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ANALYSIS OF EMPLOYMENT AND EARNINGS USING VARYING COEFFICIENT MODELS TO ASSESS SUCCESS OF MINORITIES AND WOMEN

by

AMANDA GOEDEKER
B.S. College of Charleston 2009

A thesis submitted in partial fulfillment of the requirements
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Major Professor: Marianna Pensky

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ABSTRACT

The objective of this thesis is to examine the success of minorities (black, and Hispanic/Latino employees) and women in the United States workforce, defining success by employment percentage and earnings. The goal of this thesis is to study the impact gender, race, passage of time, and national economic status reflected in gross domestic product have on the success of minorities and women. In particular, this thesis considers the impact of these factors in Science, Technology, Engineering and Math (STEM) industries. Varying coefficient models are utilized in the analysis of data sets for national employment percentages and earnings.

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LIST OF ABBREVIATIONS

BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
CEO	Chief Executive Officer
CIO	Chief Information Officer
COO	Chief Operations Officer
CTO	Chief Technical Officer
GDP	Gross Domestic Product
STEM	Science, Technology, Engineering, and Math

CHAPTER 1: INTRODUCTION

Today women hold 21 of the CEO positions at Standard & Poor's (S&P) 500 companies. So what does success for women in industry mean? Merriam Webster Dictionary (2004) defines success as achieving wealth, respect, fame or the desired result of an attempt. Psychologist Dr. Carol Dweck (2006) differentiates success found in doing ones best in learning and improving (growth mindset) versus simply establishing superiority (fixed mindset). A long term study by the Association for Psychological Science (2014) concluded men and women fundamentally define success differently. The study found men were focused on advancing society through knowledge or the creation of concrete products whereas women were more interested in keeping society vibrant and healthy. Women characterized success more broadly to include family and community investment. *The Meaning of Success: Insights from Women at Cambridge* (2014) echoes this sentiment when it is describes the most important measure of success as how you feel about yourself.

For the purpose of the following analysis, success is defined by percentage of employment and average weekly earnings. Several questions are considered in this thesis. Does race influence employment percentage or earnings? Does gender influence employment percentage or earnings? Within STEM industries, does gender or race influence employment percentages or earnings? What influence does time have on gender or racial employment percentages and earnings? What relation exists (if any) between gross domestic product and employment percentages or earnings?

Varying coefficient models are utilized to analyze the relationship between a response variable, either employment percentages or earnings, and a group of covariates including time, gender, race, and gross domestic product. Chapter 2 provides an overview of varying coefficient models and presents multiple variations from recent publications.

Chapter 3 of the thesis provides a summary of the data chosen for the analysis. Publicly available data sets from the Bureau of Labor Statistics and Bureau of Economic Analysis are utilized. Employment percentages and earnings data from the Bureau of Labor Statistics and gross domestic product data from the Bureau of Economic Analysis are consolidated for years 1997 through 2014. At the time of analysis, calendar year 2014 data was the most recent data available. Data for calendar years 2000 and 2001 is omitted from the analysis due to incomplete or unavailable data. Due to inconsistent reporting formats, all data sets were grouped based on judgment and reported at a higher level of detail than available. Employment and earnings data sets are each reported with 12 categories covering all employment industries within the United States. It is assumed analysis by more detailed occupation category will not alter the results.

Chapter 4 summarizes why varying coefficient models were chosen and presents an overview of the MATLAB program developed for this analysis. Variables considered include the passage of time, gender (male, female), race (white, black, Hispanic/Latino), and gross domestic product. Coefficients are calculated for each variable and analyzed for impact on the data set.

Chapter 5 of the thesis presents the results of each analysis. While not surprising on their own, the results are quite telling in the details. Race significantly influences both employment percentages and earnings. Non-blacks earn more than blacks, and non-Hispanics earn significantly more than Hispanics. Overall, employment of racial minorities, for both black and Hispanic/Latino, is less than their respective complement data sets. Gender considerably influences and earnings, with men earning more than women. However, there was an inconsistent correlation between employment percentages and gender. Within STEM industries, gender and race have a significant influence on employment percentage and earnings, with males, non-blacks and non-Hispanics earning more and having higher employment percentages than their respective complements. The passage of time has a minor impact on earnings, with earnings increasing with the passage of time, and no sizeable impact on employment. There is a minor correlation between gross domestic product (GDP) and earnings, with earnings increasing with an increase in GDP. The passage of time and gross domestic product had no correlation to employment by race. There is an inconsistent correlation between gross domestic product (GDP) and earnings, and no correlation to employment.

In Chapter 6 several conclusions are provided and recommendations offered to increase the success of minorities and women in workforce, specifically Science, Technology, Engineering, and Math industries.

CHAPTER 2: REVIEW OF VARYING COEFFICIENTS MODELS

Varying coefficient models are very appealing to applied and theoretical statisticians since they allow one to explore the dynamic feature of data. The varying coefficient model is a generalization of the linear regression model to the case of longitudinal data where coefficients depend on time. The varying coefficient model was introduced by Hastie and Tibshirani (1993) who noted that they arise in many applications. For longitudinal data, let $Y(t)$ be a response variable and $X_i(t)$ be a p vector of covariates, measured at time $t = t_{i1}, \ldots$ for subjects i = 1, ... , N. In this case, one observes (Y_{ij}, X_{ij}, t_{ij}), for i = 1, ... , N and j = 1, ... , n_i, where $X_{ij} = (X_{ij0}, \ldots, X_{ijp})^T$ and $\left(Y_{ij}, X_{ij}, t_{ij}\right)$ denote the *j*th outcome, covariate and time design points, respectively, of the *i*th subject. The varying coefficient model can be formulated as follows

$$Y_{ij} = X_{ij}{}^T\beta\left(t_{ij}\right) + \varepsilon_i(t_{ij}) \tag{1}$$

where $\beta(\mathrm{t}) = (\beta_1(t), \ldots, \beta_p(t))^{\mathrm{T}}$, is a vector of smooth nonparametric functions of interest and $\varepsilon_i(t)$ is a zero-mean stochastic process. The measurements are assumed to be independent for different subjects but can be correlated at different time points within each subject. In our case, the times of observations are subject-independent, and hence we have a simpler model

$$Y_{ij} = X_{ij}{}^T\beta\left(t_j\right) + \varepsilon_i(t_j) \tag{2}$$

for i = 1, …, N, j = 1, …, n. Here, $X_{ij} \epsilon R^p$ is a vector with components X_{ijk}, k = 1, …, p, and $\beta(\mathrm{t}) = (\beta_1(t), \ldots, \beta_p(t))^{\mathrm{T}}$.

The most common approach to the varying coefficient model is smoothing. In particular, one selects convenient representations of component $\beta_k(t)$ of vector $\beta(t)$ and estimates unknown parameters in this representation from data. One of the most popular methods is kernel smoothing where each $\beta_k(t)$ is written as

$$\beta_k(t) = \sum_{j=1}^{n} K_h(t, t_j) a_{jk} \tag{3}$$

where

$$K_h(t, t_j) = \frac{1}{h} K\left(\frac{t - t_j}{h}\right) \tag{4}$$

and K is the kernel function such that $\int K(t)dt = 1$ and h≥0 is a bandwidth. Coefficients a_{jk} are subsequently found by solving the least squares problem

$$\min \sum_{i=1}^{N} (y_{ij} - \sum_{k=1}^{p} \sum_{l=1}^{n} X_{ijk}\, K_h\,(t_l, t_j)\, a_{lk})^2 \tag{5}$$

for all a_{lk}. Another technique is based on approximating functions $\beta_k(t)$ by local polynomials or splines.

Hoover et al. (1998) used smoothing splines $\beta_k(t)$, k = 1, … , p, where $\beta_k(t)$ are twice continuously differentiable and their second derivatives $\beta''_1(t), \ldots, \beta''_p(t)$ are bounded and square integrable. A smoothing spline estimator of $\beta_1(t), \ldots, \beta_p(t)$ minimizes

$$J(\beta, \lambda) = \sum_{i=1}^{n} \sum_{j=1}^{n_1} [Y_{ij} - \{\sum_{l=1}^{p} [X_{ijl} \beta_l(t_{ij})]\}]^2 + \sum_{l=1}^{p} \lambda_1 \int \{\beta''_l(t)\}^2\, dt \tag{6}$$

where $\lambda = (\lambda_1, \ldots, \lambda_k)^{T}$ are positive-valued smoothing parameters which penalize the roughness of $\beta_1(t), \ldots, \beta_p(t)$. It can be shown that the minimizers of $J(\beta, \lambda)$ given by equation (6) are natural cubic splines with knots located at the distinct values of t_{ij}. Qu and Li (2005) extended results of Hoover et al. (1998) to a penalized spline method.

Qu and Li (2005) outline an estimation procedure where unknown coefficients are represented via the q-degree truncated power spline basis with the knots $m_1, \ldots, m_k$, so that

$$\beta_k(t) = \gamma_{k0} + \gamma_{k1}t + \cdots + \gamma_{kq}t^q + \sum_{j=1}^{n_k} \gamma_{k(q+p)} \left(t - m_j\right)^q{}_{+} \tag{7}$$

where $(z)^q{}_{+} = z^q \, I\,(z \geq 0)$. They find coefficients in equation (7) by minimizing the least squares (similar to equation (5)) with the quadratic penalty on coefficients γ. Parameter q and the knots are found using a goodness-of-fit test. Qu and Li outline four specific advantages of the model. First, the model is relatively simple and numerically feasible since it does not involve any nuisance parameters associated with the working correlation. Second, the inference function has an explicit asymptotic form, allowing to test whether coefficients are time varying. Also, the model enables goodness of fit tests for checking model assumptions. Finally, the authors provide an objective criterion for choosing a sufficient number of basis functions and knots. Qu and Li apply their procedure to analysis of an acquired immune deficiency syndrome (AIDS) data set.

Park et al. (2015) use combination of kernel and local-polynomial technique. In their paper, the times $t_{ij} = t_j$ are not subject dependent. In particular, they use locally linear estimators for $\beta_k(t)$ in the vicinity of t_j; j = 1, … ,

$$\beta_k(t) = a_{kj}{}^{(0)} + a_{kj}{}^{(1)}(t) \tag{8}$$

where coefficients ${a_{kj}}^{(0)}$, ${a_{kj}}^{(1)}$ are obtained by minimizing the squared sum of local differences

$$\sum_{i=1}^{N} Y_{ij} - \sum_{k=1}^{p}\left[{a_{kj}}^{(0)} + {a_{kj}}^{(1)}\left(t_j - t\right)X_{ij}\right]^2 \mathrm{K}_h(t, t_j) \tag{9}$$

where $\mathrm{K}_h(t, t_j)$ is the kernel function given by equation (4). Park, et al. (2015) examine heart disease data using a model similar to equation (9) which allows them to see whether the effect of family history, age or stress varies with blood pressure or cholesterol level.

In our case, similar to Park et al. (2015), our measurement times are subject-independent, so the model is given by equation (2). In our paper, we represent coefficients as polynomial functions, in particular

$$\beta_k(t) = \sum_{l=0}^{m_k} a_{kl} t^l \tag{10}$$

where $m_k = 2$. We carried out model selection and concluded that coefficients a_{k2} are not significant, so $m_k = 1$ after model selection.

CHAPTER 3: DATA

Publicly available data sets from the Bureau of Labor Statistics (BLS) and Bureau of Economic Analysis (BEA) are utilized in the following analyses. Employment and earnings data sets are pulled from the Bureau of Labor Statistics, and gross domestic product data from the Bureau of Economic Analysis. The data sets focus on the 18 years between 1997 and 2014, excluding 2000 and 2001 due to incomplete or unavailable data. Occupations or industry categories identified in each data set are unique and therefore grouped based on judgment. Table 1 provides a summary of the occupations provided in each data set and identifies the higher level industry category used in the following analyses.

The Bureau of Labor Statics employment and earnings data sets are taken from three tables: Table 11 Annual Averages for Employed Persons by detailed occupation, sex, race, and Hispanic or Latino ethnicity, Table 37 Annual Averages for Median weekly earnings by characteristics, and Table 39 Annual Averages of Median weekly earnings by occupation and sex.

Employment data from the Bureau of Labor Statistics Table 11 includes annual average percentage of women, black, and Hispanic/Latino employees by detailed occupation. The percentage of men, non-black, and non-Hispanic/Latino employees were calculated based on the available data. Reports for years 1997 through 2014, excluding 2000 and 2001, were consolidated and reformatted at a higher level to the industry categories outlined in Table 1.

Overall population demographics were obtained from the decennial census for calendar years 1990, 2000 and 2010 in an attempt to further analyze the employment data. A plot of employment proportion by race for the computer and math industries is provided in Figure 1. Employment proportions are calculated as percentage employed divided by population percentage. A similar calculation is done for figures 2, 3 and 4. A plot of employment proportion by race for the engineering industry compared provided in Figure 2. A plot of employment proportion by gender for the computer and math industries is provided in Figure 3. A plot of employment proportion by gender for the engineering industry is provided in Figure 4.

Table 1: Group Listing of Industry Categories from the BEA and BLS Data Sets

Industry Category	Employment and Earnings Data Set from the BEA	Gross Domestic Product Data Sets from the BLS
Management	Management	Management of Companies and Enterprises
Business	Business and Financial Operations	Finance, Insurance, Real Estate, Rental and Leasing
Computer and Math	Computer and Mathematical	Computer Systems Design and Related Services
Engineering	Architecture and Engineering	Miscellaneous Professional, Scientific, and Technical Services
Legal	Legal Occupations, Lawyers and Judges	Legal Services
Education	Education, Training, and Library	Educational Services
Arts and Entertainment	Arts, Design, Entertainment, Sports, and Media	Arts, Entertainment, Recreation, Accommodation, Food, Information
Health	Healthcare Practitioners and technical	Health Care and Social Assistance
Services	Service Occupations	Administrative and Waste Management Services, Federal, State and Other Services
Sales	Sales and Office	Retail and Wholesale Trade
Construction	Natural Resources, Construction, and Maintenance	Agriculture, Forestry, Fishing, Hunting, Construction, Mining, Utilities
Production and Transportation	Production, Transportation, and Material Moving	Transportation, Warehousing, Manufacturing

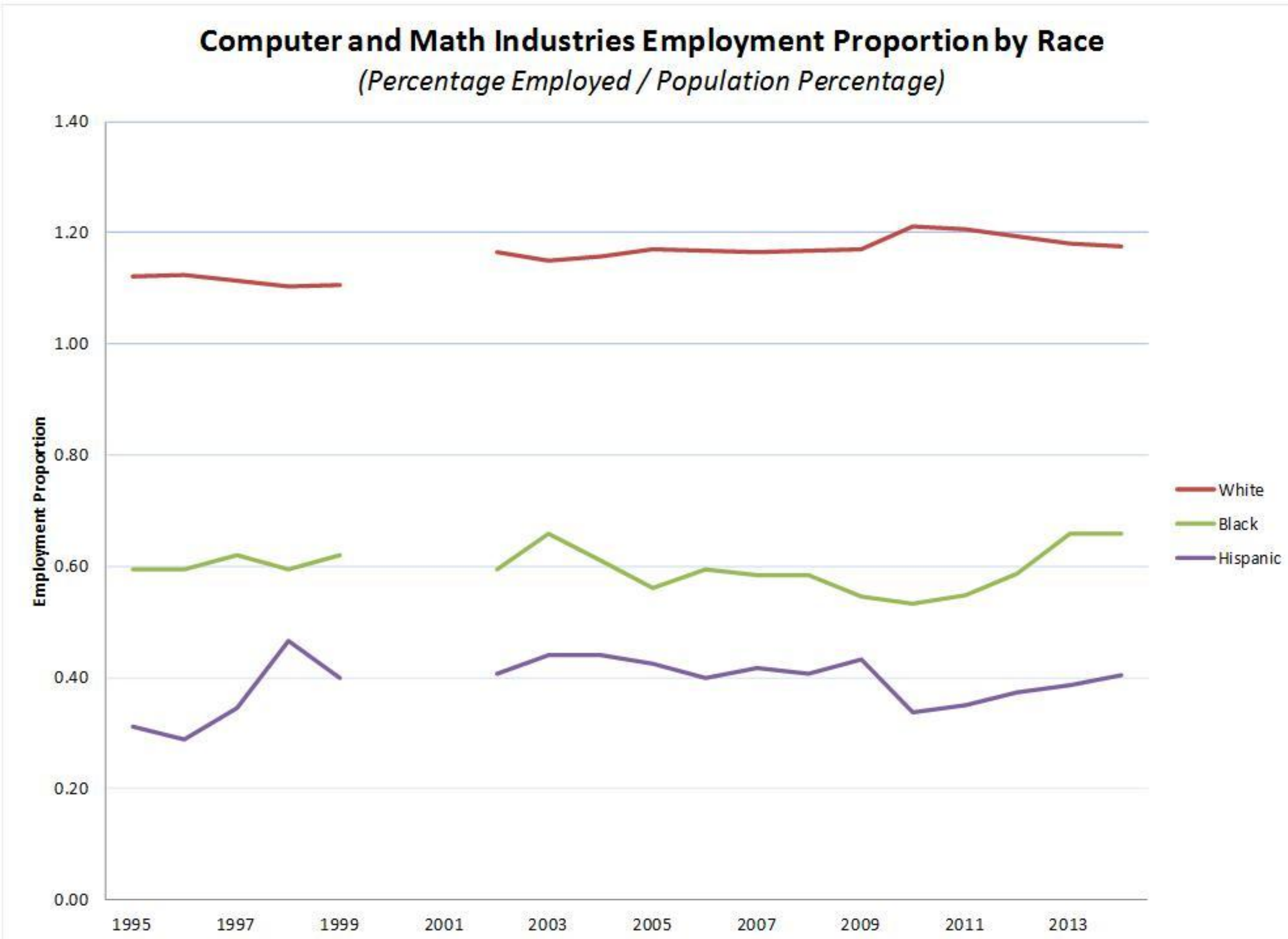

Figure 1: Graph of computer and math industries employment proportion by race for calendar years 1995 through 2014

