

# **Has Covid-19 Sparked Asian Employment Discrimination in the U.S labor market?**

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Submitted to  
CEU PU  
Department of Economics

In partial fulfillment of the requirements for the degree of Master of Arts in Economic Policy in  
Global Markets

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Vienna, Austria  
2021

## Abstract

Ongoing pandemic gave rise not only to economic challenges all over the world, but also to deep-rooted societal issue of discrimination. Covid-19 has also been called “Asian Virus”, “Chinese Virus” and as a result, many incidents of discrimination and harassment against Asians were reported over the last year. Considering the fact that millions of jobs were lost in the US in the face of Covid-19 and blame put on Asians, I seek to examine whether Asians were hit disproportionately with regards to job losses and whether Asian discrimination is reflected in the US labour market. In order to do my analysis, I use CPS dataset from January 2019 to March 2021. Statistical analysis is carried out with Stata and results show no statistically significant Asian discrimination has been observed in labour market in contrast to previous research on this topic. Policy recommendations are then provided to U.S. Department of Labor on how potential discrimination in labour market can be minimized.

**Keywords:** Covid-19, Employment Discrimination, Asian Discrimination, Labour Market Discrimination

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# Chapter 1

## Introduction

The COVID-19 health crisis has not only posed risk to lives and health of millions of people, but also led to losses of jobs and incomes of people worldwide which in turn triggered the deepest global recession in eight decades, nearly three times the depth of the 2009 financial crisis. The depth of the pandemic-spiked recession was surpassed only by the two World Wars and the Great Depression over the past century and a half. (World Bank, 2021).

The labor market all around the world had been tremendously hit by the ongoing pandemic as almost all governments started to implement restrictive measures which included restrictions on the movement of people and the shutdown of businesses and entities that involved physical interaction, all of which were aimed to slow the spread of the virus. The impacts of such measures created significant labor market disruptions as many people were left jobless, hiring of new workers had been temporarily frozen until further notice, unemployed people had been discouraged to look for job or stopped their job search for family reasons while employed people may have experienced reduced working hours or simply stopped working for a time (OEAD, 2020).

Another issue that was raised during the ongoing pandemic related to deep-rooted societal issue – racism and discrimination. Since the outbreak of the Covid-19 pandemic, news media has reported alarming amounts of Asian harassment incidents and anti-Asian beliefs across the US. This can be evidenced by the reports submitted to The Stop AAPI Hate website, which was launched in March of 2020 to track self-reported incidents of harassment. In just one month, 1,500 reports of discrimination from Asians were submitted, including verbal abuse, physical

attacks, and job discrimination (Jeung et al., 2020). Yahoo News report that crimes against Asians have risen by 200% during the pandemic (Stacey Butler, 2021), and according to CNN News, states, like New York, have seen 6900% increase in unemployment insurance claims among Asians which was by far the largest percentage increase experienced by any one racial or ethnic group (Liao, 2020).

Outbreak of COVID-19 has shaped the labor market in many ways, and given the blame put on Asians, a number of studies have been carried out and confirm that Asians or any other racial groups bear more employment losses compared to white workers (Bartik et al., 2020; Kim et al, 2021, Catalina Amuedo et al. 2021) while others confirm that unemployment hit Blacks and Hispanic most, with no significant discrimination for Asians (e.g, Fairlie et al., 2020; Cheng et al., 2020). Existing research into this topic produce controversial results and therefore, it fuelled my interest to carry out my own research into this topic.

***Research Problem and Question.*** This thesis aims to investigate to what extent the pandemic has induced labor discrimination against Asian Americans, taking into consideration other races and a number of different factors. The research question is **‘Has COVID-19 Sparked Asian Employment Discrimination?’**. There are two possible outcomes for this question. First, if Asian Americans were hit disproportionately, it would show the sign of labor market discrimination against them. Second, despite significant employment losses by Asian Americans, it might be statistically insignificant considering losses by other races were equally more pronounced or more proportional, therefore indicating no sign of discrimination.

***Research Goal.*** Existing studies into the topic of COVID-19 discrimination is concerned with topic outside the labor market and more on finding out the forms of discrimination, people’s views and how pandemic has affected welfare and mental state of people. This research contributes to this literature by focusing on how the COVID-19 pandemic has impacted

employment among Asians. The aim of this thesis is to help policymakers on addressing the issue of discrimination within and beyond the labor market.

***Thesis Structure.*** This thesis is structured as follows. Following introduction, the second chapter provides literature review to give insight into the topic. Firstly, literature review will focus on the impacts of pandemic on the US labor market, reporting findings on existing research on how COVID-19 has shaped labor market, figures on losses, most affected business sectors and regions. Secondly, literature review will report on findings of most affected demographic groups in the face of pandemic and report figures on what portion of self-employed people and businesses were affected during pandemic. Finally, literature review will provide results of existing research on COVID-19 spiked discrimination, reporting what groups were most discriminated and what were the forms of discrimination.

Following literature review, I will explain data sources, collection, reliability and limitations of the given dataset. Next, I will describe what methodology will be used to best address this question. Based on derived results from analysis, I will make interpretations before finally drawing policy implications followed by conclusion.



## Chapter 2

### Literature Review

#### 2.1 The impacts of COVID-19 on the US labor market

##### 2.1.1 Overall figures on job losses

The outbreak of COVID-19 has inserted an unprecedented shock on labor market of many countries including the United States. The peak of the pandemic in April with more than a million cases of COVID-19 and hundreds of millions of people in isolation led to the closure of many businesses, as well as the massive layoffs of workers. Handwerker et al. (2020) report that in the first quarter of 2020, several million jobless claims were filed in the United States, bringing the US unemployment rate to 15.7% in March 2020, and in May 2020 it was already 16.3% The U.S. economy lost 23 million jobs from February to April 2020. By August, jobs had rebounded to 11 million (seasonally adjusted) below February's peak. The recovery then slowed, and by November 2020 there were still 10 million fewer jobs than in February. (Bureau of Labor Statistics, 2020).

Hall and Kudlyak (2020) noted that in the face of the ongoing pandemic, the unemployed population can be divided into two groups, the first relates to “jobless unemployment” where unemployed workers do not expect a recall and second group relates to “recall-unemployment” where people are temporarily unemployed and expect a recall once financial situation improves. The figures for the former increased by over 17 million, from 800,000 in February to 18 million in April, followed by decreasing trend to 6 million in August and 3 million in November. The figures for the latter group grew later, increasing from 5 million in April to 8 million in September, and remaining unchanged through November.

