Beauty Thesis: How Skin Tone and Beauty Rankings Interact in Labor Market Outcomes

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Abstract

This paper looks at the effects of beauty and skin tone on income using data from the General Social Survey. Beauty premiums and skin tone penalties exist and have a significant impact on labor market outcomes. More beautiful people make more money, and darker skin-toned people make less money. Black men show the largest beauty premium. This research suggests that the effect of looks on income becomes even greater as skin tone is darker. White respondents show a skin tone penalty for both males and females. Industry and service jobs show significant beauty premiums, and the service industry shows a skin tone penalty. This research suggests that grooming is more significant than looks in determining income in all groups except black men.

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I. Introduction

Would you rather be wealthy or beautiful? In theory, this can be a tough question, especially based on individual preferences and values. While most would be inclined to have both wealth and looks, the rule of the game, “would-you-rather” is that you have to choose only one answer. People seem to weigh out the options differently. “Well, how rich are we talking and how ugly?” “Well, if I am wealthy, I could get plastic surgery and look however I desire.” While these questions extend beyond the normal scope of the children’s game of would-you-rather, they have economic importance in dissecting the relationship between the two options. Maybe “both” is a more realistic option if beauty leads to wealth.

Google defines beauty as “a combination of qualities, such as shape, color, or form, that pleases the aesthetic senses, especially the sight” (*Beauty - Google Search*, n.d.). While the popular adage that “beauty is in the eye of the beholder” suggests that beauty ratings are highly variable dependent on the rater, in reality, beauty standards are widely accepted and do not vary substantially within societies (Hamermesh, 2011a). If you ranked the next ten people you saw on a scale of one to five, it is unlikely someone you gave a five would receive a two from another ranker. Economics is itself a study of the allocation of scarce resources. “Economics of beauty” treats facial attractiveness as a scarce resource that can be traded for other valuable resources such as higher wages. Wages can also be traded for beauty, an example being the roughly $400 billion spent on clothing, personal care products & services by American households in 2008 (Hamermesh, 2011b).

In the global marketplace, skin lightening products are a half a billion-dollar industry, particularly in India and China, where lighter skin can lead to more advantageous marriages and jobs (*Systemic Skin Whitening/Lightening Agents*, n.d.). In various societies, skin tone is a marker for beauty and a form of social capital (Thomas, 2020). An unspecified dating app's user data suggests that black women are the "least attractive" racial/ethnic group to men (*"Least Desirable"?*, n.d.). When it comes to beauty standards, this begs the question, does skin tone interact with beauty rankings? Both have social and labor force advantages, but are they related?

Given the 'beauty premium' that leads to more attractive people earning more income and the racial biases in beauty rankings, I was guided to my research questions. Does the beauty premium differ by race and within race? Does the beauty premium differ by skin tone? Are the results statistically significant and how do they translate to economic significance? The data used to investigate these questions are from the General Social Survey (GSS), a personal interview survey conducted by a research team at the University of Chicago (*About the GSS | NORC*, n.d.).[1] The survey captures the respondents' general demographics and experiences to record broad changes in behaviors and beliefs of American society. The dataset, which was first collected in 1972, contains a plethora of variables which change over time. This paper will use the 2016 and 2018 data (5,215 observations) because these are the only years that report skin tone and facial attractiveness of the respondents.[2]

II. Literature Review

The seminal piece of work in this discipline, *Beauty and the Labor Market*, introduces the "beauty premium" which is the term used to describe the positive impact attractiveness has been found to have on wages (Daniel S. Hamermesh & Jeff E. Biddle, 1994). This study finds that in addition to the premium, there is an even more significant "beauty penalty" that detracts from

[1] The website URL is https://gss.norc.org/ .
[2] The GSS data provides information about the prior year. By this I mean, the 2016 surveys asks questions such as "In which of these groups did your earnings from {job}, from all sources for 2015 fall?" (*GSS Data Explorer | NORC at the University of Chicago*, n.d.).

wages for less attractive workers. It is asserted that while beauty can be considered a subjective trait, beauty standards are congruous within a given society and take substantial amounts of time to evolve. Later work, which attempted to break down how attractiveness increases wages through controlled experiments found that more attractive people tend to be more confident, and simulated employers have more confidence in them (Mobius & Rosenblat, 2006). This result holds when indicators of the applicant's capability beyond their resume aren't available. In the Chinese labor market, the monetary benefits from being beautiful are attributed to the increased social networks afforded by good looks (Gu & Ji, 2019). While the beauty premium in the study on the Chinese labor market is attributed to human capital and social networks, an unexplained beauty penalty for less attractive workers persists. Gu & Ji (2019) also address the potential of reverse causality in explaining the beauty premium, meaning that those who make more money can afford cosmetics, nicer clothes, or even plastic surgery.

Additional studies have been conducted to determine in which industries or settings attractiveness is most beneficial (Deryugina & Shurchkov, 2015)(Parrett, 2015). Deryugina and Shurchkov (2015) conducted an experiment using photographs and resumes to explore which industries show hiring bias. Employers for bargaining jobs showed a significant beauty premium, while data entry jobs showed a penalty for better-looking people. These biases were eliminated or "vanished" when the simulated employers were provided results from capability tests. The capability tests were basic tests for skills applicable to the jobs, such as data entry simulations. These capability measures are not always available when hiring for every job, so the beauty premium found may remain applicable in real-life hiring situations. Parrett (2015) used restaurant tipping data to explore if more attractive servers make more money than their less attractive counterparts. The study yielded results indicating that better-looking females make statistically more money in tips, primarily driven by female tippers. This study eliminated expectation bias as a potential reason for the beauty premium in this environment. Tips are rendered after service, so higher earnings were not based on more confidence in attractive people to perform their job better. Better-looking servers were projected to earn about $1,261 more in tips a year which equates to a median earner's month's rent. This finding suggests that expectation bias is not entirely responsible for good looking people earning more money.

