How Does Beauty Affect Wages?

Be Sweet and Free

Introduction

Our project examines how beauty, as measured by facial attractiveness, affects labor market outcomes, as measured by wages. Our intuition and experience suggests that more attractive people do tend to have better jobs and higher wages, but this project uses data to estimate the size of that effect. For example, do these effects hurt ugly people more than they help attractive people? Do women and men, and those of different races, experience the same consequences in wages as a result of their attractiveness? This question is interesting and relevant because nearly everyone will participate in the labor market and some point, and everyone has a somewhat unchangeable level of facial attractiveness that could influence their prospects. Understanding the level of this effect can help us better adjust for sometimes unnoticed biases based on attractiveness.

To this end, our formal research question is: *Does a person's level of beauty significantly affect their wage?*

Data

We used the data set beauty from the Wooldridge package available from R. The original data was collected from Canadian surveys in 1978, 1979 and 1981 and used in a paper published in 1994. The original paper, called *Beauty and the Labor Market* by Daniel S. Hamermesh and Jeff E Biddle, appeared in the December 1994 issue of the American Economic Review (AER).

The data set contained 1260 observations on 17 variables. Of these 17, we use the following: wage (hourly wage); belavg and abvavg (which classify people who had below average or above average looks on a scale of 1 to 5); exper (years of work experience); educ (years of education); looks (facial attractiveness on a scale of 1 to 5); black (a dummy variable for race); female (another dummy variable); south (a dummy variable for the region of Canada); bigcity and smallcity (dummy variables for city size). Additionally we used the log of wage, and squares for education and experience.

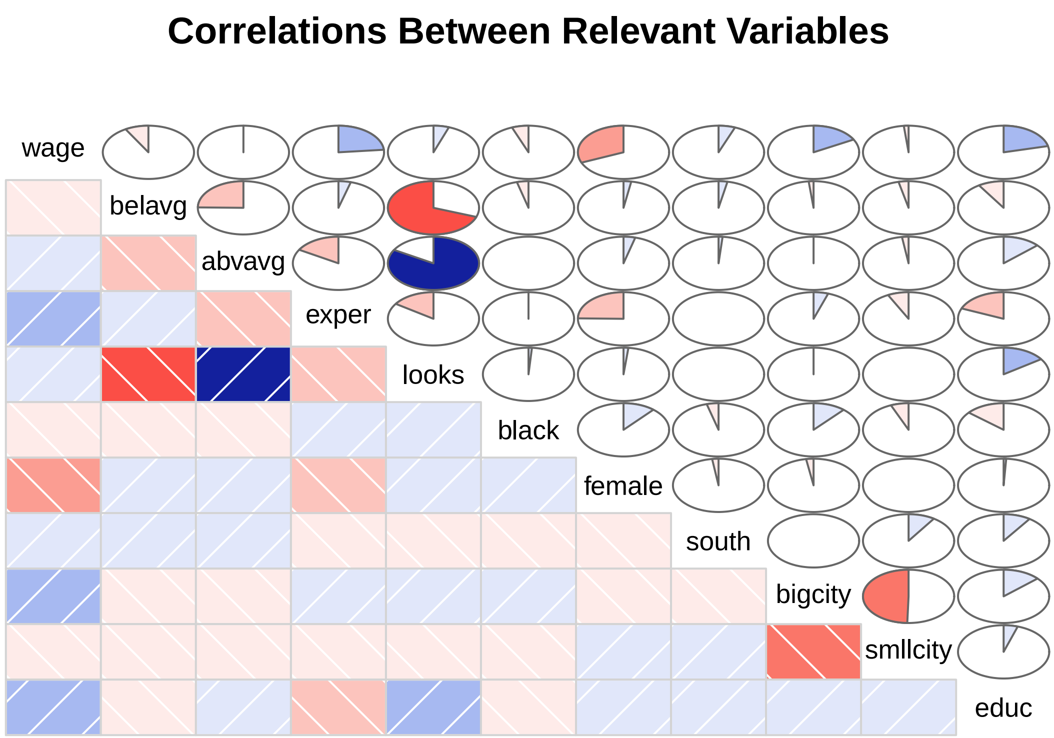
The following table shows summary statistics for the variables. Some important and/or interesting observations include:

