The Adverse Effect of the COVID-19 Labor Market Shock on Immigrant Employment: Online Appendix

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1. Measuring Remotability

This appendix describes the procedure used to arrive at our index that measures the difficulty of working remotely. We make use of two O*NET surveys: Work Context and Work Activities. The Work Context survey provides data on the frequency that a worker uses the telephone or email (never, once a year, once a month, once a week, or daily). For each attribute, we use the weighted average score, where never = 1 and daily = 5. Hence, each Work Context attribute in the O*NET has a score from 1 to 5. The attributes in the Work Activities survey include, for example, the analysis of data or information. We use the importance (as opposed to level) of each attribute which, like the work context attributes, is scored from 1 (low) to 5 (high). Thus, from the O*NET, for each occupation we have a measure of each attribute's importance ranging from 1 to 5.

Assigning the O*NET tasks to the CPS requires several steps, due to differences in occupational coding schemes. The O*NET uses Standard Occupational Classification (SOC) codes, whereas the CPS uses Census occupation codes. Furthermore, starting in January 2020, the CPS began using the 2020 Census occupation codes, which are a non-trivial break from the codes used in pre-2019 surveys. Further, although the IPUMS also codes a worker's occupation using the 1990 Census codes (i.e. the "*occ1990*" variable), this variable is not currently available in the 2020 CPS.

We proceed in two steps. We first use the 2013-2017 ACS, which include occupation coded using both the Census codes and the SOC codes, and merge the ACS data with the occupational attributes from the O*NET, using the SOC codes. Unfortunately, for some workers, the Census masks up to four of the final digits of the occupation. For example, occupation 514XXX includes occupations 514035, 514081, 514192, 514199, and refers to miscellaneous metal plastic workers. A worker in the ACS who is actually in occupation 514035 would, therefore, show up with the occupation code 514XXX. We address this issue by aggregating occupations, taking the average across the occupations of each attribute from the O*NET, and repeating this process at four levels of aggregation. So, for example, to match workers coded in the ACS with an SOC occupation 514XXX, we aggregate up three levels to 514, where the O*NET attributes for this aggregated occupation code are calculated by averaging across all occupations that begin with 514. When merging the O*NET with the ACS, we prioritize the highest level of granularity possible; for example, occupation 514194 has no masked digits, and so is merged with the O*NET at the full six-digit level. For occupations not matched at the six-digit level, we try to match at the five-digit level, then at the four-digit level, etc., until all workers are matched.

This procedure yields an ACS data file where each worker has been assigned their occupation attributes from the O*NET. We then take the average of each attribute by the Census occupation code. We keep a single observation for each Census occupation code, which we merged with the 2019 Basic Monthly CPS.

In order to assign the attributes to individuals in the 2020 Basic Monthly CPS, we make use of individuals observed during the transition between the two occupational coding schemes, i.e., persons observed in both December 2019 and January 2020. Workers in these months have occupational characteristics from the O*NET in December 2019 (prior to the occupational coding change), but not in January 2020 (after the coding change). We include only individuals who are employed in both months. We take these workers' January 2020 occupation code and assign it to December 2019. We then take the average, by 2020 Census occupation code, of their occupational attributes. The procedure yields, for each 2020 Census occupation code, a measure of the occupational attributes, which we then apply to the January to April 2020 monthly files. Note that this procedure assumes that workers did not change jobs between December 2019 and January 2020, and thus did not change occupation codes. This assumption, of course, is invalid in some cases. However, because we are averaging across workers and occupational mobility is likely to be small from month to month, the bias is likely to be small.

Our goal is to use the occupational attributes from the O*NET to develop a measure that captures the ease with which a worker in an occupation can work remotely. While the O*NET includes a rich set of occupational attributes, we want to simplify our analysis by grouping occupations into the opportunities for remote work. We use four measures that we believe would reasonably be positively related to the opportunities for remote working: Telephone (4.C.1.a.2.f), Electronic Mail (4.C.1.a.2.h), Analyzing Data or Information (4.A.2.a.4), and Interacting With Computers (4.A.3.b.1).

