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The Effect of Racial Identity on Labor Productivity in the United States

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I. Introduction

Discussions about the wage and productivity gap for minority groups have increasingly become a part of the political discourse in the past couple of decades. While these discussions primarily focus on the gender wage gap, wage gaps based on other demographic factors (i.e. race, ethnicity, immigration status, disability, etc.) are still quite prevalent in the United States (U.S.) economy. With the U.S. projected to become majority-minority by 2044, it is especially necessary to understand the effects of race on the U.S. economy. The literature regarding race and wage differentials is limited in the scope of the analysis and dated. This paper will add to the debate by attempting to incorporate a more comprehensive model than previously used. The model addresses the limitations of the existing literature: explanatory variables, appropriate controls, and sufficient observation period. Specifically, this paper will analyze the impact of racial identity on labor productivity, using individual wage as a proxy for productivity. I hypothesize that Asian workers have the highest productivity among the racial groups, followed by white workers, black workers, other race workers and finally indigenous workers.

Using data from the U.S. Census Bureau's American Community Survey from 2000 to 2015, provided by the Integrated Public Use Microdata Series (IPUMS), I construct a pooled cross-sectional model to test the impact of race on an individual's wage. I employ multiple Ordinary Least Squares regressions controlling for time (16), state (51), and industry (46) effects with dummy variables to analyze the effects of race and other explanatory variables on wages.

I hypothesize that Asian workers are the most productive group of workers because they are the racial group with the highest average wages (Guo 2016). These high average wages may be a result of Asian worker self-selection in certain industries or an economic truth to the "model minority" stereotype of Asian Americans and Asian immigrants (Maynard and Seeborg 2013; Guo 2016). I expect to find quantitative support for the model minority stereotype, by observing positive and higher coefficients for Asian workers compared to the other racial groups. The model minority stereotype of Asian Americans could partially explain why race is a determining factor of labor productivity because Asian Americans are perceived to have higher levels education and a stronger work ethic than other racial groups, so they could be considered more productive in these occupations (Guo 2016). This preferential treatment would be considered discrimination, but my model does not directly test or account for discrimination because there is no explicit measure to do so.

On the contrary, the results of my analysis show that all racial groups are predicted to make less than white workers, except in the case of high skilled Asian workers. With more education, the wage disparity between white, black and Asian workers diminishes, but predicted wages for black workers are still substantially and significantly lower than white workers. I discuss several explanations for these results within my model, but more research and nuanced models are necessary to better understand productivity differences between racial groups.

The rest of this paper will outline the existing literature on minority demographics on wage, the data sample and model, the results of the OLS regressions, and will conclude with a summary of the findings and limitations of the model.

II. Literature Review

A large majority of the existing literature on this topic focuses on minority characteristics or diversity effects on wages simultaneously, instead of exclusively focusing on an analysis of one independent variable. For example, the literature discusses effects of race *and* gender or cultural diversity *and* immigration as opposed to focusing on just one of those aspects as the sole independent model in the variable. Focusing on multiple minority characteristics prevents the literature from providing deeper and more comprehensive insight on the effect of these characteristics on productivity, especially because many of these studies are outdated. Many of these studies analyze the wage differences between black and white workers, but more updated data will allow for a study that includes other races and explanatory variables. That being said, the models in the existing literature provide a useful basis in developing the model used in this paper, that attempts to address the limitations discussed in the literature.

One study conducted by Gianmarco Ottaviano and Giovanni Peri analyzes the effect of cultural diversity on net productivity, specifically average wages and rents on immigrants and US born citizens. Ottaviano and Peri use data from the Census Public Use Microdata Sample for 1970 and 1990 to calculate rents and wages for specific groups of citizens in 160 metropolitan statistical areas (2005). They define cultural diversity as the “probability that two randomly selected individuals in a community belong to different groups” and use this definition for their independent variable (Ottaviano and Peri 2005). Using a linear-log model of specification, they conclude that an increase in the diversity index leads to an increase in average real wages and real rents.

Additionally, they find that an increase in the share of foreign-born workers (diversity within this foreign-born group has a positive, but insignificant effect) is associated with an increase in rents and wages (Ottaviano and Peri 2005). Stated more simply, Ottaviano and Peri conclude that there is “a dominant positive effect of diversity on productivity: *a more multicultural urban environment makes US-born citizens more productive*” (2005). While their study shows a correlation between diversity and productivity, they discuss other potential causes for higher wages and rents that they did not include in their regressions: foreigners’ average education, distribution of skills, productivity, amenity shocks, etc. Though studying the effects of cultural diversity (through presence of immigrants) on productivity is insightful, this paper is limited in its scope and does not specifically focus on one community or group within “diversity,” so it is difficult to practically apply this analysis.