Handwerker et al. (2020) notes that Current Population Survey data collection on temporary layoffs dates back to 1967 and data on people being on temporary layoff hit its peak at 28 percent in 1975 while in April 2020, 79 percent of unemployed workers reported they were on temporary layoff. Similar to Hall and Kudlyak, Gallant et al. (2020) distinguishes unemployed people into 2 groups: permanent and temporary and expects that economic recovery can be either greatly fuelled by those recalls or deteriorated by the increase in the number of jobless unemployment. The authors expect that recall-unemployment will be the main source of labor market recovery post-pandemic.

### **2.1.2 Most affected sectors and regions**

The most affected sectors within the US. The most affected sector is that of entertainment, including restaurants and bars, travel and transportation, and other entertaining activities such as cinemas, casinos, parks and etc. The most second affected sector includes services provided by other people such as dentists and beauty salons, followed by retail sector which include department stores and other small local shops. Last but not least is sensitive manufacturing sector which is about aircrafts and car manufacturing, for example. (Handwrecker et al., 2020; Joseph S. Vavra, 2020).

According to Matthew Dey et al. (2020), workers working for those most exposed sectors tend to earn less, making up 12% of total wages while accounting for over 20% of total employment. Also, the share of employment in those sectors varies greatly by state. Dey et al. (2020) further reports that for example, states like Nevada and Hawaii with over 30-35% of jobs in most affected sectors followed by Florida and South Carolina with figures of over 23%. This can be explained by the fact that those states have advanced tourism, thereby with many employees in the travel and transportation sector. Dey et al. (2020) also shows that midwestern agricultural

states such as Nebraska, Iowa, Arkansas and Minnesota generally have less employment in the most exposed sectors, with figures less than 18%.

Raj Chetty et al. (2020) reveals that individuals with high-income levels have dramatically reduced their spending from mid-March 2020, particularly in areas with high rates of COVID-19 infection and in sectors that require in-person interaction such as that occurring in restaurants, stores, hotels, or transportation while spending on services which can be accomplished without personal interaction were unaffected. The article by Chetty et al. (2020) demonstrates that this reduction in spending greatly reduced the revenues of small businesses as well as low-paid workers in affluent regions.

Similarly, Cho et al. (2020) find that both big and small cities experienced losses, but large metropolitan areas suffered more job losses compared to smaller towns. This finding concludes that urban areas are more vulnerable to infectious viruses because of how densely populated these areas are and since most economic activities take place in big cities, cessation of it leads to more losses. Reporting figures, Cho et al. (2020) find that in April-May 2020, employed at work rates decreased by 8.4 percentage points in non-metropolitan areas but by 14.1 percentage points in MSAs with populations greater than five million.

## **2.2 COVID-19 and Employment Discrimination**

### **2.2.1 Most affected demographic groups**

Findings by Dey et al. (2020) demonstrate that the employees of most exposed sectors are generally single parents, younger, with less education level, and work part time. Also, Handwerker et al. (2020) reports that from February to April 2020, employment in exposed sectors decreased by 38 percent while employment in less-exposed decreased by 11%. Younger

and less educated workers reported being unemployed more compared to educated and older counterparts in less exposed groups while unemployment in more exposed groups affected different demographic groups more equally.

B. Cowan's (2020) research into the most affected demographic group suggests that most vulnerable populations belonged to racial and ethnic minorities, were born outside the US, workers with disability and less-education and women with children. Latter has also been confirmed by Collins et al. (2020) who show that women with children were disproportionately affected in the labor market compared to men. Mothers, specifically if their children were of school-age or needed caregiving, worked reduced hours due to the fact that childcare places were closed.

Now talking to races, Blacks, Asians and other races were less likely to maintain their employment during pandemic compared to white workers. B. Cowan (2020) further finds that while some portion of Asians regained their employment status later, it doesn't seem to be true for blacks. Education attainment also played role in identifying who loses their job and who keeps it. Workers with only high-school diploma were 23% less likely to switch to "at-work" status from February to April, compared to those with higher education level (B.W.Cowan, 2020).

Bartik et al. (2020) report that pandemic has affected pre-pandemic disadvantaged group the most, who were already less-educated and less-skilled. He further finds that Asian Americans were 5.4 % point more likely to lose employment than Whites in April, while the figures for Blacks and Hispanics compared to Whites were 4.8 % point and 1.7 % point, respectively (Bartik et al., 2020).

Findings by Fairlie et al. (2020) show that African-Americans experienced an increase in unemployment to 16.6 percent while Latino, with an unemployment rate of 18.2 percent, were

disproportionately hard hit by COVID-19, making them more vulnerable. Authors explain that this has to do with the industries, occupation and skill-level of these workers rather than race.

Research specifically regarding Asian employment discrimination in the US due to pandemic has been carried out by Kim et al. (2021). Because Asians are more likely to have a bachelor's or higher degree than any other group (Sakamoto et al., 2009), one would not expect them to be disproportionately hit in the face of economic crisis. For example, comparatively speaking with previous recession, during the Great Recession of 2008, employment losses were most pronounced in less-educated and younger Black and Hispanic people (Hoynes et al., 2012) while Asian Americans were not a part of the minority groups who are more negatively affected by disasters compared to whites (Elsby, Bart, & Aysegul, 2010; Wang & Sakamoto, 2016). However, Kim et al. (2021) believes that employment losses by Asians during COVID-19 is contrary to these expectations considering their education level and labor market impact of previous recession, and authors believe this has to do with labor market discrimination against Asians – a group scapegoated for the outbreak COVID-19 (Strochlic, 2020).

Findings by Kim et al. (2021) show that even though Asian Americans are more educated than any other racial groups, the decline in “at-work” status for them is greater compared to other races. However, while women were not disproportionately hit than other races, Asian men were particularly hit hard as figures for “at-work” status for them dropped by 17.5 percentage points between March and April, while the drops for White, Black, and Hispanic men were by 11.0, 14.3, and 15.3 % points, respectively (Kim et al, 2021). While authors indicate at sign of possible Asian discrimination at labor market, it could possibly be explained by their level of education as those who lost jobs regained their work after lockdown and those who didn't regain their jobs had an education attainment of less than Bachelor's degree. Kim et al. concludes that Asian Americans who have a bachelor's or higher degree seem to be equally

protected from the negative impact of the lockdown to Whites while less-educated Asians were prone to employment losses.

### **2.2.2 Figures on Businesses and Self-employment**

R. Fairlie (2020) had carried out research based on CPS data on small business owners between February and April 2020. During this period, the amount of working business owners dropped by 3.3 million, or 22 percent which is considered the largest record decline, from 15 million to 11.7 million. These losses have affected almost all industries and even incorporated businesses were no exception. Further, Robert W. Fairlie reports findings on business ownership demographic factors including sex, race and age. Results show that the most affected racial group was African-Americans. Figures for African-American business owners plummeted from 1.1 million in February 2020 to 640,000 in April and this loss of 440,000 black business owners represented 41 percent of the previous level. The most affected second group was Latin business owners who bear loss of 32%, from 2.1 million to 1.4 million in the given period. This was followed by Asian business owners who suffered losses of 230,000 representing 26 percent of February levels. The losses for whites percentage-wise were the lowest, at 17% but large quantity-wise, at 1.8 million due to the fact that white people tend to own more businesses compared to others (Fairlie, 2020).

