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ABSTRACT

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Employment rates in the United States fell dramatically between February 2020 and April 2020 as the initial repercussions of the COVID-19 pandemic reverberated through the labor market. This paper uses data from the CPS Basic Monthly Files to document that the employment decline was particularly severe for immigrants. Historically, immigrant men were more likely to be employed than native men. The COVID-related labor market disruptions eliminated the immigrant employment advantage. By April 2020, immigrant men had lower employment rates than native men. The reversal occurred both because the rate of job loss for at-work immigrant men rose relative to that of natives, and because the rate at which out-of-work immigrants could find jobs fell relative to the native job-finding rate. A small part of the relative increase in the immigrant rate of job loss arises because immigrants were less likely to work in jobs that could be performed remotely and suffered disparate employment consequences as the lockdown permitted workers with more "remotable" skills to continue their work from home.

JEL Classification: J21, J61

Keywords: immigration, labor supply, COVID-19

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

George J. Borjas and Hugh Cassidy*

1. Introduction

Within a period of less than 2 months, the COVID-19 pandemic produced dramatic and historic aftershocks throughout the U.S. labor market. In December 2020, the unemployment rate stood at a near-record low of 3.5 percent (a level not seen since the early 1950s), and the number of persons in the workforce stood at a record high of 158.8 million. The first positive COVID-19 test result in the United States (in the state of Washington) was not confirmed until February 21, 2020. In New York City, which would soon become an epicenter of the pandemic, the first positive test result was not confirmed until February 23. The first (reported) COVID-related death occurred near Seattle on February 29. The situation deteriorated very quickly and dramatically after that.

Federal, state, and local governments reacted to the spread of the COVID-19 virus by adopting measures that "paused" economic activity in many sectors. The economic lockdown had swift employment repercussions. The weekly number of new claims for unemployment benefits had hovered at slightly above 200,000 in February and January 2020 (as it had throughout the entire 2019 calendar year). This number, however, increased dramatically to a historic high of 3.3 million in the week ending March 21 and skyrocketed to 6.9 million in the week ending March 28. During the month of April 2020, 20.1 million additional workers filed

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for jobless claims.[1] Not surprisingly, the unemployment rate rose steeply to 14.7 percent by April 2020, a level of unemployment not witnessed since the Great Depression.

The pandemic-related economic pause and lockdown differentially affected the employment opportunities of persons working in different sectors. Workers whose jobs could be performed remotely from home, such as teachers and customer support specialists, continued to work from their home office. Workers who provided essential services, such as health care professionals and grocery store clerks, continued their usual work routine. But job opportunities for many other workers outside these protected groups quickly evaporated.

This rapid and historic change in differential employment opportunities ensure that a great deal of research will be conducted as we attempt to understand the consequences of the labor market disruptions sparked by the pandemic.[2] This paper contributes to the literature by focusing on how the labor market shock differentially affected immigrants and natives.

Immigrants make up an increasingly important fraction of the U.S. workforce. In 1980, immigrants comprised only 6.6 percent of the workforce. By 2019, the immigrant share had risen to 17.6 percent. It is well known that immigrants have historically had different employment rates than their native-born counterparts (Borjas, 2017; Nekoei, 2013). Figure 1 illustrates the long-term trend in the employment rates of various groups using data from the Annual Social and Economic Supplement (ASEC) Files of the Current Population Surveys (CPS). Between 2000 and 2005, the employment rate of immigrant men was 5-10 percentage points *higher* than that of native men. The immigrant-native gap remained even during the Great Recession that

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[1] These data are available at https://oui.doleta.gov/unemploy/claims.asp.

[2] The work, in fact, has already started. See Cajner et al (2020) for a study in the American context and Von Gaudacker et al (2020) for an examination of the Netherlands experience. Other studies that look at impacts outside the labor market include Bergen, Herkenhoff, and Mongey (2020), Borjas (2020), Chatterji and Li (2020), and Lang, Wang, and Yang (2020).

followed the financial crisis of 2008. Although the employment rate of both groups declined, the immigrant employment advantage was still over 10 percentage points in 2010. By 2019, at the peak of the economic boom, the immigrant employment advantage was about 6 percentage points.

The figure also shows that immigrant women have historically had *lower* employment rates than their native counterparts. This employment disadvantage has remained roughly constant in the past decade. It was 12 percentage points at the bottom of the Great Recession in 2010 and 11 percentage points at the peak of the economic boom in 2019.

Our analysis uses data from the CPS Basic Monthly files to document the disproportionately adverse impact that the initial phase of the COVID-19 pandemic had on the employment of immigrants. Not surprisingly, the employment rate of both natives and immigrants declined dramatically as the aftershocks of the pandemic spread through the labor market. The adverse employment effect, however, was far larger for foreign-born workers. The employment advantage that immigrant men had enjoyed over the last two decades not only disappeared but was, in fact, reversed. By April 2020, the employment rate of immigrant men was about 2 percentage points lower than that of native men.

We also exploit the panel nature of the Basic Monthly files to track the employment opportunities of specific workers over time. This tracking allows us to calculate the rates of job loss and job finding for immigrants and natives. The panel analysis illustrates that the relative rate of job loss increased dramatically for (initially employed) immigrants between January and April 2020, while the relative probability of finding work declined dramatically for (initially out-of-work) immigrants.

Part of the adverse employment effect that the COVID-19 labor market shock had on immigrant employment can be traced to the fact that immigrants and natives tend to do different jobs. Immigrants are less likely to be employed in jobs that can be done remotely and suffered accordingly as the economic lockdown allowed workers with “remotable” skills to work from home. The difference in the types of jobs that immigrants and natives perform, however, only explains about a third of the relative decline in immigrant employment opportunities in the first few months of 2020.

2. Data and descriptive evidence

Our analysis of how the COVID-19 pandemic differentially affected employment opportunities for natives and immigrants uses the CPS Basic Monthly files, downloaded from the Integrated Public Use Microdata Series (IPUMS) (Flood et al, 2020). Throughout the analysis, we analyze the subsample of persons who are 18-64, are not enrolled in school, and are not in the Armed Forces.

We begin by illustrating the monthly trend in the employment rate (by gender) between January 2019 and April 2020 for immigrants and natives.[3] As suggested by our earlier discussion, Figure 2 shows that immigrant men were more likely to be employed than native men throughout 2019, while immigrant women were less likely to be employed than native women.

[3] The employment rate is given by the fraction of the relevant population that is working. Our definition of “work” is based on a person’s employment status in the reference week of the Basic Monthly sample. In particular, we use the IPUMS variable reporting a person’s employment status (*empstat*) and classify a person as working if he or she is “at work.” The unusual circumstances of the economic slowdown and lockdown resulting from the COVID-19 pandemic led to a very large increase in the number of persons classified as: “has job, not at work last week.” 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.”

Note that the employment paths for immigrants and natives (for each gender) tend to be roughly parallel through calendar year 2019, with all groups experiencing the same seasonal decline in employment during the summer months.

The long-term employment advantage among immigrant men, however, changed drastically as a result of the employment losses resulting from the COVID-19 pandemic. The data reveal a somewhat steeper decline in the employment rate of immigrant men, from 88.6 to 85.3 percent between February and March 2020. This contrasts with the smaller drop of 1.4 percentage points for native men in the same period (the native employment rate fell from 82.9 to 81.5 percent). The decline in the employment rate of immigrant men accelerated between March and April, with the employment rate of immigrant men falling by a dramatic 18 percentage points, as compared to the 12-point drop for natives. In fact, the decline in immigrant employment was so precipitous that April 2020 became the first month in the 21st century in which the employment advantage long enjoyed by immigrant men effectively disappeared and was, in fact, reversed. By April 2020, the employment rate of immigrant men stood at 67.1 percent, more than 2 percentage points below the 69.5 percent employment rate of natives.

The differences in the employment trends of immigrant women and native women do not seem to be as striking (at least superficially). In fact, the trend lines for the employment rates of the two groups tend to be roughly parallel between January and April 2020. Both groups began to experience a decline in their employment rate between February and March 2020, with the employment rate for immigrant women falling by about 3.4 percentage points as compared to a 2-point drop for native women. Similarly, the decline for immigrant women between March and April was again somewhat larger than for natives (14.0 versus 12.7 percentage points). Note, however, that immigrant women have had lower employment rates than native women, so that the *percent* decline in immigrant employment resulting from the pandemic was actually quite large. The pre-pandemic (February 2020) employment rate of immigrant women was 62.7 percent. By April 2020, their employment rate had fallen to 45.2 percent, so that the employment rate fell by almost 30 percent. In contrast, the employment rate of native women fell by only 20 percent.