We reduce these four attributes to a single measure using principal component analysis and extracting the first component, which is commonly used in the occupational task literature, e.g. Yamaguchi (2012, Journal of Labor Economics) and Cassidy (2019, Journal of Human Capital). This yields a single index that (presumably) measures remote workability. The index is standardized to have a mean of zero, and a standard deviation of one in the 2019-2020 Basic Monthly CPS.

2. Alternative Definition of Employment

The unprecedented labor demand shock resulting from the COVID-19 pandemic has led to concerns about whether employment status was properly coded in the CPS during the pandemic. In fact, the unusual circumstances of the economic slowdown and lockdown led to a very large increase in the number of persons classified as: "has job, not at work last week." Referring to the April 2020 Basic Monthly File, a BLS (2020) document explains:

> "Other than those who were themselves ill, under quarantine, or self-isolating due to health concerns, people who did not work during the survey reference week (April 12–18) due to efforts to contain the spread of the coronavirus should have been classified as 'unemployed on temporary layoff.' However, as happened in March, some people who were not at work during the entire reference week were not included in this category. Instead, they were misclassified as employed but not at work."[1]

Table A0 shows the magnitude of the measurement problem by reporting the weighted counts of persons for the various categories in the employment variable "*empstat*" in the Basic

[1] U.S. Bureau of Labor Statistics. May 8, 2020. "Frequently Asked Questions: The Impact of the Coronavirus (COVID-19) Pandemic on The Employment Situation for April 2020." Additional details are given in the IPUMS website, https://cps.ipums.org/cps/covid19.shtml.

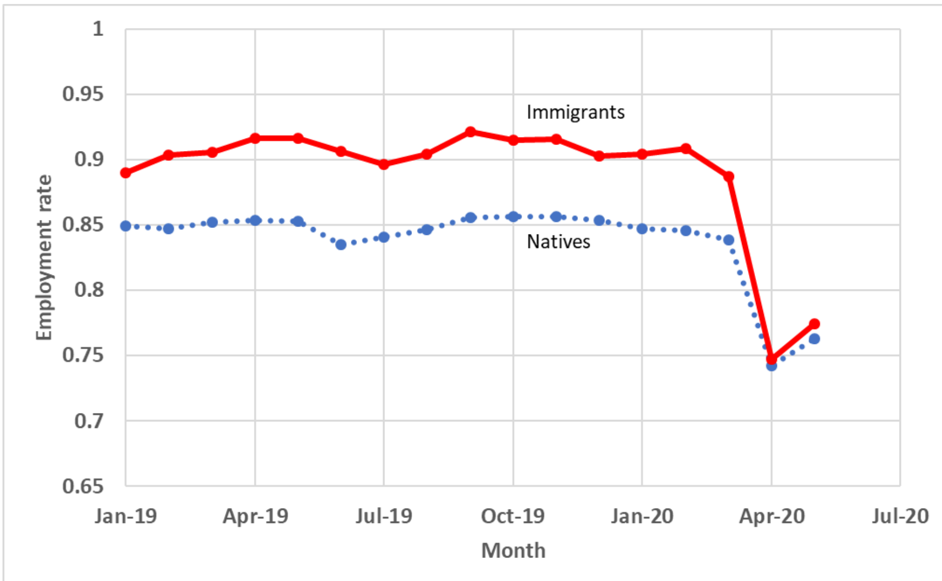
Monthly Files of 2020. Note the very large increase in the number of persons coded as “has job, not at work last week” during the pandemic months.

The analysis reported in our paper classifies a person as employed if he or she is “at work” in the CPS reference week. As a robustness check, this appendix replicates all the results from the paper, but we instead classify a person as employed if he or she is either “at work” or “has job, not at work last week.” The alternative sets of results are presented in Figures A1-A3 and Tables A1-A2.