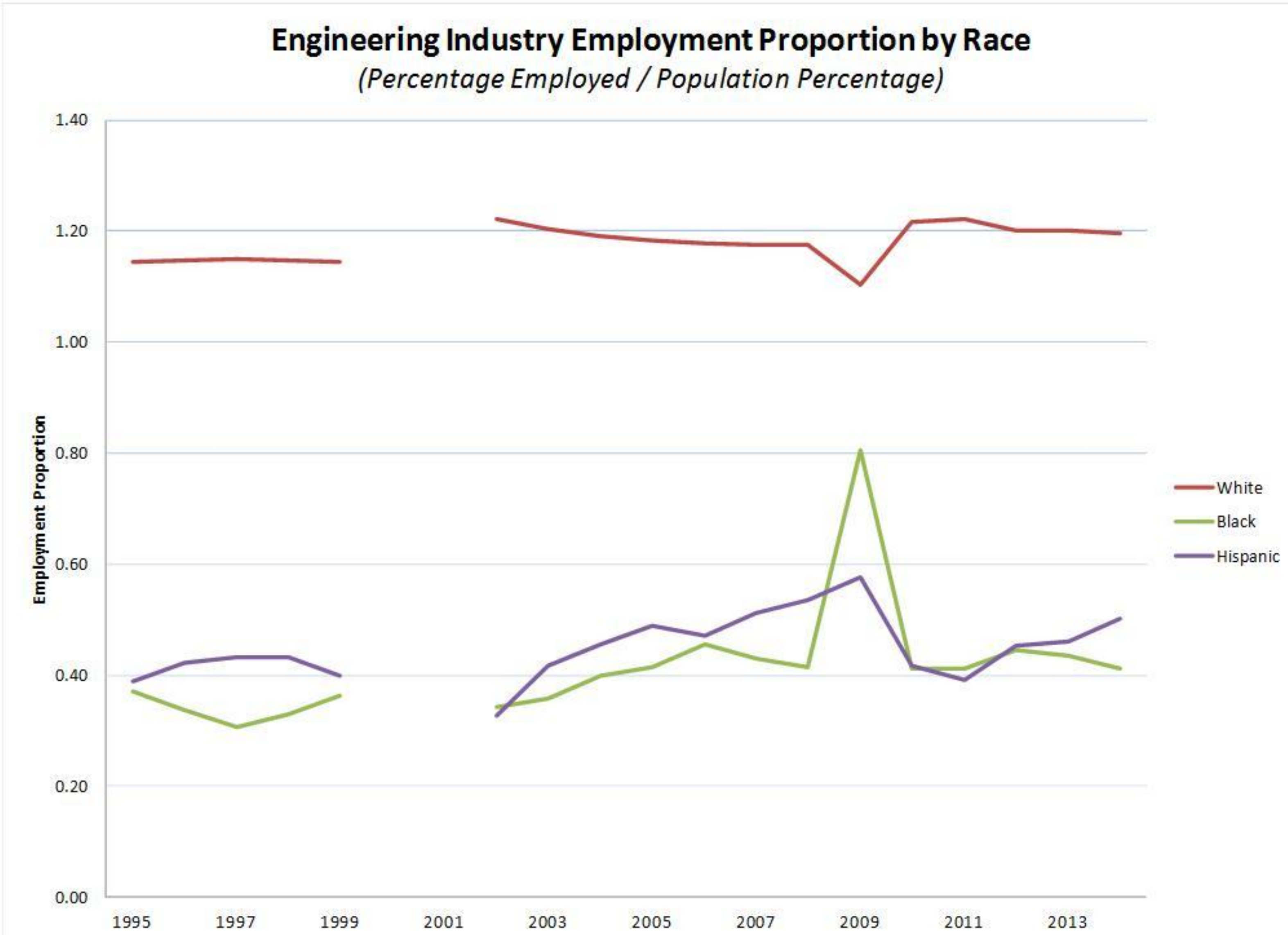

Figure 2: Graph of engineering industry employment proportion by race for calendar years 1995 through 2014

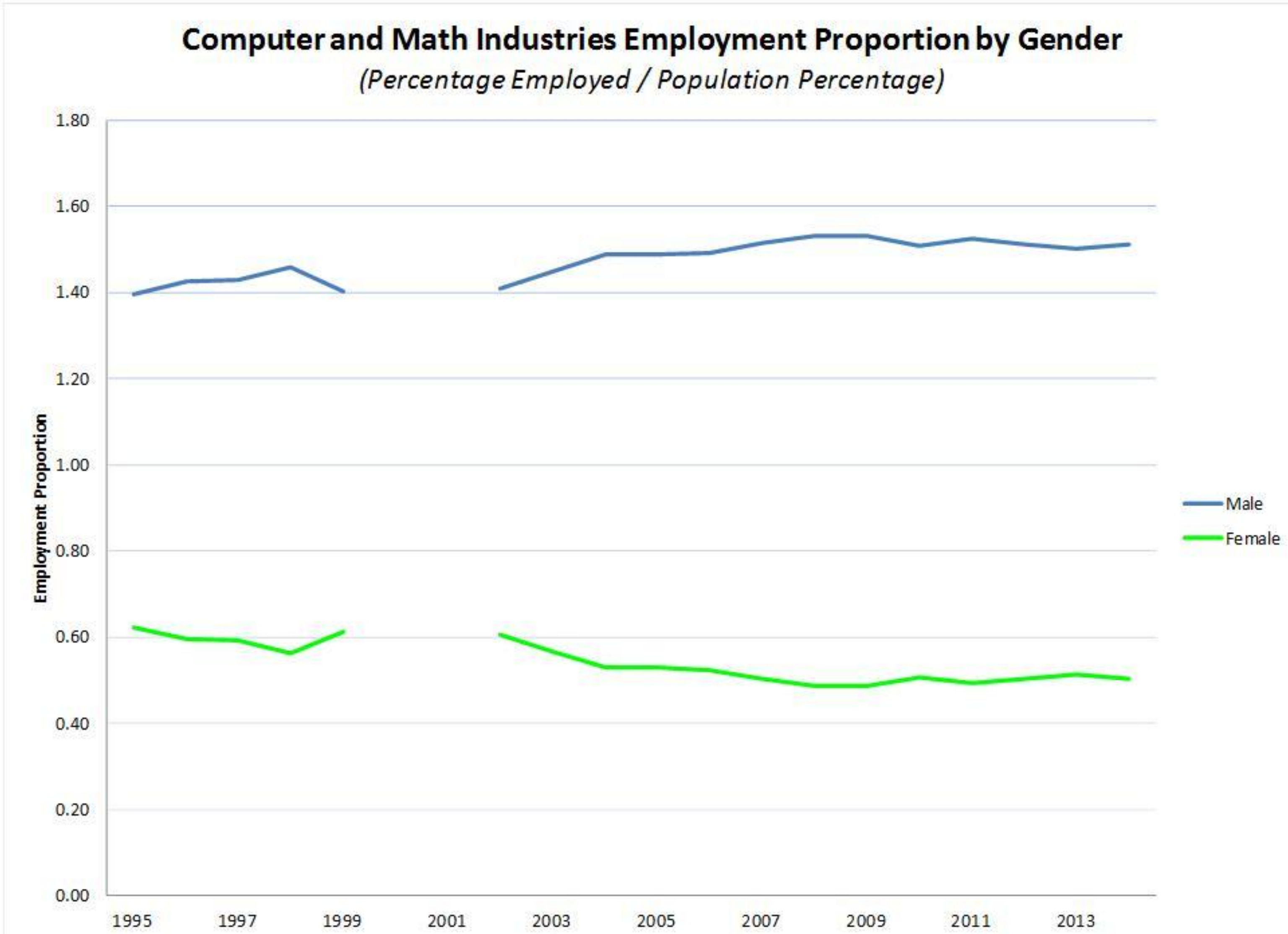

Figure 3: Graph of computer and math industries employment proportion by gender for calendar years 1995 through 2014

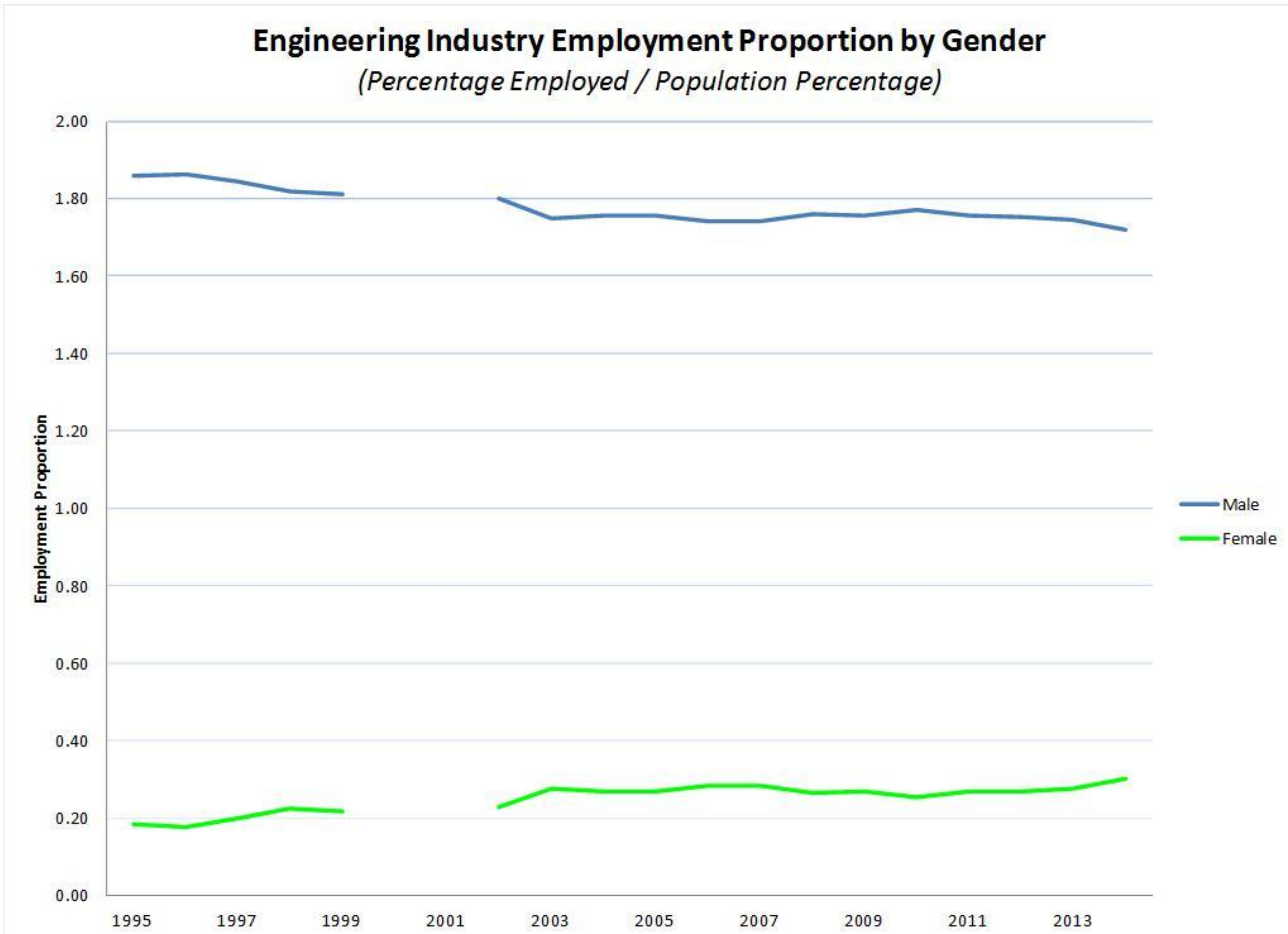

Figure 4: Graph of engineering industry employment proportion by gender for calendar years 1995 through 2014

Earnings data from the Bureau of Labor Statistics Tables 37 and 39 include annual average median weekly earnings for full-time wage and salary workers by gender (men, women) race (white, black, Hispanic/Latino, Asian), and detailed occupation. The Asian demographic was excluded from this analysis due to unavailable employment data. The data sets for years 1997 through 2014, excluding 2000 and 2001, were consolidated and reformatted at a higher level to the industry categories outlined in Table 1. A graph of average weekly earnings by race is provided in Figure 5. Plots of average weekly earnings by gender for the engineering and computer/math industries are provided in Figures 6 and 7 respectively.

The Bureau of Economic Analysis Gross Output by Industry data set includes gross output in billions of dollars. Gross domestic output, or the value of the goods and services produced by a nation during a year not including the value of income earned in foreign countries (Merriam Webster Dictionary, 2004), is included in the analyses as an economic indicator for each industry. The gross domestic product data is reformatted at a higher level to the industry categories outlined in Table 1.

Figure 5: Graph showing average weekly earnings by race for calendar years 1995 through 2014

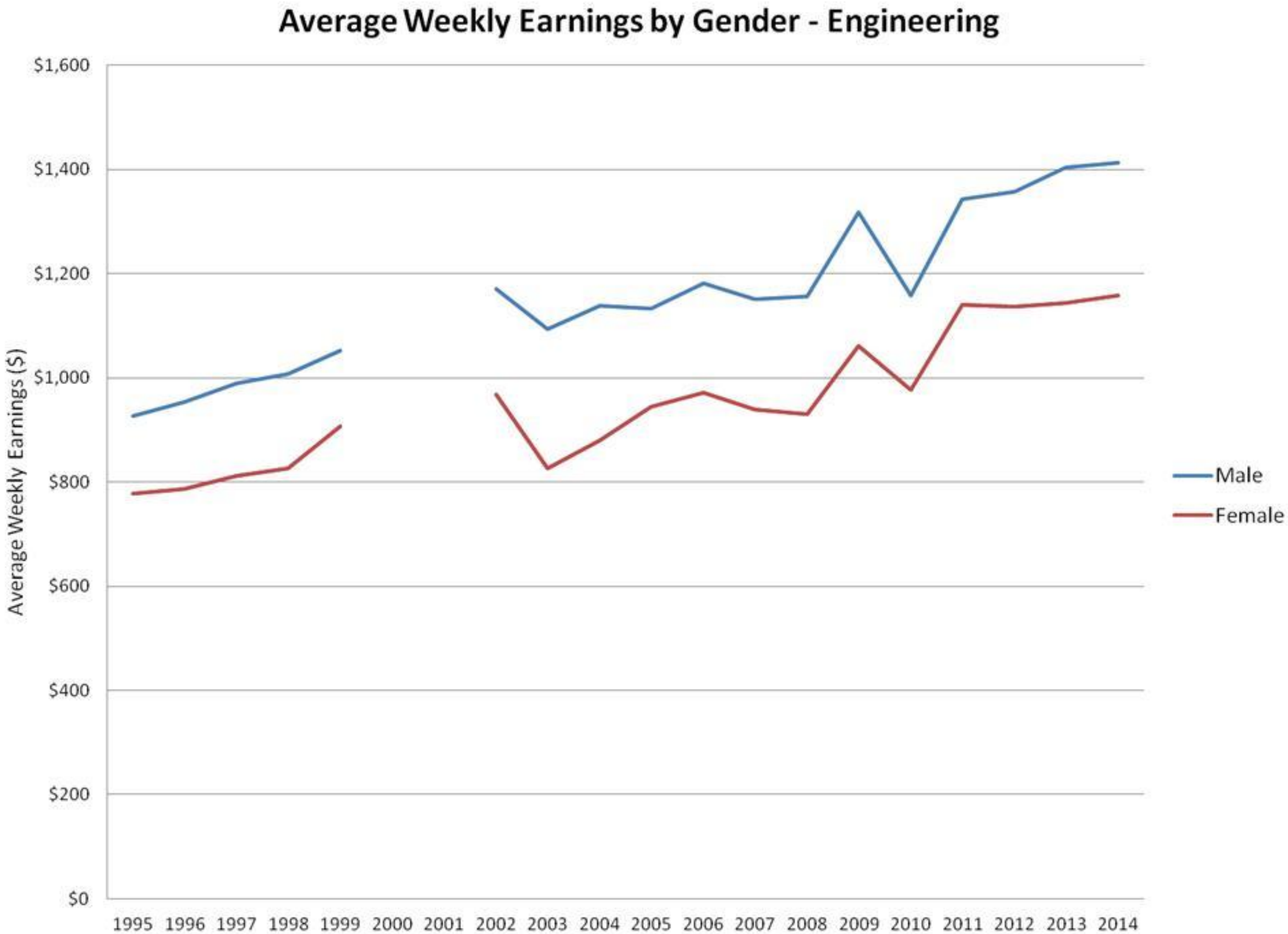

Figure 6: Graph showing average weekly earnings by gender for engineering industry for calendar years 1995 through 2014

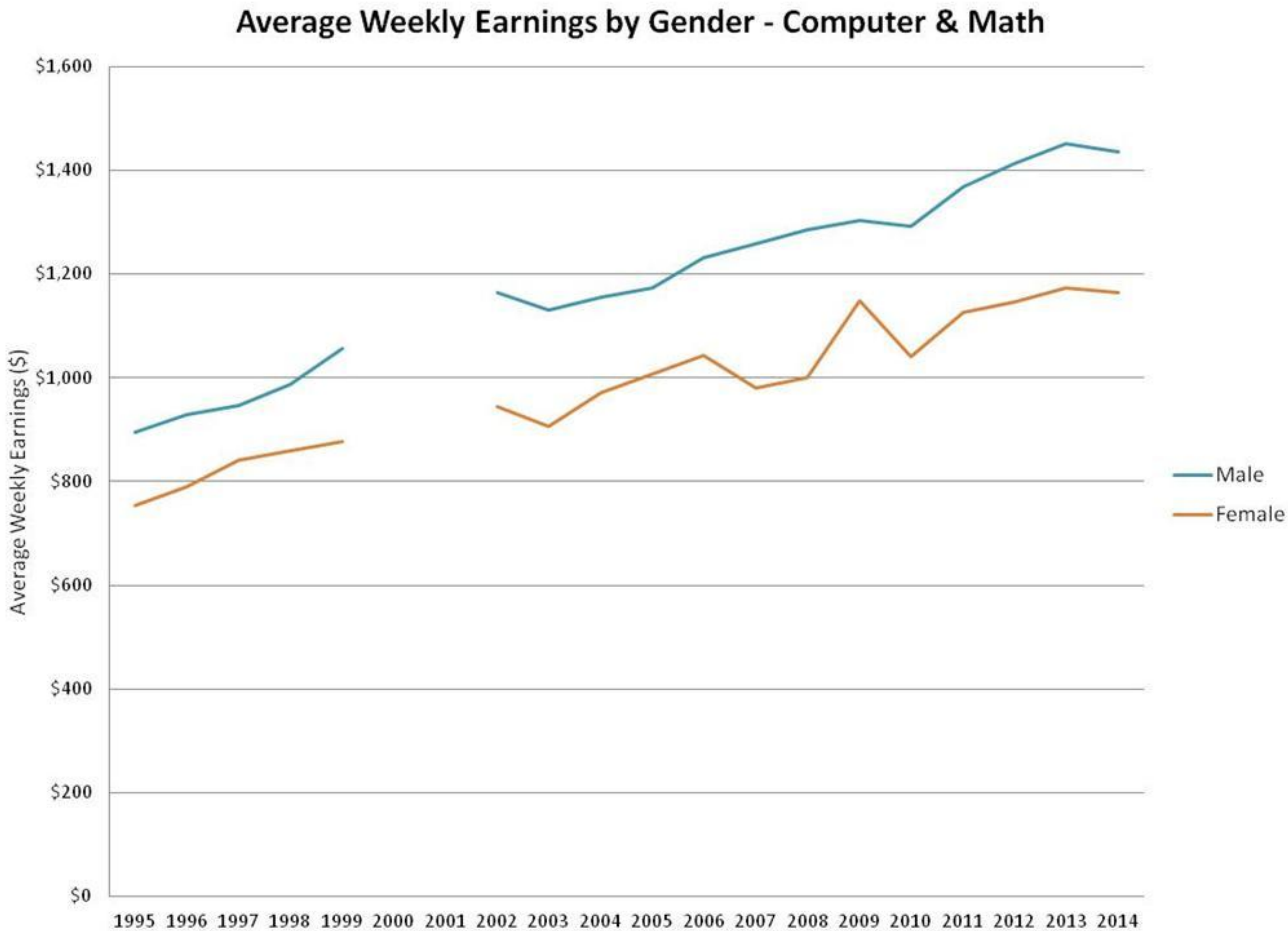

Figure 7: Graph showing average weekly earnings by gender for computer and math industries for calendar years 1995 through 2014

CHAPTER 4: ANALYSIS

Within each analysis, success is determined by either percentage of employment or earnings. Larger percentages of employment (or dollars of earnings) correlate to being more successful, and lower percentages are associated with less success. When available, the analysis is completed by industry.