Amuedo et al. (2021) studies how COVID pandemic has impacted the self-employment rate and dynamics of the Asian community in the United States, when compared to non-Hispanic whites. Results show that self-employment rate of Asians dropped by 13 percent when compared to the rate among non-Hispanic whites after January 2020. Self-employment exit rates increased substantially among Asians with the onset of the pandemic, when compared to non-Hispanic whites, by 54.5 percent. The studies conclude that self-employed Asian

Americans were hit disproportionately compared to whites, thereby suggesting that pandemic has discriminated towards self-employed Asians.

## **2.3 COVID-19 spiked discrimination**

Not only has Covid-19 brought economic issues, but also a wave of racism and xenophobia also appeared within the society worldwide. With Covid-19 also being referred to as the ‘Chinese Virus’, ‘Asian Virus’, incidents of Asian harassments and discrimination has increased tremendously worldwide. As a result, rise in racist rhetoric have coincided with increases in racist attacks. Human Rights Watch (HRW, 2020) report that anti-Asian rhetoric has not only been raised by public, but also by politicians, presidents and prominent figures of Western countries who directly or indirectly blamed China for their poor health practices and some even came up with conspiracy theories.

Existing surveys and research COVID-19 spiked discrimination within society will be discussed in this section. Ruiz et al. (2020) carried out survey on US adults in June 2020 to find out the extent of discrimination within the society and how people of different races felt and treated during pandemic. Results show that about 4 in 10 American adults state it has become common to express racist views toward Asians since the pandemic started. Almost 60% of Asian Americans and 45% of Black Americans say that it is more common for people to express racist views toward their group since the coronavirus outbreak while figures for Hispanic and white stand at 21% and 18% respectively. Also findings show that Asian Americans over 30% of Asians have been victims of racial slurs while only 8% of white people reported similar experience (Pew Research Center, 2020). In conclusion, people who identified as Asians and Blacks are more likely to report negative experience.

The Stop AAPI Hate website, which was launched in March of 2020 to track self-reported incidents, received 3,795 reports of coronavirus discrimination from Asians which come from all 50 states and the District of Columbia. Russel Jeung, Aggie J., Charlane Cayanan (2021) report that most widespread types of discrimination they face are verbal harassment (68.1%), followed by shunning (20.5%) which is the deliberate avoidance of Asian Americans. The third largest category was found to be physical assault (11.1%) while civil rights violations which include workplace discrimination, refusal of service, and being barred from transportation and etc. accounted for 8.5% of the total incidents. Last but not least, online harassment made up 6.8% of the total incidents. Further, women report hate incidents 2.3 times more than men. Youths (0 to 17 years old) report 12.6% of incidents and seniors (60 years old and older) report 6.2% of the total incidents. Chinese are the largest ethnic group (42.2%) that report experiencing hate, followed by Koreans (14.8%), Vietnamese (8.5%), and Filipinos (7.9%). Businesses are the primary site of discrimination (35.4%), followed by public streets (25.3%), and public parks (9.8%). Online incidents account for 10.8% of the total incidents (Jeung et al, 2021).

Ying Liu et al. (2020) in their research conclude that Perception of COVID-19-associated discrimination increased from March (4%) to April (10%). Non-Hispanic Black and Asians were more likely to perceive discrimination than other racial/ethnic groups. Individuals who wore face masks also perceived more discrimination than those who did not. Perceiving discrimination was subsequently associated with increased mental distress.

S. Lee and S. Waters (2020) in a sample of over 400 Asians and Asian Americans living across the United States, using both quantitative and qualitative self-report data state that compared to pre-pandemic, nearly 30% reported an increase in discrimination since the pandemic, and over 41% reported an increase in anxiety, 53% depressive symptoms, and 43% sleep



difficulties. The ways they were discriminated included being treated suspiciously in public, racist jokes, verbal and physical assault, and financial hardship because of being rejected by COVID-19 financial assistance programs or losing their jobs.

## Chapter 3

### Data

The data used in this paper come primarily from the CPS from IPUMS (Flood et al., 2020). Given that it is important to track households or individuals from 2019 to 2021, the Merged Outgoing Rotation Group (MORG) is a useful panel data to use. The data were accessed by registering as a user on the CPS-IPUMS webpage, and downloaded for analysis. The data used in this paper was organized using detailed guidance available on the CPS-IPUMS website to generate data specifically for individuals that are part of the rotating panel. The period covered in the data is January 2019 to March 2021. It is important to note that the CPS-MORG panel is rotating, with households and individuals staying in the dataset for 4 months, not being covered for 8 months, and then returning for 4 months. This is the 4-8-4 rotation period that has been covered in other papers that utilise the CPS-MORG to study COVID-19 effects as well (Kim et al., 2021). The total number of distinct individuals (between the ages 18 to 59 years) in the sample was  $N = 347,046$ , who appear at least twice over the three years, and  $N = 297,572$  who are covered at least three times in the same period.

More details on the sampling method, construction of panel, attrition, and questionnaires are available on the IPUMS website. Since the CPS follows a multi-stage stratified sampling methodology, the rotating panel operates on monthly frequency as mentioned above. The ‘Month in sample’ variable is used to distinguish individuals or households as the duration for which they are being surveyed. As the CPS sample design notes, 50% of the sample are in the same month one year earlier, and the remaining 50% are in the same month, but one year later. The maximum period for which a household or individual can appear in the sample is a 16 month period. For example, if an individual was surveyed in the January 2019 CPS, they will

be observed (at the very latest) May 2020. Similarly, an individual that was surveyed in January 2020 can potentially be tracked till May 2021. Thus, the rotating panel offers an opportunity to pool individuals across different periods in the CPS. More importantly, since March 2020, CPS also has data on COVID-19-related employment changes. For example, individuals were asked about whether they were unable to work due to the COVID-19 pandemic, or if they worked remotely due to coronavirus restrictions, or were prevented from looking for work as well.

Individuals were linked using an identification key available (`cpsidp`). The main extension of the dataset in this study was to go back to 2019 and establish a new baseline panel for households. Individuals that show up in the dataset in 2019 may reappear in 2020 (closer to COVID-19 onset and lockdown restrictions in the United States) and then again in the 2021 data. Note that it is difficult to disentangle exactly which individuals appear in which time period on the basis of the identifier alone, and therefore the analysis was pooled to three panels: (a) 2019-2020; (b) 2019-21 and (c) 2020-21. To maintain comparability, these are only for the months of January to May. This is a limitation of the data as this paper is unable to account for variations in the second half of 2019 and 2020.