It is useful to decompose the change in the employment rate implied by Figure 2 into its key components. Let E_t be the number of persons in a particular population (e.g., natives) employed at time *t*, N_t be the number who are not employed, and *P* be the (assumed constant) population. Further, let F_t be the number of persons who were not employed at time *t*, but who found a job by time *t*+1. Similarly, let L_t be the number of persons who were employed at time *t* and had lost their job by time *t*+1. The change in the employment rate observed between times *t* and *t*+1 can be written as:

$$\begin{aligned} \frac{E_t - E_{t-1}}{P} &= \frac{(F_t - L_t)}{P}, \\ &= \frac{N_t}{P} \cdot \frac{F_t}{N_t} - \frac{E_t}{P} \cdot \frac{L_t}{E_t}, \\ &= (1 - \pi_t) f_t - \pi_t \ell_t. \end{aligned} \tag{1}$$

where π_t is the employment rate at time *t*; f_t is the job-finding rate, or the fraction of persons out of work who find a job by time *t*+1; and ℓ_t is the job-loss rate, or the fraction of employed persons who are not working by the next time period. Equation (1) shows that the month-to-month changes in employment rates are a weighted average of the job-finding rate and the job-loss rate.

The sampling frame of the CPS—where a person is interviewed for 4 continuous months, is not interviewed for the next 8 months, and is then interviewed again for an additional 4 months—allows us to calculate the job-finding and the job-loss rates for the immigrant and native populations. For any given time period (say between months *t* and *t*+1), we can observe the employment status of the subsample of persons who happen to appear in two consecutive CPS surveys.[4] This tracking lets us calculate the job-finding and job-loss rates. Figure 3 shows the trends in the job loss rate between January 2019 and April 2020, while Figure 4 shows the trends in the job finding rate.

Consider initially the trends in the job-loss rate. Before the pandemic, the job loss rate of immigrant men and native men was roughly the same: about 3 to 4 percent of the employed population in month *t* in either group was not employed in month *t*+1. Note, however, that the relative job loss rate for immigrant men began to increase in March 2020 and shot up dramatically between March and April 2020. By the end of the period, the job loss rate had increased to 16.8 percent for natives, but to 24.7 percent for immigrants. Given the fact that immigrant men had very high employment rates prior to the COVID-19 labor market shock, equation (1) suggests that the key reason for the substantial drop in the relative employment rate of immigrant men was the sizable increase in their job loss rate.

The top panel of Figure 4 illustrates the trends in the job-finding rate for immigrant and native men. Interestingly, the data reveal that the job-finding rate for immigrant men was substantially higher than that of native men during the 2019 calendar year.[5] In January 2020, for example, the job-finding rate for immigrant men who were not working was 32.8 percent, while the comparable statistic for natives was only 19.7 percent. The immigrant job-finding rate then fell dramatically between January and April 2020. By April, the job-finding rate for immigrants

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[4] We used the matching variable created by IPUMS (*cpsidp*) to match specific persons across CPS cross-sections.

[5] Albert (2020) examines the fact that the job-finding rate for immigrants is relatively higher in the context of a job search model.

had dropped to 24.3 percent, a drop of over 8 percentage points. In contrast, the job-finding rate for natives declined by only 4.4 percentage points, from 19.5 to 15.1 percent in that period.

The figures also illustrate the job loss and job finding rates of immigrant and native women. Note that the decomposition of the change in the employment rate into its key ingredients strikingly shows that the job loss rate for immigrant women also increased substantially as a result of the pandemic. At the beginning of 2020, the job loss rate for immigrant women was slightly above the respective statistic for native women (5.7 percent for immigrants and 4.2 percent for natives). The (relative) job loss rate for immigrant women increased dramatically between March and April 2020, however. The job loss rate for native women in that month rose to 20.9 percent, while the rate for immigrant women rose to 29.3 percent, a gap of 8.4 percentage points. In fact, the comparison of the various trends illustrated in Figure 3 show that—regardless of gender—immigrant workers (relative to natives) found it increasingly difficult to hold on to their existing jobs.

Finally, the bottom panel in Figure 4 shows the trend in the job-finding rates for immigrant and native women. Unlike their male counterparts, immigrant women typically have lower job-finding rates than native women. Nevertheless, the data again reveal the particularly difficult conditions faced by immigrants after the COVID-19 shock. The job-finding rate of native women dropped by only 1.3 percentage points between January and March (from 12.5 to 11.1 percent). In contrast, the job-finding rate of immigrant women dropped by more than twice as much, from 9.8 percent to 6.9 percent.

For expositional convenience, much of the empirical analysis presented in the remainder of this paper focuses on the trends revealed by the four Basic Monthly samples currently available for the 2020 calendar year.[6] We will pool the data from these four cross-sections in much of what follows. Table 1 reports summary statistics for each of the four demographic groups under analysis. As expected, the summary statistics imply that immigrants are older than natives, tend to have either very little or a lot of education, and are more likely to reside in metropolitan areas and cluster in a relatively small number of states.

3. Regression Results

This section uses data from the pooled January-April 2020 CPS Basic Monthly files to document the historic changes in employment observed immediately after the COVID-19 pandemic hit the United States. The analysis documents how the labor demand shock differentially affected immigrants and natives.

It is instructive to begin by pooling the four cross-sections and estimating the following generic regression model in the pooled data:

$$y_{it} = \theta_t + \lambda_{tm} + \beta\, x_{it} + \varepsilon, \tag{2}$$

where y_{it} is a measure of employment status for person i in month t; θ_t is a vector of month fixed effects; λ_{tm} is a vector of interactions between the month fixed effects and a variable indicating if person i is an immigrant; and x_{it} is a vector of socioeconomic characteristics (discussed below). The coefficient vector θ gives the change in the employment status of natives in month t relative to their status in January 2020 (the excluded month fixed effect), while the coefficient

[6] Figure 3 generally suggests that the immigrant-native trends during the 2019 calendar year were relatively stable and that little is lost by focusing on the shorter pre-pandemic time period.

vector λ gives the corresponding gap in employment status between immigrants and natives for each month. The regression model in (2), therefore, enables us to easily summarize the basic employment trends in the data, and to document how the immigrant-native gap changes after we adjust for the different socioeconomic characteristics of the two samples. The goal of the regression analysis is to isolate which (if any) of the differences in socioeconomic characteristics explains the disproportionately adverse impact of the COVID-19 pandemic on the employment opportunities of immigrants. All regressions are estimated using ordinary least squares and are estimated separately in the samples of men and women.

The top panel of Table 2 reports the coefficient vectors (θ and λ) from regressions estimated in the male sample and where the dependent variable simply indicates if person *i* is working in month *t* (i.e., the regression is an employment rate regression). The first column, representing a regression that does not include any covariates, simply reproduces the differences in employment rates observed in the raw data. The employment rate of natives was stable between January and February 2020, declined slightly by 1.7 percentage points in March, and fell dramatically by 13.6 percentage points (relative to January) in April. The immigrant-month interactions show that immigrants enjoyed an employment advantage of 6 percentage points in January and February prior to the pandemic; that this advantage declined to about 4 percentage points in March; and that the employment advantage completely disappeared and was reversed after the pandemic hit. By April 2020, the immigrant employment rate was 2.4 percentage points below that of natives. Between January and April 2020, the immigrant-native employment gap fell by an astonishing 7.9 percentage points.

The remaining columns of the table document what happens to this gap as the regression adds various vectors of control variables. For instance, the regression in column 2 adds the person's age (as a quartic) and a vector of fixed effects measuring educational attainment.[7] Note that controlling for differences in these human capital variables barely change the magnitude of the change in the immigrant-native employment gap; that gap still fell by 7.2 percentage points in the first four months of 2020. Similarly, the inclusion of a variable indicating if the person lived in a metropolitan area and a vector of state fixed effects (to adjust for the fact that the pandemic may have had a different impact on states where immigrants tend to cluster) reveals that the immigrant-native gap still declined by 7.1 percentage points between January and April 2020.

