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IZA DP No. 15753

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ABSTRACT

Public Opinion, Racial Bias, and Labor Market Outcomes*

The effect of negative shifts in public opinion on the economic lives of minorities is unknown. We study the role of racial bias in the U.S. labor market by investigating sudden changes in public opinion about Asians following the anti-Chinese rhetoric that emerged with the COVID-19 pandemic, and associated changes in employment status and earnings. Using Current Population Survey (CPS) data from January 2019 to May 2021, we find that, unlike other minorities, Asians who worked in occupations or industries with a higher likelihood of face-to-face interactions before the pandemic were more likely to become unemployed afterwards. Consistent with a role for public opinion affecting labor market outcomes, we find that the effects are larger in magnitude in strongly Republican states, where anti-Asian rhetoric might have had more influence. Additionally, we show that, while widespread along the political spectrum, negative shifts in views of Asians were much stronger among those who voted for President Trump in 2016 and those who report watching Fox News channel.

JEL Classification: D70, D91, J15, P16

Keywords: racial bias, public opinion, minorities, unemployment, earnings

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1 Introduction

Political figures' anti-minority rhetoric and media propaganda can have substantial effects on people's willingness to engage in xenophobic and racially-motivated actions.[1] Yanagizawa-Drott (2014) and Adena et al. (2015) find that radio propaganda incited violence and anti-Semitic acts by ordinary citizens in Rwanda and pre-war Germany, respectively. More recently, Grosjean, Federico and Yousaf (forthcoming) show that the likelihood of Black drivers being stopped by the police increased after a Trump rally during his 2015-2016 Presidential campaign. Moreover, mentions of racial issues in Trump speeches exacerbated the effects among officers who were initially more stringent towards Black drivers. Müller and Schwarz (forthcoming) show that President Trump's tweets about Islam predict increases in xenophobic tweets by his followers, cable news attention paid to Muslims, and hate crimes on the following days. Furthermore, Cao, Lindo and Zhong (2022) document that the number of anti-Asian incidents spiked following Trump's initial "Chinese Virus" tweets and that this spike was significantly more pronounced in counties that supported Donald Trump in the 2016 presidential election. As suggested by Bursztyn et al. (2020), rhetoric affects people's behavior against minorities, as it facilitates expressions of anti-minority views among the prejudiced and changes the views of the unprejudiced. This in turn spurs anti-minority actions.

Despite this evidence, the effect of negative shifts in public opinion on the economic lives of minorities remains unknown. This paper aims to fill this gap. The coronavirus pandemic created a fertile setting for anti-Chinese rhetoric that contributed to expressions of racism and xenophobia against people of Asian descent (USCCR, 2020).[2] This might have led to deteriorating labor market outcomes for Asians because of discrimination by employers, customers, or both.[3] The exogenous nature of the pandemic, combined with the fact that it worsened public opinion about a single racial minority group without affecting how other groups were viewed, creates a unique opportunity for investigating the effects of racial bias on labor market outcomes.

We use data from the Current Population Survey (CPS) between January 2019 and May 2021. The rotating panel structure allows us to follow individual workers before and after the COVID-19 outbreak. We begin by showing that, similar to other minorities, Asians' likelihood of being unemployed slightly increased relative to Whites during the pandemic.[4] Any distaste for interacting

[1]See Enikolopov and Petrova (2015) and Zhuravskaya, Petrova and Enikolopov (2020) for reviews of the literature.

[2]A nationally-representative survey estimates that one in five Asians (i.e. about 4.8 million Asians) experienced hate incidents in 2020-2021 (Horse et al., 2021). Also, the Center for the Study of Hate and Extremism recently revealed that anti-Asian hate crime in large US cities increased by more than 180% in the first quarter of 2021 over the same period in 2020 (CSUSB, 2021).

[3]Evidence shows that Americans "lump together" diverse Asian ethnic groups under a single racial category (Le Espiritu, 1992; Kim, 1999; Junn and Masuoka, 2008).

[4]A large literature suggests that the labor market outcomes of minorities could be harmed because of discrimination committed by customers or co-workers. Lang and Kahn-Lang Spitzer (2020) provide a recent survey of the

with Asians should primarily affect jobs that require in-person interactions with customers or co-workers. Consistent with this hypothesis, we find that Asians who originally worked in jobs with substantial amounts of in-person interactions were much more likely to become unemployed during the pandemic. Notably, Blacks and Hispanics working in these same "in-person jobs" were not more likely to become unemployed.

We consider two different proxies to measure the likelihood of face-to-face interactions. The first one is based on the probability that a specific occupation is done remotely in the months that followed the onset of COVID-19 pandemic. This probability is constructed from a question asked about remote work in the CPS survey. A potential concern with this measure is that the composition of people in an occupation who answer the question might be affected by the pandemic itself. Thus, we check the robustness of our findings by building a second variable which categorizes (lower educated) workers in retail and personal services as those with higher likelihood of requiring in-person interactions. As workers in these industries interact heavily with customers, our findings suggest that the main source of bias against Asians in the labor market might have been discrimination by customers and employers' potential reaction to that by decreasing demand for employees of Asian descent.

Next, we investigate the earnings of workers employed during the pandemic to understand if our findings are confined to the extensive margin. Despite the smaller sample size, due to the limited availability of earnings data in the CPS relative to employment data, we find that Asians employed in predominantly face-to-face jobs report lower earnings after the pandemic began. Importantly, this is not the case for other minorities. Moreover, we find some suggestive evidence that the decline in Asians' earnings coincides with an increase in earnings for Blacks.

Then, we provide evidence in favor of the hypothesis that changes in public opinion and racial bias are the underlying mechanisms driving the increasing woes of Asians in the labor market. We also rule out several competing explanations. If changes in opinion and bias are key, one would expect to see differential effects across the political spectrum. The anti-Chinese rhetoric by President Trump and the right-wing media is likely to have played an important role in people's perception of Asians and their willingness to interact with them as workers.[5] Moreover, such rhetoric was probably received differently depending on a person's level of support for the President and their likelihood of paying attention to certain media outlets.[6] We hypothesize that states that

discrimination literature.

[5] Previous research has shown that political messages affect prejudiced attitudes against minorities (e.g. Hswen et al. (2021); Lajevardi and Abrajano (2019); Lajevardi and Oskooii (2018); Müller and Schwarz (forthcoming)).

[6] President Trump used the wording "Chinese virus" for the first time on Twitter on March 16, 2020 and repeated that expression more than 20 times before March 30, as the database website "Factbase" reports. The deliberateness of the wording was made clear when a photographer captured the script of his speech wherein Trump had crossed out the word "Corona" and replaced it with "Chinese." Fox News hosts started using the term even earlier and in many

voted more favorably for President Trump should show stronger negative reactions toward Asian workers in face-to-face work settings. Using data from the 2016 Presidential election, we find support for this hypothesis: while the negative impact on Asians in more interactive parts of the labor market is present across the entire country, the effect is strongest in the most Republican quartile of states and is the weakest in the most Democratic.

Finally, we directly examine the changes in public opinion about Asians, and other minorities, using data from Nationscape, a nationally representative survey which collects the electorates' views on a number of issues, including the favorability of different minority groups, on a weekly basis. We show that share of non-Asians who held unfavorable views of Asians increased by around 35% between the last months of 2019 and the early months of the pandemic. Although widespread along the political spectrum, negative changes in views of Asians were much stronger among those who voted for President Trump in 2016 and those who report getting their news from Fox News Channel. We see no such changes in favorability for other minorities. This is consistent with the heterogeneous labor market effects we find across different states and the hypothesis that anti-Chinese rhetoric has been received differently based on individuals' political leanings and their attention to certain media outlets.

A few other mechanisms might also be driving our results. First, it is possible that Asians working in intensive face-to-face occupations and industries are relatively over-represented in areas that experienced a steeper decline in labor market outcomes during our study period as a result of, for example, harsher lockdowns. We do not find any support for this alternative explanation. Second, our results could be driven by the negative effect of the pandemic on industries in which those types of occupations are abundant and Asians are over-represented. We show this cannot explain our findings. Third, we provide evidence against the possibility that differential risk tolerance or risk perception of COVID-19 across people of different racial backgrounds could explain our findings.

While our main contribution is to propose (and provide evidence for) public opinion as a mechanism that could affect the labor market outcomes of racial minorities, our paper also relates to the recent literature documenting that the adverse labor market outcomes of the pandemic were not equally borne by all groups of workers. In particular, during the first few months of the pandemic, job losses were concentrated among the less educated, minorities, and those working in certain sectors of the economy, such as the retail, leisure, and hospitality industries (Bartik et al., 2020; Chetty et al., 2020; Couch, Fairlie and Xu, 2020; Cowan, 2020). In addition, we contribute to bet-

occasions held China responsible for the spread of the virus. Tucker Carlson began referring to "Chinese coronavirus" in early March and stated, "China did this to the world and we should not pretend otherwise." On March 19, several of Fox News' most popular personalities state that "China has blood on its hands."

ter understanding the peculiar relative decline in Asians' employment during the pandemic (Figure A.1a). As it is evident in Figure A.1b and documented in the literature before by Elsby, Hobijn and Sahin (2010), unlike other minorities, Asians fared very similarly to Whites during the Great Recession and have been doing remarkably well in the labor market during the past few decades. The pandemic changed this dynamic: since April 2020, the Asian unemployment rate exceeded that of Whites.

2 Data

Our analysis uses three sources of data: labor market data from the Current Population Survey (CPS), 2016 Presidential election data, and data from Nationscape, a nationally representative weekly survey that collected the electorates' opinion on a number of issues.

