Racial Wage Gap, and the Effect of COVID in the United States

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Abstract

This paper studies racial wage gaps and its changes across the COVID-19 period amidst rising racist sentiments in the US. Blacks, Native Americans and Asian Americans that did not attend college experience negative wage gaps compared to Whites. The same is observed for Blacks and Native Americans when compared to the general population. However, similar findings do not surface for college-educated minorities. Across the board, a narrowing wage gap was observed, but was not specific to the COVID-19 period. The driving factor behind this trend is an increase in educational attainment. These show that education is an important determinant of downstream labour market outcomes. Policymakers should focus on increasing access to higher education for minority ethnic groups.

Keywords: Racial Wage Gap, COVID-19, US Labour Market, Education Attainment

1 Introduction

Racial disparities in the US has brought about widespread socioeconomic implications. Historically, equality has been enshrined as a key element of the social compact through The Declaration of Independence and establishing constitutional foundations for it has been established in the 14th Amendment of the US Constitution through the State Action Clause. Although these underscore overarching goals in policy-making, racial equality has not been actualised in terms of economic outcomes. The COVID-19 pandemic presents an intersection of racial tensions and economic outcomes. Not only did the pandemic break out during the Trump Presidency that sparked racist sentiments, it also brought about a global economic crisis. According to a survey by Pew Research Centre conducted in early 2021, 81% of Asian-Americans said that violence against them has been rising. This figure is high compared to the share of US adults who say the same (56%). (Pew Research Center, 2021) The underlying sentiments behind this trend reflect "an intensification of White racial anxieties in anticipation of an impending shift towards a larger non-white majority", which former President Donald Trump built his campaign and president term upon. (Kelly, 2020) His political rhetoric played a critical role in shifting social sentiments, a process that scholars have termed "trickle-down racism". (Jardina and Pinston, 2023) This is in line with responses from the ground by the same research by Pew Research Centre on reasons for the increased violence. From an economic standpoint, this seems to suggest a change in Americans' preferences on demographic ideals towards lower tolerance of racial diversity. Hence, it is worth considering whether these changes in preferences in racial composition is also reflected in terms of differential treatment of racial groups in terms of actual economic outcomes.

This paper seeks to study whether there has been a significant change in racial wage gaps for minority groups in the time period when Trump assumed presidency and the outbreak of the COVID-19 pandemic. A widening wage gaps for minority groups, especially that in Asian-Americans, would suggest the presence of discrimination, possibly due to the change in racial preferences. The study adopts a difference-in-difference to study the effect of ethnicity on wages before the Trump Presidency (in the year 2015) and at the peak of the pandemic (in the year 2020). First, it compares the wages of minority groups with White Americans, the majority ethnic group. It then compares wages between minority groups to see if there are more significant effects of discrimination on Asian-Americans. Both regressions are run with additional college and age dummies to sieve out differences within each ethnic group. This paper finds that the COVID-19 pandemic has brought about different effects across racial groups. The income gap between Asian Americans and White Americans were minimal, but Black Americans faced a negative income gap compared to White Americans. Interestingly, through the COVID-19 pandemic, Asian Americans experienced an increase in income compared to White Americans, while the negative income gap between Black and White Americans persisted. In addition, educational attainment is a consistent factor that determined the extent of wage gaps for all ethnic groups. With these findings, it is worth examining how policy makers could reframe policies to increase access to education and propensity to pursue higher education in minority groups to achieve equitable economic outcomes.

2 Literature review

Literature on racial disparities in the US labour market have gone far to show that ethnic inequality in the US labour market exists and is multi-faceted issue. Carnevale and others (Carnevale et al., 2019)studied how education backgrounds affect career outcomes (good jobs and income) between White, Black and Latino workers. They found that educational attainment is a significant factor that determines career pathways of workers, but is not the sole explanation for differences across worker ethnicities within the same jobs or industries. They acknowledged that the unobservable factor that results in such an unequitable distribution is likely attributed to discrimination. Huffman and others (Huffman and Cohen, 2019) adopted a more downstream approach to explain ethnic disparities in the labour market by looking into job segregation by ethnicity. They argue that segregation of Black workers into Black-dominated roles contributes to the racial wage gap, and the exclusion of Black workers from better-paying jobs exacerbates it. Bloome (Bloome, 2014) studies racial income inequality trends through the lens of intergenerational persistence. He finds that African Americans experience extreme intergenerational continuity and discontinuity, which bring low upward mobility and high downward mobility respectively. This translates into an offsetting effect on the upward mobility of African Americans, largely due to large economic and demographic factors. These factors are what he terms as "changing forms of disadvantage", which he argues is a better characterization of racial income inequality trends in the US. Cajner and others (Cajner et al., 2017) also investigated racial gaps in the US labour market from a longitudinal lens by looking at cyclical unemployment rates across racial groups. They found that Blacks have a higher cyclical unemployment rate than Whites, but few observable factors are able to provide an explanation for such observations. In contrast, this gap is smaller between Hispanics and Whites and can be explained by differences in educational attainment. The above arguments have provided substantial explanations on why racial inequality in the labour market still exists.

However, rhetoric is largely concentrated on comparing Blacks, Hispanics and Whites. Asians are also an ethnic minority in the US that should not be neglected. While literature comparing Asians and other ethnic groups are relatively few, some authors have provided insight into the status of Asian Americans in the US labour market. Duleep & Sanders (Duleep and Sanders, 2012) have achieved this by studying the impact of the Civil Rights Act on the rise of relative waves of U.S.-born Asian men. Their study found that anti-Asian discrimination was the main cause of wage gaps between Asians and White Americans before 1960. While the Civil Rights Act was not directed at reducing discrimination against Asians, there was a prominent labour market spillover effect for Asians, which is explained by a decline in anti-Asian discrimination and rise in relative wages of Asians in the 20 years that follow. Hilger (Hilger, 2016) looked into the growth of wages on Asians vis-à-vis other ethnic minority groups, highlighting that Asian dynastic income has grown faster than that of other ethnic minorities. He underscored earnings conditional on education and the classification of discrimination as the main factors driving the relative income growth. Notably, Asians faced taste-based discrimination while Blacks faced statistical discrimination. This makes it possible for the income of Asians to grow at an aggregate level compared to Blacks and Hispanics. These writings are meaningful in painting the backdrop of the treatment of Asian Americans in the US labour market, but may have limited applicability to today's context.

When COVID-19 hit, scholars were keen to find out the impact COVID-19 brought about to the US labour market given existing disparities. Some analysed the impact on labour market from the lens of gender inequality Albanesi and Kim (2021); Alon et al. (2020); Kim et al. (2021). Albanesi & Kim (Albanesi and Kim, 2021) pointed out that COVID-19 was unlike typical recessions, where there would be counter cyclicality of female employment. Instead, both reports found that women in all demographic groups suffered larger losses than men during the pandemic. Industries that had a high proportion of female employment also suffered larger losses. Asian Americans come under the spotlight during COVID-19, and scholars began to investigate the impact of the pandemic on Asian-American employment. Honoré & Hu (Honoré and Hu, 2023) studied the impact of the recession on unemployment rates, highlighting that Asian Americans with no college education were hit the hardest and individuals born outside the US also bore extra burden. Kim and others approached the topic by looking at the impact of the lockdown measures on unemployment rates. They found that Asian Americans were the racial group that was the most negatively impacted by the lockdown. Their findings aligned with Honoré & Hu's, where less-educated Asian Americans were significantly more likely to become unemployed or regain employment during reopening compared to Whites with similar education levels. However, highly-educated Asian Americans face equal impact as highly-educated Whites. Discussions on the impact of COVID-19 on Asian-Americans seem to suggest Asian Americans falling behind other ethnic groups in coping with the effects of COVID-19. However, there is room to further diversify findings using other indicators of labour outcomes.

3 Significance of Study

This paper seeks to consider the larger context of anti-Asian and xenophobic sentiment that began during the Trump Presidency in 2017 and peaked during the COVID-19 pandemic.

It will be meaningful to observe if anti-Asian sentiment perpetuated by political holders translates into actual labour market effects. This will shed light on the power of discourse on racial issues pertaining to Asians and its effects on labour demand. It will also bring insight on underlying drivers of discrimination that affect wage outcomes across racial groups. The findings of the paper will supplement existing literature by examining labour outcomes from wage differences between Asians and other ethnic groups as a key indicator. This will determine if there is consistency in findings from existing arguments on the impact of COVID-19 on Asian American employment outcomes and inform policy decisions.

4 Overview of Data

4.1 Data Sources

This study performs analysis based on data obtained data from Annual Social and Economic Supplement (ASEC) of the Integrated Public Use Microdata Series Current Population Survey (IPUMS). This data is based on responses from survey data of 65,000 households, administered jointly by the U.S. Census Bureau and the Bureau of Labor Statistics, and then harmonised and published by by the Minnesota Population Center University of Minnesota (nd). Several variables from the dataset have been identified and extracted. Each of these variables have been detailed as follows:

- Race: Is as reported by the groups identified to by survey respondents. Data provided is the form of categorical values which are classified into 29 groups.

- Wage: Refers to an individuals pre-tax wage and salary income. Values are continuous ranging from 0 to 10 million

- Education: Refers to the educational attainment as measured by the highest year of schooling attained. Values are discrete ranging from 1 to 125. Lower levels related to elementary education while higher levels related to more advanced educational attainment.

- Age: The age of an individual at their last birthday. Ages provided in the sample are discrete and range from 0 to 85.

4.2 Data Processing and Analysis

Given the extensive range of data available for each variable (e.g. Education values range from 1 to 125), some data processing is necessary to aggregate the data into more manageable groups. Data processing has been carried out for two variables in particular namely:

- Race: While there is extensive variation when it comes to race, this paper focuses on 4 main categories namely: Black, White, Asian and Natives. We create dummy variables for each observation within the dataset.
- Education: Educational attainment is summarised into a dummy variable indicating whether college education was attained.

