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American Income: Analyzing Workplace and Domestic Biases

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American Income: Analyzing Workplace Biases

The "American dream" involves the belief that Americans can earn their desired life with a bit of elbow-grease and hard-work. This dream perpetuates the idea that anyone, no matter their background, can achieve economic success in America. Previous literature, however, supports the idea that a person's race, sex, immigration status, or other biographical factors can affect their income. Earnings are not as straightforward as how many hours are worked per week. Many social and economic factors determine the total amount an individual earns. These factors make the American dream much more complicated. To approach this topic, a thorough understanding of past literature and robust economic modeling is required to explain these disparities. The purpose of this essay is to test for disparities in American income caused by race, sex, immigration status, and other societal factors with economic modeling in order to explain these disparities outside academia, and draw connections to the field of economics.

Literature Review

There are several societal factors that can contribute to income. When it comes to race, existing literature concludes that White men have an inherent advantage in the workplace. A study by PayScale highlights that most men of color earn lower wages than White men (Miller, 1). The gaps in wage are drastic as Hispanic men earn only 91 cents and Black men earn only 87 cents for every

White man's dollar. The only exception to this finding is Asian men, earning $1.15 for every dollar a White man earned (Miller, 2). However, this small exception is outweighed by the overall analysis of Black men's average earnings; the study finds that Black men have the highest "uncontrolled pay gap" when looking at aggregate earnings (1). This finding can be attributed to racism in the workplace. For one example, if an executive harbors prejudice, it is much harder for people of color to get promotions or job offers. Overall, existing literature points to men of color earning less income than White men. In the article, *Black Workers Still Earn Less than Their White Counterparts,* Stephan Miller cites several reasons for this income disparity. He finds that 63 percent of Black men and 61 percent of Hispanic men held individual contributor roles, compared with 56 percent of White men who held contributor roles (Miller, 3). Contributor roles are roles that do not include high-level management positions. These findings reflect that more men of color are not in management positions; however, even when men of color do hold management positions they are paid less. For example, a study by PayScale finds that Executive-level Black men with the same qualifications earned 97 cents for every dollar a White man earned (Miller, 3).

Additionally, the income disparity between White people and people of color can be attributed to generational inequity. The Center for American Progress finds that differences in generational wealth between Black and White Americans contribute to the disparity in income ("Eliminating the...", 1-15). Authors

Christian Weller and Lilly Roberts write in their work *Eliminating the Black-White Wealth Gap Is a Generational Challenge* that, “wealth provides families the means to invest in their children’s education, to start a business, relocate for new and better opportunities, buy a house, and have greater participation in the democratic process” (Weller and Roberts, 2). The social mobility that wealth provides is an important explanation for income disparities.

Regarding women, the income disparity is more severe. A study by NWLC using U.S. census data in 2016, found that when controlling for hours worked women earned merely 80 cents for every dollar a White man earned (Temple and Tucker, 1). Moreover, the NWLC analysis finds that the wage gap is even more drastic for Black women as they are paid 63 cents for every dollar a White man earns (Temple and Tucker 1). The income disparity is not only an issue of getting paid less for the same amount of work, but also an issue of unequal labor division in American households. In the article, *An Unequal Division of Labor: How Equitable Workplace Policies Would Benefit Working Mothers* Author Sarah Glynn finds empirically, that when household labor hours are compared between mothers and fathers of young children, mothers spend more combined time working, doing household labor, and caring for children than fathers (Glynn, 3). Many women in America must juggle being mothers, doing household labor (cleaning, cooking, and household maintenance), and working paid jobs. Because the division of labor is not carried equally, women may have a harder time taking on extra paid workplace responsibilities. On top of the unpaid labor burden, women often find that having children negatively affects their career path. A 2017 study by Pew Research Center finds that mothers were twice as likely as fathers to say taking time off had a negative impact on their job or career (Parker 2).

Next, existing literature points to immigrants having a higher chance of economic success than native-born Americans. Why is this? Michael Ungar Ph.D. explains in the article *Why Do Immigrants Outperform Native-Born Americans?* that immigrants showcase high amounts of ambition and a high tolerance for sacrifice and risk (Ungar, 2). Individuals that are willing to leave their old life in their native country and transport themselves into the unknown are enterprising individuals. These traits lead to great entrepreneurs. Benjamin F. Jones, author of *Immigrants to the U.S. Create More Jobs than They Take,* immigrants start businesses at a rate that is 80 percent higher than U.S.-born citizens. Moreover, Jones cites that immigrant-founded firms also pay higher wages on average than native-founded firms.

