Preemptive Economic Analysis in Employment Discrimination

Joshua D. Spizman, Ph.D.
Professor and Department Chair of Finance, College of Business Administration
Loyola Marymount University

Lawrence M. Spizman, Ph.D.
Emeritus Professor of Economics
State University of New York at Oswego
President of Spizman Economics Associates
larry.spizman@oswego.edu

Abstract

The purpose of this analysis is to provide an econometric method to determine if inadvertent discrimination exists in wages for protected employees of an individual firm. Such an analysis can be part of a first line of defense to mitigate litigation outcomes by allowing an employer to rectify disparities prior to litigation. Additionally, contract and affirmative action compliance programs can be enhanced by showing proactive initiatives and remedies.

1 Introduction

Forensic economists are retained in employment discrimination matters alleging discrimination in pay, hiring, promotion, termination and issues-based gender, age, race and national origin or ethnicity. Discrimination lawsuits are filed under some combination of federal and state statutes. The typical federal statutes are Title VII of the 1964 Civil Rights Act, The Age Discrimination in Employment Act of 1967, The Equal Pay Act of 1963, and The Americans With Disabilities Act of 1990. Since each statute allows for specific types of damages it is necessary to clarify with counsel what specific statutes apply.

Front and back pay is a typical category of damages a forensic economist is asked to estimate. A forensic economist can also determine whether discrimination exists. However, the more likely scenario is one will be retained to estimate damages rather than proving if discrimination exists.

Employers typically have a reactive approach to discrimination matters. That is, they react to the charges of discrimination once a lawsuit is filed. An economist might offer descriptive statistics that show whether a claim of lost earnings is due to discrimination. For example, an economist may compare the plaintiff's current earnings to national or regional average salaries to determine if disparities exist. They may also compare comparable salaries within the firm. Depending on how the descriptive statistics were used will lead to differences in opinions as to the appropriateness of the data used. The trier of fact will then determine which argument is more persuasive. Regardless of the outcome or analysis these approaches are reactive.

This paper takes a different approach by providing a preemptive or proactive approach to litigation. This is accomplished by developing a methodology that allows firms to identify potential discriminatory behavior prior to litigation. A preemptive or proactive approach is one step that employers can utilize to avoid or minimize legal liability associated with human resources decisions. This approach can also be useful in affirmative action plans as well as complying with regulatory requirements in audits and lawsuits brought by the U.S. and state labor departments and other government agencies.

1.1 Econometrics in Discrimination Litigation

This paper develops an econometric model whose results allow an employer to identify and/or preclude potential discriminatory problems that can be remedied prior to litigation. The utilization of the model can also be used to demonstrate that the employer was out-front in attempting to identify and rectify any discriminatory employment issues.

The use of econometric techniques is well accepted in the legal environment under the Daubert v Merrell Dow Pharmaceuticals standard.[1] Forensic economists started investigating

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[1] See Kane, Spizman and Donelson (2013) starting on page 176 for a full discussion of econometric acceptability in litigation.

econometric techniques in employment discrimination matters over three decades ago.[2] This paper further explores and develops the use of econometrics in employment discrimination matters.

In theory, any variables that can impact salary should be included in an econometric model. For example, members of the C-Suite are likely to have higher salaries than first year analysts. Hence, job rank is an explanatory variable of salary. We expand on variables of interest below. Discriminatory practices would take race and/or gender into account when determining salary. Our model shows if salary discrimination occurs (after controlling for variables that one would expect to explain salary differences) then corrective action can be taken to preempt a charge of discrimination.

The seminal work on explaining salary difference due to discrimination by gender or race is Becker (1957). Such models are referred to as taste-based discrimination which reflect preferences or prejudice. For example, a medical facility hires male physicians instead of female physicians because of personal preference for working with male physicians. Phelps (1972) developed a more formal second theory of statistical discrimination which is when an employer relies on the characteristics of the group to predict individual behavior. See Lang, Kahn-Lang Spitzer (2020) and Blau, Kahn (2017) for a full review of studies discussing the variables that explain both gender and race pay differences.

