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Multiple Linear Regression Viewpoints

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Practical Issues to Consider Before Using Propensity Score Analysis

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Research methodology involving a comparison group and an experimental group is commonly used in many academic disciplines, including education, psychology, business, and medicine where random assignment of participants to groups is not possible. Generally, quasi-experimental or regression discontinuity designs have been used when true experimental designs are not possible. More recently, propensity score analysis has been suggested to address issues associated with the analysis of covariance approach used in quasi-experimental designs, especially selection bias. Key issues not addressed in the use of propensity score analysis are discussed.

Quasi-experimental designs have become a popular alternative to experimental designs when research methodology does not afford the random assignment of subjects to groups, e.g., intact groups (Campbell & Stanley, 1963). The major concern in using analysis of covariance to test mean differences between a comparison group and an experimental group is the non-random assignment or selection bias, but also as Tracz, Nelson, Newman, and Beltran (2005) pointed out: "the outcome or dependent variable in ANCOVA is an adjusted score after the effects of the covariate have been statistically controlled or removed from the dependent variable. The adjusted dependent variable is therefore no longer the same as the original dependent variable (p. 20)". Therefore the construct being represented by the dependent variable may be altered by the use of an adjusted dependent variable mean.

Federal funding has over the years embraced the quasi-experimental design approach to research, but also adopted another alternative when using regression discontinuity (Thistlethwaite & Campbell, 1960; Schumacker, 2007). The regression discontinuity (RD) approach is similar to the non-equivalent quasi-experimental group design which uses analysis of covariance, but the assumptions and advantages are much different (Schumacker, 2008). The RD design does not have subject selection bias (pre-defined group membership) because it uses a pre-test measure to assign treatment or non-treatment status.

More recently, propensity score analysis has been presented as another approach to examine causal effects between comparison and experimental groups (McCaffrey, Ridgeway, & Morral, 2004). The steps to conduct a propensity score analysis have been outlined and compared to ANCOVA (Fraas, Newman, & Pool, 2007). The steps are:

1. Select the covariates
2. Assess the initial imbalance in the covariates
3. Estimate the propensity scores
4. Stratify the propensity scores
5. Assess the balance on the covariates across the treatment groups
6. Estimate and statistically test the difference between the treatment means

Practical Issues

The propensity score approach creates group classifications based on a distribution of scores created from using a set of covariate variables. Whenever this is done, *classification errors* can occur. The propensity score approach uses discriminant, probit, or logit regression that will output either a group classification assignment (discriminant), a probability between 0 and 1 (probit) based on normality assumption, or a probability between 0 and 1 (logit) based on linearity. In the case of discriminant group classification,a percent classification accuracy will occur. In the case of probit or logit, the researcher would create four or five groups (strata using quartiles or quintiles) based on the probability distribution. The issue is clear, where do you draw the line to create the groups – thus classification error can occur when creating the groups.

In statistics, the issue of *power and sample size* is related to the Type I error rate, alpha level of significance, directional nature of the hypothesis, and population variance. In the propensity score approach you create comparison and experimental group mean differences for each of the groups created from the quartile or quintile levels. A researcher can also test the overall effect by averaging mean differences across propensity score groups. The *sample sizes* can differ radically for each propensity score group, and therefore *power* of each independent t-test would be different than power and sample size of the overall comparison between the comparison and experimental group.

The null hypothesis *Type I error* rate for the overall comparison of the two groups is typically a one-tailed test at the 0.05 level of significance. However, the Type I error rate can be very different depending upon whether using 4 groups, 5 groups, or 6 groups. How do we decide how many groups to create based on the covariate variables selected? The number of propensity score groups will therefore affect the Type I error rate.

An *experiment-wide error rate* occurs when comparing means from several groups using the same sample of data. When several propensity score groups are created and the means are compared between the comparison and experimental groups within each propensity score group, an experiment wide error rate occurs. This usually requires a Dunn-Bonnferoni adjustment. Basically, you are using the same data and running several independent t-tests, therefore, the alpha is not 0.05 rather, 5 groups would be 0.05 / 5 = 0.01 level of significance to account for five null hypotheses being tested.