Scholz and Sicinski (2015) conduct a longitudinal study across several industries and find that facial attractiveness positively impacts the log of earnings. This longitudinal study examines the correlates of beauty and potential ways that beautiful or handsome people gained their advantage. Although attractiveness was strongly correlated with confidence and participation in varsity sports in high school, these additional variables did not cause the effects of beauty to become insignificant. Because the attractiveness ratings were scored based on high school photographs, it challenges the idea that people who make more money can afford to make themselves more beautiful. Although it is mitigated, reverse causality isn't completely eliminated as there are many covariates with attractiveness that cause hesitation to claim that good looks cause higher incomes. Factors such as family income when growing up can influence attractiveness ratings as well as labor market outcomes. Additionally, better-looking children may receive more attention from teachers while growing up (Scholz & Sicinski, 2015). Cliffod & Walster (1973) find that a teacher's biased expectations can influence a student's actual academic performance. A variety of explanations have been offered to explain the impacts of being beautiful, but the recurring theme is that attractiveness offers an advantage in the labor force.

Past literature has provided evidence supporting the existence of a beauty premium, but lacking is a breakdown of the beauty premia based on race. Becker (1957) addresses discrimination in labor markets with the premise that people have preferences for interaction with those in their same racial categories. Becker's theory of discrimination posits that people exhibit taste-based discrimination in choosing whom to hire, whom to work with and whom to buy from, all of which will lower the earnings of the minority group (Becker, 1957).

Race is a social construction and can be ambiguous. A more quantifiable measure that is related to race is skin tone. Devaraj (2018) uses the National Longitudinal Survey of Youth to determine the effects of skin tone, height, and gender on earnings. The survey used was conducted by the National Opinion Research Center (NORC) at the University of Chicago.[3] Skin tone was scored between zero and ten with zero signifying the lightest skin tone. The study found that skin tone reduced real wages by $463 per year for every skin tone darker than zero. (Devaraj et al., 2018). A separate study used data from the New Immigrant Survey to examine the effects of skin color and height on immigrants to the United States. Skin tone was reported on a scale of one to ten with ten being the darkest. Immigrants with the lightest skin tone earned roughly 17% more in wages than those with the darkest skin tone, controlling for other determinants of labor outcomes such as education, English proficiency, prior occupation, family background, ethnicity, race, and country of birth (Hersch, 2008). Like attractiveness, skin tone has a significant effect on earnings that other characteristics have not been able to explain.

What has remained undefined in the literature is how beauty rankings and skin tone interact in labor outcomes. As Becker (1957) addresses, people tend to prefer likeness. Would a black interviewer rank darker individuals higher than a white interviewer? Would a white

[3] The NORC is the same organization that conducts the General Social Survey, which provides the data used in this research

interviewer be inherently biased to find a fairer individual more attractive? Hamermesh (2011) provides an example of an Indian woman who is clearly more attractive than a white woman to argue there isn't always a bias for more "Western" looks. The problem with his example is that he offers a blatant mismatch. What happens when two individuals are more similar in appearance and the main difference is their skin tone? In this paper, I will examine the impacts of both beauty and skin tone individually as well as the impacts of their interactions on income. I will also examine how the race of the interviewer impacts the rankings of beauty and skin color and the estimates of the labor market premiums for these characteristics.

III. Data

The General Social Survey (GSS) is a face-to-face interview conducted by the National Opinion Research Center (NORC) at the University of Chicago. The survey started in 1972 and has been conducted every two years since.[4] Its aim is to record changes in American ideology and societal trends by collecting data from and about adults in America (*About the GSS | NORC*, n.d.). This extensive survey yields 6,100 variables from the 32 surveys completed throughout the years. The NORC is continually improving the methods and questions to adapt to the current time period. The data sets are publicly available for all years of the survey. For this paper, the responses from 2016 and 2018 are appended and used to answer the research questions.

For the dependent variable, annual income, the values are provided in segmented categories ranging from $10,000 and under to $170,000 and over. Theses income brackets correspond to codes between 1 and 26. To transform the codes, I take the median value of each income group and make that the value for all respondents within the range, creating a new

[4] Due to COVID-19, 2020 interviews were not conducted in the same fashion as past years.

income variable. I take the natural log of the new income variable, which yields the values that provide the dependent variable in the regressions.

In this analysis, I use variables for attractiveness, grooming, skin tone, race, and weight to identify physical characteristics that may impact income. An interviewer scored the attractiveness rating on a 1-5 scale. One is very unattractive, two is unattractive, three is about average, four is attractive, and five is very attractive. The ratings were ascribed at the discretion of the interviewer, who received no specific rating instructions. The grooming rating followed the same process. The interviewer ranked interviewees on a scale of 1-5, with 1 indicating a very poorly groomed individual and 5 indicating a very well-groomed individual. Interviewers were provided a showcard to give a standard for facial color rankings.[5] One corresponds to the lightest skin tone, and ten corresponds to the darkest skin tone with a gradient in between. Weight is scored on a scale from 1-5 based on the interviewer's discretion. For weight, a score of 1 corresponds to very overweight and 5 corresponds with very underweight.

For other determinants of income, I use years of education, age, age squared, average weekly hours worked, and family income when the respondent was 16 years old. The variable for education reports the highest year of school completed. A score of 12 indicates that the interviewee graduated high school. As Gu & Ji (2019) address, age and age squared serve as suitable replacements for experience. Age impacts physical appearance and is highly correlated with experience, so it serves well to use this variable in the regression instead of work experience, which is unavailable in the dataset. Age squared helps account for the nonlinear effects of experience on income as age increases. The average weekly hours worked directly impact annual income for many workers, so it is an essential control for estimating income.

[5] A reproduction of the skin tone card given to interviewers is shown in Figure 1 in the appendix.

