Public Opinion, Racial Bias, and Labor Market Outcomes *

Kaveh Majlesi,† Silvia Prina‡ and Paul Sullivan§

June 27, 2022

Abstract

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 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, and those who stayed employed experienced a significant drop in earnings. These findings are consistent with discrimination by employers or customers. The effects are more evident in strongly Republican states, where anti-Asian rhetoric might have had more of an effect. Consistent with a role for public opinion affecting labor market outcomes, 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.

Keywords: Racial bias, Public Opinion, Minorities; Unemployment; Earnings
JEL Classification: D70, D91, J15, P16

*We are grateful to Sandra Black, James Dana, Michael Kuhn, Nishith Prakash, and Robert Triest for helpful comments and discussions. All errors are our own.

†Monash University, Lund University, CEPR and IZA. E-mail: kaveh.majlesi@monash.edu.

‡Northeastern University, Department of Economics, 310A Lake Hall, 360 Huntington Avenue, Boston, MA 02115, United States. E-mail: s.prina@northeastern.edu.

§American University, Department of Economics, 4400 Massachusetts Avenue NW, Washington, D.C. 20016, United States. E-mail: sullivan@american.edu.

1 Introduction

Leaders' anti-minority rhetoric and media propaganda can have substantial effects on people's willingness to engage in xenophobic 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, Müller and Schwarz (forthcoming) show that President Trump's tweets about Islam-related topics predict increases in xenophobic tweets by his followers, cable news attention paid to Muslims, and hate crimes on the following days. Hswen et al. (2021) show that the phrase and hashtag "Chinese virus," used to describe the COVID-19 virus by President Trump and many of his allies in the right-wing media, were associated with significant increases in anti-Asian sentiments.[2] (Bursztyn et al., 2020) suggest a mechanism by which rhetoric affects people's behavior against minorities. It facilitates expressions of anti-minority views among the prejudiced and changes the views of the unprejudiced, which spur 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).[3] This might have led to deteriorating labor market outcomes for Asians because of discrimination by employers, customers, or both.[4] The quasi-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.

Our empirical analysis uses data from the Current Population Survey (CPS) between January 2019 and May 2021. The rotating panel structure of the data allows us to follow individual workers before and after the COVID-19 outbreak. First, we show that, similar to other minorities, Asians' likelihood of being unemployed slightly increased relative to Whites during the pandemic. A large literature suggests that the labor market outcomes of minorities could be harmed because of discrimination committed by customers or co-workers.[5] Building on this work, we hypothesize that any distaste for interacting with Asians should primarily affect jobs that require in-person

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

[2] While they are unable to assess the relationship between hateful hashtags and hate crimes, the connection is plausible because many tweets and hashtags implied violence and might have contributed to the rise in hate incidents (Gover, Harper and Langton, 2020).

[3] 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).

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

[5] See Altonji and Blank (1999) for a survey of the discrimination literature.

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 use two different proxies to measure the likelihood of face-to-face interactions. The first relies on the probability that a specific occupation is done remotely in the months that followed the onset of COVID-19 pandemic, extracted from a question asked 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 and that could bias our estimates. Thus, we check the robustness of our findings by, alternatively, categorizing (lower educated) workers in certain industries, namely retail and personal services, as those with higher likelihood of requiring in-person interactions.

We also 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. 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.

Although we do not causally establish that changes in public opinion and racial bias are the underlying mechanisms driving the increases in woes of Asians in the labor market, we provide evidence in favor of this hypothesis and 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 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.[6] Moreover, such rhetoric is likely to have been received differently based on their level of support for the President and the likelihood of paying attention to certain media outlets.[7] We hypothesize that states that voted more favorably for President Trump show stronger negative reactions to Asian workers in face-to-face work settings. Using data from the 2016 Presidential

[6] 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)).

[7] 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 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."

election, we find support for this hypothesis: while the negative impact on Asians in more interactive parts of the economy is visible all over the country, the effect is strongest in the most Republican quartile of states and is the weakest in the most Democratic.

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. 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 the 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 these findings. First, they could be explained by the possibility 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 hypothesis. Second, our data analysis does not indicate that industry sorting across different racial groups played a role. We also show evidence against the possibility that differential risk tolerance 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 less educated, minorities, and more vulnerable populations 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 better 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 did 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. It is a large nationally representative panel of households 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: households 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.