Though written several years prior, Christofides and Swidinsky’s examination of the labor market disadvantages that arise due to minority and gender status in Canada, uses a more robust model that mitigates some of the limitations observed in Ottaviano and Peri’s paper. Using the 1989 Labour Market Activity Survey (in Canada), Christofides and Swidinsky analyzed the effect of productivity related factors (education, citizenship, job training/tenure, occupation, industry, region, etc.) on wages for female and visibly minority individuals. In this study, they do not look at individual minority groups, instead they pool minorities as one category in Canada (1994). Their results show that less than 30% of the observed wage gaps in the comparison groups can be explained by the differences in productivity-related characteristics, and that the large residuals can be attributed to wage discrimination (1994). The research in this paper and others has policy implications: raising the issue of more pay-equity legislation necessary to address the explicit and implicit occupational segregation of racial groups.

Looking at two racial groups, specifically white and black workers, a 1996 paper analyzes the significance of race in early career wages, in response to William Wilson's assertion (in a 1980 paper) that race was "declining in significance as a determinant of economic rewards" (Cancio, Evans, Maume). The authors compare the net effect of race on hourly wages in two cohorts of white and black workers from the 1976 and 1985 Panel Studies of Income Dynamics. For Wilson's assertion to hold true, they needed to observe that the net effects of race in 1985 were less than the net effects of race in 1976. The results from their pooled analysis show that the disparity between white men's earnings compared to black men's earnings was greater in 1985 than 1976. They argue that the reversal in the trend that Wilson observed could be due to a failure of the government in addressing anti-discriminatory hiring practices and sufficiently implementing affirmative action (Cancio, Evans, Maume 1996). By using current demographic data, I want to see if the disparity they observed persists today, and whether this disparity exists among other racial groups.

Lori Reid's 1998 paper pushes the literature forward by focusing on studying the effects of the sex or race/ethnic composition of an occupation on starting wage levels. Using National Longitudinal Survey of Youth data from 1979 to 1987, Reid attempts to understand how the presence of certain minority group, high composition of black/Latinx or female workers, affect the wages of another group. Reid does not find consistent evidence that race/ethnic composition of occupation has a negative effect on wages. In her pooled model with dummies for race/ethnicity and sex, she is not able to support the claim that an occupation with a higher black/Latinx composition has negative effects on wages similar to the negative effects on wages in occupations with a high composition of women (Reid 1998).

She argues that there is a lack of evidence supporting the idea that certain occupations are devalued with a high minority presence and that comparable worth policies may not be as effective in addressing race/ethnic discrimination (Reid 1998). She also suggests that "the cultural devaluation of minorities creates a different kind of labor market discrimination against minorities that is created by the cultural devaluation of women," because minorities did not make up a large enough proportion of the market, at the time (Reid 1998). Though I do not want to study the effects of one racial group's occupational presence on another group's productivity, because of Reid's model, I will include a dummy treatment for female workers in my model to adequately address the negative effects on wages that female workers experience.

In an attempt to address some of the limitations of the previous research on race effects on productivity, Chad Sparber assesses the aggregate effects of racial diversity on labor productivity. Using decennial census data from 1980 to 2000, Sparber uses two-stage weighted least squares with fixed effects to test for the effect of racial diversity on average wages paid to workers per industry, per state (2009). At the industry level, Sparber concludes that industries that require problem solving, customer service, and creative decision making benefit from diversity, while sectors that require high levels of teamwork are harmed by racial diversity (2009). This paper's model is inspired by Sparber's model and incorporates aspects from the models previously discussed to create a model that mitigates some of the limitations discussed in this review.

This paper will add to the debate on race effects on wages by looking specifically at individual race groups in the United States. By using updated data with a model that specifically addresses some of the limitations outlined in the literature, I will provide insight into how a specific racial identity impacts labor productivity in this county and discuss some of the implications of this information.

III. Methodology and Data

The literature suggests that the ideal model for this research question is a log-linear specification. Using Ordinary Least Squares regressions will be the simplest way to compare the different factors that affect labor productivity in addition to race. Log-linear specifications will also enable me to isolate each racial group and test the effects of certain explanatory variables, in addition to my pooled analysis.

The regressions in this paper assess the effect of racial identity on labor productivity in the U.S. for every year between 2000 and 2015. The U.S. American Community Survey provides data for an individual's race, wage, age, education, industry of employment, occupation, and various other control variables that this paper will utilize to answer my research question.[1] The Integrated Public Use Microdata Series (IPUMS) has provided this U.S. Census data and has restored comparability by translating industry and occupation codes to their 1990 equivalent. These industry codes will be categorized into 46 industry classifications that will be used as controls examined by this model.

The ACS data does not provide a direct measure of output per worker, so an appropriate proxy for labor productivity is necessary. Sparber calculates average wages paid to workers for each state-industry cell as his proxy, citing Euler's theorem that weighted average wage is directly proportional to average labor productivity as his justification (2009). Assuming firms pay their workers their marginal product, this proxy is acceptable for the model. I will also be using wages paid to workers as a proxy for their productivity, controlling for the differences between industry, time, and state. Age will be used as a proxy for work experience, as more work experience tends to correlate with a higher salary.[2] This model will also include education because it is certainly a determinate of a person's ability to earn wage. Furthermore, education in the U.S. is correlated with race, so some of the regressions will employ a race*education interaction term to understand the effect that education has on labor productivity for each racial group.