The bottom panel of the table reports the analogous coefficients estimated in the sample of women. The employment rate of native women was relatively stable in January and February, declined by 2.0 percentage points in March, and fell by 15.2 percentage points (relative to January) in April. Note, however, that the raw employment gap between native and immigrant women did not change much during the period. It stood at 13.4 percent in January and increased slightly to 14.8 percent in April. The inclusion of controls for educational attainment and location barely changes that conclusion; the gap widened by 1.4 percentage points in the unadjusted regression and by 0.7 percentage points in the full specification.

As noted earlier, we can use the sampling frame of the CPS to track the employment status of a particular person over time and create two additional dependent variables, the job-loss and job-finding rates, that are the key determinants of trends in the employment rate. Specifically, we used the panel nature of the Basic Monthly files to construct a variable indicating if an employed person suffered a job loss. In particular, we determine whether a

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[7] The educational attainment fixed effects include indicators for less than high school, high school graduate, some college, and at least a college degree.

person who was employed in month *t* was not employed in month *t*+1. Depending on the placement of a person within the CPS sampling sequence, we can create this job loss variable a maximum of three times for any given person (with the maximum represented by a person who was interviewed continuously between January and April 2020). We also created the analogous variable that indicates if a person who is not employed in the initial period found work by the following month.

We estimated regressions analogous to equation (1) but using the job loss and job finding probabilities as dependent variables. Table 3 reports the key coefficients from the panel regression on the conditional probability of job loss, while Table 4 reports the analogous coefficients from the regression on the conditional probability of becoming employed.

Consider initially the results obtained in the sample of men, reported in the top panel of the table. The regression coefficients in the first column can be used to calculate the job loss rates in the raw data. The rate of job loss for a native man employed in February was 1.8 percentage points higher than for a native man employed in January. The rate of job loss, however, increased by 13.3 percentage points (relative to the January level) for a native man employed in March.

The immigrant-native gap in the conditional probability of job loss was essentially zero in January. The gap increased slightly to 1.8 percentage points for those employed in February and increased further to 8.0 percent for those employed in March. Note that the regression coefficients in Table 3 imply that the probability that an employed native man would lose his job within a month rose by 13.3 percent between January and March. The analogous increase for an employed immigrant man was 21.3 percent.[8]

The remaining columns of Table 3 show what happens to the immigrant-native gap in the conditional probability of job loss as the regression adjusts for differences in socioeconomic characteristics between the two groups. It is evident that most of the controls do little to the measured gap: The 8.0 percentage point gap in March falls slightly to 7.3 percentage points even after the regression controls for differences in educational attainment, age, state of residence, and metropolitan status. The size of the standardized gap, however, declines more noticeably when the regressors include a vector of job characteristics, as measured by (nearly 800) occupation and industry fixed effects.[9] In particular, the most general specification reported in the last column of the table show that the job-loss gap in March (after controlling for all variables) falls from the raw 8.0 percent to 6.3 percent, a decline of over 20 percent.

It is worth noting an important conceptual difference in the way that the occupation and industry fixed effects are introduced in Tables 2 and 3. In particular, these fixed effects in the panel regression essentially capture an *interaction* between time (i.e., pre- and post-COVID) and job type. In other words, it is the incidence of job loss for an employed person that is sensitive to the type of job held (rather than just the general level of whether a person works or not). The implied link between job loss and job type during the COVID-19 pandemic is not surprising because some jobs were able to be "transported" to a home office during the lockdown in March and April 2020; other jobs were deemed essential (ensuring that those jobs continued to exist in

[8] We also estimated regression models that included data from the Basic Monthly samples of the first half of 2019 to net out any potential seasonal effects that might affect the rate of job loss or job finding between February and April 2020. These differenced regressions are very similar to those reported in Tables 3 and 4.

[9] When examining the determinants of job loss between month *t* and month *t*+1, the industry and job characteristics are obtained from the survey data reported in month *t*.

the typical workplace); and still other jobs ceased to exist as many plants and offices closed down.

The fact that the observed immigrant-native job loss gap is sensitive to the inclusion of job characteristics suggests that immigrants were more susceptible to job loss during the pandemic because fewer of them were working in “protected” jobs. We explore this implication of the regression results in more detail below. It is important to emphasize, however, that although job characteristics seem to matter, they do not come close to providing a satisfactory explanation for why immigrant employment opportunities declined so drastically as a result of the COVID-19 pandemic.

The bottom panel of Table 3 reports the analogous panel regressions for women. Note that the conditional probability of job loss for a native woman rose noticeably between January and February (by 2.5 percent), and by a striking 16.7 percent by March 2020. Equally important, note that the panel regressions document a significant increase in the probability of job loss for immigrant women relative to native women. The immigrant-native gap in the conditional probability of job loss in January was a relatively small 1.5 percent (and statistically significant). This gap increased to 4.6 percentage points for those employed in February and rose further to 8.4 percent for those employed in March.

The remaining columns of the table document the behavior of the measured immigrant-native gap in job loss rates as the regression controls for differences in socioeconomic characteristics between the two groups. Note that controlling for age, educational attainment, metropolitan status, and state of residence still imply a substantial 8.0 percentage point immigrant-native gap in job loss rates in March 2020. As with the male regressions, the inclusion of the occupation and industry fixed effects reduces the gap to 6.7 percent, a bit less than a 20 percent reduction. The differences in the types of jobs held by the two groups, therefore, again help to explain a (small) part of the increase in the immigrant-native gap in the probability of job loss during the COVID-19 pandemic.

Table 4 reports the estimated coefficients from analogous regressions where the dependent variable is the probability that a person who is not employed at time *t* finds a job within the next month.[10] The first column of the table reports the key coefficients when the regression does not adjust for any differences in socioeconomic characteristics. The probability that an out-of-work native man would find work within a month declined dramatically by March 2020; it fell by 4.4 percentage points between January and March 2020. At the same time, the advantage that out-of-work immigrants traditionally enjoyed in finding employment contracted dramatically. In January, the job-finding rate was 13.4 percentage points higher for out-of-work immigrant men. By March, that advantage had narrowed to 9.3 percent.

The remaining columns of the table show that adjusting for differences in various socioeconomic characteristics does not reduce the immigrant advantage in finding work. Even in the full regression specification reported in column 34, the probability an out-of-work person would find a job in the tumultuous March-April 2020 period was 9.4 percentage points higher for immigrants.

The bottom panel of Table 4 reports the regression coefficients when the job-finding model is estimated using the sample of out-of-work women. Not surprisingly, the job-finding rate for native women declined slightly between January and March. At the same time, however,

[10] Note that the construction of the probability of finding a job requires that a person be out of work in the initial period. The occupation and industry fixed effects, therefore, are not included in the regressions reported in Table 4. In fact, the occupation/industry information is missing for about 77 percent of the sample used in the regressions, and the information for the remaining 23 percent refers to the characteristics of the worker's previous job.

the immigrant disadvantage in finding work widened. In January, the average out-of-work immigrant woman had a 2.8 percentage point lower probability of finding work than a native woman. This disadvantage grew to 4.2 percentage points by March 2020. As the last column of the table shows, however, the entire immigrant-native gap in job finding rates disappears after adjusting for socioeconomic characteristics, particularly those describing the type of occupation and industry that had employed an out-of-work person in the recent past.

4. Undocumented status and employment trends

The regression results reported in the previous section did not distinguish by immigration status, even though a large fraction of the immigrant population is undocumented and undocumented immigrants may be affected differentially by the COVID-19 labor market shock. According to the latest estimates from the Department of Homeland Security (Baker, 2019), there were 12.0 million undocumented immigrants in the United States in January 2015, accounting for about 27.8 percent of the foreign-born population. The immigration status of a foreign-born person is obviously likely to affect labor market opportunities, and that impact may be particularly conspicuous during severe economic downturns.

Although the Basic Monthly CPS does not provide a variable indicating whether a particular foreign-born person is undocumented, a flurry of recent papers use imputation methods that attempt to assign every foreign-born person in the CPS (or ACS) an “immigration status” code. These imputation methods have been used to study labor supply differences between legal and undocumented immigrants (Borjas, 2017), the impact of the Deferred Action for Childhood Arrivals (DACA) executive action on the education of immigrant children (Hsin and Ortega, 2018) and on labor market outcomes (Amuedo-Dorantes and Antman, 2017), and the wage penalty to undocumented immigration (Borjas and Cassidy, 2019).

It would be of interest to determine if the historic disruptions resulting from the COVID-19 pandemic have had a particular deleterious effect on undocumented immigrants because their employment contract is so tenuous, or if the kinds of jobs typically held by undocumented workers "protected" them from the economic consequences. We build on the work of Passel and Cohn (2014) to impute an "immigration status" indicator for the foreign-born persons sampled in the January-April 2020 Basic CPS files.