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 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 eight standard high-level categories shown in Table A.2.[11] Occupations are defined using 2010 Census codes, which are at the three digit level.[12] We classify workers

[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."

[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 Chinese and non-Chinese.

[11] These industries are manufacturing, transportation, wholesale trade, retail trade, finance, business services, personal services, and professional services.

[12] Occupations have 4 digits, but the last digit is always zero, so we state that the system uses 3 digits.

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 the 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.[14]

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

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.[15] 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

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

[14] Section 4 discusses some potential limitations of our measure and examines the robustness of our findings to an alternative measure based on the O*NET database which classifies occupations based on remote work and face-to-face interactions using pre-pandemic occupation-level data.

[15] 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.

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.[16] 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 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.

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,

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

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

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 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:

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

2.2 CPS Descriptive Statistics

Table A.2 shows descriptive statistics by race for the baseline time period.[17] 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 $\$1,369$, which is 18% 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] 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.

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 (12%) 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. The largest differences are found in manufacturing, where Asian and Black workers are roughly half as likely to be employed compared to Whites or Hispanics. 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 14.3% for Whites to 19.3% for Hispanics) and personal services (ranging from 4.4% for Whites to 7.2% 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. 69% of Hispanic workers are employed in BMR occupations, while the corresponding fraction for Black workers is 60%.

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]

[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.

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 1 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 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.

[19]The organizers weight 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.

[20]The same table with April 2020 designated as the cutoff month (making March 2020 the earliest possible base month) is shown in Appendix Table A.4.

Table 1: 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)
Asian	0.026	0.025	-0.006	-0.009	-0.008	-0.011	-0.007	-0.015
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.013)
Black	0.031	0.027	0.026	0.030	0.031	0.023	0.033	0.000
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.009)	(0.007)	(0.010)
Hispanic	0.032	0.028	0.026	0.026	0.027	0.030	0.020	0.018
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)	(0.016)
Below Median Remote (BMR)		0.033	0.028	0.029	0.018	0.035	0.013	0.019
		(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)
Asian × BMR			0.073	0.074	0.060	0.039	0.061	0.076
			(0.009)	(0.009)	(0.009)	(0.013)	(0.014)	(0.025)
Black × BMR			0.004	0.004	0.002	0.005	-0.008	0.025
			(0.007)	(0.007)	(0.007)	(0.014)	(0.009)	(0.015)
Hispanic × BMR			0.004	0.003	0.001	-0.007	-0.007	0.005
			(0.006)	(0.006)	(0.006)	(0.010)	(0.008)	(0.018)
One Digit Industry	N	N	N	N	Y	Y	Y	Y
Observations	216,552	216,552	216,552	216,552	216,552	67,047	107,029	42,476
Individuals	67,186	67,186	67,186	67,186	67,186	20,980	33,169	13,037

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. ‡ Columns (4) and (5) controls for Census regions (Northeast, Midwest, South, and West). Census region controls are excluded from columns (6)-(8) because State Redness is based on region. † Explain redness measure.

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 2.6 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.

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, stemming from the unfortunate labelling of COVID-19 by some in the public sphere as the "China virus." Next, we attempt to rule out other competing explanations and examine the strength of the evidence in favor of this hypothesis.

The Role of Geographical Sorting

Our findings in column (3) of Table 1 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 the four Census regions (i.e. Northeast, Midwest, South, and West).

As the estimates show, the results are unchanged. Thus, geographical sorting is unlikely to be the main driver of our findings.[21]

The Role of Industry Sorting

Next, we assess the potential role of industry 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. However, it is important to keep in mind that, 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 interesting to see if the results hold when we control for baseline industry of employment. Column (5) controls for the aggregate one-digit industries discussed in Section 2.1.1 in addition to Census regions. Again, the key results remain unchanged - alone among all minorities, Asians employed in occupations unfriendly to remote work are much more likely to become unemployed over the pandemic.[22]

The Role of Risk Aversion

A concern might be that Asians are more risk averse than other groups and, given that jobs that require in-person interactions are riskier in the aftermath of the pandemic, Asian workers in these occupations are more likely to quit their jobs. While we cannot directly test this in our data, we provide two pieces of suggestive evidence that this is unlikely to be true. First, 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. 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.[23] 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*

[21] 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. However, their study focuses on the early months of the pandemic, i.e. up until June 2020.

[22] 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.

[23] *"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?"*

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.[24]

Second, in Appendix Table A.3 we report the estimates of Table 1 for the sample that adds those who leave the labor force and extend 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 1. 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 increase in 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.