The equation[3]:

$$ln(wage)it = \sum\beta_i * Race_{i,t,s} + Educ_{i,t,s} + Age_{i,t,s} + Age^2_{i,t,s} + Sex_{i,t,s} + ind + time + state + e_{i,t}$$

Where:

i = industry, t = 16 years, s = 51
Wage = wage and salary income
Race = race dummy for White, Asian, Black, Indigenous, Other
Educ = years of schooling
Age = age
Age^2 = age squared
Sex = dummy treatment for female
Ind = industry indicator dummies (46 industries)
Time = time indicator dummies (16 years)
State = state indicator dummies (51)

The regressions will be a pooled-cross sectional analysis of this data. I will control for the unobserved factors specific to industries, states, and time during the 16-year period of observation. The race variable is a placeholder for dummy variables for each of the racial groups—the regressions will include dummy variables for each group to specifically analyze the estimated productivity per each group. The percent change in predicted wages per each racial group compared to white workers will be considered the net labor productivity effect. See tables below for summary statistics for the variables used:

Total observations: 18,718,601

Categorical Variables:

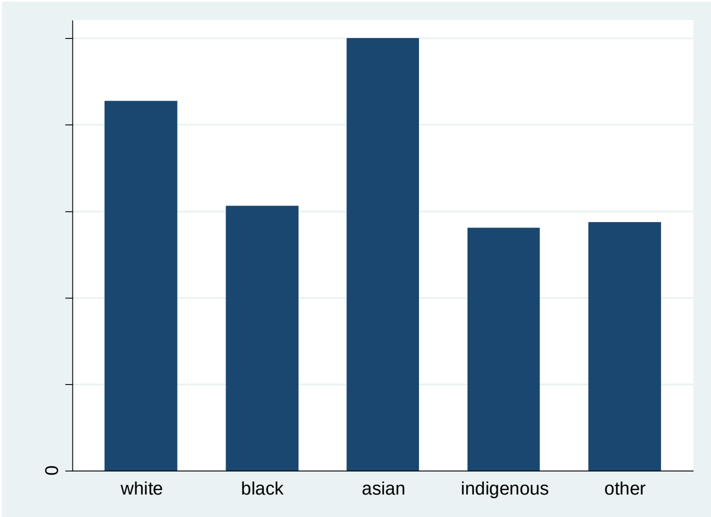
Variable Name	Value	Frequency	Percent
Race	White	14,913,680	79.67
	Black	1,737,526	9.28
	Asian	885,240	4.73
	Indigenous	156,006	0.83
	Other (2+races)	1,026,149	5.48
Education	Primary	420,386	2.25
	Secondary	7,753,443	41,42
	Post-secondary	8,373,259	44.73
	Graduate/professional	2,171,513	11.6
Skill level	Low	3,167,457	16.92
	Mid	9,235,839	49.34
	High	6,315,305	33.74
Years in the USA	N/A	16,091,202	85.96
	0-5	340,980	1.82
	6-10	376,712	2.01
	11-15	391,461	2.09
	16-20	366,222	1.96
	21+	1,152,024	6.15
Sex	Female	9,111,394	48.68
	Male	9,607,207	51.32

Continuous variables:

Variable	Mean	Std. Dev.	Minimum	Maximum
Income	41069.35	49891.93	4	666000
Log of income	10.024	1.298	1.386	13.409
Age	41.831	14.514	16	97
Age^2	1960.536	1262.594	256	9409

IV. Results

Looking at a graph of the pooled data shows that average wages differ between the racial groups. The graph shows that Asian workers have the highest average wages, followed by white workers, black workers, other workers, and indigenous workers.



Of course, controlling for time, industry and state would alter these numbers, however, I still hypothesize that Asian workers would be the most productive racial group in the country because of their high average wage per capita. However, the results of my regressions disprove this hypothesis.

The model as described previously resulted in the preliminary rejection of my hypothesis: Asian workers are more productive than their peer racial groups. This model shows that Asians are predicted to make 7.72% less than their white peers, black workers make 20.2% less than their white peers, indigenous workers make 20.3% less than their white peers, and other race workers make 9.63% less than their white peers, when controlling for industry, state and time. Asian workers have the highest labor productivity for people of color in the United States, but they are still considered less productive than white workers because they are paid almost 8% less. The R^2 value of this regression was 39.2%, meaning that less than 40% of the variation in wages can be attributed to race, age, sex and education.