The purpose of the race analysis is to determine the success of racial minorities, by examining the impact racial demographics has on employment percentages and earnings. Within the data sets provided by the Bureau of Labor Statistics, two minority demographics had consistent reporting results: black and Hispanic/Latino. The race analysis determines success for each racial demographic by comparing it to the respective complement data set. It should be noted the Bureau of Labor Statistics draws unrealistic divides in race, with each individual employee categorized as either white, black, Hispanic/Latino, or other, but not a mixture of races. It is assumed many individuals are in multiple racial categories. However, it is also assumed reclassification will not significantly impact the results of this analysis.

Similarly, the purpose of the gender analysis is to determine the success of women by investigating the impact gender has on employment percentages and earnings. The Bureau of Labor Statistics data sets provided results for women and men. The gender analysis determines success of each gender by comparing it to the counterpart data set. Contrary to the racial analysis, the overwhelming majority of employees will fall into only one of these two categories.

The STEM analysis focuses on the success of minorities (black, and Hispanic/Latino employees) and women in the Computer, Math and Engineering industries. While the Technology industry is a critical element of STEM, the Bureau of Labor Statistics data sets did not provide results at a level of detail sufficient to consistently segregate the industry. Similar to the prior analyses, it is assumed inclusion of such Technology industries will not impact the results of this analysis.

4.1 Description of Methodology

The employment and earnings data sets are dynamic, with results changing year over year. Therefore, varying coefficient models are used to perform the analyses. We analyze the relationship between a response, either employment percentages or earnings, and a group of covariates including time, gender, race, and gross domestic product.

The race, gender and STEM analyses will fit the data sets with the following varying-coefficient models.

$$\%\ of\ Employment\ (Women) = C + (G_1 \times M) + (\mathrm{T} \times M) + (P_1 \times M) \tag{11}$$

$$Average\ Weekly\ Earnings\ (Women) = C + (G_2 \times N) + (\mathrm{T} \times N) + (P_2 \times N) \tag{12}$$

$$\%\ of\ Employment\ (Black) = C + (R_3 \times M) + (\mathrm{T} \times M) + (P_3 \times M) \tag{13}$$

$$Average\ Weekly\ Earnings\ (Black) = C + (R_4 \times N) + (\mathrm{T} \times N) + (P_4 \times N) \tag{14}$$

$$\%\ of\ Employment\ (Hispanic) = C + (R_5 \times M) + (\mathrm{T} \times M) + (P_5 \times M) \tag{15}$$

$$Average\ Weekly\ Earnings\ (Hispanic) = C + (R_6 \times N) + (\mathrm{T} \times N) + (P_6 \times N) \tag{16}$$

where C is some constant, T is time, G_j a gender (0 for male, 1 for female), P_k is the GDP, R_q is race covariate vector (0 for white, 1 for black; 0 for white, 1 for Hispanic/Latino), M is average employment percentage, and N is average weekly earnings.

4.2 Description of MATLAB Program

MATLAB Software, a programming tool for algorithm development, data analysis, and numeric computation, is used to develop multivariable regression models. The program analyses the employment and earnings data sets. The program contains four analyses: earnings by race (white, black, Hispanic/Latino), earnings by gender (male, female), employment by race (white, black, Hispanic/Latino), and employment by gender (male, female). The program is provided in the Appendix.

4.2.1 Multivariable Regression Analysis Part 1: Earnings by Race and Gender

The program begins by reading data for race and gender analyses of earnings. The earnings vector contains the following six earnings categories: total male, total female, white male, white female, black male, black female, Hispanic/Latino male, and Hispanic/Latino female. Covariate vectors for time, race, gender, gross domestic product, and a constant are formed. The constant is simply a vector of all ones. The time variable is defined for years 1995 through 2014, with one corresponding to 1995 and 20 corresponding to 2014. Years six and seven, 2000 and 2001 respectively, are excluded due to incomplete data sets. The race analysis contains one variable for black employees and a separate variable for Hispanic/Latino employees. Black or Hispanic/Latino employees are represented with ones and non-black or non-Hispanic/Latino employees are represented with zeros. Likewise, female employees are represented with ones, and male employees are represented with zeros. The gross domestic product (GDP) variable is defined for years 1995 through 2014, with one corresponding to 1995 and 20 corresponding to 2014. Years 2000 and 2001 are excluded due to incomplete data sets. The time and GDP variables are repeated five times to have consistent vector lengths. The covariates matrix is created by combining the constant, time, gender, black, Hispanic/Latino, and GDP vectors. Finally, regression is run and the program output provides the covariates for constant, time, gender, black, Hispanic/Latino, and GDP variables.

Earnings data is not available by race by industry, so this first earnings analysis is done in total. The following earnings analysis by gender provides industry level of detail.

4.2.2 Multivariable Regression Analysis Part 2: Earnings by Industry by Gender

Earnings data is available by industry and gender, so a more detailed supplemental analysis of earnings is performed. The analysis is completed one industry at a time, and the output consolidates the analyses into a single table. The overall earnings vector contains data for each of the 12 industries identified in Table 1 broken out by male and female. The program begins by reading data for gender analysis of earnings for a single industry. For each industry, covariate vectors for time, gender, gross domestic product, and a constant are formed. Similar to the analysis in Part 1, the constant is a vector of all ones. Time is defined for years 1995 through 2014, with one corresponding to 1995 and 20 corresponding to 2014, and excluding 2000 and 2001 due to incomplete data. The GDP data set by industry is incomplete for 1995 and 1996, so Analysis Parts 2, 3, and 4 utilize time variables beginning with 3 (calendar year 1997). Female employees are represented with ones, and male employees are represented with zeros. The gross domestic product (GDP) variable is defined for years 1997 through 2014, with three corresponding to 1997 and 20 corresponding to 2014. Years 2000 and 2001 are excluded due to incomplete data sets. The time and GDP variables are repeated twice to have consistent vector lengths. The covariates matrix is created by combining the industry constant, time, gender, and GDP vectors. Finally, regression is run for gender (male, female) analysis of the industry earnings data set. This process is repeated for the remaining 11 industry categories previously identified in Table 1. The program output provides a 12x4 matrix of covariates for constant, time, gender, and GDP variables for each industry.

A similar analysis for employment follows.

4.2.3 Multivariable Regression Analysis Part 3: Employment by Industry by Gender

Employment data is available by industry and gender, so a thorough analysis of employment is performed. Similar to Part 2, the analysis is done one industry at a time, and the output consolidates the analyses into a single table. The overall employment vector contains data for each of the 12 industries identified in Table 1 broken out by male and female. The program begins by reading data for gender analysis of employment for a single industry. For each industry, covariate vectors for time, gender, gross domestic product, and a constant are formed. Similar to the analysis in Part 2, the constant is a vector of all ones. Female employees are represented with ones, and male employees are represented with zeros. Time and gross domestic product variables created in Analysis Part 2 are utilized again in these employment analyses. The covariates matrix is created by combining the industry constant, time, gender, and gross domestic product vectors. Finally, regression is run for gender (male, female) analysis of the industry employment data set. This process is repeated for the remaining 11 industry categories. The program output provides a 12x4 matrix of covariates for constant, time, gender, and gross domestic product variables for each industry.

The final analysis provides a comparable review of employment data by race.

4.2.4 Multivariable Regression Analysis Part 4: Employment by Industry by Race

Employment data is available by industry and race, so a detailed analysis of employment is accomplished. The analysis is performed one industry at a time, and the output consolidates the analyses into a single table. The overall employment vector contains data for each of the 12 industries identified in Table 1 broken out by white, black, and Hispanic/Latino. The program begins by reading data for race analysis of employment for a single industry. For each industry, covariate vectors for time, race, gross domestic product, and a constant are formed. Similar to the analysis in Part 3, the constant is a vector of all ones. Two vectors are created for each race analysis. Black or Hispanic/Latino employees are represented with ones, and non-black or non-Hispanic/Latino employees are represented with zeros. Time and gross domestic product variables created in Analysis Part 2 are utilized again in these employment analyses. The covariates matrix is created by combining the industry constant, time, race (black and Hispanic/Latino), and gross domestic product vectors. Finally, regression is run for race (black, Hispanic/Latino) analysis of the industry employment data set. This process is repeated for the remaining 11 industry categories. The program output provides a 12x4 matrix of covariates for constant, time, race (black and Hispanic/Latino), and gross domestic product variables for each industry.

In Chapter 5, the results of the analyses are discussed.

CHAPTER 5: RESULTS

5.1 Results of Race Analysis

The earnings analysis by racial demographics is summarized below is Table 2. Complete analysis results including betas, sigma variance-covariance matrix, matrix of residuals E, estimated variance-covariance matrix of the regression coefficients CovB and the value of the log likelihood objective function after the last iteration logL are available in Appendix B. The passage of time has a minor impact in earnings, with earnings increasing with the passage of time. Gender has a sizeable impact, with males earning more than women. Race has a larger impact, with non-blacks earning more than blacks, and non-Hispanics earning significantly more than Hispanics. It is assumed a minority falling in to two of these categories (black or Hispanic/Latino women) experience the largest wage gaps from the majority (while males). There is also a small correlation between gross domestic product (GDP) and earnings, with earnings increasing with an increase in GDP. Most notably, the correlation between earnings and GDP is nearly three times that of time, so more than the passage of time year over year, a healthy economy (increase in gross domestic product) leads to increased earnings.

Table 2: Overall Weekly Earnings Analysis coefficients

Industry	Constant	Time	Gender	Black	Hispanic	GDP
Total (All Industries)	$232.59	$7.66	-$74.22	-$146.56	-$220.33	$28.6

The employment analysis by racial demographics is summarized below in Table 3. Complete analysis results including betas, sigma variance-covariance matrix, matrix of residuals E, estimated variance-covariance matrix of the regression coefficients CovB and the value of the log likelihood objective function after the last iteration logL are available in Appendix E. The passage of time and gross domestic product had no correlation to employment by race and are therefore excluded from table 3. Black employment was less than non-blacks in all categories, with the largest variance in the Engineering industry and the smallest variance in the Services industry. Similarly, Hispanic/Latino employment was less than non-Hispanics/Latinos in all categories, with the largest variance in the Legal and Engineering industries, and the smallest variance in the Services industry.

Table 3: Analysis of Race Impact on Average Employment Percentage by Industry

Industry	Constant	Black	Hispanic
Management	86.0%	-78.9%	-79.0%
Business	82.6%	-72.2%	-75.7%
Computer and Math	87.4%	-80.1%	-82.2%
Engineering	88.9%	-83.7%	-82.9%
Legal	88.3%	-82.3%	-82.7%
Education	82.9%	-73.1%	-75.4%
Arts and Entertainment	86.1%	-80.0%	-78.3%
Health	85.4%	-76.5%	-79.7%
Services	64.3%	-48.1%	-44.8%
Sales	77.9%	-67.2%	-66.5%
Construction	71.0%	-63.8%	-49.1%
Production and Transportation	67.0%	-52.4%	-48.5%

5.2 Results of Gender Analysis

The earnings analysis by gender is summarized below is Table 4. Complete analysis results including betas, sigma variance-covariance matrix, matrix of residuals E, estimated variance-covariance matrix of the regression coefficients CovB and the value of the log likelihood objective function after the last iteration logL are available in Appendix C. Gross domestic product had no correlation to earnings by race and is therefore excluded from table 4. Unlike the employment analysis by race, time has an inconsistent impact on earnings when analyzed by gender. With the exception of Management, Legal and Health industries, earnings increase with the passage of time. Management and Legal earnings showed a minor decline in earnings with the passage of time, whereas Health industry earnings had a more sizeable decline with the passage of time. With the exception of the Management industry, gender has a sizeable impact, with males earning more than women. The largest variance in earnings occurs in the Legal and Health industries. There is also an inconsistent correlation between gross domestic product (GDP) and earnings. While the results are negligible in many industries, the Legal and Health industries have largest positive correlations, with earnings increasing as GDP increases. To the contrary, Management and Engineering have sizeable negative correlations, with earnings decreasing as gross domestic product increases.

Table 4: Analysis of Gender Impact on Average Weekly Earnings by Industry

Industry	Constant	Time	Gender
Management	$919.00	-$56.50	$282.00
Business	$881.60	$22.80	-$141.40
Computer and Math	$912.80	$20.90	-$213.90
Engineering	$1,188.00	$47.20	-$215.10
Legal	$956.40	-$39.90	-$603.40
Education	$725.80	$19.10	-$193.80
Arts and Entertainment	$787.50	$19.70	-$92.10
Health	$763.40	-$305.00	-$273.00
Services	$243.10	$1.70	-$105.70
Sales	$594.90	$14.90	-$180.40
Construction	$298.60	$10.40	-$162.40
Production and Transportation	$298.60	$10.40	-$162.40

The employment analysis by gender is summarized below in Table 5. Complete analysis results including betas, sigma variance-covariance matrix, matrix of residuals E, estimated variance-covariance matrix of the regression coefficients CovB and the value of the log likelihood objective function after the last iteration logL are available in Appendix D. The passage of time and gross domestic product had no correlation to employment by race and are therefore excluded from Table 5. There was an inconsistent correlation between employment and gender, with women employment less than men in all categories, with the exception of Business, Education, Health, Services and Sales industries. As expected, there are significantly more women employed in the Education industry, and fewer women in the Construction and Production/Transportation Industries.

Table 5: Analysis of Gender Impact on Average Employment Percentage by Industry

Industry	Constant	Gender
Management	57.3%	-14.7%
Business	45.7%	8.7%
Computer and Math	72.9%	-45.8%
Engineering	86.8%	-73.5%
Legal	55.4%	-10.8%
Education	25.8%	48.3%
Arts and Entertainment	52.0%	-4.0%
Health	37.9%	24.2%
Services	42.4%	15.2%
Sales	40.4%	19.3%
Construction	94.5%	-89.0%
Production and Transportation	77.3%	-54.6%

5.3 Results of STEM Analysis

In the final analyses, focus is placed on the STEM industries, Computer/Math and Engineering. The following analyses concentrate on the impact gender has on STEM earnings, and the impact of gender and race on employment within STEM industries.

The STEM earnings analysis by gender is summarized below is Table 6. Gross domestic product had no correlation to STEM earnings by gender and is therefore excluded from Table 6. Time has a minimal impact on STEM earnings when analyzed by gender, with earnings increasing slightly year over year. Gender has a considerable impact on STEM earnings, with males earning more than women. The variance in earnings is similar for both Computer/Math and Engineering industries.

Table 6: Analysis of Gender Impact on Average Weekly Earnings by STEM Industry

Industry	Constant	Time	Gender
Computer and Math	$912.80	$20.90	-$213.90
Engineering	$1,188.00	$47.20	-$215.10

The STEM employment analysis of racial demographics is summarized below in Table 7. The passage of time and gross domestic product had no correlation to employment by race and are therefore excluded from Table 7. In both STEM industries, Computer and Math and Engineering, there are significantly fewer racial minorities. As seen in Figures 1 and 2, the proportion of black employees is consistently between 0.5 and 0.75 of the Computer and Math workforce, and near 0.4 for the Engineering workforce, with the exception of 2009. The proportions for Hispanic/Latino employees are even worse, at 0.25 to 0.45 for the Computer and Math workforce and 0.35 to 0.6 for Engineering.