If the aforementioned hypothesis is correct, one would expect to see differential effects across the political spectrum. The anti-Asian rhetoric by President Trump and 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 run our main specification on 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 1, columns (6)-(8). Column (6) shows the results for the quartile of the most Democratic states, column (7) for the two middle quartiles, and column (8) 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 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

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

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 answer could be 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. In the top panel we show the share of the electorate with an unfavorable views of Asians, Blacks, and Latinos, broken down by those who voted for President Trump and others, across two periods—a pre-period that includes the last three months of 2019 and a post-period that includes March 2020, when Asians started to become the target of blame in certain public spheres, and the following two months. In the bottom panel, we break down the figures into those who report getting their news from Fox News Channel and others. 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.

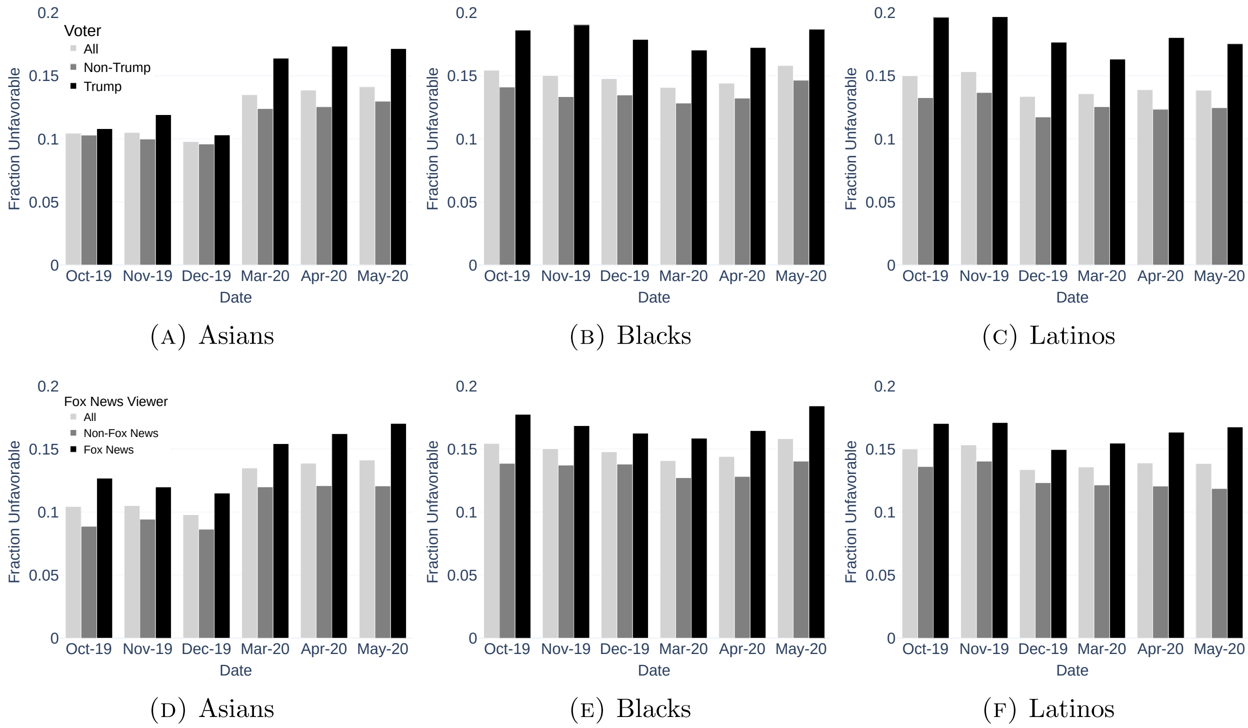
Although widespread along the political spectrum, negative changes in views of Asians were much stronger among those who voted for President Trump in 2016 and those who report getting their news from Fox News Channel. The share of those with unfavorable views was similar among non-Trump voters and Trump-voters before the pandemic—both stand 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.[25] 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 1 and the hypothesis that the 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 subsections of the population that corresponds to the pattern of labor market outcomes we find in Table 1.

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

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.

4 Alternative Measure of Face-to-Face Interactions

In our analysis so far, we have proxied for face-to-face occupations 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.[26] 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. This could bias our estimates.

