Review of Economic Analysis 14 (2022) 319-333 1973-3909/2022319

The Ability to Work Remotely: Measures and Implications

KATHRYN LANGEMEIER
Federal Reserve Board *

MARIA D. TITO
Federal Reserve Board

Our paper explores how the ability to work remotely has changed over time, its relationship with demographic characteristics and employment outcomes, and the role it played during the pandemic recession. We focus on two different remote work indexes, a measure of "no physical presence"—proposed by Dingel and Neiman (2020)—and a measure of "remote communications"—presented by Montenovo et al. (2020). While the two measures suggest a similar prevalence of remote work in recent years and display fairly similar behaviors across demographic groups and in terms of wage and employment outcomes, their evolution is significantly different. While the share of occupations that require no physical presence has remained relatively constant since July 2003, the share of those occupations featuring remote communications increased more than 40 percentage points over the same period. Those differing evolutions paint a starkly different picture of the role of remote work during the pandemic: Compared to a counterfactual scenario that keeps the remote classification constant at the 2004 levels for each measure, the index of no physical presence suggests that there would have been little changes in terms of aggregate hours losses during the pandemic, while the index of remote communications points to much larger declines in aggregate hours. Even without much change in the ability of working remotely, the trend towards more remote work underscores the importance of the hours margin as an additional dimension for the realization of gains from working at home.

Keywords: Remote Work, Work from Home, Hours Worked, Pandemic Recession, Covid-19

JEL Classifications: J24, J60

At the onset of the COVID-19 recession, a large share of the employed switched to remote work. Individual- and firm-level surveys indicated that the switch affected between 35 and 45 percent of workers.[1] The switch is even more remarkable if considering that, through early

---

* The views expressed in the article are those of the authors and do not necessarily reflect those of the Federal Reserve System. We would like to thank John Roberts for his insightful comments

1 See, for example, Bartik et al. (2020) and Brynjolfsson et al. (2020)

2020, the share of people who worked from home across various surveys had remained remarkably stable.[2] This recent pick-up in working from home could point to significant changes in the potential of remote work. This note explores how the ability to work remotely has changed over time, its relationship with demographic characteristics and employment outcomes, and the role it played during the pandemic recession.

In the recent literature, two contributions have proposed systematic approaches, based on occupation characteristics, aimed at identifying jobs that can be performed at home. Dingel and Neiman (2020) present a remote work index that looks extensively at work context and activities and flags, in particular, physical aspects of jobs—such as, physically dealing with aggressive people; being exposed to disease or infection; inspecting equipment, structure, or materials; etc.[3] Because of this characterization, the remote work index proposed by Dingel and Neiman (2020) effectively captures occupations that can be performed at home because they require "*no physical presence"*—our preferred designation hereafter. Montenovo et al. (2020) describe a more concise index, focusing on email, phone, and memo usage; as such, we will refer to the Montenovo et al. (2020) measure as identifying occupations featuring "*remote communications*".[4]

The first objective of our note is to study the evolution of those measures. Using the definitions from Dingel and Neiman (2020) and Montenovo et al. (2020), we construct indexes of remote work from the Occupation Information Network (O*Net) questionnaires from July 2003 through February 2022, the latest available data. We then match those indexes with Bureau of Labor Statistics (BLS) data from the Current Population Survey (CPS) to measure the prevalence of remote work in overall employment.

Figure 1 describes the evolution of employment shares in remote occupations according to the no physical presence (left panel) and the remote communications (right panel) indexes. The two indexes present very different evolutions. While the no physical presence index has remained relatively constant, the remote communications index has gradually increased over time, gaining more than 40 percentage points in terms of employment shares relative to July

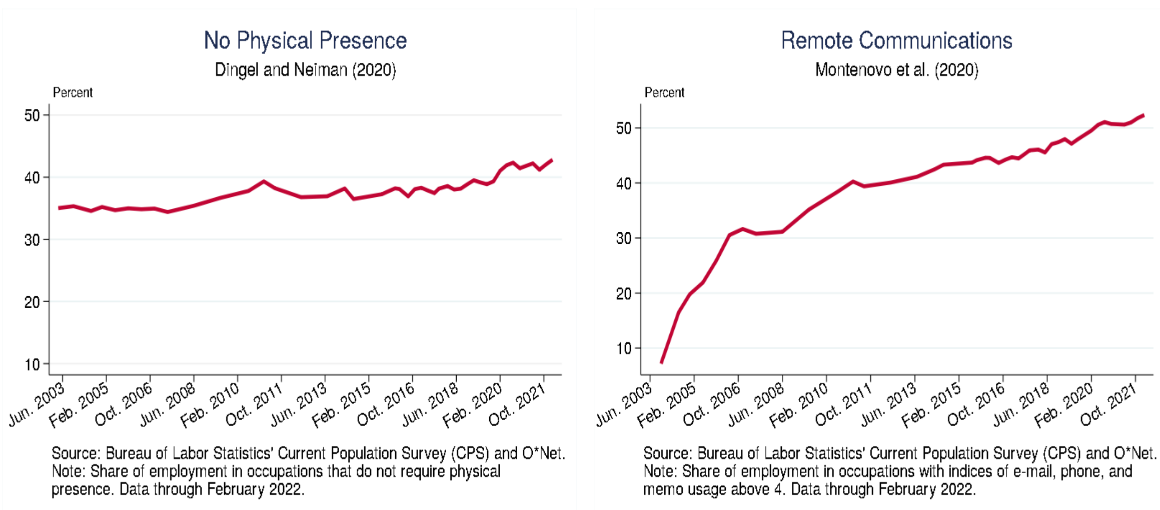
[2] See Mas and Pallais (2020).