2 Methodology to identify discrimination

We employ multivariate regression analysis to explain salary of employees. The dependent variable (left-hand side) is salary and is being evaluated for discrimination. The independent variables, or the explanatory variables, determine salary. Any variable that a company uses that influences salary (and, likely, hiring) decisions should be included. Examples of such variables are experience, education, and job position as well as hierarchy within the company. This is not necessarily an exhaustive list.

Our linear model to explain salary is:

$$Salary = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n + \varepsilon \qquad (1)$$

[2] Piette (1991), Hawley (1992)

The model's coefficients b_0, b_1, b_2 etc. show the magnitude of the effect that the explanatory variables (x_1, x_2, x_3, …, x_n) have on salary. If education is a variable that explains salary, then various levels of education would be represented by x_i. In theory, one would only include explanatory variables that you expect to impact salary. In other words, we expect the coefficients to be statistically significant.

Companies should not use race, gender, and/or religion to determine salary. Our methodology is designed to preemptively identify discrimination in employee salary. In theory, one would not include these variables to explain salary in Equation (1). We modify Equation (1) and include discrimination variables below:

$$Salary = b_0 + b_1 x_1 + \cdots + b_n x_n + b_{n+1} x_{n+1} + \cdots + b_m x_m + \varepsilon \qquad (2)$$

In Equation (2), x_{n+1} through x_m represent variables such as gender and race. The coefficients, b_{n+1} through b_m should not be statistically significant. If they are, this is evidence of salary discrimination because variables x_1, …, x_n control for everything that, in theory, should go into salary decisions. To show how this methodology identifies discrimination when setting salaries, we simulate data for three separate companies. We then explain how the simulation is used and then implement the above methodology to identify the discrimination.

3 Simulation of company data

To show how Equation (2) can identify discriminatory practices pertaining to salary, we simulate the employee structure for three companies. Each company makes salary decisions based on job rank and has a structure of five distinct ranks.

Table 1 reports our simulation inputs and the mean base pay. Each company has the same job rank structure and mean base pay. The five levels of jobs are analyst, associate, vice president, senior vice president, and director where director is at the top of the hierarchy and analyst is an entry-level position. Panel A reports the percent of employees by job rank and the mean base pay by rank. The mean base pay is determined by percentage differences. For example, an associate earns 20% more than an analyst, on average, while a director earns 50% more than a senior vice president, on average.

We design the employee breakdown to have an equal number of male and female employees. In our simulated structure, Company B discriminates towards male employees by paying them a $5,000 premium, across all job ranks. Panel C reports the diversity breakdown by race, using six categories determined by the United States Census Bureau (2021). Company B discriminates towards "White alone, non-Hispanic" by paying a $10,000 premium above the mean across all job ranks and discriminates against "Black or African American alone, non-Hispanic" by paying a discount of $5,000 below the mean across all job ranks.

We simulate a company structure of 500 employees. We use the random number generator function RAND in Microsoft Excel to create a series of three separate random number series of five hundred employees. According to the Excel documentation, "RAND returns an evenly distributed random real number greater than or equal to 0 and less than 1."[3] We use the random number to determine the job rank, gender, and diversity of each employee. For example, to determine gender, we use one of the three random number series. If the random number is less than or equal to 0.50, then the gender is male and if it is greater than 0.50, then the gender is female. We use a similar methodology to determine the job rank and race. For example, for the series of random numbers to determine rank, if the number is between 0 and 0.45, we classify the employee as an analyst, between 0.45 and 0.70, the employee is an associate, and so on. By utilizing three distinct random number series we allow for variability across rank, gender, and diversity (in other words, all analysts are not male employees).

[3] https://support.microsoft.com/en-us/office/rand-function-4cbfa695-8869-4788-8d90-021ea9f5be73, accessed on November 15, 2022.

Table 2 reports our simulated employee data.