Second, non-remoteness does not perfectly predict if a job has to be performed face-to-face 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. This point is also made by Avdiu and Nayyar (2020), who develop an occupation

[26] 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.

level index of face-to-face interactions using O*NET data, and compare it to the O*NET based occupation-level measures of remote work developed by Dingel and Neiman (2020).[27] They find that the retail trade and personal service industries are the most intensive in face-to-face interactions. This finding is consistent with the fact that many jobs in these industries seem likely to require face-to-face interpersonal interactions because of their nature.

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 one-digit industry codes in the CPS include transportation, wholesale trade, retail trade, finance, business services, personal services, professional services and manufacturing. We estimate a model similar to the one in Table 1, 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 a retail sales or personal services industry. We limit the sample to workers with not more than high school education, as one would expect it is the low-skill workers employed in the aforementioned two industries (retail and personal services) to interact intensively with other people.[28] Consequently, the control group should be comparable.[29]

Table 2 reports the results. The FTF dummy coefficient is positive and statistically significant indicating that unemployment increased more in industries that rely more on face-to-face work. 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 to experience the largest drops in employment. 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 smaller in the most Democratic states. Consistent with the findings in Table 1, the difference between the most Democratic-leaning and the most Republican quartiles is large (almost three times in magnitude) highlighting a higher unemployment for Asians working in face-to-face industries after COVID-19 in more Republican states where anti-Asian rhetoric might have been received and spread more strongly.

[27] O*NET contains data from hundreds of questions about approximately 900 occupations. Research studying face-to-face interactions and remote work uses data from a limited number of questions related to the type of work done on-the-job in each occupation.

[28] For example, a computer programmer' job working in retail industry should not be categorized as face-to-face.

[29] Appendix Table A.5 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.

Table 2: Regressions: Unemployment and Face-to-Face Industry (Low Education Workers Only)

	US	Redness Quartiles†		
	US (1)‡	1st (Blue States) (2)	2nd and 3rd (3)	4th (Red States) (4)
Asian	0.036	0.025	0.033	0.038
	(0.010)	(0.016)	(0.016)	(0.025)
Black	0.043	0.025	0.046	0.016
	(0.006)	(0.012)	(0.008)	(0.011)
Hispanic	0.023	0.023	0.008	0.023
	(0.004)	(0.007)	(0.005)	(0.011)
Face-to-Face Industries (FTF)	0.043	0.078	0.039	0.014
	(0.004)	(0.010)	(0.006)	(0.007)
Asian × FTF	0.081	0.043	0.086	0.116
	(0.019)	(0.031)	(0.028)	(0.054)
Black × FTF	0.011	-0.001	0.004	0.034
	(0.013)	(0.027)	(0.016)	(0.028)
Hispanic × FTF	0.021	-0.003	0.023	-0.001
	(0.009)	(0.016)	(0.012)	(0.022)
Observations	101,318	28,280	51,452	21,586
Individuals	32,922	9,315	16,695	6,912

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, a constant, gender, and a quadratic in age. The omitted race is White. Standard errors clustered at the individual level. ‡ Column (1) controls for Census regions (Northeast, Midwest, South, and West). Census region controls are excluded from columns (2)-(4) because State Redness is based on region. † Explain redness measure.

5 Earnings

Next, we quantify the effects of the pandemic on earnings. Table 3 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 transition to unemployment, and we are interested to examine if our findings extend beyond the employment status.

Column (1) in Table 3 reports the estimates of the change in earnings on racial categories. The estimated coefficient for Asians suggests a \$25.15 drop in earnings for Asians compared to Whites. This difference is large in magnitude: the median change in earnings went up by \$19.23 and the median weekly baseline earnings is \$923. 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 1, 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 \$82.08 lower earnings change than Whites with the same observable characteristics. This effect is large: it corresponds to 9% of median weekly earnings ($\frac{82.08}{923} = 0.09$). To provide further context for the magnitude of this estimate, the estimated penalty for Asians in BMR occupations is over 2.5 times larger than that of workers without a college degree.[30] As the estimates in columns (4) and (5) show, these findings are robust to controlling for Census regions and industry of employment in the base period.

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

[30] The coefficient estimate for the college graduate dummy is \$30.87 and is not shown in Table 3 to save space.