Interviewees are asked how many hours they worked the prior week, which I use to control for hours worked per week in the regressions. The respondents report their industry of work which is useful for capturing the relevant impacts of beauty and skin tone for varying industries.[6] Gu & Ji (2019) find that family status impacts wages as it can determine what opportunities an individual has available due to their familial connections. This data set provides a variable for the interviewee's estimate of their family income when they were 16 years old. The values for family income when 16 are ranked between 1 and 5, with one equating to "far below average" and five equating to "far above average."[7] This variable will help control for social network advantages that individuals coming from higher-income families may have.

To characterize the interviewer, I use the interviewer id and variables for the interviewer's race, age, and sex. There are 139 interviewers and the fewest number of interviews conducted by an individual was 3 and the most was 156. These variables will allow me to use interviewer characteristics and interviewer fixed effects in robustness checks.

The following tables show the descriptive statistics for all of the variables of interest discussed above. For the categorical data for race, gender, and the interviewers' gender and race. I created dummy variables. White, black and other are the dummy variables for race. Male and female are the dummy variables for gender. Table 1 presents the demographics of respondents and interviewers regarding their race and gender. The dataset does not provide much granularity for respondents' race and classifies respondents as either white, black, or other. Additionally, the dataset only offers two finite genders, male or female. The summary of the demographics of the

[6] I grouped the industry codes provided into four main groups. My groupings can be found in the appendix.
[7] This variable has potential for bias as self-reporting may be a problem as it can be hard to know where one falls on the wealth distribution relative to the rest of America. I think it is easier to know where you fall relative to your community. The respondents are being asked to look back though so hopefully they are old enough to recognize where their family income fell on the spectrum of wealth.

sample reveals that there are more females than males in the sample. White respondents represent 72.6% of the total sample. Additionally, white interviewers comprise 68.25% of the total interviewers and the large majority of interviewers are female.

Table 1: Race and Gender of Respondents and Interviewers

Male	44.57%
Female	55.43%
White	72.60%
Black	16.86%
Other	10.54%
Male interviewer	12.22%
Female interviewer	87.78%
White interviewer	68.25%
Black interviewer	14.34%
Hispanic interviewer	10.60%
Asian interviewer	0.44%
Multiracial interviewer	6.38%

Table 2 presents descriptive statistics for variables used in the analysis for the total sample, not just those working and thus included in the income regressions. The average individual income in this sample is $47,385.44. According to the United States Census Bureau, the reported median household income was $63,179 for 2018 (Bureau, n.d.). The bureau reports median values for households compared to the mean values for individuals from this sample. The average for looks in this sample is 3.33, which is slightly above the definition of "average looks." The average skin tone is 2.39, which is roughly a deep tan. The average weight is between "slightly overweight" and "about the right weight." The average age in this sample is 49 years old but includes respondents from age 18 to 89. The average individual in this sample works 41.08 hours a week and has completed almost two years of post-secondary education.

Table 2: Descriptive Statistics of Full Sample

Variable	Number of Observations	mean (s.d.)	min	max
Income	2,995	47385.44	500	180000
		(41615.99)		
Rated looks	4,693	3.33	1	5
		(0.77)		
Rated grooming	4,708	3.46	1	5
		(0.79)		
Rated skin tone	4,713	2.39	1	10
		(1.85)		
Weight	4,703	2.70	1	5
		(0.73)		
Age	5,198	49.06	18	89
		(17.86)		
Years of education	5,203	13.74	0	20
		(2.97)		
Family income at 16	5,104	2.72	1	5
		(0.94)		
Hours worked in week prior	3,027	41.08	1	89
		(14.46)		
Interviewer age	5,215	56.41	20	85
		(12.22)		

Table 3 presents the descriptive statistics segregated by gender. It is important to separate males and females to determine statistical differences between the genders. The men in this sample have an average income of $56,272.13, while the females have an average income of $39,136.26, but the difference is not statistically significant. Women have significantly higher-rated looks and rated grooming. The men in this sample weigh significantly more than women based on the 1-5 scale. The women in this sample had statistically lower family wealth than men at 16 years old and work significantly less hours per week.

Table 3: Descriptive Statistics by Gender
(Standard deviations are presented in parentheses below mean values.)

	Male Respondents (n=2,328)	Female Respondents (n=2,887)
Income	56272.13	39136.26
	(45024.35)	(36297.26)
Rated looks	3.27	3.38*
	(0.74)	(0.79)
Rated grooming	3.39	3.52*
	(0.80)	(0.78)
Rated skin tone	2.38	2.39
	(1.83)	(1.86)
Weight	2.78	2.63*
	(0.68)	(0.76)
Age	48.75	49.30
	(17.69)	(18.00)
Years of education	13.70	13.77
	(2.99)	(2.96)
Family income at 16	2.75	2.69*
	(0.95)	(0.93)
Hours worked in week prior	44.38	38.02*
	(14.85)	(13.36)
Interviewer age	56.58	56.29
	(11.99)	(12.39)

*indicates there is a significant difference between males and females for this variable at the 5% significance level

Table 4 shows the descriptive statistics segregated by race. Once again, it is important to separate racial groups to determine statistical differences between the racial groups in this sample. The summary statistics show that the average income for white respondents is $51,055.81. The average income for black respondents is $35,290.04, and for other race respondents is $42,061.13. Black and other race respondents' annual income is statistically different from white respondents, but not from one another. All three racial groups have significantly different skin tone rankings. The average skin tone for white respondents is 1.58, the average for black respondents is 5.44, and the average for other race respondents is 2.92. The average ages of each racial group are statistically different from one another with white respondents being the oldest and other race respondents being the youngest. Average years of education and family income at 16 are significantly different for all three defined racial groups.

Table 4: Descriptive Statistics by Race
(Standard deviations are presented in parentheses below mean values.)