Table 7: Analysis of Race Impact on Average Employment Percentage by STEM Industry

Industry	Constant	Black	Hispanic
Computer and Math	87.4%	-80.1%	-82.2%
Engineering	88.9%	-83.7%	-82.9%

The STEM employment analysis by gender is summarized below in Table 8. The passage of time and gross domestic product had no correlation to employment by gender and are therefore excluded from Table 8. In both STEM industries, Computer and Math and Engineering, there are far fewer women employed than men. As shown in Figure 1, the proportion of females in the computer and math industries workforce has been less than 0.65 since 1995 and declining year over year. The discrepancy in the Engineering industry is even more drastic. The proportion of females in the engineering industry was consistently 0.15 to 0.4 between 1995 and 2014. Unlike the Computer and Math industries, the proportion is minimally increasing year over year.

Table 8: Analysis of Gender Impact on Average Employment Percentage by STEM Industry

Industry	Constant	Gender
Computer and Math	72.9%	-45.8%
Engineering	86.8%	-73.5%

CHAPTER 5: CONCLUSION

The preceding analysis has shown that women, black, and Hispanic/Latino employees are underrepresented in with STEM industries. For those working in STEM fields, women, black and Hispanic/Latino employees earn less than their counterparts. Given these imbalances, how are leaders encouraging minorities and women to pursue careers in STEM and reduce the success gap in these industries?

Marillyn Hewson, the first female CEO and President of global defense company Lockheed Martin, notes a need for more mentors and role models for students, people who can advise them about a STEM career and help them get on the right track, and communicate more success stories to which the students can relate. She also calls for a need to show women how rewarding a STEM career can be. "Earning a degree in science, technology, engineering and math is not easy, but it will prepare them for an extremely rewarding and exciting career. As industry leaders and role models we need to break down the stereotypes that sometimes discourage women and minorities to pursue these vital careers." (*100 CEO Leaders in STEM*, 2013)

Adriane Brown, President and Chief Operations Officer (COO) of Intellectual Ventures, recommends women get comfortable with being uncomfortable, continually ask to work on hard problems that are a stretch, where there is the opportunity to make big gains. (*Women Leaders in STEM*, 2012)

The greatest recommendation comes from Archana (Archie) Deskus, Vice President and Chief Information Officer (CIO) for Baker Hughes. Mrs. Deskus encourages minorities and women to be flexible and take risks. "It takes courage, but taking risks encourages growth. Define your career aspirations, values, and goals. If an opportunity aligns, have courage, take a risk, and go for it. Do not fear change, but rather embrace new challenges and opportunities that come your way." (*100 CIO/CTO Leaders in STEM*, 2015)

APPENDIX A: REGRESSION MATLAB PROGRAM

```
%  ANALYSIS PART 1: EARNINGS, RACE, GENDER

%  Reading data for race/gender analysis of EARNINGS (white, black,

%  hispanic/latino):

EarnRace = [EarningsData19952014(:,18:20), EarningsData19952014(:,34:36)];

EarnRace = [EarnRace(1:5,:);EarnRace(8:20,:)];

EarnRaceVec = reshape(EarnRace,108,1);

%  Forming covariates for race/gender analysis of earnings:

time = [1:5,8:20]';

t = time;

GDPTotal = [GDPTotal19952014(1:5,1); GDPTotal19952014(8:20,1)];

GDP = GDPTotal;

for i=1:5

    t=[t;time];

    GDP = [GDP; GDPTotal];

end

GDP = reshape(GDP, 108,1);

covariate_race_earn_constant = ones(108,1);
```

```
covariate_race_earn_gender = [zeros(54,1); ones(54,1)];

covariate_race_earn_black = [zeros(18,1); ones(18,1); zeros(36,1); ones(18,1); zeros(18,1)];

covariate_race_earn_hispanic = [zeros(36,1); ones(18,1);zeros(36,1); ones(18,1)];

covariates_earn_race = [covariate_race_earn_constant t covariate_race_earn_gender
covariate_race_earn_black covariate_race_earn_hispanic GDP];

% Running regression for race/gender analysis of earnings (white, black,

% hispanic/latino):

[EARNING_RACE_Covariates_Constant_Time_Gender_Black_Hispanic_GDP,
SigmaEarningsRace,EEarningsRace,CovBEarningsRace,logLEarningsRace]  =
mvregress(covariates_earn_race,EarnRaceVec)

%  ANALYSIS PART 2: EARNINGS, INDUSTRY, GENDER

time = [3:5,8:20]';

t = time;

t=[t;time];

%  Reading data for gender analysis of MANAGEMENT INDUSTRY EARNINGS:

EarnMGMTIndustry = [EarningsData19952014(:,21), EarningsData19952014(:,38)];

EarnMGMTIndustry = [EarnMGMTIndustry(3:5,:);EarnMGMTIndustry(8:20,:)];

EarnMGMTIndustryVec = reshape(EarnMGMTIndustry,32,1);
```

```
% Forming covariates for gender analysis of MANAGEMENT INDUSTRY EARNINGS:

GDPMGMTIndustry = GDPIndustry19972014(:,2);

GDPMGMTIndustryVec = reshape(GDPMGMTIndustry,16,1);

GDPMGMTIndustryVec = [GDPMGMTIndustryVec; GDPMGMTIndustryVec];

covariate_earn_mgmt_constant = ones(32,1);

covariate_earn_mgmt_gender = [zeros(16,1); ones(16,1)];

covariates_earn_mgmt = [covariate_earn_mgmt_constant t covariate_earn_mgmt_gender
GDPMGMTIndustryVec];

% Running regression for gender analysis of MANAGEMENT INDUSTRY EARNINGS:

 [EARNINGS_MGMT_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsMgmt,EEarningsMgmt,CovBEarningsMgmt,logLEarningsMgmt] =
mvregress(covariates_earn_mgmt,EarnMGMTIndustryVec);

% Reading data for gender analysis of BUSINESS INDUSTRY EARNINGS:

EarnBUSIndustry = [EarningsData19952014(:,22), EarningsData19952014(:,39)];

EarnBUSIndustry = [EarnBUSIndustry(3:5,:);EarnBUSIndustry(8:20,:)];

EarnBUSIndustryVec = reshape(EarnBUSIndustry,32,1);

% Forming covariates for gender analysis of BUSINESS INDUSTRY EARNINGS:

GDPBUSIndustry = GDPIndustry19972014(:,3);
```

```
GDPBUSIndustryVec = reshape(GDPBUSIndustry,16,1);

GDPBUSIndustryVec = [GDPBUSIndustryVec; GDPBUSIndustryVec];

covariate_earn_BUS_constant = ones(32,1);

covariate_earn_BUS_gender = [zeros(16,1); ones(16,1)];

covariates_earn_BUS = [covariate_earn_BUS_constant t covariate_earn_BUS_gender
GDPBUSIndustryVec];

% Running regression for gender analysis of BUSINESS INDUSTRY EARNINGS:

 [EARNINGS_BUS_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsBUS,EEarningsBUS,CovBEarningsBUS,logLEarningsBUS] =
mvregress(covariates_earn_BUS,EarnBUSIndustryVec);

%  Reading data for gender analysis of COMPUTER & MATH INDUSTRY EARNINGS:

EarnCOMP_MATHIndustry = [EarningsData19952014(:,23), EarningsData19952014(:,39)];

EarnCOMP_MATHIndustry =
[EarnCOMP_MATHIndustry(3:5,:);EarnCOMP_MATHIndustry(8:20,:)];

EarnCOMP_MATHIndustryVec = reshape(EarnCOMP_MATHIndustry,32,1);

% Forming covariates for analysis of COMPUTER & MATH INDUSTRY EARNINGS:

GDPCOMP_MATHIndustry = GDPIndustry19972014(:,4);

GDPCOMP_MATHIndustryVec = reshape(GDPCOMP_MATHIndustry,16,1);
```

GDPCOMP_MATHIndustryVec = [GDPCOMP_MATHIndustryVec;

GDPCOMP_MATHIndustryVec];

covariate_earn_COMP_MATH_constant = ones(32,1);

covariate_earn_COMP_MATH_gender = [zeros(16,1); ones(16,1)];

covariates_earn_COMP_MATH = [covariate_earn_COMP_MATH_constant t

covariate_earn_COMP_MATH_gender GDPCOMP_MATHIndustryVec];

% Running regression for gender analysis of COMPUTER & MATH INDUSTRY EARNINGS:

[EARNINGS_COMP_MATH_Covariates_Constant_Time_Gender_GDP,

SigmaEarningsCM,EEarningsCM,CovBEarningsCM,logLEarningsCM] =

mvregress(covariates_earn_COMP_MATH,EarnCOMP_MATHIndustryVec);

% Reading data for gender analysis of ENGINEERING INDUSTRY EARNINGS:

EarnENGRIndustry = [EarningsData19952014(:,24), EarningsData19952014(:,40)];

EarnENGRIndustry = [EarnENGRIndustry(3:5,:);EarnENGRIndustry(8:20,:)];

EarnENGRIndustryVec = reshape(EarnENGRIndustry,32,1);

% Forming covariates for analysis of ENGINEERING INDUSTRY EARNINGS:

GDPENGRIndustry = GDPIndustry19972014(:,5);

GDPENGRIndustryVec = reshape(GDPENGRIndustry,16,1);

GDPENGRIndustryVec = [GDPENGRIndustryVec; GDPENGRIndustryVec];

```
covariate_earn_ENGR_constant = ones(32,1);

covariate_earn_ENGR_gender = [zeros(16,1); ones(16,1)];

covariates_earn_ENGR = [covariate_earn_ENGR_constant t covariate_earn_ENGR_gender
GDPENGRIndustryVec];

% Running regression for gender analysis of ENGINEERING INDUSTRY EARNINGS:

 [EARNINGS_ENGR_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsEN,EEarningsEN,CovBEarningsEN,logLEarningsEN] =
mvregress(covariates_earn_ENGR,EarnENGRIndustryVec);

%  Reading data for gender analysis of LEGAL INDUSTRY EARNINGS:

EarnLGLIndustry = [EarningsData19952014(:,25), EarningsData19952014(:,41)];

EarnLGLIndustry = [EarnLGLIndustry(3:5,:);EarnLGLIndustry(8:20,:)];

EarnLGLIndustryVec = reshape(EarnLGLIndustry,32,1);

% Forming covariates for analysis of LEGAL INDUSTRY EARNINGS:

GDPLGLIndustry = GDPIndustry19972014(:,6);

GDPLGLIndustryVec = reshape(GDPLGLIndustry,16,1);

GDPLGLIndustryVec = [GDPLGLIndustryVec; GDPLGLIndustryVec];

covariate_earn_LGL_constant = ones(32,1);
```

```
covariate_earn_LGL_gender = [zeros(16,1); ones(16,1)];

covariates_earn_LGL = [covariate_earn_LGL_constant t covariate_earn_LGL_gender
GDPLGLIndustryVec];

% Running regression for gender analysis of LEGAL INDUSTRY EARNINGS:

 [EARNINGS_LGL_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsLG,EEarningsLG,CovBEarningsLG,logLEarningsLG] =
mvregress(covariates_earn_LGL,EarnLGLIndustryVec);

%  Reading data for gender analysis of EDUCATION INDUSTRY EARNINGS:

EarnEDUIndustry = [EarningsData19952014(:,26), EarningsData19952014(:,42)];

EarnEDUIndustry = [EarnEDUIndustry(3:5,:);EarnEDUIndustry(8:20,:)];

EarnEDUIndustryVec = reshape(EarnEDUIndustry,32,1);

% Forming covariates for analysis of EDUCATION INDUSTRY EARNINGS:

GDPEDUIndustry = GDPIndustry19972014(:,7);

GDPEDUIndustryVec = reshape(GDPEDUIndustry,16,1);

GDPEDUIndustryVec = [GDPEDUIndustryVec; GDPEDUIndustryVec];

covariate_earn_EDU_constant = ones(32,1);

covariate_earn_EDU_gender = [zeros(16,1); ones(16,1)];
```

```
covariates_earn_EDU = [covariate_earn_EDU_constant t covariate_earn_EDU_gender
GDPEDUIndustryVec];

% Running regression for gender analysis of EDUCATION INDUSTRY EARNINGS:

 [EARNINGS_EDU_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsED,EEarningsED,CovBEarningsED,logLEarningsED] =
mvregress(covariates_earn_EDU,EarnEDUIndustryVec);

%  Reading data for gender analysis of ARTS INDUSTRY EARNINGS:

EarnARTIndustry = [EarningsData19952014(:,27), EarningsData19952014(:,43)];

EarnARTIndustry = [EarnARTIndustry(3:5,:);EarnARTIndustry(8:20,:)];

EarnARTIndustryVec = reshape(EarnARTIndustry,32,1);

% Forming covariates for analysis of ARTS INDUSTRY EARNINGS:

GDPARTIndustry = GDPIndustry19972014(:,8);

GDPARTIndustryVec = reshape(GDPARTIndustry,16,1);

GDPARTIndustryVec = [GDPARTIndustryVec; GDPARTIndustryVec];

covariate_earn_ART_constant = ones(32,1);

covariate_earn_ART_gender = [zeros(16,1); ones(16,1)];

covariates_earn_ART = [covariate_earn_ART_constant t covariate_earn_ART_gender
GDPARTIndustryVec];
```

```
% Running regression for gender analysis of ARTS INDUSTRY EARNINGS:

 [EARNINGS_ART_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsAR,EEarningsAR,CovBEarningsAR,logLEarningsAR] =
mvregress(covariates_earn_ART,EarnARTIndustryVec);

%  Reading data for gender analysis of HEALTH INDUSTRY EARNINGS:

EarnHLTIndustry = [EarningsData19952014(:,28), EarningsData19952014(:,44)];

EarnHLTIndustry = [EarnHLTIndustry(3:5,:);EarnHLTIndustry(8:20,:)];

EarnHLTIndustryVec = reshape(EarnHLTIndustry,32,1);

% Forming covariates for analysis of HEALTH INDUSTRY EARNINGS:

GDPHLTIndustry = GDPIndustry19972014(:,9);

GDPHLTIndustryVec = reshape(GDPHLTIndustry,16,1);

GDPHLTIndustryVec = [GDPHLTIndustryVec; GDPHLTIndustryVec];

covariate_earn_HLT_constant = ones(32,1);

covariate_earn_HLT_gender = [zeros(16,1); ones(16,1)];

covariates_earn_HLT = [covariate_earn_HLT_constant t covariate_earn_HLT_gender
GDPHLTIndustryVec];

% Running regression for gender analysis of HEALTH INDUSTRY EARNINGS:
```

```
[EARNINGS_HLT_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsHT,EEarningsHT,CovBEarningsHT,logLEarningsHT] =
mvregress(covariates_earn_HLT,EarnHLTIndustryVec);

%  Reading data for gender analysis of SERVICES INDUSTRY EARNINGS:

EarnSRVIndustry = [EarningsData19952014(:,29), EarningsData19952014(:,45)];

EarnSRVIndustry = [EarnSRVIndustry(3:5,:);EarnSRVIndustry(8:20,:)];

EarnSRVIndustryVec = reshape(EarnSRVIndustry,32,1);

% Forming covariates for analysis of SERVICES INDUSTRY EARNINGS:

GDPSRVIndustry = GDPIndustry19972014(:,10);

GDPSRVIndustryVec = reshape(GDPSRVIndustry,16,1);

GDPSRVIndustryVec = [GDPSRVIndustryVec; GDPSRVIndustryVec];

covariate_earn_SRV_constant = ones(32,1);

covariate_earn_SRV_gender = [zeros(16,1); ones(16,1)];

covariates_earn_SRV = [covariate_earn_SRV_constant t covariate_earn_SRV_gender
GDPSRVIndustryVec];

% Running regression for gender analysis of SERVICES INDUSTRY EARNINGS:

[EARNINGS_SRV_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsSV,EEarningsSV,CovBEarningsSV,logLEarningsSV] =
mvregress(covariates_earn_SRV,EarnSRVIndustryVec);
```

```
%  Reading data for gender analysis of SALES INDUSTRY EARNINGS:

EarnSALIndustry = [EarningsData19952014(:,30), EarningsData19952014(:,46)];

EarnSALIndustry = [EarnSALIndustry(3:5,:);EarnSALIndustry(8:20,:)];

EarnSALIndustryVec = reshape(EarnSALIndustry,32,1);

% Forming covariates for analysis of SALES INDUSTRY EARNINGS:

GDPSALIndustry = GDPIndustry19972014(:,11);

GDPSALIndustryVec = reshape(GDPSALIndustry,16,1);

GDPSALIndustryVec = [GDPSALIndustryVec; GDPSALIndustryVec];

covariate_earn_SAL_constant = ones(32,1);

covariate_earn_SAL_gender = [zeros(16,1); ones(16,1)];

covariates_earn_SAL = [covariate_earn_SAL_constant t covariate_earn_SAL_gender
GDPSALIndustryVec];

% Running regression for gender analysis of SALES INDUSTRY EARNINGS:

 [EARNINGS_SAL_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsSA,EEarningsSA,CovBEarningsSA,logLEarningsSA] =
mvregress(covariates_earn_SAL,EarnSALIndustryVec);

%  Reading data for gender analysis of CONSTRUCTION INDUSTRY EARNINGS:

 EarnCSTIndustry = [EarningsData19952014(:,31), EarningsData19952014(:,47)];
```

```
EarnCSTIndustry = [EarnCSTIndustry(3:5,:);EarnCSTIndustry(8:20,:)];

EarnCSTIndustryVec = reshape(EarnCSTIndustry,32,1);

% Forming covariates for analysis of CONSTRUCTION INDUSTRY EARNINGS:

GDPCSTIndustry = GDPIndustry19972014(:,12);

GDPCSTIndustryVec = reshape(GDPCSTIndustry,16,1);

GDPCSTIndustryVec = [GDPCSTIndustryVec; GDPCSTIndustryVec];

covariate_earn_CST_constant = ones(32,1);

covariate_earn_CST_gender = [zeros(16,1); ones(16,1)];

covariates_earn_CST = [covariate_earn_CST_constant t covariate_earn_CST_gender
GDPCSTIndustryVec];

% Running regression for gender analysis of CONSTRUCTION INDUSTRY EARNINGS:

 [EARNINGS_CST_Covariates_Constant_Time_Gender_GDP,
SigmaEarningsCO,EEarningsCO,CovBEarningsCO,logLEarningsCO] =
mvregress(covariates_earn_CST,EarnCSTIndustryVec);

%  Reading data for gender analysis of PRODUCTION & TRANSPORTATION INDUSTRY
EARNINGS:

EarnPTSIndustry = [EarningsData19952014(:,31), EarningsData19952014(:,47)];

EarnPTSIndustry = [EarnPTSIndustry(3:5,:);EarnPTSIndustry(8:20,:)];
```