Further to this, we have only considered data between 2015 and 2020 as well as restricted the sample to only include individuals who were in the labour force at that time.

4.3 Summary Statistics

Broadly, trends within the variables 'AGE', 'INCWAGE' and 'EDUC' remain fairly consistent across all 3 years with some slight changes. For Age, all three years are noted to have a leftward skew with most individuals responding to the survey being between the ages of 30 to 50. For INCWAGE, a bell shaped distribution is noted. However, a slight skew to the right is noted throughout the years with more higher income individuals being survey than in other prior years. Lastly, for the EDUC variable, a consistent trend is noted with a rightward skew towards higher education.

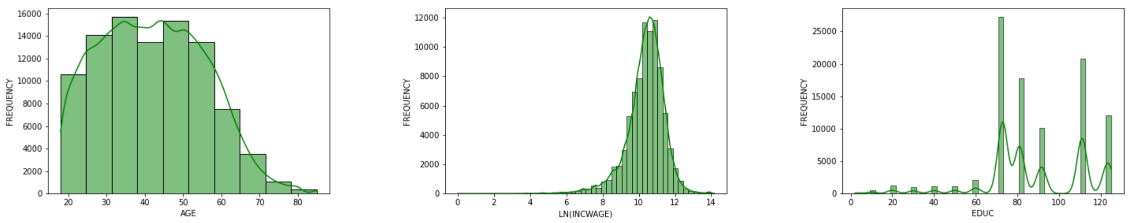

Figure 1: All Sample (2015)

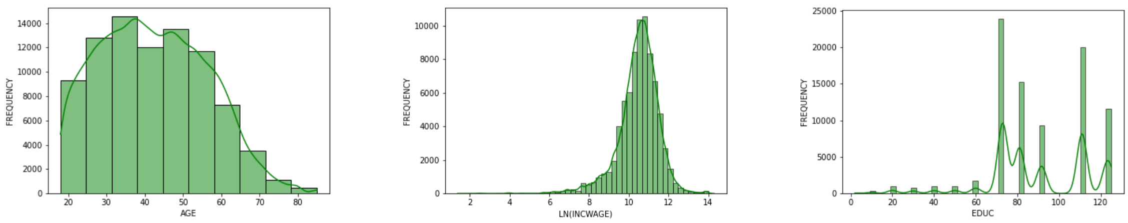

Figure 2: All Sample (2018)

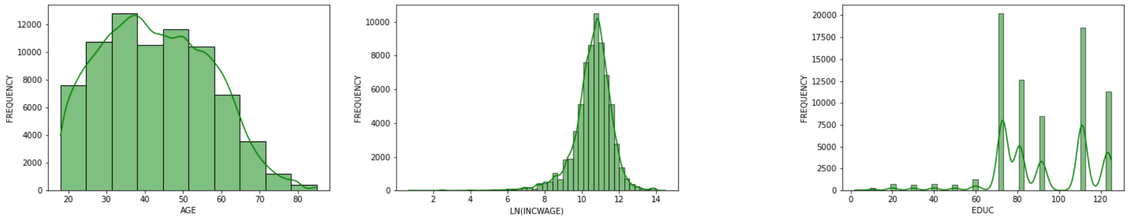

Figure 3: All Sample (2020)

2015 Sample	**Age**			**Wage**			**Education**		
	Min	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**
All	18	85	42.15	0	1,399,999	45,148.22	2	125	88.48
Black	18	85	41.46	0	1,110,000	35,043.75	2	125	86.00
Asian	18	85	41.17	0	1,099,999	49,113.18	2	125	93.60
White	18	85	42.40	0	1,399,999	46,441.44	2	125	88.43
Native	18	80	39.87	0	1,099,999	38,042.50	10	125	81.17

Table 1: 2015 Summary Statistics

Summary statistics for the variables in the study have been outlined below for both 2015 and 2020. It is encouraging to note that the mean wages for all racial groups have grown between 2015 and 2020. Notably, the Asian subgroup registered the largest increase in growth, with its mean wage surging by over 30 percent across 2015 and 2020.
Despite general improvements across all racial groups, the wage disparity continued to persist. The Asian sub-sample continues to register the highest mean wage while the black and native sub-samples are noted to have the lowest mean wage. Furthermore, in terms of education, the Asian sub-sample dominated with the highest education level of 93.6 which is around 5 points higher than that of the White sub-sample. Conversely, the Black and Native sub-sample continue to register among the lowest levels across all samples evaluated.

Interestingly, a closer analysis of the data shows that while the Asian sub-sample may have a higher mean education level, the White sub-sample continues to have a higher maximum in wages . This suggests that there may be other factors at play, possibly race, which is worth investigating further. This phenomenon becomes more stark in 2020 with the difference in maximum wages between the Asian and White sub-sample now even further apart.

2020 Sample	Age			Wage			Education		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
All	18	85	43.07	0	1,999,999	56,263.57	2	125	91.29
Black	18	85	43.04	0	1,099,999	45,453.75	2	125	88.80
Asian	18	77	41.77	0	1,099,999	64,553.43	2	125	97.66
White	18	85	43.25	0	1,999,999	57,057.98	2	125	91.01
Native	18	85	42.40	0	312,000	37,909.99	2	125	82.98

Table 2: 2020 Summary Statistics

5 Methodology: Model Set-up

In our study, we employed a difference-in-differences approach, analysing wage information from 2015 and 2020. We selected 2015 as the baseline year to represent conditions prior to the Trump administration and the increased prevalence of racial hate speech across different sectors. This setup enables us to examine the evolution of wage gaps before and after notable socio-political changes, shedding light on their potential effects on wage structures among diverse racial and ethnic categories.

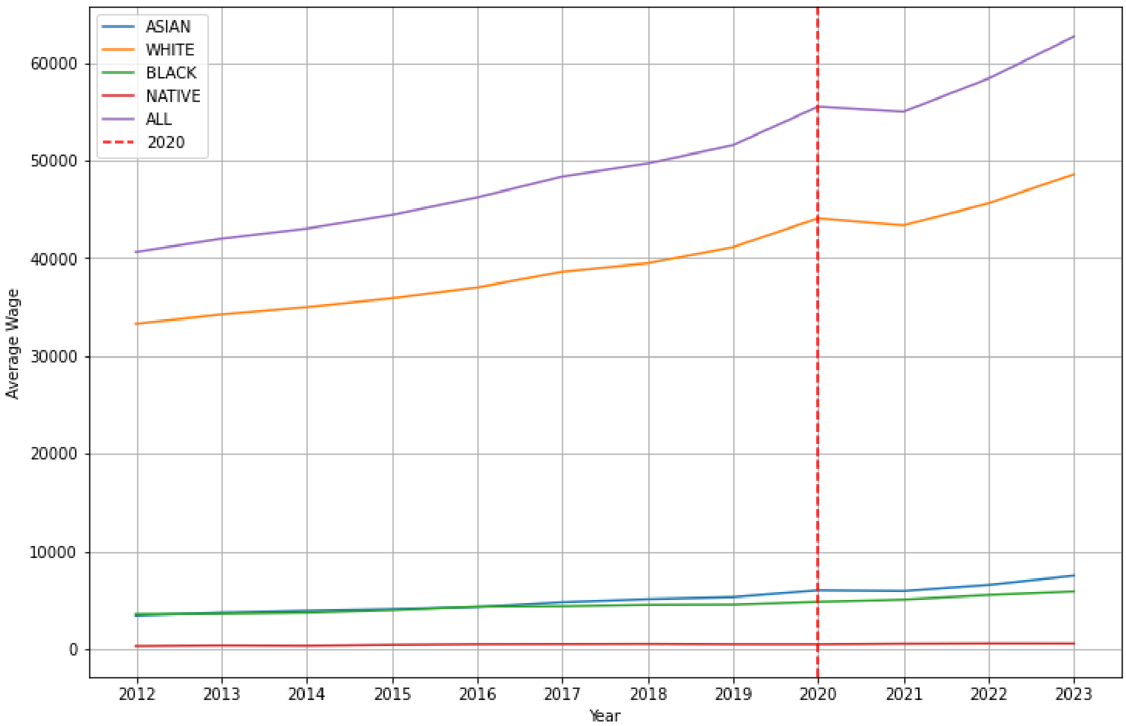

Figure 4: Average wage by race over time

The wage figures from 2020 constitute our experimental group, marking the era following Donald Trump's election and the reported rise in racial hate discourse. This period is particularly critical to our analysis as it encompasses both the socio-political factors that may affect wage inequalities based on race and ethnicity and the broad economic and societal impacts of the COVID-19 outbreak. From Figure 4, we see that average wages run parallel to each other, while trajectories of some racial groups appear to diverge in 2020.

By comparing the wage data between 2015 and 2020, we seek to identify the influence of these intertwined factors on wage trends, aiming to provide a detailed exploration of the shifts in wage disparities among various racial and ethnic groups throughout this pivotal five-year period.

