we plot the fraction of respondents that switched to working remotely. As we saw in Figure 2, the highest fractions now working from home are in the Northeast. The South and parts of the Midwest show substantially less remote work. It is important to keep in mind that some of these point estimates are fairly imprecise.

2.2 By gender and age

In Figure 3 we report responses by inferred gender. Fractions are computed separately for males and females, and then a slope graph is used to show differences. Within all questions at a 95% confidence interval, the differences between gender are not statistically significant. Within our sample, however, it appears that men were modestly more likely to continue to commute to work, and likewise women more were more likely to report switching from commuter to work from home status. Men were also slightly more likely to have been recently furloughed or laid-off. Consistently working from home workers show little different in gender composition.

In Figure 4 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 statistically significant, and, as Figure 4 shows, younger workers (above age 25) are more likely to have been converted to work from home from commuting.

Figure 2: Responses by US region

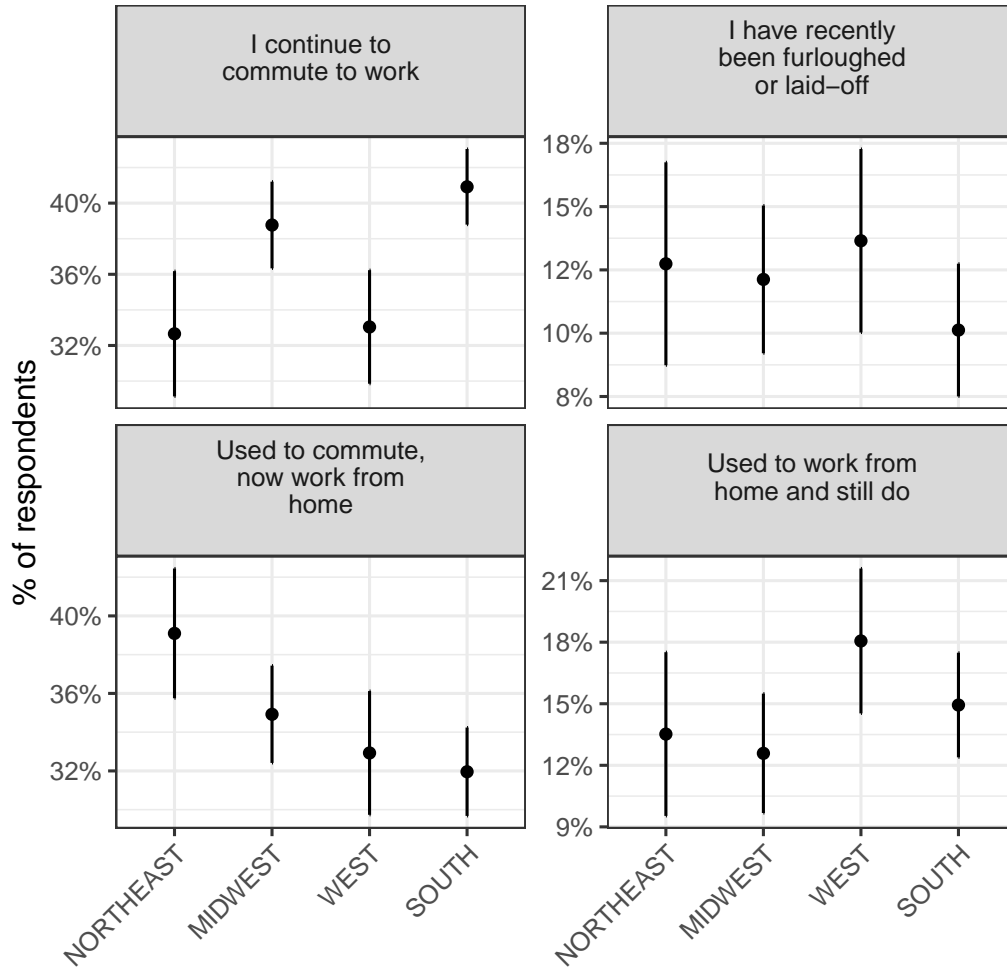


Figure 3: Responses by gender

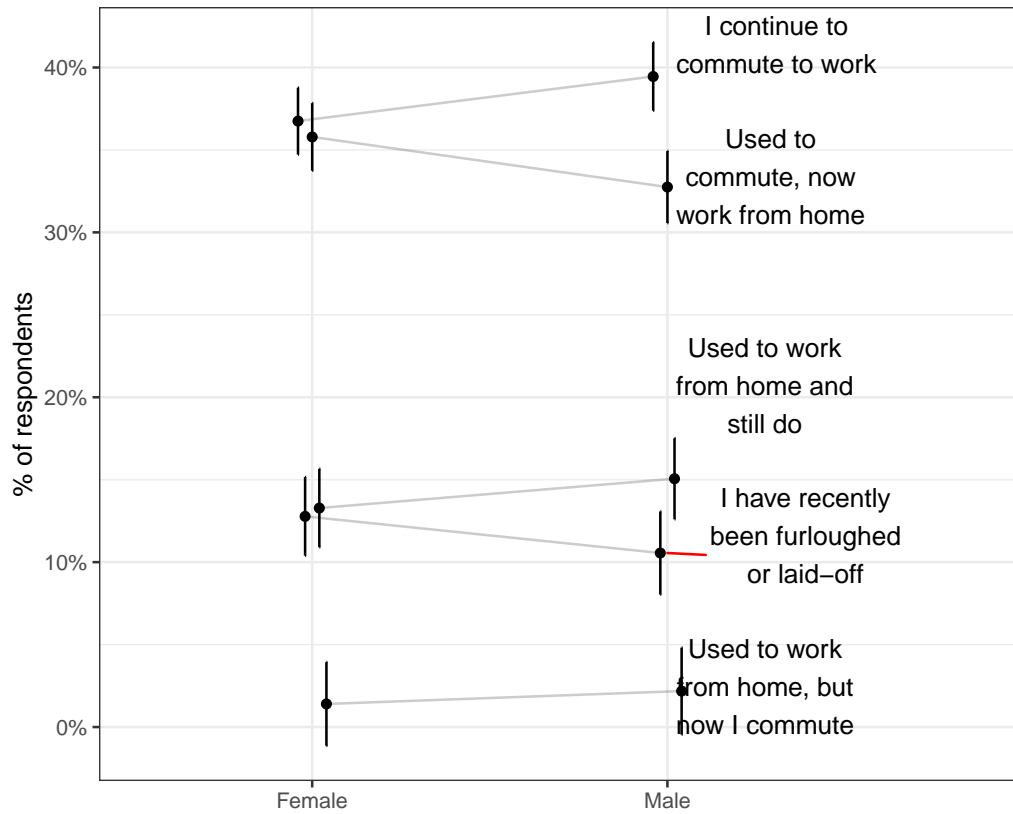
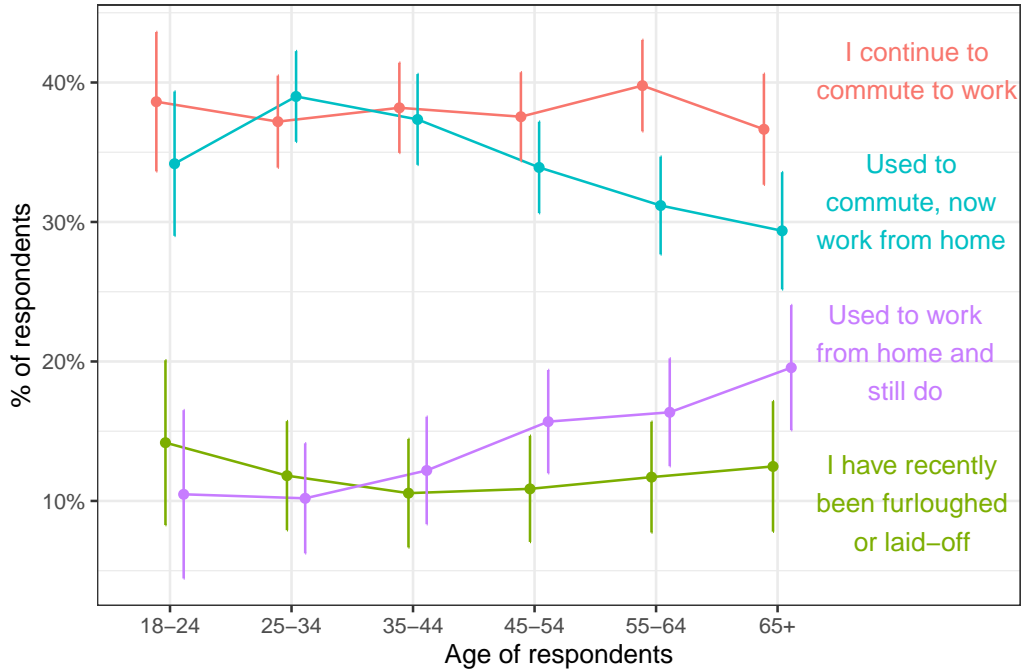