Finally, the *covariates selected* and the *order of variable entry* affect the logit regression results (Schumacker, Anderson, & Ashby, 1999). *Model validity* is called into question based on what covariates are selected. How do we determine which covariate variables are significant that we want to use? The criteria for selection is usually select variables with little correlation between themselves and little to no correlation with the independent variables (point-biserial correlation with comparison/experimental group variable), but high correlation with the dependent variables. The order of entry of the covariate variables also affects logit regression results, so depending on the order of the variables entered into the analysis, a covariate variable may or may not be significant – thus affecting which ones a researcher might select to use. **Note:** Stepwise regression is not to be used!

Conclusion

Researchers today have several options to choose from when selecting a research design. Experimental designs with random assignment of subjects will always be the gold standard for cause-effect interpretations. Quasi-experimental designs were introduced to accommodate research where random assignment of subjects to control and experimental groups were not possible, hence the use of comparison groups. The main issue has always been the comparability of the subjects in the groups (selection bias), so matching on key variables or the use of covariate variables were used to "equate" the groups as best possible. A third approach, regression discontinuity (Trochim, 1984) was also adopted for use in non-equivalent design research, but was not used extensively, possibly based on reasons offered by McNeil (1984). Currently, a fourth approach is being advocated, namely, propensity score analysis.

Propensity score analysis has several practical issues that can affect results and interpretation. The first is that classification errors can occur depending on how the strata are divided to create the propensity score groups. The next is that the sample size of each propensity score group will be smaller than the overall sample size effect when testing mean differences in an ANCOVA or regression-discontinuity approach. Power is also affected given the smaller sample sizes. In testing the research hypothesis, a Type I error rate is present because of the number of propensity score groups created, basically the probability of finding a mean difference increases. An experiment-wide error rate is present so a Dunn-Bonnferoni adjustment is necessary given the number of t-tests conducted. Some other critical issues appear when determining what covariate variables to use. Obviously a review of the research literature will help in this regard, but selecting covariate variables using some modeled fit criteria may not be appropriate. Another serious concern is that the order of variables in a logistic regression equation can affect results. Finally, model validity becomes an issue because depending on what variable covariates are used, propensity score groups formed, and the nature of the dependent variable construct, results can vary dramatically. So, before embracing propensity score analysis be aware of these practical issues that can impact results and interpretation.

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Incorporating Substantive Knowledge Into Regression Via A Bayesian Approach To Modeling

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A multiple regression example is used to illustrate advantages of a Bayesian approach that incorporates situation-specific substantive information over frequentist and Bayesian approaches that ignore such information. Frequentist and Bayesian analyses of a traditional regression model produced nearly identical results. A Bayesian analysis of a modified model yielded preferred estimates of parameters and quality of prediction.

Regression models are useful for characterizing patterns and quantifying the relationships that exist among observable variables. An important and widespread application of regression is to facilitate predictions for an outcome. In applied analyses, regression model parameters are estimated based on sample data; frequently the estimated parameters are then used to make predictions for future cases whose outcomes are not known. The utility of a regression model for making predictions for future cases is therefore limited by the information that is available when it is constructed. The current work illustrates how using a Bayesian approach allows the researcher to incorporate substantive information about the problem to augment the information available from sample data to obtain preferred estimates of the parameters and the quality of prediction. Specifically, it will be shown in the context of a regression model for educational achievement tests that incorporating boundary constraints via a Bayesian approach to regression modeling yields preferred estimates of parameters and measures of prediction accuracy compared to traditional approaches.

Comparisons of frequentist and Bayesian approaches typically highlight the presence of prior distributions in the Bayesian framework. A common criticism of the Bayesian approach is that it is "only as good as the priors", meaning that if the prior distributions poorly match the structure of the data in the population, the Bayesian approach will suffer relative to a frequentist approach. On the other hand, as demonstrated in the current work, prior distributions can be a mechanism for incorporating substantive information into the model. While this is certainly one of the main ways that the two approaches differ, we will demonstrate that prior distributions are not the only way to incorporate characteristics of the substantive problem into the analysis. In the current example, it is argued that placing substantively motivated boundaries on the prior distribution and the likelihood—which are easily incorporated in a Bayesian approach with flexible estimation routines—yields preferred estimates of parameters and prediction quality. This is illustrated in the context of regression with small samples, where the substantive information that is brought to bear augments the information in the data.