[3] In Dingel and Neiman (2020), a job cannot be performed at home *if either* the average respondent indicates that he/she uses e-mail less than once a month; is physically dealing with aggressive people; is exposed to disease, infections, minor burns, cuts, bites, or stings; works outdoor every day; wears specialized or common protective equipment; spends time walking and running; *or if* it is very important to perform physical activities; to handle or move objects; to control machine and processes; to operate vehicles or mechanized devices; to perform or work directly with the public; to inspect equipment, structures, or material; to repair and maintain electronic or mechanical equipment.

[4] In Montenovo et al. (2020), a job is flagged as "remote" if e-mail, phone, or memo usage is very important.

2003.[5,6,7] Looking at the more recent history, the discrepancies between the two indexes appear more contained. Occupations that require no physical presence represented 41 percent of CPS employment in February 2020, at the onset of the pandemic, while the share of employment in occupations characterized by remote communications was a little higher, reaching almost 50 percent by that time.[8] Over the past two years, the increasing trends in the two indexes has continued, with the index of no physical presence representing 43 percent of employment and that of remote communications at 52 percent in the February 2022 data.

Figure 1. Measuring the Ability to Work Remotely



5 Using the Occupational Employment Statistics (OES) data, which covers 200,000 establishments—compared with about 4,500 household interviews for CPS—the remote communications index has grown from 9.8 million in 2003 to 57.7 million workers in February 2020; the no physical presence has, instead, grown only from 39.5 million to 44.5 million workers. Our analysis relies on CPS because of the availability of worker observable characteristics.

6 The gradual evolution of remote work observed in the remote communications measure appears more aligned with the behavior of other measures. In particular, the CPS Supplement data indicate that, in 2004, the share of remote employment was 15 percent compared with 16.5 percent for the remote communications index and 34.6 percent for the no physical presence index.

7 The remote communications index increases significantly between 2003 and 2004; those increases are not linked to survey or methodological changes. We cannot exclude, however, that survey respondents answered the questions used for the construction of the index differently over time, especially since those survey waves were among the first ones administered.

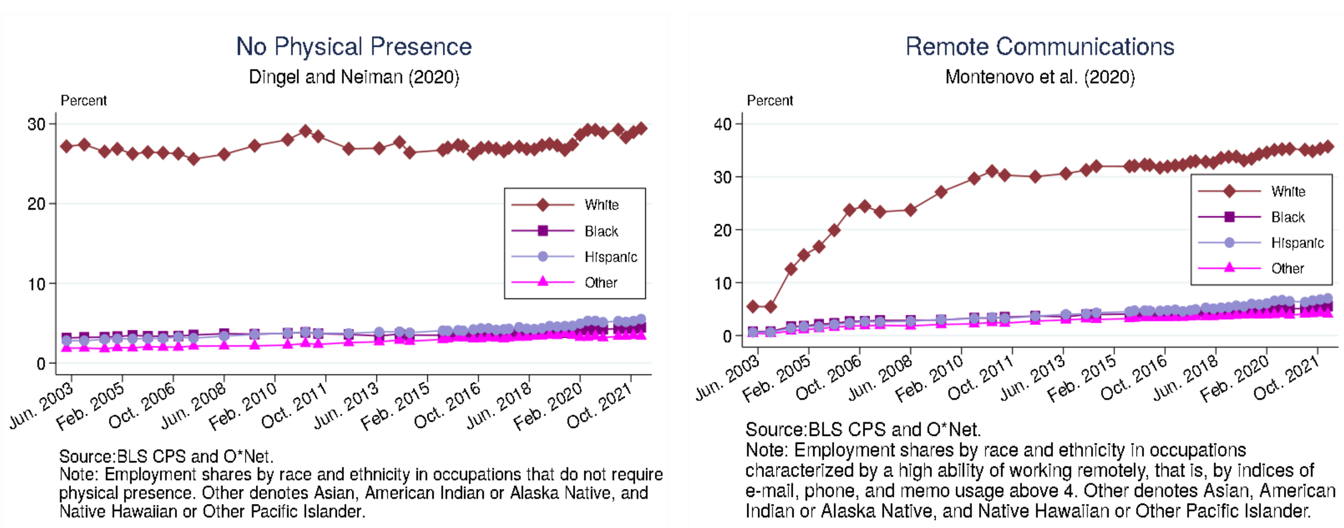
8 Dingel and Neiman (2020) match the remote index with the OES data and estimate that, using the February 2020 O*Net survey, 37 percent of jobs could be performed at home according to their definition.

Next, we explore demographic correlates of remote work, extending the analysis by Mongey and Weinberg (2020). Figure 2 focuses on three main characteristics: race and ethnicity, age, and education level.[9] The average distribution of remote work along these dimensions is consistent with the idea that highly teleworkable jobs tend to be in nonproduction/supervisory occupations, which are characterized by a disproportionately higher share of white employment (top panel) and require higher levels of education (bottom panel). Moreover, the prevalence of remote employment is more pronounced for those in the prime age group—that is, those between 25 and 64 years of age—while the share of remote jobs is more limited for those outside of that age range. We also looked at employment shares in remote occupations by gender, where the likelihood of men and women to be in a remote job appears fairly close. All told, the average disparities across demographic groups are relatively similar for each measure.