## **Chapter 4**

### **Descriptive Analysis**

In all analyses, sample weights provided by CPS were used for statistical methods. Table 1 below provides a snapshot of the key summary statistics by year-month.

**Table 1: Summary Statistics**

Year	2019			2020			2021		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Age (years)	7,86,976	39.09	12.07	4,92,481	38.49	12.16	99,638	38.02	12.12
Proportion female	7,86,976	0.51	0.50	4,92,481	0.51	0.50	99,638	0.51	0.50
Household size	7,86,976	2.70	1.51	4,92,481	2.69	1.52	99,638	2.62	1.52
Proportion married	7,86,976	0.52	0.50	4,92,481	0.50	0.50	99,638	0.48	0.50
Non-citizen	7,86,976	0.08	0.28	4,92,481	0.08	0.27	99,638	0.08	0.28
Race									
White	7,67,589	0.81	0.39	4,80,623	0.81	0.39	96,918	0.80	0.40
Black	7,67,589	0.11	0.31	4,80,623	0.11	0.32	96,918	0.12	0.32
Asian	7,67,589	0.06	0.24	4,80,623	0.07	0.25	96,918	0.06	0.25
Other	7,67,589	0.01	0.12	4,80,623	0.01	0.12	96,918	0.02	0.12
Education level									
Non or preschool	7,86,976	0.00	0.05	4,92,481	0.00	0.05	99,638	0.00	0.05
Up to grade 4	7,86,976	0.00	0.06	4,92,481	0.00	0.06	99,638	0.00	0.06
Up to grades 5 or 6	7,86,976	0.01	0.10	4,92,481	0.01	0.09	99,638	0.01	0.09
Up to grade 10	7,86,976	0.01	0.11	4,92,481	0.01	0.11	99,638	0.01	0.12
High school diploma or equivalent	7,86,976	0.28	0.45	4,92,481	0.28	0.45	99,638	0.28	0.45
Some college, but no degree	7,86,976	0.18	0.39	4,92,481	0.18	0.38	99,638	0.18	0.38
Bachelor's degree	7,86,976	0.22	0.42	4,92,481	0.23	0.42	99,638	0.23	0.42
Master's degree	7,86,976	0.09	0.29	4,92,481	0.09	0.29	99,638	0.09	0.28
Asian heritage									
Asian Indian	CEU eTD Collection	62,249	0.01	0.12	33,938	0.02	0.13		
Chinese		62,249	0.01	0.11	33,938	0.01	0.12		
Filipino		62,249	0.01	0.09	33,938	0.01	0.10		
Japanese		62,249	0.00	0.06	33,938	0.00	0.06		
Korean		62,249	0.00	0.07	33,938	0.01	0.07		
Vietnamese		62,249	0.01	0.07	33,938	0.01	0.08		
Other Asian		62,249	0.01	0.11	33,938	0.01	0.11		
COVID-related variables									

CEU eTD Collection

Worked remotely due to COVID-19				2,10,833	0.26	0.44	51,994	0.23	0.42
Unable to fund work due to COVID-19				2,95,618	0.11	0.32	72,132	0.06	0.24
Paid for work not done during COVID-19				33,707	0.14	0.35	4,388	0.12	0.33
Could not look for work due to COVID-19				65,996	0.10	0.30	16,332	0.08	0.27
<i>Employment status</i>									
Armed forces	7,86,976	0.01	0.08	4,92,481	0.01	0.08	99,638	0.01	0.09
At work	7,86,976	0.73	0.44	4,92,481	0.69	0.46	99,638	0.69	0.46
Has job, not at work last week	7,86,976	0.02	0.15	4,92,481	0.03	0.17	99,638	0.02	0.15
Unemployed, experienced worker	7,86,976	0.03	0.16	4,92,481	0.05	0.23	99,638	0.05	0.21
Unemployed, new worker	7,86,976	0.00	0.05	4,92,481	0.00	0.05	99,638	0.00	0.05
Not in labor force, unable to work	7,86,976	0.05	0.22	4,92,481	0.05	0.21	99,638	0.05	0.21
Not in labor force, other	7,86,976	0.14	0.34	4,92,481	0.15	0.36	99,638	0.16	0.36
Not in labor force, retired	7,86,976	0.02	0.14	4,92,481	0.02	0.15	99,638	0.02	0.14

*Source:* Own calculations using CPS-MORG (2019-2021) data from IPUMS (Flood et al., 2020). *Note:* Data on COVID-related variables were introduced in March 2020, and data on race was not available for the rotating sample for January to April 2021.

The key variable of interest in the employment status, which is captured in a large range of codes in the CPS. Of the broader categories, not in labour force (NILF; on account of school, retired etc.), employed (at work, or not in work in the last week), and unemployed (experienced or new worker). This data was recoded to simplify the employment status for analysis -- the employment status was either classified as employed or unemployed, and NILF was recoded in missing. Additionally, the data on COVID-19-related employment changes were also recoded to be binary. Values of 99 were treated as missing, and summary statistics can be interpreted as proportions. From Table 1, we see that employment status has changed by approximately 4 percent between 2019 (73% reporting at work) and 2020 (69% reporting at work). There is some fraction who retain their job but did not report working in the last reference week (up from 2 to 3% between 2019 and 2020, which reduces further to 2% in 2021). A majority of the 4% reported being unemployed as an experienced worker (up from 3% in 2019 to 5% in 2020, and continues to remain at 5% as of 2021).

Table 2 shows differences between those identifying as Asian and all other races in our sample, across all three years. Apart from employment status, all other variables differed statistically significantly between Asian and non-Asian sample respondents. Thus, Asian respondents are likely to be, on average, 0.76 years younger than non-Asians, have slightly more household members on average, and about 10.3% more likely to be married. On average, Asian individuals in the sample were also nearly 25% less likely to hold citizenship status in the United States at the time of the survey. In terms of employment status, nearly 95% of both Asian as well as non-Asians were likely to be employed throughout the survey periods. When this is disaggregated by year and months, it is revealed that between January and June in 2020 (at the height of the pandemic in the United States), was the only period in which Asian employment was significantly lower than that of their non-Asian counterparts. The results from a proportions test found that, on average, 91.8% of the Asian sample was employed, compared