I. Data: Methods, Results, Findings

Our data on American income comes from Kaggle and is titled "Adult Census Income". This data was extracted from the 1994 Census bureau database by Ronny Kohavi and Barry Becker. The spreadsheet recorded the following data points: yearly income, age, education (in years), education (by the institution), race, sex, native country, working-class, marital status, hours worked per week, capital gain, capital loss, and relationship. It is important to note that the data collected had gaps within the spreadsheet, resulting in missing information. To correct this, we wrote the Python code to avoid regressing any variable that included a [?] within the column of data. This way, we avoided including regressors that displayed gaps in the data reported. Additionally, in models one and two we utilized binary regressors of 0 and 1, as well as expressing income on a binary (above 50,000 dollars and below 50,000 dollars). Every variable analyzed was normalized prior to processing. The threshold of 50,000 dollars was assigned because the U.S. Census data we chose to analyze strictly provided income in relation to this amount (above or below). We created three models on the coding program Python to analyze regressors in the data set. A linear model (model 1), a logistic model (model 2), and a neural network (model 3).

Model 1, the linear regression, regressed average income on the regressors of Age, Education (in the number of years), race, sex, and native country. Through Python, we wrote code to determine the “regression score” or (in the case of the linear model) the amount that the regressors explain the variance in the data set. Specifically for the linear model, the regression score would reflect the R squared value of the regression. Python indicates that the R squared value for our linear regression was 0.19. Interpreted, this shows that our chosen regressors explained around 19% of the variance in the data set. Considering we only utilized six regressors in the linear model, this is a reasonable percentage to explain the contribution to data variance. While most variables are regressed on a binary, two It is also important to note that Figure 1 below illustrates the results we garnered from the linear regression.

Figure 1: Linear Regression Results Table

Regressor	Code Restraints	Coefficient
Income (Inc)	If income>50,000, Inc=1 If income<50,000, Inc=0	N/A
Age (age)	Age= number of years alive	0.0063147***
Education (edu)	Education=number of years	0.05462131***
Race (rac)	If race is White, rac=1, If other race, rac=0	0.0556723***
Sex (sex)	If sex is female, sex=1 If sex is male, sex=0	-0.17422091***
Native Country (nat)	If native country is USA, nat=1 If native country is not USA, nat=0	-0.01726149**

Looking at figure one there are several notable findings. First, consistent with our hypothesis and background research, being White presents an inherent advantage when it comes to income. Analyzing the regression results, our findings indicate that the coefficient for being White is 0.056 and the coefficient for education is 0.055. These coefficients mean that being White is statistically equivalent to having an additional year of education when it comes to income. Both statistics indicate a 5-6% chance of being wealthier (earning above 50,000 dollars). As mentioned prior, this finding is not because White people are inherently smarter, but because they have an innate advantage when it comes to generational inequality and workplace discrimination. Second, the coefficient for being female was -0.174. This shows a negative relationship between wealth and being female. Specifically, this coefficient indicates women are 17.4% less likely to earn above 50,000 dollars. Consistent with the literature and our hypothesis, this variable could be due to workplace sexism, the gender pay gap, or the undue burden of unpaid labor women face (domestic housework). Third, the linear regression reveals that being born in the United States presents a slight disadvantage. The coefficient for native country was -0.017, meaning that if a person was born in the United States, they are 1.7% less likely to earn above 50,000 dollars. Our prior literature research explains this finding by indicating that many immigrants may be entrepreneurs; therefore, earning a higher income.

Model two was a logistic regression analysis regressing the dependent variable of income on the following regressors: age, working class, education (in number of years), marital status, race, sex, hours worked per week, and native country. The regression score for model two was 0.79 indicating that the percentage of times the regression predicted correctly was around 80%. This percentage is extremely robust and indicates a strong predictive accuracy. Below, figure two illustrates the results gleaned from the logistic regression.