We next simulate the salary for each employee across each of the three companies in our model. To accomplish this, we use the Excel function, RANDBETWEEN. RANDBETWEEN generates a random integer between two specified numbers with a uniform distribution. For analysts, we use the (70,000;80,000), for associates, (85,000;95,000), for vice president, (107,500;117,5000), for senior vice president, (141,250; 151,250), and for directors, (214,375;224,375). This allows for an expected mean reported in Table 1, Panel A. For company B, we add $5,000 to all male employees' salaries. For company C, we add $10,000 to all employees classified as "White alone, non-Hispanic" and subtract $5,000 for all employees classified as "Black or African American alone, non-Hispanic" regardless of gender or job role.

4 Empirical evidence of salary discrimination

Using our simulated data, we employ linear regression analysis to show how to identify and explain salary discrimination. First, we report descriptive statistics of the simulated salary data. For brevity, we report all three companies in a single table. Table 3 reports the mean, minimum, and maximum salary information by various groups for Company A, Company B, and Company C. Panel A is by job rank, Panel B is by gender, and Panel C is by race.

Company A can be considered our base case. This company determines salary purely on job rank. When comparing Company B to Company A, there is a slightly higher salary for each job rank. However, when comparisons are based on gender in Panel B, the higher salary is coming from the premium they pay male employees. Comparing Company C to Company A, we see a slightly higher salary across all job ranks relative to Company A. In Panel B, we see this is also across both male and female employees. This is because Company B does not discriminate on gender, but rather race. In Panel C, we see that on average, Company C salaries are higher for "White alone, non-Hispanic" than Company A and Company C salaries are lower for "Black or African American alone, non-Hispanic" than Company A, picking up the salary discrimination. Of s importance to note is that all other categories are identical.

Table 4 reports the variables we use in the multivariate regression analysis. Since the categorical variables (e.g., gender) are not continuous, we use dummy variables for each category. We run three regression models to identify salary discrimination. All three models control for job rank. Model (1) controls for gender only, Model (2) controls for race only, and Model (3) controls for both gender and race. When controlling for both gender and race, we interact dummy variables. In Model (1), the constant represents Female Directors. In Model (2), the constant represents “Asian alone, non-Hispanic” Directors. In Model (3), the constant represents Female, “Asian alone, non-Hispanic” Directors. Essentially, the linear regression model assumes that salary can be represented as a linear function (i.e., a straight-line function) of the employment factors defined in Table 4.

Table 5, Table 6, and Table 7 report our regression results for each company separately. Table 5 reports regression results for Company A. Across all three models, only job rank variables are statistically significant and can explain the salary level. Gender and race variables are not statistically significant in any model. Table 6 reports regression results for Company B. The coefficient on the male dummy variable is positive and statistically significant. This shows that males, on average, are paid more than females, regardless of job rank. Hence, Table 6 provides evidence of salary discrimination based on gender.

Table 7 reports regression results for Company C. In Table 7, Model (2) and Model (3) show that “White alone, non-Hispanic” earn more on average and “Black or African American alone, non-Hispanic” earn less on average. Both coefficients are statistically significant. Notice in Model (1) that males earn more than females. However, when controlling for race variables, there is no statistically significant difference for males. Model (1) suffers from an omitted variable bias and shows the importance of having as much employee data as possible to include in the model.

Overall, Table 5, Table 6, and Table 7 show how one can test for salary discrimination across company employees. Table 5 provides an example of a company with no salary discrimination. Table 6 provides an example of what a company that discriminates based on gender might look like and Table 7 provides an example of how our methodology would show salary discrimination based on race.

5 Application of Model

The above model provides the theoretical foundation for determining whether discrimination exists for a specific employer. Engagement by a firm[4] goes beyond the theoretical foundation and

[4] The firm can be an individual firm who retains the Forensic Economist directly or legal counsel who acts as an intermediary for a specific firm.

is used to determine the existence of discrimination. While the econometrics is straightforward, the difficulty lies in obtaining the necessary data to perform the analysis. Fortunately, firms that commit to such a study will likely have much of the data required in a format (often Excel spreadsheet) that can simplify the process or at the minimum provide a good starting point. The absence of such data will require much more effort to obtain data. In either situation the necessary data points to perform the analysis is required.