2.1 The Current Population Survey

The CPS is the primary source of official US labor market statistics (Flood et al., 2020). It is a large nationally representative panel of dwellings that includes comprehensive monthly data on employment outcomes. The panel element of the data makes it possible to study how workers were affected by the COVID-19 pandemic over time, as opposed to relying on aggregate statistics or repeated cross sectional data. Specifically, the CPS is a rotating panel: individuals in a dwelling are interviewed for four consecutive months, are not in the sample for the next eight months, and then are interviewed again for four more consecutive months.[7]

2.1.1 Employment and Demographic Variables

The sample consists of individuals between the ages of 18 and 70 and excludes those who are not employed in the last month they show up in the data before March 2020. Employment status is measured using a binary variable that equals one for those who are employed, and zero for those who are unemployed.[8] Our unemployed category includes respondents who report being employed but are "absent from work." The motivation is that the BLS has acknowledged that during the pandemic, some individuals who reported being absent from work were misclassified as employed when they should have been classified as unemployed (BLS, 2020).[9] Earnings are measured using

[7]Since the CPS is a sample of dwellings, if someone moves, the person/household that moved into the dwelling replaces them in the sample. However, we show that there is no discernible difference across different racial groups in our analysis in their likelihood to drop from the sample before and after the pandemic.

[8]We also show the results when we expand the sample to include those who are employed in the base period but are out of the labor force later on.

[9]In our sample approximately 2% of individuals are categorized as "absent from work."

respondents' reported weekly job earnings.

We categorize individuals into four groups based on race: Asian and Pacific Islanders, White, Black, and Hispanic.[10] The "White" group would be more accurately be described as "non-Hispanic White" but we refer to it as "White" for ease of exposition. Industry is defined using 1990 Census codes, which we aggregate into sixteen standard two-digit categories shown in Table 1.[11] Occupations are defined using 2010 Census codes, which are at the three-digit level.[12] We classify workers as having a college education if they hold a degree beyond a high school diploma.

In addition to these standard job related variables, we construct a measure of the extent to which different occupations might require face-to-face, in-person interaction. During the pandemic, the CPS added a survey question that provides new evidence on remote work. Starting in May 2020, individuals were asked if they teleworked or worked from home for pay in the last four weeks due to the pandemic. We compute the fraction of workers in each three-digit occupation (as defined above) who reported teleworking between May 2020 and March 2021 and use it as a measure of an occupation's tendency to require in-person interactions.[13] We then create a binary variable, BMR, which is equal to one if an occupation is below the median in fraction of workers reporting remote work/telework — a "Below Median Remote (BMR)" job. Throughout the text, we refer to this binary variable as a measure of how amenable an occupation is to remote work ("remoteness"), and the extent of in-person interactions required by a job. One major advantage of this measure is that it is based on what workers actually experienced as some employers abruptly shifted toward telework during the pandemic.

2.1.2 Measuring Longitudinal Changes in Employment Status and Earnings

We define the pre-pandemic period as the months between January 2019 and February 2020. The pandemic period begins in April 2020 and ends in May 2021, and is indexed by $t = 1, ..., T$. Below, we explain how the rotating panel structure of the data determines our January 2019-May 2021 sample period.

Employment Status

[10] Although Hispanic is an ethnicity, we refer to these groups as races in the remainder of the paper to ease exposition. Among Asians, CPS data do not distinguish between different nationalities. Since discriminatory actions against Asians mostly targeted East Asians, we believe our findings underestimate the true effects on the targeted groups.

[11] The industries are agriculture, mining, construction, non-durable manufacturing, durable manufacturing, transportation, communications, wholesale trade, retail trade, finance, business services, personal services, entertainment, health, educational services, and other professional services.

[12] Occupations have four digits, but the last digit is always zero, so we state that the system uses three digits.

[13] We stop in March 2021 because vaccines became widely available in the U.S. afterwards.

For each individual in the CPS, we define their "base time period" for employment status, indexed by $t = B$, as the last pre-pandemic month that they are in the sample before the cutoff month of March 2020. As a result, the base period is always February 2020 or earlier.[14] Importantly, the rotating panel structure of the data, which is described in detail below, implies that the base time period varies across individuals. Base employment status for individual i is denoted by the binary variable $E_i(B)$, and monthly employment status over the $t = 1, ..., T$ months of the pandemic is represented by the binary variable $E_i(t)$. They are equal to one if a person is employed in a given time period and zero if she is unemployed. The pandemic period begins in April 2020 ($t = 1$). The sample includes individuals in the CPS who are observed in both the pre- and post-pandemic periods, and are employed in the baseline period.

Table A.1 illustrates the structure of the data for two CPS cohorts.[15] The cohort who entered the CPS in January 2019 (labeled 2019-1 cohort) was surveyed for the first four months of 2019, rotated out of the sample for eight months, and then re-entered the data from January to April of 2020. For individuals in this cohort, their base employment status, $E_i(B)$, corresponds to the calendar month of February 2020. These individuals are observed once during the COVID period, in April 2020, and their employment status for this month is denoted by $E_i(t = 1)$. The 2019-1 cohort is the oldest one in our study, because these individuals are in their 8th sample period at the start of the COVID period. At the other end of the spectrum, the newest cohort eligible for our analysis is February 2020. These individuals have base month of February 2020, the final pre-COVID month before the cutoff of March 2020, and exit the CPS in May 2021. Based on the oldest and newest possible cohorts, our study period begins in January 2019 and ends in May 2021. These examples shows that, although our data spans $T = 14$ months of the COVID-19 pandemic, the panel data is unbalanced because individuals are observed for limited windows in the COVID-19 period depending on when their cohort entered the CPS.

As shown in Table A.1, the September 2019 cohort (labeled 2019-9 cohort) entered the CPS in September 2019. For this group, the base month is December 2019. When individuals in this cohort rotate back into the sample in September 2020, they contribute four monthly observations to the pandemic period: $E_i(t)$, where $t = 6, ..., 9$. As these examples illustrate, there are two types of variation in the time dimension of the sample: variation across cohorts in the length of time that elapses between the base and pandemic periods, and variation in the number of months that each cohort is observed during the pandemic period. We control for both cohort and time effects

[14] Our results are robust to ending the pre-pandemic period in March 2020. We exclude March 2020 as a potential base period because Figure A.1a shows that labor market conditions began to deteriorate in March. Nevertheless, our findings do not change if we use April 2020 as the cutoff month.

[15] In the official terminology of the CPS cohorts are referred to as "rotation groups."

throughout the empirical analysis.

Our empirical analysis of employment is based on the change in employment status between the base month and the pandemic period for all individuals who are employed in the base month. $\Delta E_i(t)$ is a binary variable equal to one each month that a person is not employed during the pandemic period, conditional on being employed in the base period. The variable is equal to zero each month during the pandemic period that the person is employed. Specifically,

$$\Delta E_i(t) = \begin{cases} 1 & \text{if } E_i(B) = 1 \text{ and } E_i(t) = 0 \\ 0 & \text{if } E_i(B) = 1 \text{ and } E_i(t) = 1 \end{cases} \tag{1}$$

for the $t = 1, ..., T$ months of the pandemic sample period. This variable captures the negative labor market outcome of becoming, and possibly remaining, unemployed over the pandemic.

Earnings

Weekly labor earnings are available in the CPS only in the 4th and 8th months that each respondent is in the sample. This implies a smaller number of observations for earnings compared to employment. Our analysis of earnings focuses on individual level changes in earnings from the pre-COVID-19 period to the COVID-19 period. An individual's base earnings, denoted $Y_i(B)$, is simply their pre-pandemic earnings, which is always recorded in their 4th survey month. After rotating out of the sample for eight months, individuals again report their pandemic earnings in their 8th, and final, survey month $Y_i(C)$. Based on the structure of the earnings data, the oldest CPS cohort with valid earnings data for our study was in their 4th survey month in April 2019, while the most recent cohort was in their 4th survey month in February 2020.

Table A.1 shows that the January 2019 cohort (2019-1 cohort) reported their base earnings ($Y(B)$) in April 2019, their 4th survey month. One year later, in April 2020, this cohort reports their earnings at the start of the COVID-19 sample period ($Y(C)$). As this example shows, earnings observations for a given person are always one year apart.

For each individual i with positive labor earnings in both the base period (B) and COVID-19 period (C), the year-over-year change in weekly labor earnings is:

$$\Delta Y_i = Y_i(C) - Y_i(B). \tag{2}$$

2.2 CPS Descriptive Statistics

Table 1 shows descriptive statistics by race for the baseline time period.[16] Asian workers are the highest educated racial group by a wide margin: nearly 70% of them in the baseline sample hold at least a college degree. The pattern in weekly earnings mirrors educational attainment. Asians have the highest baseline period average weekly earnings at $1,361, which is 19% higher than Whites, and far exceeds the earnings of Black and Hispanic workers.

Turning to geography, there are clear differences in the distribution of races across the US. Asians are concentrated in the West (41%) and most underrepresented in the Midwest (13%). Hispanics are similarly concentrated in the West (43%) and are also likely to live in the South (35%). Blacks are by far the most likely race to live in the South (64%).[17]

There are also large differences in the political leanings of the areas where different races reside. The majority of Asians (59%) live in states with the lowest level of support for President Trump, as defined below in sub-section 2.3. They are least likely to live in states with a high support for President Trump (7%). Asians are not unique among minority groups in their relative lack of representation in these states - both Black (13%) and Hispanic (9%) workers are also least likely to reside in such states.

Although there are differences across races in the industry of employment at baseline, on the whole, the differences do not seem especially large, particularly relative to the sizeable geographic and educational differences discussed previously. Some of the largest differences are found in construction, where Asian and Black workers are roughly half as likely to be employed compared to Whites, and Hispanics are over-represented. Since industries labeled in the CPS as "retail trade" and "personal services" will play a prominent role in our empirical analysis, we note that racial employment shares are fairly stable across both retail trade (ranging from 14.5% for Whites to 19.7% for Hispanics) and personal services (ranging from 2.4% for Whites to 5.6% for Asians).