Figure 2: Logistic Regression Results

Regressor	Code Restraints	Coefficient
Income (Inc)*	If income>50,000, Inc=0 If income<50,000, Inc=1	N/A
Working Class (wkc)	If working class is Private, wkc=1, If working class is other, wkc=0	-0.04218019*
Age (age)	Age= number of years alive	-0.43987964***
Education (edu)	Education=number of years	-1.00469262***

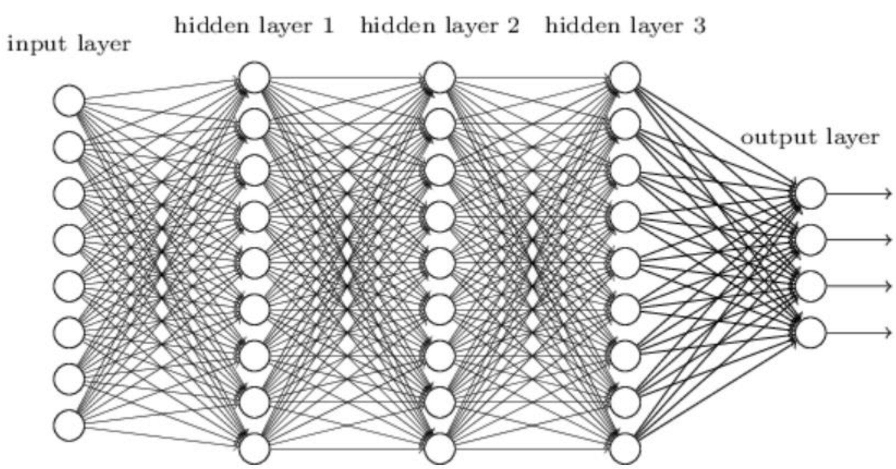
Marital Status (mar)	If married, mar=1 If not married, mar=0	-1.1108317***
Race (rac)	If race is White, rac=1, If other race, rac=0	-0.07375374***
Sex (sex)	If sex is female, sex=1 If sex is male, sex=0	0.06995755**
Hours Worked per Week (hrs)	hrs= number of hours worked per week	-0.36644182***
Native Country (nat)	If native country is USA, nat=1 If native country is not USA, nat=0	-0.10043231***

Figure two displays several important findings. Many of these findings are intuitive. To start, the coefficient for hours per week was -0.37 indicating that hours per week and having a low income has a negative relationship. Logically, this finding holds as working more hours yields a greater influx of money. Next, the coefficient of education (-1) has a negative relationship with earning a lower income as more years of education would lead to higher-paying jobs. Third, age has a negative relationship with being low income as older individuals may have the experience needed for higher-paying jobs. Lastly, marriage has a negative relationship with being low income. The marriage coefficient is -1.1108317 indicating someone who is married is less likely to be low income. Intuitively, this finding is because people who get married are more financially stable than the average single person. There may be some collinearity associated with this factor as most people who get married are older.

Next, model two presents important conclusions that are consistent and inconsistent with prior models and literature. The first of which is that being White yields a positive correlation with earning above 50,000 dollars. This finding is consistent with the empirical data presented in the linear model regarding the race regressor. Additionally, the logistic model finds that being a woman is negatively correlated with earning above 50,000 dollars. Lastly, the logistic model finds being a U.S.-born citizen is positively correlated with earning above 50,000 dollars. This finding is inconsistent with the linear model. This may be due to the addition of more regressors and the fit of a different model.

Model three, the neural network, was created with two objectives in mind. First, to show how well a (nearly) perfect model could predict incomes (the upper limit) of this data. Second, to predict the incomes of new data points not in the data set. A neural network is a tool that statisticians typically use to determine the predictive power in a model, which is why it is used in this paper to measure each model's strength. The neural network operates by first being fit to the training data on Python (this is the input layer). Then, the neural network is then tested on the test data (the output layer). While the output of the neural network on Python (our tool of choice) only displays the predictive power result, the mechanisms of the math are complex, and it is worth understanding how this result is received. Michael Nielson explains this mathematical concept in the book *Neural Networks and Deep Learning.* For the purposes of understanding the methodology further, Nielson's illustration of a neural network will be provided in figure 3 below:

Figure 3: The Process of a Neural Network

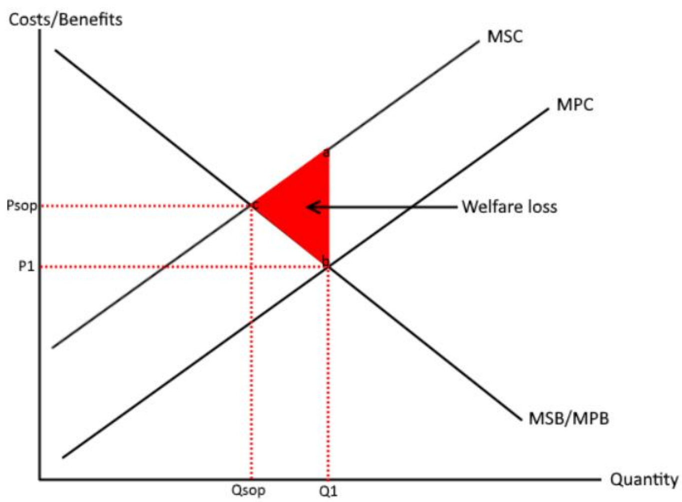


The results of our neural network indicate that our model was able to classify 80.1% of data correctly. This result highlights that an almost perfect model would have a predictive accuracy around 80.1%. Significantly, our logistic model has a predictive accuracy of 79.4% indicating that its predictive power is extremely close to that of a near perfect model.

II. Relations to Economic Concepts

Income disparities are important for economists to analyze because they can create negative externalities in society. The Inaugural World Inequality Report (2018) asserted the following: “Economic inequality is widespread and to some extent inevitable. It is our belief, however, that if rising inequality is not properly monitored and addressed, it can lead to various sorts of political, economic, and social catastrophes” (“World inequality report,” 1). The textbook *Managerial Economics and Strategy* explains that externalities create a market failure in society, causing economic inefficiency (Perloff, 552). Specifically, a negative externality reflects that the private cost of production for a firm does not match the social cost of production (Perloff, 552). In the case of income inequality, the amount of inequality costs produced by firms (private cost), does not match that of the social cost of inequality produced (social cost). Figure three illustrates the overproduction of inequality resulting in deadweight loss/welfare loss (in the red shaded area). Note that Marginal Social Cost will be represented by MSC, Marginal Private Cost will be represented by MPC, and overall benefit will be represented by Marginal Social Benefit (MSB) divided by Marginal Private Benefit (MPB). On the axis on the graph, Q1 represents the inefficient quantity of inequality, and Qsop is the efficient quantity of inequality. Psop represents the efficient ratio of cost to benefit, while P1 represents the inefficient ratio of cost to benefit.

Figure 3: Negative Externality of Income Inequality

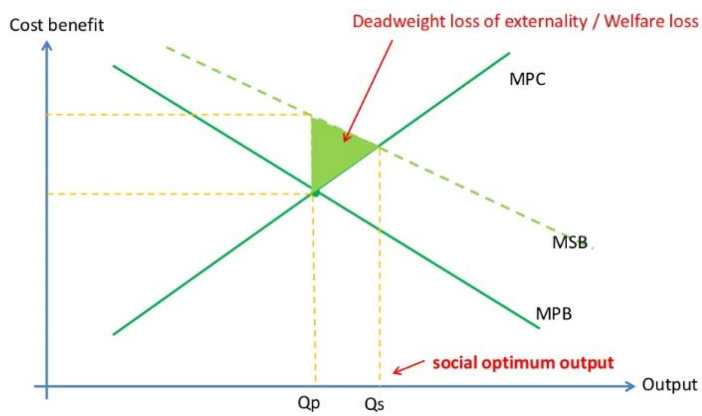


The figure illustrates that if the quantity of inequality decreases to Qsop where marginal social cost equals overall benefit, the welfare loss is diminished. If inequality remains at Q1 (where marginal private cost equals overall benefit, then the red triangle representing welfare loss is prevalent because the external cost between marginal social cost and marginal private cost is above the overall benefit (marginal cost is greater than marginal benefit. This outcome creates an inefficiency in regard to inequality. Morten Nyborg Stostad and Frank Cowell in their academic study *Inequality as an Externality: Consequences for Tax Design* reason that income inequality is a negative externality is because it affects the utility of other individuals in society, even though those individuals did not actively decide to experience the costs of benefits (Stostad and Cowell, 3). This reasoning fits with the textbook definition of an externality provided by

Managerial Economics and Strategy. Specifically, one negative externality consequence found in a 2013 study by Bonica contends that income inequality yields political polarization in the United States, highlighting the role of political donations (Bonica, 24-103). A simple solution to this would be government intervention with anti-discrimination policies. A common way to fix externalities in economics is through government intervention as it provides a social gain (Perloff, 556).