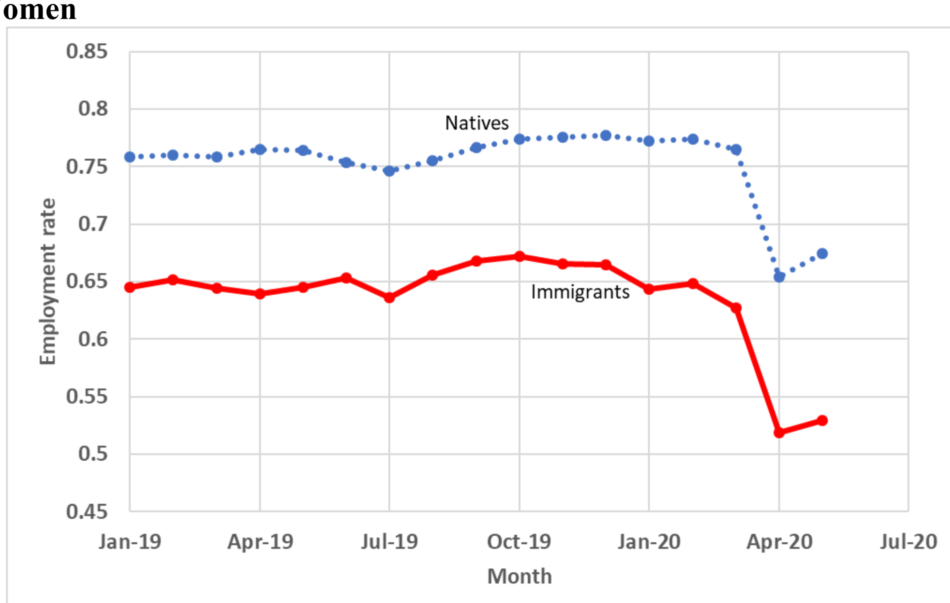
Given this broader definition of being employed, the data naturally reveal higher employment rates and less job loss in both the pre-pandemic and pandemic periods. However, our results are qualitatively unchanged. Immigrants still experienced greater job loss during the pandemic that cannot be explained by demographic characteristics, but can partly be explained by the industry and occupational differences between natives and immigrants prior to the pandemic, notably occupational remotability.

Figure A1. Employment rates in Basic Monthly CPS, January 2019-April 2020 (using broader definition of being employed)

A. Men



B. Women

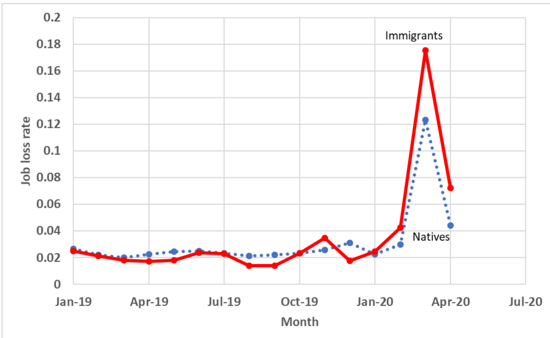


Notes: All samples consist of persons aged 18-64 who are not enrolled in school. A person is classified as employed if he or she is either "at work" or "has job, but not at work last week."

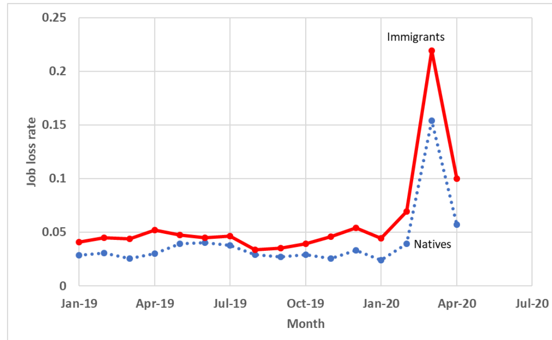
Figure A2. The job loss and job-finding rates, January 2019-May 2020 (using broader definition of being employed)