	White Respondents (n=3,793)	Black Respondents (n=875)	Other Race Respondents (n=547)
Income	51055.81	35290.04*	42061.13*
	(43496.08)	(29663.89)	(40930.88)
Rated looks	3.32	3.36	3.36
	(0.78)	(0.74)	(0.74)
Rated grooming	3.46	3.49	3.43
	(0.80)	(0.79)	(0.76)
Rated skin tone	1.58	5.44*	2.92*$^{+}$
	(0.77)	(1.99)	(1.29)
Weight	2.68	2.69	2.78*$^{+}$
	(0.72)	(0.80)	(0.67)
Age	50.69	45.69*	43.14*$^{+}$
	(18.03)	(16.01)	(16.11)
Years of education	13.96	13.33*	12.83*$^{+}$
	(2.87)	(2.62)	(3.82)
Family income at 16	2.81	2.52*	2.39*$^{+}$
	(0.90)	(0.97)	(1.02)
Hours worked in week prior	41.32	40.68	40.14
	(14.55)	(14.02)	(14.49)
Interviewer age	56.93	55.04	55.02
	(12.38)	(11.38)	(12.18)

*indicates the starred variable (for either black or other race respondents) is statistically different from white respondents at the 5% significance level
$^{+}$indicates the variable for other race respondents is statistically different from black respondents at the 5% significance level

IV. Rated Looks

One of the key variables in this study is the rated attractiveness of respondents by interviewers. Past literature has indicated that a single judge for beauty is as efficient as a panel, suggesting that a single interviewer might be valid for ranking beauty (Huo & Pedroni, 2020). As mentioned, Hamermesh (2011) argues that beauty is not as subjective as some might think, and rarely will beauty rankings vary significantly across raters. Still, because there is no finite way for ranking attractiveness, the rated looks variable is based on the interviewer's discretion and can lead to bias. I will conduct robustness checks to account for discrepancies or biases in beauty rankings. With 139 interviewers, there is potential for measurement error in rated looks.

Table 5 shows the results of regressing the respondent's looks on the respondents' race, the interviewer's race, and the respondent's race interacted with the interviewer's race. Based on the coefficients, black interviewers are the harshest critics of black respondents followed by other race interviewers rating black respondents. The third harshest critics are black interviewers rating white respondents. These results argue for including interviewer fixed effects in the large sample regressions, and interviewer demographics in the regressions where small sample sizes preclude the full set of interviewer fixed effects.

Table 5: Effects of Race and Race of Respondent on Beauty Ratings,
Total Sample
(Dependent variable is the rated looks of respondents)

	Total sample
Black	0.123***
	(0.0370)
Other race	0.0784
	(0.0478)
Black interviewer	-0.123***
	(0.0405)
Other race interviewer	-0.0790**
	(0.0387)
Black x Black interviewer	-0.129*
	(0.0740)
Black x Other interviewer	-0.169**
	(0.0790)
Other x Other interviewer	-0.0630
	(0.0886)
Other x Black interviewer	-0.0176
	(0.0970)
Constant	3.345***
	(0.0156)
Observations	4,671
R-squared	0.008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Additionally, rated looks might be highly correlated with grooming and weight. Table 6 shows the correlations between interviewer-rated looks, rated grooming and rated weight. Given the significant correlations between looks, grooming and weight, I will conduct robustness checks to see if the beauty premium holds when controlling for these other characteristics.

Table 6: Correlation Matrix Between Looks, Grooming, and Weight
(P values for the two tailed tests that the correlation is equal to zero are included in parentheses.)

	Rated looks	Rated grooming	Rated Weight
Rated looks	1		
Rated grooming	0.4163 (0.00)	1	
Rated weight	0.1742 (0.00)	0.1626 (0.00)	1

V. Methodology

I will begin my analysis by estimating the following equation using OLS with robust standard errors.

$$\ln(income) = \beta_0 + \beta_1 Beauty_i + \beta_2 Skintone_i + \rho X_i + \varepsilon_i$$

Where X_i is a vector of controls for individual *i* including a dummy variable for female (males are the comparison group), dummy variables for black and other race (whites are the comparison group), age, age squared, years of education, family income at 16, hours worked per week, and interviewer fixed effects. For smaller sample sizes, I use dummy variables for interviewer race and gender to control for potential biases based on interviewer characteristics. For the industry controls, I classify industry of work into four main groups: 1) industry, construction, manufacturing, and wholesale, 2) service industry, 3) government, education, military, and 4) amusement, gambling, recreation. In the regression, the coefficients of interest are β_1 and β_2. β_1, the coefficient on beauty, shows the percentage impact an additional unit of facial attractiveness will have on yearly income. β_2, the coefficient on skin tone, represents the percentage impact an additional unit darker skin tone has on income.

I then augment the initial regression to determine whether the effects of attractiveness are different for different skin tones.

$$\ln(income)i = \beta_0 + \beta_1 Beauty_i + \beta_2 Skintone_i + \beta_3 Beautytone_i + \rho X_i + \varepsilon_i$$

Beautytone is an interaction term between beauty and skin tone, and its coefficient β_3 will determine whether the impact of beauty on income changes with different skin tone ratings. It will also indicate whether the impact of skin tone varies with different beauty rankings.

I will run the above regressions using the entire sample, separate samples of women and men, and separate samples of white respondents, black respondents, and other race respondents. I will break down the initial regressions further by both race and gender to isolate which groups experience the most significant effects of beauty and skin tone. These regressions show the different impacts of beauty and skin tone for each respective group. As mentioned, because of the differences of ratings across interviewers and the potential for measurement error, I will estimate the regressions including interviewer fixed effects for the large samples and reviewer demographics for the smaller samples. Additionally, I will interact the race of the interviewer with beauty and skin tone rankings and estimate separate regressions for each race to see whether own race reviewer ratings of beauty and skin tone have differential impacts on income. As a robustness check, I will test whether any beauty impacts on income hold up with controls for grooming and weight. The final robustness check will be using instrumental variable estimation to control for two-way causation associated with the beauty variables. I will use reviewer characteristics and reviewer fixed effects as instruments.

