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Salary Equity Studies: An Analysis of Using the Blinder-Oaxaca Decomposition to Estimate Differences in Faculty Salaries by Gender

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Parameter estimates for equity studies tested for stability are described. Bootstrap simulation can test whether parameter estimates remain stable given changes in the sample data; fractional polynomials can be used to access functional form specification; and variance inflation factors can be used to test for multicollinearity.

Keywords: Equity studies; Blinder-Oaxaca decomposition, stability, bootstrap simulation, fractional polynomial analysis, variance inflation factors.

Introduction

Significant progress has been made in gender and racial equality over the last several decades since the introduction of the Equal Pay Act of 1963 and the Civil Rights Act of 1964 (Baker, Wendt, & Slonaker, 2002). However, many researchers believe that inequities continue to exist in higher education in the areas of hiring practices, salary, promotion and tenure (Perna, 2005; Hampton, et al, 2000; Sampson & Moore, 2008). Although many national studies continue to address gender and racial equity in academia, it is necessary and prudent to conduct studies within individualized institutions to address all of the variables within these institutions that could affect equity (McLaughlin & McLaughlin, 2003).

Gender and Race Equity

Study after study has concluded that a society where men and women are treated equitably in higher education - or where the gap between white and minority professionals is being bridged - does not currently exist.

Regarding the status of higher education the National Center for Education Statistics (2009) reported that, in the fall of 2007, 55% of those tenured were male as compared to 41% females. Furthermore, four out of five faculty tenured during that same semester were reportedly white (Caucasian). Women in academia also fall significantly below their male counterparts in academic rank, salary and full-time status (Jacob, 2004). Throughout the public sector internationally, the wage differential is significantly lower for women (Fransson & Thörnqvist, 2006; Kjeldal, Rindfleish, & Sheridan, 2005; Lips, 2003); women are also significantly underrepresented within government systems as well as in high-ranking business positions (Connell, 2006).

Although there are a plethora of equity studies involving gender at the local and national level, few examine these issues considering race/ethnicity equity (Barbezat, 2002). This is due in part to the fact that there are not many minority faculty. For example, Barbezat (2002) found that no minority groups constitute more than 5% of faculty involved in teaching and research at the university/college level. Hearn (in Barbezat, 2002) concludes that trends in salary equity for minorities cannot be studied due to the low numbers of minorities in academia. Compensation for minorities in academia, as compared to Caucasian faculty, has not been investigated in relationship to how being a male or female faculty of color affects outcomes.

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The Study of Equity

One of the most famous gender equity studies was the Massachusetts Institute of Technology (MIT, 1999). Gender issues were brought to the forefront due to international media attention. Of interest was the notion that despite diversity incentives at MIT, women faculty were not considered to be equal with their male counterparts (Bailyn, 2003). Bailyn pointed out that, although there have been many equity studies conducted within academia, there had not been any noticeable effect on the policies or practices at such universities. Fewer studies results quantified the experiences of race or ethnicity as compared with Caucasians in academia or the workforce, and when researchers did take race into account, they frequently lacked statistical power as the sample size is often too small to find a reasonably sized effect (Toutkoushian, 1998).

Authors of several studies sought to explain the lack of advancement for women and minorities in academia and other disciplines. For example, Ash et al. (2004) conducted a cross-sectional study of women in academic medicine and found that female physicians earned less in both academia and private practice, but also did not advance to higher ranks as compared to their male counterparts. Some of these differences were explained by other factors, such as the fact that women have significantly less productivity with publishing (Cooperstein, 2008; Friedman, 2004) and that women's careers are more affected by family responsibilities (Friedman, 2004). Probert (2005) found that high rates of separation and divorce and family needs accounted for some of the disparity in academic rank. Peterson et al. (2004) concluded, on the basis of a self-reported questionnaire, that minorities in academic medicine are promoted at a slower rate and failed to attain more senior academic ranks as compared to their white counterparts.

Equity in academia and the workforce continues to be a hotly debated topic. Multiple studies conclude that disparities exist for both women and minorities, particularly in terms of salary and senior positions, but many argued that these differences may in fact be due to unexplained factors (Green & Ferber, 2005; Ferber & Loeb, 2002). Others argued that such salary disparities were due to continued discrimination (Gibelman, 2003). Historically, salary equity studies were divided into two different types, (1) total wage gap studies that examine the differences in the average salary for different groups of employees, and (2) unexplained wage gap studies where employee characteristics are considered in order to try and account for these differences (Toutkoushian, 1998).