In rough terms, the Passel-Cohn algorithm identifies the foreign-born persons in a particular sample (such as the CPS ASEC) sample who are likely to be legal, and then classifies the residual group of foreign-born persons as likely to be undocumented. The residual method classifies a foreign-born person as a *legal* immigrant if any of the following conditions hold:

a. that person arrived before 1980;
b. that person is a citizen;
c. that person receives Social Security benefits, SSI, Medicaid, Medicare, or Military Insurance;
d. that person is a veteran, or is currently in the Armed Forces;
e. that person works in the government sector;
f. that person resides in public housing or receives rental subsidies, or that person is a spouse of someone who resides in public housing or receives rental subsidies;
g. that person was born in Cuba (as practically all Cuban immigrants were granted refugee status);

h. that person's occupation requires some form of licensing (such as physicians, registered nurses, air traffic controllers, and lawyers);

i. that person's spouse is a legal immigrant or citizen.

We use this algorithm to create the undocumented status identifier in the March 2019 ASEC file (see the details in Borjas, 2017). It is not possible to apply the algorithm directly to the CPS Basic Monthly files because many of the variables required to impute undocumented status (such as receipt of various types of benefits) are not available in the Basic Monthly files. After imputing the immigration status of each foreign-born person in the 2019 CPS ASEC data, we then used the IPUMS-created identifier for a particular person in the CPS sample (*cpsidp*) to match the subsample of persons who appear in both the March 2019 ASEC file and in at least one of the 2020 Basic Monthly files. It is obvious that measurement error can (and very likely will) enter the exercise at various stages, including the Pew imputation algorithm itself, the restriction that we can only identify the undocumented status of persons who appear in both the March 2019 ASEC and the monthly Basic files in 2020, and the fact that the construction of the person-level identifier in the CPS (*cpsidp*) does not perfectly match the same person across different cross-sections. Nevertheless, this exercise may well provide the only (admittedly rough) information that can be gathered from available data about how the COVID-19 demand shock affected the employment opportunities of undocumented immigrants.

Because of the various measurement issues noted above (and the small sample of undocumented immigrants who can be matched in the various CPS files), we conduct an empirical exercise that provides the simplest and most transparent way of summarizing the evidence. In particular, we focus on examining the immigrant-native gap in the rate of job loss between March 2020 and April 2020.[11] The dependent variable, therefore, is the conditional probability that a person employed in March 2020 was out of work by April 2020.

The regression coefficients reported in Table 5 give the adjusted difference in the rate of job loss between a particular type of immigrant and natives. In both the male and female samples, the data indicate that both legal and undocumented immigrants have higher job loss rates than natives. In the male sample, the undocumented immigrants tend to have the highest job loss rates (although this pattern disappears once the regression includes occupation and industry fixed effects). Not surprisingly, the coefficients are imprecisely estimated so that the difference between legal immigrants and undocumented immigrants is generally not statistically significant. In contrast, undocumented immigrant women have lower job loss rates than legal immigrant women regardless of the regression specification (although these differences are again not statistically significant). In sum, the regressions provide suggestive evidence that the job losses resulting from the pandemic may have been particularly severe for undocumented men.

5. Occupations, remote working, and job losses

The results presented in Section 3 suggest that occupation plays an important role in understanding why some groups of workers suffered particularly heavy job losses as a result of the pandemic. In this section, we attempt to identify some characteristics of an occupation that may be driving the historic job losses observed in the spring of 2020. We also show how immigrant-native differences in those occupational characteristics are partly responsible for the relative increase in the rate of job loss among immigrants.

[11] Because the calculation of the job finding rate requires that the person be out of work in the initial period, the sample size for undocumented immigrants tends to be small.

During the economic slowdown caused by the COVID-19 pandemic, many workers were encouraged and able to perform their jobs remotely. Presumably, persons who do the type of work that can be done "off-site" would face a lower risk of job loss. We created an index designed to measure the occupation's "remotability" by using data from the Occupational Information Network (O*NET). Dingel and Neiman (2020) have also used the O*NET data to develop a related "*teleworkable*" measure. Although we use a roughly similar approach, there are several important differences in how we go about constructing the remotability index.

We use the *Work Context* and *Work Activities* surveys of O*NET to identify four distinct characteristics of occupations that may measure the ease of remote working: the frequency of telephone conversations on the job, the frequency of using electronic mail, whether the job breaks down information or data into separate parts, and whether the job requires that the worker interact with computers (such as programming). We then used principal components to merge the information provided by these four characteristics into a single remotability index; a higher value of the index would indicate that the occupation was more remotable.[12]

It turns out that immigrants, on average, hold jobs that are less suitable for remote work. Table 6 pools the data for the Basic Monthly CPS Files between January 2019 and February 2020 (i.e., prior to the pandemic disruption) and estimates a regression model where the index of remotability is the dependent variable. The index is standardized so that it has a mean of zero and a standard deviation of one. Note that immigrants are far less likely to work in remotable jobs, regardless of the set of control variables. The raw data suggests that immigrant men have a remotability index that is about one-quarter of a standard deviation below that of native men, while the index for immigrant women is nearly half a standard deviation below that of native

[12] See the Appendix for details.

women.[13] In short, the pre-pandemic occupation distribution of immigrants made them particularly vulnerable to a labor demand shock that may have generated substantial job losses for those employed in non-remotable occupations.

We now examine the link between the probability that an employed person suffers a job loss and the remotability of the job. To simplify the graphical presentation, we classify occupations into three categories based on the value of the index: “Low remotability,” “Medium remotability,” and “High remotability.” The cutoff values of the index were chosen so that the number of workers in each grouping was (roughly) equal. The occupations that are highly remotable include actuaries and database administrators. The occupations that have low remotability include crossing guards and flaggers or graders and sorters for agricultural products.

Figure 4 shows that the rate of job loss between March and April 2020 was far higher for workers employed in jobs that were least remotable. In January 2020, for example, the rate of job loss for men employed in occupations with a high degree of remotability was 2.4 percent, while the rate of job loss in the occupations with the lowest degree of remotability was 5.0 percent, a difference of only 2.6 percentage points. Although the rate of job loss rose dramatically for all occupations, the rise was particularly steep for workers employed in the least remotable jobs. In March 2020, the rate of job loss was 27.4 percent for the least remotable jobs but only 9.3 percent for the most remotable jobs, a difference of 18.1 percentage points. The visually striking correlation between our index and the rate of job loss suggests that our classification of occupations captures an important aspect of a worker’s ability to do their job outside the traditional work setting.

[13] The table also reports the coefficients of the education fixed effects. Note that the remotability index is significantly higher for the most educated workers.

We now revisit the job loss regressions first reported in Table 3 to explore the importance of the occupation's remotability index in accounting for the increasing gap in the job loss rate between immigrants and natives. For expositional convenience, we focus on the determinants of the rate of job loss between March and April 2020. Table 7 summarizes the evidence.

The regression in the first column includes only the immigrant fixed effect and shows the high rate of job loss of immigrants relative to natives. Immigrant men had a 7.8 percentage point higher probability of job loss in the period. Adding controls for education, age, state, and metropolitan status (column 3) has little effect on the immigrant coefficient. Column 4 adds the occupation's remotability index as a regressor. Consistent with the implications of Figure 5, workers in more remotable occupations suffered a much lower probability of job loss. Specifically, a one standard deviation increase in an occupation's remotability index lowered the job loss rate by 6.0 percentage points. Further, the coefficient measuring the immigrant-native gap in the rate of job loss falls to 5.8 percentage points, a reduction of about 25 percent from the unadjusted gap.

The final column of the table controls for occupation fixed effects instead of occupational remotability, and shows that using the remotability index explains as much of the change in the immigrant coefficient as the full set of occupation fixed effects (once we include industry fixed effects). In other words, our index of the job's remotability changes the immigrant-native gap as much as the inclusion of nearly 500 occupation fixed effects. The implication, of course, is that part of the disproportionate adverse employment effects of the COVID-19 pandemic on immigrant employment arose because immigrants tended to hold jobs that were less suitable for remote working.