Table 3: Regression of Change in Earnings on Race and Remote Occupation

	(1)	(2)	(3)	(4)‡	(5)‡
Asian	-25.151	-25.255	7.518	5.052	4.245
	(14.025)	(14.025)	(18.133)	(18.201)	(18.255)
Black	9.131	8.258	-19.669	-19.396	-20.795
	(11.208)	(11.232)	(17.010)	(17.125)	(17.137)
Hispanic	-3.858	-4.736	-8.086	-10.210	-10.848
	(9.762)	(9.791)	(15.932)	(16.022)	(16.024)
Below Median Remote (BMR)		8.308	7.789	8.333	11.504
		(7.065)	(8.059)	(8.066)	(8.416)
Asian × BMR			-82.080	-82.115	-81.370
			(28.546)	(28.547)	(28.622)
Black × BMR			48.091	47.747	48.437
			(22.604)	(22.607)	(22.608)
Hispanic × BMR			5.277	4.494	6.383
			(20.016)	(20.025)	(20.043)
One Digit Industry	N	N	N	N	Y
Observations	34,802	34,802	34,802	34,802	34,802

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. ‡ Columns (4) and (5) control for Census regions (Northeast, Midwest, South, and West).

6 Conclusions

In this paper we highlight the role of public opinion on racial minorities' labor market outcomes. Political figures' rhetoric, social media activity, and media commentaries constantly change how minorities are viewed and the ease of expression against them. While such rhetoric could lead to extreme actions, the literature has been silent on what happens to the economic lives of minorities when the public opinion turns against them.

We examine the consequences of the anti-Chinese rhetoric that emerged in the U.S. with COVID-19 pandemic and resulted in rises in xenophobic actions against people of Asian descent. We analyze a representative panel of American workers from the CPS, both before and after the onset of the pandemic and show that labor market outcomes for Asians who worked in occupations and industries more prone to face-to-face interactions deteriorated with the pandemic. Also, Asians who remained employed experienced a significant hit to their 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 outcomes in the labor market in more interactive sectors of the economy are limited to the 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 received differently based on level of support for him and the likelihood of paying attention to 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 went up 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 are unlikely to be the major drivers of our findings.

Our paper is the first to show that racial bias generated by political rhetoric and indoctrination by the media can have detrimental effects on employment and earnings of the targeted group and shed more light on the potential role of media in shaping the life outcomes of individuals who come from minority backgrounds.

References

Adena, Maja, Ruben Enikolopov, Maria Petrova, Veronica Santarosa, and Ekaterina Zhuravskaya. 2015. "Radio and the Rise of the Nazis in Prewar Germany." *The Quarterly Journal of Economics*, 130(4): 1885–1939.

Altonji, Joseph G, and Rebecca M Blank. 1999. "Race and gender in the labor market." *Handbook of labor economics*, 3: 3143–3259.

Avdiu, Besart, and Gaurav Nayyar. 2020. "When face-to-face interactions become an occupational hazard: Jobs in the time of COVID-19." *Economics Letters*, 197: 109648.

Bartik, Alexander W., Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matt Unrath. 2020. "Measuring the labor market at the onset of the COVID-19 crisis." National Bureau of Economic Research.

BLS. 2020. "BLS Statement on Effects of COVID-19 on Employment Data." *https://www.bls.gov/covid19/effects-of-covid-19-pandemic-and-response-on-the-employment-situation-news-release.htm*, Accessed: 2022-03-6.

Bursztyn, Leonardo, Ingar K Haaland, Aakaash Rao, and Christopher P Roth. 2020. "Disguising prejudice: Popular rationales as excuses for intolerant expression." National Bureau of Economic Research.

Chetty, Raj, John Friedman, Nathaniel Hendren, Michael Stepner, and The Opportunity Insights Team. 2020. "The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data." National Bureau of Economic Research w27431, Cambridge, MA.

Couch, Kenneth A., Robert W. Fairlie, and Huanan Xu. 2020. "Early Evidence of the Impacts of COVID-19 on Minority Unemployment." *Journal of Public Economics*, 192: 104287.

Cowan, Benjamin W. 2020. "Short-Run Effects of COVID-19 on US Worker Transitions." National Bureau of Economic Research.

CSUSB. 2021. "Report to the Nation: Anti-Asian Prejudice Hate Crime - City Data Chart (June 1, 2021)." *https://www.csusb.edu/sites/default/files/AAPI%20City%20Chart_As%20of%20May%2028%202021%205%20PM.docx*, Accessed: 2022-03-22.

Dingel, Jonathan I., and Brent Neiman. 2020. "How many jobs can be done at home?" *Journal of Public Economics*, 189.