5.1 Wages of Minority races compared to Whites

In comparing the racial wage gap in minority races, compared to Whites, we used the following model:

$$\begin{aligned} log(INCWAGE) =& \beta_0 + \beta_1 Asian + \beta_2 Black + \beta_3 Native + \delta_0 Y2020 \\ &+ \delta_1 Asian \cdot Y2020 + \delta_2 Black \cdot Y2020 + \delta_3 Native \cdot Y2020 + u \end{aligned}$$

We then included college dummies to control for educational differences:

$$\begin{aligned} log(INCWAGE) =& \beta_0 + \beta_1 Asian + \beta_2 Black + \beta_3 Native + \beta_4 College + \delta_0 Y2020 \\ &+ \delta_1 Asian \cdot Y2020 + \delta_2 Black \cdot Y2020 + \delta_3 Native \cdot Y2020 \\ &+ \delta_4 College \cdot Y2020 + \delta_5 Asian \cdot College \cdot Y2020 \\ &+ \delta_6 Black \cdot College \cdot Y2020 + \delta_7 Native \cdot College \cdot Y2020 + u \end{aligned}$$

We then added age variables as a proxy for work experience:

$$\begin{aligned} log(INCWAGE) =& \beta_0 + \beta_1 Asian + \beta_2 Black + \beta_3 Native + \beta_4 College + \beta_5 Age \\ &+ \beta_6 Age^2 + \delta_0 Y2020 + \delta_1 Asian \cdot Y2020 + \delta_2 Black \cdot Y2020 \\ &+ \delta_3 Native \cdot Y2020 + \delta_4 College \cdot Y2020 \\ &+ \delta_5 Asian \cdot College \cdot Y2020 + \delta_6 Black \cdot College \cdot Y2020 \\ &+ \delta_7 Native \cdot College \cdot Y2020 + u \end{aligned}$$

In our model, *log(INCWAGE)* signifies the logarithmic transformation of wage income, adjusted for inflation to reflect 2015 dollar values. The terms *Asian*, *Black*, and *Native* function as dummy variables indicating the racial category of the respondents. The variable *College* is also a dummy variable, assigned a value of 1 for respondents who possess an advanced educational degree—namely, a Bachelor's, Master's, Professional school, or Doctorate degree—and 0 otherwise. The *Y2020* variable serves as a dummy for the year 2020, capturing the economic and social implications of the onset of the COVID-19 pandemic.

5.2 Wages of each Minority race compared to others

Following the initial analysis, we conducted a comparative assessment of wages for each racial group against all other individuals not belonging to that specific racial group. This approach allows us to isolate the wage disparities that exist uniquely for Asian, Black, and Native individuals when compared against the collective wages of individuals outside of each respective racial category.

To delve deeper into the dynamics of educational attainment and its impact on wage disparities, we performed two additional analyses. These analyses segmented the respondents based on their level of educational attainment: those with college education (including Bachelor's, Master's, Professional school, or Doctorate degrees) and those without such higher education credentials. This bifurcation enabled us to explore how wage differences manifest within each racial group when further stratified by education level, offering nuanced insights into the interplay between race and education in determining wage outcomes.

The model we used is as follows:

$$log(INCWAGE) = \beta_0 + \beta_1 White + \beta_2 Age + \beta_3 Age^2 + \delta_0 Y2020 + \delta_1 White \cdot Y2020 + u$$

$$log(INCWAGE) = \beta_0 + \beta_1 Asian + \beta_2 Age + \beta_3 Age^2 + \delta_0 Y2020 + \delta_1 Asian \cdot Y2020 + u$$

$$log(INCWAGE) = \beta_0 + \beta_1 Black + \beta_2 Age + \beta_3 Age^2 + \delta_0 Y2020 + \delta_1 Black \cdot Y2020 + u$$

$$log(INCWAGE) = \beta_0 + \beta_1 Native + \beta_2 Age + \beta_3 Age^2 + \delta_0 Y2020 + \delta_1 Native \cdot Y2020 + u$$

6 Findings

6.1 Wages amongst different racial minorities compared to whites

	Dependent variable: LINCWAGE		
	(no college dummies)	(with college dummies)	(with college dummies and age)
Intercept	9.415***	9.063***	8.905***
	(0.012)	(0.014)	(0.027)
AGE			−0.020***
			(0.004)
AGE^2			0.024***
			(0.004)
C(YEAR)[T.2020]	0.320***	0.325***	0.321***
	(0.017)	(0.022)	(0.022)
COLLEGE		1.016***	1.005***
		(0.024)	(0.024)
C(YEAR)[T.2020]:COLLEGE		−0.125***	−0.123***
		(0.035)	(0.035)
ASIAN	0.078**	−0.134***	−0.129***
	(0.037)	(0.050)	(0.050)
ASIAN:C(YEAR)[T.2020]	0.111**	0.136*	0.136*
	(0.054)	(0.076)	(0.076)
ASIAN:C(YEAR)[T.2020]:COLLEGE		−0.109	−0.109
		(0.108)	(0.108)
ASIAN:COLLEGE		0.192***	0.196***
		(0.074)	(0.074)
BLACK	−0.299***	−0.266***	−0.263***
	(0.032)	(0.037)	(0.037)
BLACK:C(YEAR)[T.2020]	0.167***	0.129**	0.126**
	(0.049)	(0.058)	(0.058)
BLACK:C(YEAR)[T.2020]:COLLEGE		−0.028	−0.022
		(0.107)	(0.107)
BLACK:COLLEGE		0.246***	0.243***
		(0.072)	(0.072)
NATIVE	−0.589***	−0.446***	−0.438***
	(0.089)	(0.097)	(0.097)
NATIVE:C(YEAR)[T.2020]	0.285**	0.319**	0.312**
	(0.135)	(0.148)	(0.148)
NATIVE:C(YEAR)[T.2020]:COLLEGE		−0.210	−0.208
		(0.340)	(0.339)
NATIVE:COLLEGE		0.179	0.171
		(0.230)	(0.230)
Observations	169613	169613	169613
Residual Std. Error	3.140 (df=169605)	3.103 (df=169597)	3.102 (df=169595)
F Statistic	103.147*** (df=7; 169605)	318.733*** (df=15; 169597)	286.866*** (df=17; 169595)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: Effects of COVID on Racial Wage gap amongst different racial groups

From our analysis in Table3, without taking in to consideration college attainment and age, Asians earned 7.8% more than their white counterparts, with this increasing to 18.8% in 2020 during the onset of COVID. However, after taking college attainment into account, we see that Asians who did not attend college earned 13.4% lesser than their white counterparts. However, this gap narrowed in 2020, and resulted in them earning 0.02% more than their white counterparts. Conversely, Asians who have attended college earned wages 19.2% higher compared to their white counterparts. This did not change in 2020, during the onset of COVID. When we controlled for age (as proxies for work experience), the results were qualitatively similar.

On the other hand, Black individuals faced a substantial negative income gap in earning 29.9% less than Whites, a disparity that narrowed during the pandemic in 2020, which resulted in Blacks earning 13.3% lesser. After controlling for college attainment, we noted that Blacks who did not attend college earned 26.6% less than their White counterparts, this gap narrowed to 13.7% in 2020. On the other hand, Blacks who have attained college education earn 24.6% more than their white counterparts, this did not have a significant change in 2020. These results do not differ qualitatively controlling for age (as proxies for work experience).

Native Americans, fared the worst, earning 58.9% less than their white counterparts, this wage gap narrowed in 2020, resulting in them earning 30% lesser. After taking college attainment into consideration, we noted that Natives who have not attained college education earned 44.6% less than their white counterparts, with their wage gap narrowing to 12.7% in 2020. However, Natives who have attained college education did not have wages that are different from their white counterparts.

Respondents with college education attainment earned approximately 101% more than their counterparts. However, difference in wages between respondents who have been to college and those who have not have narrowed by 12.5% in 2020. After including age, as proxies for work experience, our results were consistent with our model with only college dummies.

We further re performed our analysis to compare 2015 data to 2019 data to ascertain whether results from Table3 are unique to 2020 (i.e. associated with COVID), or part on an ongoing trend. From our analysis of racial income gap in racial income gap for 2015 and 2019 (Table 4), and interpreting coefficients with significance higher than 5%, we noted that wage increases are observed across the board from 2015 to 2019, with variations mainly due to education attainment. Similarly, Blacks and Natives had a significant negative income gap compared to Whites. For Blacks, the income disparity changed in 2019, resulting in a narrowing of wage income gap. However, this wage increase in 2019 was not present for Blacks who have attended college. Likewise in 2019, the difference between wages of college attendees compared to non-college attendees have narrowed, albeit to a lower extent of 9.4% in 2019.

The results of this initial analysis for robustness shows that wage disparities between the different racial groups demonstrated consistent patterns. Narrowing of wage gap in 2020 is unique for some racial groups, and part of an ongoing trend for others.

	Dependent variable: Log INCWAGE		
	(no college dummies)	(with college dummies)	(with college dummies and age)
Intercept	9.415***	9.063***	8.859***
	(0.012)	(0.014)	(0.026)
AGE			-0.013***
			(0.004)
AGE^2			0.018***
			(0.004)
C(YEAR)[T.2019]	0.222***	0.230***	0.228***
	(0.017)	(0.021)	(0.021)
COLLEGE		1.016***	1.002***
		(0.024)	(0.024)
C(YEAR)[T.2019]:COLLEGE		-0.094***	-0.092***
		(0.035)	(0.035)
ASIAN	0.078**	-0.134***	-0.128**
	(0.037)	(0.050)	(0.050)
ASIAN:COLLEGE		0.192***	0.198***
		(0.074)	(0.074)
ASIAN:C(YEAR)[T.2019]	0.060	0.047	0.046
	(0.053)	(0.073)	(0.072)
ASIAN:C(YEAR)[T.2019]:COLLEGE		0.002	0.003
		(0.105)	(0.105)
BLACK	-0.299***	-0.266***	-0.262***
	(0.032)	(0.037)	(0.037)
BLACK:COLLEGE		0.246***	0.243***
		(0.073)	(0.073)
BLACK:C(YEAR)[T.2019]	0.173***	0.188***	0.184***
	(0.047)	(0.055)	(0.055)
BLACK:C(YEAR)[T.2019]:COLLEGE		-0.155	-0.148
		(0.104)	(0.104)
NATIVE	-0.589***	-0.446***	-0.435***
	(0.089)	(0.098)	(0.098)
NATIVE:COLLEGE		0.179	0.166
		(0.232)	(0.232)
NATIVE:C(YEAR)[T.2019]	-0.069	-0.033	-0.034
	(0.129)	(0.141)	(0.141)
NATIVE:C(YEAR)[T.2019]:COLLEGE		-0.147	-0.143
		(0.335)	(0.335)
Observations	180792	180792	180792
Residual Std. Error	3.159 (df=180784)	3.122 (df=180776)	3.122 (df=180774)
F Statistic	70.022*** (df=7; 180784)	320.311*** (df=15; 180776)	289.430*** (df=17; 180774)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: Effects Racial Wage gap amongst different racial groups (2015 vs. 2019)