While the results for women closely mirror those found in the male sample, a few differences are worth noting. First, controlling for remotability leads to an even larger reduction in the immigrant coefficient for women than men, from an unadjusted gap of 8.3 percentage points down to only 4.3 percentage points, a reduction of nearly 50 percent. In addition, a one standard deviation increase in an occupation's remotability index lowered the job loss rate for women by 10.2 percentage points, a much higher marginal effect than what is observed for men (6.0 percentage points). This large gender difference, however, is narrowed when the regression also includes industry fixed effects in column 5.

6. Summary

Immigrants now make up nearly a fifth of the U.S. workforce. Immigrant men have historically had higher employment rates than native men, while immigrant women have had lower employment rates than native women. The historic COVID-19 labor market shock, which led to unprecedented job losses for American workers, differentially affected the employment opportunities of immigrant and native workers, with the job losses suffered by immigrant workers being higher than those suffered by their native counterparts.

We used data from the CPS Basic Monthly files to document the disproportionately adverse impact that the initial phase of the COVID-19 pandemic had on the employment of immigrants. The employment rate of both natives and immigrants declined precipitously as the economic consequences of the pandemic spread through the labor market. The employment decline, however, was much larger for foreign-born workers. The employment advantage that immigrant men had long experienced was, in fact, reversed. By April 2020, the employment rate of immigrant men was 2 percentage points below that of native men.

We also exploited the panel nature of the CPS files to track the employment opportunities of specific workers over time. The tracking exercise lets us calculate the rate of job loss: the fraction of persons who are employed at a particular point in time but who are not at work in the subsequent month. The tracking also lets us calculate the job-finding rate: the fraction of persons who are initially not at work, but who find work in the subsequent month. The panel analysis reveals that the relative rate of job loss for (initially employed) immigrant men and women increased dramatically between January and April 2020, and that the relative probability of finding work declined dramatically for (initially out-of-work) immigrant men and women.

Our study suggests that part of the adverse effect that the COVID-19 pandemic had on relative immigrant employment resulted from differences in the type of work that immigrant and native workers do. Immigrants were less likely to be employed in jobs that could be performed from a remote setting and suffered disparate employment consequences because the lockdown allowed disproportionately more native workers to stay at home and remain employed.

References

Amuedo-Dorantes, Catalina, and Francisca Antman. 2017. "Schooling and labor market effects of temporary authorization: evidence from DACA," *Journal of Population Economics* 31(1): 339-373.

Albert, Christoph. 2020. "The Labor Market Impact of Immigration: Job Creation vs. Job Competition," *American Economic Journal, Macroeconomics*, forthcoming.

Baker, Bryan. 2019. "Estimates of the Illegal Alien Population Residing in the United States: January 2015," Department of Homeland Security, Office of Immigration Statistics.

Borjas, George J. 2017. "The Labour Supply of Undocumented Immigrants," *Labour Economics* 46: 1-13.

Borjas, George J. 2020. "Demographic Determinants of Testing Incidence and COVID-19 Infections in New York City Neighborhoods," NBER Working Paper No. 26952.

Borjas, George J. and Hugh Cassidy. 2019. "The Wage Penalty of Undocumented Immigrants," *Labour Economics* 61.

Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, Ahu Yildirmaz. 2020. "The U.S. Labor Market During the Beginning of the Pandemic Recession," NBER Working Paper No. 27159.

Cassidy, Hugh. 2019. "Occupational Attainment of Natives and Immigrants: A Cross-Cohort Analysis," *Journal of Human Capital*, 13(3): 375-409.

Chatterji, Pinka and Yue Li.2020. Effects of the COVID-19 Pandemic on Outpatient Providers in the US," NBER Working Paper No. 27173.

Dingel, Jonathan I. and Brent Neiman. 2020. "How Many Jobs Can be Done at Home?" NBER Working Paper No. 26948, April 2020.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 7.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V7.0

Hsin, Amy and Francesc Ortega. 2018. "The Effects of Deferred Action for Childhood Arrivals on the Educational Outcomes of Undocumented Students," *Demography* 55: 1487-1506.

Lang. Hanming, Long Wang, Yang Yang, "Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China," NBER Working Paper No. 26906, April 2020.

Nekoei, Arash. 2013. "Immigrants' Labor Supply and Exchange Rate Volatility," American Economic Journal: Applied Economics 4: 144-164.

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."

Von Gaudecker, Hans Martin, Radost Holler, Lena Janys, Bettina Siflinger, and Christian Zimpelman. 2020. "Labour Supplly in the Early Stages of the COVID-19 Pandemic: Empirical Evidence on Hours, Home Office, and Expectations," IZA Discussion Paper No. 13158.

Yamaguchi, Shintaro. 2012. "Tasks and Heterogeneous Human Capital," *Journal of Labor Economics*, 30(1): 1-53.

Appendix: Construction of an index measuring the ease of remote working

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.

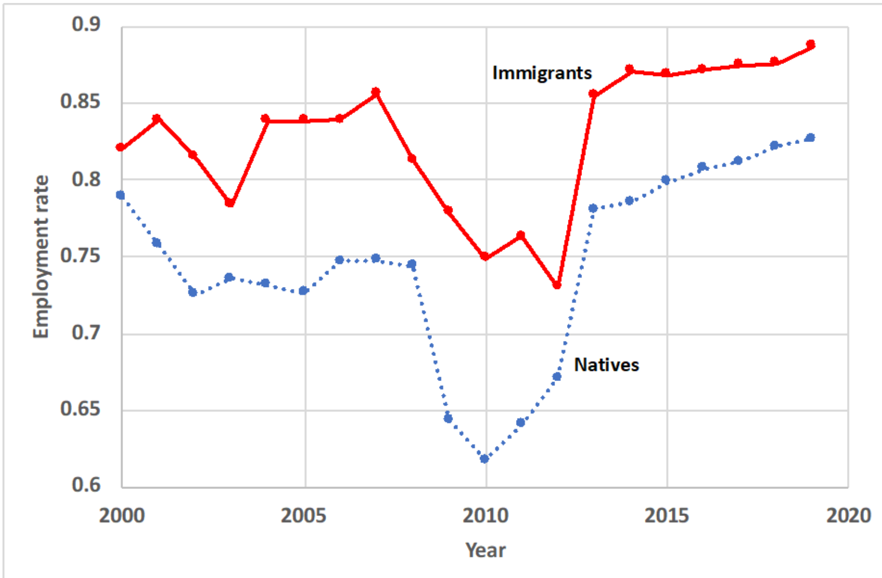
In order to assign the attributes to individuals in the 2020 Basic Monthly CPS, we make use of individuals observed during the transition between the two occupational coding schemes, i.e., persons observed in both December 2019 and January 2020. Workers in these months have occupational characteristics 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).

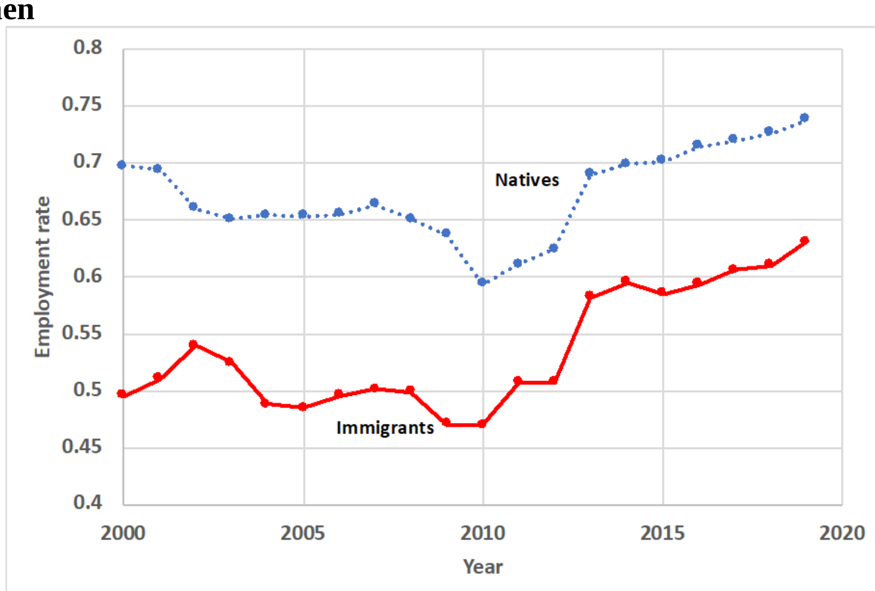
We reduce these four attributes to a single measure using principal component analysis and extracting the first component, which is commonly used in the occupational task literature (e.g., Yamaguchi 2012, Cassidy 2019). This yields a single index that (presumably) measures remote workability. The index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