Focusing on changes in remote employment shares across those dimensions, the static nature of the aggregate no physical presence index transpires across all demographic groups except for college-educated workers.

Figure 2: Differences in the Ability to Work Remotely along Demographic Characteristics

Figure 2a: Race and Ethnicity



[9] The figure decomposes the contribution of each group to the total share of employment in remote occupations by either measure.

Figure 2b: Age

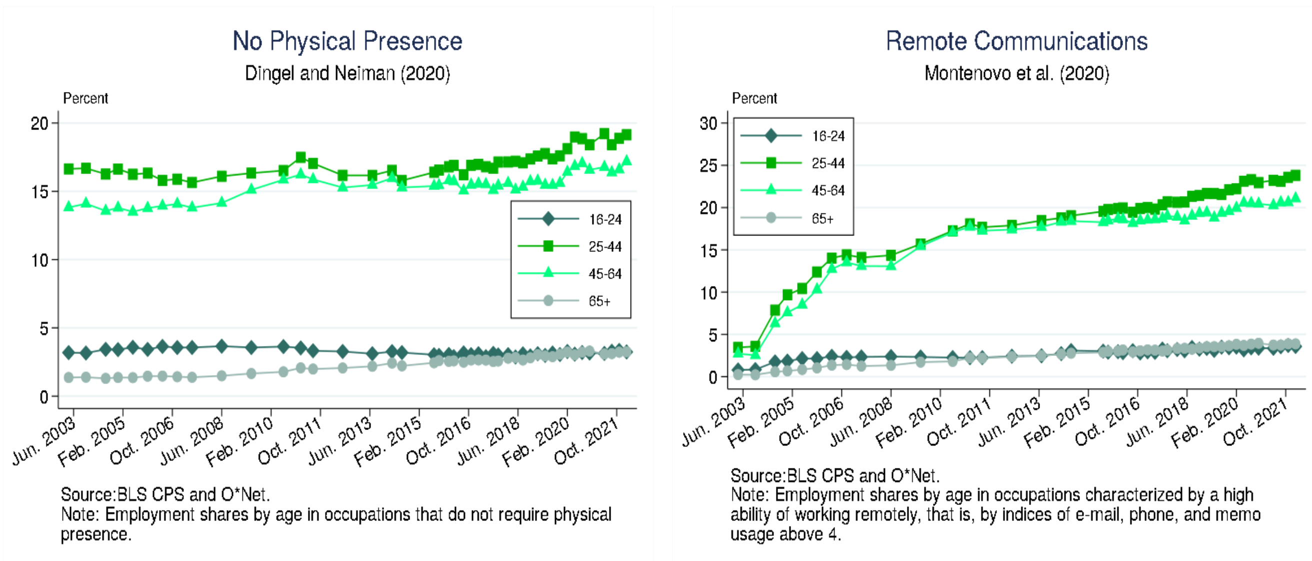
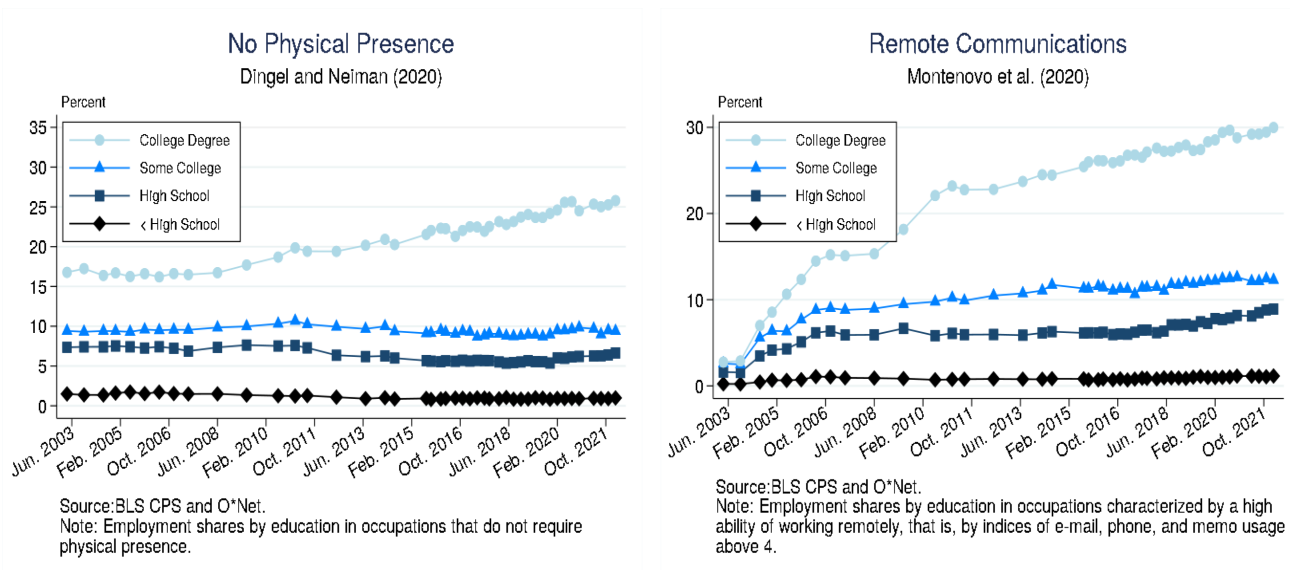


Figure 2c: Education Level



For the remote communications index, the group that represented the largest share of remote employment in 2003—white, 25-to-64, college-educated—grew at a steady pace over time, while the share of remote jobs in all other groups remained at consistently low levels. Naturally, differential trends in remote work across demographic groups could reflect many different factors—such as the increase in the pool of college-educated workers or a shift towards supervisory occupations—in addition to worker selection into remote occupations.