6.2 Wage Privilege of Whites

	Dependent variable: Log INCWAGE		
	(All)	(College)	(Non-College)
Intercept	8.979***	10.692***	8.348***
	(0.032)	(0.053)	(0.039)
AGE	−0.019***	−0.035***	−0.013***
	(0.004)	(0.006)	(0.005)
AGE^2	0.025***	0.021***	0.025***
	(0.004)	(0.006)	(0.005)
C(YEAR)[T.2020]	0.475***	0.272***	0.446***
	(0.033)	(0.050)	(0.043)
WHITE	0.162***	0.010	0.224***
	(0.025)	(0.040)	(0.031)
WHITE:C(YEAR)[T.2020]	−0.159***	−0.069	−0.130***
	(0.037)	(0.056)	(0.048)
Observations	169,613	62,218	107,395
Residual S Error	3.139 (df=169607)	2.892 (df=62212)	3.td.211 (df=107389)
F Statistic	154.476*** (df=5; 169607)	67.881*** (df=5; 62212)	145.414*** (df=5; 107389)
Note: *p<0.1; **p<0.05; ***p<0.01			

Table 5: Wage differences between Whites and all non-whites (2015 vs. 2020)

	Dependent variable: Log INCWAGE		
	(All)	(College)	(Non-College)
Intercept	8.928***	10.715***	8.283***
	(0.031)	(0.052)	(0.039)
AGE	-0.012***	-0.025***	-0.007
	(0.004)	(0.006)	(0.005)
AGE^2	0.019***	0.010*	0.021***
	(0.004)	(0.006)	(0.005)
C(YEAR)[T.2019]	0.334***	0.174***	0.333***
	(0.032)	(0.049)	(0.041)
WHITE	0.161***	0.011	0.222***
	(0.025)	(0.040)	(0.031)
WHITE:C(YEAR)[T.2019]	-0.114***	-0.039	-0.107**
	(0.036)	(0.056)	(0.046)
Observations	180792	64865	115927
Residual Std. Error	3.159 (df=180786)	2.908 (df=64859)	3.228 (df=115921)
F Statistic	113.213*** (df=5; 180786)	61.918*** (df=5; 64859)	138.855*** (df=5; 115921)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: Wage differences between Whites and all non-whites (2015 vs. 2019)

From our results in table 5, we see that whites, earn 16.2% more than their non-white counterparts, this wage gap narrowed by 15.9% to 0.3% in 2020. However, when taking college attainment into account, we see that Whites who have attended college did not earn significantly different wages than their non white counterparts, this did not change in 2020. On the other hand non-college educated whites earned 22.4% than their non-white counterparts, with it decreasing by 13% to 9.4% in 2020.

These same trends were observed when we compared 2015 wages to 2019 wages in

Table 6. Thus we conclude that the the narrowing of wage gap between non-college educated whites, and their non-White counterparts that was observed in 2020 as part of an ongoing trend.

6.3 Wage differences of Asians compared to all non- Asians

	Dependent variable: Log INCWAGE		
	(All)	(College)	(Non-College)
Intercept	9.088***	10.695***	8.524***
	(0.026)	(0.044)	(0.031)
AGE	-0.019***	-0.035***	-0.013***
	(0.004)	(0.006)	(0.005)
AGE^2	0.026***	0.021***	0.025***
	(0.004)	(0.006)	(0.005)
C(YEAR)[T.2020]	0.340***	0.216***	0.337***
	(0.016)	(0.025)	(0.021)
ASIAN	0.133***	0.034	-0.076
	(0.037)	(0.050)	(0.051)
ASIAN:C(YEAR)[T.2020]	0.087	0.013	0.113
	(0.054)	(0.071)	(0.078)
Observations	169613	62218	107395
Residual Std. Error	3.139 (df=169607)	2.892 (df=62212)	3.212 (df=107389)
F Statistic	154.879*** (df=5; 169607)	67.691*** (df=5; 62212)	134.299*** (df=5; 107389)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: Wages of Asians compared to all non-Asians (2015 vs. 2020)

	Dependent variable: Log INCWAGE		
	(All)	(College)	(Non-College)
Intercept	9.035***	10.717***	8.458***
	(0.025)	(0.043)	(0.030)
AGE	-0.012***	-0.025***	-0.007
	(0.004)	(0.006)	(0.005)
AGE^2	0.019***	0.010*	0.021***
	(0.004)	(0.006)	(0.005)
C(YEAR)[T.2019]	0.239***	0.138***	0.248***
	(0.016)	(0.024)	(0.020)
ASIAN	0.134***	0.032	-0.075
	(0.037)	(0.051)	(0.051)
ASIAN:C(YEAR)[T.2019]	0.040	0.041	0.022
	(0.053)	(0.070)	(0.074)
Observations	180792	64865	115927
Residual Std. Error	3.159 (df=180786)	2.908 (df=64859)	3.228 (df=115921)
F Statistic	111.281*** (df=5; 180786)	62.331*** (df=5; 64859)	127.050*** (df=5; 115921)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: Wages of Asians compared to all non-Asians (2015 vs. 2019)

In general Asians earned 13.3% more than non-Asians. However, after taking college attainment into account, there was not significant difference in wages earned for Asians with college attainment, and their non-Asian counterpart (Table 7). Similarly, for Asians with no college attainment, the wages they earned did not differ significantly from their non-Asian counterpart. During the inset of COVID in 2020, wages of Asians, regardless of education level also did not differ from non-Asians. Similar trends were observed in comparing 2015 with 2019 wage data (Table 8)

6.4 Wage differences of Blacks compared to all non- Blacks

	Dependent variable: Log INCWAGE		
	(All)	(College)	(Non-College)
Intercept	9.139***	10.704***	8.551***
	(0.026)	(0.043)	(0.031)
AGE	-0.019***	-0.035***	-0.013***
	(0.004)	(0.006)	(0.005)
AGE^2	0.026***	0.021***	0.025***
	(0.004)	(0.006)	(0.005)
C(YEAR)[T.2020]	0.332***	0.209***	0.330***
	(0.016)	(0.024)	(0.021)
BLACK	-0.294***	-0.027	-0.239***
	(0.032)	(0.058)	(0.038)
BLACK:C(YEAR)[T.2020]	0.145***	0.100	0.103*
	(0.049)	(0.083)	(0.060)
Observations	169613	62218	107395
Residual Std. Error	3.139 (df=169607)	2.892 (df=62212)	3.211 (df=107389)
F Statistic	166.118*** (df=5; 169607)	67.777*** (df=5; 62212)	143.431*** (df=5; 107389)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: Wages of Blacks compared to all non-Blacks (2015 vs. 2020)

	Dependent variable: Log INCWAGE		
	(All)	(College)	(Non-College)
Intercept	9.086***	10.727***	8.485***
	(0.025)	(0.043)	(0.031)
AGE	-0.012***	-0.025***	-0.008
	(0.004)	(0.006)	(0.005)
AGE^2	0.020***	0.011*	0.021***
	(0.004)	(0.006)	(0.005)
C(YEAR)[T.2019]	0.225***	0.142***	0.226***
	(0.016)	(0.024)	(0.020)
BLACK	-0.292***	-0.026	-0.238***
	(0.032)	(0.058)	(0.038)
BLACK:C(YEAR)[T.2019]	0.163***	0.022	0.175***
	(0.047)	(0.081)	(0.057)
Observations	180792	64865	115927
Residual Std. Error	3.158 (df=180786)	2.908 (df=64859)	3.228 (df=115921)
F Statistic	123.743*** (df=5; 180786)	61.843*** (df=5; 64859)	134.605*** (df=5; 115921)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: Wages of Blacks compared to all non-Blacks (2015 vs. 2019)

Blacks experienced a substantial wage disparity compared to their non-Black peers, and earned 29.5% less than their non-Black peers. This negative wage gap narrowed by 14.5%

to 14.9% in 2020 during the onset of COVID. Amongst Blacks with college education attainment, there was no noticeable wage disparity in comparison to their non-Black counterparts, indicating the absence of a negative wage gap for this subgroup. This situation remained consistent even with the advent of COVID-19 in 2020. On the other hand, Blacks without college education, had a pronounced negative wage gap relative to their non-Black counterparts who also lacked college education, with Blacks earning 23.9% less. This wage discrepancy narrowed in 2020 by 10.3% to 13.6% in 2020.

When comparing wages in 2015 and 2019 (Table 10), we noted that the results in 2020 were also present in 2019, indicating that this narrowing of wage gap between non-college Blacks and non-Blacks, and in general, is part of an ongoing pattern, and not due to a single event, like COVID.

6.5 Wage differences of Natives compared to all non- Natives

	Dependent variable: Log INCWAGE		
	(All)	(College)	(Non-College)
Intercept	9.112***	10.703***	8.526***
	(0.025)	(0.043)	(0.031)
AGE	-0.019***	-0.035***	-0.013***
	(0.004)	(0.006)	(0.005)
AGE^2	0.026***	0.021***	0.025***
	(0.004)	(0.006)	(0.005)
C(YEAR)[T.2020]	0.346***	0.217***	0.340***
	(0.015)	(0.023)	(0.020)
NATIVE	-0.547***	-0.252	-0.378***
	(0.089)	(0.194)	(0.100)
NATIVE:C(YEAR)[T.2020]	0.243*	0.085	0.274*
	(0.134)	(0.284)	(0.153)
Observations	169613	62218	107395
Residual Std. Error	3.139 (df=169607)	2.892 (df=62212)	3.212 (df=107389)
F Statistic	155.419*** (df=5; 169607)	67.895*** (df=5; 62212)	136.791*** (df=5; 107389)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 11: Wages of Natives compared to non- Natives (2015 vs. 2020)

Our analysis (table 11) reveals that, on average, Native individuals experience a significant wage disparity compared to non-Natives, and earned 54.7% lesser in wages compared to non-Natives, this difference narrowed by 24.3% to 30.4% in 2020. Similar to findings among college-educated Blacks, the wages of college-educated Natives do not show a significant difference when compared to non-Natives, indicating an absence of a notable wage gap within this group. Conversely, Natives without a college education face a substantial wage gap, earning 37.8% less than their non-Native counterparts. This negative wage gap reducedby 27.4% to 10.4% in 2020.