Elsby, Michael W., Bart Hobijn, and Aysegul Sahin. 2010. "The Labor Market in the Great Recession." National Bureau of Economic Research.

Enikolopov, Ruben, and Maria Petrova. 2015. "Media capture: empirical evidence." In *Handbook of media Economics.* Vol. 1, 687–700. Elsevier.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde. 2018. "Global evidence on economic preferences." *The Quarterly Journal of Economics*, 133(4): 1645–1692.

Gover, Angela R, Shannon B Harper, and Lynn Langton. 2020. "Anti-Asian hate crime during the COVID-19 pandemic: Exploring the reproduction of inequality." *American journal of criminal justice*, 45(4): 647–667.

Horse, Aggie J. Yellow, Russell Jeung, R. Lim, B. Tang, M. Im, L. Higashiyama, L. Schweng, and M. Chen. 2021. "Stop AAPI hate national report." *Stop AAPI Hate: San Francisco, CA, USA.*

Hswen, Yulin, Xiang Xu, Anna Hing, Jared B Hawkins, John S Brownstein, and Gilbert C Gee. 2021. "Association of "# covid19" versus "# chinesevirus" with anti-Asian sentiments on Twitter: March 9–23, 2020." *American Journal of Public Health*, 111(5): 956–964.

Junn, Jane, and Natalie Masuoka. 2008. "Asian American identity: Shared racial status and political context." *Perspectives on Politics*, 6(4): 729–740.

Kim, Claire Jean. 1999. "The racial triangulation of Asian Americans." *Politics & society*, 27(1): 105–138.

Lajevardi, Nazita, and Kassra A.R. Oskooii. 2018. "Old-fashioned racism, contemporary islamophobia, and the isolation of Muslim Americans in the age of Trump." *Journal of Race, Ethnicity, and Politics*, 3(1): 112–152.

Lajevardi, Nazita, and Marisa Abrajano. 2019. "How negative sentiment toward Muslim Americans predicts support for Trump in the 2016 Presidential Election." *The Journal of Politics*, 81(1): 296–302.

Le Espiritu, Yen. 1992. *Asian American panethnicity: Bridging institutions and identities.* Vol. 231, Temple University Press.

Leip, Dave. 2017. "Atlas of U.S. Presidential Elections."

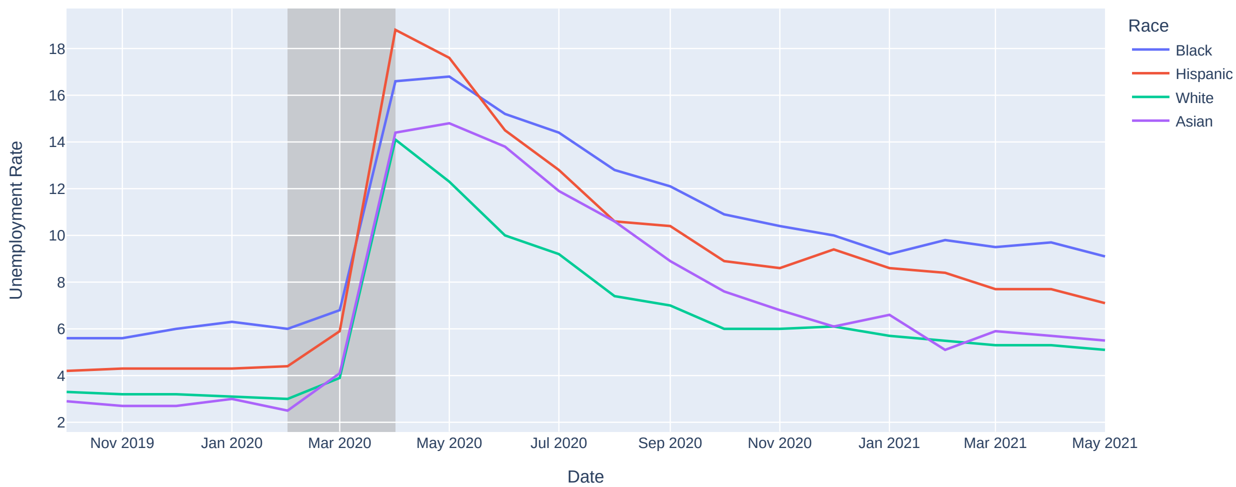
Müller, Karsten, and Carlo Schwarz. forthcoming. "From hashtag to hate crime: Twitter and anti-minority sentiment." *American Economic Journal: Applied Economics.*

USCCR. 2020. "The U.S. Commission on Civil Rights Expresses Concern Over Growing Anti-Asian Racism and Xenophobia Amid the COVID-19 Outbreak." *https://www.usccr.gov/files/press/2020/03-20-Racism-and-Coronavirus-Stmt.pdf*, Accessed: 2022-03-01.

