The Ability to Work Remotely: Measures and Implications

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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.[2] The switch is even more remarkable if considering that through early 2020 the share of people who worked from home across various surveys had remained remarkably stable at relatively low levels; furthermore, this switch could point to significant changes in the potential of remote work.[3] 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.[4] 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*".[5]

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 2020. We then match those indexes with Bureau of Labor Statistics (BLS) data from the Current Population Survey (CPS) to measure the significance of remote work in overall employment.

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[1] 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.

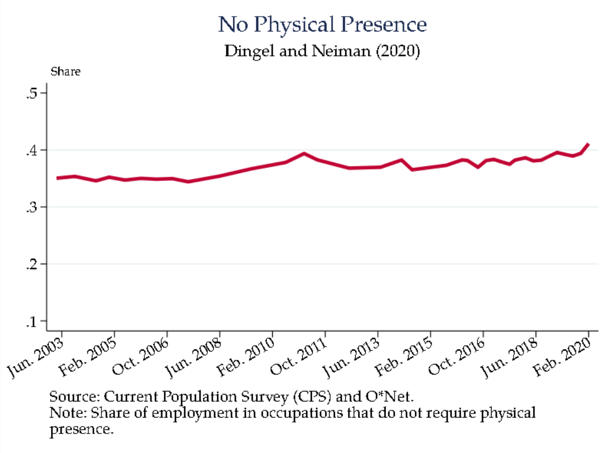
[2] See Bartik et al. (2020) and Brynjolfsson et al. (2020)

[3] See Mas and Pallais (2020).

[4] In Dingel and Neiman (2020), a job cannot be performed at home if *either* the average respondent indicates that he/she is 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* 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.

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

Figure 1. Measuring the Ability to Work Remotely



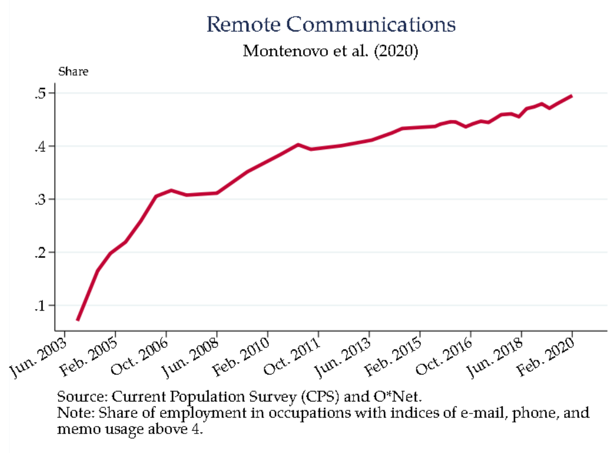


Figure 1 describes the evolution of employment shares in remote occupations according to the no physical presence (left panel) and the remote communications (right panel) indexes. The two indexes present very different evolutions. While the no physical presence index has remained relatively constant, the remote communications index has gradually increased over time, gaining more than 40 percentage points in terms of employment shares relative to July 2003.[6,7] Looking at the more recent history, the discrepancies between the two indexes appear more contained. Occupations that require no physical presence represented about 42 percent of CPS employment in February 2020, while the share of employment in occupations characterized by remote communications was a little higher, reaching almost 50 percent before the pandemic recession.[8]

Next, we explore demographic correlates of remote work. Figure 2 focuses on three main characteristics: race and ethnicity, age, and education level. 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 appear fairly close.[9] All told, the average disparities across demographic groups appear relatively similar for each measure.

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[6] Using the OES data, 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.

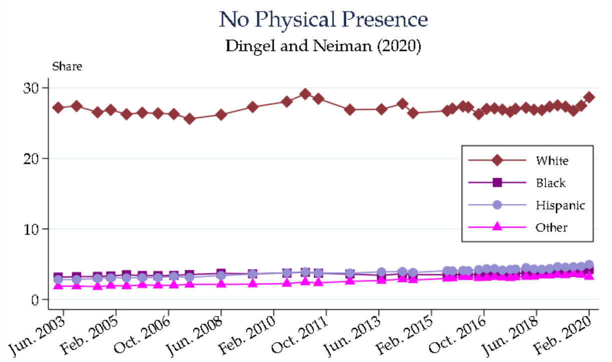
[7] The gradual evolution of remote work observed in the remote communications measure appears roughly consistent with CPS Supplement data from 2004, which sets the share of remote employment at 15 percent.

[8] Dingel and Neiman (2020) match the remote index with the Occupational Employment Statistics and estimate that 37 percent of workers are employed in remote occupations according to their definition.