Our methodology should be used with cross-sectional data, since it contains information for each employee about various employment factors, such as gender, ethnicity, service time, annual salary, education level, years of service, etc. A firm may have time series data (the employment factors over time). Our methodology should then be implemented on a year-by-year basis as it will not work with pooled data.

5.1 Data and Potential Issues

Once the data is received, it is important to go through it checking for errors and/or inconsistencies before running the analysis. The following discuss some common and potential issues that can arise with data provided by a firm. First, it will be necessary to determine if the employee is full time (40 hours per week) or part-time (less than 40 hours). Base salaries should be reported as an annual salary. For those who work part-time their salaries should be converted to an annual salary, by assuming they work forty hours per week to standardize the variable of interest (salary).

The number of years of service acts as a proxy for experience. Many employees may be hired with prior experience from previous jobs. Years of service is likely to be with the firm being analyzed. A potential robustness check would be to use the number of years since a degree was awarded to proxy for experience, if the firm is able to provide this data. The number of years of service should be shown by race, gender, and hierarchy of jobs within the firm. The hierarchy is similar to that in Table 1, Panel A. Firms may have more than the six-job rank structure used in this analysis. In addition to years of service, educational levels are necessary data. Prior job experience is also useful data to have but may not be readily available.

Race or ethnicity of each employee shows the diversity of the employees within the firm. Because of self-identification issues it may be difficult to attach a race or ethnic category to each employee. Panel C in Table 2 shows the diversity of the employees. Gender may be a bit more complicated than one would think, depending on how each employee self-identifies their gender. This may or may not be an issue, but it is best to be aware that it can become an issue.

Upon gathering the above data, summary tables can be created. One table can present mean annual salary by education. Another table can have mean annual salary by race. A third table can have mean annual salary by hierarchy. Each table should have the total sample size (N) for both the total population and for gender. These tables can show average base salaries by gender, education, race, or hierarchy without controlling for any other potential variables that explain salary differences. The table format is useful since they are descriptive statistics that are easy to understand and explain. Some questions might be: what is the average number of years of employment by race, gender, and hierarchy? Do years of service by hierarchy increase with more senior positions? Do higher levels of education show greater base salary? Hopefully, the descriptive statistics tables will answer these questions.

An important caveat with univariate statistics is they may show the appearance of discrimination. For example, when comparing male and female employees, male employees may show a higher salary on average. It is important to explain that one does not conclude discrimination in these situations because other important variables are not being controlled for. For example, if all male employees have master's degrees while no female employees do, then males may earn a higher wage due to their level of education.

Upon presenting and explaining the results of the descriptive statistics the multivariate regression analysis can be used to determine if there is some level of discrimination that may contribute to differences in base salary levels other than total experience, level of education, or job hierarchy.

6 Conclusion

This paper provides a method to take a preemptive approach to litigation by identifying potential discriminatory behavior by firms as it pertains to employee salaries. This approach is one way for employers to minimize legal liability. This approach focuses on discrimination in pay around gender, age, race, and/or national origin or ethnicity. While proactive, this method, as presented, should not be used to search for discrimination as it pertains to hiring, promotion, and termination decisions. We leave that for future research and extensions.