EarnPTSIndustryVec = reshape(EarnPTSIndustry,32,1);

% Forming covariates for analysis of PRODUCTION & TRANSPORTATION INDUSTRY EARNINGS:

GDPPTSIndustry = GDPIndustry19972014(:,12);

GDPPTSIndustryVec = reshape(GDPPTSIndustry,16,1);

GDPPTSIndustryVec = [GDPPTSIndustryVec; GDPPTSIndustryVec];

covariate_earn_PTS_constant = ones(32,1);

covariate_earn_PTS_gender = [zeros(16,1); ones(16,1)];

covariates_earn_PTS = [covariate_earn_PTS_constant t covariate_earn_PTS_gender GDPPTSIndustryVec];

% Running regression for gender analysis of PRODUCTION & TRANSPORTATION INDUSTRY EARNINGS:

[EARNINGS_PTS_Covariates_Constant_Time_Gender_GDP, SigmaEarningsPT,EEarningsPT,CovBEarningsPT,logLEarningsPT] = mvregress(covariates_earn_PTS,EarnPTSIndustryVec);

EARNINGS_Industry_Constant_Time_Gender_GDP = [EARNINGS_MGMT_Covariates_Constant_Time_Gender_GDP EARNINGS_BUS_Covariates_Constant_Time_Gender_GDP EARNINGS_COMP_MATH_Covariates_Constant_Time_Gender_GDP EARNINGS_ENGR_Covariates_Constant_Time_Gender_GDP

EARNINGS_LGL_Covariates_Constant_Time_Gender_GDP

EARNINGS_EDU_Covariates_Constant_Time_Gender_GDP

EARNINGS_ART_Covariates_Constant_Time_Gender_GDP

EARNINGS_HLT_Covariates_Constant_Time_Gender_GDP

EARNINGS_SRV_Covariates_Constant_Time_Gender_GDP

EARNINGS_SAL_Covariates_Constant_Time_Gender_GDP

EARNINGS_CST_Covariates_Constant_Time_Gender_GDP

EARNINGS_PTS_Covariates_Constant_Time_Gender_GDP]'

SigmaEarnings = [SigmaEarningsMgmt, SigmaEarningsBUS, SigmaEarningsCM, SigmaEarningsEN, SigmaEarningsLG, SigmaEarningsED, SigmaEarningsAR, SigmaEarningsHT, SigmaEarningsSV, SigmaEarningsSA, SigmaEarningsCO, SigmaEarningsPT]

EEarningsRace = [EEarningsMgmt, EEarningsBUS, EEarningsCM, EEarningsEN, EEarningsLG, EEarningsED, EEarningsAR, EEarningsHT, EEarningsSV, EEarningsSA, EEarningsCO, EEarningsPT]

CovBEarningsRace = [CovBEarningsMgmt, CovBEarningsBUS, CovBEarningsCM, CovBEarningsEN, CovBEarningsLG, CovBEarningsED, CovBEarningsAR, CovBEarningsHT, CovBEarningsSV, CovBEarningsSA, CovBEarningsCO, CovBEarningsPT]

logLEarningsRace = [logLEarningsMgmt, logLEarningsBUS, logLEarningsCM, logLEarningsEN, logLEarningsLG, logLEarningsED, logLEarningsAR, logLEarningsHT, logLEarningsSV, logLEarningsSA, logLEarningsCO, logLEarningsPT]

% ANALYSIS PART 3: EMPLOYMENT, INDUSTRY, GENDER

% NOTE: Time and GDP variables were created in the above earnings analyses and are utilized again in the below employment analyses.

% Reading data for gender analysis of MANAGEMENT INDUSTRY EMPLOYMENT:

EmployMGMTGender = [EmploymentData19952014(:,2), EmploymentData19952014(:,15)];

EmployMGMTGender = [EmployMGMTGender(3:5,:); EmployMGMTGender(8:20,:)];

EmployMGMTGenderVec = reshape(EmployMGMTGender,32,1);

% Forming covariates for gender analysis of MANAGEMENT INDUSTRY EMPLOYMENT:

covariate_employ_MGMT_constant = ones(32,1);

covariate_employ_MGMT_gender = [zeros(16,1); ones(16,1)];

covariate_employ_earn = [EarningsData19952014(3:5,1);EarningsData19952014(8:20,1); EarningsData19952014(3:5,1);EarningsData19952014(8:20,1)];

covariates_employ_MGMT_gender = [covariate_employ_MGMT_constant t covariate_employ_MGMT_gender covariate_employ_earn GDPMGMTIndustryVec];

% Running regression for gender analysis of MANAGEMENT INDUSTRY EMPLOYMENT:

[EMPLOYMNT_GENDER_Covariates_MGMT, SigmaEMPMgmt,EEMPMgmt,CovBEMPMgmt,logLEMPMgmt] = mvregress(covariates_employ_MGMT_gender,EmployMGMTGenderVec);

```
%  Reading data for gender analysis of BUSINESS INDUSTRY EMPLOYMENT:

EmployBUSGender = [EmploymentData19952014(:,3), EmploymentData19952014(:,16)];

EmployBUSGender = [EmployBUSGender(3:5,:); EmployBUSGender(8:20,:)];

EmployBUSGenderVec = reshape(EmployBUSGender,32,1);

%  Forming covariates for gender analysis of BUSINESS INDUSTRY EMPLOYMENT:

covariate_employ_BUS_constant = ones(32,1);

covariate_employ_BUS_gender = [zeros(16,1); ones(16,1)];

covariates_employ_BUS_gender = [covariate_employ_BUS_constant t
covariate_employ_BUS_gender covariate_employ_earn GDPBUSIndustryVec];

%  Running regression for gender analysis of BUSINESS INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_GENDER_Covariates_BUS,
SigmaEMPBUS,EEMPBUS,CovBEMPBUS,logLEMPBUS]  =
mvregress(covariates_employ_BUS_gender,EmployBUSGenderVec);

%  Reading data for gender analysis of COMPUTER & MATH INDUSTRY EMPLOYMENT:

EmployCOMP_MATHGender = [EmploymentData19952014(:,4),
EmploymentData19952014(:,17)];

EmployCOMP_MATHGender = [EmployCOMP_MATHGender(3:5,:);
EmployCOMP_MATHGender(8:20,:)];

EmployCOMP_MATHGenderVec = reshape(EmployCOMP_MATHGender,32,1);
```

% Forming covariates for gender analysis of COMPUTER & MATH INDUSTRY EMPLOYMENT:

covariate_employ_COMP_MATH_constant = ones(32,1);

covariate_employ_COMP_MATH_gender = [zeros(16,1); ones(16,1)];

covariates_employ_COMP_MATH_gender = [covariate_employ_COMP_MATH_constant t covariate_employ_COMP_MATH_gender covariate_employ_earn GDPCOMP_MATHIndustryVec];

% Running regression for gender analysis of COMPUTER & MATH INDUSTRY EMPLOYMENT:

[EMPLOYMNT_GENDER_Covariates_COMP_MATH, SigmaEMPCM,EEMPCM,CovBEMPCM,logLEMPCM] = mvregress(covariates_employ_COMP_MATH_gender,EmployCOMP_MATHGenderVec);

% Reading data for gender analysis of ENGINEERING INDUSTRY EMPLOYMENT:

EmployENGRGender = [EmploymentData19952014(:,5), EmploymentData19952014(:,18)];

EmployENGRGender = [EmployENGRGender(3:5,:); EmployENGRGender(8:20,:)];

EmployENGRGenderVec = reshape(EmployENGRGender,32,1);

% Forming covariates for gender analysis of ENGINEERING INDUSTRY EMPLOYMENT:

covariate_employ_ENGR_constant = ones(32,1);

covariate_employ_ENGR_gender = [zeros(16,1); ones(16,1)];

```
covariates_employ_ENGR_gender = [covariate_employ_ENGR_constant t
covariate_employ_ENGR_gender covariate_employ_earn GDPENGRIndustryVec];

%  Running regression for gender analysis of ENGINEERING INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_GENDER_Covariates_ENGR,
SigmaEMPEN,EEMPEN,CovBEMPEN,logLEMPEN]  =
mvregress(covariates_employ_ENGR_gender,EmployENGRGenderVec);

%  Reading data for gender analysis of LEGAL INDUSTRY EMPLOYMENT:

EmployLGLGender = [EmploymentData19952014(:,6), EmploymentData19952014(:,19)];

EmployLGLGender = [EmployLGLGender(3:5,:); EmployLGLGender(8:20,:)];

EmployLGLGenderVec = reshape(EmployLGLGender,32,1);

%  Forming covariates for gender analysis of LEGAL INDUSTRY EMPLOYMENT:

covariate_employ_LGL_constant = ones(32,1);

covariate_employ_LGL_gender = [zeros(16,1); ones(16,1)];

covariates_employ_LGL_gender = [covariate_employ_LGL_constant t
covariate_employ_LGL_gender covariate_employ_earn GDPLGLIndustryVec];

%  Running regression for gender analysis of LEGAL INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_GENDER_Covariates_LGL,
SigmaEMPLG,EEMPLG,CovBEMPLG,logLEMPLG]  =
mvregress(covariates_employ_LGL_gender,EmployLGLGenderVec);
```

```
%  Reading data for gender analysis of EDUCATION INDUSTRY EMPLOYMENT:

EmployEDUGender = [EmploymentData19952014(:,7), EmploymentData19952014(:,20)];

EmployEDUGender = [EmployEDUGender(3:5,:); EmployEDUGender(8:20,:)];

EmployEDUGenderVec = reshape(EmployEDUGender,32,1);

%  Forming covariates for gender analysis of EDUCATION INDUSTRY EMPLOYMENT:

covariate_employ_EDU_constant = ones(32,1);

covariate_employ_EDU_gender = [zeros(16,1); ones(16,1)];

covariates_employ_EDU_gender = [covariate_employ_EDU_constant t
covariate_employ_EDU_gender covariate_employ_earn GDPEDUIndustryVec];

%  Running regression for gender analysis of EDUCATION INDUSTRY EMPLOYMENT:

[EMPLOYMNT_GENDER_Covariates_EDU,
SigmaEMPED,EEMPED,CovBEMPED,logLEMPED]  =
mvregress(covariates_employ_EDU_gender,EmployEDUGenderVec);

%  Reading data for gender analysis of ARTS INDUSTRY EMPLOYMENT:

EmployARTGender = [EmploymentData19952014(:,8), EmploymentData19952014(:,21)];

EmployARTGender = [EmployARTGender(3:5,:); EmployARTGender(8:20,:)];

EmployARTGenderVec = reshape(EmployARTGender,32,1);
```

```
%  Forming covariates for gender analysis of ARTS INDUSTRY EMPLOYMENT:

covariate_employ_ART_constant = ones(32,1);

covariate_employ_ART_gender = [zeros(16,1); ones(16,1)];

covariates_employ_ART_gender = [covariate_employ_ART_constant t
covariate_employ_ART_gender covariate_employ_earn GDPARTIndustryVec];

%  Running regression for gender analysis of ARTS INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_GENDER_Covariates_ART,
SigmaEMPAR,EEMPAR,CovBEMPAR,logLEMPAR]  =
mvregress(covariates_employ_ART_gender,EmployARTGenderVec);

%  Reading data for gender analysis of HEALTH INDUSTRY EMPLOYMENT:

EmployHLTGender = [EmploymentData19952014(:,9), EmploymentData19952014(:,22)];

EmployHLTGender = [EmployHLTGender(3:5,:); EmployHLTGender(8:20,:)];

EmployHLTGenderVec = reshape(EmployHLTGender,32,1);

%  Forming covariates for gender analysis of HEALTH INDUSTRY EMPLOYMENT:

covariate_employ_HLT_constant = ones(32,1);

covariate_employ_HLT_gender = [zeros(16,1); ones(16,1)];
```

```
covariates_employ_HLT_gender = [covariate_employ_HLT_constant t
covariate_employ_HLT_gender covariate_employ_earn GDPHLTIndustryVec];

%  Running regression for gender analysis of HEALTH INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_GENDER_Covariates_HLT,
SigmaEMPHT,EEMPHT,CovBEMPHT,logLEMPHT]  =
mvregress(covariates_employ_HLT_gender,EmployHLTGenderVec);

%  Reading data for gender analysis of SERVICES INDUSTRY EMPLOYMENT:

EmploySRVGender = [EmploymentData19952014(:,10), EmploymentData19952014(:,23)];

EmploySRVGender = [EmploySRVGender(3:5,:); EmploySRVGender(8:20,:)];

EmploySRVGenderVec = reshape(EmploySRVGender,32,1);

%  Forming covariates for gender analysis of SERVICES INDUSTRY EMPLOYMENT:

covariate_employ_SRV_constant = ones(32,1);

covariate_employ_SRV_gender = [zeros(16,1); ones(16,1)];

covariates_employ_SRV_gender = [covariate_employ_SRV_constant t
covariate_employ_SRV_gender covariate_employ_earn GDPSRVIndustryVec];

%  Running regression for gender analysis of SERVICES INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_GENDER_Covariates_SRV,
SigmaEMPSV,EEMPSV,CovBEMPSV,logLEMPSV]  =
mvregress(covariates_employ_SRV_gender,EmploySRVGenderVec);
```

```
%  Reading data for gender analysis of SALES INDUSTRY EMPLOYMENT:

EmploySALGender = [EmploymentData19952014(:,11), EmploymentData19952014(:,24)];

EmploySALGender = [EmploySALGender(3:5,:); EmploySALGender(8:20,:)];

EmploySALGenderVec = reshape(EmploySALGender,32,1);

%  Forming covariates for gender analysis of SALES INDUSTRY EMPLOYMENT:

covariate_employ_SAL_constant = ones(32,1);

covariate_employ_SAL_gender = [zeros(16,1); ones(16,1)];

covariates_employ_SAL_gender = [covariate_employ_SAL_constant t
covariate_employ_SAL_gender covariate_employ_earn GDPSALIndustryVec];

%  Running regression for gender analysis of SALES INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_GENDER_Covariates_SAL,
SigmaEMPSA,EEMPSA,CovBEMPSA,logLEMPSA]  =
mvregress(covariates_employ_SAL_gender,EmploySALGenderVec);

%  Reading data for gender analysis of CONSTRUCTION INDUSTRY EMPLOYMENT:

EmployCSTGender = [EmploymentData19952014(:,12), EmploymentData19952014(:,25)];

EmployCSTGender = [EmployCSTGender(3:5,:); EmployCSTGender(8:20,:)];

EmployCSTGenderVec = reshape(EmployCSTGender,32,1);
```

```
%  Forming covariates for gender analysis of CONSTRUCTION INDUSTRY EMPLOYMENT:

covariate_employ_CST_constant = ones(32,1);

covariate_employ_CST_gender = [zeros(16,1); ones(16,1)];

covariates_employ_CST_gender = [covariate_employ_CST_constant t
covariate_employ_CST_gender covariate_employ_earn GDPCSTIndustryVec];

%  Running regression for gender analysis of CONSTRUCTION INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_GENDER_Covariates_CST,
SigmaEMPCO,EEMPCO,CovBEMPCO,logLEMPCO]  =
mvregress(covariates_employ_CST_gender,EmployCSTGenderVec);

%  Reading data for gender analysis of PRODUCTION & TRANSPORTATION INDUSTRY
EMPLOYMENT:

EmployPTSGender = [EmploymentData19952014(:,13), EmploymentData19952014(:,26)];

EmployPTSGender = [EmployPTSGender(3:5,:); EmployPTSGender(8:20,:)];

EmployPTSGenderVec = reshape(EmployPTSGender,32,1);

%  Forming covariates for gender analysis of PRODUCTION & TRANSPORTATION
INDUSTRY EMPLOYMENT:

covariate_employ_PTS_constant = ones(32,1);

covariate_employ_PTS_gender = [zeros(16,1); ones(16,1)];
```

```
covariates_employ_PTS_gender = [covariate_employ_PTS_constant t
covariate_employ_PTS_gender covariate_employ_earn GDPPTSIndustryVec];

% Running regression for gender analysis of PRODUCTION & TRANSPORTATION
INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_GENDER_Covariates_PTS,
SigmaEMPPT,EEMPPT,CovBEMPPT,logLEMPPT] =
mvregress(covariates_employ_PTS_gender,EmployPTSGenderVec);

EMPLOYMNT_Industry_Constant_Time_Gender_Earnings_GDP =
[EMPLOYMNT_GENDER_Covariates_MGMT EMPLOYMNT_GENDER_Covariates_BUS
EMPLOYMNT_GENDER_Covariates_COMP_MATH
EMPLOYMNT_GENDER_Covariates_ENGR EMPLOYMNT_GENDER_Covariates_LGL
EMPLOYMNT_GENDER_Covariates_EDU EMPLOYMNT_GENDER_Covariates_ART
EMPLOYMNT_GENDER_Covariates_HLT EMPLOYMNT_GENDER_Covariates_SRV
EMPLOYMNT_GENDER_Covariates_SAL EMPLOYMNT_GENDER_Covariates_CST
EMPLOYMNT_GENDER_Covariates_PTS]'

SigmaEMP = [SigmaEMPMgmt, SigmaEMPBUS, SigmaEMPCM, SigmaEMPEN,
SigmaEMPLG, SigmaEMPED, SigmaEMPAR, SigmaEMPHT, SigmaEMPSV, SigmaEMPSA,
SigmaEMPCO, SigmaEMPPT]

EEMPRace = [EEMPMgmt, EEMPBUS, EEMPCM, EEMPEN, EEMPLG, EEMPED,
EEMPAR, EEMPHT, EEMPSV, EEMPSA, EEMPCO, EEMPPT]
```

```
CovBEMPRace = [CovBEMPMgmt, CovBEMPBUS, CovBEMPCM, CovBEMPEN,
CovBEMPLG, CovBEMPED, CovBEMPAR, CovBEMPHT, CovBEMPSV, CovBEMPSA,
CovBEMPCO, CovBEMPPT]

logLEMPRace = [logLEMPMgmt, logLEMPBUS, logLEMPCM, logLEMPEN, logLEMPLG,
logLEMPED, logLEMPAR, logLEMPHT, logLEMPSV, logLEMPSA, logLEMPCO,
logLEMPPT]

%  ANALYSIS PART 4: EMPLOYMENT, RACE, INDUSTRY

%  NOTE:  Time and GDP variables were created in the above earnings

%  ANALYSIS PART 2 and are utilized again in the below employment analyses.

t = [t; time];

%  Reading data for race analysis of MANAGEMENT INDUSTRY EMPLOYMENT:

EmployMGMTRace = [EmploymentData19952014(:,28), EmploymentData19952014(:,41),
EmploymentData19952014(:,54)];

EmployMGMTRace = [EmployMGMTRace(3:5,:); EmployMGMTRace(8:20,:)];

EmployMGMTRaceVec = reshape(EmployMGMTRace,48,1);

%  Forming covariates for race analysis of MANAGEMENT INDUSTRY EMPLOYMENT:

GDPMGMTIndustryVec = [GDPMGMTIndustryVec; GDPMGMTIndustryVec];

GDPMGMTIndustryVec = GDPMGMTIndustryVec(1:48,1);

covariate_employ_MGMT_race_constant = ones(48,1);
```

```
covariate_employ_MGMT_black = [zeros(16,1); ones(16,1); zeros(16,1)];

covariate_employ_MGMT_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_MGMT_race_constant t
covariate_employ_MGMT_black covariate_employ_MGMT_hispanic
GDPMGMTIndustryVec];

%  Running regression for race analysis of MANAGEMENT INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_RACE_Covariates_MGMT
,SigmaEMPRMgmt,EEMPRMgmt,CovBEMPRMgmt,logLEMPRMgmt] =
mvregress(covariates_employ_race,EmployMGMTRaceVec);

%  Reading data for race analysis of BUSINESS INDUSTRY EMPLOYMENT:

EmployBUSRace = [EmploymentData19952014(:,29), EmploymentData19952014(:,42),
EmploymentData19952014(:,55)];

EmployBUSRace = [EmployBUSRace(3:5,:); EmployBUSRace(8:20,:)];

EmployBUSRaceVec = reshape(EmployBUSRace,48,1);

%  Forming covariates for race analysis of BUSINESS INDUSTRY EMPLOYMENT:

GDPBUSIndustryVec = [GDPBUSIndustryVec; GDPBUSIndustryVec];

GDPBUSIndustryVec = GDPBUSIndustryVec(1:48,1);

covariate_employ_BUS_race_constant = ones(48,1);

covariate_employ_BUS_black = [zeros(16,1); ones(16,1); zeros(16,1)];
```

```
covariate_employ_BUS_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_BUS_race_constant t
covariate_employ_BUS_black covariate_employ_BUS_hispanic GDPBUSIndustryVec];

%  Running regression for race analysis of BUSINESS INDUSTRY EMPLOYMENT:

[EMPLOYMNT_RACE_Covariates_BUS,SigmaEMPRBUS,EEMPRBUS,CovBEMPRBUS,log
LEMPRBUS] = mvregress(covariates_employ_race,EmployBUSRaceVec);

%  Reading data for race analysis of COMPUTER & MATH INDUSTRY EMPLOYMENT:

EmployCOMP_MATHRace = [EmploymentData19952014(:,30),
EmploymentData19952014(:,43), EmploymentData19952014(:,56)];

EmployCOMP_MATHRace = [EmployCOMP_MATHRace(3:5,:);
EmployCOMP_MATHRace(8:20,:)];

EmployCOMP_MATHRaceVec = reshape(EmployCOMP_MATHRace,48,1);

%  Forming covariates for race analysis of COMPUTER & MATH INDUSTRY
EMPLOYMENT:

GDPCOMP_MATHIndustryVec = [GDPCOMP_MATHIndustryVec;
GDPCOMP_MATHIndustryVec];

GDPCOMP_MATHIndustryVec = GDPCOMP_MATHIndustryVec(1:48,1);

covariate_employ_COMP_MATH_race_constant = ones(48,1);

covariate_employ_COMP_MATH_black = [zeros(16,1); ones(16,1); zeros(16,1)];
```