VARIABLES	(1) original ln_incwage
asian	-0.0772***
	(0.00115)
black	-0.202***
	(0.000870)
indigenous	-0.203***
	(0.00287)
other	-0.0963***
	(0.00108)
2.neweduc	0.199***
	(0.00165)
3.neweduc	0.587***
	(0.00167)
4.neweduc	1.100***
	(0.00180)
age	0.182***
	(0.000119)
age2	-0.00188***
	(1.40e-06)
sex	-0.376***
	(0.000527)
Constant	5.871***
	(0.00618)
Observations	18,690,811
R-squared	0.392

Due to the 2008 recession, many workers took jobs involving less skill or education than they qualify for just to be able to pay their expenses. Replacing education in this model with skill level of occupation changed the coefficients on the race variables, which raises some interesting questions.[4] This alternative model did not change the coefficients in the same proportion as in the first model: it predicted that Asian workers make only 4.6% less than their white peers, black workers make 17.8% less, indigenous workers make 21.3% less than their white peers, and other race workers made 11.3% less than their white peers. The race coefficients in these 2 models are statistically significant. When explaining productivity based on skill level instead of education, Asian and black workers are predicted to be relatively more productive, but indigenous and other workers are predicted to be relatively less productive.

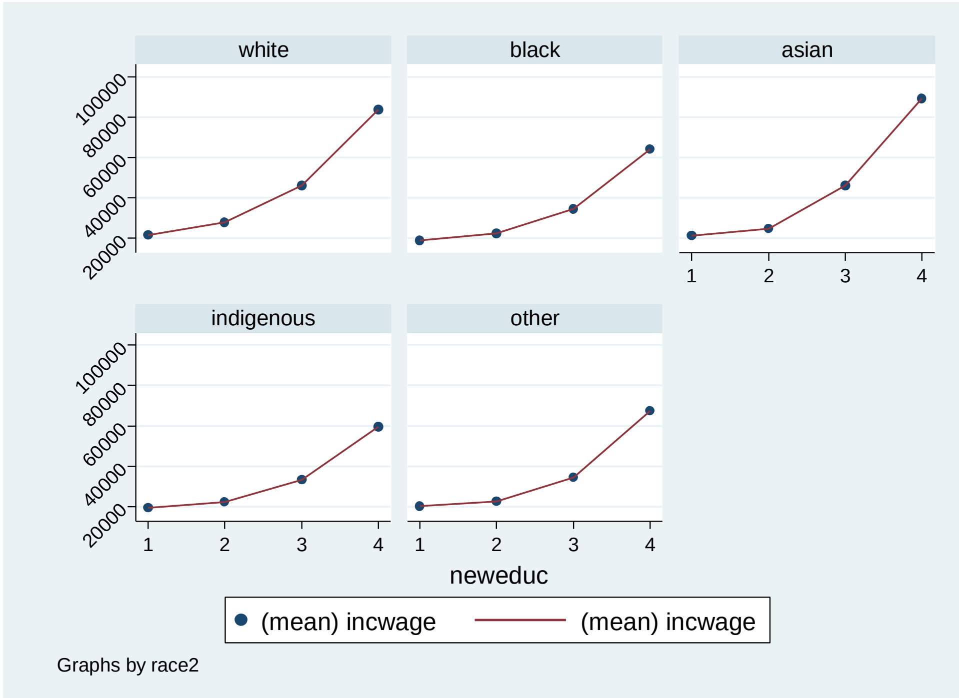
Why does framing productivity as a factor of skill level and not education benefit the relative performance of Asian and black workers and harm indigenous and other race workers? To provide more insight into this discrepancy, the third and fourth models utilized interaction terms for race*education and race*skill level to understand how sensitive each racial group is to a change in education or skill level.

	(1) skills
VARIABLES	**ln_incwage**
asian	-0.0460***
	(0.00113)
black	-0.178***
	(0.000867)
indigenous	-0.213***
	(0.00283)
other	-0.113***
	(0.00106)
2.skill	0.307***
	(0.000817)
3.skill	0.914***
	(0.000857)
age	0.180***
	(0.000119)
age2	-0.00186***
	(1.39e-06)
sex	-0.414***
	(0.000526)
Constant	5.957***
	(0.00592)
Observations	18,690,811
R-squared	0.401