Figure 1. Employment rate in CPS-ASEC, 2000-2018

A. Men



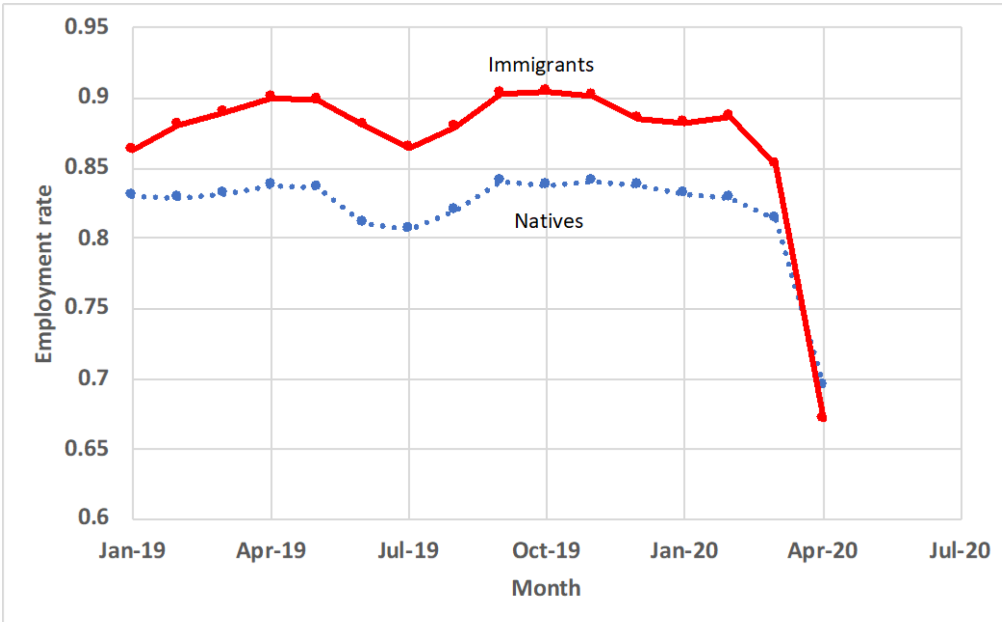
B. Women



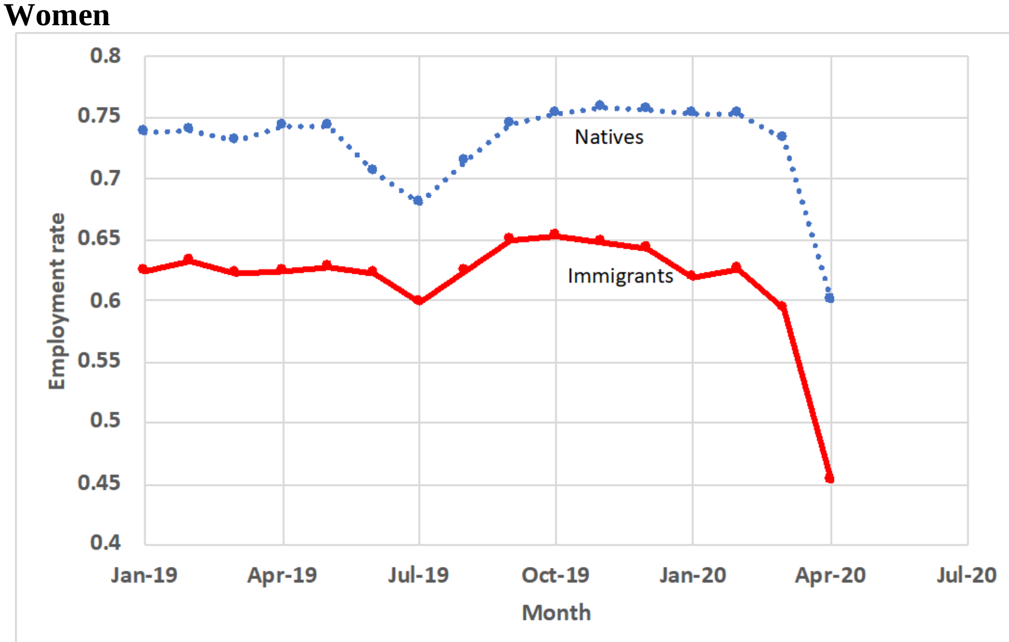
Notes: All samples consist of persons aged 18-64 who are not enrolled in school. The employment rate gives the fraction of persons who are "at work."

Figure 2. Employment rate in Basic Monthly CPS, January 2019-April 2020

A. Men



B. Women



Notes: All samples consist of persons aged 18-64 who are not enrolled in school. The employment rate gives the fraction of persons who are "at work."
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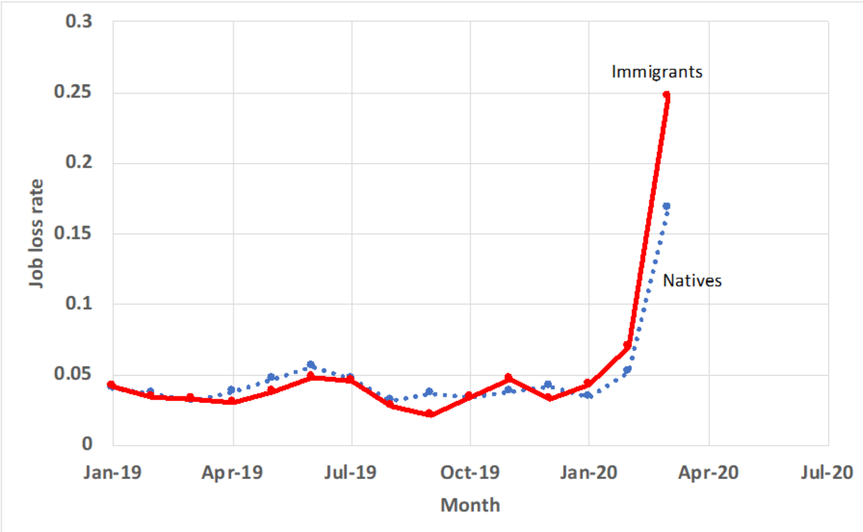
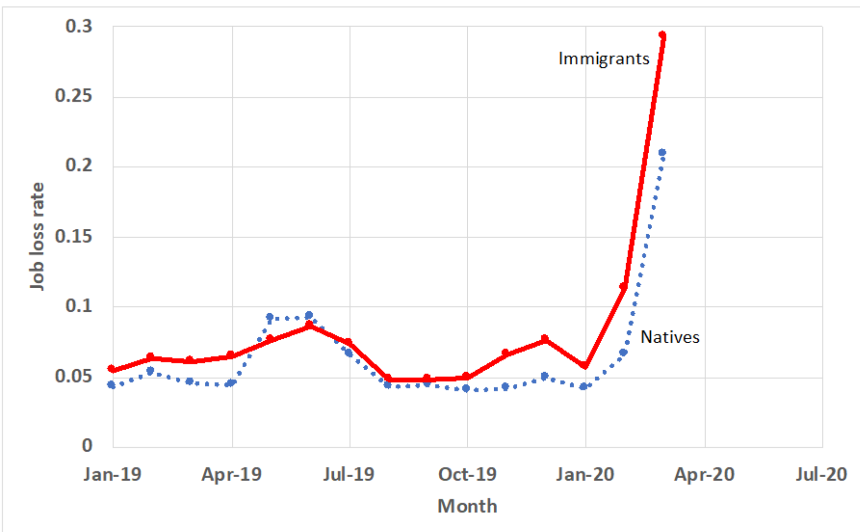
Figure 3. The job loss rate, matched Basic Monthly CPS, January 2019-April 2020