to 92.7% of the non-Asian sample during this period (z-test statistic = 5.13,  $p < 0.001$ ). This continued to be lower during the latter half of 2020 (June to December), with Asian sample reporting 93.2% employment on average, compared to 94.1% among non-Asians (z-test statistic = 3.52,  $p < 0.001$ ). During the same months in 2021, Asian respondents' employment status had considerably improved; 94.6% reported being employed in the sample, compared to 93.3% in the non-Asian sample (z-test statistic = -3.56,  $p < 0.001$ ). This implies that Asian employment status dipped briefly during 2020, but has since regained to the original position of 2019, and is in fact now about 3% higher on average within the Asian community than pre-pandemic (2020). Note that this does not appear to vary by citizenship status, as differences between proportions of Asians who were citizens and Asians who were not citizens showed. For example, there are virtually no differences in the proportion of individuals employed between Asian citizens and Asian non-citizens across the years as well as within each specific time period. The largest difference is of 0.4% in the June to December months of 2020, where Asian citizens had 93.1% employment, and Asian non-citizens had *higher* employment (93.5%), but the difference was not statistically significant (z-test statistic = 0.69,  $p = 0.49$ ). This suggests that the differences within the Asian community may not be driven by citizenship status, and that there may be other factors at play.



**Table 2: Test for differences between Asians and non-Asians (2019-2021)**

	<b>Non-Asian</b>	<b>Asian</b>	<b>Difference</b>	<b>test statistic</b>	<b>p-value</b>
Age	39.19	38.43	0.76	19.56	0.000
Household size	2.69	2.93	-0.25	-50.34	0.000
Marital status	0.514	0.616	-0.103	-63.56	0.000
Citizen status	0.934	0.686	0.248	280.58	0.000
Employed	0.948	0.949	-0.001	-0.82	0.410
Worked remotely due to COVID	0.241	0.406	-0.165	-55.85	0.000
Unable to work due to COVID	0.099	0.115	-0.016	-9.62	0.000
Paid but did not work during COVID	0.148	0.107	0.041	7.01	0.000
Unable to look for work	0.089	0.101	-0.011	-3.48	0.001

*Source:* Own calculations using 2019, 2020, and 2021 (up to May) data from CPS-MORG (Flood et al., 2020). *Note:* Test statistic for first two rows (age and size of household) is t-test, and z-test for differences in proportions for the remaining variables. Two-sided test p-values are reported in the last column.

Table 3 shows the COVID-19-related employment changes between and within panel in our sample. The term “overall” refers to the average in the entire sample (across months), whereas the term “between” refers to the variation (measured by the standard deviation) between the different months in the survey, as is representative of variations across the sample over time. The term “within” refers to variations across the sample within each month in the survey – which could be driven by some of the individual characteristics (such as race, age, sex, etc.). Across the four COVID-related employment change variables, there is more variation between than within, suggesting that there is extensive changes over time in having to work from home,

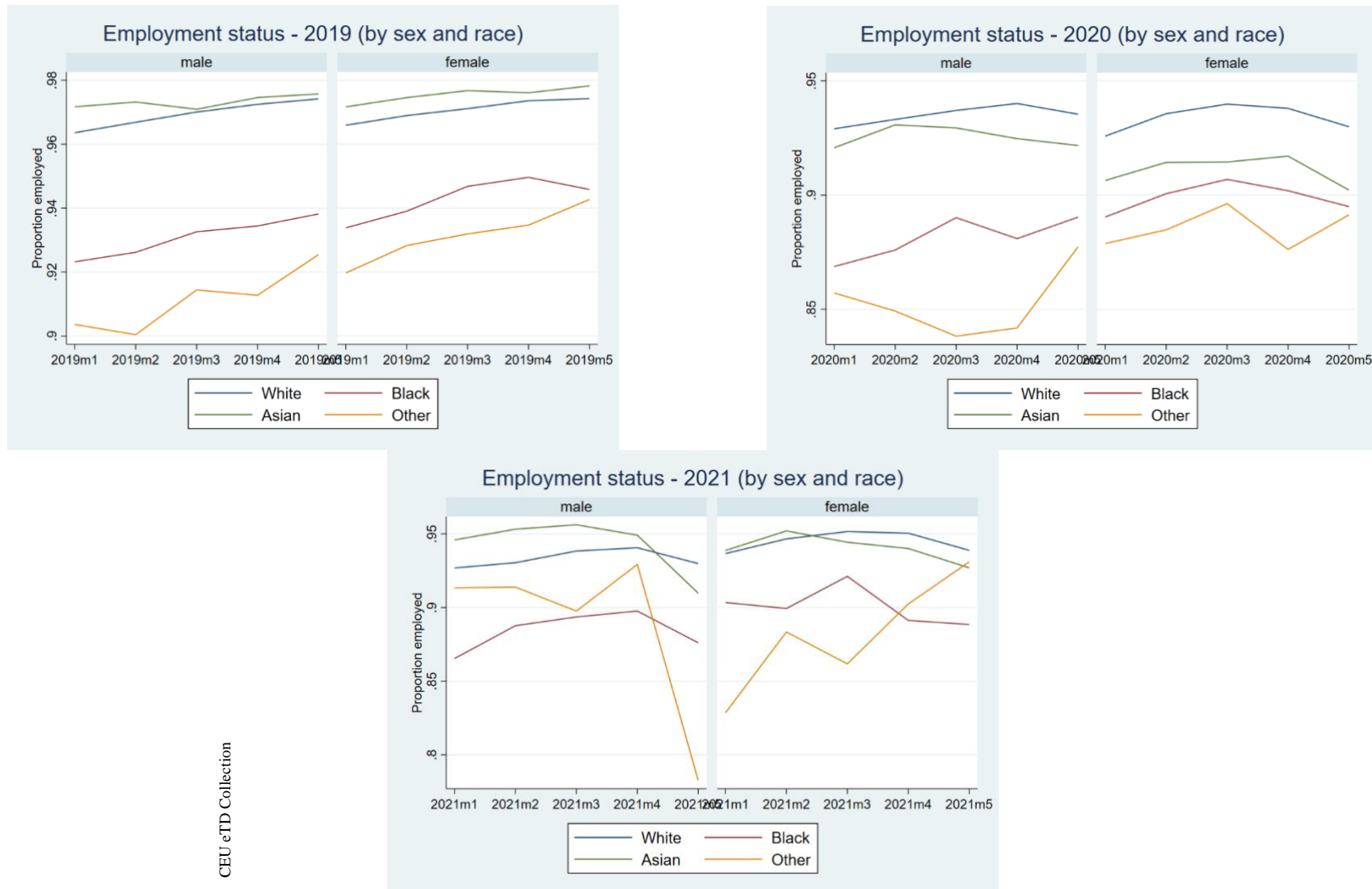
being unable to work, being paid for hours not worked, or prevented from looking for a job. Although the overall fraction of those who reported being prevented from looking for a job due to COVID-19 (9%) is relatively small, there are standard deviations up to 28.6% in this variable.