Green and Ferber (2005) attempted to introduce many variables that are often not included in equity studies in order to evaluate whether they help to explain the gap in earnings. Many researchers have argued that when comparing salary and other equity data, if there is a difference, it is assumed that the difference implies discrimination. However, such differences may in fact be due to unexplained variables that are not included in the study (O'Neill, 2003). Some of the variables that helped explain the reduction in salary for women have included controlling for factors such as experience, educational history, field of study and scholarly productivity (Toutkoushian, 1998, Creamer, 1998).

McLaughlin and McLaughlin (2003) argued that scholarly productivity has been operationally defined by multiple methods in the history of equity studies. For example, researchers have examined the number of publications, the number of times a researcher's work is cited, internal and external grant dollars received, and the quality of publications as markers to indicate scholarly productivity. These studies argue that, without measures of scholarly productivity, only the magnitude of the salary differences can be estimated, not which employees need a review of their salaries in order to correct the inequities.

Additional variables studied in salary equity studies have included age (differences in pay disparity for younger faculty appears be less as compared to more senior faculty) (Toutkoushian, 1998), and seniority. Although McLaughlin and McLaughlin (2003) argued that rewarding seniority does not make sense and is probably not an appropriate variable to include because most faculty are rewarded for productivity as opposed to how many years they have been a faculty member. Another controversial variable in the study of salary equity involved part-time status. Women engaged in significantly more hours in part-time work as compared with male faculty (Thornley, 2007; Jacobs, 2003), although many researchers did not include part-time faculty or contingent faculty despite the fact that in academia there is a trend towards hiring these contingent faculty (Curtiss, 2005).

Marital status and children (Jacobs & Winslow, 2004), as well as discipline specialty, have been extensively studied. Umbach (2006) argued that labor market conditions may affect salary; he argues that disciplines with a high concentration of women and heavy teaching loads were valued less in the academy and therefore more inequities existed. Gibelman (2003) expanded on this idea to include differential patterns of salaries associated with fields that are primarily female, e.g. nursing and social work, and concluded that gender is a better predictor of salary than any of the characteristics or variables that are typically studied within an equity analysis.

Further, Becker & Toutkoushian (2003) noted that many studies include factors such as academic experience, seniority, academic attainment and - most controversial of all - academic rank. They argued that salary and rank go hand and hand; if a woman is not promoted despite the necessary qualifications, this leads to salary regression and qualifies as rank discrimination. Despite the importance of rank in salary equity, they reviewed a number of studies that did not include academic rank as a factor in predicting salaries. They also argued that because faculty tend not to be terminated when they are tenured, yet if a faculty member is not promoted, it does not appear to look like discrimination.

Methods for studying equity remain an important topic because estimating wage gap differences based on gender and minority status have important and far-reaching consequences. Recent legislation such as the Lilly Ledbetter Fair Pay Act of 2009 and the Paycheck Fairness Act, brought equity discrimination to the forefront by allowing employees to file lawsuits for current and past equity discrimination in their place of employment (Deere, 2010). Furthermore, company officers fear that when inequities do exist, not only will they be at risk for litigation, but this also affects employee's morale and work performance (Romanoff, Boehm & Benson, 1986).

Given the vast body of research on equity studies, it is clear that many studies relied on statistical methods and techniques to make an inference to a larger population of interest. However, one limitation of most of the previous research was that many studies did not assess whether parameter estimates obtained for a gender or race salary inequity remain stable given small changes in the underlying data. This is an important consideration that often is ignored because methods and techniques are often not easily available to access model stability. Clearly, if small changes in the sample data produce parameter estimates that vary greatly, then any inferences would be suspect. Also, if a statistical model is considered, then the functional form of the model needs to be correct. Various functional forms can often give different and contradictory parameter estimates. Given that claims of discrimination are often based on the findings of such analyses, accessing the stability of any findings is crucial for making a valid inference.