Beside the variation associated with demographic characteristics, occupations with the ability to work remotely also differ in terms of labor market outcomes: Tables 1 and 2 explore differences in employment status, while Figure 3 and Table 3 highlight differences in wages. In both tables, columns (1)-(3) refer to the no physical presence index, while columns (4)-(6) characterize the results for occupations characterized by remote communications. Looking at the results in Table 1, we find that people in occupations with the ability to work from home by either measure are less likely to be inactive (panel A) or unemployed (panel B). [10] The magnitude of the effect is slightly lower after controlling for worker observables—including demographic characteristics highlighted above—in columns (2) and (5), and a large set of fixed effects—state-year, industry-year, and month—in columns (3) and (6), but the coefficients continue to imply mostly significant differences. Interestingly, the impact of remote work appears more relevant on the unemployment margin compared to inactivity, and we'll focus on the unemployed for the rest of this note.

To disentangle the effect of remote work on flows in and out of unemployment from the effect on the stock of the unemployed, we have also linked individuals month-to-month and identified sequences of individuals moving between employment and unemployment status. Table 2 summarizes our result for *entry* (panel A)—that is, the transition from unemployment to employment—and *exit* (panel B)—that is, the transition from employment to unemployment—relative to the initial status.

Our results imply that, while working in an occupation that requires no physical presence marginally affects only the probability of exit, workers in jobs characterized by remote communications enjoy both a higher probability of finding a job and a lower probability of exiting from employment.

Using a gross flow framework à la Shimer (2012), our estimates imply that individuals in remote communications jobs face a 10 percent higher job finding probability and an almost 50 percent employment exit probability compared with people in other occupations, while the effect on exit is marginal—with a reduction of 10 percent on the probability of exit—for individuals in jobs that require no physical presence.[11]

Turning to wages, Figure 3 points to large aggregate differences in average wages across remote and non-remote occupations by either index.

[10] Occupation and industry characteristics for the inactive—that is, people out of the labor force—and the unemployed are based on their previous jobs.

[11] Shimer (2012) estimates a job finding rate of around 30 percent and an employment exit rate of around 3 percent in BLS data between 1990 and 2010.

Table 1: Remote Work and Out-of-Employment Probabilities

Panel A: Inactivity

Variables	(1)	(2)	(3)	(4)	(5)	(6)
			Inactive$_t$			
No Physical Presence$_t$	-0.002**	-0.0003	0.0003			
	(0.001)	(0.001)	(0.001)			
Remote Comm$_t$				-0.005***	-0.003***	-0.003***
				(0.001)	(0.000)	(0.000)
Worker Observables	n	y	y	n	y	y
Month FE	n	n	y	n	n	y
State-Year FE	n	n	y	n	n	y
Industry-Year FE	n	n	y	n	n	y
Obs.	2,571,909	2,571,909	2,571,909	2,365,712	2,365,712	2,365,712
R-squared	0.001	0.009	0.010	0.001	0.009	0.010

Panel B. Unemployment

Variables	(1)	(2)	(3)	(4)	(5)	(6)
			Unemployed$_t$			
No Physical Presence$_t$	-0.021***	-0.005**	-0.005*			
	(0.004)	(0.003)	(0.003)			
Remote Comm$_t$				-0.036***	-0.020***	-0.020***
				(0.004)	(0.003)	(0.003)
Worker Observables	n	y	y	n	y	y
Month FE	n	n	y	n	n	y
State-Year FE	n	n	y	n	n	y
Industry-Year FE	n	n	y	n	n	y
Obs.	2,543,805	2,543,805	2,543,805	2,340,145	2,340,145	2,340,145
R-squared	0.002	0.029	0.041	0.008	0.032	0.042

Source: BLS CPS and O*Net.

Inactive$_t$: indicator equal to 1 if out of the labor force at time t.

Unemployed$_t$: indicator equal to 1 if unemployed at time t.

Physical Presence$_t$: indicators equal to 1 for occupations that do not require physical presence.

Remote Comm$_t$: indicator equal to 1 for occupations that require high use of e-mails, memos, and telephone.

Legend: *** denotes significance at 1 percent level, ** significance at 5 percent, and * significance at 10 percent.

Notes: Cross-sectional regressions. Columns (2)-(3) and (5)-(6) include worker observables (age, gender, race, ethnicity, education, marital status, citizenship, tenure, and metro dummies); columns (3) and (6) also add month, state-year, and industry-year fixed effects. Robust standard errors, clustered at the occupation level, are reported in parenthesis.