- The mean wage is \$6.30 an hour, which seems very low by our standards. However, adjusting for inflation, it is actually \$18.30, not considering greater purchasing power in 1980.
- The mean for looks is 3.186. Since on a scale of 1 to 5, 3 was "average", this suggests that people were slightly generous in their ratings of other people's attractiveness - or that our sample was slightly above average in looks.
- Only 34% of the people in this data set are female. This is not surprising since, especially back in 1980, women are less likely to participate in the work force.
- Only 7.4% of the people in this data set are black. Again, this isn't surprising since Canada is quite ethnically homogeneous.

```
##
## ================================================================
## Statistic   N    Mean   St. Dev.  Min  Pctl(25) Pctl(75)  Max
## ----------------------------------------------------------------
## wage      1,260  6.307   4.661   1.020  3.708    7.695   77.720
## lwage     1,260  1.659   0.595   0.020  1.310    2.041   4.353
## belavg    1,260  0.123   0.329     0      0        0       1
## abvavg    1,260  0.304   0.460     0      0        1       1
## exper     1,260 18.206   11.963    0      8        27      48
```

```
## looks      1,260  3.186   0.685    1      3        4       5
## union      1,260  0.272   0.445    0      0        1       1
## goodhlth   1,260  0.933   0.250    0      1        1       1
## black      1,260  0.074   0.262    0      0        0       1
## female     1,260  0.346   0.476    0      0        1       1
## married    1,260  0.691   0.462    0      0        1       1
## south      1,260  0.175   0.380    0      0        0       1
## bigcity    1,260  0.219   0.414    0      0        0       1
## smllcity   1,260  0.467   0.499    0      0        1       1
## service    1,260  0.274   0.446    0      0        1       1
## expersq    1,260 474.483 534.645   0      64       729    2,304
## educ       1,260 12.563   2.624    5      12        13      17
## ---------------------------------------------------------------
```

Below we have a correlation diagram for the variables included in our analysis. We see that the strongest negative correlation with wage comes from female; women earning less than men is a very strong trend. The variables with several positive correlations with wage are experience, big city, and education. What about looks, above and below average? Looks had a weaker positive correlation with wage, as did above average. Below average actually had a larger effect on depressing wages than above average did on raising wages. This primes us to expect that although our regressions will show a correlation between looks and wage, education, experience, gender and city size are all more significant predictors of success in the labor market.



Empirical Framework

To justify using the Ordinary Least Squares (OLS) technique, we will show that our data satisfies the Classical Linear Model Assumptions. The first assumption (MLR.1) is that our model is linear in parameters. All of our regressions are linear in parameters. The second assumption (MLR.2) is that of random sampling. Our data is taken from the Canadian Quality of Life (QOL) study that used random sampling, and the subset of data we have access to in Wooldridge is a random sample from that set. The third assumption (MLR.3) is no perfect collinearity. Although we have strong multicollinearity between some of our variables, there is no perfect collinearity. The fourth assumption (MLR.4) is zero conditional mean. This is a result of the previous assumptions and holds in our model. The fifth assumption (MLR.5) of homoscedasticity also holds, as tested by the BP test for all the regressions we included (see Results section). The sixth assumption of normality is unnecessary due to the asymptotic properties of estimators associated with our large sample size. Because all these assumptions hold, we can say that OLS is the Best Linear Unbiased Estimator (BLUE). All of our regressions will use OLS.

Since the main objective is to determine how looks affect wages, we chose wages as the initial regressand. The main decision concerning the regressand is to determine if the data would fit a level-level framework better or if the line would fit a log-level form better. Since we anticipate diminishing returns from additional education, experience and looks at a certain point, it makes sense to choose the log-level model. This model also produced higher R^2 values in all our tests. Because of this, most all of our models use the log-level model with some tests on level-level models for comparison. Since looks is the key variable in question it is always included in some form among the regressors.