**Table 3: COVID-19-related employment changes between and within year-months**

<b>Due to COVID-19, proportion reporting:</b>		<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>	<b>Obs</b>
Worked remotely	overall	0.251	0.433	0	1	N = 377544
	between		0.388	0	1	n = 141370
	within		0.206	-0.499	1	
Unable to work	overall	0.100	0.300	0	1	N = 523384
	between		0.258	0	1	n = 185978
	within		0.183	-0.650	0.850	
Pay for hours not worked	overall	0.145	0.352	0	1	N = 52310
	between		0.359	0	1	n = 34876
	within		0.129	-0.605	0.895	
Prevented from job search	overall	0.090	0.287	0	1	N = 115644
	between		0.286	0	1	n = 50022
	within		0.156	-0.660	0.840	

Source: CPS-MORG (Flood et al., 2020)

Figure 1 contains three panels that show the changes in employment status by race and sex, which is the key research question in this paper. Although there is no clear discrimination evident from 2019 graphs, the 2020 graph indicates that individuals (both men and women, but particularly men) who identified as white reported higher employment on average in these months, followed by Asian men, and then by Asian women. All these groups reported higher employment in the pandemic and lockdown period (Jan to May 2020) than black individuals.



**Figure 1: Changes in employment status by sex and race over time (January to May 2019, 2020, and 2021).**

## Chapter 5

### Methodology

To test whether race had any correlation with employment status in the CPS-MORG panel between 2019 and 2020, multivariate regressions were run separately for the two years. As a result of having panel data, there will be some fraction of individuals who were surveyed in, say, Jan 2019, who will show up again in May 2020, so the constructed dataset is amenable for panel regression techniques. The main dependent variable is the employment status, which is recoded into a binary dependent variable: it takes the value of 1 if the individual reported being at work or having a job but not being at work (or being part of the armed forces), and zero if the individual reported being unemployed (either as an experienced or as a new worker). Those not in the labour force are recoded to missing, and are therefore not included in the analysis. This definition departs from what is mentioned in Kim et al. (2021), who also use not in labor force individuals in their “Not at work” category.

#### 5.1 Empirical model

Since the employment status is a binary variable, the appropriate regression technique should reflect this to minimize biased regression estimates. Therefore, the logistic regression model is used with maximum likelihood estimation and odds ratios are reported for ease of interpretation.

Specifically, the model that is estimated is defined as below:

$$\pi(\mathbf{X}) = \frac{\exp(X\beta)}{1+\exp(X\beta)} \quad (1)$$

Where,  $\pi$  is the probability that a particular individual in the sample is employed, as a function of a vector of independent variables ( $\mathbf{X}$ ). These are defined below. Maximum likelihood methods are used to estimate Equation 1, fixed effects are included in the panel regression to control for any time-invariant changes in the rotating sample characteristics.

It is also important to examine if there were any differences in COVID-related unemployment specifically associated with race. This helps examine whether there was any change in employment due to COVID-19-related factors. There are three main (binary) dependent variables that were used here: (a) Worked remotely due to COVID-19 pandemic; (b) Unable to work due to COVID-19 pandemic; and (c) Prevented from looking for work due to COVID-19 pandemic. For each of these, we estimate the model in Equation (1) using the same set of explanatory variables ( $\mathbf{X}$ ). The explanatory variables are detailed below.

## 5.2 Explanatory variables

The main (explanatory) independent variables included are age, squared age, household size, whether the individual was a United States citizen, sex (male or female), race (white, black, Asian, other), educational qualification obtained, and month in sample. The key independent variable of interest is race, and since it is a categorical variable, the base category must be defined – white is defined as the most frequently occurring race, and therefore is treated as the base.

Odds ratios are interpreted as the change in odds of being employed relative to the case of being unemployed. From equation (1), this is the ratio of the probability of observing a “success”

(i.e., being employed) to the probability of observing a failure (i.e., being unemployed). Thus, the equation for computing an odds ratio is given by:

$$Odds = \frac{\pi(X)}{1 - \pi(X)} \quad (2)$$

The interpretation of the Odds ratio is that if it is equal to 1, then there is no different in the odds between employed and unemployed; if it is greater than 1, then the odds are increased for the employed; and if it is lower than 1, then the odds are reduced for the employed. Thus, any odds ratios from these regressions are interpreted as change in odds of employment relative to individuals identifying as White. For convenience, individuals that identified as more than one race (Black-Asian, White-Black) were not included in the analysis.

All regressions and summary statistics were computed using the statistical software Stata 16.1. The dataset was declared as a panel dataset using the `xtset` command with survey weights provided by IPUMS using the `svyset` command. The command `xtlogit` was used with fixed effects and odds ratios options for the main regression results.

## Chapter 6

### Findings and results

Table 4 contains the results of the year-wise logistic regression of socio-demographics and race on employment status in 2019 (January to May) and 2020 (January to May). The results indicate that there was no statistically significant change in odds of employment during both the years indicated by race, relative to the base category of White individuals. However, being in the “Other” category (which includes Hispanic individuals), there is a statistically significant reduction in odds of being employed (relative to White individuals) in 2019. In fact, the fixed effects regression shows that older individuals were more likely to be employed in the first five months of 2019, but that there is no statistically significant effect of age on the odds of being employed in 2020. The results from 2019 indicate that a one-year increase in age of the individual (holding other factor constant) was associated with a 20 percentage point increase in the odds of being employed in 2019. However, this effect was not linear, as the squared-age term is lower than 1. Notably, in 2019, the odds of a non-citizen being employed reduced sharply (by nearly  $1 - 0.236 = 0.764$ ; i.e., 76.4 percentage points), but there was no statistically significant effect detected in 2020. This could be on account of changes to visa regulations for hiring of non-citizens under President Donald Trump.

In both estimations, the month in sample effect is very strong and statistically significant. This means that the results vary widely depending on which month the individual is being surveyed in. Controlling for this is critical to account for any time-varying changes in the characteristics of the sample. However, time-invariant characteristics (such as race, sex), which are part of the key research questions in this paper are still captured by the regression model when we include month in sample as a control variable.