	Dependent variable: Log INCWAGE		
	(All)	(College)	(Non-College)
Intercept	9.060***	10.726***	8.461***
	(0.025)	(0.043)	(0.030)
AGE	-0.012***	-0.025***	-0.007
	(0.004)	(0.006)	(0.005)
AGE^2	0.019***	0.010*	0.021***
	(0.004)	(0.006)	(0.005)
C(YEAR)[T.2019]	0.245***	0.145***	0.251***
	(0.015)	(0.023)	(0.019)
NATIVE	-0.545***	-0.253	-0.375***
	(0.089)	(0.195)	(0.101)
NATIVE:C(YEAR)[T.2019]	-0.095	-0.211	-0.063
	(0.129)	(0.283)	(0.145)
Observations	180792	64865	115927
Residual Std. Error	3.158 (df=180786)	2.908 (df=64859)	3.228 (df=115921)
F Statistic	121.340*** (df=5; 180786)	63.175*** (df=5; 64859)	132.717*** (df=5; 115921)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: Wages of Natives compared to non- Natives (2015 vs. 2019)

Unlike previous models for Blacks, when comparing wages between 2015 and 2019, we noted an absence of the narrowing of wage gap in 2019 (Table12). Thus, indicating that narrowing of wage gap in 2020 was an anomaly for Natives.

6.6 Establishing causality

From the our analysis above, we find that college education attainment is a significant factor in narrowing the racial wage gap. As such, we performed an instrumental variable analysis in an attempt to establish causality of college education attainment in the changes of the racial income gap.

A previous research found that individuals who have attained college education are more likely to be married, and stay married, compared to their peers who did not attend college (Wang, 2015). As such, we used marriage status as our instrument for instrumental variable analysis. Respondents who are currently married are assigned a dummy variable 1, the rest are assigned 0. We then regress these Marriage dummies against College attainment dummies.

From the results of the first stage regression (Table 13), we noted that *MARRIED* has positive and significant coefficients at 5%. Regression F statistic being significant (at 5%), and higher than 10. From this, we conclude that *MARRIED* is a strong and valid instrument

Next, we performed the second stage regression using the fitted values of the first stage regression in place of college dummies for the model with college dummies and age

	Dependent variable: COLLEGE
	(IV1)
Intercept	0.280***
	(0.002)
MARRIED	0.150***
	(0.002)
Observations	169613
R^2	0.024
Adjusted R^2	0.024
Residual Std. Error	0.476 (df=169611)
F Statistic	4093.690*** (df=1; 169611)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 13: First stage IV regression College dummies against Marriage status

specified n Section 5.1. We compared the results of our second stage regression against results from our regression with college dummies in table3. From the results of the second stage regression and comparison in table 14, we can see that qualitative interpretations of our results are largely consistent with our results from Table 1 with the exception of Asians. This could be due to Asians being more likely than non-Asians to be married and stay married (Pew Research Center, 2012). In particular for Blacks, we noted an college attendance had an even larger effect in narrowing the racial wage gap after controlling for potential endogeneity. However, as with our previous results, we find that the impact of college in narrowing the racial wage gap varies across different races.

	Dependent variable: Log INCWAGE	
	(IV2)	(Table 1: College dummies and age)
Intercept	7.859***	8.905***
	(0.061)	(0.027)
AGE	-0.025***	-0.020***
	(0.004)	(0.004)
AGE^2	0.025***	0.024***
	(0.004)	(0.004)
COLLEGE		1.005***
		(0.024)
fittedCoL	4.164***	
	(0.160)	
C(YEAR)[T.2020]	0.663***	0.321***
	(0.089)	(0.022)
C(YEAR)[T.2020]:COLLEGE		-0.123***
		(0.035)
C(YEAR)[T.2020]:fittedCoL	-0.924***	
	(0.235)	
ASIAN	0.158	-0.129***
	(0.189)	(0.050)
ASIAN:C(YEAR)[T.2020]	-0.058	0.136*
	(0.277)	(0.076)
ASIAN:C(YEAR)[T.2020]:COLLEGE		-0.109
		(0.108)
ASIAN:C(YEAR)[T.2020]:fittedCoL	0.442	
	(0.735)	
ASIAN:COLLEGE		0.196***
		(0.074)
ASIAN:fittedCoL	-0.198	
	(0.502)	
BLACK	-0.696***	-0.263***
	(0.154)	(0.037)
BLACK:C(YEAR)[T.2020]	0.304	0.126**
	(0.235)	(0.058)
BLACK:C(YEAR)[T.2020]:COLLEGE		-0.022
		(0.107)
BLACK:C(YEAR)[T.2020]:fittedCoL	-0.529	
	(0.673)	
BLACK:COLLEGE		0.243***
		(0.072)
BLACK:fittedCoL	1.611***	
	(0.442)	
NATIVE	-0.957**	-0.438***
	(0.422)	(0.097)
NATIVE:C(YEAR)[T.2020]	0.386	0.312**
	(0.644)	(0.148)
NATIVE:C(YEAR)[T.2020]:COLLEGE		-0.208
		(0.339)
NATIVE:C(YEAR)[T.2020]:fittedCoL	-0.445	
	(1.797)	
NATIVE:COLLEGE		0.171
		(0.230)
NATIVE:fittedCoL	1.366	
	(1.190)	
Observations	169613	169613
Residual Std. Error	3.126 (df=169595)	3.102 (df=169595)
F Statistic	133.118*** (df=17; 169595)	286.866*** (df=17; 169595)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 14: 2nd stage IV regression results for College dummies compared to results in table 1

6.7 Discussion of findings

Our research revealed that the racial wage gap varies across different educational levels and racial demographics. Wage changes during the onset of COVID in 2020 vary across different racial groups. While we observed a reduction in racial wage gap 2020, this was also present in 2019, indicating a broader, ongoing trend.

The study has highlighted that racial minorities without college attainment consistently face a negative wage gap in comparison to their white counterparts. Conversely, this persistent wage difference is not evident among the college-educated demographic. This finding emphasises the important role of education in bridging the income wage gap. It suggests that policymakers should prioritise facilitating access to higher education for various racial groups. With a detailed understanding of the educational barriers, and specific faced by each group, policymakers can devise targeted and effective strategies. Such initiatives are crucial in promoting equity and substantially narrowing the racial wage gap

7 Test for Robustness

7.1 F Test

An F Test can be employed to investigate two models, a larger more complex model and a simpler model. In this study, we evaluate 3 iterations of the original equation. The equations evaluated are as listed below.

Equation 1 is the simplest form used in this study using just race as a independent variable.

3 MAIN EQUATIONS EVALUATED

$$\begin{aligned} log(INCWAGE) =& \beta_0 + \beta_1 Asian + \beta_2 Black + \beta_3 Native + \delta_0 Y2020 \\ &+ \delta_1 Asian \cdot Y2020 + \delta_2 Black \cdot Y2020 + \delta_3 Native \cdot Y2020 + u \end{aligned}$$

$$\begin{aligned} log(INCWAGE) =& \beta_0 + \beta_1 Asian + \beta_2 Black + \beta_3 Native + \beta_4 College + \delta_0 Y2020 \\ &+ \delta_1 Asian \cdot Y2020 + \delta_2 Black \cdot Y2020 + \delta_3 Native \cdot Y2020 \\ &+ \delta_4 College \cdot Y2020 + \delta_5 Asian \cdot College \cdot Y2020 \\ &+ \delta_6 Black \cdot College \cdot Y2020 + \delta_7 Native \cdot College \cdot Y2020 + u \end{aligned}$$

$$\begin{aligned} log(INCWAGE) =& \beta_0 + \beta_1 Asian + \beta_2 Black + \beta_3 Native + \beta_4 College + \beta_5 Age \\ &+ \beta_6 Age^2 + \delta_0 Y2020 + \delta_1 Asian \cdot Y2020 + \delta_2 Black \cdot Y2020 \\ &+ \delta_3 Native \cdot Y2020 + \delta_4 College \cdot Y2020 \\ &+ \delta_5 Asian \cdot College \cdot Y2020 + \delta_6 Black \cdot College \cdot Y2020 \\ &+ \delta_7 Native \cdot College \cdot Y2020 + u \end{aligned}$$

Comparing	**Eqn 1 VS Eqn 2**	**Eqn 1 VS Eqn 3**	**Eqn 2 VS Eqn 3**
Null Hypothesis	'COLLEGE' =0	AGE=0	AGE=0','COLLEGE=0'
F Test Statistic	4,111.95	504.8	2,846.3
P Value	0	1.09e-11	0

Table 15: F Test results

The resulting f-statistics suggests for the comparison between Eqn 1 and Eqn 2 with the former being the simple model, that we should Reject the null hypothesis that the College Coefficient should be equivalent to 0. This implies a preference for Eqn 2 over Eqn 1.

When comparing Eqn 1 with that of Eqn 3 given that the p values is less than the 5 percent significant level, we can reject H_0 that the Age coefficient should be equivalent to 0. This suggests that Equation 3 is preferred to Equation 1.

When Equation 2 and 3 are compared against each other, H_0 should again be rejected with AGE and COLLEGE coefficients not equivalent to 0.