Figure 4: Responses by inferred age



Survey respondents in older age groups also reported *remaining* working remotely with greater propensities. These results are directionally consistent with the 2019 Census Bureau (2018), 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 further in future work.

The fractions laid-off or furloughed by US State are shown in Figure 6.

In Figure 7 we plot the fraction of respondents working from home versus

Figure 5: Fraction now working remotely, by US State

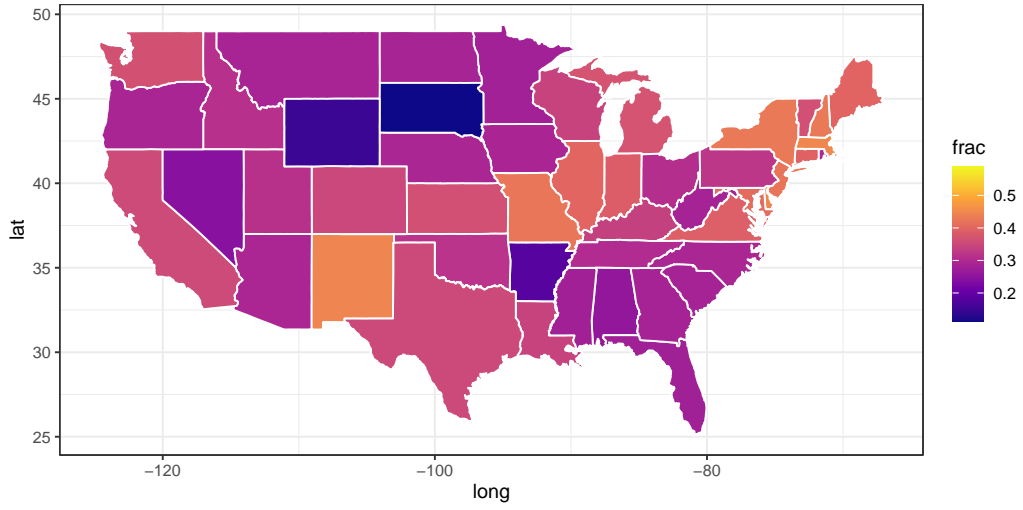


Figure 6: Fraction Laid-off/furloughed, by US State

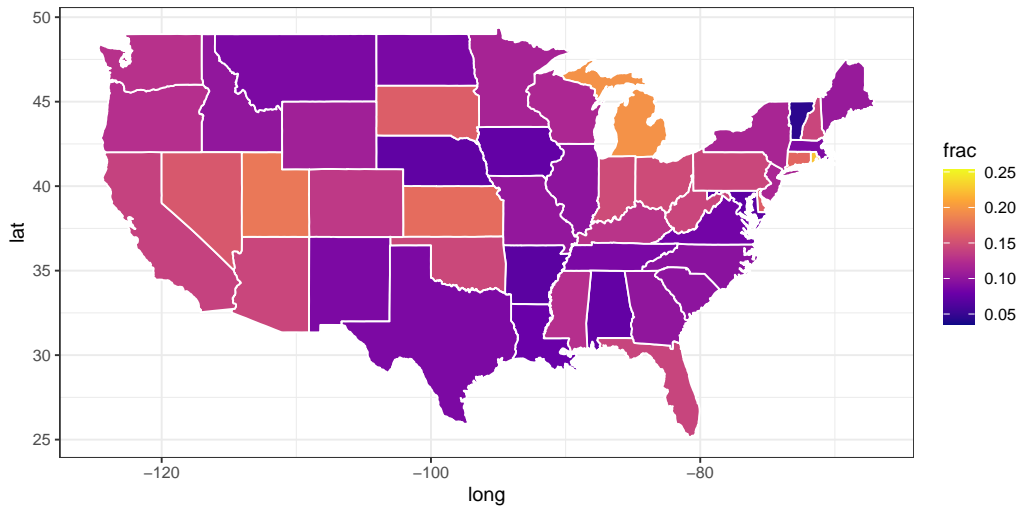
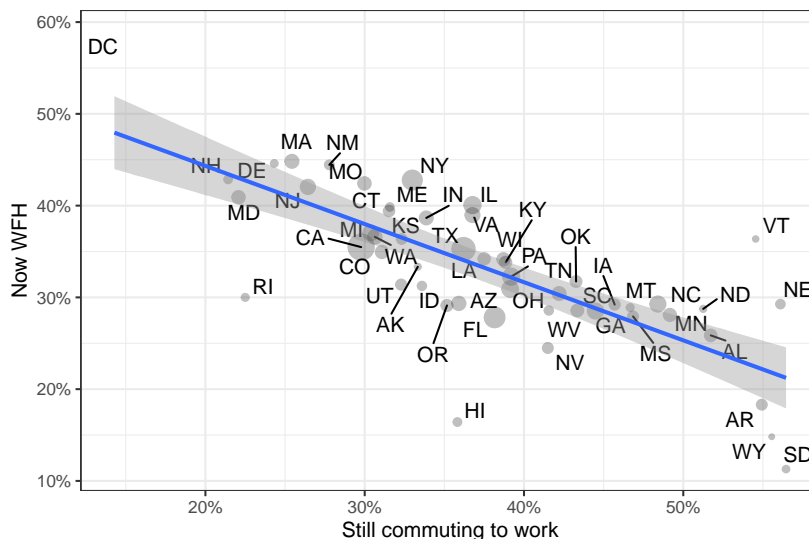


Figure 7: Still commuting versus work from home fractions by US State



the fraction still commuting by US state. There is a clear negative relationship, suggesting a fraction of current commuters will likely—or could—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.

Table 1 documents how heterogeneity in COVID infection rates (measured as the log of cases per 100,000 individuals⁶) affects switching to remote work or continuing to work from home. Column (1) shows that a 100% rise in COVID-19 cases per 100k individuals is associated with a 5% rise in the fraction of workers who switch to working from home. Column (2) shows a similar rise in COVID-19 incidence as predicting a 5.4% fall in the fraction of those continuing to commute. We would expect these relationships if higher spread is associated with higher responsiveness of government or individuals. Surprisingly, we do not find a strong relationship between our measure of

⁶Data accessed on April 5, 2020 from The New York Times website: <https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html#states>

incidence and survey reports of being furloughed or laid-off. 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.

Table 1: Predicting remote work by state incidence of COVID-19

	<i>Dependent variable:</i>		
	(1)	(2)	(3)
	Work from home	Continue to commute	Furloughed or laid-off
	(1)	(2)	(3)
Log cases per 100k pop	0.0501*** (0.0116)	-0.0545*** (0.0147)	-0.000305 (0.00700)
Constant	0.136*** (0.0472)	0.590*** (0.0590)	0.122*** (0.0275)
Observations	51	51	51
R ²	0.230	0.188	0.000

Notes: Significance indicators: $p \leq 0.05$: *, $p \leq 0.01$: ** and $p \leq .001$: ***.