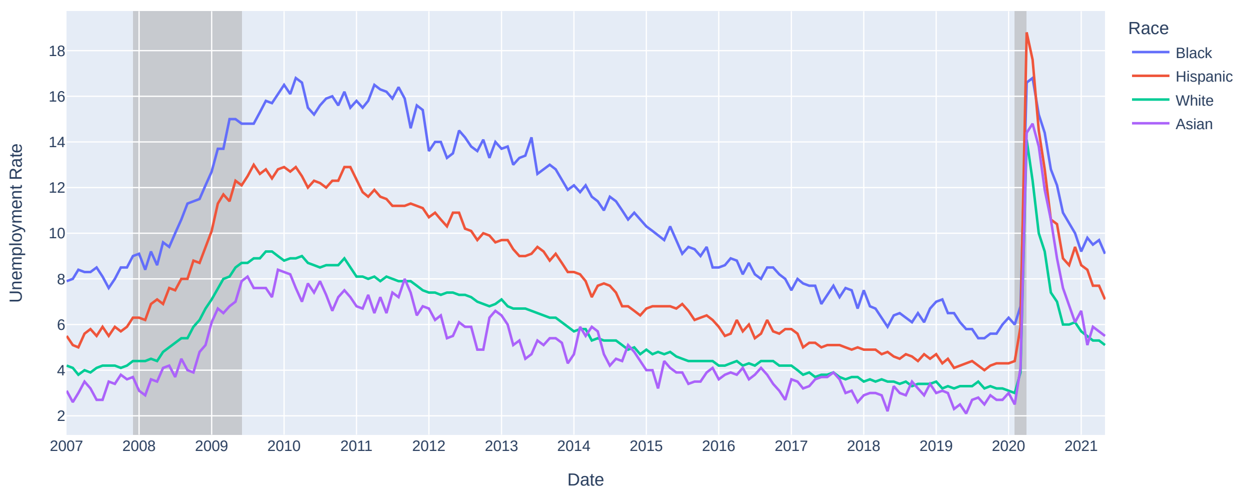
Yanagizawa-Drott, David. 2014. "Propaganda and conflict: Evidence from the Rwandan genocide." *The Quarterly Journal of Economics*, 129(4): 1947–1994.

Zhuravskaya, Ekaterina, Maria Petrova, and Ruben Enikolopov. 2020. "Political effects of the internet and social media." *Forthcoming, Annual Review of Economics. DOI/10.1146/annurev-economics-081919-050239.*

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: Descriptive Statistics by Race

	White (1)	Asian (2)	Black (3)	Hispanic (4)	All (5)
College Degree	0.560	0.699	0.431	0.294	0.518
Male	0.530	0.532	0.450	0.562	0.527
Age	44.936	42.488	43.021	40.656	44.020
Below Median Remote (BMR) Work Occupation*	0.460	0.435	0.602	0.687	0.504
Census Region					
Northeast	0.186	0.204	0.141	0.111	0.172
South	0.331	0.260	0.637	0.354	0.359
Midwest	0.258	0.130	0.127	0.103	0.217
West	0.225	0.406	0.095	0.433	0.252
Redness Quartiles†					
1st (Blue States)	0.272	0.586	0.297	0.418	0.312
2nd and 3rd	0.494	0.343	0.578	0.494	0.494
4th (Red States)	0.234	0.070	0.125	0.088	0.194
Industry					
Manufacturing	0.228	0.160	0.147	0.293	0.226
Transportation	0.070	0.070	0.110	0.076	0.074
Wholesale Trade	0.026	0.022	0.016	0.025	0.025
Retail Trade	0.143	0.169	0.164	0.193	0.153
Finance	0.077	0.079	0.065	0.053	0.073
Business Services	0.078	0.123	0.077	0.081	0.081
Personal Services	0.044	0.072	0.050	0.058	0.048
Professional Services	0.334	0.305	0.372	0.220	0.320
Weekly Earnings‡	$1,163.48	$1,368.92	$906.96	$862.15	$1,112.26
Observations (employment)	47,692	3,799	6,299	9,396	67,186
Observations (earnings)	25,159	1,936	3,170	4,537	34,802

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. † Describe Redness measure. ‡ Weekly earnings are for the baseline month for the earnings regressions.