A. Men



B. Women

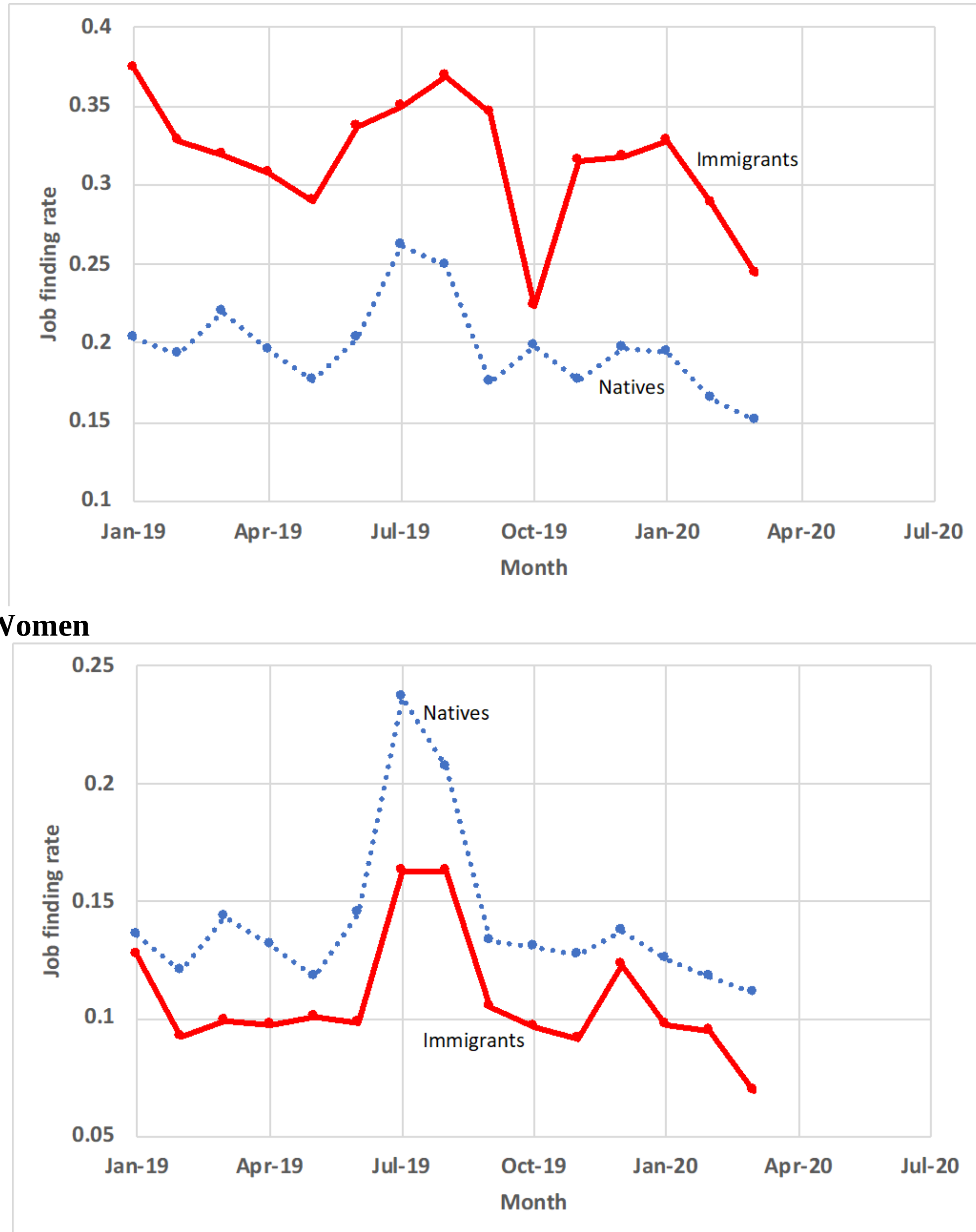


Notes: The dependent variable is set to unity if the person was “at work” at time *t* but was not “at work” at time *t*+1, and zero otherwise. The sample consists of persons who can be matched across two consecutive CPS files and were employed in the initial period.

Figure 4. The job finding rate, matched Basic Monthly CPS, January 2019-April 2020

A. Men

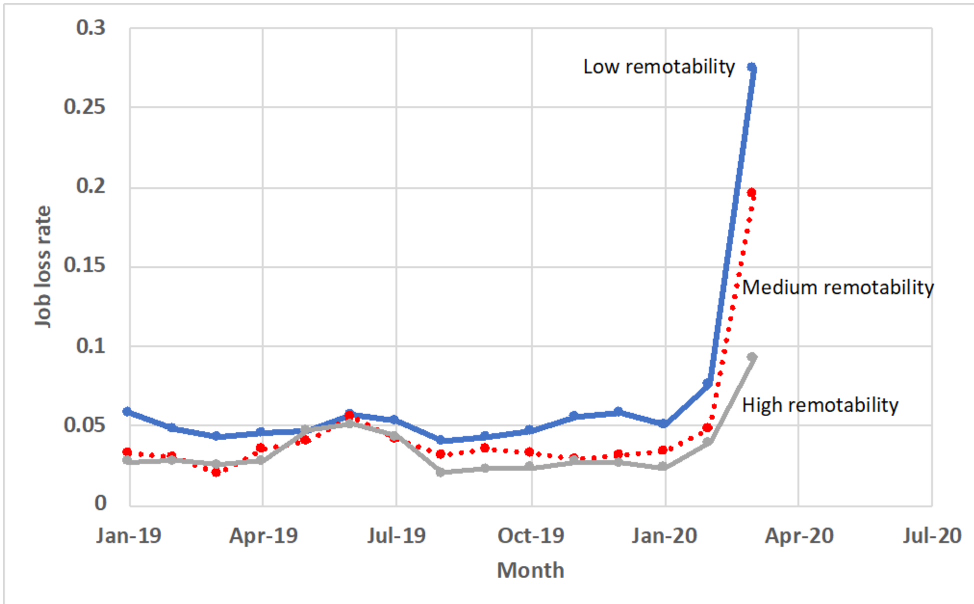
B. Women



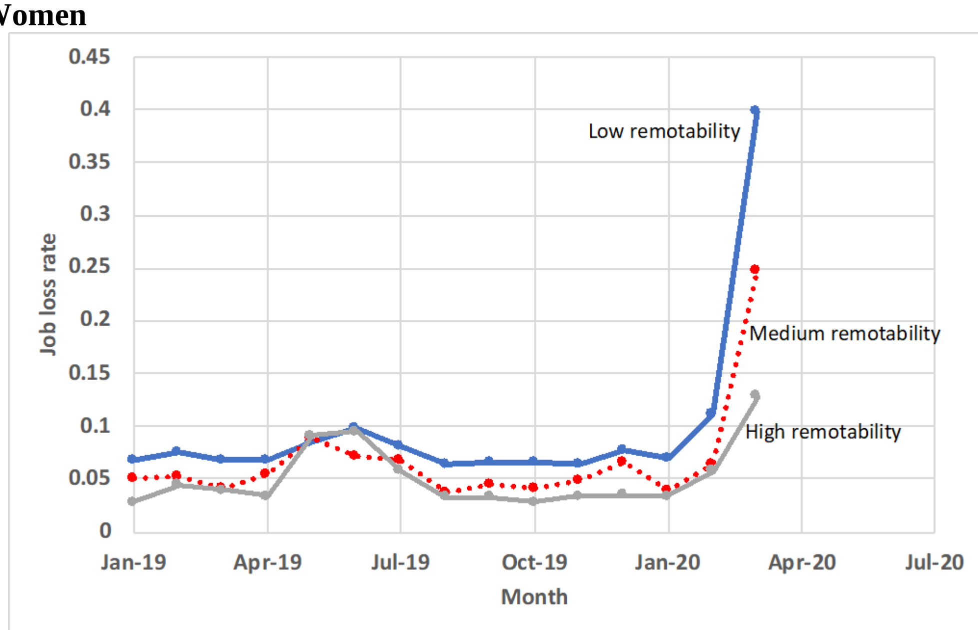
Notes: The dependent variable is set to unity if the person was not "at work" at time *t* but was "at work" at time *t*+1, and zero otherwise. The sample consists of persons who can be matched across two consecutive CPS files and were not employed in the initial period.

Figure 5. Job loss and the remotability of work

A. Men



B. Women



Notes: The dependent variable is set to unity if the person was "at work" at time *t* but was not "at work" at time *t*+1, and zero otherwise. The sample consists of persons who can be matched across two consecutive CPS files and were employed in the initial period. 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 1. Summary statistics in pooled January-April 2020 Basic Monthly CPS

Variable	Native Men	Immigrant men	Native women	Immigrant women
Employment rate (percent)	79.3	82.2	71.0	57.2
Mean age	36.7	39.3	37.2	39.5
Education:				
Less than high school	6.4	22.4	4.9	20.0
High school graduates	32.5	26.8	24.8	25.4
Some college	26.7	15.3	28.3	15.5
College graduates	34.4	35.5	42.0	39.1
Percent residing in metro area	85.8	96.0	85.9	96.5
Percent living in:				
California	7.5	20.0	7.4	20.1
Texas	5.1	9.1	5.3	9.4
Florida	3.6	6.8	3.7	7.0
New York	3.3	6.8	3.5	7.6
Illinois	2.5	3.5	2.4	3.4
Percent living in largest 5 states	22.0	46.2	22.3	47.5
Number of observations	72,197	13,516	74,479	14,318

Notes: The sample consists of persons aged 18-64 who are not enrolled in school. The employment rate gives the fraction of persons who are “at work.”