7.2 Multi-collinearity Test

A graphical test for strong relationships was carried out at the onset of this study so as to identify any potential signs of multi-collinearity. Graphically, no discernible relationship could be identified between the dependent variables in this study. Nevertheless, given that relationships between some of these variables have been reported in the literature, it is advisable to check for any multi-collinearity issues in our model.

To test for multi-collinearity we compute the Variance Inflation Factors for each variable and selected interaction terms .

Variable	**VIF**
AGE	13.94
LINCWAGE	3.12
ASIAN	9.16
NATIVE	7.84
WHITE	13.83
BLACK	8.88
COLLEGE	14.82
AGE_ASIAN	8.57
AGE_NATIVE	7.97
AGE_BLACK	9.37
AGE_COLLEGE	14.02
COLLEGE_ASIAN	2.02
COLLEGE_NATIVE	1.20
COLLEGE_BLACK	1.45

Table 16: VIF Test results

Our analysis reveals significant multi-collinearity between the variables AGE, WHITE and *COLLEGE* with others in the dataset. Although WHITE does not feature in the models used in the study, *AGE* and COLLEGE does. On closer examination it becomes clear that multi-collinearity predominantly impacts the variables AGE_COLLEGE and AGE whereas for COLLEGE, none of the interaction terms suggested the existence of further multi-collinearity.

Despite the presence of multi-collinearity, it is worth noting that it only affects the estimates of the variables in question. Considering the fact that AGE_COLLEGE, AGE and COLLEGE are not key variables to be interpreted within this study it is unlikely to have a singificant impact on the study's results.

Nevertheless, the existence of relatively high multi-collinearity suggests it may be advisable to drop these variables in future iterations of this model.

8 Potential Areas of Bias

When critically evaluating the model, the paper acknowledges some of the drawbacks associated with the proposed model and have been highlighted as follows.

8.1 Measurement Errors

The main data source used within this study has been the data obtained from the Annual Social and Economic Supplement (ASEC) of the Integrated Public Use Microdata Series Current Population Survey (IPUMS). Two key measurement issues impacting the accuracy of the data has been highlighted as follows:

- Respondent Integrity : A key variable in this study has been the wages earned by individuals. Wage data has been collected through survey responses.
  It has been well documented in the literature that overstating or understating their income is a common issue among respondents. Empirical research Jeffrey C. Moore and Edward J. Welniak (2000) have found that often lower income individuals tend to overstate their income while high income individuals tend to understate it. This trend has been noted within the US which results in some measurement issues in this regard Kim and Tamborini (2012).

- Definitions: The US survey results use a specific definition when collecting information on wages. Respondents are asked specifically to "Report amount before deductions for taxes, bonds, dues, or other items". This results in a downward bias in wage data. High income individuals often receive a substantial proportion of their income through other means (e.g. equity, bonds) which are not included in this definition. It is likely that the wage disparity has been understated.

8.2 Simultaneous Causality

The study carried out above evaluates the impact of independent variables on dependent variables. While providing information on their inter-relationship, it does not consider the impact of a dependent variable on that of the independent one.

The study evaluates 4 variables (*Wages, Race, Education* and *Age*) that are often closely related with each other. Thus far, the analysis has only considered the impact of the other 3 variables on wages but has not considered the possibility of the reverse. This is a real concern in this analysis considering wages have a significant impact on education specifically. Often individuals with a higher income are able to afford to study for a longer period of time. This is a relationship that is well documented in the literature. For instance, in a study conducted by Smith in 2021, it is found that minimum wage has a strong impact on high school drop out rates (Smith, 2021). It was noted to be particularly so for lower income households. As such, it is important to consider the reverse impact of wages on education.

To tackle this, it may be useful to introduce a lagged wage variable into the equation. This will require the relaxation of the assumption that strict exogenity exists. However, given data constraints where the survey does not provide information of an individuals previous wage, we cannot correct for this in our current model.

9 Possible Reasons for Findings

Despite the increased xenophobic and anti-Asian rhetoric by Trump especially during COVID-19, significant increase in racial discrimination against minority ethnic groups for that period did not show up in our findings. Trends in wage gaps were likely a continuation of developments in the labour market prior to the pandemic and the Trump presidency. Our findings show that racial wage gaps, though narrowing, is still a pertinent issue in the US labour market that requires attention. Two key trends stand out from the broader trends. First, college-education is a key driver to narrowing wage gaps across the board. Second, positive and negative discrimination is present for Blacks and Natives when compared with their White counterparts and the larger population, depending on whether they have a college education. College-educated Blacks are more highly valued than Whites while non-college educated Blacks and Native Americans are less valued than their White counterparts. However, Asian Americans do not face the same discrimination in wages compared to Blacks and Natives. As a baseline, this shows college education is an important determinant for wages. However, racial preferences bring about distortions to the skills-based wage mechanism for Blacks and Native Americans.

Yet, not every minority ethnic group faces negative discrimination in wages. For example, college educated Asian Americans experienced an large increase in positive wage gaps compared to White over the COVID-19 period. This could be due to the industry that this segment of the labour force is concentrated in.

Figure 5: Asian representation and relative wage in occupations with median wage of USD100,000 or more in 2019

From Figure 5, we observe that there is a large concentration of Asian Americans in occupations in the healthcare sector (Physicans, Pharmacists, Dentists, Surgeons) and other high-value added sectors of the economy (Software developers, engineers). Occupations in this sector require highly specialised skills and there are fewer substitutes for workers that fit these roles. During the pandemic, when the healthcare sector becomes essential, wage increases could have been given to this industry to retain workers. This suggest that wage changes based on racial preferences alone may have played a smaller role as college-educated Asians would have had increased positive skills gap from the skills-based wage mechanism. As such, racial preferences likely extend a minimal effect in labour market outcomes in specialised and essential sectors like the healthcare sector.

In addition, Blacks receive an additional premium in wages if they have a college education, likely reflecting the emphasis on diversity in the workplace in the US. As there are fewer close substitutes to Blacks with a higher education compared to Whites, they receive higher wages. On the other hand, the jobs that non-college educated Americans are in are likely to be blue-collar jobs that have a relatively homogeneous job scope. This means that this segment of the labour force has many close substitutes available, and racial preferences will be more reflected more starkly in wage differences. Interestingly, non-educated Asians do not seem to be discriminated against from the non-educated general population.

10 Policy Implications

From a policy standpoint, this means that the volatility in sentiments brought about by frequent political transitions are unlikely to show up as changes in racial preferences in the labour market. To target inequitable outcomes from existing racial preferences in the market, intervention measures should be focused on Blacks and Native Americans that do not have a college education. This underscores the importance of upstream intervention policies to help minority ethnic groups attain higher education. Given that it is difficult to fundamentally change the racial preferences of employers, ensuring that Blacks and Native Americans obtain a college education would help them face less negative discrimination in the workforce. At the same time, an increase in the supply of college-educated Blacks would increase the number of substitutes and potentially reduce the positive wage gaps between them and the white counterparts. This signifies the importance of affirmative action the US previous adopted to increase access to higher education for racial minorities, especially if discrimination is proven to exist in college admissions. College and Universities previously considered race as part of their applicant review process. However, the U.S. Supreme Court ruled this approach unconstitutional, leading U.S. higher education institutions to eliminate race as a criterion in admissions decisions (Mangan, 2023). Similarly, the allocation of student financial aid based on race and ethnicity was discontinued. These changes are anticipated to reduce college enrollment rates among racial minorities, potentially leading to lower levels of higher education attainment within these groups (Colin and Cook, 2023). A survey done by Gallup's Center on Black Voices found that more than half of Black adults (52%) believe the Court's ruling will make it more difficult for Black applicants to attend college. This is higher than the share of Asians who think that same way (23%) (McCarthy, 2024). This is contrasted with policies enacted in China, where priority is given to members of minority races in for university admission, the result of enacting such policies have resulted in improvement in educational and labour outcomes of racial minorities (Ding et al., 2017)

This seems to suggest that the US government is changing its method of policy application to promote equality among races. Top-down affirmative action is no longer a viable policy option. Instead of broad-based intervention measures, the US can consider Singapore's approach in harnessing the effort of grassroots communities in supporting educational outcomes, and in term employment outcomes. Singapore has established self-help groups for all ethnic groups - MENDAKI for the Malays and SINDA for the Indians - to look into support and outreach measures to improve socio-economic outcomes. In particular, the Malays do not perform as well as their Chinese and Indian counterparts academically and have a lower university admissions rate. Since its establishment in 1982, the MENDAKI rolled out multiple strategies including subsidising tutoring services, establishing mentorship programs and raising awareness in Malay parents on the value of educational attainment. These have served well in increasing university attainment in Malays over the decades (Matthews, 2017). Singapore has also incorporated community contributions to self-help groups in its social security savings scheme, the Central Provident Fund (CPF). A small payment will be deducted as part of CPF contributions from employees to a fund that is managed by the self-help group representative of their race or religion (Central Provident Fund Board, nd). This is a fair way of ensuring financial aid is channeled to the vulnerable segments of each race. A similar model of community efforts can be adopted in the US to channel resources to support university attainment in Blacks and Native Americans in a meritocratic system. This would be an effective and palatable way of promoting long-term equality in employment outcomes for minority groups in an increasingly partisan political environment.

In addition, the US government can consider strengthening financial and social support for social issues more pertinent in minority groups. According to the Lumina Foundation-Gallup 2023 State of Higher Education study, Black bachelor's students are twice as likely (36%) as other bachelor's students (18%) to have additional responsibilities as caregivers or full-time workers (Gallup and Foundation, 2024). Increasing financial support for low-income families and caregivers across the board would benefit Blacks who have balance additional responsibilities and higher education, which would lower the barrier to entry to enrol in university.