6. Results

These results have been interpreted through a one-point increase in looks or skin tone, holding all other controls constant. A one standard deviation change in looks ratings is 0.77, which is slightly less than a one-point increase. The standard deviation of skin tone for the entire sample is 1.85, so a one standard deviation change equates to a roughly two-point change in skin tone. The standard deviation of skin tone for white respondents is 0.77, which is less than a one-point increase. For black respondents, the standard deviation of skin is 1.99, meaning a one standard deviation change equates to a two-point change in rated skin tone. For other race respondents, the standard deviation of skin tone is 1.29, which is larger than a one-unit change in skin tone.

The initial results from the entire sample are shown in Table 7. They indicate that beauty and skin tone are both significant in determining annual income. As column 1 shows, a one-unit increase in attractiveness equates to a 9.14% increase in annual income. This result is in line with past literature that has found a beauty premium in the labor market for more attractive individuals. An additional shade darker skin tone translates to a 5.43% decrease in annual income. The impact of being black or a race other than white is not significant when skin tone is included. The initial regression indicates that being female translates to a 41.8% decrease in wages .[8] The second and third columns show the impacts of beauty and skin tone segregated by gender. The second column indicates that, a one-unit increase in beauty for males equates to a 14% increase in annual income, significant at the 1% level. For the entire sample of women, facial attractiveness is not significant in determining wages. For only males, skin tone is not

[8] For all coefficients above 0.1 I use the exact interpretation of a log-lin model (e^coefficient – 1)

significant. For females a one-unit darker shade of skin tone equates to a 6.52% decrease in annual income, significant at the 5% level.

Table 7: Effects of Beauty
Skin Tone and Race on Income,
Total Sample and by Gender
(Dependent variable is the natural logarithm of income)

	Total sample	Males	Females
Rated looks	0.0914***	0.131***	0.0573
	(0.0266)	(0.0388)	(0.0375)
Skin tone	-0.0543***	-0.0354	-0.0652**
	(0.0194)	(0.0275)	(0.0301)
Black	0.0242	-0.121	0.0850
	(0.0921)	(0.131)	(0.143)
Constant	5.314***	5.880***	4.514***
	(0.401)	(0.514)	(0.591)
Observations	2,237	1,092	1,145
R-squared	0.389	0.408	0.424

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Controls include: a dummy variable for being female, a dummy for being black, a dummy for being other race, age, age squared, education, family income at 16, hours worked in week prior, year of survey, interviewer fixed effects

Table 8 shows the effects of beauty and skin tone on income for white, black, and other race respondents. Beauty is significant across all defined racial groups at the 5% level. For white respondents, an additional unit of beauty translates to a 6.9% increase in annual income. For black and other race respondents, an additional beauty unit translates to a roughly 19.8% increase in annual income. Skin tone only remains significant for white respondents. An additional unit darker skin tone for white respondents translates to a 12.5% decrease in annual income.

Table 8: Effects of Beauty and Skin Tone on Income
by Race
(Dependent variable is the natural logarithm of income)

	White	Black	Other
Rated looks	0.0690**	0.181**	0.180**
	(0.0283)	(0.0712)	(0.0844)
Skin tone	-0.118***	-9.69e-05	-0.0737
	(0.0319)	(0.0251)	(0.0469)
Constant	5.555***	5.019***	5.066***
	(0.302)	(0.751)	(0.807)
Observations	1,624	380	233
R-squared	0.348	0.222	0.355

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Controls include: a dummy variable for being female, age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

Table 9 presents the effects of beauty and skin tone for males segregated by race. For white males, an additional unit of beauty translates to a 7.87% increase in earnings, and a unit darker skin tone equates to a 7.24% decrease in annual income. This result indicates that an additional unit of beauty for white men counteracts the negative impact of a darker unit of skin tone. For black males, an additional unit of attractiveness results in a 33.6% increase in wages, significant at the 1% level. This result is a substantial beauty premium for black men, but it should be noted that the sample size is 157 respondents. For other race men, neither looks nor skin tone are significant in determining wages.

Table 9: Effects of Beauty and Skin Tone on Income for Males by Race
(Dependent variable is the natural logarithm of income)

	White	Black	Other
Rated looks	0.0787**	0.290***	0.136
	(0.0368)	(0.0878)	(0.163)
Skin Tone	-0.0724**	-0.00709	-0.0554
	(0.0367)	(0.0365)	(0.0538)
Constant	5.784***	5.937***	5.587***
	(0.381)	(0.941)	(1.394)
Observations	817	157	118
R-squared	0.312	0.155	0.380

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Controls include: age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

Table 10 shows the results of beauty and skin tone for females. For white women, a one-unit darker shade of skin tone lowers wages by 19%. For black women, neither looks nor skin tone are found to be significant in determining wages. For other race women, an additional unit of beauty results in a 20.4% increase in wages.

Table 10: Effects of Beauty and Skin Tone on Income for Females by Race
(Dependent variable is the natural logarithm of income)

	White	Black	Other
Rated looks	0.0616	0.127	0.186*
	(0.0413)	(0.0957)	(0.102)
Skin tone	-0.174***	0.0113	-0.110
	(0.0542)	(0.0336)	(0.0871)
Constant	4.812***	4.089***	4.412***
	(0.436)	(1.046)	(1.058)
Observations	807	223	115
R-squared	0.326	0.274	0.342

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Controls include: age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

Table 11 presents the results from the regressions segregated by industry of work. The first column is for construction, manufacturing, wholesale, and general industry-related jobs. In these types of jobs, an additional unit of beauty results in a 12.9% increase in wages. The second column shows how looks and skin tone affect annual income for the service industry. An additional unit of beauty rank in the service industry increases wages by 11.7%, while darker skin tone decreases wages by 5.17%. The third column shows that for government jobs, there are no significant beauty or skin tone premiums. The fourth column shows that in the amusement, gambling, and recreation industries, a unit darker skin tone results in a 56.7% decline in income. Being black in this industry leads to a significant boost in annual income indicated by the coefficient of 1.514. The two results in this regression are somewhat contradictory as the average skin tone for a black respondent in this sample is 5.44. If someone is black and is of average darkness, the positive effect of being black on income disappears. With the sample size of only 44, this result is not generalizable.