The final employment-related variable is the binary variable indicating whether a worker's baseline job was in an occupation below the median in frequency of pandemic remote work, BMR. Despite clear differences in educational attainment and region of residence between Whites and Asians, both racial groups have very similar rates of working in BMR occupations at baseline (46% for Whites and 44% for Asians). In contrast, Hispanic and Black workers are far more likely to work in occupations where telework is less common. Fully 69% of Hispanic workers are employed in BMR occupations, while the corresponding fraction for Black workers is 60%.

[16] Recall from the discussion of the data that in order to be part of the sample, an individual must be employed in their baseline time period, so these descriptive statistics are conditional on employment.

[17] Although we present descriptive statistics at the level of broad Census regions, our empirical analysis controls for state fixed effects in order to capture geographical sorting of different races.

2.3 2016 Presidential election data

In order to gauge the heterogeneity of effects based on differential political leanings, we combine information on labor market outcomes with data on the 2016 Presidential Election. The data are from Dave Leip's Atlas of US Elections (Leip, 2017) which tracks votes received by presidential candidates in each county. For our analysis, we collapse these data at the state level, and group them into the following three aggregated categories based on the share of votes received by President Trump: the first quartile of state votes for President Trump (lowest vote share or "blue states"), the middle two quartiles ("moderate states"), and finally, the fourth quartile ("red states").[18]

2.4 Nationscape

Nationscape is an 18-month election study conducted by researchers at UCLA that completed more than 6,000 interviews each week. It started in July 2019 and concluded February 2021. Each weekly survey is released as its own dataset. The sample is weighted to be representative of the U.S. adult population.[19] We use questions on the how favorably different racial groups are viewed, and their dynamics over time, to measure changes in (the expression of) public opinion.

3 Empirical Analysis and Results

We start by quantifying the effects of the pandemic by racial background, visually shown in Figure A.1a, by estimating a regression of $\Delta E_i(t)$ on race. The main specifications use panel linear probability models where the dependent variable is $\Delta E_i(t)$, the binary variable that indicates individual i was unemployed in month t of the pandemic, conditional on being employed in the baseline. The models include CPS cohort (rotation group) fixed effects, year-month fixed effects, and a standard set of controls for college graduation, gender, and a quadratic in age. Standard errors are clustered at the individual level. Our primary interest is investigating the role of race in determining transition into unemployment, and how race interacts with characteristics of the baseline jobs that individuals held before the pandemic.

Column (1) of Table 2 confirms that the aggregate trends observed in Figure A.1a are reflected in longitudinal transitions into unemployment: Asians, Blacks, and Hispanics are more likely than

[18]The blue states are CA, CT, DE, DC, IL, MD, NJ, NY, OR, RI, VT, and WA. The red states are AL, AR, ID, KY, NE, ND, OK, SD, TN, UT, WV, and WY. AK and HI are excluded.

[19]The data is weighted on gender, the four major census regions, race, Hispanic ethnicity, household income, education, age, language spoken at home, nativity (U.S.- or foreign-born), 2016 presidential vote, and the urban-rural mix of the respondentâs ZIP code. They also weight on the following interactions: Hispanic ethnicity by language spoken at home, education by gender, gender by race, race by Hispanic origin, race by education, and Hispanic origin by education.

Whites to become unemployed during the COVID-19 pandemic. The coefficient estimates suggest that, even after controlling for gender, age, educational attainment, and cohort and time fixed effects, each minority race is approximately three percentage points more likely to be unemployed after the pandemic (2.6, 3.1, and 3.2 p.p. for Asians, Blacks, and Hispanics, respectively).[20] These relationships are precisely estimated, and are quite large in magnitude. To provide some context for the magnitudes, the mean of the binary dependent variable, which is the probability of being unemployed over the pandemic period conditional on baseline employment, is 0.096.

In column (2) we add the below median remote occupation dummy, BMR, to the model. The intent is to understand how workers in occupations that are more likely to take place in-person are affected by the pandemic and whether this by itself can account for some of the racial differences described above. The estimates show that individuals employed in non-remote intensive occupations in the baseline period were 3.3 p.p. more likely to be unemployed after the pandemic. Notably, adding the BMR occupation dummy does not significantly change the estimated effect of race on the probability of job loss: Asians, Blacks and Hispanics are still more likely than Whites to be unemployed after the pandemic. This suggests that the remote employment share differences across races cannot explain the higher drop in employment experienced by minorities.

Column (3) reports the estimates of our main regression specification, which includes the interaction terms between race/ethnicity and our BMR index for occupations. While the coefficient estimates for Black, Hispanic, and BMR do not change significantly, the coefficient on Asian decreases considerably (from 2.5 p.p. in column (1) to -0.6 p.p. in column (3)). In addition, the coefficient estimate for the interaction between Asian and BMR is large and positive: Asians employed in BMR occupations are 7.3 p.p. more likely to be unemployed. These findings suggest that the increase in Asian unemployment is driven by Asians working in occupations that are more likely to require face-to-face interactions. Interestingly, this pattern is not observed among any other racial minority — the corresponding BMR interactions are small in magnitude and not statistically different from zero for both Black and Hispanic workers.[21]

These results raise the question of why Asians, a minority group that typically outperforms all other racial groups in the labor market, would perform relatively worse than Whites during the pandemic and more importantly why, unlike other minority groups, the increase in unemployment is confined to Asians working in occupations that are less suited to remote work? One potential explanation is increases in bias against people of Asian background as a result of worsening public

[20] Our main findings do not change when using April 2020 as the cutoff month (making March 2020 the earliest possible base month).

[21] We show the results are robust to allowing remote occupation to enter the model through functional forms other than the binary BMR specification.

opinion potentially stemming from the unfortunate labelling of COVID-19 by some in the public sphere as the "Chinese virus." Next, we attempt to rule out other competing explanations and provide evidence in support of this hypothesis.

The Role of Geographical Sorting

Our findings in column (3) of Table 2 could be explained by the possibility that Asians who work in BMR occupations are over-represented in areas which experienced a steeper decline in labor market outcomes during the period of study as a result of, for example, harsher lockdowns. To test if our results are driven by Asians sorting into specific parts of the country, as shown in 2.2, in column (4) we control for state fixed effects. As the estimates show, the results are unchanged. Thus, geographical sorting is unlikely to be the main driver of our findings.[22]

The Role of Industry and Occupation Sorting

What we pick up as the effect of less remote-friendly occupations could be driven by the negative effect of the pandemic on industries in which those types of occupations are abundant and Asians are over-represented. To the extent that job losses in certain industries pick up the effect of industry level face-to-face jobs, this would not be a threat to our interpretation of findings. Nevertheless, it is informative to see if the results hold when we control for baseline industry of employment. Column (5) of Table controls for the aggregate one-digit industries while column (6) controls for the aggregate two-digit industries discussed in Section 2.1.1 in addition to state effects. The findings remain unchanged. Alone among all minorities, Asians employed in occupations unfriendly to remote work are much more likely to become unemployed over the pandemic.[23]

As Asian workers are strongly over-represented in STEM, even after controlling for education, one might worry that differential unemployment responses in tech versus non-tech industries could be a confounding factor. The fact that estimates are almost unchanged when including progressively more extensive industry controls (i.e. moving from column (5) to column (6)) is reassuring.[24]

Finally, we run a robustness check to show that the estimates in Table 2 are unlikely to be explained by unobservables correlated with our remoteness measure, BMR, that differ by

[22] Relying on the four aggregate Census regions and data from the early months of the pandemic (i.e. up until June 2020), Couch, Fairlie and Xu (2020) argue that Asians suffered in the labor market because of a weaker labor market in the West where they are over-represented. Here we go beyond that by looking at the state of residence.

[23] Occupations in essential industries are more likely to be performed in-person. As a result, the fact that non-essential industries were plausibly affected more negatively by the pandemic could not be the driver of our findings.

[24] Estimates are unchanged even when we control for three-digit industries (results available upon request), even though one should keep in mind that, the higher the level of detail at the industry level, the more problematic, as workers sort endogenously across industries. Also, using more detailed industry groupings results in losing statistical power when we divide the sample for heterogeneity analysis in subsequent sections, since there would be 220 three-digit industry fixed effects. Nevertheless, it is instructive that we see little change in our findings when we progressively increase controls from one- to two- to three-digit industry codes.

race/ethnicity. For example, if stockers were unlikely to be laid-off but cashiers were, and if Asians are more likely to be cashiers, we do not want to attribute the difference to race. Appendix Table 3 replicates Table 2, but instead of including BMR as an explanatory variable, it includes two-digit *occupation* fixed effects and uses BMR only as an interaction. Results show that, when controlling for detailed occupation dummies, the coefficient estimates of the interaction between BMR and Asian are still very large.[25]

The Role of Risk Aversion and COVID-19 Risk Perception

An alternative interpretation of our findings is that Asians might have a higher risk perception of COVID-19 or be more risk averse than other groups in general and shy away from jobs that require in-person interactions as a result. For example, early on during the pandemic, Chinese Americans might have been more aware of the dangers of COVID-19 because of their connections with China and associated awareness of the severity of the pandemic. Consequently, they might have acted more conservatively and opted out of working in more face-to-face settings.

First, we document that Asians are not more likely than other groups to report that the pandemic curtailed their interactions with friends. We use the "2020 American Life Panel Survey on Impacts of COVID-19," a survey conducted by the RAND American Life Panel (ALP) to assess the effects of the pandemic on individuals and households. In particular, we rely on Wave 1 of this survey conducted in May 2020 and look at the responses to the following question: "Since the coronavirus outbreak first started, how much has it prevented you from interacting with your friends?" The possible answers are: 1 Not at all; 2 A little; 3 Somewhat, 4 Very much; and 5 Totally. We use these answers as a proxy for how conservative people of different races became in interacting with others when the pandemic happened. We find that, while the average response for Asians is 3.31, the average for people of other races except White/Caucasian is 3.39, and the one for White/Caucasians is 3.51.