The US could also consider examining regulations surrounding inclusive campuses and the relevant enforcement mechanisms in place. With such regulations in place, proper action will be taken when reports of discrimination against minority groups are made, helping students from minority groups feel protected when instances of discrimination occur. To strengthen these mechanisms, institutes of higher education can consider appointing people of colour on their leadership teams. This would ensure that the voices of people of minority groups are heard and accelerate the implementation of comprehensive anti-discrimination policies. As such, fewer students from minority groups would be discouraged from applying to college due to fears of being discriminated against, and those already enrolled in college are less likely drop out prior to completion from discrimination.

11 Conclusion

This paper investigates for the presence of increased negative wage gaps faced by minority races in the US in the context of increased hate sentiments during the Trump Presidency and the COVID-19 pandemic. This was done through a difference-in-difference was conducted with controls for age and college education. Comparisons were made between each minority group with Whites, as well as each each minority group with the general population. The paper found significant income gaps between Blacks compared to White, Blacks compared to the general population and Natives compared to Whites. This reflects the presence of racial preferences in the labour market. This is especially poignant in negative wage gaps that Blacks and Native Americans that do not have college education face. However, there was no significant increase in negative wage gaps observed across the COVID-19. Instead, a narrowing wage gap was observed. Further tests show that this narrowing wage gap is not a result of COVID-19, but an ongoing trend since 2015. As such, the COVID-19 likely had insignificant effect on the changes in wage gaps. The main driver for narrowing wage gaps is also due to an increase in education attainment across the board. Therefore, in order to achieve more equitable outcomes in income levels across racial groups, it is imperative to tackle upstream issues in college education to level out the playing field. As the US moves away from affirmative action in top-down legislation, bottom-up measures like outreach and support groups should be considered to help minority groups enrol and complete college education. Other policies that enhance protection against discrimination in colleges should also be explored to achieve positive long-term downstream outcomes in employment income.

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Appendix

Appendix A: R code for Data retrieval from IPUSMS

```
ddi <- read_ipums_ddi("cps_00008.xml")
ipumsdata <- read_ipums_micro(ddi)

head(ipumsdata)

ipumsdata_df<- as.data.frame(ipumsdata)
write.csv(ipumsdata_df, file = "ipumsdata_df8.csv",
row.names = FALSE)
```