Table 11: Effects of Beauty and Skin Tone on Income
by Industry
(Dependent variable is the natural logarithm of income)

	Industry	Service	Government	Amusement
Rated Looks	0.121**	0.111***	0.0232	0.104
	(0.0533)	(0.0345)	(0.0463)	(0.345)
Skin tone	-0.0566	-0.0517**	0.0177	-0.449*
	(0.0394)	(0.0245)	(0.0365)	(0.233)
Black	-0.272	0.000249	-0.0733	1.514**
	(0.188)	(0.121)	(0.176)	(0.715)
Constant	5.564***	5.514***	4.525***	7.807**
	(0.642)	(0.316)	(0.659)	(3.456)
Observations	473	1,293	417	44
R-squared	0.299	0.346	0.349	0.402

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Controls include: a dummy variable for being female, a dummy for being black, a dummy for being other race, gender, race, age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

Table 12 shows the results from the regression with the interaction between beauty and skin tone. The first column shows the results from the entire sample. The coefficient on the interaction term between looks and skin tone suggests that the adverse effects of darker skin tones lessen with higher beauty rankings. An alternative interpretation is that for darker individuals, beauty matters more. The second column of Table 12 shows the results for only males in the sample, and the third shows the results for only females. As shown in the all-male sample, the interaction term between looks and beauty remains significant, suggesting that beauty matters more for darker men. Table A1 in the appendix presents the insignificant results of the interaction term divided by race.

Table 12: Effects of Beauty
Skin Tone and Race on Income,
Total Sample and by Gender
(Dependent variable is the natural logarithm of income)

	Total Sample	Males	Females
Rated looks	0.0266	0.00219	0.0428
	(0.0405)	(0.0585)	(0.0548)
Skin tone	-0.159***	-0.209***	-0.133*
	(0.0566)	(0.0779)	(0.0732)
Looks x Skin tone	0.0321**	0.0517**	0.0202
	(0.0151)	(0.0224)	(0.0201)
Black	-0.0217	-0.190	0.106
	(0.0878)	(0.120)	(0.118)
Constant	5.629***	6.168***	4.696***
	(0.279)	(0.339)	(0.368)
Observations	2,237	1,092	1,145
R-squared	0.329	0.302	0.306

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Controls include: a dummy variable for being female, a dummy for being black, a dummy for being other race, age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

Table 13 shows the effects of beauty, skin tone, interviewer race, and interactions between interviewer race and rated beauty as well as interactions between interviewer race and skin tone rankings on annual income. The first column is for the entire sample, and the following three are segregated by race. None of the results show the race of the interviewer is significant in determining the effect of beauty on annual income.

Table 13: Effects of Beauty Skin Tone and Race of the Interviewer on Income, Total Sample and by Race
(Dependent variable is the natural logarithm of income)

	Total sample	White	Black	Other
Rated looks	0.0943***	0.0874***	0.164	0.135
	(0.0313)	(0.0336)	(0.106)	(0.111)
Skin tone	-0.0475**	-0.134***	0.0203	-0.0582
	(0.0208)	(0.0407)	(0.0374)	(0.0687)
Black interviewer	0.138	0.213	0.248	-0.351
	(0.223)	(0.292)	(0.514)	(1.035)
Other race interviewer	0.0628	0.273	-0.308	-0.284
	(0.239)	(0.289)	(1.050)	(0.750)
Black interviewer*Beauty	-0.0292	-0.119	0.0571	0.119
	(0.0683)	(0.0911)	(0.129)	(0.242)
Other interviewer*Beauty	0.0189	-0.0239	0.110	0.0897
	(0.0644)	(0.0724)	(0.263)	(0.178)
Black interviewer*Skin tone	-0.00148	0.157**	-0.0685	-0.0107
	(0.0271)	(0.0693)	(0.0540)	(0.115)
Other interviewer*Skin tone	-0.0232	-0.0406	0.0120	-0.0463
	(0.0315)	(0.0821)	(0.0779)	(0.112)
Constant	5.443***	5.509***	5.013***	5.101***
	(0.267)	(0.314)	(0.826)	(0.844)
Observations	2,237	1,624	380	233
R-squared	0.327	0.351	0.225	0.356

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Controls include: a dummy variable for gender, age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

7. Robustness Checks

As a robustness check, I examined whether the effects of looks remain significant when grooming is included or if grooming is a substitute for looks. Table 14 presents the effects of beauty, grooming, and race for the entire sample and is broken down by gender. The results indicate that for the entire sample, an additional unit of grooming equates to a 17.6% increase in annual wages. The coefficient on looks lost its significance once grooming was added to the regression. Table 15 presents the effects of grooming broken down by racial groups. For men, women, white respondents, and black respondents, rated grooming is more significant than rated looks in estimating annual income. For these groups, grooming has a larger magnitude impact on earnings. For other race respondents, neither grooming nor looks are significant in estimating annual income when grooming is included in the regression.