covariate_employ_COMP_MATH_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_COMP_MATH_race_constant t covariate_employ_COMP_MATH_black covariate_employ_COMP_MATH_hispanic GDPCOMP_MATHIndustryVec];

% Running regression for race analysis of COMPUTER & MATH INDUSTRY EMPLOYMENT:

[EMPLOYMNT_RACE_Covariates_COMP_MATH, SigmaEMPRCM,EEMPRCM,CovBEMPRCM,logLEMPRCM] = mvregress(covariates_employ_race,EmployCOMP_MATHRaceVec);

% Reading data for race analysis of ENGINEERING INDUSTRY EMPLOYMENT:

EmployENGRRace = [EmploymentData19952014(:,31), EmploymentData19952014(:,44), EmploymentData19952014(:,57)];

EmployENGRRace = [EmployENGRRace(3:5,:); EmployENGRRace(8:20,:)];

EmployENGRRaceVec = reshape(EmployENGRRace,48,1);

% Forming covariates for race analysis of ENGINEERING INDUSTRY EMPLOYMENT:

GDPENGRIndustryVec = [GDPENGRIndustryVec; GDPENGRIndustryVec];

GDPENGRIndustryVec = GDPENGRIndustryVec(1:48,1);

covariate_employ_ENGR_race_constant = ones(48,1);

covariate_employ_ENGR_black = [zeros(16,1); ones(16,1); zeros(16,1)];

```
covariate_employ_ENGR_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_ENGR_race_constant t
covariate_employ_ENGR_black covariate_employ_ENGR_hispanic GDPENGRIndustryVec];

%  Running regression for race analysis of ENGINEERING INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_RACE_Covariates_ENGR,
SigmaEMPREN,EEMPREN,CovBEMPREN,logLEMPREN] =
mvregress(covariates_employ_race,EmployENGRRaceVec);

%  Reading data for race analysis of LEGAL INDUSTRY EMPLOYMENT:

EmployLGLRace = [EmploymentData19952014(:,32), EmploymentData19952014(:,45),
EmploymentData19952014(:,58)];

EmployLGLRace = [EmployLGLRace(3:5,:); EmployLGLRace(8:20,:)];

EmployLGLRaceVec = reshape(EmployLGLRace,48,1);

%  Forming covariates for race analysis of LEGAL INDUSTRY EMPLOYMENT:

GDPLGLIndustryVec = [GDPLGLIndustryVec; GDPLGLIndustryVec];

GDPLGLIndustryVec = GDPLGLIndustryVec(1:48,1);

covariate_employ_LGL_race_constant = ones(48,1);

covariate_employ_LGL_black = [zeros(16,1); ones(16,1); zeros(16,1)];

covariate_employ_LGL_hispanic = [zeros(32,1); ones(16,1)];
```

```
covariates_employ_race = [covariate_employ_LGL_race_constant t
covariate_employ_LGL_black covariate_employ_LGL_hispanic GDPLGLIndustryVec];

%  Running regression for race analysis of LEGAL INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_RACE_Covariates_LGL,
SigmaEMPRLG,EEMPRLG,CovBEMPRLG,logLEMPRLG] =
mvregress(covariates_employ_race,EmployLGLRaceVec);

%  Reading data for race analysis of EDUCATION INDUSTRY EMPLOYMENT:

EmployEDURace = [EmploymentData19952014(:,33), EmploymentData19952014(:,46),
EmploymentData19952014(:,59)];

EmployEDURace = [EmployEDURace(3:5,:); EmployEDURace(8:20,:)];

EmployEDURaceVec = reshape(EmployEDURace,48,1);

%  Forming covariates for race analysis of EDUCATION INDUSTRY EMPLOYMENT:

GDPEDUIndustryVec = [GDPEDUIndustryVec; GDPEDUIndustryVec];

GDPEDUIndustryVec = GDPEDUIndustryVec(1:48,1);

covariate_employ_EDU_race_constant = ones(48,1);

covariate_employ_EDU_black = [zeros(16,1); ones(16,1); zeros(16,1)];

covariate_employ_EDU_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_EDU_race_constant t
covariate_employ_EDU_black covariate_employ_EDU_hispanic GDPEDUIndustryVec];
```

```
%  Running regression for race analysis of EDUCATION INDUSTRY EMPLOYMENT:

 [EMPLOYMNT_RACE_Covariates_EDU,
SigmaEMPRED,EEMPRED,CovBEMPRED,logLEMPRED] =
mvregress(covariates_employ_race,EmployEDURaceVec);

%  Reading data for race analysis of ARTS INDUSTRY EMPLOYMENT:

EmployARTRace = [EmploymentData19952014(:,34), EmploymentData19952014(:,47),
EmploymentData19952014(:,60)];

EmployARTRace = [EmployARTRace(3:5,:); EmployARTRace(8:20,:)];

EmployARTRaceVec = reshape(EmployARTRace,48,1);

%  Forming covariates for race analysis of ARTS INDUSTRY EMPLOYMENT:

GDPARTIndustryVec = [GDPARTIndustryVec; GDPARTIndustryVec];

GDPARTIndustryVec = GDPARTIndustryVec(1:48,1);

covariate_employ_ART_race_constant = ones(48,1);

covariate_employ_ART_black = [zeros(16,1); ones(16,1); zeros(16,1)];

covariate_employ_ART_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_ART_race_constant t
covariate_employ_ART_black covariate_employ_ART_hispanic GDPARTIndustryVec];

%  Running regression for race analysis of ARTS INDUSTRY EMPLOYMENT:
```

```
[EMPLOYMNT_RACE_Covariates_ART,
SigmaEMPRAR,EEMPRAR,CovBEMPRAR,logLEMPRAR] =
mvregress(covariates_employ_race,EmployARTRaceVec);

%  Reading data for race analysis of HEALTH INDUSTRY EMPLOYMENT:

EmployHLTRace = [EmploymentData19952014(:,35), EmploymentData19952014(:,48),
EmploymentData19952014(:,61)];

EmployHLTRace = [EmployHLTRace(3:5,:); EmployHLTRace(8:20,:)];

EmployHLTRaceVec = reshape(EmployHLTRace,48,1);

%  Forming covariates for race analysis of HEALTH INDUSTRY EMPLOYMENT:

GDPHLTIndustryVec = [GDPHLTIndustryVec; GDPHLTIndustryVec];

GDPHLTIndustryVec = GDPHLTIndustryVec(1:48,1);

covariate_employ_HLT_race_constant = ones(48,1);

covariate_employ_HLT_black = [zeros(16,1); ones(16,1); zeros(16,1)];

covariate_employ_HLT_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_HLT_race_constant t
covariate_employ_HLT_black covariate_employ_HLT_hispanic GDPHLTIndustryVec];

%  Running regression for race analysis of HEALTH INDUSTRY EMPLOYMENT:
```

```
 [EMPLOYMNT_RACE_Covariates_HLT,
SigmaEMPRHT,EEMPRHT,CovBEMPRHT,logLEMPRHT] =
mvregress(covariates_employ_race,EmployHLTRaceVec);

%  Reading data for race analysis of SERVICES INDUSTRY EMPLOYMENT:

EmploySRVRace = [EmploymentData19952014(:,36), EmploymentData19952014(:,49),
EmploymentData19952014(:,62)];

EmploySRVRace = [EmploySRVRace(3:5,:); EmploySRVRace(8:20,:)];

EmploySRVRaceVec = reshape(EmploySRVRace,48,1);

%  Forming covariates for race analysis of SERVICES INDUSTRY EMPLOYMENT:

GDPSRVIndustryVec = [GDPSRVIndustryVec; GDPSRVIndustryVec];

GDPSRVIndustryVec = GDPSRVIndustryVec(1:48,1);

covariate_employ_SRV_race_constant = ones(48,1);

covariate_employ_SRV_black = [zeros(16,1); ones(16,1); zeros(16,1)];

covariate_employ_SRV_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_SRV_race_constant t
covariate_employ_SRV_black covariate_employ_SRV_hispanic GDPSRVIndustryVec];

%  Running regression for race analysis of SERVICES INDUSTRY EMPLOYMENT:
```

```
 [EMPLOYMNT_RACE_Covariates_SRV,
SigmaEMPRSV,EEMPRSV,CovBEMPRSV,logLEMPRSV] =
mvregress(covariates_employ_race,EmploySRVRaceVec);

%  Reading data for race analysis of SALES INDUSTRY EMPLOYMENT:

EmploySALRace = [EmploymentData19952014(:,37), EmploymentData19952014(:,50),
EmploymentData19952014(:,63)];

EmploySALRace = [EmploySALRace(3:5,:); EmploySALRace(8:20,:)];

EmploySALRaceVec = reshape(EmploySALRace,48,1);

%  Forming covariates for race analysis of SALES INDUSTRY EMPLOYMENT:

GDPSALIndustryVec = [GDPSALIndustryVec; GDPSALIndustryVec];

GDPSALIndustryVec = GDPSALIndustryVec(1:48,1);

covariate_employ_SAL_race_constant = ones(48,1);

covariate_employ_SAL_black = [zeros(16,1); ones(16,1); zeros(16,1)];

covariate_employ_SAL_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_SAL_race_constant t
covariate_employ_SAL_black covariate_employ_SAL_hispanic GDPSALIndustryVec];

%  Running regression for race analysis of SALES INDUSTRY EMPLOYMENT:
```

```
[EMPLOYMNT_RACE_Covariates_SAL,
SigmaEMPRSA,EEMPRSA,CovBEMPRSA,logLEMPRSA] =
mvregress(covariates_employ_race,EmploySALRaceVec);

%  Reading data for race analysis of CONSTRUCTION INDUSTRY EMPLOYMENT:

EmployCSTRace = [EmploymentData19952014(:,38), EmploymentData19952014(:,51),
EmploymentData19952014(:,64)];

EmployCSTRace = [EmployCSTRace(3:5,:); EmployCSTRace(8:20,:)];

EmployCSTRaceVec = reshape(EmployCSTRace,48,1);

%  Forming covariates for race analysis of CONSTRUCTION INDUSTRY EMPLOYMENT:

GDPCSTIndustryVec = [GDPCSTIndustryVec; GDPCSTIndustryVec];

GDPCSTIndustryVec = GDPCSTIndustryVec(1:48,1);

covariate_employ_CST_race_constant = ones(48,1);

covariate_employ_CST_black = [zeros(16,1); ones(16,1); zeros(16,1)];

covariate_employ_CST_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_CST_race_constant t
covariate_employ_CST_black covariate_employ_CST_hispanic GDPCSTIndustryVec];

%  Running regression for race analysis of CONSTRUCTION INDUSTRY EMPLOYMENT:
```

[EMPLOYMNT_RACE_Covariates_CST, SigmaEMPRCO,EEMPRCO,CovBEMPRCO,logLEMPRCO] = mvregress(covariates_employ_race,EmployCSTRaceVec);

% Reading data for race analysis of PRODUCTION & TRANSPORTATION INDUSTRY EMPLOYMENT:

EmployPTSRace = [EmploymentData19952014(:,39), EmploymentData19952014(:,52), EmploymentData19952014(:,65)];

EmployPTSRace = [EmployPTSRace(3:5,:); EmployPTSRace(8:20,:)];

EmployPTSRaceVec = reshape(EmployPTSRace,48,1);

% Forming covariates for race analysis of PRODUCTION & TRANSPORTATION INDUSTRY EMPLOYMENT:

GDPPTSIndustryVec = [GDPPTSIndustryVec; GDPPTSIndustryVec];

GDPPTSIndustryVec = GDPPTSIndustryVec(1:48,1);

covariate_employ_PTS_race_constant = ones(48,1);

covariate_employ_PTS_black = [zeros(16,1); ones(16,1); zeros(16,1)];

covariate_employ_PTS_hispanic = [zeros(32,1); ones(16,1)];

covariates_employ_race = [covariate_employ_PTS_race_constant t covariate_employ_PTS_black covariate_employ_PTS_hispanic GDPPTSIndustryVec];

% Running regression for race analysis of PRODUCTION & TRANSPORTATION INDUSTRY EMPLOYMENT:

```
[EMPLOYMNT_RACE_Covariates_PTS,
SigmaEMPRPT,EEMPRPT,CovBEMPRPT,logLEMPRPT] =
mvregress(covariates_employ_race,EmployPTSRaceVec);

EMPLOYMNT_Industry_Constant_Time_Black_Hispanic_GDP =
[EMPLOYMNT_RACE_Covariates_MGMT EMPLOYMNT_RACE_Covariates_BUS
EMPLOYMNT_RACE_Covariates_COMP_MATH EMPLOYMNT_RACE_Covariates_ENGR
EMPLOYMNT_RACE_Covariates_LGL EMPLOYMNT_RACE_Covariates_EDU
EMPLOYMNT_RACE_Covariates_ART EMPLOYMNT_RACE_Covariates_HLT
EMPLOYMNT_RACE_Covariates_SRV EMPLOYMNT_RACE_Covariates_SAL
EMPLOYMNT_RACE_Covariates_CST EMPLOYMNT_RACE_Covariates_PTS]'

SigmaEMPR = [SigmaEMPRMgmt, SigmaEMPRBUS, SigmaEMPRCM, SigmaEMPREN,
SigmaEMPRLG, SigmaEMPRED, SigmaEMPRAR, SigmaEMPRHT, SigmaEMPRSV,
SigmaEMPRSA, SigmaEMPRCO, SigmaEMPRPT]

EEMPRRace = [EEMPRMgmt, EEMPRBUS, EEMPRCM, EEMPREN, EEMPRLG,
EEMPRED, EEMPRAR, EEMPRHT, EEMPRSV, EEMPRSA, EEMPRCO, EEMPRPT]

CovBEMPRRace = [CovBEMPRMgmt, CovBEMPRBUS, CovBEMPRCM, CovBEMPREN,
CovBEMPRLG, CovBEMPRED, CovBEMPRAR, CovBEMPRHT, CovBEMPRSV,
CovBEMPRSA, CovBEMPRCO, CovBEMPRPT]
```

logLEMPRRace = [logLEMPRMgmt, logLEMPRBUS, logLEMPRCM, logLEMPREN, logLEMPRLG, logLEMPRED, logLEMPRAR, logLEMPRHT, logLEMPRSV, logLEMPRSA, logLEMPRCO, logLEMPRPT]