Appendix B: Python codes

```
import pandas as pd
import os
os.chdir('C:/Users/User/iCloudDrive/Uni work/
Panel Econometrics and Data Analysis ECON6031/IPUMS')

IPUMS = pd.read_csv('ipumsdata_df8.csv')

#Adding dummy for Asian race
asian_values = [650, 651, 652, 700, 801,
802, 803, 804, 805, 806, 807, 808, 809]
IPUMS['ASIAN'] = 0
IPUMS.loc[IPUMS['RACE'].isin(asian_values), 'ASIAN'] = 1

#Adding dummy for White race
white_values = [100]
IPUMS['WHITE'] = 0
IPUMS.loc[IPUMS['RACE'].isin(white_values), 'WHITE'] = 1

#Adding dummy for BLACK race
black_values = [200]
IPUMS['BLACK'] = 0
IPUMS.loc[IPUMS['RACE'].isin(black_values), 'BLACK'] = 1

#Adding dummy for Native race
native_values = [300]
IPUMS['NATIVE'] = 0
IPUMS.loc[IPUMS['RACE'].isin(native_values), 'NATIVE'] = 1

#Adding dummy for ALL race
IPUMS['ALL'] = 1

#Filtering for only all in Labour force
IPUMS= IPUMS[IPUMS['LABFORCE']==2]
```

```
# Calculate average wages for each racial group and year
average_wages_by_year_race = IPUMS.groupby('YEAR').agg({
    'INCWAGE': 'mean',
    'ASIAN': lambda x: (IPUMS.loc[x.index, 'INCWAGE'] * x)
    .mean(),
    'WHITE': lambda x: (IPUMS.loc[x.index, 'INCWAGE'] * x)
    .mean(),
    'BLACK': lambda x: (IPUMS.loc[x.index, 'INCWAGE'] * x)
    .mean(),
    'NATIVE': lambda x: (IPUMS.loc[x.index, 'INCWAGE'] * x)
    .mean(),
    'ALL': lambda x: (IPUMS.loc[x.index, 'INCWAGE'] * x)
    .mean()
}).reset_index()

import matplotlib.pyplot as plt

plt.figure(figsize=(12, 8))

for race in ['ASIAN', 'WHITE', 'BLACK', 'NATIVE', 'ALL']:
    plt.plot(average_wages_by_year_race['YEAR'],
    average_wages_by_year_race[race], marker=None,
    abel=race)

# Highlight the intervention year
plt.axvline(x=2020, color='r', linestyle='--', label='2020')

#plot parallel trends
plt.xlabel('Year')
plt.ylabel('Average Wage')
plt.xticks(average_wages_by_year_race['YEAR'].unique())
plt.legend(fontsize='medium')
plt.grid(True)
plt.show()

#Filtering data for 2015-2020
f_IPUMS = IPUMS[IPUMS['YEAR'].isin
```

```
([2015,2026, 2027,2018,2019,2020])]
#Rebasing wage income to 2015 values
# Define boolean masks for each year
filtered_rows_2016 = f_IPUMS['YEAR'] == 2016
filtered_rows_2017 = f_IPUMS['YEAR'] == 2017
filtered_rows_2018 = f_IPUMS['YEAR'] == 2018
filtered_rows_2019 = f_IPUMS['YEAR'] == 2019
filtered_rows_2020 = f_IPUMS['YEAR'] == 2020

# Ensure INCWAGE and INCWELFR columns are of float64 type
before performing the operations
f_IPUMS['INCWAGE'] = f_IPUMS['INCWAGE'].astype(float)
f_IPUMS['INCWELFR'] = f_IPUMS['INCWELFR'].astype(float)

# Create new columns for adjusted INCWAGE and INCWELFR values
f_IPUMS['ADJ_INCWAGE'] = f_IPUMS['INCWAGE']

# Apply adjustment factors to the new columns for each year
f_IPUMS.loc[filtered_rows_2016, 'ADJ_INCWAGE'] *= 0.98637124
f_IPUMS.loc[filtered_rows_2017, 'ADJ_INCWAGE'] *= 0.965798666
f_IPUMS.loc[filtered_rows_2018, 'ADJ_INCWAGE'] *= 0.942770706
f_IPUMS.loc[filtered_rows_2019, 'ADJ_INCWAGE'] *= 0.925989826
f_IPUMS.loc[filtered_rows_2020, 'ADJ_INCWAGE'] *= 0.914706153

##########################################################
##########################################################
#DID for 2015 vs. 2020 data
#Filter data for 2015 and 2020 for DID analysis
DID_IPUMS = f_IPUMS[f_IPUMS['YEAR'].isin([2015,2020])]

#Apply log tranformation to wages
DID_IPUMS['LINCWAGE'] = np.log1p(DID_IPUMS['INCWAGE'])

############################################################
# difference in difference (DiD):
##Minority race vs. Whites
```

```
#no college dummies
reg_didy1= smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR) + BLACK*C(YEAR) + NATIVE*C(YEAR)',
data=DID_IPUMS)
results_didy1 = reg_didy1.fit()

#w college dummies
reg_didz1 = smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR)*COLLEGE + BLACK*C(YEAR)*COLLEGE
+ NATIVE*C(YEAR)*COLLEGE',
data=DID_IPUMS)
results_didz1 = reg_didz1.fit()

#w age and college dummies
reg_didy1A= smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR)*COLLEGE + BLACK*C(YEAR)*COLLEGE
+ NATIVE*C(YEAR)*COLLEGE + AGE + AGE^2',
data=DID_IPUMS)
results_didy1A = reg_didy1A.fit()

from stargazer.stargazer import Stargazer
stargazerzy1 = Stargazer
([results_didy1, results_didz1, results_didy1A])
stargazerzy1.render_latex()

##########################################################
#Creating different data frames for college/ non-college
DID_IPUMS_COL = DID_IPUMS[DID_IPUMS['COLLEGE'] == 1]
DID_IPUMS_NOCOL = DID_IPUMS[DID_IPUMS['NO_COLLEGE'] == 1]


#DID for different racial groups vs. all
#Wage differces All (WHITE)
reg_didW = smf.ols(formula='LINCWAGE ~ WHITE*C(YEAR)
+AGE+ AGE^2', data=DID_IPUMS)
results_didW = reg_didW.fit()
print(results_didW.summary())
```

```
#college educated (WHITE)
reg_didWC = smf.ols(formula='LINCWAGE ~ WHITE*C(YEAR)
+AGE+ AGE^2', data=DID_IPUMS_COL)
results_didWC = reg_didWC.fit()
print(results_didWC.summary())

#Non college educated (WHITE)
reg_didWNC = smf.ols(formula='LINCWAGE ~ WHITE*C(YEAR)
+AGE+ AGE^2', data=DID_IPUMS_NOCOL)
results_didWNC = reg_didWNC.fit()
print(results_didWNC.summary())

from stargazer.stargazer import Stargazer
stargazerW = Stargazer
([results_didW, results_didWC, results_didWNC])
stargazerW.render_latex()

#Wage differences All (ASIAN)
reg_didA = smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR)+AGE+AGE^2', data=DID_IPUMS)
results_didA = reg_didA.fit()
print(results_didA.summary())

#college educated (ASIAN)
reg_didAC = smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR)+AGE+AGE+AGE^2', data=DID_IPUMS_COL)
results_didAC = reg_didAC.fit()
print(results_didAC.summary())

#Non college educated (ASIAN)
reg_didANC = smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR)+AGE+AGE^2', data=DID_IPUMS_NOCOL)
results_didANC = reg_didANC.fit()
print(results_didANC.summary())

from stargazer.stargazer import Stargazer
```

```
stargazerA = Stargazer
([results_didA, results_didAC, results_didANC])
stargazerA.render_latex()

#Wage differences (BLACK)
reg_didB = smf.ols(formula='LINCWAGE ~
BLACK*C(YEAR)+AGE+AGE^2', data=DID_IPUMS)
results_didB = reg_didB.fit()
print(results_didA.summary())

#college educated (BLACK)
reg_didBC = smf.ols(formula='LINCWAGE ~
BLACK*C(YEAR)+AGE+AGE^2', data=DID_IPUMS_COL)
results_didBC = reg_didBC.fit()
print(results_didBC.summary())

#Non college educated (BLACK)
reg_didBNC = smf.ols(formula='LINCWAGE ~
BLACK*C(YEAR)+AGE+AGE^2', data=DID_IPUMS_NOCOL)
results_didBNC = reg_didBNC.fit()
print(results_didBNC.summary())

from stargazer.stargazer import Stargazer
stargazerB = Stargazer
([results_didB, results_didBC, results_didBNC])
stargazerB.render_latex()

#Wage differences (NATIVE)
reg_didN = smf.ols(formula='LINCWAGE ~
NATIVE*C(YEAR)+AGE+AGE^2', data=DID_IPUMS)
results_didN = reg_didN.fit()
print(results_didN.summary())

#college educated (NATIVE)
reg_didNC = smf.ols(formula='LINCWAGE ~
NATIVE*C(YEAR)+AGE+AGE^2', data=DID_IPUMS_COL)
results_didNC = reg_didNC.fit()
```

```
print(results_didNC.summary())

#Non college educated (NATIVE)
reg_didNNC = smf.ols(formula='LINCWAGE ~
NATIVE*C(YEAR)+AGE+AGE^2', data=DID_IPUMS_NOCOL)
results_didNNC = reg_didNNC.fit()
print(results_didNNC.summary())

from stargazer.stargazer import Stargazer
stargazerN = Stargazer
([results_didN, results_didNC, results_didNNC])
stargazerN.render_latex()

###########################################################
###########################################################
#DID ROBUSTNESS USING 2015 vs. 2019 data
DID_IPUMSK = f_IPUMS[f_IPUMS['YEAR'].isin([2015, 2019])]

#Apply log transformation
DID_IPUMSK['LINCWAGE'] = np.log1p(DID_IPUMSK['INCWAGE'])

##Minority race vs. Whites

#No college dummies
reg_didy2= smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR) + BLACK*C(YEAR) + NATIVE*C(YEAR)',
data=DID_IPUMSK)
results_didy2 = reg_didy2.fit()

#w college dummies:
reg_didz2 = smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR)*COLLEGE + BLACK*C(YEAR)*COLLEGE
+ NATIVE*C(YEAR)*COLLEGE', data=DID_IPUMSK)
results_didz2 = reg_didz2.fit()

# w college dummies and Age:
reg_didz2a = smf.ols(formula='LINCWAGE ~
```

```
ASIAN*C(YEAR)*COLLEGE + BLACK*C(YEAR)*COLLEGE
+ NATIVE*C(YEAR)*COLLEGE + AGE + AGE^2',
data=DID_IPUMSK)
results_didz2a = reg_didz2a.fit()

from stargazer.stargazer import Stargazer
stargazerzy2 = Stargazer
([results_didy2, results_didz2, results_didz2a])
stargazerzy2.render_latex()

#####################################################################
#Creating differnt data frames for all, college, non-college
DID_IPUMSK_COL = DID_IPUMSK[DID_IPUMSK['COLLEGE'] == 1]
DID_IPUMSK_NOCOL = DID_IPUMSK[DID_IPUMSK['NO_COLLEGE'] == 1]

#DID for different racial groups vs. all
#Wage differnces (WHITE)
reg_didWK = smf.ols(formula='LINCWAGE ~
WHITE*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK)
results_didWK = reg_didWK.fit()

#college educated (WHITE)
reg_didWCK = smf.ols(formula='LINCWAGE ~
WHITE*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK_COL)
results_didWCK = reg_didWCK.fit()

#Non college educated (WHITE)
reg_didWNCK = smf.ols(formula='LINCWAGE ~
WHITE*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK_NOCOL)
results_didWNCK = reg_didWNCK.fit()

from stargazer.stargazer import Stargazer
stargazerWK = Stargazer
([results_didWK, results_didWCK, results_didWNCK])
stargazerWK.render_latex()

#Wage differences (ASIAN)
```

```
reg_didAK = smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK)
results_didAK = reg_didAK.fit()

#college educated (ASIAN)
reg_didACK = smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK_COL)
results_didACK = reg_didACK.fit()

#Non college educated (ASIAN)
reg_didANCK = smf.ols(formula='LINCWAGE ~
ASIAN*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK_NOCOL)
results_didANCK = reg_didANCK.fit()

from stargazer.stargazer import Stargazer
stargazerAK = Stargazer
([results_didAK, results_didACK, results_didANCK])
stargazerAK.render_latex()

#Wage differences (BLACK)
reg_didBK = smf.ols(formula='LINCWAGE ~
BLACK*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK)
results_didBK = reg_didBK.fit()

#college educated (BLACK)
reg_didBCK = smf.ols(formula='LINCWAGE ~
BLACK*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK_COL)
results_didBCK = reg_didBCK.fit()

#Non college educated (BLACK)
reg_didBNCK = smf.ols(formula='LINCWAGE ~
BLACK*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK_NOCOL)
results_didBNCK = reg_didBNCK.fit()

from stargazer.stargazer import Stargazer
stargazerBK = Stargazer
([results_didBK, results_didBCK, results_didBNCK])
```

```
stargazerBK.render_latex()

#Wage differences (NATIVE)
reg_didNK = smf.ols(formula='LINCWAGE ~
NATIVE*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK)
results_didNK = reg_didNK.fit()

#college educated (NATIVE)
reg_didNCK = smf.ols(formula='LINCWAGE ~
NATIVE*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK_COL)
results_didNCK = reg_didNCK.fit()

#Non college educated (NATIVE)
reg_didNNCK = smf.ols(formula='LINCWAGE ~
NATIVE*C(YEAR)+AGE+AGE^2', data=DID_IPUMSK_NOCOL)
results_didNNCK = reg_didNNCK.fit()

from stargazer.stargazer import Stargazer
stargazerNK = Stargazer
([results_didNK, results_didNCK, results_didNNCK])
stargazerNK.render_latex()

#################################################################
#################################################################
#IV on College dummies

#creating Marriage dummies
married_values = [1, 2]
DID_IPUMS['MARRIED'] = 0
DID_IPUMS.loc[DID_IPUMS['MARST'].isin(married_values),
'MARRIED'] = 1

regIV1 = smf.ols(formula ='COLLEGE ~ MARRIED', data= DID_IPUMS)
resultsIV1 = regIV1.fit()
print(resultsIV1.summary())
from stargazer.stargazer import Stargazer
stargazerIV = Stargazer([resultsIV1])
```

```
stargazerIV.render_latex()

fittedCoL = resultsIV1.fittedvalues.values
regIV2 = smf.ols(formula = 'LINCWAGE ~
ASIAN*C(YEAR)*fittedCoL + BLACK*C(YEAR)*fittedCoL
+ NATIVE*C(YEAR)*fittedCoL+ AGE+ AGE^2', data = DID_IPUMS)
resultsIV2 = regIV2.fit()

from stargazer.stargazer import Stargazer
stargazerIV2 = Stargazer([resultsIV2, results_didy1A])
stargazerIV2.render_latex()

####################################################################
####################################################################
#F-Tests
# EQN 1 and EQN 2

hypothesis = ['COLLEGE=0']
ftest = results_didz1.f_test(hypothesis)

fstat1 = ftest.statistic
fpval1 = ftest.pvalue

print(fstat1)
print(fpval1)

df=pd.DataFrame()

df['1a'] =  fstat1
df['1b'] =  fpval1

# EQN 2 and EQN 3
reg_didz = smf.ols(formula='LINCWAGE ~ AGE + AGE^2 +
ASIAN*C(YEAR)*COLLEGE + BLACK*C(YEAR)*COLLEGE
+ NATIVE*C(YEAR)*COLLEGE', data=DID_IPUMS)
results_didz = reg_didz.fit()
```

```
hypothesis = ['AGE=0']
ftest = results_didz.f_test(hypothesis)

fstat2 = ftest.statistic
fpval2 = ftest.pvalue

df['2a'] =  fstat2
df['2b'] =  fpval2

print(fstat2)
print(fpval2)

# EQN 3 and EQN 1

hypothesis = ['AGE=0','COLLEGE=0']
ftest = results_didz.f_test(hypothesis)

fstat3 = ftest.statistic
fpval3 = ftest.pvalue

print(fstat3)
print(fpval3)

df['3a'] =  fstat3
df['3b'] =  fpval3

####################################################################
# Multicolinearity test

from statsmodels.stats.outliers_influence
import variance_inflation_factor
# VIF dataframe

temp = DID_IPUMS[['AGE','LINCWAGE','ASIAN','NATIVE',
'WHITE','BLACK','COLLEGE']]

temp['AGE_ASIAN'] = temp['AGE']*temp['ASIAN']
```

```
temp['AGE_NATIVE'] = temp['AGE']*temp['NATIVE']
temp['AGE_BLACK'] = temp['AGE']*temp['BLACK']
temp['AGE_COLLEGE'] = temp['AGE']*temp['COLLEGE']

temp['COLLEGE_ASIAN'] = temp['COLLEGE']*temp['ASIAN']
temp['COLLEGE_NATIVE'] = temp['COLLEGE']*temp['NATIVE']
temp['COLLEGE_BLACK'] = temp['COLLEGE']*temp['BLACK']

vif_data = pd.DataFrame()
vif_data["feature"] = temp.columns

vif_data["VIF"] = [variance_inflation_factor(temp.values, i)
                   for i in range(len(temp.columns))]

print(vif_data)
```