Table 14: Effects of Beauty Grooming
Skin tone and Race on Income,
Total Sample and by Gender
(Dependent variable is the natural logarithm of income)

	Total sample	Males	Females
Rated looks	0.0286	0.0481	0.00815
	(0.0290)	(0.0411)	(0.0413)
Rated grooming	0.162***	0.195***	0.141***
	(0.0299)	(0.0437)	(0.0440)
Skin tone	-0.0497***	-0.0327	-0.0583*
	(0.0192)	(0.0268)	(0.0301)
Black	0.00794	-0.143	0.0659
	(0.0913)	(0.129)	(0.142)
Constant	5.008***	5.588***	4.181***
	(0.412)	(0.525)	(0.607)
Observations	2,237	1,092	1,145
R-squared	0.398	0.423	0.430

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Controls include: a dummy variable for being female, a dummy for being black, a dummy for being other race, age, age squared, education, family income at 16, hours worked in week prior, year of survey, interviewer fixed effects

Table 15: Effects of Beauty and Grooming on Income by Race
(Dependent variable is the natural logarithm of income)

	White	Black	Other
Rated looks	0.0200	0.0960	0.0395
	(0.0308)	(0.0823)	(0.101)
Rated grooming	0.129***	0.184***	0.128
	(0.0315)	(0.0652)	(0.1000)
Skin tone	-0.118***	0.00355	-0.0580
	(0.0318)	(0.0248)	(0.0515)
Constant	5.338***	4.777***	4.875***
	(0.308)	(0.753)	(0.803)
Observations	1,624	380	233
R-squared	0.356	0.236	0.320

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Controls include: a dummy variable for being female, age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

Table 16 presents the effects of grooming for males in the sample broken down by racial group. White men and other race men experience more significant grooming premiums than beauty premiums. For black men in the sample, beauty remains significant with a large coefficient. An additional unit of beauty for black men translates to a roughly 29% increase in annual income, and grooming is insignificant.

Table 16: Effects of Beauty and Grooming Skin Tone on Income for Males by Race
(Dependent variable is the natural logarithm of income)

	White	Black	Other
Rated looks	0.0102	0.251**	-0.0777
	(0.0405)	(0.112)	(0.168)
Rated grooming	0.157***	0.0812	0.333***
	(0.0440)	(0.105)	(0.125)
Skin tone	-0.0782**	-0.00733	-0.0458
	(0.0367)	(0.0365)	(0.0545)
Constant	5.563***	5.810***	5.265***
	(0.391)	(0.958)	(1.352)
Observations	817	157	118
R-squared	0.325	0.158	0.420

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Controls include: age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

Table 17 presents the effects of grooming for women in the sample broken down by racial group. Previously, white and black women didn't show a beauty premium, but now these two groups show a significant grooming premium. For these women, grooming is more important than looks, even though the two are correlated. For white women, a one-unit increase in grooming equates to a 12.2% increase in annual income. For black women, a one-unit increase in grooming equates to a 31.3% increase in annual income.

Table 17: Effects of Beauty Grooming and Skin Tone on Income for Females by Race
(Dependent variable is the natural logarithm of income)

	White	Black	Other
Rated looks	0.0235	0.00190	0.156
	(0.0443)	(0.108)	(0.127)
Rated grooming	0.115***	0.272***	0.0604
	(0.0442)	(0.0843)	(0.147)
Skin tone	-0.170***	0.0210	-0.109
	(0.0541)	(0.0336)	(0.0890)
Constant	4.579***	3.807***	4.320***
	(0.441)	(1.025)	(1.050)
Observations	807	223	115
R-squared	0.332	0.300	0.343

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Controls include: age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

These results imply that it is grooming, rather than looks, which impacts income. But once we focus on grooming, there is considerable potential for reverse causality. Those who are well groomed may experience premiums in the labor market based on how they look. It is also possible that those who make more money can afford to spend more on their grooming and appearance. As a result, I estimate an instrumental variable regression. I use reviewer characteristics and reviewer fixed effects as instruments to test grooming's causal relationship with income. The coefficient on grooming fell while the standard error increased causing grooming to becoming insignificant in the instrumental variable regression. It is hard to comment on grooming's actual impact on earnings because the instruments themselves don't pass the test of relevance. Despite passing the exogeneity test, the instruments don't explain enough of the variation in grooming to be proper instruments.

Table 18 presents the effects of weight on annual income. For the total sample, being slightly underweight has a significant negative impact on wages. When broken down by gender, males continue to show a detrimental impact of being slightly underweight. The negative weight penalty is only present for males and disappears when respondents are very underweight. The beauty premiums found hold with controls for weight.

Table 18: Effects of Beauty and Weight on Income
(Dependent variable is the natural logarithm of income)

	Total sample	Males	Females
Rated looks	0.0879***	0.0894***	0.0850**
	(0.0254)	(0.0341)	(0.0362)
Very overweight	-0.0532	-0.0636	-0.0285
	(0.0768)	(0.127)	(0.0984)
Slightly overweight	0.00431	-0.0737	0.0679
	(0.0445)	(0.0662)	(0.0610)
Slightly underweight	-0.219***	-0.378***	-0.00153
	(0.0831)	(0.110)	(0.125)
Very underweight	0.220	0.349	0.256
	(0.168)	(0.447)	(0.186)
Skin tone	-0.0505***	-0.0396*	-0.0597**
	(0.0182)	(0.0235)	(0.0273)
Constant	5.498***	5.986***	4.587***
	(0.256)	(0.333)	(0.366)
Observations	2,237	1,092	1,145
R-squared	0.329	0.308	0.304

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Controls include: age, age squared, education, family income at 16, hours worked in week prior, year of survey, race and gender of interviewer dummies

8. Discussion

The results presented support past findings that more attractive individuals experience a beauty premium in the labor market. I'm unable to prove that beauty has a causal relationship with increased income or conjecture exactly how the premium manifests itself. For all but black men, the beauty premium seems to be a grooming premium. Those who make more money may be able to afford to spend more on their appearance. It is also possible that higher-paying jobs require more polished and attractive appearances. There are many options for what drives the relationship between higher income and beauty, but this research shows that the premium is experienced differently for different racial groups and genders. Specifically, black men experience the largest beauty premium. An additional unit of beauty equates to a roughly 29% increase in annual wages for black men. The interaction between beauty and skin tone showed that for darker skin tones, beauty is more important. This result indicates that attractiveness possibly has the power to negate some effects of biases against darker-skinned individuals in the labor market. Additionally, this research suggests that the service industry shows significant premiums for beauty and penalties for skin tone. The beauty premium in the service industry could be due to consumer preferences for better-looking individuals or better functioning by attractive people due to increased confidence.