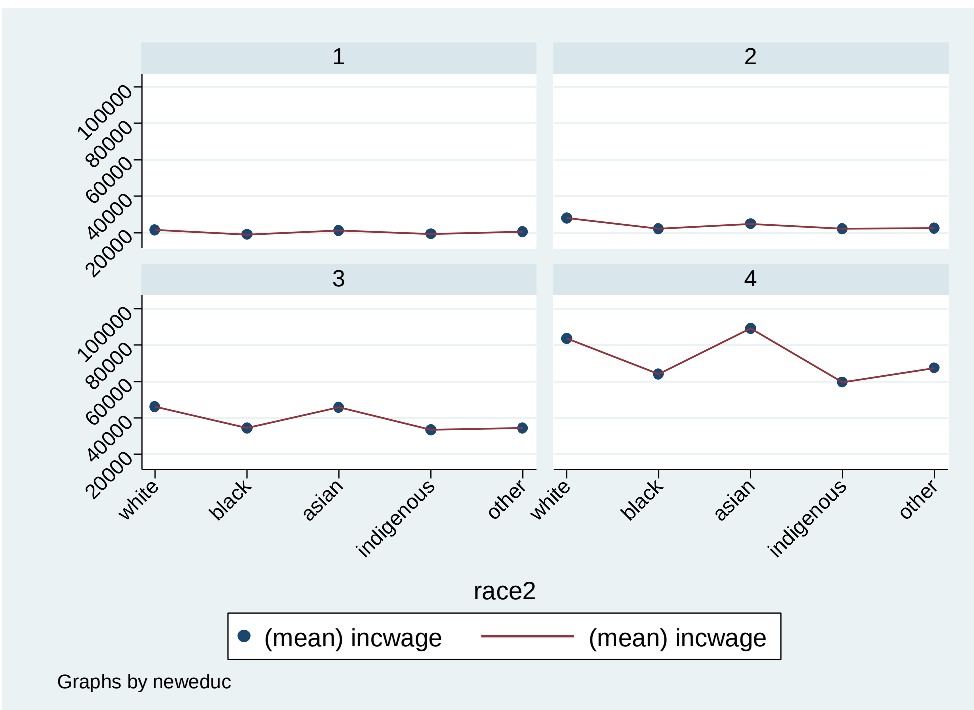
Interacting race with education showed how much more or less productive each race was with an extra level of education. For Asian and indigenous workers, these interaction terms were not statistically significant but for black and other race workers, they were. Black workers were predicted to be more productive with an extra level of education, but black workers with graduate level education were still predicted to make 12.63% less than white workers with the same level of education. Asian workers with graduate level education were predicted to make 5.877% less than their peers. For indigenous and other race workers, adding another level of education seemed to have further decreased their predicted level of wages. If they are even more burdened by an extra level of education compared to the other racial groups, this suggests there are other factors in the market or model related to education level and race that may explain the discrepancy in the pattern. The following graphs provide a visual representation of the sensitivity each racial group has toward an extra level of education.

VARIABLES	(3) ASIAN ln_incwage	(4) BLACK ln_incwage	(5) INDIGENOUS ln_incwage	(6) OTHER ln_incwage
asian	-0.0604***	-0.0765***	-0.0772***	-0.0778***
	(0.00683)	(0.00115)	(0.00115)	(0.00115)
black	-0.202***	-0.184***	-0.202***	-0.202***
	(0.000870)	(0.00779)	(0.000870)	(0.000870)
indigenous	-0.204***	-0.204***	-0.192***	-0.203***
	(0.00287)	(0.00287)	(0.0164)	(0.00287)
other	-0.0965***	-0.0967***	-0.0963***	-0.0398***
	(0.00108)	(0.00108)	(0.00108)	(0.00331)
2.neweduc	0.201***	0.202***	0.199***	0.211***
	(0.00170)	(0.00168)	(0.00166)	(0.00194)
3.neweduc	0.588***	0.588***	0.587***	0.604***
	(0.00171)	(0.00170)	(0.00167)	(0.00195)
4.neweduc	1.099***	1.096***	1.100***	1.116***
	(0.00186)	(0.00184)	(0.00181)	(0.00206)
age	0.182***	0.182***	0.182***	0.182***
	(0.000119)	(0.000119)	(0.000119)	(0.000120)
age2	-0.00188***	-0.00188***	-0.00188***	-0.00188***
	(1.40e-06)	(1.40e-06)	(1.40e-06)	(1.40e-06)
sex	-0.376***	-0.376***	-0.376***	-0.375***
	(0.000527)	(0.000527)	(0.000527)	(0.000527)
1.race#2.neweduc	-0.0490***	-0.0323***	-0.00886	-0.0245***
	(0.00718)	(0.00789)	(0.0169)	(0.00364)
1.race#3.neweduc	-0.0101	-0.0166**	-0.0162	-0.104***
	(0.00700)	(0.00788)	(0.0170)	(0.00373)
1.race#4.neweduc	0.00163	0.0577***	-0.00420	-0.127***
	(0.00719)	(0.00825)	(0.0203)	(0.00546)
Constant	5.870***	5.870***	5.871***	5.857***
	(0.00619)	(0.00619)	(0.00618)	(0.00625)
Observations	18,690,811	18,690,811	18,690,811	18,690,811
R-squared	0.392	0.392	0.392	0.392

Average wages vs. education level by race



Average wages vs. race by education level



The graphs show that, on average, Asian workers have higher wages moving from post-secondary to graduate level education and have the highest wages for post-secondary and graduate educated workers. However, the regression results show that black workers benefit the most moving from post-secondary to graduate level education, relatively, even though they are still predicted to make far less compared to their Asian and white peers.