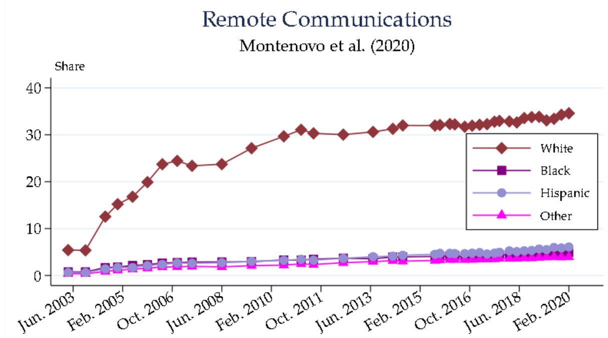
[9] Our results are shown in figure A1; the figure also points to a recent uptick in remote work among women.

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

Figure 2a: Race and Ethnicity

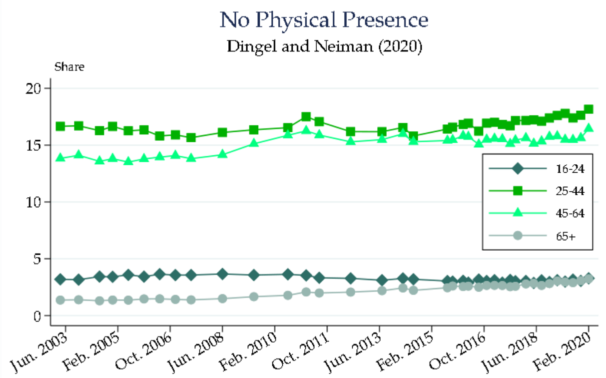


Source: Bureau of Labor Statistics.
Note: Employment shares by race and ethnicity in occupations that do not require physical presence. Other denotes Asian, American Indian or Alaska Native, and Native Hawaiian or Other Pacific Islander.

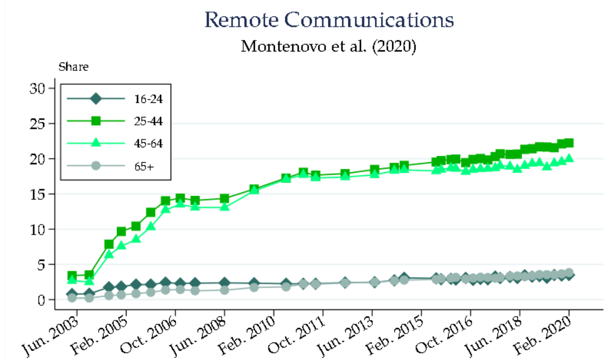


Source: Bureau of Labor Statistics.
Note: Employment shares by race and ethnicity in occupations characterize by a high ability of working remotely, that is, by indices of e-mail, phone, an memo usage above 4. Other denotes Asian, American Indian or Alaska Nati and Native Hawaiian or Other Pacific Islander.

Figure 2b: Age

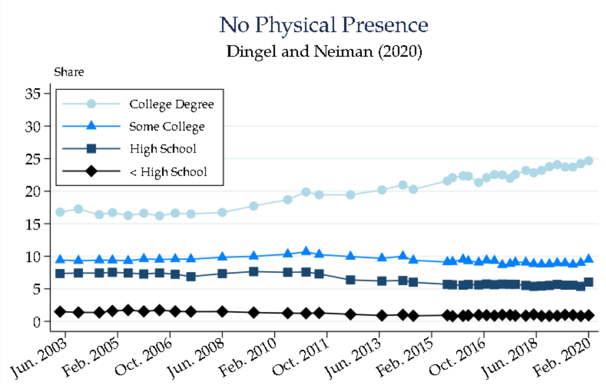


Source: Bureau of Labor Statistics.
Note: Employment shares by age in occupations that do not require physical presence.

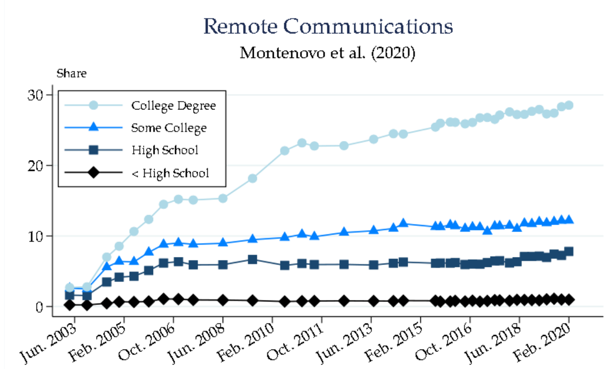


Source: Bureau of Labor Statistics.
Note: Employment shares by age in occupations characterized by a high ability of working remotely, that is, by indices of e-mail, phone, and memo usage above 4.