The skin tone penalties indicate that darker skin-toned individuals make less annual income compared to their lighter counterparts. It is unclear if skin tone is more important than race for determining income. Within the three defined racial groups, white respondents are the only group that exhibited skin tone penalties. The findings suggest that there is a positive effect of paler skin tones among white respondents. The racial groups in this study are self-reported, and as there is no clear standard for racial categorizations, there is potential for significant variations in the “white” category. The skin tone penalty among white respondents may be due to varying notions of racial or ethnic identity. The penalty may be driven by someone’s race not being perceived as white rather than bias against their skin tone as a white person. Someone from the Middle East may fall into the white racial category yet experience ethnic discrimination in the labor market. It is possible that skin tone is the basis for varying perceptions of race. This being said, it is also possible that skin tone is what is driving the discrimination, even within racial groups. People may have a preference against tanner white people in the labor force.

The skin tone penalties are especially noteworthy as they show the adverse effects of skin tone when holding all other factors determining income constant. Due to systemic injustices, certain minority groups with darker skin tones often have less access to opportunities and support in the labor market. For example, certain groups of people have less access to education and family connections. On top of these labor market disadvantages, darker skin tone individuals are experiencing bias based on their physical appearance alone.

As the results show, grooming is more important than looks in determining annual income for the majority of the samples. Past research has discussed the potential that “grooming matters more than attractiveness when it comes to gaining a higher income” (Martinez, 2020). An article in the Live Science, a science news website, suggests that one’s grooming may indicate how competent a worker is and how well they will function in their professional role (Miller, n.d.). Past studies have shown that for minority men, grooming has a positive impact on wages. It has been speculated that minority men have to overcome a variety of stereotypes and groom themselves to fit commonly accepted standards (Brooks, n.d.). The results of my research show that black men’s premium is a beauty premium, not a grooming premium, which is not exactly in line with the articles discussed. However, the results support the notion that black men experience premiums based on their physical appearance. For black women in the sample, the grooming premium is larger and more significant than the beauty premium. The sizable grooming premium for black women indicates that this group has to spend time and money on how they look to fit societal standards.

It remains that beauty and grooming are highly correlated and have the potential for reverse causality. Those who are more beautiful may understand the benefits of looking good and put more effort into their appearance. More beautiful people may also appear more well-groomed with less effort. It is also possible that those who are well-groomed appear more attractive as they have taken time to adhere to social standards. Regardless of whether beauty or grooming has more power in determining annual income, it stands that the way you look matters in labor market outcomes.

7. Conclusion

This paper's findings beg the question, what can we do about labor market discrimination? Regarding the skin tone penalties found, we can all try to be more cognizant of our potential biases against individuals with darker skin. Bias training can be implemented whenever possible to make employers and employees more aware of implicit biases they may have against not just different racial groups, but also against darker skin tones. We should all be taking active steps to decrease discrimination and change any negative perceptions or biases against individuals with dark skin tones.

Like skin tone, being more attractive leads to different labor market outcomes. Unlike skin tone, it is harder to actively work against beauty premiums. Given that it is unknown exactly how beauty premiums manifest and a large portion of the premiums exist in the service industry, it difficult to call for change. Changing the preference for beautiful people would call for societal shifts that may not be plausible or as obviously beneficial as reducing biases against skin tone. What we can say is that if we as a society can decrease bias based on race and skin tone, then hopefully minority groups won't have to exhibit high beauty and grooming to make up for the adverse labor market outcomes from skin tone.

Additionally, given what this study has shown about the impacts of grooming on income, as an individual there is potential to improve one's labor market outcome by grooming properly for a role. There is potential for job training programs to include guidance on adequate grooming for the workplace. The U.S. Department of Labor funds training programs to help individuals enhance their employment prospects. The programs "are aimed at boosting worker's employability and earnings and are delivered primarily by states" (*Training | U.S. Department of Labor*, n.d.). Government sponsored training programs could focus a section of the training on teaching participants appropriate grooming to hopefully improve their labor market outcomes.

Appendix

Image 1: This is the skin tone card given to the interviewers to rank respondents for the *ratetone* variable.

Breakdown of the industries from the GSS

Utilities and construction
170-770

Food industries
1180-1280

Manufacturing, production, and refining
1370-3990

Wholesale Trade
4070-4590

General Merchandise Stores
4670-5390

Not specified retail trade
5470-5790

Information services
6070-6780

Professional, scientific, and technical services
6870-7490

Administrative and support services

7570-7780

Schools and instruction, and educational support services
7790-7890

Health care services. * revisit
7970-8290

Additional services
8370-8470
9290

Amusement, gambling, and recreation
8560-8590

Personal services
8660-9090

Organizations related to govt
9160-9190
*9190 may not be related to govt

General govt and support
9370-9590

Military
9670-9870

New Breakdowns

Industry, Construction, Manufacturing, Wholesale
170-4590

Services
4670-7780
7970-8470
8660-9090
9290

Government, education, military
7790-7890
9160-9190
9370-9870

Amusement, gambling, and recreation
8560-8590

Table A1: Effects of Beauty
Skin Tone and Race on Income
by Race
(Dependent variable is the natural logarithm of income)

	White	Black	Other
Rated looks	0.0701	-0.0151	0.174
	(0.0668)	(0.199)	(0.246)
Skin tone	-0.115	-0.128	0.0123
	(0.142)	(0.127)	(0.271)
Looks x Skin tone	-0.000695	0.0393	-0.0220
	(0.0409)	(0.0363)	(0.0798)
Constant	5.552***	5.520***	4.851***
	(0.360)	(0.947)	(1.094)
Observations	1,624	380	233
R-squared	0.348	0.212	0.315

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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