Table 2: Remote Work and Unemployment Flows

Panel A: Flows into Employment

Variables	(1)	(2)	(3)	(4)	(5)	(6)
			Entry$_t$			
No Physical Presence$_t$	0.045***	0.009	0.005			
	(0.010)	(0.007)	(0.007)			
Remote Comm$_t$				0.073***	0.040***	0.041***
				(0.009)	(0.007)	(0.007)
Worker Observables	n	y	y	n	y	y
Month FE	n	n	y	n	n	y
State-Year FE	n	n	y	n	n	y
Industry-Year FE	n	n	y	n	n	y
Obs.	124,170	124,170	124,170	113,405	113,405	113,405
R-squared	0.003	0.062	0.092	0.009	0.064	0.094

Panel B: Flows into Unemployment

Variables	(1)	(2)	(3)	(4)	(5)	(6)
			Exit$_t$			
No Physical Presence$_t$	-0.018***	-0.005**	-0.004*			
	(0.003)	(0.002)	(0.002)			
Remote Comm$_t$				-0.032***	-0.018***	-0.018***
				(0.003)	(0.002)	(0.002)
Worker Observables	n	y	y	n	y	y
Month FE	n	n	y	n	n	y
State-Year FE	n	n	y	n	n	y
Industry-Year FE	n	n	y	n	n	y
Obs.	2,419,636	2,419,636	2,419,636	2,226,741	2,226,741	2,226,741
R-squared	0.002	0.026	0.037	0.006	0.026	0.038

Source: BLS CPS and O*Net.

Entry$_t$: indicator equal to 1 if the individual moves from unemployment to employment between time t and t-1.

Exit$_t$: indicator equal to 1 if the individual moves from employment to unemployment between time t and t-1.

Physical Presence$_t$: indicators equal to 1 for occupations that do not require physical presence.

Remote Comm$_t$: indicator equal to 1 for occupations that require high use of e-mails, memos, and telephone

Remaining notes: see table 1

Legend: *** denotes significance at 1 percent level, ** significance at 5 percent, and * significance at 10 percent.

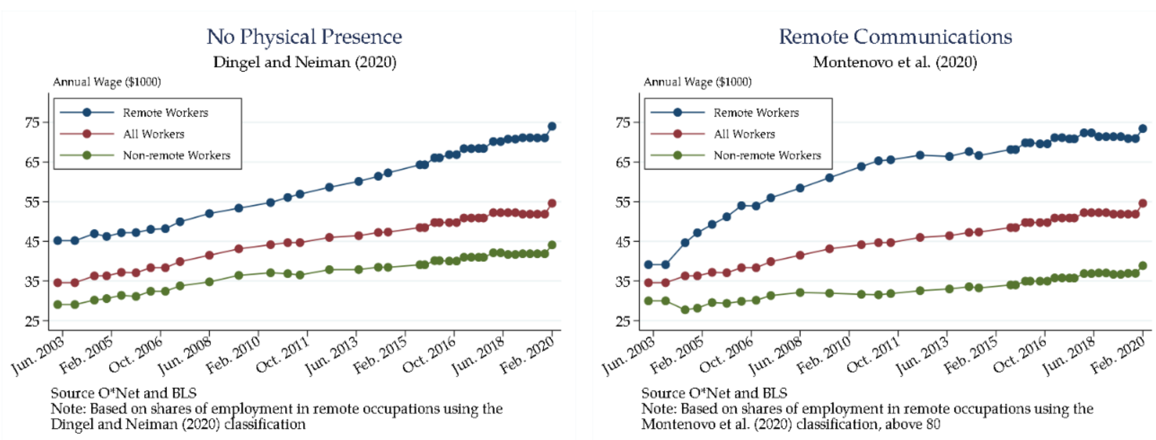
Notes: Cross-sectional regressions. Columns (2)-(3) and (5)-(6) include worker observables (age, gender, race, ethnicity, education, marital status, citizenship, tenure, and metro dummies); columns (3) and (6) also add month, state-year, and industry-year fixed effects. Robust standard errors, clustered at the occupation level, are reported in parenthesis

Those who are able to work remotely have higher annual wage outcomes, with some slight differences across the indexes. Among those differences, the remote communications index shows a persistently wider gap than the no physical presence index, partly reflecting very anemic growth in non-remote workers' wages for the former measure.

To control for the variation in hours across occupations, Table 3 summarizes the variation in hourly wages across remote and non-remote jobs. The "remote" wage premium remains significant after including worker observables and fixed effects in our regressions. Using the specifications in columns (3) and (6), we find that a worker in an occupation that require no physical presence receives a 15 percent of a standard deviation (sd) higher hourly wage, while those employed in occupations characterized by remote communications enjoys around 35 percent of a sd higher hourly wage.[12]

The variation of employment outcomes for remote relative to other occupations underscores the scope of a role for remote work during the most recent recession. To more precisely understand the part that the switch to working remotely played in the past recession, we look at two pieces of evidence. First, we repeat the analysis in Tables 1 and 3 with remote indexes that reflect the February 2020 occupation characteristics. With a fixed classification of remote jobs, the correlation with employment outcomes will not be driven by shifts across occupations or changes in tasks within occupation. Furthermore, we'll disentangle a baseline impact of remote work on unemployment outcomes from the effect during the pandemic using an interaction between our indexes and an indicator variable equal to one during March and April 2020.[13]

Figure 3: Differences in Wage Outcomes by Ability to Work Remotely



[12] In our sample, one standard deviation of log hourly wages is 0.65.