**Table 4: Logistic regression results of employment status**

VARIABLES	(1) 2019	(2) 2020
Age	1.200** (0.102)	0.993 (0.0759)
Squared-age	0.998** (0.00108)	1.000 (0.000984)
Female	0.843 (0.261)	0.806 (0.308)
Black	0.785 (0.368)	0.451 (0.220)
Asian	0.931 (0.637)	1.569 (1.040)
Other	0.116* (0.142)	0.973 (1.032)
Married	0.946 (0.193)	0.945 (0.223)
Non-citizen	0.236*** (0.132)	1.363 (0.503)
month in sample, household level	1.198*** (0.0146)	0.855*** (0.00954)
Observations	23,731	29,190
Number of unique individuals	6,725	8,411

*Note:* Results are odds ratios of logistic regression of employment status on independent variables. Odds ratios on education qualification not reported. Standard errors of odds ratios in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 5 contains the results of the logistic regression on COVID-related employment changes, and thus use the sample of 2020 and 2021 jointly. As with the results one employment, it is clear that age is positively associated with employment, and remote working on account of COVID-19 related closures in the United States. Older individuals were 19.4 percentage points more likely to be working remotely, but as seen by the lower odds of squared age, the association is not linear. The results suggest no statistically significant changes in employment status on account of COVID that are linked to identifying as Asian. However, there is a statistically significant reduction in the odds of being prevented from looking for work due to



COVID-19 for individuals identifying as Black. This implies that Black individuals (both men and women), were less likely to be prevented from looking for work due to COVID-19, relative to the case of their White peers.

Notably, there is an increase in the odds of Asian individuals reporting being unable to work (22 percent points increase), but this effect is not statistically significant. Therefore, it cannot be concluded that there was more discrimination against the Asian community in light of COVID-19-related restrictions. When the race term is interacted with the sex term, any subgroup changes can be inferred. Although none of these results are statistically significant, it suggests that across all races (relative to White males), there was some increase in the inability to work as a result of COVID-19 pandemic. However, since the odds ratios are not statistically significant, it is not clear whether this is on account of discrimination toward women belonging to these particular races.

Similar to the Table 4, there is a statistically strong effect of the month-in-sample on the COVID-19 related employment changes. The later the month, the lower the odds of reporting changes in employment due to COVID-19, which is consistent with pandemic policy responses in the United States at the time. This implies that as individuals were surveyed later in the dataset, they are significantly less likely to report facing these issues due to COVID-19 in the CPS. For example, individuals surveyed one month later in the sample were 35 percentage points less likely to report being unable to work due to COVID-19. This could be on account of frequent changes in the employment scenario in the United States on account of COVID-19.

**Table 5: Logistic Regression results of COVID-related employment changes**

VARIABLES	(1) worked remotely for pay due to covid-19 pandemic	(2) unable to work due to covid- 19 pandemic	(3) prevented from looking for work due to covid-19 pandemic
Age	1.194*** (0.0711)	1.021 (0.0494)	0.966 (0.128)
Squared age	0.998*** (0.000747)	1.000 (0.000605)	0.999 (0.00168)
Female	1.253 (0.323)	0.755 (0.178)	2.319 (1.867)
Black	0.995 (0.474)	0.822 (0.332)	0.0474** (0.0699)
Asian	0.676 (0.376)	1.221 (0.532)	1.34e-06 (0.00101)
Other	3.11e-07 (0.000222)	1.795 (1.481)	1.029e+06 (8.719e+08)
Female x Black	1.284 (0.843)	1.193 (0.625)	2.726 (3.661)
Female x Asian	2.353 (1.775)	1.380 (0.761)	2.113e+06 (1.592e+09)
Female x Other	2.780e+07 (1.987e+10)	0.124 (0.163)	0 (2.88e-09)
Married	1.123 (0.161)	0.902 (0.121)	1.134 (0.412)
Non-citizen	0.616* (0.178)	1.513* (0.380)	0.227* (0.201)
month in sample, household level	0.749*** (0.00527)	0.650*** (0.00459)	0.824*** (0.0143)
Observations	72,930	79,822	12,289
Number of individuals	22,399	24,714	4,189

*Note:* Results are odds ratios of logistic regression of COVID-related variables on independent variables. Odds ratios on education qualification not reported. Standard errors of odds ratios in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

In Table 6, the Asian race category is further disaggregated to examine the changes in the employment status for 2019 and 2020. This is a much smaller sample in the overall CPS rotating panel. This allows investigation of whether specific sub-groups within the Asian community were more or less likely to be employed across three periods.

**Table 6: Asian sub-group and Employment Status (2019 and 2020)**

VARIABLES	(1) 2019	(3) 2020
Age	1.039 (0.0945)	0.934 (0.0760)
Squared-age	1.000 (0.00115)	1.001 (0.00104)
Female	0.921 (0.0579)	0.993 (0.0678)
Chinese	0.916 (0.231)	0.920 (0.198)
Filipino	2.331** (0.935)	0.965 (0.328)
Japanese	1.681 (0.652)	1.156 (0.438)
Korean	5.781* (6.023)	1.231 (0.645)
Vietnamese	4.616** (3.497)	0.904 (0.420)
Other Asian	2.356* (1.198)	1.261 (0.595)
Married	1.967* (0.747)	1.027 (0.352)
Non-citizen	1.307 (0.407)	1.324 (0.339)
Constant	1.343 (0.409)	0.726 (0.171)
Observations	1,623	2,765

*Note:* Results are odds ratios of logistic regression of employment status (binary) on independent variables. Odds ratios on education qualification not reported. Standard errors of odds ratios in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

The results suggest that although Filipino individuals increased their odds of being employed in 2019, there was no statistically significant change in employment levels that carried over to 2020. Note that these are only individuals who identified as Asian and are in the rotating panel, and hence the sample is highly specific and small relative to the overall regression estimates reported in Tables 4 and 5. Compared to the base category of Asian Indians (not included here), only individuals who identified as Japanese or Korean may have not had reduced odds of

employment during the pandemic period (2020). However, these effects are not statistically significant, and more research is needed to examine this claim rigorously.

Finally, in Table 7, the COVID-related employment changes on Asians are examined separately between 2020 and 2021, using the same specification as in Equation (1), with interactions for sex and race as in Table 5. The additional period of the latter half of the pandemic (2020, June to December) is also included to investigate if COVID-related employment changes varied within 2020. The results show that there is no clear indication of race-based changes in COVID-related employment parameters in the sample across all three time periods under consideration. The estimates are imprecise as the odds ratios are estimated using fixed effects and estimates did not converge even after 100 iterations. The results on age are the only statistically significant effects that were obtained, and primarily only for 2020 – there is a 21.1% percentage increase in the odds for older individuals to be working remotely due to COVID-19 between Jan and May of 2020, and 46.1% increase in the odds of being unable to work due to COVID-19 in the latter half of 2020 (June to December), although the latter effect is only significant at the 10% level. The overall lack of statistically significant effects of race, as well as race and sex on employment changes due to COVID-19 are indicative that the estimations are unable to find any evidence of race or sex-based discrimination in terms of employment status on account of the pandemic in the United States during 2020 as well as using more recent data for 2021.