Models 1 and 2

With the regressand and the initial key regressors decided the first couple of models were constructed (fig 1 and 2). Since it is expected that there would be many other factors involved in determining wage these functions are primarily designed to be an initial baseline for comparisons against future models. It also serves as an initial step to determine if the level-level or the log-level form of model should be used.

Fig 1.

$$wage = \beta_0 + \beta_1 exper + \beta_2 educ + \beta_3 looks$$

Fig 2.

$$log(wage) = \beta_0 + \beta_1 exper + \beta_2 educ + \beta_3 looks$$

When we compared the two models, the R^2 for Model 1 was 0.1265, while for Model 2 it was 0.2065. This confirms our hypothesis that the log-level model is preferable because it can model diminishing returns. Additionally, interpreting the results will be easier when we can refer to percentage changes in wages rather than absolute changes in wages in 1980 dollars. For the rest of the models, we will use the log-level model.

Model 3

In the original AER paper, the authors noted that very few people were rated as 1s or 5s on the beauty scale ("very homely" or "exceptionally beautiful"). Because of this, we decide to split looks into categories of below average (1 and 2), average (3) and above average (4 and 5). This helps us see whether the strength of looks' effect on wages is bigger for unattractive or attractive people. Model 3 (fig. 3) is one that tests these variables with those of average beauty as the control group. The results of these types of models show a better picture of how individuals with different levels of beauty are affected differently.

Fig. 3

$$log(wage) = \beta_0 + \beta_1 exper + \beta_2 educ + \beta_3 belavg + \beta_4 abvavg$$

We did not expect this model to be much better than Model 2 since it uses the same general framework, and this was shown in the R^2 of 0.2085, only slightly better. Above average was non-significant, but we will continue to keep it in the model so we can compare below and above average to the same category of average.

Model 4

There are undoubtedly other factors that come into play when determining wage so we added other variables for this model. Generally, race and gender have strong effects on wages, as does location. For this reason, we added those variables to our model, all as binary variables. We think there might be some interaction among the variables as well so interactions between female and below average as well as interactions between black and below average are introduced in some of our our models (fig 4). The interaction terms prove to be insignificant though so interaction terms were dropped from future models.

Fig. 4

$$log(wage = \beta_0+\beta_1 exper+\beta_2 educ+\beta_3 belavg+\beta_4 abvavg+\beta_5 black+\beta_6 female+\beta_7 south+\beta_8 female*belavg+\beta_9 black*belavg)$$

Model 5

The education and experience variables appear to be the most influential factors in determining wage so some model designs included quadratic variables by squaring both wage and experience (fig 5). Our final model includes experience squared but our results indicated that education squared should not be included.

Fig. 5

$$log(wage = \beta_0 + \beta_1 exper + \beta_2 educ + \beta_3 belavg + \beta_4 abvavg + \beta_5 black + \beta_6 female + \beta_7 educ^2 + \beta_8 exper^2$$

Results

Testing the models described above eventually leads to the conclusion that the model with the best fit for the equation, as measured by adjusted R^2, is $log(wage) = \beta_0 + \beta_1 exper + \beta_2 educ + \beta_3 belavg + \beta_4 abvavg + \beta_5 south + \beta_6 female + \beta_7 black + \beta_8 exper^2 + \beta_9 bigcity + \beta_1 0smllcity$. The results for this model are reported below.

```
##
## ================================================
##                         Dependent variable:
##                     ---------------------------
##                               lwage
## ------------------------------------------------
## exper                        0.04***
##                              (0.004)
##
## educ                         0.06***
##                              (0.01)
##
## belavg                      -0.15***
##                              (0.04)
##
## abvavg                        0.001
##                              (0.03)
##
## south                        0.07**
##                              (0.04)
##
## female                      -0.44***
##                              (0.03)
##
## black                        -0.10*
##                              (0.05)
##
## I(exper2)                   -0.001***
##                             (0.0001)
##
```

```
## bigcity                        0.27***
##                                (0.04)
##
## smllcity                       0.10***
##                                (0.03)
##
## Constant                       0.56***
##                                (0.08)
##
## -----------------------------------------------
## Observations                    1,260
## R2                              0.39
## Adjusted R2                     0.38
## Residual Std. Error      0.47 (df = 1249)
## F Statistic          78.87*** (df = 10; 1249)
## ===============================================
## Note:               *p<0.1; **p<0.05; ***p<0.01
```