Context and Data

The data used in the analyses come from the first three end-of-chapter exams associated with the course Networking Basics, the first of a four-course curriculum in the Cisco Networking Academy Program. Students in this program come from a wide variety of educational backgrounds, and are typically progressing toward certification that will allow them to work as computer networking professionals servicing home or business settings. For researchers of the Cisco Networking Academy Program, operational work in this context frequently involves characterizing relationships between performance on early exams and performance on later exams using regression. Moreover, the complexities of the online administration of exams yields situations in which sample sizes for such analyses vary considerably. As such, the regression analyses in operational work may employ small samples. This work illustrates the usage of Bayesian approaches to modeling that allow for the incorporation of substantive knowledge to improve data analysis in such contexts. The primary data used in the analyses consist of total scores from 50 students on the three exams. For each exam, scores in the population had the potential to range from zero to the number of items on the exam. There were 16 items on the first exam; in this sample, total scores ranged from 4 to 16, (M = 14.10, SD = 2.02). There were 18 items on the second exam; in the sample, total scores ranged from 3 to 18, (M = 14.34, SD = 3.29). The third exam had 15 items; in the sample, total scores ranged from 1 to 15 (M = 12.22, SD = 2.96). The zero-order correlations between the chapter exams are as follows: Chapters 1 and 2, 0.58; Chapters 1 and

3, 0.69; Chapters 2 and 3, 0.68. A second data set, consisting of test scores from 1950 students, was used in a follow-up analysis as described below.

Classical and Bayesian Analyses of a Traditional Regression Model

In each analysis, the scores on the first and second exams in the curriculum were used to predict scores on the third exam.

Classical Analysis. A traditional model regressing the third exam on the first and second exams is given by

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \varepsilon_i \,, \tag{1}$$

where X_{i1}, X_{i2}, and Y_i denote the total scores on the first, second, and third exams, respectively, for subject i, and $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$. A classical approach to model estimation treats the parameters as fixed unknowns, commonly employing maximum likelihood (ML) or equivalently least squares estimation. Following the model in (1) and assumptions regarding errors, the likelihood function may be written as

$$L(\beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2 \mid \mathbf{X}, \mathbf{Y}) = \prod_{i=1}^{N} N(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2}, \sigma_\varepsilon^2) \tag{2}$$

where **X** and **Y** are the full collections of predictor and dependent variables, respectively. Straightforward differentiation and analysis yields well-known closed form solutions for ML estimators of the parameters (e.g., Rencher, 2000).

Bayesian Analysis. A Bayesian approach to modeling differs from the classical approach by treating each entity as a random variable that can be characterized via probability distributions (Gelman, Carlin, Stern, & Rubin, 1995). A prior distribution is specified for unknown model parameters and the posterior distribution is given by Bayes' theorem:

$$P(\beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2 \mid \mathbf{X}, \mathbf{Y}) = \frac{P(\beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2) P(\mathbf{Y} \mid \beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2, \mathbf{X})}{\int\limits_{\beta_0}\int\limits_{\beta_1}\int\limits_{\beta_2}\int\limits_{\sigma_\varepsilon^2} P(\beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2) P(\mathbf{Y} \mid \beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2, \mathbf{X})} \tag{3}$$

$$\propto P(\beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2) P(\mathbf{Y} \mid \beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2, \mathbf{X})$$

where $P(\mathbf{Y} \mid \beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2, \mathbf{X})$ is the conditional distribution of the data or likelihood function given in (2) and $P(\beta_0, \beta_1, \beta_2, \sigma_\varepsilon^2)$ is the prior distribution for the model parameters.

The prior distribution is constructed via specifying independent components. Frequently, diffuse prior distributions are employed in situations where prior knowledge is limited. The current analysis adopts this approach to highlight the comparability between the classical approach and the Bayesian approach to the traditional model under such specifications. We specify diffuse generalized prior distributions (Press, 1989) in the form of normal distributions for the intercept and coefficients and an inverse-gamma distribution for the residual variance (for alternative specifications of prior distributions in regression and related contexts see Gelman et al., 1995; Gill, 2007; Lee, 2007)

$$\begin{gathered} P(\beta_0) \sim N(0,\ 10{,}000); \\ P(\beta_1) \sim N(0,\ 10{,}000); \\ P(\beta_2) \sim N(0,\ 10{,}000); \\ P(\sigma_\varepsilon^2) \sim Inv-G(.01, .01). \end{gathered} \tag{4}$$