Table 2. Regressions estimated in pooled CPS cross-sections (January-April 2020)

Variable	(1)	(2)	(3)
A. Men			
February	-0.002	-0.003	-0.003
	(0.003)	(0.003)	(0.003)
March	-0.017	-0.019	-0.020
	(0.004)	(0.004)	(0.004)
April	-0.136	-0.139	-0.139
	(0.0054)	(0.005)	(0.005)
January × Immigrant	0.050	0.063	0.067
	(0.007)	(0.007)	(0.007)
February × Immigrant	0.057	0.070	0.075
	(0.006)	(0.007)	(0.007)
March × Immigrant	0.039	0.054	0.059
	(0.008)	(0.008)	(0.008)
April × Immigrant	-0.024	-0.009	-0.004
	(0.011)	(0.010)	(0.011)
B. Women			
February	0.000	-0.001	-0.001
	(0.003)	(0.003)	(0.003)
March	-0.020	-0.022	-0.022
	(0.004)	(0.004)	(0.004)
April	-0.152	-0.157	-0.157
	(0.005)	(0.005)	(0.005)
January × Immigrant	-0.134	-0.099	-0.096
	(0.009)	(0.009)	(0.009)
February × Immigrant	-0.126	-0.089	-0.086
	(0.009)	(0.009)	(0.009)
March × Immigrant	-0.141	-0.103	-0.099
	(0.010)	(0.010)	(0.010)
April × Immigrant	-0.148	-0.106	-0.103
	(0.011)	(0.010)	(0.011)
Includes:			
Education, age	No	Yes	Yes
State, metro	No	No	Yes

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is set to unity if the person works in the CPS reference week and zero otherwise. The regressions in the male (female) sample have 85,713 (88,797) observations.

Table 3. Panel regressions on month-to-month conditional probability of job loss (January-April 2020)

Variable	(1)	(2)	(3)	(4)
A. Men				
March	0.018	0.018	0.019	0.020
	(0.003)	(0.003)	(0.003)	(0.003)
April	0.133	0.134	0.135	0.135
	(0.005)	(0.005)	(0.005)	(0.005)
February × Immigrant	0.009	0.006	0.003	-0.009
	(0.005)	(0.005)	(0.005)	(0.006)
March × Immigrant	0.018	0.014	0.009	-0.004
	(0.007)	(0.007)	(0.007)	(0.007)
April × Immigrant	0.080	0.076	0.073	0.063
	(0.013)	(0.012)	(0.012)	(0.012)
B. Women				
March	0.025	0.026	0.026	0.025
	(0.004)	(0.004)	(0.004)	(0.004)
April	0.167	0.168	0.168	0.169
	(0.006)	(0.006)	(0.006)	(0.005)
February × Immigrant	0.015	0.010	0.009	-0.010
	(0.007)	(0.007)	(0.007)	(0.008)
March × Immigrant	0.046	0.040	0.039	0.024
	(0.009)	(0.009)	(0.010)	(0.010)
April × Immigrant	0.084	0.081	0.080	0.067
	(0.015)	(0.015)	(0.015)	(0.014)
Includes:				
Education, age	No	Yes	Yes	Yes
State, metro	No	No	Yes	Yes
Industry, occupation	No	No	No	Yes

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 sample consists of persons who can be matched across two consecutive CPS files and were employed in the initial period. The regressions in the male (female) sample have 36,458 (32,693) observations.

Table 4. Panel regressions on month-to-month conditional probability of finding work (January-April 2020)

Variable	(1)	(2)	(3)
A. Men			
March	-0.030	-0.031	-0.030
	(0.013)	(0.013)	(0.013)
April	-0.044	-0.048	-0.049
	(0.013)	(0.013)	(0.012)
February × Immigrant	0.134	0.135	0.139
	(0.032)	(0.033)	(0.033)
March × Immigrant	0.124	0.118	0.123
	(0.032)	(0.032)	(0.033)
April × Immigrant	0.093	0.091	0.094
	(0.030)	(0.030)	(0.030)
B. Women			
March	-0.007	-0.007	-0.006
	(0.009)	(0.009)	(0.009)
April	-0.014	-0.016	-0.016
	(0.009)	(0.009)	(0.009)
February × Immigrant	-0.028	-0.019	-0.022
	(0.012)	(0.012)	(0.013)
March × Immigrant	-0.023	-0.014	-0.017
	(0.013)	(0.013)	(0.013)
April × Immigrant	-0.042	-0.028	-0.030
	(0.012)	(0.012)	(0.012)
Includes:			
Education, age	No	Yes	Yes
State, metro	No	No	Yes

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is set to unity if the person was not employed at time *t* but was employed at time *t*+1, and zero otherwise. The sample consists of persons who can be matched across two consecutive CPS files and were not employed in the initial period. The regressions in the male (female) sample have 6,825 (12,078) observations.

Table 5. Impact of immigration status on the conditional probability of job loss between March 2020 and April 2020

Variable	(1)	(2)	(3)	(4)
A. Men				
Legal immigrants	0.071	0.080	0.057	0.041
	(0.022)	(0.022)	(0.022)	(0.023)
Undocumented immigrants	0.103	0.092	0.070	0.018
	(0.038)	(0.040)	(0.038)	(0.039)
C. Women				
Legal immigrants	0.085	0.091	0.072	0.051
	(0.027)	(0.027)	(0.028)	(0.026)
Undocumented immigrants	0.074	0.046	0.036	0.028
	(0.048)	(0.050)	(0.050)	(0.051)
Includes:				
Education, age	No	Yes	Yes	Yes
State, metro	No	No	Yes	Yes
Industry, occupation	No	No	No	Yes

Notes: Robust standard errors in parentheses. The sample consists of persons whose immigration status can be imputed (i.e., they appeared in the March 2019 ASEC) and who can be matched across the March and April 2020 consecutive Basic Monthly file cross-sections and were employed in the initial period. The regressions in the male (female) sample have 4,327 (3,858) observations.

Table 6. Determinants of remotability index prior to pandemic

Variable	(1)	(2)	(3)
A. Men			
Immigrant	-0.280	-0.214	-0.137
	(0.012)	(0.010)	(0.008)
Education:			
High school graduates		0.303	0.181
		(0.012)	(0.012)
Some college		0.738	0.476
		(0.013)	(0.013)
College graduates		1.639	1.046
		(0.012)	(0.012)
B. Women			
Immigrant	-0.453	-0.354	-0.206
	(0.013)	(0.011)	(0.009)
Education:			
High school graduates		0.574	0.346
		(0.017)	(0.016)
Some college		0.962	0.599
		(0.017)	(0.016)
College graduates		1.567	0.996
		(0.016)	(0.016)
Includes:			
Age	No	Yes	Yes
State, metro	No	Yes	Yes
Industry	No	No	Yes

Notes: Robust standard errors in parentheses, clustered by the CPS individual identifier. The dependent variable is the remotability index of the worker’s occupation measured so that it has a mean of zero and a standard deviation of one. The omitted education category is high school dropouts. The sample consists of persons who are employed and includes data from January 2019 to February 2020. The regressions in the male (female) sample have 275,782 (244,186) observations.

Table 7. Impact of remotability on the rate of job loss between March 2020 and April 2020

Variable	(1)	(2)	(3)	(4)	(5)	(6)
A. Men						
Immigrant	0.078	0.081	0.073	0.058	0.051	0.053
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)
Remotability index:				-0.060	-0.054	
				(0.005)	(0.005)	
B. Women						
Immigrant	0.083	0.082	0.077	0.043	0.048	0.048
	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)
Remotability index				-0.102	-0.067	
				(0.006)	(0.007)	
Includes:						
Educ, age	No	Yes	Yes	Yes	Yes	Yes
State, metro	No	No	Yes	Yes	Yes	Yes
Industry	No	No	No	No	Yes	Yes
Occupation	No	No	No	No	No	Yes

Notes: Robust standard errors in parentheses. 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. The regressions in the male (female) sample have 10,872 (9,742) observations.