The purpose of this study is three-fold. First, a study on salary equity is described that uses the Blinder-Oaxaca decomposition to partition a wage difference as both a portion that can be explained as well as a portion that is left unexplained. Second, a series of simulation analyses is presented that can be used to assess the stability the parameter estimates that are found using the Blinder-Oaxaca decomposition. Third, fractional polynomial modeling is introduced as a way to determine the appropriate functional form of a regression model and variance inflation factors are calculated to assess model stability.

Methodology

The Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973) is a fairly simple extension of multiple regression modeling that is often used to describe wage differences between two different groups. The basic idea behind the Blinder-Oaxaca decomposition is to partition the estimated effect of a binary predictor variable into two portions: one portion that represents the explained difference between the two groups, and the other portion that describes the unexplained difference between the two groups. For example, a binary predictor variable could be used to describe gender (i.e., male is assigned the value of 0; female is assigned the value of 1). Many studies have used the Blinder-Oaxaca technique to decompose wage differences into explained and unexplained portions, and often the unexplained portion is used to infer discrimination (Neumark, 1988).

Data

A sample of n = 110 newly hired tenure-track faculty were considered for this study. The sample represented all newly hired tenure-track faculty members who joined the institution during a four-year period between the years 2004 and 2008. Variables considered for this study are described in detail below.

Predictor Variables

- Year of hire: This is a series of five separate binary variables that represent the beginning of the academic year of hire (YR04, YR05, YR06, YR07, YR08). For the YR04 variable, if a faculty member was hired during the academic year 2004-2005, then they are assigned the value 1. If they were not hired during the 2004-2005 academic year, they are assigned the value 0. Similar assignments are made for the faculty hires for the years 2005-2006, 2006-2007, 2007-2008 and 2008-2009.

- Rank at hire: This is a series of three separate binary variables that represent the rank at hire (ASST, ASSOC, PROF). For the ASSOC variable, if a faculty member was hired as an Associate Professor, they are assigned the value 1. If they were not hired as an Associate Professor, they are assigned the value 0. Similar assignments were made for Assistant (ASST) and Full Professor (PROF).

- Age at hire: This is a continuous predictor variable representing a new faculty member's age in years at the time of hire.

- School of hire: This is a series of five binary variables representing the new hire's school (Arts and Sciences, Education, Business, Engineering and Technology, Other).

- Female: This is a binary variable representing new faculty's self-identified gender (Female = 0 if the new hire identifies as Male, and Female = 1 if the new hire identifies as Female).

- Minority: This is a binary variable representing new faculty's self-identified minority status (Minority = 0 if the new hire identifies as White/Caucasian, and Minority = 1 if the new hire identifies as Non-White/Caucasian).

Means and standard deviations for the continuous predictor variables are presented in Table 1, percentages for the binary control variables are presented in Table 2.

Response Variable

- Ln(Wages): This variable represents the natural logarithm of yearly wages (in dollars). As with many wage studies, the natural logarithm of the yearly wages was used in order to estimate a constant percentage effect (Wooldridge, 2002, 2003).

Table 1: Mean and Standard Deviation for Continuous Variables Yearly Wages and Age at Hire for Newly Hired Faculty (n = 111)

Continuous Variable	Mean	Standard Deviation
Yearly Wages	60127.52	11002.19
Age at Hire	41.41	9.42

Table 2: Percentages of Binary Variables for Tenured and Tenure-Track New Faculty Hires

Binary Variable	Percentage
Year of Hire 04	21.62
Year of Hire 05	18.92
Year of Hire 06	18.92
Year of Hire 07	20.72
Year of Hire 08	19.82
Assistant	80.91
Associate	15.45
Full Professor	3.64
Arts & Science	49.55
Business	20.72
Engineering & Technology	6.30
Education	18.02
Other	5.41
Female	45.05
Male	54.95
Minority*	19.44
White/Caucasian	80.56

*Three observations did not self-report

The results from the following generalized ln-wage equation for the model that includes males and females pooled together are presented in Table 3.

$$\ln(wage) = \beta_0 + \beta_1 YEAR + \beta_2 RANK + \beta_3 AGE + \beta_4 SCHOOL + \beta_5 GENDER + \varepsilon \quad (1)$$

Initial Blinder-Oaxaca Results

Version 10 of STATA® was used to conduct the Blinder-Oaxaca decomposition technique to estimate the wage difference between males and females and to partition the wage difference into two components (Jann, 2008). The explained component is determined based on observed characteristics, and the unexplained component is based on unobserved characteristics (Jann, 2008). The results from these analyses are summarized in Table 4.