In addition, we consider the survey "Well Being 556 - COVID-19 Attitudes and Perceptions" conducted in October 2020 by ALP. A question in this survey asks "If you were diagnosed with COVID-19 how concerned would you be about your ability to recover from it?" The possible answers are: 1 Not concerned; 2 Slightly; 3 Somewhat; 4 Moderately; 5 Extremely. The mean value for Asians is 3.47 and for other races except White/Caucasian is 3.86. Although because of small sample sizes (500 individuals) none of these differences are significant, they suggest Asians did not behave more conservatively than others after COVID-19.

[25]Note that we cannot control for three-digit occupation dummies, since our BMR measure is constructed based on differences in occupations at that level.

It is also possible that Asians could be more risk averse than other groups. Moreover, given that jobs that require in-person interactions are riskier in the aftermath of the pandemic, Asian workers in those occupations might have quit their jobs. While we cannot directly test this in our data, we provide suggestive evidence that this is unlikely to be true. We rely on Global Preference Survey (Falk et al., 2018) to measure risk preferences across Asian countries versus the rest of the world and see if Asians have less risk tolerance.[26] The Global Preference Survey (GPS) is an experimentally validated survey data set of economic and social preferences from 76 countries representing approximately 90% of the world population. Risk preferences in GPS are elicited through a series of related quantitative questions as well as one qualitative question (see Falk et al. (2018) for details). The quantitative survey measure consists of a series of five interdependent hypothetical binary choices, a format commonly referred to as a "staircase" (or "unfolding brackets") procedure. Choices are between a fixed lottery, in which the individual could win x or zero, and varying sure payments, y.[27] The qualitative item asks for the respondentsâ self-assessment of their willingness to take risks on an 11-point Likert scale, *"In general, how willing are you to take risks?"*. Using data presented in the Online Appendix for Falk et al. (2018), one can see that the average risk tolerance in East and Southeast Asian countries is very close to the average of other countries, both measured around zero.[28]

Finally, in Appendix Table A.3 we report the estimates of Table 2 for a sample that adds those who leave the labor force and expands the outcome variable to capture both unemployment and leaving the labor force. If Asians were more risk averse, one would expect to see exit from the labor market as a consequence of higher likelihood of exposure to the virus in more in-person jobs. The estimates however, are very similar to the ones in Table 2. This tends to indicate that workers are switching to unemployment and not exiting the labor force.

Potential Mechanism: The Role of Public Opinion

Our hypothesis is that the underlying phenomenon driving the increasing woes of Asians in the labor market during the aftermath of the pandemic was the changes in public opinion about people of Asian descent and the rise in animosity against them. Next, we provide some evidence in support of this argument.

[26] Although the authors rely on monetary lotteries to infer risk tolerance, there is a large literature that shows risk preferences are correlated across multiple domains, from financial investments to decisions about health to job choice to leisure activities (Barsky et al., 1997; Dohmen et al., 2011; Zhong et al., 2009).

[27] *"Please imagine the following situation. You can choose between a sure payment of a particular amount of money, or a draw, where you would have an equal chance of getting amount x or getting nothing. We will present to you five different situations. What would you prefer: a draw with a 50% chance of receiving amount x, and the same 50% chance of receiving nothing, or the amount of y as a sure payment?"*

[28] See https://www.briq-institute.org/global-preferences/rankings2-0-0

If the aforementioned hypothesis is correct, one would expect to see differential effects across the political spectrum. The anti-Chinese rhetoric by President Trump and the right-wing media is likely to have played a role in people's perception of Asians and their willingness to interact with them as workers. Moreover, such rhetoric is likely to have been received differently based on their level of support for the President and likelihood of paying attention to certain media outlets.

In order to test this hypothesis, we estimate our main specification separately for different quartiles of political views, proxied by workers' state of residence in the baseline period. We rank all 50 states from the most Democratic to the most Republican using the county level share of Republican votes in the 2016 presidential race and construct the quartiles of Republican and Democratic states.

Estimates are reported in Table 2, columns (7)-(9). Column (7) shows the results for the quartile of the most Democratic states, column (8) for the two middle quartiles, and column (9) for the quartile of the most Republican states. Irrespective of the political landscape, the effect of being Asian stays almost constant. The coefficient estimate for the interaction term of Asian and below median remoteness however, is smaller in the most Democratic group of states. The difference between the most Democratic and the most Republican quartiles, while not statistically significant, is large and points to Asians being more likely to lose face-to-face jobs in areas where support for the former president was higher and, presumably, the anti-Asian rhetoric had more of an effect. It is worth noting that the interaction variable stays significantly positive even in the most Democratic states, indicating the bias against Asians might have played a factor throughout all parts of the political spectrum.

Next, we directly examine the changes in public opinion about Asians, and other minorities, using data from Nationscape, a nationally representative survey which collects the electorates' views on a number of issues, including favorability of different groups of the population, on a weekly basis. The survey asks "How favorable is your impression of Asians"? The possible answers are: 1) Very favorable, 2) Somewhat Favorable, 3) Somewhat unfavorable, 4) Very unfavorable, or 5) Haven't heard enough. We combine the unfavorable categories (3 and 4) into one, calculate the share of non-Asians with unfavorable views of Asians, and take monthly averages. We do the same for Blacks and Latinos.

Figure 1 shows the results. The top panel shows the share of the electorate with an unfavorable views of Asians, Blacks, and Latinos, broken down by those who voted for President Trump (or not) and time. The monthly data span two periods—a pre-period that includes the last three months of 2019 and a post-period that begins in March 2020, when Asians started to become the target of blame in certain public spheres. In the bottom panel, we disaggregate the opinion data by those who report getting their news from Fox News Channel versus other news sources. While around 10% of the non-Asian population held unfavorable views of Asians during the last three months of 2019, this figure goes up by more than 35% during the first three months of the pandemic.

Although widespread along the political spectrum, negative changes in views of Asians were much stronger among those who voted for President Trump in 2016 and those who report getting their news from Fox News Channel. Strikingly, the share holding unfavorable views was similar among non-Trump voters and Trump-voters before the pandemic—both stand at around 10%. However, while the share of those with unfavorable views among non-Trump voters went up by around 25% during the early months of the pandemic, it increased by around 55% among Trump-voters.[29] Similarly, the increase in unfavorable views of Asians is more salient among Fox News watchers.

We see no such changes in favorability of other minorities. This is consistent with the heterogeneous labor market effects we find across different states in the last three columns of Table 2 and the hypothesis that anti-Chinese rhetoric was received differently based on individuals' political leanings and their attention to certain media outlets.

One should note that we cannot rule out that racial bias against Asians would not have intensified in the absence of the anti-Chinese rhetoric from President Trump and the right-wing media. Nevertheless, Figure 1 shows that, regardless of its cause, public opinion about Asians changed for the worse in specific subgroups of the population that corresponds to the pattern of labor market outcomes we find in Table 2.

4 Alternative Measure of Face-to-Face Interactions

In our analysis so far, we have proxied for face-to-face jobs by measuring how likely is that a certain occupation to have taken place remotely in the aftermath of the pandemic. This could be problematic for two reasons. First, the index is constructed using data from people who answer the survey question about their occupations after the onset of the pandemic. As a result, those who lose their jobs or exit the labor market may not answer the question.[30] If people of certain characteristics in a given occupation (e.g. those who are less able to do their jobs remotely) are more likely to lose their jobs, the index is affected by our treatment variable —the coronavirus pandemic.

Second, non-remoteness does not perfectly predict if a job has to be performed face-to-face

[29]Note that, non-Trump voters include all those who did not vote for Trump, including those who did not participate in the election.

[30]This concern is mitigated by the fact that the remote work question asks respondents about telework over the past four weeks, so an individual could be currently unemployed but still answer the question.

with the customer or even the employer, although we believe there should be a high correlation. As an example, truck drivers do not do their jobs remotely but they don't necessarily face clients or managers often.

As a robustness check, we construct a second measure of face-to-face work by taking into account various industries' differential reliance on in-person interactions before the pandemic. The two-digit industry classifications in the CPS are agriculture, mining, construction, manufacturing of non-durable goods, manufacturing of durable goods, transportation, communications, wholesale trade, retail trade, finance, business services, personal services, entertainment, health, educational services, and other professional services. Arguably, retail trade and personal services are the two industries with the highest level of face-to-face interactions.

We estimate a model similar to the one in Table 2, where we replace the remoteness measure (BMR) with a face-to-face industry dummy (hereafter FTF) that takes value one if an individual's base-period job was in the retail trade or personal services industries. In the main analysis, we limit the sample to workers with at most a high school diploma, as one would expect that it is the low-skilled workers employed in the aforementioned two industries that interact intensively with other people. For example, a computer programmer working in a retail industry should not be categorized as someone working in a face-to-face setting.[31]

Table 4 reports the results. The FTF dummy coefficient is positive and statistically significant, indicating that unemployment increased more for workers in industries that rely more heavily on face-to-face interactions. Moreover, as the coefficients of the interaction terms in column (1) show, Asians in industries with the largest face-to-face components (i.e. retail trade and personal services) are the ones who experience the largest increases in unemployment. The interaction coefficient is also positive and statistically significant for Hispanics, but it is a quarter of the size of the one for Asians.