[13] The impact of remote work on inactivity during the pandemic recession continue to be more marginal and roughly in line with the findings for the stock of the unemployed. The results, though not reported here, are available upon request.

Table 3: Remote Work and Wage Effects

Variables	(1)	(2)	(3)	(4)	(5)	(6)
			Log Hourly Wage$_t$			
No Physical Presence$_t$	0.354***	0.140***	0.105***			
	(0.057)	(0.036)	(0.030)			
Remote Comm$_t$				0.520***	0.282***	0.224***
				(0.051)	(0.035)	(0.031)
Worker Observables	n	y	y	n	y	y
Month FE	n	n	y	n	n	y
State-Year FE	n	n	y	n	n	y
Industry-Year FE	n	n	y	n	n	y
Obs.	530,106	530,106	530,106	489,481	489,481	489,481
R-squared	0.062	0.334	0.407	0.157	0.360	0.417

Source: BLS CPS and O*Net.

Log Hourly Waget : hourly wage, in log-s, at time t.

Physical Presencet: indicators equal to 1 for occupations that do not require physical presence

Remote Commt: indicator equal to 1 for occupations that require high use of e-mails, memos, and telephone.

Legend: *** denotes significance at 1 percent level, ** significance at 5 percent, and * significance at 10 percent.

Notes: Cross-sectional regressions. Columns (2)-(3) and (5)-(6) include worker observables (age, gender, race, ethnicity, education, marital status, citizenship, tenure, and metro dummies); columns (3) and (6) also add month, state-year, and industry-year fixed effects. Robust standard errors, clustered at the occupation level, are reported in parenthesis.

Our results for the first part of the analysis are shown in Tables 4 and 5. Our indices of remote work based on the February 2020 characteristics are generally associated with a lower probability of unemployment and higher wages over the entire sample. In addition, during the pandemic recession, workers in remote occupations by either measure were even less likely to be unemployed but did not enjoy any additional wage gains. Our results on the interactions between remote work, measured by the remote communications index, and the unemployment probability are roughly in line with the findings in Montenovo et al. (2020), with the caveat that about half of the effect arises even outside of the pandemic recession.[14]

The differential employment outcomes for remote occupations are also reflected in the patterns of hours associated to remote jobs during the recent pandemic.[15]

[14] More precisely, our estimates are a little above Montenovo et al. (2020)'s finding with the differences due to the fact that they consider the "recently" unemployed, while our analysis in Tables 1 and 4 is for the entire stock of the unemployed.

[15] The behavior of hours in occupations characterized by remote work tend to differ from the pattern in aggregate hours also during the Great Recession, the only other downturn covered in our sample, consistent with the differences in demographics and observables highlighted in this note.

Table 4: Remote Work and Probability of Being Unemployed during the Pandemic

Variables	(1)	(2)	(3)	(4)	(5)	(6)
			Unemployed$_t$			
No Physical Presence$_t$	-0.026***	-0.010**	-0.005			
	(0.005)	(0.004)	(0.004)			
No Physical Presence$_t$ * Pandemic$_t$	-0.021***	-0.022***	-0.015***			
	(0.006)	(0.006)	(0.005)			
Remote Comm$_t$				-0.046***	-0.033***	-0.032***
				(0.005)	(0.005)	(0.004)
Remote Comm$_t$ * Pandemic$_t$				-0.043***	-0.043***	-0.037***
				(0.007)	(0.007)	(0.006)
Worker Observables	n	y	y	n	y	y
Month FE	n	n	y	n	n	y
State-Year FE	n	n	y	n	n	y
Industry-Year FE	n	n	y	n	n	y
Obs.	1,095,917	1,095,917	1,095,917	865,422	865,422	865,422
R-squared	0.004	0.034	0.057	0.012	0.038	0.063

Source: BLS CPS and O*Net.

Unemployed$_t$: indicator equal to 1 if unemployed at time t.

Physical Presence$_t$: indicators equal to 1 for occupations that do not require physical presence.

Pandemic$_t$: indicator equal to 1 for March and April 2020.

Remote Comm$_t$: indicator equal to 1 for occupations that require high use of e-mails, memos, and telephone.

Legend: *** denotes significance at 1 percent level, ** significance at 5 percent, and * significance at 10 percent.

Notes: Cross-sectional regressions. Columns (2)-(3) and (5)-(6) include worker observables (age, gender, race, ethnicity, education, marital status, citizenship, tenure, and metro dummies); columns (3) and (6) also add month, state-year and industry-year fixed effects. Robust standard errors, clustered at the occupation level, are reported in parenthesis.

Figure 4 compares three outcomes: the trend in hours across all occupations, the trend in hours across jobs characterized by remote communications, and the trend across jobs requiring no physical presence. Consistent with the findings in Table 4, remote occupations by either index experienced a significantly smaller decline over the two months of the pandemic recession; as a result, the rebound in hours for remote occupations appears more gradual, but the level of hours at occupations requiring no physical presence or characterized by remote communications remains above the level of hours at all jobs throughout the middle of 2021. Since differences in the patterns of hours for the two indexes are minimal, our evidence so far suggests that either measure is representative of the status of remote work in the post-pandemic period.