Figure 2c: Education Level



Source: Bureau of Labor Statistics.
Note: Employment shares by education in occupations that do not require physical presence.



Source: Bureau of Labor Statistics.
Note: Employment shares by education in occupations characterized by a high ability of working remotely, that is, by indices of e-mail, phone, and memo usage above 4.

Looking at their evolution, the static nature of the aggregate no physical presence index transpires across all demographic groups except for college-educated workers. 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 occupation—in addition to worker selection into remote occupations.

Beside variation associated with demographic characteristics, occupations with the ability to work remotely also differ in terms of labor market outcomes: Table 1 explores differences in employment status, while figure 3 and table 2 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 unemployed. The magnitude of the effect is slightly lower after controlling for worker observables—including demographic characteristics, important correlates of remote work—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 point to significant differences.

Table 1: Remote Work and Unemployment Probability

	(1)	(2)	(3)	(4)	(5)	(6)
Variables			Unemployed$_t$			
No Physical Presence$_t$	-0.020***	-0.007**	-0.006*			
	(0.004)	(0.003)	(0.003)			
Remote Comm$_t$				-0.033***	-0.017***	-0.017***
				(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.	55,485	55,485	55,485	2,008,383	2,008,383	2,008,383
R-squared	0.003	0.023	0.027	0.009	0.032	0.039

Source: O*Net and CPS.

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

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

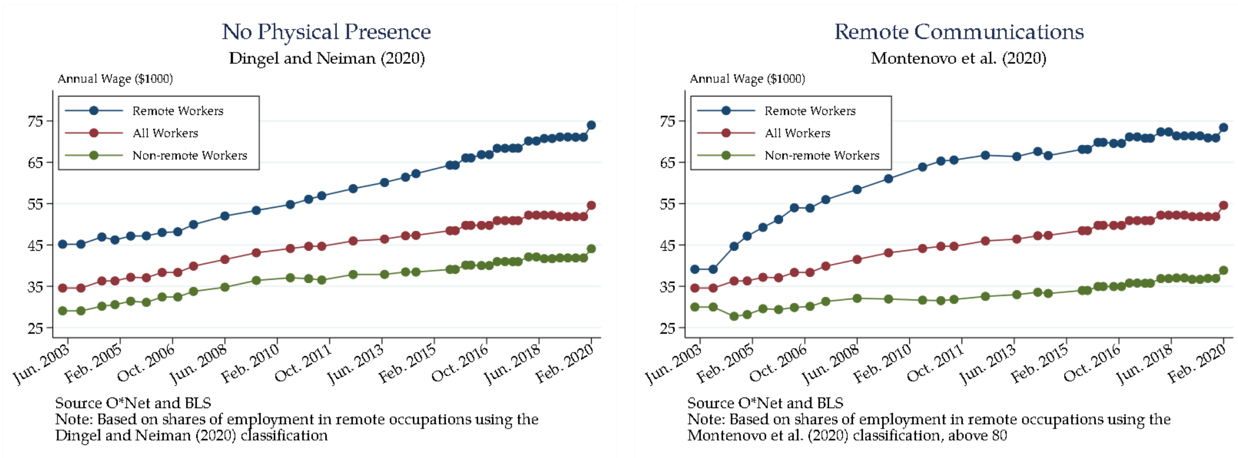
Physical Presence$_t$: indicators equal to 1 for occupations that do not require physical presence.

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 state-date and industry-date fixed effects. Robust standard errors, clustered at the occupation level, are reported in parenthesis.

Moving to wages, figure 3 highlights large aggregate differences in average wages across remote and non-remote occupations by either index. Those who are able to work remotely have higher annual wage outcomes, with some slight differences across the indexes. Among main differences, the remote communications index shows a persistently wider gap than the no physical presence index, partly reflecting very anemic growth in non-remote worker's wages for the former measure.

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



To control for the variation in hours across occupations, table 2 summarizes differences in hourly wages for remote relative to 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 a 35 percent of a sd higher hourly wage.[10]

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

Table 2: Remote Work and Wage Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Variables			Log Hourly Wage$_t$			
No Physical Presence$_t$	0.341***	0.137***	0.100***			
	(0.061)	(0.041)	(0.038)			
Remote Comm$_t$				0.516***	0.273***	0.224***
				(0.054)	(0.038)	(0.035)
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.	11,672	11,672	11,672	419,389	419,389	419,389
R-squared	0.065	0.334	0.374	0.154	0.366	0.415

Source: O*Net and CPS.