A. Job loss rate

Men

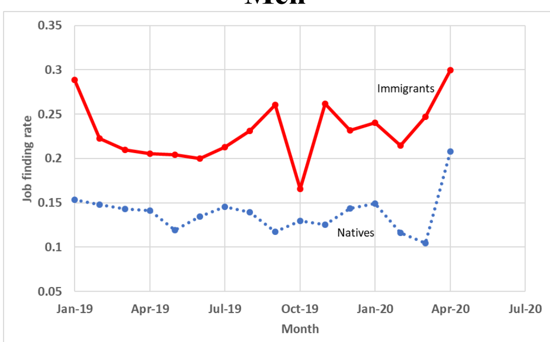


Women

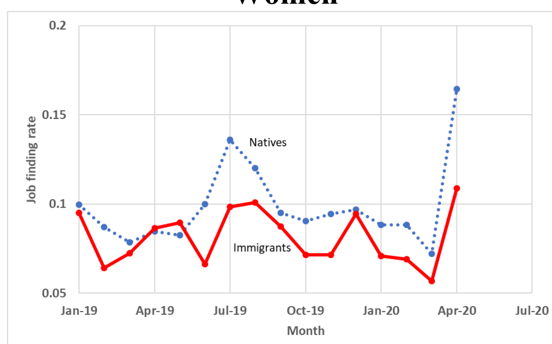


B. Job-finding rate

Men



Women



Notes: The job loss rate gives the fraction of persons who were employed at time *t* but were not employed at time *t*+1. The job-finding rate gives the fraction of persons who were not employed at time *t* but were employed at time *t*+1. The sample consists of persons who can be matched across two consecutive CPS files.

Figure A3. Job loss and the remotability of work (using broader definition of being employed)

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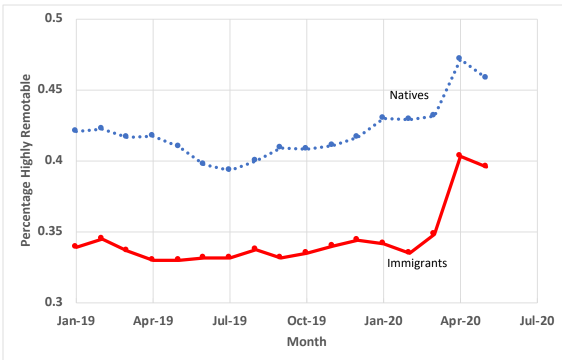
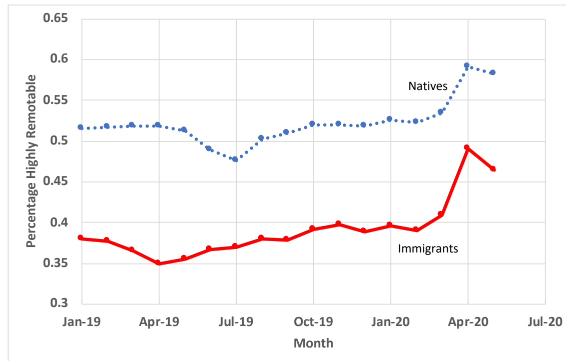
A. Employment in high-remotability jobs

Men

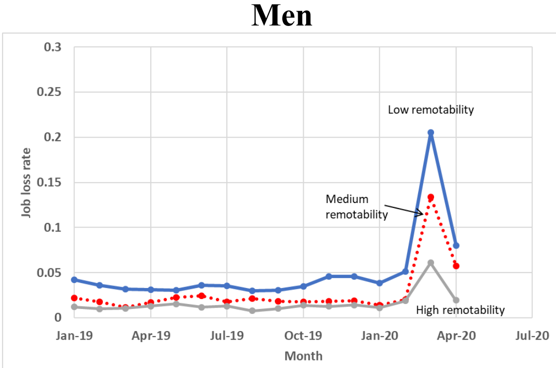


Women

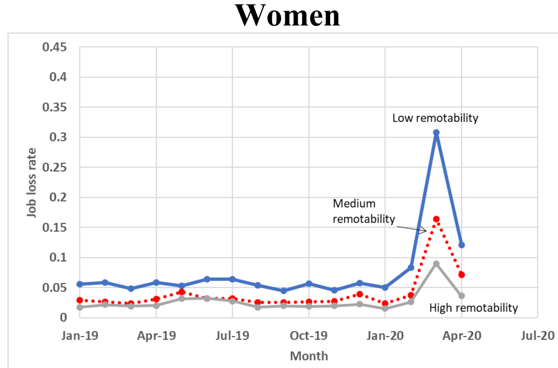


B. Job loss rate, by degree of remotability

Men



Women



Notes: The job loss rate gives the fraction of persons who were employed at time *t* but were not employed at time *t*+1. The sample consists of persons who can be matched across two consecutive CPS files. The remotability index uses data from O*NET to measure the ease with which a job can be performed from a remote setting; see text for details on the construction of the index.