Table 1: Simulated employee structure inputs

Panel A: Job rank structure and mean base pay

	% of company employees	Mean Base Pay
Analyst	45.0%	$75,000.00
Associate	25.0%	$90,000.00
Vice President	15.0%	$112,500.00
Senior Vice President	10.0%	$146,250.00
Director	5.0%	$219,375.00

Panel B: Gender breakdown of company employees

		Salary Premium/Discount to mean		
	% of company employees	Company A	Company B	Company C
Male	50.0%		+$5,000	
Female	50.0%			

Panel C: Diversity breakdown of company employees*

		Salary Premium/Discount to mean		
	% of company employees	Company A	Company B	Company C
Hispanic	15.0%			
White alone, non-Hispanic	60.0%			+$10,000
Black or African American alone, non-Hispanic	15.0%			-$5,000
American Indian and Alaska Native alone, non-Hispanic	2.5%			
Asian alone, non-Hispanic	5.0%			
Native Hawaiian and Other Pacific Islander alone, non-Hispanic	2.5%			

*Classifications are from the United States Census Bureau (2021)

Table 2: Description of simulated employee data

Panel A: Job rank structure and mean base pay

	Number of company employees	% of company employees
Analyst	243	48.6%
Associate	128	25.6%
Vice President	60	12.0%
Senior Vice President	51	10.2%
Director	18	3.6%
TOTAL	500	

Panel B: Gender breakdown of company employees

	Number of company employees	% of company employees
Male	249	49.8%
Female	251	50.2%
TOTAL	500	

Panel C: Diversity breakdown of company employees

	Number of company employees	% of company employees
Hispanic	81	16.2%
White alone, non-Hispanic	301	60.2%
Black or African American alone, non-Hispanic	67	13.4%
American Indian and Alaska Native alone, non-Hispanic	18	3.6%
Asian alone, non-Hispanic	23	4.6%
Native Hawaiian and Other Pacific Islander alone, non-Hispanic	10	2.0%
TOTAL	500	

Table 3: Descriptive statistics of simulated salary data by company

Panel A: Job rank structure and mean base pay

	Company A			Company B			Company C		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Analyst	$74,844	$70,021	$79,999	$77,354	$70,092	$84,999	$80,173	$65,206	$89,995
Associate	$90,010	$85,123	$94,966	$92,627	$85,123	$99,966	$95,362	$80,123	$104,966
Vice President	$112,751	$107,613	$117,367	$115,168	$107,887	$122,367	$118,668	$104,523	$127,367
Senior Vice President	$146,768	$141,488	$151,223	$148,827	$141,488	$156,139	$151,277	$136,488	$161,223
Director	$219,105	$215,254	$224,276	$221,883	$215,254	$229,276	$225,216	$212,532	$234,276
Total	$95,805	$70,021	$224,276	$98,295	$70,092	$229,276	$101,155	$65,206	$234,276

Panel B: Gender breakdown of company employees

	Company A			Company B			Company C		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Male	$95,276	$70,021	$224,276	$100,276	$75,021	$229,276	$101,250	$65,206	$232,169
Female	$96,329	$70,092	$223,528	$96,329	$70,092	$223,528	$101,059	$66,223	$234,276
Total	$95,805	$70,021	$224,276	$98,295	$70,092	$229,276	$101,155	$65,206	$234,276

Panel C: Diversity breakdown of company employees

	Company A			Company B			Company C		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Hispanic	$94,863	$70,770	$218,295	$97,456	$70,770	$221,521	$94,863	$70,770	$218,295
White alone, non-Hispanic	$96,504	$70,021	$224,276	$99,096	$70,109	$229,276	$106,504	$80,021	$234,276
Black or African American alone, non-Hispanic	$100,970	$70,206	$223,528	$102,761	$70,206	$223,528	$95,970	$65,206	$218,528
American Indian and Alaska Native alone, non-Hispanic	$85,140	$71,171	$112,677	$88,196	$73,056	$117,677	$85,140	$71,171	$112,677
Asian alone, non-Hispanic	$88,001	$70,095	$219,915	$90,610	$70,264	$219,915	$88,001	$70,095	$219,915
Native Hawaiian and Other Pacific Islander alone, non-Hispanic	$84,920	$70,092	$109,811	$86,920	$70,092	$109,811	$84,920	$70,092	$109,811