In columns (2)-(4), we divide the sample by states' political orientation to investigate the differential effects of political leanings on employment status of Asians. The coefficient estimate for the interaction term of Asians and FTF is smallest in the most Democratic states. Consistent with the findings in Table 2, the difference between the most Democratic-leaning and the most Republican-leaning is large — almost three times in magnitude. After controlling for other factors, the highest unemployment probability for an Asian working in a face-to-face industry is found in strongly Republican states where anti-Asian rhetoric might have been best received and spread

[31] Appendix Table A.2 shows the estimates for the full sample. The face-to-face industry is defined as a dummy equal to one if an individual works in personal services or retail and does not have college education. The results are very similar. Alternatively, one can define treatment only based on industry of employment without differentiating on college education. When we do that, we get similar, but slightly weaker, estimates. This is expected, since face-to-face jobs are better captured when limiting the sample to those without higher education.

most strongly.

Given retail and personal services' reliance on interaction with customers, and less so with co-workers, these findings also suggest that the main source of bias against Asians in the labor market might have been discrimination by customers and, potentially, employers' reaction to that by decreasing demand for employees of Asian descent.[32]

5 Additional Robustness Checks

While the binary measures of remote work BMR and FTF are easy to interpret, it is possible that they could make the results sensitive to the distribution of remoteness within race/ethnicity. Tables 5 and 6 consider a continuous variable and quartiles of remoteness, respectively. In particular, for Table 5, we construct a continuous measure of remoteness using the same occupation-level frequency of post-COVID-19 telework data that the BMR variable is based on. To obtain the variable Standardized Non-Remote work (SNR), we first standardize the occupation-level telework frequency so that it has a mean of zero and standard deviation of one. Then, we multiply it by -1 so that increases in SNR indicate jobs where telework is less common.[33] In Table 6, we consider quartiles of remote work based on the occupation-level frequency of post-COVID-19 telework. Estimates from both tables support our previous findings with the binary measures of remote work, BMR and FTF, shown in Tables 2 and 4. The linear specification confirms our main findings from the binary treatment of remoteness—Asians in less remote friendly jobs were more likely to lose their jobs during the pandemic. Importantly, Table 6 shows monotonic increases in the probability of unemployment for Asian workers as their base job becomes less amenable to remote work (higher quartiles of remoteness). Moreover, consistently across quartiles of remoteness, Asians are more likely to lose their jobs in states that voted more favorably for Trump in 2016.

A concern about our findings might be that some individuals appear in the panel analysis more often than others because of their cohort assignment or attrition from the data. However, note that, individuals from different racial backgrounds do not differentially drop from the data. Specifically, the average number of observations contributed to the panel regressions is 3.2 for Whites, 3.2 for Asians, 3.1 for Blacks, and 3.1 for Hispanics. Also, since each wave is nationally representative, it is unlikely that cohort assignment would differ across races. To provide further assurance that

[32] The O*NET database contains information about the activities performed in different occupations. However, the data on interpersonal interactions do not distinguish between interactions that occur in-person versus those that occur remotely. As a result, we prefer to rely on classification by industries where in-person interactions with customers are common.

[33] Multiplying be -1 makes the sign of the SNR regression coefficient comparable to the BMR variable. Negative coefficients on both indicate that unemployment is more likely in jobs where telework is less common.

this is not a concern, we estimate the same regression specifications in Table 2 using only the first pandemic observation for each individual. This way, we have the same weight for each individual in the sample. Estimates reported in Appendix Table A.4 show very similar results to the ones in Table 2. Unique among all races, Asians in BMR jobs were more likely to become unemployed during the pandemic. In fact, the estimated magnitude of this relationship is even larger than in the main regression specification. Based on the panel regression estimates (Table 2), Asians in BMR jobs are 5.9 percentage points more likely than whites in the same jobs to become unemployed. This estimate is 7.1 percentage points in the version of the model shown in Appendix Table A.4.

6 Earnings

Next, we quantify the effects of the pandemic on earnings. Table 7 shows estimates of a regression of the change in a person's weekly labor earnings from the pre-pandemic base period to the COVID-19 period. As discussed in section 2.1.2, given the limited availability of earnings data in the CPS, the dependent variable is an individual level year-over-year change in earnings, and each individual contributes at most one observation to this regression. The sample includes only workers who are employed and report positive labor earnings both in the base period and during the pandemic. We acknowledge that, by doing this, we select on treatment. As we showed before, COVID-19 led to changes in employment status for some workers. However, including those with zero earnings would make it very difficult to interpret the estimates in this exercise, as one would not know if a potential negative effect on earnings originates from changes in earnings or transitions into unemployment, and we are interested in examining if our findings extend beyond the employment effects presented in the previous section.

Column (1) in Table 7 reports estimates of how changes in earnings vary across racial categories. The estimated coefficient for Asians suggests a $25.48 drop in earnings for Asians compared to Whites. This difference is large in magnitude: the median earnings change is $19.23 and the median weekly baseline earnings is $905. In contrast to the experience of Asians, there is no evidence that the changes in earnings for Black or Hispanic workers differed from that of White workers. Furthermore, as shown in column (2), controlling for baseline employment in a BMR occupation does not significantly alter the estimated relationship between race and changes in earnings. Similar to the unemployment findings in Table 2, this suggests that differential employment in BMR occupations across races cannot account for the lower negative changes in earnings experienced by Asian workers during the pandemic.

Column (3) adds the interactions between race and BMR employment. The estimates reveal that Asians working in more interactive occupations experienced a \$75.50 *lower* earnings change than Whites with the same observable characteristics. This difference is large: it corresponds to 8% of median weekly earnings ($\frac{75.50}{905} = 0.08$). To provide further context for the magnitude of this estimate, the estimated penalty for being an Asian in a BMR occupation is over 2.5 times larger than the penalty for not having a college degree.[34] As the estimates in columns (4) and (5) show, these findings are robust to controlling for state fixed effects and industry of employment in the base period.

These results show that, in addition to facing a higher risk of unemployment during the pandemic, Asians in face-to-face jobs were also harmed by substantial losses in earnings even if they remained employed. Finally, all specifications including race-remoteness interactions show that, in marked contrast to the experience of Asians, Black workers in BMR jobs realized *larger* earnings growth than Whites in the same type of job.

These results, taken together with our finding that the negative employment outcomes of Asians are driven by unemployment, as opposed to voluntarily exits from the labor force, suggest that changes in the labor market outcomes of Asians after the pandemic are driven by changes in labor demand and not labor supply.

7 Conclusions

This paper highlights the relation between public opinion and racial minorities' labor market outcomes. Political figures' rhetoric, social media activity, and media commentaries constantly change how minorities are viewed and the ease of publicly expressing negative views towards them. Despite this, the literature has been silent on what happens to the economic lives of minorities when public opinion turns against them. We examine the consequences of the anti-Chinese rhetoric that emerged in the U.S. with COVID-19 pandemic by investigating a representative panel of American workers from the Current Population Survey, both before and after the onset of the pandemic. Our analysis shows that labor market outcomes for Asians who worked in occupations and industries more prone to face-to-face interactions deteriorated during the pandemic. In addition to facing an increased risk of unemployment, Asians in these jobs who remained employed experienced a significant decline in earnings.

Although we cannot establish direct causal links between changes in opinion and labor market outcomes of Asians, we provide evidence in support of our hypothesis. First, we show that the negative labor market outcomes for workers in in more interactive sectors of the economy are

[34]The coefficient estimate for the college graduate dummy is \$30.09 and is not shown in Table 7 to save space.

confined to Asians, and do not extend to any other racial minority group. We also document that the effects are more pronounced in states that voted heavily in favor of President Trump in 2016. This is consistent with the fact that anti-Chinese rhetoric by President Trump might have been more favorably received by his supporters, and the audience of certain media outlets, such as Fox News, that called the COVID-19 virus the "Chinese (or China) Virus." Moreover, we show that unfavorable views of Asians increased by much more among those who voted for President Trump and those who get their news from Fox News. Finally, we argue that geographical and industry sorting or differential risk perception of Covid across racial backgrounds are unlikely to be the major drivers of our findings.

Our paper is the first to show that an increases in racial bias — plausibly generated and intensified by political rhetoric and indoctrination by the media — can have detrimental effects on the employment and earnings of the targeted group. More generally, we shed more light on the potential role of media and public opinion in shaping the life outcomes of individuals who come from minority backgrounds. Finally, our results raise caution about the potential additional consequences of the increasingly divisive racial rhetoric that is currently apparent in politics and the media in the United States, and beyond.

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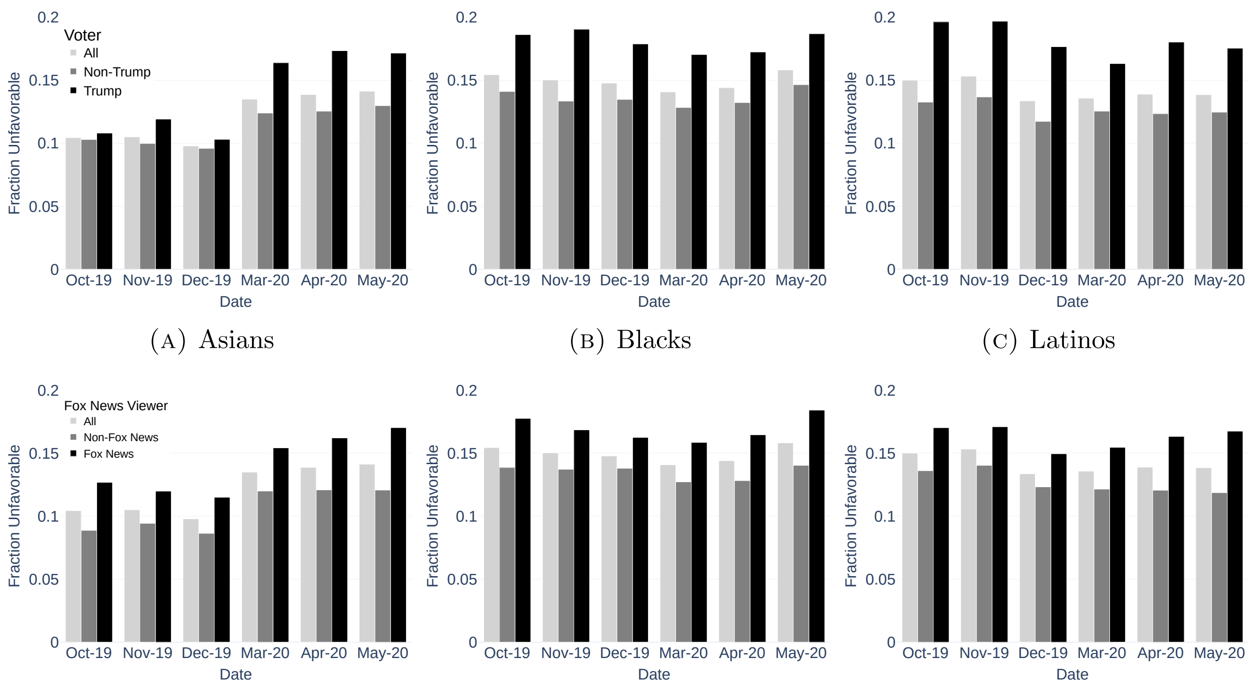
Figure 1: Unfavorable Opinions of Different Races Over Time by Trump Voting and Fox News Viewership



(A) Asians (B) Blacks (C) Latinos

(D) Asians (E) Blacks (F) Latinos

Notes: Data Source: Nationscape Survey.