Notice in Table 4 that the mean of the ln(wages) for the generalized ln-wage equation is estimated to be approximately 11.02 for males and 10.95 for females. This suggests that there is a total wage difference of 0.069 as represented on the logarithmic scale. The exponentiated results from the last column in Table 4 (which express the estimate on the dollar scale) indicate that the (geometric) mean yearly wages for males is estimated to be approximately $61,160.46 as compared to approximately $57,057.39 for females. This indicates that there is an estimated total wage difference of approximately 7.19% between male and female new faculty hires. The decomposition portion of Table 4 suggests that if females were hired with the same characteristics as males (for example if females had the same year at hire, age at hire, rank at hire, and school of hire), then the total wage gap observed between males and females would be decreased by approximately 4.78%. This leaves a wage gap of approximately 2.30% that cannot be accounted for by the given observed characteristics between male and female new faculty hires.

Model Instability

Many different scenarios can generate different and often contradictory parameter estimates. Such differences can often be attributed to the model not being stable given changes in the underlying data, the functional form of the model being not being specified correctly, or some of the predictor variables being highly correlated with each other. Model instability can occur if small changes in the data generate vastly different parameter estimates (Royston & Sauerbrei, 2009). Also, if the functional form of the model is not specified correctly, then differences from different model specifications can also generate vastly different parameter estimates (Griffin, Montgomery & Rister, 1987; Royston & Sauerbrei, 2008, 2009). Furthermore, including predictor variables that are highly correlated with each other can also cause the estimated parameters to be unstable (Graham, 2003; Lesik, 2010).

Assessing Model Instability Due to Changes in the Data: Bootstrapping

One of the more common techniques for assessing model instability due to small changes in the underlying data is to use bootstrap resampling (Sauerbrei & Schumacher, 1992). Bootstrap resampling entails drawing repeated samples (with replacement) from the sample of interest, estimating the parameter of interest, empirically estimating the distribution for the parameter of interest, and finally determining if the parameter of interest is significant in the model.

A bootstrap simulation program was written for version 10 of STATA® (see Appendix). This program draws a bootstrap sample from the initial 110 new faculty hires and then conducts the Blinder-Oaxaca decomposition. Line 5 of the bootstrap program [generate nsamp = cond(sex, 49, 61)] ensures that the bootstrap sample was drawn to represent the underlying percentages of males and females at the institution (of the 110 new faculty hires, 49 were females and 61 were males). The mean exponentiated percent unexplained difference for the simulation analysis run with 10,000 replicates was 2.2260% with a standard deviation of 1.3173%. The distribution of the mean exponentiated unexplained difference is shown in Figure 1. It was also found that for all of the bootstrap resamples, 58.86% had significant unexplained differences ($p < 0.10$).

Also calculated from the bootstrap simulation analysis were descriptive statistics of the unexplained differences being negative (this would indicate that males made less than females). Of the 10,000 simulation analyses, only 444 (only 4.44%) indicated that the unexplained percent difference was negative. Of these 444 bootstrap samples, only 13 were significant at the 10% level, thus suggesting that only 0.13% of the 10,000 bootstrap simulations showed that males made less than females (significant at the 10% level). Given these results of the bootstrap simulation, it appears that the estimated unexplained percent difference stable, even given small changes in the underlying data set.

Assessing Model Stability from Functional Form Misspecification: Fractional Polynomial Modeling

Because the Blinder-Oaxaca decomposition used in this study is a simple extension of ordinary least squares regression, it relies on some basic model assumptions. One such assumption is that the functional form of the model is specified correctly with respect to the relationship between the continuous predictor variables and the response variable. Different functional forms can often yield different and even contradictory parameter estimates.