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

Remote Comm$_t$: indicator equal to 1 for occupations that require high use of e-mails, memos, and telephone.
Physical Presence$_t$: indicators equal to 1 for occupations that do not require physical presence.
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 state-date and industry-date fixed effects. Robust standard errors, clustered at the occupation level, are reported in parenthesis.

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 table 1 and 2 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 capture the impact of remote work during the pandemic using an interaction between our indexes and an indicator variable equal to one during March and April 2020.

Table 3: Remote Work and Probability of Being Unemployed during the Pandemic

	(1)	(2)	(3)	(4)	(5)	(6)
Variables			Unemployed$_t$			
No Physical Presence$_t$	-0.029***	-0.012**	-0.006			
	(0.007)	(0.005)	(0.005)			
No Physical Presence$_t$ * Pandemic$_t$	-0.018***	-0.018***	-0.014***			
	(0.005)	(0.005)	(0.004)			
Remote Comm$_t$				-0.054***	-0.039***	-0.035***
				(0.006)	(0.005)	(0.005)
Remote Comm$_t$ * Pandemic$_t$				-0.030***	-0.031***	-0.027***
				(0.005)	(0.005)	(0.005)
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.	866,974	866,974	866,974	865,731	865,731	865,731
R-squared	0.004	0.037	0.059	0.013	0.042	0.063

Source: O*Net and CPS.

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

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

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

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

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 state-date and industry-date fixed effects. Robust standard errors, clustered at the occupation level, are reported in parenthesis.

Our results are shown in tables 3 and 4. 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. However, 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 gain.

Table 4: Remote Work and Wages during the Pandemic

	(1)	(2)	(3)	(4)	(5)	(6)
Variables			Log Hourly Wage$_t$			
No Physical Presence$_t$	0.317***	0.120***	0.087**			
	(0.058)	(0.038)	(0.035)			
No Physical Presence$_t$ * Pandemic$_t$	-0.006	0.003	0.003			
	(0.012)	(0.010)	(0.010)			
Remote Comm$_t$				0.468***	0.251***	0.225***
				(0.048)	(0.030)	(0.026)
Remote Comm$_t$ * Pandemic$_t$				-0.011	0.008	0.008
				(0.011)	(0.010)	(0.010)
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	182,335	182,335	182,335	182,051	182,051	182,051
R-squared	0.056	0.303	0.336	0.136	0.325	0.354

Source: O*Net and CPS.

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

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

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

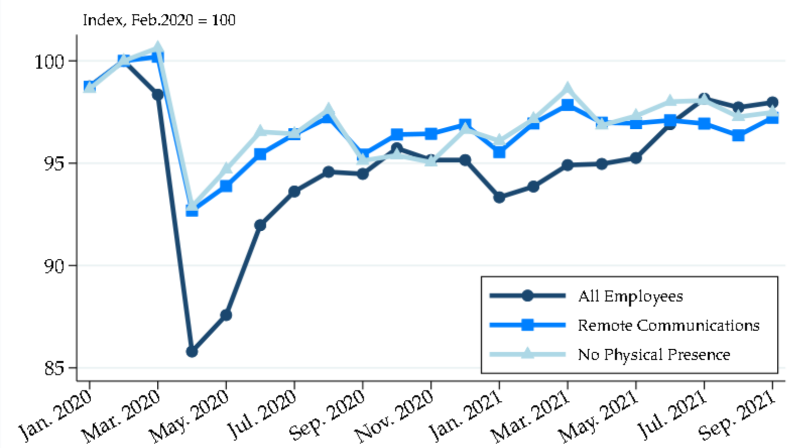
Physical Presence$_t$: indicators equal to 1 for occupations that do not require physical presence.

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 state-date and industry-date fixed effects. Robust standard errors, clustered at the occupation level, are reported in parenthesis.