Table 4: Definitions of multi-variate regression variables

Variable name	Variable definition
Male	A dummy variable equal to one if the employee is male and zero otherwise.
White	A dummy variable equal to one if the employee is categorized as “White alone, non-Hispanic” and zero otherwise.
Hispanic	A dummy variable equal to one if the employee is categorized as “Hispanic” and zero otherwise.
Black	A dummy variable equal to one if the employee is categorized as “Black or African American alone, non-Hispanic” and zero otherwise.
American Indian	A dummy variable equal to one if the employee is categorized as “American Indian and Alaska Native alone, non-Hispanic” and zero otherwise.
Native Hawaiian	A dummy variable equal to one if the employee is categorized as “Native Hawaiian and Other Pacific Islander alone, non-Hispanic” and zero otherwise.
Analyst	A dummy variable equal to one if the hierarchy is categorized as “Analyst” and zero otherwise.
Associate	A dummy variable equal to one if the hierarchy is categorized as “Associate” and zero otherwise.
VP	A dummy variable equal to one if the hierarchy is categorized as “Vice President” and zero otherwise.
SVP	A dummy variable equal to one if the hierarchy is categorized as “Senior Vice President” and zero otherwise.

Table 5: Regression Analysis: Company A

	Model (1)	Model (2)	Model (3)
Male	154.34		-788.11
	(0.59)		(-0.64)
White		-145.24	-635.36
		(-0.23)	(-0.69)
Hispanic		593.83	42.57
		(0.86)	(0.04)
Black		-718.28	-1,378.08
		(-1.01)	(-1.38)
American Indian		-804.60	-574.48
		(-0.87)	(-0.40)
Native Hawaiian		-1,449.60	-1,357.63
		(-1.30)	(-0.91)
Male x White			921.11
			(0.72)
Male x Hispanic			1,041.91
			(0.75)
Male x Black			1,439.08
			(1.00)
Male x American Indian			-278.31
			(-0.15)
Male x Native Hawaiian			-500.49
			(-0.22)
Analyst	-144,252.67***	-144,216.64***	-144,218.81***
	(-200.86)	(-201.93)	(-200.35)
Associate	-129,089.62***	-128,992.34***	-128,956.51***
	(-174.45)	(-174.83)	(-173.41)
VP	-106,342.60***	-106,301.19***	-106,283.15***
	(-134.58)	(-135.27)	(-133.85)
SVP	-72,314.96***	-72,202.07***	-72,139.70***
	(-89.64)	(-89.86)	(-89.22)
Constant	219,019.04***	219,182.45***	219,587.06***
	(309.29)	(241.10)	(200.44)
Observations	500	500	500
R-squared	0.99	0.99	0.99

** significant at the 10 percent level*
*** significant at the 5 percent level*
**** significant at the 1 percent level*

Table 6: ***Regression Analysis: Company* B**

	Model (1)	Model (2)	Model (3)
Male	5,154.34***		4,211.89***
	(19.56)		(3.43)
White		-147.95	-635.36
		(-0.18)	(-0.69)
Hispanic		583.33	42.57
		(0.63)	(0.04)
Black		-1,481.86	-1,378.08
		(-1.57)	(-1.38)
American Indian		-387.89	-574.48
		(-0.32)	(-0.40)
Native Hawaiian		-2,095.48	-1,357.63
		(-1.42)	(-0.91)
Male x White			921.11
			(0.72)
Male x Hispanic			1,041.91
			(0.75)
Male x Black			1,439.08
			(1.00)
Male x American Indian			-278.31
			(-0.15)
Male x Native Hawaiian			-500.49
			(-0.22)
Analyst	-144,252.67***	-144,481.11***	-144,218.81***
	(-200.86)	(-152.26)	(-200.35)
Associate	-129,089.62***	-129,149.33***	-128,956.51***
	(-174.45)	(-131.74)	(-173.41)
VP	-106,342.60***	-106,661.23***	-106,283.15***
	(-134.58)	(-102.15)	(-133.85)
SVP	-72,314.96***	-72,796.98***	-72,139.70***
	(-89.64)	(-68.19)	(-89.22)
Constant	219,019.04***	222,048.62***	219,587.06***
	(309.29)	(183.83)	(200.44)
Observations	500	500	500
R-squared	0.99	0.99	0.99