The generalized ln(wage) model given in equation (1) is specified such that the continuous predictor variable which corresponds to the age at hire is linear. Fractional polynomial modeling was used to see if changes in the functional form of the generalized ln(wage) model would present different parameter estimates. Fractional polynomial modeling can be used to determine if a linear model is appropriate for virtually any type of regression modeling, even logistic regression (i.e. Hosmer & Lemeshow, 2000).

The basic idea underlying fractional polynomial modeling is to include powers of continuous predictor variables to determine if this improves the fit of the model (Royston & Sauerbrei, 2008, 2009). Royston and Altman (1994) suggest that a restricted set of fractional polynomial powers is sufficient in transforming continuous predictor variables for better model fit.

Given a single continuous predictor variable (as is the case with this study), the general form of a population linear regression model is:

$$y = \beta_0 + \beta_1 x_1 + \varepsilon$$

Powers of the continuous variable, $f_k(x_1)$ can be included into the regression model as follows:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i \cdot f_k(x_1) + \varepsilon$$

Table 3: Parameter Estimates, Standard Errors and 95% Confidence Intervals for the Predictor Variables of the Generalized ln(wage) Equation (1) for all New Full-Time Tenure-Track Faculty Who were Hired During the Academic Years 2004-2008 (*n* = 110).

Variable	Parameter Estimate [Standard Error]	95% Confidence Interval
Year 04	-0.1443*** [0.0180]	-0.1801, -0.1085
Year 05	-0.0827*** [0.0187]	-0.1198, -0.0457
Year 06	-0.0603** [0.0187]	-0.0974, -0.0232
Year 07	-0.0335~ [0.0183]	-0.0699, 0.0030
Assistant	-0.3403*** [0.0365]	-0.4127, -0.2679
Associate	-0.0904* [0.0348]	-0.1594, -0.0214
Age at Hire	0.0012 [0.0008]	-0.0003, 0.0027
Arts & Sciences	-0.0409 [0.0255]	-0.0915, 0.0098
Business	0.0727* [0.0299]	0.0134, 0.1320
Engineering & Technology	0.0725* [0.0338]	0.0053, 0.1397
Education	0.0030 [0.0283]	-0.0531, 0.0592
Gender	-0.0227~ [0.0121]	-0.0468, 0.0013
Constant	11.3074*** [0.0599]	11.1884, 11.4263
R-squared	0.8900	
Adjusted R-Squared	0.8764	
Sample Size	110	

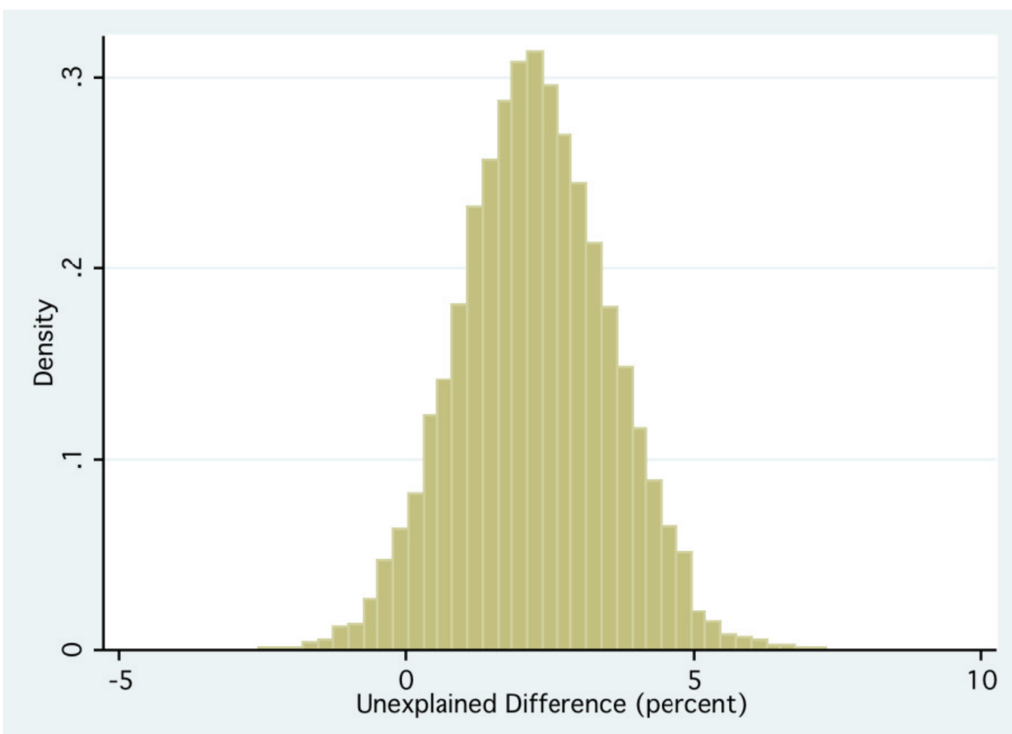
~ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 4: Ln-Scale Parameter Estimates and Exponentiated Estimates (in Dollars), and Standard Errors for the Blinder-Oaxaca Decomposition for Initial Faculty Salaries Based on Gender