Table 5: Remote Work and Wages during the Pandemic

	(1)	(2)	(3)	(4)	(5)	(6)
Variables			Log Hourly Wage$_t$			
No Physical Presence$_t$	0.314***	0.118***	0.085**			
	(0.057)	(0.037)	(0.035)			
No Physical Presence$_t$ * Pandemic$_t$	-0.004	0.007	0.006			
	(0.012)	(0.010)	(0.010)			
Remote Comm$_t$				0.440***	0.240***	0.221***
				(0.053)	(0.035)	(0.029)
Remote Comm$_t$ * Pandemic$_t$				-0.014	0.006	0.007
				(0.013)	(0.011)	(0.011)
Worker Observables	n	y	y	n	y	y
Month FE	n	n	y	n	n	y
State-Year FE	n	n	y	n	n	y
Industry-Year FE	n	n	y	n	n	y
Observations	231,579	231,579	231,579	181,024	181,024	181,024
R-squared	0.056	0.298	0.332	0.123	0.319	0.349

Source: BLS CPS and O*Net.

Log Hourly Wage$_t$: hourly wage, in log-s, at time t.

Physical Presence$_t$: indicators equal to 1 for occupations that do not require physical presence.

Pandemic$_t$: indicator equal to 1 for March and April 2020.

Remote Comm$_t$: indicator equal to 1 for occupations that require high use of e-mails, memos, and telephone.

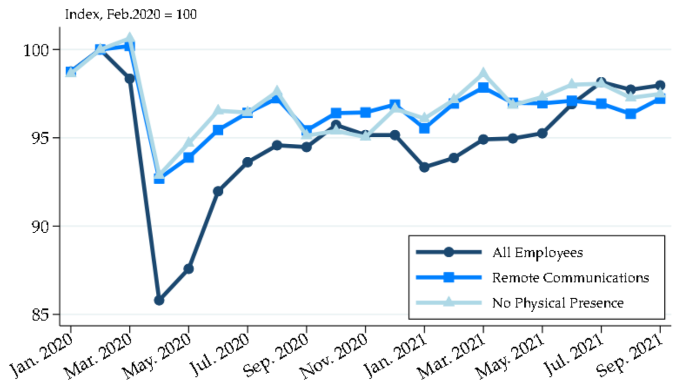
Legend: *** denotes significance at 1 percent level, ** significance at 5 percent, and * significance at 10 percent.

Notes: Cross-sectional regressions. Columns (2)-(3) and (5)-(6) include worker observables (age, gender, race, ethnicity, education, marital status, citizenship, tenure, and metro dummies); columns (3) and (6) also add month, state-year and industry-year fixed effects. Robust standard errors, clustered at the occupation level, are reported in parenthesis.

In the second part of our analysis, we look at the counterfactual declines in hours in March and April 2020 had the ability of working remotely for each occupation remained at the same levels as in July 2004.[16] Specifically, for each occupation with the ability to work remotely in February 2020 but not in July 2004, we attribute the average decline in hours of non-remote occupations over the recession period rather than the actual decline; we then look at the decline in total hours for this counterfactual scenario. The results for our exercise are shown in Figure 5, with the left panel focusing on the index of no physical presence and the right panel displaying the effect for the index of remote communications.

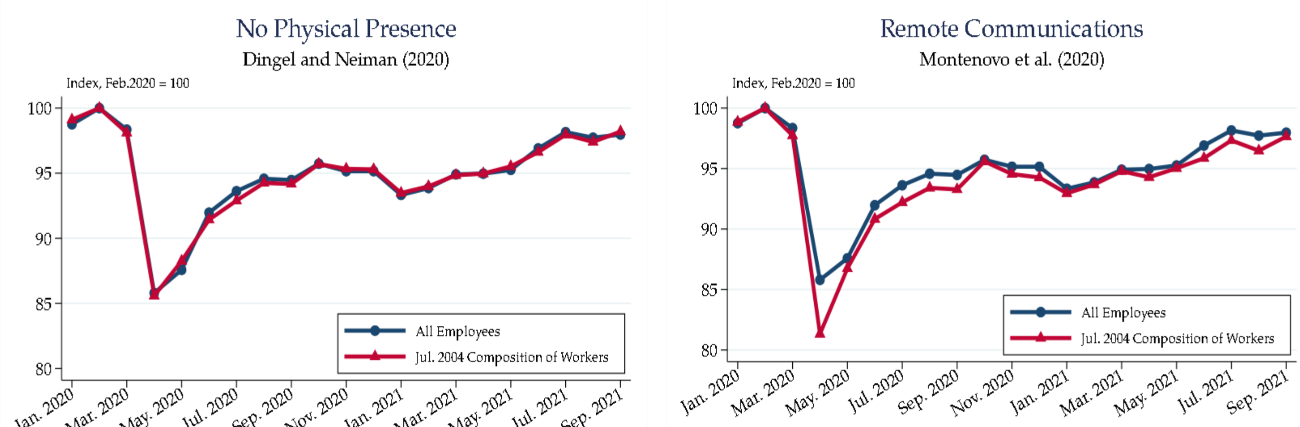
[16] We chose July 2004 as a reference period to match our comparison with the CPS supplement data on remote work for that year. Using data from April 2003, our results for the no physical presence measure would be little changed, while the counterfactual for the remote communications index would imply larger declines.