** significant at the 10 percent level*
*** significant at the 5 percent level*
**** significant at the 1 percent level*

Table 7: ***Regression Analysis: Company*** **C**

	Model (1)	Model (2)	Model (3)
Male	988.99*		-788.11
	(1.66)		(-0.64)
White		9,854.76***	9,364.64***
		(15.50)	(10.16)
Hispanic		593.83	42.57
		(0.86)	(0.04)
Black		-5,718.28***	-6,378.08***
		(-8.03)	(-6.39)
American Indian		-804.60	-574.48
		(-0.87)	(-0.40)
Native Hawaiian		-1,449.60	-1,357.63
		(-1.30)	(-0.91)
Male x White			921.11
			(0.72)
Male x Hispanic			1,041.91
			(0.75)
Male x Black			1,439.08
			(1.00)
Male x American Indian			-278.31
			(-0.15)
Male x Native Hawaiian			-500.49
			(-0.22)
Analyst	-144,989.91***	-144,216.64***	-144,218.81***
	(-89.08)	(-201.93)	(-200.35)
Associate	-129,822.36***	-128,992.34***	-128,956.51***
	(-77.41)	(-174.83)	(-173.41)
VP	-106,476.76***	-106,301.19***	-106,283.15***
	(-59.46)	(-135.27)	(-133.85)
SVP	-73,796.25***	-72,202.07***	-72,139.70***
	(-40.36)	(-89.86)	(-89.22)
Constant	224,666.45***	219,182.45***	219,587.06***
	(139.99)	(241.10)	(200.44)
Observations	500	500	500
R-squared	0.96	0.99	0.99

** significant at the 10 percent level*
*** significant at the 5 percent level*
**** significant at the 1 percent level*

References

Age Discrimination in Employment Act (ADEA) 1967, U.S. Equal Employment Opportunity Commission, Washington DC: see: https://www.eeoc.gov/statutes/age-discrimination-employment-act-1967.

Americans with Disabilities Act (ADA) 1990. U.S. Equal Employment Opportunity Commission, Washington DC, see: https://www.eeoc.gov/statutes/titles-i-and-v-americans-disabilities-act-1990-ada

Becker, Gary S. (1957) (1971). *The Economics of Discrimination*. 2nd ed.: Chicago University Press.

Blau, Francine D., and Lawrence M. Kahn (2017). "The gender wage gap: Extent, trends, and explanations." *Journal of Economic Literature* 55 (3): 789-865.

Equal Pay Act of 1963, U.S. Equal Employment Opportunity Commission, Washington DC. See: https://www.eeoc.gov/statutes/equal-pay-act-1963.

Hawley Clifford B. (1992). "Methodological Issues When Using Simple Models to Investigate Employment Discrimination." *Journal of Forensic Economics 6(1): 23-32.*

Kane, John, Lawrence Spizman, Don Donelson (2013)."Educational Attainment Model for a Minor Child: The Next Generation." *Journal of Forensic Economics 24(2): 175-190.*

Lang, Devin, and Ariella Kahn-Lang Spitzer (2020). "Race Discrimination: An Economic Perspective." *Journal of Economic Perspectives* 34 (2) : 68-89.

Phelps, Edmund, S. (1972). "The Statistical Theory of Racism and Sexism." *The American Economic Review* 62 (4): 659-661.

Piette Michael J. (1991). "Economic Methodology and the Analysis of Employment Discrimination." *Journal of Forensic Economics 4(3): 307-316.*

Title VII of the Civil Rights Act of 1964. U.S. Equal Employment Opportunity Commission, Washington DC. See: https://www.eeoc.gov/statutes/title-vii-civil-rights-act-1964.

United States Census Bureau (2021). See: https://www.census.gov/newsroom/blogs/random-samplings/2021/08/measuring-racial-ethnic-diversity-2020-census.html