APPENDIX B: EARNINGS RACE ANALYSIS OUTPUT

EARNING_RACE_Covariates_Constant_Time_Gender_Black_Hispanic_GDP =

232.5928

7.6603

-74.2222

-146.5556

-220.3333

0.0286

SigmaEarningsRace =

4.3749e+03

EEarningsRace =

15.3111

29.5888

23.3546

21.6306

21.5032

38.3791

33.3414

28.2909

18.4348

17.9016

29.7970

60.3769

84.5088

71.3910

62.9480

68.7210

59.5100

54.0112

14.8666

-362.8556

6.9102

21.1862

18.0587

5.9346

19.8970

11.8464

-19.0097

-5.5428

-11.6475

1.9324

7.0644

0.9465

6.5036

1.2765

-13.9344

-16.4332

31.6444

25.9222

19.6880

16.9640

9.8365
5.7124
2.6747
-3.3758
-15.2319
-17.7651
-17.8697
14.7102
-484.1578
1.7243
-1.7186
2.0543
-10.1567
-6.6555
-49.4667
-48.1889
-53.4231

-51.1471
-59.2746
-40.3987
-40.4364
-45.4869
-54.3430
-59.8762
-57.9808
-36.4009
-17.2689
-20.3868
-15.8298
-26.0568
-28.2678
-34.7666
35.0888
32.3666

24.1324
27.4084
13.2809
31.1568
30.1192
22.0687
-4.7874
-3.3206
-4.4252
10.1547
42.2866
34.1688
22.7258
9.4987
2.2878
-11.2110
67.8666

60.1444

40.9102

38.1862

26.0587

26.9346

22.8970

9.8464

-1.0097

-8.5428

9.3525

30.9324

43.0644

23.9465

19.5036

5.2765

11.0656

-0.4332

CovBEarningsRace =

1.0e+04 *

2.7294	0.0739	-0.0081	-0.0122	-0.0122	-0.0003
0.0739	0.0022	-0.0000	-0.0000	-0.0000	-0.0000
-0.0081	-0.0000	0.0162	0.0000	0.0000	0.0000
-0.0122	-0.0000	0.0000	0.0243	0.0122	0.0000
-0.0122	-0.0000	0.0000	0.0122	0.0243	0.0000
-0.0003	-0.0000	0.0000	0.0000	0.0000	0.0000

logLEarningsRace =

-605.9619

APPENDIX C: EARNINGS GENDER ANALYSIS OUTPUT

EARNINGS_Industry_Constant_Time_Gender_GDP =

1.0e+03 *

0.9190	0.0565	-0.2820	-0.0011
0.8816	0.0228	-0.1414	-0.0000
0.9128	0.0209	-0.2139	0.0003
1.1880	0.0472	-0.2151	-0.0006
0.9564	-0.0399	-0.6034	0.0040
0.7258	0.0191	-0.1938	0.0000
0.7875	0.0197	-0.0921	-0.0001
-0.7634	-0.3050	-0.2730	0.0038
0.2431	0.0017	-0.1057	0.0001
0.5949	0.0149	-0.1804	-0.0000
0.2986	0.0104	-0.1624	0.0001
0.2986	0.0104	-0.1624	0.0001

SigmaEarnings =

1.0e+05 *

Columns 1 through 11

0.0751   0.0334   0.0129   0.0252   1.1496   0.0161   0.3098   0.6483   0.0006   0.0085
0.0099

Column 12

0.0099

EEarningsRace =

1.0e+03 *

Columns 1 through 11

-0.0814   -0.0729   -0.0598   -0.0105   -0.2103   -0.0535   0.0020   -0.2488   -0.0163   0.0107
-0.0314

-0.1037   -0.0146   -0.0496   -0.0103   -0.1459   -0.0599   -0.0247   -0.0619   -0.0096   0.0165
-0.0250

-0.0825   0.0127   -0.0085   0.0154   -0.1294   -0.0572   0.0034   0.1974   -0.0078   0.0490   -
0.0304

-0.1037   0.0617   0.0351   0.0543   0.1120   -0.0554   0.0271   0.4435   0.0024   0.0849   -
0.0405

0.0339   -0.0710   -0.0202   -0.0536   -0.0768   0.0012   0.0393   -0.0984   0.0088   -0.0112
0.0345

0.0357 -0.1007 -0.0169 -0.0177 -0.0032 0.0339 0.0524 -0.0295 0.0080 -0.0099

0.0163

0.0265 -0.0933 -0.0222 -0.0299 -0.0614 0.0185 0.0640 -0.0706 -0.0037 0.0004

-0.0195

0.0694 -0.0189 0.0105 0.0095 0.1382 0.0080 0.1104 -0.0018 -0.0026 -0.0043 -

0.0096

0.0964 0.1184 0.0095 -0.0199 -0.0146 0.0264 0.0771 0.0470 0.0044 0.0016 -

0.0146

0.1305 0.1216 0.0110 -0.0294 0.1455 0.0198 0.0935 0.0518 0.0114 0.0058 -

0.0082

0.0378 0.0828 0.0095 0.0533 0.2756 0.0483 0.0769 0.0490 -0.0035 -0.0134

0.0554

0.0463 0.1050 -0.0285 -0.1333 0.2337 0.0256 0.0809 0.1642 0.0033 -0.0214

0.0375

-0.0625 -0.0417 0.0212 0.0347 0.3191 0.0501 0.0889 0.0770 0.0042 -0.0301

0.0281

-0.0067 -0.0154 0.0401 0.0318 0.4530 0.0548 0.1402 0.1962 -0.0109 -0.0101

0.0214

-0.0105 -0.0490 0.0553 0.0480 -1.4088 -0.0845 -0.9250 -0.9615 -0.0025 -0.0336

0.0023

-0.0254 -0.0247 0.0136 0.0575 0.3733 0.0240 0.0935 0.2464 0.0145 -0.0350 -
0.0163

0.0686 0.0345 0.0492 0.0276 0.0842 0.0402 -0.0789 -0.2028 -0.0006 -0.0600
0.0081

0.0513 0.0288 0.0373 0.0249 0.0656 0.0319 -0.0546 -0.0679 0.0031 -0.0531
0.0084

0.0775 0.0232 0.0255 0.0856 0.0760 0.0275 -0.0475 0.0164 -0.0002 -0.0376 -
0.0029

-0.0257 0.0241 0.0290 0.0675 0.3065 0.0303 -0.0329 0.0855 0.0060 -0.0357 -
0.0041

-0.0831 -0.0376 -0.0303 -0.1055 -0.1574 -0.0011 -0.0577 -0.0574 0.0175 0.0132
0.0330

-0.0943 0.0058 0.0140 -0.0616 -0.1158 0.0007 -0.0295 -0.0105 0.0117 0.0135
0.0057

-0.0805 0.0182 0.0247 -0.0028 -0.1430 0.0053 0.0061 -0.0066 0.0030 0.0108
0.0009

-0.0516 0.0315 0.0365 0.0157 -0.0914 -0.0043 -0.0065 0.0332 -0.0009 0.0280
0.0108

0.1644 -0.0532 -0.0536 -0.0168 -0.0601 -0.0029 -0.0189 0.0390 0.0011 0.0180
0.0128

0.1575 -0.0560 -0.0601 -0.0393 0.0149 0.0115 0.0116 0.0238 -0.0019 0.0311

0.0563

0.1348 0.0692 0.0684 0.0114 0.1231 0.0100 -0.0160 0.0620 -0.0048 0.0200

0.0328

0.1003 -0.0625 -0.0676 -0.0992 0.1371 0.0163 0.0299 0.1372 -0.0111 0.0200

0.0110

-0.1125 0.0008 -0.0079 0.0468 0.1676 0.0038 0.0419 0.1860 -0.0081 0.0143 -

0.0345

-0.1007 -0.0019 -0.0140 0.0250 0.1854 -0.0264 0.0623 0.2042 -0.0132 0.0123 -

0.0152

-0.0985 0.0034 -0.0088 0.0031 -0.8053 -0.1168 0.1591 -0.6885 0.0002 0.0058 -

0.0142

-0.1074 -0.0282 -0.0424 0.0176 0.2127 -0.0262 0.0316 0.2464 -0.0018 -0.0006

-0.1088

Column 12

-0.0314

-0.0250

-0.0304

-0.0405

0.0345
0.0163
-0.0195
-0.0096
-0.0146
-0.0082
0.0554
0.0375
0.0281
0.0214
0.0023
-0.0163
0.0081
0.0084
-0.0029
-0.0041
0.0330

0.0057

0.0009

0.0108

0.0128

0.0563

0.0328

0.0110

-0.0345

-0.0152

-0.0142

-0.1088

CovBEarningsRace =

1.0e+06 *

Columns 1 through 11

0.0073 0.0011 -0.0005 -0.0001 0.0095 0.0006 -0.0002 -0.0000 0.0019 0.0002 -
0.0001

0.0011 0.0003 -0.0000 -0.0000 0.0006 0.0000 -0.0000 -0.0000 0.0002 0.0000
0.0000

-0.0005 -0.0000 0.0009 0.0000 -0.0002 -0.0000 0.0004 0.0000 -0.0001 0.0000

0.0002

-0.0001 -0.0000 0.0000 0.0000 -0.0000 -0.0000 0.0000 0.0000 -0.0000 -0.0000

-0.0000

Columns 12 through 22

-0.0000 0.0150 0.0014 -0.0002 -0.0000 0.4095 0.0197 -0.0072 -0.0025 0.0048

0.0008

-0.0000 0.0014 0.0001 -0.0000 -0.0000 0.0197 0.0013 0.0000 -0.0001 0.0008

0.0002

-0.0000 -0.0002 -0.0000 0.0003 0.0000 -0.0072 0.0000 0.0144 -0.0000 -0.0001

0.0000

0.0000 -0.0000 -0.0000 0.0000 0.0000 -0.0025 -0.0001 -0.0000 0.0000 -0.0001

-0.0000

Columns 23 through 33

-0.0001 -0.0001 0.4128 0.0270 -0.0019 -0.0004 2.4694 0.3414 -0.0041 -0.0045

0.0007

0.0000 -0.0000 0.0270 0.0019 -0.0000 -0.0000 0.3414 0.0478 -0.0000 -0.0006

0.0001

0.0002 -0.0000 -0.0019 -0.0000 0.0039 0.0000 -0.0041 -0.0000 0.0081 0.0000 -

0.0000

-0.0000 0.0000 -0.0004 -0.0000 0.0000 0.0000 -0.0045 -0.0006 0.0000 0.0000 -
0.0000

Columns 34 through 44

0.0001 -0.0000 -0.0000 0.0043 0.0003 -0.0001 -0.0000 0.0014 0.0001 -0.0001 -
0.0000

0.0000 -0.0000 -0.0000 0.0003 0.0000 -0.0000 -0.0000 0.0001 0.0000 -0.0000 -
0.0000

-0.0000 0.0000 0.0000 -0.0001 -0.0000 0.0001 0.0000 -0.0001 -0.0000 0.0001
0.0000

-0.0000 0.0000 0.0000 -0.0000 -0.0000 0.0000 0.0000 -0.0000 -0.0000 0.0000
0.0000

Columns 45 through 48

0.0014 0.0001 -0.0001 -0.0000

0.0001 0.0000 -0.0000 -0.0000

-0.0001 -0.0000 0.0001 0.0000

-0.0000 -0.0000 0.0000 0.0000

logLEarningsRace =

Columns 1 through 11

-188.1989 -175.2096 -159.9989 -170.7168 -231.8433 -163.5615 -210.8645 -222.6774 -111.6357 -153.2814 -155.8156

Column 12

-155.8156

APPENDIX D: EMPLOYMENT GENDER ANALYSIS OUTPUT

EMPLOYMNT_Industry_Constant_Time_Gender_Earnings_GDP =

57.3437	-0.0000	-14.6875	0.0000	0.0000
45.6500	0.0000	8.7000	-0.0000	0.0000
72.8750	-0.0000	-45.7500	0.0000	0.0000
86.7562	-0.0000	-73.5125	0.0000	0.0000
55.4063	0.0000	-10.8125	-0.0000	0.0000
25.8375	-0.0000	48.3250	0.0000	-0.0000
51.9813	0.0000	-3.9625	-0.0000	-0.0000
37.9125	0.0000	24.1750	0.0000	-0.0000
42.3937	-0.0000	15.2125	0.0000	-0.0000
40.3625	0.0000	19.2750	-0.0000	-0.0000
94.5125	-0.0000	-89.0250	0.0000	-0.0000
77.3125	0.0000	-54.6250	-0.0000	0.0000

SigmaEMP =

Columns 1 through 11

75.7937 5.8737 4.4569 1.9075 89.6643 0.4648 2.0428 430.4573 1.7793 32.0661
3.2861

Column 12

1.2211

EEMPRace =

Columns 1 through 11

-15.0437 4.8500 -3.2750 3.0438 17.8937 -1.5375 -1.2813 36.8875 -1.7937 9.4375
-3.4125

-14.4437 5.8500 -1.7750 1.7438 15.9937 -1.1375 -3.3813 35.7875 -1.8937 9.3375
-2.8125

-15.1438 3.2500 -3.9750 2.2438 15.6938 -0.7375 -1.8813 37.9875 -2.7937 9.5375
-3.5125

-15.5438 1.7500 -3.6750 1.6438 15.2938 -0.8375 -1.7813 32.8875 -2.2937 10.6375
-2.7125

5.5563 -1.0500 -1.6750 -0.8562 -1.6063 0.3625 0.4187 -11.6125 0.4063 -4.1625
0.7875

5.9563 -1.4500 0.1250 -0.5562 -4.3063 0.7625 1.0187 -11.1125 0.8063 -4.2625
0.9875

5.4563 -1.5500 0.1250 -0.5562 -4.8063 0.3625 0.2187 -11.1125 0.3063 -3.6625
0.8875

5.9562 -0.6500 0.4250 -1.2562 -7.1063 -0.0375 -0.7813 -11.3125 0.3063 -3.6625
0.7875

5.1562	-1.5500	1.5250	-1.1562	-6.9063	0.8625	0.9187	-11.5125	0.4063	-3.7625	1.2875
5.2562	-1.8500	2.3250	-0.2563	-7.3062	0.1625	0.2188	-12.5125	0.4063	-3.5625	1.2875
5.2562	-1.9500	2.3250	-0.5562	-5.2062	-0.1375	1.4187	-12.5125	0.4063	-3.3625	1.0875
4.4562	-0.5500	1.3250	0.3438	-4.2062	0.3625	1.8187	-12.2125	0.8063	-3.2625	0.8875
4.5563	-0.9500	2.1250	-0.3562	-5.2062	0.5625	1.9187	-12.3125	1.7063	-2.6625	1.2875
4.0563	-1.4500	1.5250	-0.4562	-5.8063	0.5625	-0.2813	-12.9125	1.3063	-2.1625	1.1875
4.4563	-1.3500	1.0250	-0.8562	-6.2063	0.3625	0.8187	-12.3125	1.0063	-2.2625	0.8875
4.0563	-1.3500	1.5250	-2.1562	-6.2063	0.0625	0.6187	-12.1125	0.9063	-2.1625	1.0875
15.0438	-4.8500	3.2750	-3.0437	-17.8938	1.5375	1.2812	-36.8875	1.7938	-9.4375	3.4125
14.4438	-5.8500	1.7750	-1.7437	-15.9938	1.1375	3.3812	-35.7875	1.8938	-9.3375	2.8125

15.1437	-3.2500	3.9750	-2.2437	-15.6937	0.7375	1.8812	-37.9875	2.7938	-9.5375	3.5125
15.5438	-1.7500	3.6750	-1.6437	-15.2937	0.8375	1.7812	-32.8875	2.2938	-10.6375	2.7125
-5.5562	1.0500	1.6750	0.8563	1.6062	-0.3625	-0.4188	11.6125	-0.4062	4.1625	-0.7875
-5.9562	1.4500	-0.1250	0.5563	4.3062	-0.7625	-1.0188	11.1125	-0.8062	4.2625	-0.9875
-5.4562	1.5500	-0.1250	0.5563	4.8062	-0.3625	-0.2188	11.1125	-0.3062	3.6625	-0.8875
-5.9563	0.6500	-0.4250	1.2563	7.1062	0.0375	0.7812	11.3125	-0.3062	3.6625	-0.7875
-5.1563	1.5500	-1.5250	1.1563	6.9062	-0.8625	-0.9188	11.5125	-0.4062	3.7625	-1.2875
-5.2563	1.8500	-2.3250	0.2562	7.3063	-0.1625	-0.2188	12.5125	-0.4062	3.5625	-1.2875
-5.2563	1.9500	-2.3250	0.5562	5.2063	0.1375	-1.4188	12.5125	-0.4062	3.3625	-1.0875
-4.4563	0.5500	-1.3250	-0.3438	4.2063	-0.3625	-1.8188	12.2125	-0.8062	3.2625	-0.8875

-4.5562 0.9500 -2.1250 0.3563 5.2063 -0.5625 -1.9188 12.3125 -1.7062 2.6625

-1.2875

-4.0562 1.4500 -1.5250 0.4562 5.8062 -0.5625 0.2812 12.9125 -1.3062 2.1625

-1.1875

-4.4562 1.3500 -1.0250 0.8563 6.2062 -0.3625 -0.8188 12.3125 -1.0062 2.2625

-0.8875

-4.0562 1.3500 -1.5250 2.1563 6.2062 -0.0625 -0.6188 12.1125 -0.9062 2.1625

-1.0875

Column 12

-2.0125

-1.9125

-1.4125

-0.0125

-1.0125

-0.3125

-0.2125

-0.1125

-0.3125

0.2875

1.2875

1.4875

1.0875

0.8875

1.2875

0.9875

2.0125

1.9125

1.4125

0.0125

1.0125

0.3125

0.2125

0.1125

0.3125

-0.2875

-1.2875

-1.4875

-1.0875

-0.8875

-1.2875

-0.9875

CovBEMPRace =

1.0e+04 *

Columns 1 through 11

0.8963 0.0430 -0.0005 -0.0018 -0.0005 0.0413 0.0015 -0.0000 -0.0001 0.0000
0.0370