The differential employment outcomes for remote occupations are also reflected in the decline in hours observed in the recent pandemic. Figure 4 compares the decline in hours across all occupations, across those characterized by remote communications, and across those requiring no physical presence. Consistent with the findings in table 3, remote occupations by either index experienced a significantly smaller decline over the two months of the pandemic recession; as a result, the recovery in remote occupations appears more gradual, but the level of hours at occupations requiring no physical presence or characterized by remote communications remains above the number 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 remote workers in the current post-pandemic period

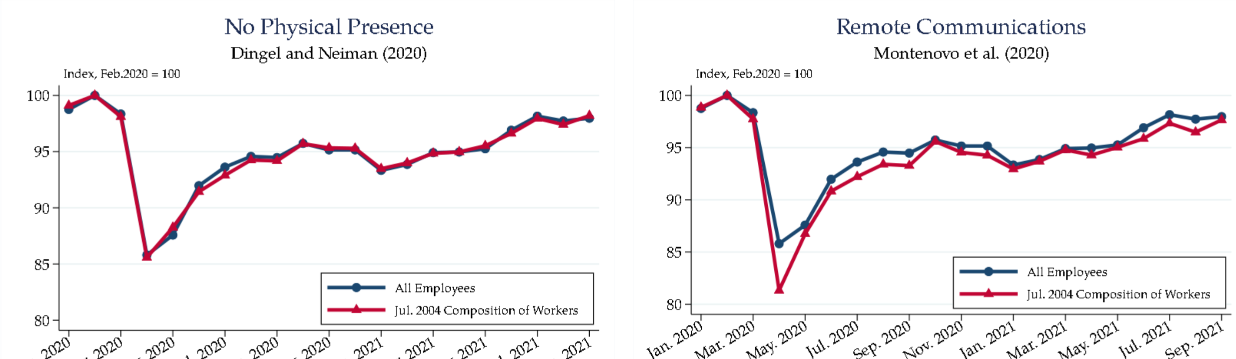
Figure 4: Impact on Hours during the Pandemic Recession



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.

Second, we look at the counterfactual declines in hours had the ability of working remotely for each occupation remained at the same levels as in July 2004. Specifically, for each occupation with the ability to work remotely in February 2020 but not in July 2004, we impute the average decline in hours of non-remote occupations and look at the impact in the decline in total hours for this counterfactual scenario. The results for this exercise are shown in figure 5, with the left panel focusing on the index of no physical presence, while the right panel display the effect of the index of remote communications.

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 5 summarizes our results and includes a comparison with the overall impact on hours and GDP in 2020.

Table 5. 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 Presence	-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, 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 counterfactual points to a stronger rebound in hours starting in the third quarter, the hours index with remote classification based on the July 2004 data continues to track a touch below the actual hours.

The significant decline in hours has been reflected in the pattern of GDP growth, also shown in line (4). Naturally, the divergence between hours and GDP growth point to 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.[11] The two indexes display a very different evolution in how many jobs can be performed at home, but either because our ability of working remotely has significantly 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 continue to boost GDP growth going forward.

References

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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* 130: 165–218.

[11] 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.

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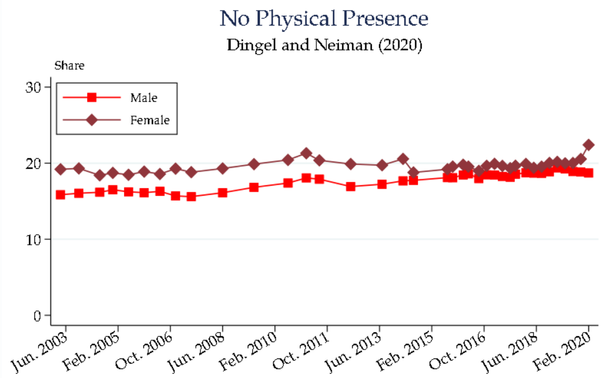
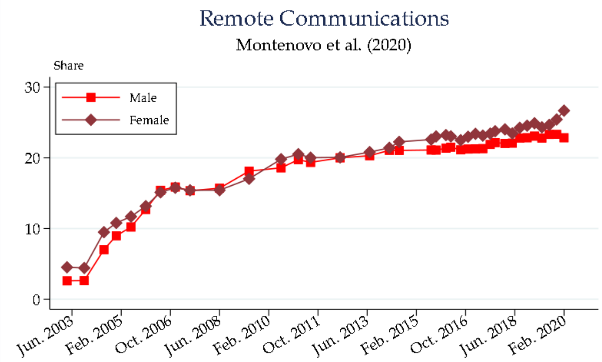
Morikawa, M (2020), “Productivity of working from home during the COVID-19 pandemic: Evidence from an employee survey”, *Covid Economics* 49: 123–139.

Appendix

Figure A1: Ability to Work Remotely by Gender



Source: Bureau of Labor Statistics.
Note: Employment shares by gender in occupations that do not require physical presence.



Source: Bureau of Labor Statistics.
Note: Employment shares by gender in occupations characterized by a high ability of working remotely, that is, by indices of e-mail, phone, and memo usage above 4.