Before we make conclusions about this model, we wanted to do a test for heteroskedasticity, one assumption mentioned in the Empirical Framework section. We used the LM-statistic BP-test, which produced a p-value of 0.485, far above the threshold for rejecting the null of homoscedasticity. Our model meets the assumption of homoscedasticity.

```
##
##  studentized Breusch-Pagan test
##
## data:  mrm9b
## BP = 9.5043, df = 10, p-value = 0.485
```

Using the coefficients from the table, our best model is: $log(wage) = 0.56 + 0.04exper + 0.06educ - 0.15belavg + 0.001abvavg + 0.07south - 0.44female - 0.1black - 0.001exper^2 + 0.27bigcity + 0.1smllcity$

This model has the highest adjusted R^2 of any of our models: 0.38. So, the model can only account for 38 percent of the differences in wages among different people. This is still somewhat surprising since we included many variables that are thought to account for most differences in wages, like education, experience, gender and location.

Except for above average and black, all of our variables are significant at the 5% level. Experience, education, below average, female, experience squared, big city, and small city were all significant at the 1% level.

As this is a log-level model, all changes in wage are measure by percent. Answering the original question, those with below average looks earn 16.47% less in wages than those who are average looking, as indicated by the estimated coefficient $\hat{\beta}_6$. We cannot conclude much about the effects of being above average in looks, as the confidence interval for the value spans both the positive and negative sides of 0, as shown below. At least, we can conclude that while having below average looks is damaging to one's wage, if one has at least average looks it does not help that much to be far above average.

```
##                     2.5 %        97.5 %
## (Intercept)  0.4047163784  0.7192262390
## exper        0.0331946084  0.0501706518
## educ         0.0462153811  0.0673536385
## belavg      -0.2347423148 -0.0713300724
## abvavg      -0.0579644001  0.0601943455
## south        0.0001830422  0.1378098003
## female      -0.4985531893 -0.3853749121
## black       -0.1986923415  0.0049141384
## I(exper^2)  -0.0008487785 -0.0004686875
```

```
## bigcity      0.1914084663  0.3395119633
## smllcity     0.0367507812  0.1580854440
```

In looking at experience, we see that wages increase due to experience, as expected, and decrease with the variable $exper^2$. This is expected, as time in the workforce gives diminishing returns to the worker, and most raises occur in the early years. After 68 years of experience (value calculated by hand), the totals of exper and $exper^2$ reach a peak, and experience starts to give negative returns according to the model. By this time most individuals have retired, so this turning point has little effect on the predictions of the model.

The other dummy variables, except for black, are significant at the 1% level. The coefficient for black, like that of abvavg, has a confidence interval which spans 0 at the 5% level, and no interpretation at the level can be made. Our model does report the coefficient to be significant at the 10%, indicating that at that level wages are expected to decrease by 9.9%.

South, bigcity, and small city, the three dummy variables representing location, are all shown to be positively correlated with wages when compared to base, northern Canada and small cities. The coefficient for female, on the other hand, indicates a large drop in percentage wage when compared to men.

Conclusion

Our model shows that having below average looks depresses wages, though having above average looks does not seem to help wages grow beyond those of someone with average looks. As expected, looks does not have such a significant effect on wages as other variables like experience, education and especially gender.

One area that we could not study with this data set but were interested in is whether the wage premium for attractiveness varies across job type. For example, someone in sales probably needs to be more attractive than someone who spends the day behind a computer coding, or in a warehouse. We researched this question and found a 2017 paper by Todd Stinebrickner, Ralph Stinebrickner and Paul Sullivan called "Beauty, Job Tasks, and Wages: A New Conclusion About Employer Taste-Based Discrimination." Their paper concludes that "a wage premium exists only in jobs where attractiveness is plausibly a productive characteristic" so it cannot be mainly the result of employers preferring more attractive people in general. If this result is true, then it suggests that the wage premium for attractive people in these sorts of sectors is probably higher than what we report in our finds.