Differential Category	Ln-Scale Parameter Estimate [Standard Error]	Exponentiated Parameter Estimate [Standard Error]
Males	11.0213*** [0.0220]	61160.46*** [1348.526]
Females	10.9518*** [0.0224]	57057.39*** [1275.899]
Total Difference	0.0694* [0.0314]	1.0719* [0.0337]
Decomposition		
Explained Difference	0.0467 [0.0298]	1.0478 [0.0312]
Unexplained Difference	0.0227* [0.0116]	1.0230* [0.0118]

~ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Figure 1: Distribution of the Unexplained Wage Difference for the 10,000 Bootstrap Samples Using the Blinder-Oaxaca Decomposition



$\{-2, -1, -0.5, 0, 0.5, 1, 2, 3\}$. The powers of the continuous variable x_1 can then be included in the model:

$$f_k(x_1) = \begin{cases} x^p & \text{if } p_k \neq p_{k-1} \\ f_{k-1}(x_1) \cdot \ln(x_1) & \text{if } p_k = p_{k-1} \end{cases},$$

where $k = 1, 2, 3, \ldots$. For example if k = 2, with powers 0.5 and 0.5, then $f_1(x_1) = x_1^{0.5}$ and $f_2(x_1) = x_1^{0.5} \cdot \ln(x_1)$. Therefore, $y = \beta_0 + \beta_1 x_1^{0.5} + \beta_2 x_1^{0.5} \cdot \ln(x_1) + \varepsilon$. For another example if it is supposed that k = 4 with powers -2, 2, 3 and 3, then $f_1(x_1) = x_1^{-2}$, $f_2(x_1) = x_1^{2}$, $f_3(x_1) = x^3$, and $f_4(x_1) = f_3(x_1)\ln(x_1) = x_1^3 \cdot \ln(x_1)$. Thus,

$$y = \beta_0 + \beta_1 x_1^{-2} + \beta_2 x_1^2 + \beta_3 x_1^3 + \beta_4 x_1^3 \cdot \ln(x_1) + \varepsilon.$$

Version 10 of STATA® was used to find the best fractional model that has a maximum of k = 4 (STATA Corporation, 2005). The STATA routine fracpoly finds the best fractional polynomial models for each of the values. For example, the best model for k = 2 has the powers -2 and -2. The table also provides deviance statistics and p-values for comparing the improvement in fit for each successive pairs of models (Royston & Altman, 1994). The deviance statistic is calculated as follows:

$$D = n\left[1 - \overline{w} + \ln\left(\frac{2\pi}{SSR}\right)\right],$$

where n is the sample size, $\overline{w}$ is the mean of the normalized weights, and SSR is the residual sum of squares. Although somewhat conservative, these p-values indicate whether the fit of the model improved by including the predictor variable with the additional powers (see Table 5).

Based on the p-values presented in Table 5, no improvement is observed in model fit for including the predictor variable that represents the age at hire, as well as any fractional powers of the variable. Thus, the age at hire is not significant in predicting starting salaries for new faculty hires.