A natural question is how these various measures are affecting UI claims by state. In Table 2, we combine our data with that on UI claims from Goldsmith-Pinkham and Sojourner (2020).

We regress the log of two weeks of UI claims in a state on the state’s population and the log state-specific fraction for each of the response possibilities. Unsurprisingly, across all specifications, the state population explains a great deal of the variation in UI claims. We are interested in asking whether our survey measures account for some of the residual variation.

To interpret these results, consider a state i that has population Pop_i , an employment rate of E_i and a COVID-induced fraction of the working population laid-off of LO_i . If UI claims perfectly measured lay-offs, then the state’s UI claims would be $Pop_i E_i LO_i$ and so a regression of log UI claims on the log of each of the terms should give each component a coefficient on 1. In the regressions in Table 2, we use a state-specific employment rate

pre-COVID calculated from our own survey and the state population.

Table 2: Predicting UI claims by state

	<i>Dependent variable:</i>			
	Log state two week UI claims			
	(1)	(2)	(3)	(4)
Log state population	0.967*** (0.063)	0.936*** (0.066)	0.996*** (0.066)	0.992*** (0.068)
Still commuting frac. (log)	-0.744*** (0.254)			
Switch to WFH frac. (log)		0.695*** (0.248)		
Laid-off frac. (log)			0.255 (0.204)	
Still WFH (log)				0.101 (0.218)
log(lfpr)	-0.393 (0.808)	-0.598 (0.825)	-0.189 (0.862)	-0.110 (0.878)
Constant	-4.185*** (1.097)	-2.283* (1.211)	-3.209** (1.238)	-3.456** (1.326)
Observations	50	50	50	50
R ²	0.854	0.852	0.833	0.828
Adjusted R ²	0.845	0.843	0.822	0.817

Notes: Significance indicators: $p \leq 0.05$: *, $p \leq 0.01$: ** and $p \leq .001$: ***.

In Column (1), we append the state-specific fraction reporting that they were still commuting to work. The higher the fraction reporting still commuting, the lower the UI claims for that state. States that still have large numbers commuting to work should have fewer lay-offs, and so the coefficient on the fraction still commuting should be negative.

In Column (2), the greater the fraction that reports working from home, the *higher* the UI claims. The fraction working from home should, on the one hand, have a protective effect, keeping workers from filing for UI, but on other hand, a state with a high WFH fraction has likely had a particularly

severe labor market shock, with many additional workers laid-off. What seems likely is that workers who would otherwise be continuing to commute to work are splitting into (a) work-from-home or (b) filing for UI. As states impose further restrictions on mobility, we should be able to get a sense of the resulting increases in UI filings based on how many workers can be successfully transitioned to remote work.

Surprisingly, Column (3), which includes a direct measure of reported lay-offs has the “right” sign, but is small in magnitude. Furthermore, our expectation is that the elasticity of UI claims to the number laid-off should be 1. However, not all states have the same ability to process claims, and so there is an omitted variable, r_i , that is the probability that a truly laid-off worker is able to file an UI claim successfully. If r_i falls the larger the magnitude of LO_i , then the coefficient on LO_i would be biased downward.

2.3 Implications and suggestions for future work

These are a set of preliminary analyses of an 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 business 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.

Additional work to understand these changes is needed. Future research will address how state-specific occupational distributions will affect the share of labor performed by remote workers, as well as the impact of the occupational distribution on the UI system. 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 the 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.

Critical to those decisions made by employers are the productivity effects of remote work. More evidence is needed to evaluate the productivity changes induced by allowing work from home. Relatedly, what percentage of tasks can be done remotely and how does it vary across professions and industries? Can we also observe (and explain) heterogeneity across states? These task-specific questions will be the focus of our next round of surveys.

For the COVID-19 pandemic in particular, we are also interested in how the disease spreads differentially across types of jobs. Remote work is one way in which employers can protect both the health and job security of their employees.

3 Conclusion

We document some early facts about how the US labor force is responding to COVID-19 pandemic. In particular, we find that in the past four weeks over one third of the labor force has switched to remote work. The state-level COVID-19 infection rates predict these switches. 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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