Table 1: Descriptive Statistics by Race

	White (1)	Asian (2)	Black (3)	Hispanic (4)	All (5)
College	0.556	0.697	0.428	0.292	0.515
Male	0.529	0.532	0.451	0.562	0.527
Age	44.780	42.440	42.911	40.505	43.873
Below Median Remote (BMR) Work Occupation*	0.463	0.436	0.603	0.689	0.506
Census Region					
Northeast	0.186	0.203	0.141	0.110	0.172
South	0.330	0.260	0.636	0.352	0.358
Midwest	0.259	0.130	0.128	0.104	0.217
West	0.225	0.406	0.095	0.434	0.252
Redness Quartiles†					
Blue	0.272	0.586	0.296	0.418	0.312
Moderate	0.495	0.344	0.578	0.493	0.494
Red	0.234	0.070	0.126	0.088	0.194
Industry					
Agriculture	0.029	0.006	0.010	0.046	0.028
Mining	0.009	0.004	0.002	0.006	0.007
Construction	0.076	0.025	0.039	0.128	0.077
Manufacturing (non-durable)	0.040	0.040	0.044	0.052	0.042
Manufacturing (durable)	0.074	0.085	0.053	0.059	0.070
Transportation	0.045	0.046	0.087	0.056	0.050
Communications	0.025	0.024	0.023	0.019	0.024
Wholesale Trade	0.026	0.022	0.016	0.025	0.025
Retail Trade	0.145	0.171	0.167	0.197	0.156
Finance	0.077	0.079	0.064	0.053	0.072
Business Services	0.078	0.123	0.077	0.081	0.081
Personal Services	0.024	0.056	0.034	0.040	0.029
Entertainment	0.021	0.017	0.016	0.018	0.020
Health	0.120	0.120	0.167	0.086	0.120
Educational Services	0.113	0.086	0.102	0.070	0.104
Other Professional Services	0.100	0.098	0.101	0.063	0.095
Weekly Earnings‡	$1,144.68	$1,360.96	$898.02	$854.14	$1,096.67
Observations (employment)	48,028	3,824	6,351	9,490	67,693
Observations (earnings)	26,137	1,977	3,272	4,649	36,035

Notes: Entries are means. All descriptive statistics except weekly earnings are for the baseline sample period of the employment regressions. *Below median remote (BMR) work occupation is a dummy variable equal to 1 if the person's base job was in an occupation below the median in frequency of post-COVID-19 telework/remote work. † "Redness Quartiles" groups states based on the share of votes received by President Trump in the 2016 election. The groups are: the 1st quartile (lowest vote share or "blue states", the middle two quartiles ("moderate states"), and the fourth quartile ("red states"). ‡ Weekly earnings are for the baseline month for the earnings regressions.

Table 2: Regressions: Unemployment and Remote Occupation

	Race and Remote Occupation						Redness Quartiles†		
							1st (Blue States)	2nd and 3rd	4th (Red States)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Asian	0.026	0.025	-0.006	-0.018	-0.017	-0.015	-0.009	-0.007	-0.014
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.013)
Black	0.031	0.027	0.026	0.026	0.027	0.028	0.026	0.037	-0.001
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)	(0.007)	(0.010)
Hispanic	0.032	0.028	0.026	0.021	0.023	0.024	0.030	0.022	0.023
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)	(0.015)
Below Median Remote (BMR)		0.033	0.028	0.030	0.019	0.027	0.041	0.021	0.025
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)
Asian × BMR			0.073	0.073	0.060	0.059	0.038	0.060	0.078
			(0.009)	(0.009)	(0.009)	(0.009)	(0.013)	(0.014)	(0.025)
Black × BMR			0.004	0.004	0.002	0.000	0.002	-0.009	0.026
			(0.007)	(0.007)	(0.007)	(0.007)	(0.014)	(0.009)	(0.015)
Hispanic × BMR			0.003	0.000	-0.002	-0.004	-0.011	-0.008	0.002
			(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.008)	(0.018)
Fixed Effects									
One-Digit Industry	N	N	N	N	Y	N	N	N	N
Two-Digit Industry	N	N	N	N	N	Y	Y	Y	Y
State	N	N	N	Y	Y	Y	Y	Y	Y
Observations	217,920	217,920	217,920	217,920	217,920	217,920	67,439	107,725	42,756
Individuals	67,693	67,693	67,693	67,693	67,693	67,693	21,130	33,424	13,139

Notes: Binary dependent variable is equal to one if a person is employed in the base month, and is unemployed in the current month. Sample period is 1/2019-5/2021. Below median remote (BMR) is a dummy variable equal to 1 if the person's base job was in an occupation below the median in frequency of post-COVID-19 telework. All models include year-month fixed effects, CPS rotation group cohort fixed effects, a college graduation dummy, a constant, gender, and a quadratic in age. The omitted race is White. Standard errors clustered at the individual level. † "Redness Quartiles" groups states based on the share of votes received by President Trump in the 2016 election. The groups are: the 1st quartile (lowest vote share or "blue states", the middle two quartiles ("moderate states"), and the fourth quartile ("red states").

Table 3: Regressions: Unemployment and Remote Occupation with Two Digit Occupation Fixed Effects

	Race and Remote Occupation						Redness Quartiles†		
							1st (Blue States)	2nd and 3rd	4th (Red States)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Asian	0.026	0.024	-0.001	-0.013	-0.012	-0.011	-0.006	-0.004	-0.013
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.014)
Black	0.031	0.026	0.025	0.025	0.027	0.028	0.025	0.038	-0.002
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)	(0.007)	(0.010)
Hispanic	0.032	0.024	0.027	0.021	0.024	0.024	0.029	0.022	0.023
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)	(0.015)
Asian × Below Median Remote			0.057	0.058	0.050	0.050	0.029	0.051	0.071
			(0.009)	(0.009)	(0.008)	(0.008)	(0.012)	(0.013)	(0.025)
Black × Below Median Remote			0.001	0.002	-0.001	-0.002	-0.001	-0.012	0.026
			(0.007)	(0.007)	(0.007)	(0.007)	(0.014)	(0.009)	(0.014)
Hispanic × Below Median Remote			-0.003	-0.005	-0.010	-0.010	-0.018	-0.013	-0.001
			(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.008)	(0.018)
Two Digit Occupation	N	Y	Y	Y	Y	Y	Y	Y	Y
One Digit Industry	N	N	N	N	Y	N	N	N	N
Two Digit Industry	N	N	N	N	N	Y	Y	Y	Y
State	N	N	N	Y	Y	Y	Y	Y	Y
Observations	217,920	217,920	217,920	217,920	217,920	217,920	67,439	107,725	42,756

Notes: Binary dependent variable is equal to one if a person is employed in the base month, and is unemployed in the current month. Sample period is 1/2019-5/2021. Below median remote (BMR) is a dummy variable equal to 1 if the person's base job was in an occupation below the median in frequency of post-COVID-19 telework. All models include year-month fixed effects, CPS rotation group cohort fixed effects, a college graduation dummy, a constant, gender, and a quadratic in age. The omitted race is White. Standard errors clustered at the individual level.The two-digit occupations are 1. Management, Business and Financial Operations, 2. Computer and Mathematical, 3. Architecture and Engineering, 4. Life, Physical, and Social Science, 6. Social Service, 7. Legal, 8. Education, 9. Arts Entertainment and Media, 10. Healthcare Practitioner, 11. Healthcare Support, 12 Protective Service, 13. Food Preparation and Service, 14. Building and Grounds Maintenance, 15. Personal Care and Service, 16. Sales, 17. Office and Administrative Support, 18. Farming and Fishing, 19. Construction and Extraction, 20. Maintenance and Repair, 21. Production, 22. Transportation and Moving. † "Redness Quartiles" groups states based on the share of votes received by President Trump in the 2016 election. The groups are: the 1st quartile (lowest vote share or "blue states", the middle two quartiles ("moderate states"), and the fourth quartile ("red states").