Figure 4: Impact on Hours during the Pandemic Recession



Source: O*Net and CPS.
Notes: Decline in aggregate hours relative to February 2020. Remote communications refer to occupations with high usage of phone, e-mail, and memos; no physical presence refers to occupations that do not require physical presence.

Figure 5: Impact on Hours: Counterfactual Exercise



Source: O*Net and CPS.
Notes: Decline in aggregate hours relative to February 2020. No physical presence refers to occupations that do not require physical presence.

Source: O*Net and CPS.
Notes: Decline in aggregate hours relative to February 2020. Remote communications refer to occupations with high usage of phone, e-mail, and memos.

No changes in the ability of working remotely would have implied minimal effects in the hours decline observed in March and April 2020 for the index of no physical presence. The impact on hours, instead, would have been significantly more pronounced had the index of remote communications remained at the same level as that of July 2004. Table 6 summarizes our results and includes a comparison with the overall impact on hours and GDP in 2020.

Table 6. Working from Home: Impact on Hours

		2020			
		Q1	Q2	Q3	Q4
(1)	Total Hours Decline (a.r.)	-3.6%	-36.5%	25.8%	7.2%
	Countefactuals as of Jul. 2004				
(2)	No Physical Presence	-3.7%	-36.6%	26.6%	7.3%
(3)	Remote Communications	-4.5%	-42.1%	35.3%	8.2%
(4)	Memo: GDP growth (a.r.)	-4.9%	-31.3%	33.6%	4.5%

Source: BLS CPS,O*Net, and authors' calculations.

Note: Total hours decline denotes the aggregate decline in usual hours. The counterfactual scenarios assume that occupations that could not performed at home in July 2004 by either measure experienced the same declines as non-teleworkable occupations in 2020 during the pandemic recession.

There are slight differences between the counterfactual scenario for the no physical presence index and the actual decline in hours, as shown in lines (1) and (2) of the table. For the remote communications index, instead, the increase in the ability of remote work prevented a further decline in hours of 0.9 percentage points (pp) in 2020Q1 and of 5.6 pp in 2020Q2.

While the "remote communications" counterfactual points to a stronger rebound in hours starting in the third quarter, the level of the hours index for remote jobs based on the July 2004 data tracks a touch below the observed trend in hours over that period.

All told, our analysis suggests that the ability of working remotely has had a meaningful impact on aggregate hours during the pandemic, although the effect could reflect either an increase in the ability of working remotely with the adoption of remote communications and or a switch to remote work for those occupations requiring no physical presence.

The significant decline in hours during the pandemic has affected the pattern of GDP growth, shown in line (4). Naturally, the divergence between hours and GDP growth reflects the impact of productivity growth, another important dimension in the analysis of the ability of working remotely. While the evidence on the effect of remote work on productivity is mixed, our results point to the significant contribution of the ability to work remotely to the hours margin.[17] The two indexes display a very different evolution in how many jobs can be performed at home. However, either because our ability to work remotely has significantly

[17] The seminal work by Bloom at al. (2015) point to productivity gains associated with remote work since it would allow workers to better organize business and home tasks. Yet, using Japanese survey data, Morikawa (2020) finds that productivity in June 2020 was only about 60% to 70% of what it was in the workplace in June 2019.

increased over the past two decades or because the pandemic has prompted an acceleration towards telecommuting, the resulting gains in hours from remote work will likely persist, contributing to a higher level of GDP.

References

Bartik, A. W., Z. B. Cullen, E. L. Glaeser, M. Luca, and C. T. Stanton (2020), What jobs are being done at home during the Covid-19 crisis? Evidence from firm-level surveys, *NBER Working Paper n. 27422*.

Bloom, N., J. Liang, J. Roberts and Z. J. Ying (2015), Does working from home work? Evidence from a Chinese experiment, *Quarterly Journal of Economics, Vol.* 130, pag. 165–218.

Bureau of Labor Statistics (2020), Current Population Survey, available at https://www.census.gov/programs-surveys/cps/data/datasets.html

Bureau of Labor Statistics (2020), Occupational Employment Statistics, available at https://www.bls.gov/oes/tables.htm

Brynjolfsson E., J.J. Horton, A. Ozimek, D. Rock, G. Sharma, and H.Y. TuYe (2020), COVID-19 and remote work: an early look at US data, *NBER Working Paper n. 27344*.

Dingel, J. and B. Neiman (2020), How many jobs can be done at home?, *Journal of Public Economics,* Vol. 189.

Mas, A. and A. Pallais (2020), Alternative work arrangements, *Annual Review of Economics, Vol.* 12, pag. 631–658.

Mongey, S. and Weinberg, A. (2020), Characteristics of workers in low work-from-home and high personal-proximity occupations. *Becker Friedman Institute for Economic White Paper*.

Montenovo L., X. Jiang, F.L. Rojas, I.M. Schmutte, K.I. Simon, B.A. Weinberg, and C. Wing (2020), Determinants of disparities in COVID-19 job losses, *NBER Working Paper n. 27132*.

Morikawa, M. (2020), Productivity of working from home during the COVID-19 pandemic: Evidence from an employee survey, *Covid Economics, Vol.* 49, pag. 123–147.

Occupation Information Network Center, (2022), O*Net Database, available at https://www.onetcenter.org/database.html.

Shimer, R. (2012), Reassessing the Ins and Outs of Unemployment, *Review of Economic Dynamics*, 15(2), pp. 127-148.