Table A0. Weighted number of adult persons by employment status, January-May 2020 (in millions)

Employment status	January	February	March	April	May
At work	106.2	106.0	103.1	85.6	91.4
Has job, not at work last week	2.5	2.6	3.9	7.3	5.4
Unemployed, experienced worker	4.3	4.3	4.9	15.1	13.6
Unemployed, new worker	0.3	0.3	0.2	0.2	0.2
Not in labor force, unable to work	5.7	5.7	5.6	5.6	5.6
Not in labor force, other	14.6	14.7	15.6	20.2	19.2
Not in labor force, retired	1.7	1.5	1.5	1.6	1.9
Total	135.4	135.1	134.9	135.6	137.2

Notes: The counts are estimated in the sample of persons aged 18-64, who are not enrolled in school and are not in the Armed Forces.

Table A1. Panel regressions on month-to-month conditional probability of job loss (using broader definition of being employed, January 2019-May 2020)

	Men				Women			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	-0.003	-0.006	-0.009	-0.007	0.013	0.007	0.003	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
× Feb 2020	0.016	0.009	0.005	0.007	0.016	0.018	0.015	0.014
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
× March 2020	0.055	0.055	0.037	0.046	0.052	0.049	0.033	0.027
	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.013)
× April 2020	0.031	0.026	0.028	0.024	0.030	0.029	0.026	0.025
	(0.008)	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
Remotability index				-0.007				-0.009
				(0.000)				(0.001)
× Feb 2020				-0.004				-0.013
				(0.002)				(0.003)
× March 2020				-0.039				-0.070
				(0.004)				(0.006)
× April 2020				-0.010				-0.018
				(0.003)				(0.004)
Includes:								
Education, age	No	Yes	Yes	Yes	No	Yes	Yes	Yes
State, metropolitan status	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry	No	No	Yes	No	No	No	Yes	No
Occupation	No	No	Yes	No	No	No	Yes	No

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is set to unity if the person was employed at time *t* but was not employed at time *t*+1, and zero otherwise. The remotability index is defined to have zero mean and unit variance. All independent variables are interacted with observation period, where four periods are included: 1) pre-pandemic (Jan 2020 and earlier); 2) February 2020; 3) March 2020; and 4) April 2020. All specifications also include controls for calendar month. The regressions in the male (female) sample have 206,635 (181,061) observations.

Table A2. Undocumented immigration and the conditional probability of job loss (using broader definition of being employed)

Variable	Men				Women			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	-0.015	-0.020	-0.035	-0.021	0.037	0.018	0.011	0.017
	(0.009)	(0.010)	(0.012)	(0.010)	(0.016)	(0.017)	(0.019)	(0.017)
× Pandemic	0.069	0.060	0.053	0.051	0.021	0.023	0.009	0.000
	(0.022)	(0.022)	(0.025)	(0.022)	(0.029)	(0.029)	(0.030)	(0.029)
Undocumented Immigrant	0.009	-0.016	-0.007	-0.017	0.034	0.010	0.041	0.008
	(0.016)	(0.017)	(0.021)	(0.017)	(0.035)	(0.036)	(0.041)	(0.035)
× Pandemic	0.067	0.068	0.020	0.057	0.012	-0.007	-0.011	-0.008
	(0.043)	(0.042)	(0.043)	(0.041)	(0.061)	(0.061)	(0.067)	(0.061)
Education, age	No	Yes	Yes	Yes	No	Yes	Yes	Yes
State, metropolitan status	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry	No	No	Yes	No	No	No	Yes	No
Occupation	No	No	Yes	No	No	No	Yes	No
Remotability index	No	No	No	Yes	No	No	No	Yes

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The pre-pandemic period covers the period between December 2019 to February 2020. The pandemic period covers from March 2020 to May 2020. The dependent variable is set to unity if the (initially employed) person lost a job during the relevant period. All independent variables are interacted with the two period fixed effects. The regressions in the male (female) sample have 8,184 (7,477) observations.