Table 4: Regressions: Unemployment and Face-to-Face Industry (Low Education Workers Only)

		Redness Quartiles†		
	US	1st (Blue States)	2nd and 3rd	4th (Red States)
	(1)	(2)	(3)	(4)
Asian	0.026	0.026	0.028	0.046
	(0.010)	(0.016)	(0.016)	(0.025)
Black	0.036	0.017	0.051	0.019
	(0.006)	(0.012)	(0.008)	(0.011)
Hispanic	0.016	0.024	0.011	0.027
	(0.004)	(0.008)	(0.006)	(0.011)
Face-to-Face Industry (FTF)	0.041	0.077	0.038	0.014
	(0.004)	(0.010)	(0.005)	(0.007)
Asian × FTF	0.080	0.045	0.086	0.108
	(0.019)	(0.030)	(0.028)	(0.053)
Black × FTF	0.011	0.001	0.003	0.034
	(0.012)	(0.026)	(0.016)	(0.027)
Hispanic × FTF	0.017	-0.004	0.020	-0.008
	(0.009)	(0.016)	(0.012)	(0.022)
Observations	102,546	28,609	52,077	21,860
Individuals	33,379	9,442	16,927	7,010

Notes: Binary dependent variable is equal to one if a person is employed in the base month, and is unemployed in the current month. Sample includes workers whose highest degree completed is at most high school. Sample time period is 1/2019-5/2021. Face-to-Face Industry (FTF) is a dummy variable equal to 1 if the person's base job was in the retail sales or personal services industries. All models include year-month fixed effects, CPS rotation group cohort fixed effects, state fixed effects, a constant, gender, and a quadratic in age. The omitted race is White. Standard errors clustered at the individual level.† "Redness Quartiles" groups states based on the share of votes received by President Trump in the 2016 election. The groups are: the 1st quartile (lowest vote share or "blue states", the middle two quartiles ("moderate states"), and the fourth quartile ("red states").

Table 5: Regressions: Unemployment and Continuous Measure of Non-Remoteness

	Race and Remote Occupation					Redness Quartiles†		
						1st (Blue States)	2nd and 3rd	4th (Red States)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asian	0.026	0.029	0.039	0.026	0.021	0.014	0.030	0.035
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.014)
Black	0.031	0.027	0.027	0.026	0.027	0.025	0.031	0.010
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.007)	(0.005)	(0.007)
Hispanic	0.032	0.026	0.027	0.020	0.021	0.022	0.017	0.021
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)	(0.009)
Std Non-Remote Work		0.021	0.018	0.019	0.019	0.027	0.016	0.015
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Asian × (SNR)			0.029	0.028	0.023	0.013	0.023	0.032
			(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.011)
Black × (SNR)			0.004	0.003	0.001	-0.001	-0.002	0.019
			(0.003)	(0.003)	(0.003)	(0.007)	(0.005)	(0.008)
Hispanic × (SNR)			0.002	-0.000	-0.002	-0.006	-0.005	0.005
			(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.010)
Two Digit Industry	N	N	N	N	Y	Y	Y	Y
State	N	N	N	Y	Y	Y	Y	Y
Observations	217,920	217,920	217,920	217,920	217,920	67,439	107,725	42,756
Individuals	67,693	67,693	67,693	67,693	67,693	21,130	33,424	13,139

Notes: Binary dependent variable is equal to one if a person is employed in the base month, and is unemployed in the current month. Sample period is 1/2019-5/2021. Standardized Non-Remote Work (SNR) is obtained by standardizing the person's base job occupation-level frequency of post-COVID-19 telework. It is then multiplied by -1 so that increases in SNR indicate jobs where telework is less common. All models include year-month fixed effects, CPS rotation group cohort fixed effects, a college graduation dummy, a constant, gender, and a quadratic in age. The omitted race is White. Standard errors clustered at the individual level. † "Redness Quartiles" groups states based on the share of votes received by President Trump in the 2016 election. The groups are: the 1st quartile (lowest vote share or "blue states", the middle two quartiles ("moderate states"), and the fourth quartile ("red states").

Table 6: Regressions: Unemployment and Quartiles of Remote Work

	Race and Remote Occupation					Redness Quartiles†		
						1st (Blue States)	2nd and 3rd	4th (Red States)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asian	0.026	0.026	-0.012	-0.024	-0.019	-0.009	-0.010	-0.026
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.016)
Black	0.031	0.027	0.017	0.017	0.020	0.020	0.025	0.005
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.011)	(0.009)	(0.015)
Hispanic	0.032	0.026	0.026	0.020	0.022	0.029	0.022	0.022
	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.011)	(0.009)	(0.028)
Bottom Quartile Remote		0.052	0.046	0.049	0.046	0.072	0.038	0.037
		(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.005)	(0.006)
2nd Quartile Remote		0.035	0.028	0.031	0.034	0.048	0.027	0.029
		(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	(0.004)	(0.006)
3rd Quartile Remote		0.016	0.013	0.014	0.019	0.029	0.015	0.011
		(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)
Asian × Bottom Quartile Remote			0.100	0.101	0.087	0.051	0.090	0.100
			(0.014)	(0.014)	(0.013)	(0.020)	(0.021)	(0.034)
Asian × 2nd Quartile Remote			0.064	0.063	0.046	0.028	0.044	0.078
			(0.010)	(0.010)	(0.010)	(0.015)	(0.016)	(0.035)
Asian × 3rd Quartile Remote			0.021	0.019	0.016	0.005	0.013	0.035
			(0.009)	(0.009)	(0.009)	(0.013)	(0.016)	(0.028)
Black × Bottom Quartile Remote			0.012	0.013	0.008	-0.020	0.009	0.026
			(0.010)	(0.010)	(0.010)	(0.020)	(0.013)	(0.022)
Black × 2nd Quartile Remote			0.014	0.012	0.009	0.026	-0.003	0.014
			(0.009)	(0.009)	(0.009)	(0.018)	(0.012)	(0.021)
Black × 3rd Quartile Remote			0.018	0.017	0.015	0.010	0.023	-0.012
			(0.010)	(0.010)	(0.010)	(0.017)	(0.014)	(0.020)
Hispanic × Bottom Quartile Remote			-0.002	-0.005	-0.006	-0.023	-0.009	0.000
			(0.008)	(0.008)	(0.008)	(0.014)	(0.011)	(0.030)
Hispanic × 2nd Quartile Remote			0.008	0.004	-0.001	0.003	-0.011	0.001
			(0.009)	(0.009)	(0.009)	(0.015)	(0.011)	(0.033)
Hispanic × 3rd Quartile Remote			0.000	0.001	0.001	-0.001	-0.002	-0.001
			(0.009)	(0.009)	(0.009)	(0.016)	(0.012)	(0.033)
Two Digit Industry	N	N	N	N	Y	Y	Y	Y
State	N	N	N	Y	Y	Y	Y	Y
Observations	217,920	217,920	217,920	217,920	217,920	67,439	107,725	42,756
Individuals	67,693	67,693	67,693	67,693	67,693	21,130	33,424	13,139

Notes: Binary dependent variable is equal to one if a person is employed in the base month, and is unemployed in the current month. Sample period is 1/2019-5/2021. Quartiles of remote work are based on the occupation-level frequency of post-COVID-19 telework. All models include year-month fixed effects, CPS rotation group cohort fixed effects, a college graduation dummy, a constant, gender, and a quadratic in age. The omitted race is White. Standard errors clustered at the individual level. † "Redness Quartiles" groups states based on the share of votes received by President Trump in the 2016 election. The groups are: the 1st quartile (lowest vote share or "blue states", the middle two quartiles ("moderate states"), and the fourth quartile ("red states").

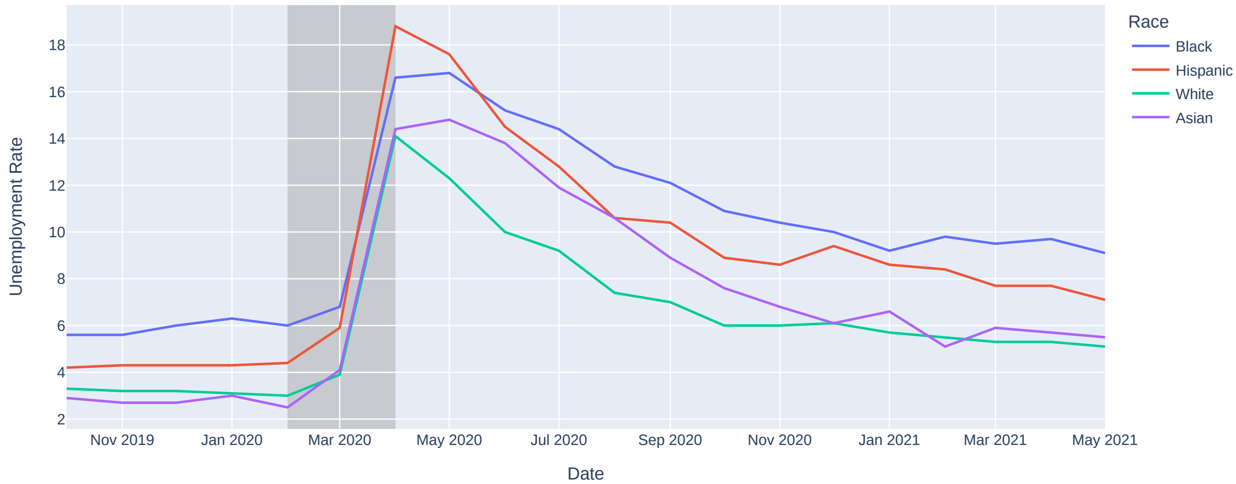
Table 7: Regression of Change in Earnings on Race and Remote Occupation

	(1)	(2)	(3)	(4)	(5)
Asian	-25.476	-25.565	4.804	0.411	0.266
	(13.849)	(13.849)	(17.961)	(18.293)	(18.354)
Black	8.923	8.174	-23.450	-23.249	-24.137
	(11.008)	(11.032)	(16.794)	(17.029)	(17.042)
Hispanic	-3.976	-4.725	-9.542	-15.001	-15.111
	(9.613)	(9.641)	(15.775)	(16.225)	(16.230)
BMR		7.113	5.348	8.104	12.002
		(6.943)	(7.903)	(7.947)	(8.655)
Asian × BMR			-75.501	-76.834	-74.429
			(28.141)	(28.156)	(28.239)
Black × BMR			54.370	54.717	56.618
			(22.233)	(22.267)	(22.280)
Hispanic × BMR			7.855	4.792	6.137
			(19.760)	(19.802)	(19.851)
Two Digit Industry	N	N	N	N	Y
State	N	N	N	Y	Y
Observations	36,035	36,035	36,035	36,035	36,035