Highly Correlated Predictor Variables: Variance Inflation Factors

One common technique to determine if the predictor variables are highly correlated with each other is to calculate the variance inflation factor for each predictor variable in the generalized ln(wage) model. Variance inflation factors (VIF) for each predictor variable can be found by assigning each predictor variable as the response variable and running a regression analysis with all the other predictor variables. The VIF for each variable can then be calculated as follows:

$$VIF_j = \frac{1}{1 - R_j^2},$$

where j = 1, 2, … p – 1, where p is the total number of beta parameters being estimated in the model (including the constant parameter), and R_j^2 is the coefficient of determination for the model in which variable x_i is represented as the response and all the other variables are included as predictor variables (Lesik, 2010). None of the variance inflation factors were above 10, thus suggesting that the individual predictor variables do not appear to be highly correlated with each other (the minimum VIF was 1.143 and the maximum was 6.453).

Conclusion

Concern over methods related to estimating the wage gaps in equity studies prompted our interest in determining the stability of wage gap estimates that are found in equity studies. As employers and employees are increasingly sensitive to gender and race equity for salary, an increasing number of studies are being done in both the public and private sector internationally (Fransson & Thornqvist, 2006). Authors of many equity studies, as well as studies on related topics, note concern over the stability of the estimate of the wage gap between males and females; yet to date, these concerns have not been addressed (Graham, 2003; Griffin, et al., 1987; Royston & Sauerbrei, 2008).

Table 5: Results of Fractional Polynomial Model Comparisons for the Generalized ln(wage) Equation

Age at Hire	Degrees of Freedom	Deviance	Residual Standard Deviation	Difference in Deviance	*p*-value	Powers
Not in Model	0	-322.579	0.059468	2.300	0.987	
Linear	1	-324.516	0.059253	0.363	1.000	1
k = 1	2	-324.663	0.059213	0.216	1.000	-2
k = 2	4	-324.675	0.059521	0.203	0.996	-2 -2
k = 3	6	-324.871	0.059783	0.008	0.997	0 0 0
k = 4	8	-324.879	0.060102	---	---	-2 -2 -2 -2

This study shows that the estimate of the wage gap between males and females remained stable given small changes in the underlying data as well as for various fractional powers of the continuous predictor variable that represents the age at hire. Also, none of the predictor variables were highly correlated with each other, thus there was no concern that highly correlated predictor variables could be influencing the estimated parameters. Given more powerful statistical software for bootstrap simulations and fractional polynomial analysis, as well as calculating variance inflation factors, these tools can be used to ensure that the estimates provided herein are not only accurate, but are stable given small changes in the data as well as the functional form of the regression model at hand.

Although this study was conducted in order to address some of the concerns that can generate unstable parameter estimates, there are still some limitations to note. One limitation of the Blinder-Oaxaca decomposition is that it can only decompose a regression model based on only two groups. Even though two groups are adequate to quantify gender, the decomposition cannot be used to compare more than two groups, such as would be the case with various classifications of race.

Limitations to fractional polynomial modeling include loss of power and sensitivity to outliers (Royston & Sauerbrei, 2008). Furthermore, because fractional polynomial modeling can identify the powers of a continuous predictor variable that suggest the best model fit, including continuous predictor variables with such powers can greatly increase the complexity of a regression model, thus making interpretation more difficult.

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Appendix:
STATA program for bootstrap resampling.

```
program BlinderSim, rclass
version 10.1
	drop _all
	use "BlinderOaxaca.dta"
	generate nsamp = cond(sex, 49, 61)
	bsample nsamp, strata(sex)
	oaxaca lnwage yr04 yr05 yr06 yr07 asst
assoc ageathire as business engrtech educ,
by(sex) pooled
	matrix list e(b)
	matrix list e(V)
	matrix define C = e(b)
	matrix define S = e(V)
	local undiff = el(C,1,5)
	local seundiff = sqrt(el(S,5,5))
	local zstat = `undiff'/`seundiff'
	local pvalue = 2*normal(-abs(`zstat'))
		if `pvalue' <= 0.10 {
			local inmodel = 1
			}
			else {
			local inmodel = 0
			}
	local expundiff = 100*(exp(`undiff')-1)
	local checkval = 0
		if `expundiff' < 0 {
			local checkval = 1
			}
			else {
			local checkval = 0
			}
	return scalar undiff = `undiff'
	return scalar seundiff = `seundiff'
	return scalar zstat = `zstat'
	return scalar pvalue = `pvalue'
	return scalar inmodel = `inmodel'
	return scalar expundiff = `expundiff'
	return scalar checkval = `checkval'
end
```