0.0430 0.0022 -0.0000 -0.0001 -0.0000 0.0015 0.0001 -0.0000 -0.0000 -0.0000
0.0016

-0.0005 -0.0000 0.0009 0.0000 -0.0000 -0.0000 -0.0000 0.0001 0.0000 0.0000 -
0.0000

-0.0018 -0.0001 0.0000 0.0000 0.0000 -0.0001 -0.0000 0.0000 0.0000 -0.0000 -
0.0001

-0.0005 -0.0000 -0.0000 0.0000 0.0000 0.0000 -0.0000 0.0000 -0.0000 0.0000 -
0.0000

Columns 12 through 22

0.0016 -0.0000 -0.0001 -0.0000 0.0132 0.0005 -0.0000 -0.0000 0.0000 0.6830

0.0243

0.0001 0.0000 -0.0000 -0.0000 0.0005 0.0000 -0.0000 -0.0000 -0.0000 0.0243

0.0009

0.0000 0.0001 -0.0000 -0.0000 -0.0000 -0.0000 0.0000 0.0000 0.0000 -0.0006 -

0.0000

-0.0000 -0.0000 0.0000 0.0000 -0.0000 -0.0000 0.0000 0.0000 -0.0000 -0.0016

-0.0001

-0.0000 -0.0000 0.0000 0.0000 0.0000 -0.0000 0.0000 -0.0000 0.0000 0.0003

0.0000

Columns 23 through 33

-0.0006 -0.0016 0.0003 0.0036 0.0002 -0.0000 -0.0000 -0.0000 0.0183 0.0008 -

0.0000

-0.0000 -0.0001 0.0000 0.0002 0.0000 -0.0000 -0.0000 -0.0000 0.0008 0.0000

0.0000

0.0011 0.0000 -0.0000 -0.0000 -0.0000 0.0000 0.0000 0.0000 -0.0000 0.0000

0.0000

0.0000 0.0000 -0.0000 -0.0000 -0.0000 0.0000 0.0000 0.0000 -0.0000 -0.0000 -

0.0000

-0.0000 -0.0000 0.0000 -0.0000 -0.0000 0.0000 0.0000 0.0000 -0.0000 -0.0000

0.0000

Columns 34 through 44

-0.0000 -0.0000 4.6846 0.3441 -0.0027 -0.0065 -0.0030 0.0185 0.0004 -0.0000

-0.0001

-0.0000 -0.0000 0.3441 0.0363 -0.0000 -0.0002 -0.0004 0.0004 0.0000 0.0000 -

0.0000

-0.0000 0.0000 -0.0027 -0.0000 0.0054 0.0000 0.0000 -0.0000 0.0000 0.0000 -

0.0000

0.0000 0.0000 -0.0065 -0.0002 0.0000 0.0000 0.0000 -0.0001 -0.0000 -0.0000

0.0000

0.0000 0.0000 -0.0030 -0.0004 0.0000 0.0000 0.0000 0.0000 -0.0000 0.0000 -

0.0000

Columns 45 through 55

0.0000 0.3445 0.0141 -0.0002 -0.0006 -0.0000 0.0230 0.0008 -0.0000 -0.0001

0.0000

-0.0000 0.0141 0.0006 0.0000 -0.0000 -0.0000 0.0008 0.0000 -0.0000 -0.0000

0.0000

0.0000 -0.0002 0.0000 0.0004 -0.0000 -0.0000 -0.0000 -0.0000 0.0000 0.0000 -

0.0000

-0.0000 -0.0006 -0.0000 -0.0000 0.0000 0.0000 -0.0001 -0.0000 0.0000 0.0000
-0.0000

0.0000 -0.0000 -0.0000 -0.0000 0.0000 0.0000 0.0000 0.0000 -0.0000 -0.0000
0.0000

Columns 56 through 60

0.0086 0.0003 -0.0000 -0.0000 0.0000

0.0003 0.0000 0.0000 -0.0000 0.0000

-0.0000 0.0000 0.0000 -0.0000 0.0000

-0.0000 -0.0000 -0.0000 0.0000 -0.0000

0.0000 0.0000 0.0000 -0.0000 0.0000

logLEMPRace =

Columns 1 through 11

-114.6543 -73.7339 -69.3172 -55.7384 -117.3432 -33.1492 -56.8350 -142.4436 -54.6259 -
100.8908 -64.4412

Column 12

-48.6020

APPENDIX E: EMPLOYMENT RACE ANALYSIS OUTPUT

EMPLOYMNT_Industry_Constant_Time_Black_Hispanic_GDP =

85.9812	-0.0000	-78.9438	-79.0000	0.0000
82.6063	-0.0000	-72.1563	-75.6625	0.0000
87.4250	0.0000	-80.0500	-82.2250	-0.0000
88.8563	0.0000	-83.6500	-82.9187	-0.0000
88.3125	0.0000	-82.2688	-82.6688	-0.0000
82.8500	-0.0000	-73.1062	-75.4437	0.0000
86.1063	0.0000	-80.0187	-78.3000	-0.0000
85.4125	0.0000	-76.5313	-79.7063	-0.0000
64.2875	-0.0000	-48.0813	-44.7812	0.0000
77.8937	-0.0000	-67.2187	-66.4625	0.0000
70.9562	0.0000	-63.7813	-49.0875	-0.0000
66.9625	0.0000	-52.4250	-48.4625	0.0000

SigmaEMPR =

Columns 1 through 11

1.5630   1.5598   0.7521   3.1751   3.3795   1.2035   1.2728   7.4961   3.9803   6.0290
16.0872

Column 12

12.7499

EEMPRRace =

Columns 1 through 11

0.5188 -0.1063 1.9750 3.5438 5.0875 1.0500 3.0937 6.9875 3.5125 6.4063
8.8438

-1.0812 0.7937 1.1750 3.2438 4.3875 1.7500 2.0937 6.3875 3.1125 5.3063
8.6438

-1.0812 -1.5063 1.4750 3.1438 2.5875 1.8500 1.9937 6.0875 2.2125 5.5063
8.2438

-1.4812 -3.2063 0.1750 2.8438 3.6875 0.9500 0.8937 5.1875 0.0125 4.0063
4.5438

2.3188 1.8937 -1.0250 1.5438 -0.3125 0.2500 -0.2063 -0.4125 1.4125 0.4063
0.5438

1.8188 1.2937 -0.4250 0.5438 -0.4125 0.8500 0.2937 -0.9125 1.0125 0.5063
0.0438

1.7188 1.0937 0.3750 -0.0562 -1.2125 0.3500 0.8937 -0.7125 0.7125 -0.1937 -
1.1562

0.7188 0.7937 0.2750 -0.3562 -0.5125 0.0500 -0.6063 -1.6125 0.3125 -0.5937 -
2.3562

0.3187 -0.3063 0.1750 -0.5562 -1.0125 -0.0500 -0.5063 -1.2125 -0.0875 -1.3937
-3.2562

0.3187 0.0937 0.2750 -0.6562 -1.9125 0.4500 -0.5063 -1.5125 -0.3875 -1.6937
-2.8562

0.3188 0.0937 0.4750 -5.9562 0.1875 0.1500 -1.6063 -2.8125 -0.2875 -1.4937 -
1.9562

0.0188 0.4937 0.3750 -0.8562 -0.3125 -0.2500 -0.4063 -2.4125 -0.8875 -1.7937
-2.6562

0.0188 -0.2063 -0.0250 -0.4562 -1.0125 -0.8500 -1.2063 -2.1125 -0.6875 -2.3937
-2.7562

-1.6813 -0.4063 -0.9250 -1.8562 -2.8125 -2.0500 -1.0063 -3.3125 -2.7875 -3.6937
-3.4562

-0.9813 -0.3063 -2.0250 -1.8562 -2.7125 -1.8500 -1.0063 -3.3125 -3.2875 -4.0938
-4.5562

-1.7813 -0.5063 -2.3250 -2.2562 -3.7125 -2.6500 -2.2062 -4.3125 -3.8875 -4.7938
-5.8562

1.3625 1.4500 0.1250 -1.5063 -3.2438 0.9562 -1.0875 -5.2812 1.3937 -2.5750
0.9250

2.6625 1.6500 -0.1750 -1.2063 -1.7438 0.2562 0.1125 -4.6812 1.3937 -1.7750
0.8250

2.7625 3.5500 0.1250 -0.8063 -0.8438 0.1562 0.5125 -4.4813 2.0937 -1.9750
0.8250

1.9625 2.5500 -0.0750 -1.0063 -1.3438 0.3562 -0.3875 -4.1813 1.3938 -2.1750
0.2250

-1.1375 -1.1500 0.7250 -0.8063 -0.0438 0.0562 0.3125 1.2187 -0.8062 0.2250
0.0250

-1.1375 -0.8500 0.1250 -0.3063 0.3562 -0.3438 0.0125 1.1187 -0.6062 0.1250 -
0.2750

-1.0375 -0.6500 -0.4750 -0.1063 -0.0438 0.1562 -0.1875 1.0187 -0.4062 0.5250
-0.0750

-0.8375 -0.4500 -0.0750 0.3938 0.4562 0.0562 0.6125 1.7187 -0.3062 0.5250 -
0.3750

-0.7375 0.0500 -0.1750 0.0938 0.6562 -0.1438 -0.3875 1.3187 -0.7062 0.9250 -
0.0750

-0.6375 -1.0500 -0.1750 -0.1062 0.9562 -0.5438 0.0125 1.3188 -0.3062 0.8250
-0.2750

-0.8375 -1.1500 -0.6750 4.6937 0.4562 -0.5438 0.6125 2.2188 -0.8062 0.5250 -
0.3750

-0.6375 -0.6500 -0.6750 -0.0063 0.4562 -0.3438 -0.5875 1.9188 -0.9062 0.6250
-0.4750

-0.7375 -0.6500 -0.4750 -0.0063 1.2562 -0.0438 -0.0875 1.1187 -0.8062 0.6250

-0.6750

-0.1375 -0.6500 0.0250 0.3937 1.0562 -0.2438 -0.0875 1.7188 -0.3062 1.1250 -

0.1750

-0.5375 -1.0500 0.9250 0.2937 0.1562 -0.3438 0.4125 1.6187 -0.3062 1.1250 -

0.1750

-0.3375 -0.9500 0.9250 -0.0063 1.4562 0.5562 0.2125 2.3188 -0.0062 1.3250

0.1250

-1.8812 -1.3437 -2.1000 -2.0375 -1.8438 -2.0063 -2.0063 -1.7062 -4.9063 -3.8313

-9.7687

-1.5812 -2.4437 -1.0000 -2.0375 -2.6438 -2.0063 -2.2063 -1.7062 -4.5063 -3.5313

-9.4687

-1.6812 -2.0437 -1.6000 -2.3375 -1.7438 -2.0063 -2.5063 -1.6063 -4.3063 -3.5313

-9.0687

-0.4812 0.6563 -0.1000 -1.8375 -2.3438 -1.3063 -0.5063 -1.0063 -1.4063 -1.8313

-4.7687

-1.1812 -0.7437 0.3000 -0.7375 0.3562 -0.3063 -0.1063 -0.8063 -0.6063 -0.6313

-0.5687

-0.6812 -0.4438 0.3000 -0.2375 0.0563 -0.5063 -0.3063 -0.2063 -0.4063 -0.6313

0.2313

-0.6812	-0.4438	0.1000	0.1625	1.2562	-0.5062	-0.7063	-0.3062	-0.3063	-0.3313	1.2313
0.1188	-0.3438	-0.2000	-0.0375	0.0562	-0.1063	-0.0063	-0.1063	-0.0063	0.0687	2.7313
0.4188	0.2562	-0.0000	0.4625	0.3562	0.1937	0.8937	-0.1062	0.7937	0.4687	3.3313
0.3188	0.9562	-0.1000	0.7625	0.9562	0.0937	0.4937	0.1938	0.6937	0.8687	3.1313
0.5188	1.0562	0.2000	1.2625	-0.6438	0.3937	0.9937	0.5938	1.0937	0.9687	2.3313
0.6188	0.1562	0.3000	0.8625	-0.1438	0.5937	0.9937	0.4938	1.7937	1.1687	3.1313
0.7188	0.8562	0.5000	0.4625	-0.2438	0.8937	1.2937	0.9938	1.4937	1.7687	3.4313
1.8188	1.0562	0.9000	1.4625	1.7562	2.2938	1.0937	1.5938	3.0937	2.5687	3.6313
1.5188	1.3562	1.1000	1.5625	2.5562	2.1937	0.5937	1.6937	3.5937	2.9687	4.7313
2.1188	1.4562	1.4000	2.2625	2.2562	2.0938	1.9938	1.9938	3.8937	3.4687	5.7313

Column 12

2.5375

1.3375

0.7375

-1.6625

-0.8625

-0.0625

-0.2625

-0.7625

-1.2625

-1.8625

15.8375

-1.8625

-1.6625

-2.4625

-3.7625

-3.9625

0.5625
1.1625
1.1625
0.5625
0.3625
-0.6375
-0.4375
-0.3375
0.0625
-0.0375
-1.0375
-0.6375
-0.8375
-0.7375
0.3625
0.4625
-3.1000

-2.5000

-1.9000

1.1000

0.5000

0.7000

0.7000

1.1000

1.2000

1.9000

-14.8000

2.5000

2.5000

3.2000

3.4000

3.5000

CovBEMPRRace =

Columns 1 through 11

1.0509 0.1486 -0.0977 -0.0977 -0.0072 2.9939 0.1775 -0.0975 -0.0975 -0.0012

0.7560

0.1486 0.0357 0.0000 0.0000 -0.0015 0.1775 0.0148 0.0000 0.0000 -0.0001

0.0836

-0.0977 0.0000 0.1954 0.0977 -0.0000 -0.0975 0.0000 0.1950 0.0975 -0.0000 -

0.0470

-0.0977 0.0000 0.0977 0.1954 -0.0000 -0.0975 0.0000 0.0975 0.1950 -0.0000 -

0.0470

-0.0072 -0.0015 -0.0000 -0.0000 0.0001 -0.0012 -0.0001 -0.0000 -0.0000 0.0000

-0.0071

Columns 12 through 22

0.0836 -0.0470 -0.0470 -0.0071 12.6584 1.1861 -0.1984 -0.1984 -0.0296 8.0959

0.3856

0.0138 0.0000 0.0000 -0.0010 1.1861 0.1247 0.0000 0.0000 -0.0030 0.3856

0.0259

0.0000 0.0940 0.0470 -0.0000 -0.1984 0.0000 0.3969 0.1984 -0.0000 -0.2112

0.0000

0.0000 0.0470 0.0940 -0.0000 -0.1984 0.0000 0.1984 0.3969 -0.0000 -0.2112

0.0000

-0.0010 -0.0000 -0.0000 0.0001 -0.0296 -0.0030 -0.0000 -0.0000 0.0001 -0.0490

-0.0027

Columns 23 through 33

-0.2112 -0.2112 -0.0490 2.4023 0.4046 -0.0752 -0.0752 -0.0328 11.3338 0.7403

-0.0796

0.0000 0.0000 -0.0027 0.4046 0.0800 -0.0000 -0.0000 -0.0062 0.7403 0.0519

0.0000

0.4224 0.2112 -0.0000 -0.0752 -0.0000 0.1504 0.0752 0.0000 -0.0796 0.0000

0.1591

0.2112 0.4224 -0.0000 -0.0752 -0.0000 0.0752 0.1504 0.0000 -0.0796 0.0000

0.0796

-0.0000 -0.0000 0.0003 -0.0328 -0.0062 0.0000 0.0000 0.0005 -0.0100 -0.0007

-0.0000

Columns 34 through 44

-0.0796 -0.0100 190.5214 26.3184 -0.4685 -0.4685 -0.3442 28.8566 2.2463 -0.2488

-0.2488

0.0000 -0.0007 26.3184 3.6867 0.0000 0.0000 -0.0480 2.2463 0.1884 0.0000

0.0000

0.0796 -0.0000 -0.4685 0.0000 0.9370 0.4685 -0.0000 -0.2488 0.0000 0.4975

0.2488

0.1591 -0.0000 -0.4685 0.0000 0.4685 0.9370 -0.0000 -0.2488 0.0000 0.2488

0.4975

-0.0000 0.0000 -0.3442 -0.0480 -0.0000 -0.0000 0.0006 -0.0145 -0.0012 -0.0000

-0.0000

Columns 45 through 55

-0.0145 20.7452 1.2115 -0.3768 -0.3768 -0.0148 15.4530 0.6137 -1.0054 -1.0054

-0.0100

-0.0012 1.2115 0.0865 -0.0000 -0.0000 -0.0010 0.6137 0.0591 0.0000 0.0000 -

0.0006

-0.0000 -0.3768 -0.0000 0.7536 0.3768 0.0000 -1.0054 0.0000 2.0109 1.0054

0

-0.0000 -0.3768 -0.0000 0.3768 0.7536 0.0000 -1.0054 0.0000 1.0054 2.0109

0

0.0000 -0.0148 -0.0010 0.0000 0.0000 0.0000 -0.0100 -0.0006 0 0

0.0000

Columns 56 through 60

12.2473 0.4864 -0.7969 -0.7969 -0.0079

0.4864 0.0468 0.0000 0.0000 -0.0005

-0.7969 0.0000 1.5937 0.7969 -0.0000

-0.7969   0.0000   0.7969   1.5937   -0.0000

-0.0079   -0.0005   -0.0000   -0.0000   0.0000

logLEMPRRace =

Columns 1 through 11

-78.8283 -78.7779 -61.2713 -95.8374 -97.3346 -72.5550 -73.8990 -116.4541 -101.2619 -111.2271 -134.7816

Column 12

-129.2016

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