Some externalities related to our research are, on the contrary, positive externalities. According to the textbook *Managerial Economics and Strategy,* positive externality occurs when the private marginal benefit is less than the social marginal benefit, indicating the underproduction of a good or service (Perloff, 552). In our case, the positive externality is that of immigration. Our data reflects that immigrants are much more likely to earn above 50,000 dollars. Accepting immigrants would lead to more consumption and in turn, more economic growth. Additionally, Alex Nowrasteh of Forbes elaborates on this idea by emphasizing immigrants create more jobs than U.S.-born citizens on average and they also create higher-paying jobs (Nowrastah, 1-14). Because our data indicates immigrants have a higher likelihood of earning above 50,000 dollars, this finding could indicate that immigrant-owned businesses are also often successful at staying in the market. An influx of immigration would not only benefit immigrants themselves (private benefit), but it would also benefit others by creating more higher-paying, stable jobs (social benefit). Because the private benefit is lower than the social benefit, this indicates an under-acceptance of immigrants to the United States resulting in deadweight loss. Illustrated below in figure four is the result of an under acceptance of immigrants to the United States. Note that the vertical axis once again represents the cost benefit ratio, and the horizontal axis represents output. This time, Qp represents the inefficient quantity and Qs represents the social optimum output. Because Qp provides immigration at a point where the marginal social benefit (MSB) is above the marginal private cost (MPC), it is producing an inefficiency in the market leading to welfare loss (highlighted in the green triangle).

Figure 4: Positive Externality of Immigration



This externality displays a slightly different economic scenario. Instead of overproducing a good or service, the actor is underproducing. Above, the actor is the U.S. Department of Immigration, and they are underproducing opportunities for United States citizenship. A straightforward way to fix this externality would be to allow more immigration to the United States by increasing quotas for citizenship.

III. Conclusions

There are several examples in existing academia that study the disparities in income by demographic. Past literature points to disparities due to race, sex, and immigration status. While literature concludes that being a person of color and being female can negatively affect income, other sources indicate that being an immigrant in the United States can present an income advantage. Our research findings mostly confirm our hypothesis and the arguments made by other authors. Our logistic model presented robust predicting power at around 79.4%. Because our neural network (model three) confirmed that an almost perfect model would have a predictive power of around 80%, we can confirm that our results from our economic models have a high predictive power. First, we concluded there is a positive relationship between being White and earning above 50,000 dollars. This finding is consistent throughout all models and with outside literature. The reason for this result may be racism in the workplace or the White privilege of generational wealth (as discussed in the literature section). Second, there is a negative relationship between being female and earning above 50,000 dollars. This result is consistent throughout all models and supports existing literature on the female income gap. Logically, this result may be a product of sexism, or the undue burden placed on women in the household (as discussed in the literature section). Lastly, we find through model one that being an immigrant has a positive correlation with earning above 50,000 dollars. This finding is consistent with the past literature presented. Many authors predict immigrants perform better because they have similar qualities to successful entrepreneurs (ambition, grit, and risk-taking). However, we find a discrepancy with our second model as it shows U.S.-born citizens are 10% more likely to earn above 50,000 dollars. This conclusion could be due to the changing of the model structure (linear to logistic) or the introduction of other regressors. Additionally, if you control for other factors that have a positive correlation with wealth, this may lead to a result that indicates immigrants at an economic disadvantage. It may be hard for this model to capture the complexities between immigration as income is measured on a binary. The income distributions of immigrants may present in a way that is hard to analyze when income is measured as simply above 50,000 dollars or below 50,000 dollars. Further research may be needed to determine the relationship between immigration and wealth. In relation to economic concepts, income inequality was displayed to be a negative externality as it creates unpleasant ripple effects throughout society, such as political polarization. Moreover, it was concluded that immigration is a positive externality as increasing immigration would only serve to benefit society more (by creating high-paying, stable jobs).

Overall, this research aimed to test disparities due to demographic differences and explain them and their relation to economics. This topic is important in developing a more equitable world for all Americans by correcting discriminatory patterns. Additionally, this information can serve as evidence that immigration does not harm the United States economy, instead, it significantly improves it. Ultimately, the American dream comes down to making social mobility accessible to everyone. Tackling income disparities will help to make the American dream an American reality.

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