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

	Race and Remote Occupation				
	(1)	(2)	(3)	(4)‡	(5)‡
Asian	0.043	0.042	0.008	0.004	0.005
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Black	0.059	0.054	0.048	0.052	0.052
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Hispanic	0.045	0.039	0.037	0.035	0.037
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
Below Median Remote		0.048	0.042	0.043	0.029
		(0.003)	(0.003)	(0.003)	(0.003)
Asian × BMR			0.077	0.077	0.059
			(0.011)	(0.011)	(0.011)
Black × BMR			0.012	0.011	0.009
			(0.009)	(0.009)	(0.009)
Hispanic × BMR			0.006	0.004	0.002
			(0.008)	(0.008)	(0.008)
Observations	247533	247533	247533	247533	247533
Individuals	73932	73932	73932	73932	73932

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. ‡ Columns (4) and (5) controls for Census regions (Northeast, Midwest, South, and West). Census region controls are excluded from columns (6)-(8) because State Redness is based on region.

Table A.4: Regressions: Unemployment and Remote Occupation (April 2020 Cutoff Month)

	Race and Remote Occupation					Redness Quartiles†		
						1st (Blue States)	2nd and 3rd	4th (Red States)
	(1)	(2)	(3)	(4)‡	(5)‡	(6)	(7)	(8)
Asian	0.023	0.022	-0.007	-0.010	-0.009	-0.013	-0.005	-0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.014)
Black	0.028	0.025	0.020	0.024	0.025	0.017	0.027	0.003
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)	(0.007)	(0.010)
Hispanic	0.029	0.025	0.027	0.027	0.028	0.031	0.022	0.011
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)	(0.015)
Below Median Remote (BMR)		0.032	0.027	0.028	0.018	0.033	0.013	0.020
		(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)
Asian × BMR			0.071	0.071	0.057	0.036	0.060	0.071
			(0.009)	(0.009)	(0.009)	(0.013)	(0.014)	(0.027)
Black × BMR			0.008	0.008	0.006	0.008	-0.002	0.019
			(0.007)	(0.007)	(0.007)	(0.014)	(0.009)	(0.015)
Hispanic × BMR			-0.001	-0.002	-0.005	-0.011	-0.013	0.004
			(0.006)	(0.006)	(0.006)	(0.011)	(0.008)	(0.018)
One Digit Industry	N	N	N	N	Y	Y	Y	Y
Observations	206,228	206,228	206,228	206,228	206,228	63,628	101,954	40,646
Individuals	63,179	63,179	63,179	63,179	63,179	19,623	31,208	12,348

Notes: Binary dependent variable is equal to one if a person is employed in the base month, and is unemployed in the current month. Base month is March 2020 or earlier. 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. ‡ Columns (4) and (5) controls for Census regions (Northeast, Midwest, South, and West). Census region controls are excluded from columns (6)-(8) because State Redness is based on region. † Explain redness measure.

Table A.5: 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	0.006	-0.000	0.009	0.013
	(0.004)	(0.006)	(0.007)	(0.013)
Black	0.032	0.030	0.028	0.014
	(0.004)	(0.007)	(0.005)	(0.008)
Hispanic	0.029	0.036	0.017	0.025
	(0.003)	(0.006)	(0.004)	(0.009)
Face-to-Face Industry (FTF)	0.043	0.081	0.038	0.015
	(0.004)	(0.010)	(0.005)	(0.007)
Asian × FTF	0.110	0.068	0.111	0.143
	(0.017)	(0.027)	(0.024)	(0.050)
Black × FTF	0.021	-0.006	0.023	0.034
	(0.012)	(0.025)	(0.015)	(0.027)
Hispanic × FTF	0.014	-0.017	0.015	-0.002
	(0.009)	(0.016)	(0.012)	(0.022)
Observations	216,552	67,047	107,029	42,476
Individuals	67,186	20,980	33,169	13,037

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, a college graduation dummy, a constant, gender, and a quadratic in age. The omitted race is White. Standard errors clustered at the individual level. ‡ Column (1) controls for Census regions (Northeast, Midwest, South, and West). Census region controls are excluded from columns (2)-(4) because State Redness is based on region. † Explain redness measure.