**Table 7: COVID-19-related employment changes in 2020 and 2021 and race**

	<b>Jan to May 2020</b> worked remotely for pay due to covid-19 pandemic	<b>June to Dec 2020</b> worked remotely for pay due to covid-19 pandemic	<b>Jan to May 2021</b> worked remotely for pay due to covid-19 pandemic	<b>Jan to May 2020</b> unable to work due to covid-19 pandemic	<b>June to Dec 2020</b> unable to work due to covid-19 pandemic	<b>Jan to May 2021</b> unable to work due to covid-19 pandemic	<b>Jan to May 2020</b> prevented from looking for work due to covid-19 pandemic	<b>June to Dec 2020</b> prevented from looking for work due to covid-19 pandemic	<b>Jan to May 2021</b> prevented from looking for work due to covid-19 pandemic
Age	1.211** (0.101)	0.731 (0.182)	0.984 (0.316)	1.013 (0.0628)	1.461* (0.322)	1.508 (0.399)	0.791 (0.167)	0.641 (0.407)	0.168 (0.206)
Squared age	0.998** (0.00105)	1.004 (0.00298)	1.001 (0.00394)	1.000 (0.000776)	0.995* (0.00294)	0.994 (0.00345)	1.002 (0.00268)	1.005 (0.00803)	1.020 (0.0138)
Female	1.375 (0.477)	3.583e+40 (0)	0 (0)	0.883 (0.262)	1.317 (1.264)	3.725 (5.619)	4.929 (5.706)	4.849 (0)	
Black	0.806 (0.668)	4.249e+08 (2.084e+17)	1.333 (1.889)	0.544 (0.273)	314.9 (5,227)		7.50e-07 (0.000423)	0 (0)	
Asian	0.749 (0.451)			1.329 (0.728)		1.482e+42 (0)	9.97e-07 (0.000893)		
Other	0 (0)	0 (0)	8.383e+80 (0)	2.603e+06 (3.711e+09)	3.435e+49 (0)	0 (0)	1.437e+06 (2.223e+09)		
Female x Black	1.152 (1.159)	3.990e+08 (0)	2.939e+85 (0)	1.521 (1.012)	0.00475 (0.0791)		2.538e+06 (1.431e+09)	0.271 (0.408)	
Female x Asian	1.794 (1.631)	10,340 (0)		1.667 (1.113)		1.441e+42 (0)	1.576e+12 (1.996e+15)		
Married	1.222 (0.243)	0.435 (0.253)	0.351 (0.292)	0.966 (0.174)	0.953 (0.441)	0.655 (0.461)	1.272 (0.702)	2.626e+16 (6.916e+24)	1.026e+12 (3.968e+17)
Non- citizen	0.911 (0.334)	1.666 (2.369)	0 (0)	1.568 (0.451)		0 (0)	0.219* (0.201)		
Obs	32,710	11,117	3,930	39,477	12,006	3,232	5,858	1,713	708

*Note:* Results are odds ratios of logistic regression of COVID-related binary dependent variables (employment) on independent variables. Odds ratios on education qualification not reported. Convergence was not achieved in most estimates and therefore only a maximum of 100 iterations were performed. Interaction for Female x Other omitted due to lack of sufficient observations. Standard errors of odds ratios in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

## Chapter 7

### Policy Implications

In the face of COVID-19 and millions of job losses, government must ensure that all workers have equal access to unemployment benefits. Different states have different unemployment benefit limits. Pew Research Center (2020) demonstrates that states with more black residents are less likely to receive unemployment benefits. For example, in Massachusetts, where 9% of the population are Black, 66% of residents without jobs received unemployment benefits. In Florida and North Carolina, black population constitutes 17% and 22% of residents respectively, yet less than 10% of unemployed residents receive jobless aid (Desilver, 2020). Further, studies by N. Browne and W. Spriggs (2020) demonstrate that only 13% of Black people out of work from April to June received unemployment benefits, compared with 24% of White workers, 22% of Hispanic workers and 18% of workers of other races (Kofman & Fresques, 2020).

These figures suggest that states whose population consist of more racial diversity should increase their funding for unemployment benefits, specifically in the times of COVID-19 where most disadvantaged groups do not belong to white group, which in contrast receive most unemployment benefits. Therefore, US Department of Labor should encourage institutional cooperation at federal level.

In order to minimize discrimination in the labour market, during the reopening phases of the economy, US Department of Labor could further advocate blind recruitment by companies where hiring managers will not have information on race, age, sex and disability status of the

applicants, thereby selecting applicants purely based on their qualifications such as educational attainment and previous job experience. This will make selection process more transparent.



## Chapter 8

### Conclusion

COVID-19 which started out as a health crisis turned into an economic crisis, given stoppage of economic activities, closures of businesses and losses of employment by millions of people. The tremendous impact of the pandemic and the way it shaped the labor market is undeniable. Considerable proportion of people who could carry out their work remotely were able to secure their jobs, while those who needed in-person interaction mostly have stopped working or been made redundant. Ongoing health crisis didn't only give rise to economic crisis, but also to societal crisis considering the wave of increased racism and xenophobia as Asians were blamed for the outbreak of COVID-19.

In the face of millions of job losses and wave of racism, question arises what type of workers mostly has lost their jobs. Existing research into this topic confirms that people belonging to ethnic/racial minority, younger, less-educated, mothers with children were most affected by the pandemic. Some existing research suggests that racial groups were hit disproportionately which indicates at the sign of labor market discrimination.

Given the blame put on Asians and labor market disruptions, this paper aimed at answering question of whether pandemic sparked Asian employment discrimination in the labor market. My findings show that there was no statistically significant change in odds of employment of Asians during both 2019 and 2020 the years indicated by race, relative to the base category of White individuals. However, being in the "Other" category (which includes Hispanic individuals), there is a statistically significant reduction in odds of being employed (relative to White individuals) in 2019.

This work contributes to literature review by uncovering how employment of Asians were affected during the times of COVID-19 in the US labor market. Results show that between January and June in 2020 (at the height of the pandemic in the United States), was the only period in which Asian employment was significantly lower than that of their non-Asian counterparts. Despite this, Asians regained their original position of 2019 in the reopening phases, and as of 2021, their employment is 3% higher on average within the Asian community than pre-pandemic (2020). Regression analysis shows that age is positively associated with employment.

In the face of such labor market disruptions, it is important that all American citizens and workers have equal access to opportunities. Two policy recommendations are given to the US Department of Labor. First, states with more ethnic and racial diversity should be encouraged to increase their unemployment benefit funds. This can be achieved by institutional cooperation at federal level. Second, during the reopening months, Department of Labor must advocate blind recruitment process where hiring managers wouldn't have access to information about race, age, sex and disability, thereby judging candidates purely based on their qualifications.

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