When interacting race with skill level instead of education, I get very different results than with the third model.[5] In this model, Asian workers in high skilled jobs are predicted to make 2.55% more than their white peers, but in mid skilled jobs they are predicted to make 12.44% less than their peers. High skilled black workers are predicted to make 15.78% less than their white peers, while mid skilled black workers are predicted to make 18.26% less. The net perceived productivity increase black workers have moving from mid to high skilled jobs is not as high as their productivity increase with graduate level education compared to post-secondary. Other race workers are expected to make even less in high skilled jobs than compared to holding mid skilled occupations.

While these results do not fully support my hypothesis, it is not completely unsurprising that there is still such a significant and substantial wage difference between racial groups in the United States, especially given the amount of soft racial discrimination (economic, social and political) prevalent in American society. Racial discrimination could in part explain why non-white workers are predicted to make less than white workers, however, my model cannot empirically test for discrimination, and more research is necessary to develop a model that can.

VARIABLES	(1) asianskill ln_incwage	(2) blackskill ln_incwage	(3) indskill ln_incwage	(4) otherskill ln_incwage
asian	-0.0514***	-0.0458***	-0.0461***	-0.0464***
	(0.00323)	(0.00113)	(0.00113)	(0.00113)
black	-0.179***	-0.190***	-0.178***	-0.177***
	(0.000867)	(0.00196)	(0.000867)	(0.000867)
indigenous	-0.214***	-0.213***	-0.214***	-0.213***
	(0.00283)	(0.00283)	(0.00632)	(0.00283)
other	-0.115***	-0.114***	-0.113***	-0.0220***
	(0.00106)	(0.00106)	(0.00106)	(0.00213)
2.skill	0.310***	0.306***	0.307***	0.316***
	(0.000828)	(0.000857)	(0.000820)	(0.000842)
3.skill	0.909***	0.911***	0.914***	0.924***
	(0.000868)	(0.000894)	(0.000859)	(0.000878)
1.race#2.skill	-0.0730***	0.00739***	0.00623	-0.114***
	(0.00363)	(0.00227)	(0.00740)	(0.00253)
1.race#3.skill	0.0769***	0.0322***	-0.0125	-0.145***
	(0.00355)	(0.00243)	(0.00813)	(0.00301)
age	0.180***	0.180***	0.180***	0.180***
	(0.000119)	(0.000119)	(0.000119)	(0.000119)
age2	-0.00186***	-0.00186***	-0.00186***	-0.00186***
	(1.39e-06)	(1.39e-06)	(1.39e-06)	(1.39e-06)
sex	-0.414***	-0.415***	-0.414***	-0.414***
	(0.000526)	(0.000526)	(0.000526)	(0.000526)
Constant	5.956***	5.959***	5.957***	5.952***
	(0.00592)	(0.00592)	(0.00592)	(0.00592)
Observations	18,690,811	18,690,811	18,690,811	18,690,811
R-squared	0.401	0.401	0.401	0.401

Given the multitude of factors that affect labor productivity, it will be interesting to see how these wage differentials shift over the long-term, with such an influx of immigrants over the past couple of decades and the projection that the country will become majority-minority by 2044. There is a possibility that in the long-term the productivity disparity between races will lessen, especially among Asians. When controlling for how long a foreign-born person has been living in the United States, the coefficient for Asian workers in the original model decreased to -5.35% (-2.36% for the skills model).[6] The coefficients for the other races did not change by more than a few tenths, but it is still interesting to note that time spent in the U.S. is a determinant of a person’s predicted productivity, if they are foreign-born.

Though statistically significant, a distinct pattern in the predicted wages of racial groups does not emerge, suggesting that there are several explanations for the wage differentials, both within the model and the labor market.

V. Limitations of the model

The model is based on the assumption that all workers are identical and that all firms pay their workers their marginal product. Clearly, if wages differ between workers so much if only their race is different, maybe firms do not pay all workers their marginal product. Ceteris paribus, wage differentials between workers of differing racial identity must mean that employers and the market do believe that not all workers are identical. If so, wage may not be the best proxy for labor productivity in this model because it is not just a measure of a worker's marginal product, but a measure of other factors as well. Even though race is clearly still a determinant of wages, despite the passage of the Civil Rights Act of 1964 that prohibited discrimination by employers based on race, there are some gaps in the model that could also explain the wage differentials.

For example, the model categorizes racial groups and skill of occupation vary broadly. "Asian" grouped all Asian ethnicities and nationalities into one category; this broad category could provide conflicting results because labor workforce composition in skilled occupations is very different among the major ethnic groups. Indians, Chinese, Japanese and Koreans tend to occupy high-skilled jobs, while Filipinos, Vietnamese and other Asians tend to occupy mid and low-skilled jobs (Department of Labor 2016). When aggregated into one broad category, the results of the regressions may not be applicable to all ethnic groups. Additionally, the "other" group was a category created to represent the racial groups that did not fit into the other 4 categories. This category included people of Hispanic and Latinx origin, along with other races and ethnicities that are not similar, which could explain why the results for other workers did not follow the same patterns as the Asian and black workers' results.