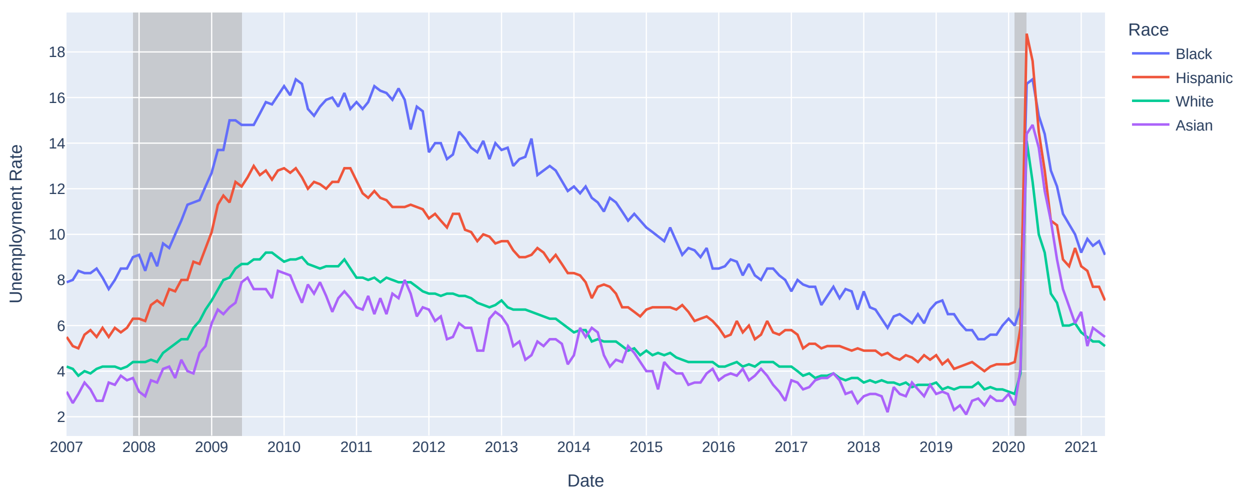
Notes: Dependent variable is the change in weekly earnings from the base month to the COVID-19 sample month. Sample period is 1/2019-2/2021. Below median remote (BMR) is a dummy variable equal to 1 if the person's base job was in an occupation below the median in frequency of post-COVID-19 telework. All models include year-month fixed effects, a college graduation dummy, a constant, gender, and a quadratic in age.

Appendix

Figure A.1: U.S. Unemployment Rate Over Time by Race



(a) COVID-19 Period



(b) Great Recession through COVID-19 Period

Notes: Great recession and COVID-19 recession shaded in grey. Data source: CPS monthly unemployment rate (FRED database).

Table A.1: Example Cohorts from the CPS Rotating Panel Data

	Pre-COVID-19															COVID-19													
Year	2019												2020												2021				
Calendar Month	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5
COVID-19 Month																1	2	3	4	5	6	7	8	9	10	11	12	13	14
Cohorts																													
2019-1 cohort	1	2	3	$4^{\dagger}$									5	$6^{\&}$	7	$8^{*,\ddagger}$													
Employment														$E(B)$		$E(1)$													
Earnings				$Y(B)$												$Y(C)$													
2019-9 cohort									1	2	3	$4^{\&,\dagger}$									5^{*}	6^{*}	7^{*}	$8^{*,\ddagger}$					
Employment												$E(B)$									$E(6)$	$E(7)$	$E(8)$	$E(9)$					
Earnings												$Y(B)$												$Y(C)$					

Numerical entries are consecutive months (1-8) when each cohort is interviewed.
$^{\&}$ Denotes base month for the unemployment ($U(B)$) regressions.
* Denotes COVID-19 sample period for the unemployment regressions.
† Denotes base month for the earnings ($Y(B)$) regressions.
‡ Denotes COVID-19 sample period for the earnings regressions.

Table A.2: Unemployment and Face-to-Face (FTF) Industry: FTF Industry Defined as Non-College Graduates in Personal Services and Retail Industries

		Redness Quartiles†		
	US	1st (Blue States)	2nd and 3rd	4th (Red States)
	(1)	(2)	(3)	(4)
Asian	-0.002	-0.003	0.007	0.015
	(0.004)	(0.006)	(0.007)	(0.013)
Black	0.029	0.030	0.032	0.014
	(0.004)	(0.007)	(0.005)	(0.008)
Hispanic	0.025	0.032	0.019	0.028
	(0.003)	(0.006)	(0.004)	(0.009)
Face-to-Face Industry (FTF)	0.042	0.081	0.036	0.015
	(0.004)	(0.010)	(0.005)	(0.007)
Asian × FTF	0.112	0.072	0.108	0.140
	(0.017)	(0.027)	(0.024)	(0.049)
Black × FTF	0.021	-0.004	0.021	0.037
	(0.012)	(0.025)	(0.015)	(0.026)
Hispanic × FTF	0.010	-0.017	0.012	-0.008
	(0.009)	(0.016)	(0.012)	(0.021)
Observations	217,920	67,439	107,725	42,756
Individuals	67,693	21,130	33,424	13,139

Notes: Binary dependent variable is equal to one if a person is employed in the base month, and is unemployed in the current month. Sample time period is 1/2019-5/2021. Face-to-Face Industry (FTF) is a dummy variable equal to 1 if the person's base job was in a retail sales or personal services industry and the person does not have a college degree. All models include year-month fixed effects, CPS rotation group cohort fixed effects, state fixed effects, a college graduation dummy, a constant, gender, and a quadratic in age. The omitted race is White. Standard errors clustered at the individual level. † Explain redness measure.

Table A.3: Regressions: Unemployment or Out of the Labor Force and Remote Occupation

	Race and Remote Occupation				
	(1)	(2)	(3)	(4)	(5)
Asian	0.044	0.042	0.010	-0.008	-0.003
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Black	0.062	0.057	0.049	0.046	0.049
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Hispanic	0.046	0.040	0.039	0.028	0.031
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
Below Median Remote		0.049	0.043	0.046	0.042
		(0.003)	(0.003)	(0.003)	(0.003)
Asian $\times$ Below Median Remote			0.074	0.074	0.057
			(0.011)	(0.011)	(0.011)
Black $\times$ Below Median Remote			0.014	0.013	0.009
			(0.009)	(0.009)	(0.009)
Hispanic $\times$ Below Median Remote			0.003	-0.000	-0.005
			(0.008)	(0.008)	(0.008)
Two-Digit Industry	N	N	N	N	Y
State	N	N	N	Y	Y
Observations	236,073	236,073	236,073	236,073	236,073
Individuals	70,803	70,803	70,803	70,803	70,803

Notes: Binary dependent variable is equal to one if a person is employed in the base month, and is either out of the labor force or unemployed in the current month. Sample period is 1/2019-5/2021. Below median remote (BMR) is a dummy variable equal to 1 if the person's base job was in an occupation below the median in frequency of post-COVID-19 telework. All models include year-month fixed effects, CPS rotation group cohort fixed effects, a college graduation dummy, a constant, gender, and a quadratic in age. The omitted race is White. Standard errors clustered at the individual level.

Table A.4: Regressions: Unemployment and Remote Occupation: One Observation per Individual

	Race and Remote Occupation					Redness Quartiles†		
						1st (Blue States)	2nd and 3rd	4th (Red States)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asian	0.043	0.042	0.002	-0.014	-0.008	0.001	0.002	-0.023
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)	(0.011)	(0.023)
Black	0.038	0.033	0.044	0.043	0.047	0.049	0.050	0.034
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.013)	(0.010)	(0.020)
Hispanic	0.037	0.031	0.033	0.028	0.033	0.044	0.027	0.045
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.011)	(0.009)	(0.024)
Below Median Remote		0.056	0.052	0.055	0.049	0.068	0.042	0.048
		(0.003)	(0.003)	(0.003)	(0.004)	(0.008)	(0.005)	(0.007)
Asian × Below Median Remote			0.092	0.094	0.071	0.039	0.079	0.094
			(0.012)	(0.012)	(0.012)	(0.017)	(0.020)	(0.039)
Black × Below Median Remote			-0.018	-0.019	-0.022	-0.036	-0.020	-0.016
			(0.010)	(0.010)	(0.010)	(0.018)	(0.013)	(0.026)
Hispanic × Below Median Remote			-0.002	-0.005	-0.011	-0.022	-0.015	-0.019
			(0.008)	(0.008)	(0.008)	(0.015)	(0.011)	(0.028)
Two-Digit Industry	N	N	N	N	Y	Y	Y	Y
State	N	N	N	Y	Y	Y	Y	Y
Observations	67,693	67,693	67,693	67,693	67,693	21,130	33,424	13,139

Notes: Binary dependent variable is equal to one if a person is employed in the base month, and is unemployed in the current month. Sample period is 1/2019-5/2021. Below median remote (BMR) is a dummy variable equal to 1 if the person's base job was in an occupation below the median in frequency of post-COVID-19 telework. All models include year-month fixed effects, CPS rotation group cohort fixed effects, a college graduation dummy, a constant, gender, and a quadratic in age. The omitted race is White. † "Redness Quartiles" groups states based on the share of votes received by President Trump in the 2016 election. The groups are: the 1st quartile (lowest vote share or "blue states", the middle two quartiles ("moderate states"), and the fourth quartile ("red states").