Furthermore, the categories of high, mid and low-skilled occupations raise some questions about fair wages per occupation and industry. While administrative and farm jobs might be considered low-skilled, there is a high probability that the two workers with similar productivity determining factors are paid different wages because of the nature of their job. Likewise, some occupations I categorized as mid-skilled may be considered low or high-skilled on the unofficial spectrum. Moreover, racial identity itself may not be the determinant of wages, but if certain racial groups are a larger part of a labor force for an occupation that is notoriously underpaid or that does not match its skill classification, then the coefficients will reflect such a wage discount.

Another issue with the model is that it is missing several variables that are important factors in determining wages. The ACS does not provide sufficient data for a person's employment situation: membership in a labor union, position level (management/subordinate), employer/firm size, presence of a human resources department, etc. These variables would serve as additional explanatory variables for wage differentials and could have provided additional insight into the determining factors of labor productivity in the U.S. Union membership and position level especially would have been useful variables to include in the model because they really do affect how much a person can earn in many industries. The model used in this paper should be pushed further in future studies of labor productivity for these data to have substantial policy implications.

Further research on racial identity and labor productivity should focus on developing an adequate measure of labor productivity within the data available. Additionally, a model that addresses the diversity within racial groups and other determining factors of labor productivity will provide more reliable results that show if and how race impacts labor productivity. The limitations of my model make it difficult to suggest some explanations as to why wages differ so much between racial groups, but a model that mitigates these limitations may provide more insight into the relationship between race and labor productivity.

VI. Conclusion

In conclusion, there is a correlation between racial identity and labor productivity in the United States. All major racial groups are expected to make far less than their white counterparts, except in the case of high-skilled Asian workers who were the only racial group expected to make more than their white peers. The disparity in wages between racial groups is smallest when moving to the highest level of education or skill level of occupation, suggesting that education is an important determinant of productivity.

Though racial identity does show a significant and substantial correlation with labor productivity, the model used in this paper had several limitations that could have produced some spurious results. The categories of skill level and race were not specific enough to provide practical results. Moreover, several variables that could have further explained labor productivity were not available in the ACS dataset to include in the models. Future research in the field of labor productivity should take care to develop models that adequately address the specificity needed in the explanatory and race variables in order to provide results with practical significance and policy implications.

VII. References

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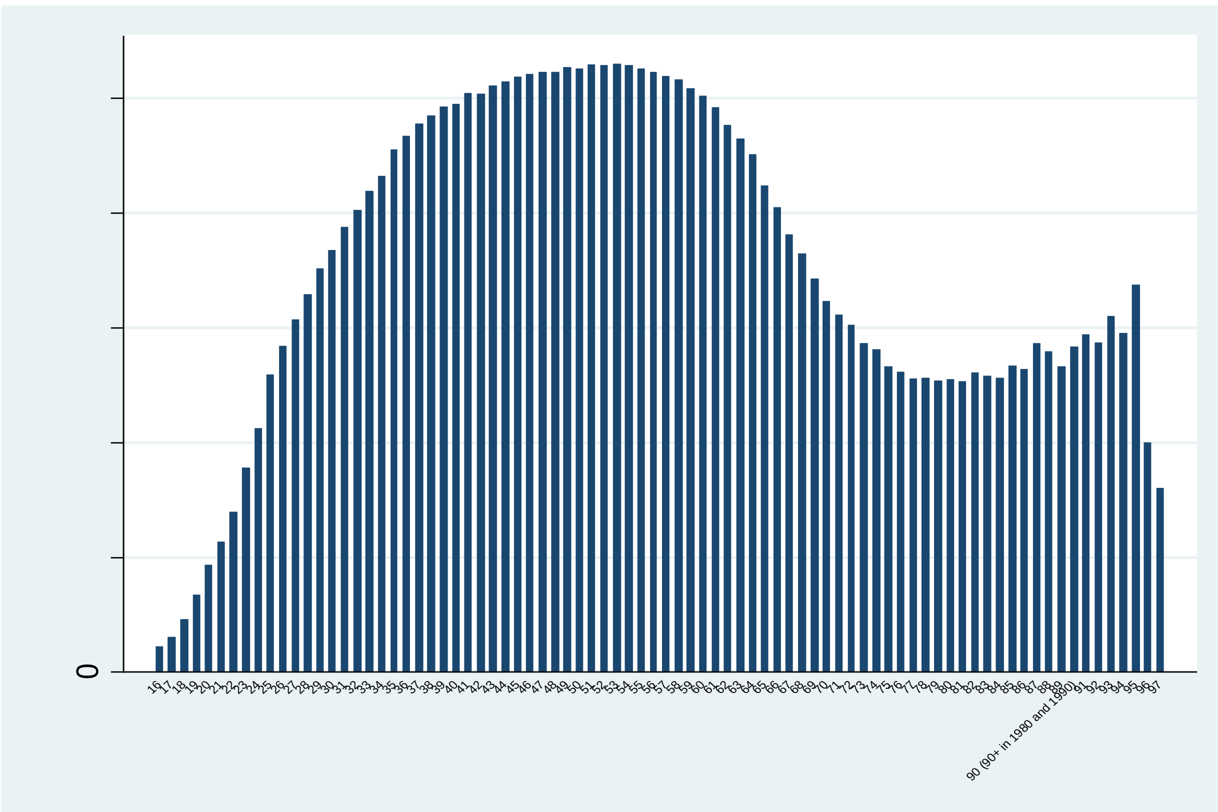
VIII. Appendices

Appendix I:

Average wage vs. Age



Appendix II:

Descriptions and Calculations of variables

Source: U.S. American Community Survey (2000-2015) via IPUMS

Variable	Description
Incwage	Wage and salary income paid by employers
Ln_incwage	Log(incwage)
Education	Years spent at each level: primary, secondary, post-secondary, graduate/professional
Race	Self-identified race: white, black, Asian (Chinese + Japanese + other Asian), indigenous, other (2+ or other minor race)
Sex	1 for female, 0 for male
Age^2	Age*age
Yrsusa2	How long a foreign-born person has been living in the, intervalled
Skill	1 = low, 2 = mid, 3 = high

Appendix III:

Regressions with years in the USA

VARIABLES	(1) yearsusa ln_incwage	(2) skillyrs ln_incwage
1.yrsusa2	-0.169***	-0.147***
	(0.00197)	(0.00192)
2.yrsusa2	-0.0280***	-0.0118***
	(0.00166)	(0.00161)
3.yrsusa2	-0.0449***	-0.0387***
	(0.00160)	(0.00157)
4.yrsusa2	-0.0482***	-0.0507***
	(0.00164)	(0.00162)
5.yrsusa2	0.0200***	0.00975***
	(0.00102)	(0.000994)
asian	-0.0535***	-0.0236***
	(0.00127)	(0.00125)
black	-0.201***	-0.177***
	(0.000871)	(0.000867)
indigenous	-0.204***	-0.214***
	(0.00287)	(0.00283)
other	-0.0872***	-0.104***
	(0.00111)	(0.00110)

2.neweduc	0.183***	
	(0.00171)	
3.neweduc	0.570***	
	(0.00173)	
4.neweduc	1.086***	
	(0.00185)	
age	0.182***	0.180***
	(0.000120)	(0.000120)
age2	-0.00188***	-0.00186***
	(1.40e-06)	(1.39e-06)
sex	-0.376***	-0.415***
	(0.000527)	(0.000526)
2.skill		0.305***
		(0.000819)
3.skill		0.912***
		(0.000859)
Constant	5.895***	5.964***
	(0.00619)	(0.00592)
Observations	18,690,811	18,690,811
R-squared	0.392	0.401

Appendix IV:

Break down of skill level for occupations

Low skill

Transportation and Material Moving = 9000-9750

Food Preparation and Serving = 4000-4150

Building and Grounds Cleaning and Maintenance = 4200-4250

Farm/fish/forest = 6050-6130

Security = 3930-3950

Mid skill

Personal Care and Service = 4300-4650

Sales and Related = 4700-4965

Office and Administrative Support = 5000-5940

Construction = 6200-6765

Extraction = 6800-6940

Production = 7700-8965

Technicians = 1550-1560

Healthcare Support = 3600-3650

Military = 9830

Farm/fish/forest = 6005-6040

Installation, Maintenance, and Repair = 7000-7630

Protective Service = 3700-3910

Arts, Design, Entertainment, Sports, and Media = 2600-2920

High skill

Life, Physical, and Social Science = 1600-1980

Community and Social Services = 2000-2060

Legal = 2100-2150

Education, Training, and Library = 2200-2550

Management in Business, Science, and Arts = 10-430

Business Operations Specialists = 500-730

Financial Specialists = 800950

Computer and Mathematical = 1000-1240

Architecture and Engineering = 1300-1540

Healthcare Practitioners and Technicians = 3000-3540

Military = 9800-9820

IX. Endnotes

[1]The ACS is a weighted sample to ensure that sufficient data for certain populations in certain geographical locations exists. The data I obtained for this paper will be weighted in all of the regressions because unweighting the data is not within my capabilities at this time.

[2] Appendix I for graph of wage vs. age

[3] Appendix II for descriptions and calculations of the variables

[4] Skill level of occupation (low, medium, high) is typically determined by assessing the education needed and wage paid to that worker in that occupation. When categorizing the occupation codes provided into low/mid/high I used a value judgement based only on how much education/work experience would be necessary for that occupation. Understandably, if a variable based on wage is regressed against wages, there could be some issues with the results, but this issue does not seem to arise in my regression.

[5] See Appendix IV for the breakdown of skill level for occupations

[6] See Appendix III for the regression results with the yrsusa2 variable added