Though analytical solutions to the model are available under certain choices of distributional forms (e.g., Gelman et al., 1995), they are frequently intractable for complex problems. The current work employs Markov chain Monte Carlo (MCMC; e.g. Gilks, Richardson, & Spiegelhalter, 1996) estimation to conduct the analyses, as MCMC algorithms capitalize on the proportionality relationship in (3) to provide a flexible framework that allows for the estimation of complex models. MCMC consists of taking a series of draws to form a chain such that, in the limit, the chain converges to a stationary distribution such that subsequent draws may be viewed as draws from the stationary distribution (see Gilks et al., 1996 for details and an overview of popular MCMC algorithms). In a Bayesian analysis, we construct the chain so that the stationary distribution is the posterior distribution of interest.

MCMC estimation was conducted in WinBUGS (Spiegelhalter, Thomas, Best, & Lunn, 2007) via the package R2WINBUGS (Sturtz, Ligges, & Gelman, 2005) in the R statistical environment (R Core Development Team, 2008). Annotated WinBUGS code for running this model and later models are contained in the Appendix. Steps in an MCMC analysis include monitoring the convergence of the chain(s), determining the number of iterations to discard as burn-in, and summarizing the remaining draws for the parameters.

Bayesian Analysis of a Modified Model

The modified model incorporates existing knowledge about the range of actual outcome possibilities in a way that the traditional regression model neglects. Specifically, the values of the criterion variable necessarily fall between zero and 15, the lowest and highest possible scores, respectively, on the Chapter 3 exam. A more thorough Bayesian analysis includes such substantive knowledge in the probability model (Gelman et al., 1995). The model modifications used here to incorporate that knowledge include changes to the prior distribution and changes to the likelihood.

The prior distribution for the intercept (β_0) is changed from a normal distribution to a uniform distribution bounded by the potential response range on the outcome variable. The prior distributions for the remaining parameters are made less diffuse to facilitate convergence of the more complex modified model, though these priors are still quite diffuse:

$$\begin{aligned} P(\beta_0) &\sim U(0, 15); \\ P(\beta_1) &\sim N(0, 1000); \\ P(\beta_2) &\sim N(0, 1000); \\ P(\sigma_\varepsilon^2) &\sim Inv-G(1,\ 1). \end{aligned} \tag{5}$$

The likelihood is altered by modifying the regression model, where the predicted values are adjusted to take into account the maximum possible score on the criterion. For students who would otherwise be predicted to score above 15 by the prediction equation (1), the out-of-bounds predicted score is changed to equal 15, which we designate to be the "adjusted predicted score". Given the positive bivariate relationships, the prior distribution for β_0 effectively serves to bound the predicted values below by 0. Estimation and convergence assessment were conducted using the same tools reported above for the original model.

We note that this modified model is similar in spirit to censored regression models (Tobin, 1958) for which ML and Bayesian approaches to estimation have been developed (Chib, 1992). However, censored regression models are limited in that they do not directly constrain the regression parameters and the proper interpretation of the parameters concerns the relationships between the predictors and the latent dependent variable. In the model adopted here, the use of the prior distribution in (5) directly constrains the intercept in accordance with substantive theory and yields parameters that concern the relationships between the predictors and the observed dependent variable.

Results

Table 1 summarizes the results of the models. For the classical analysis, ML estimates, standard errors, and 95% confidence intervals are reported, as is R^2. For the Bayesian analyses, history plots of the draws for each parameter and the Brooks-Gelman-Rubin diagnostic (Brooks & Gelman, 1998; Gelman & Rubin, 1992) were examined to determine that 1000 iterations were sufficient to burn-in the chains for both the traditional and modified regression model. For each model, the results in Table 1 were thus computed using iterations 1001 to 4000 for each of the three chains, for a total of 9000 iterations. Posterior means, standard deviations, and 95% credibility intervals are reported for the parameters and R^2.

Table 1. Summary of Results of Classical and Bayesian Analyses for the primary dataset.

	Classical Analysis of Traditional Model			Bayesian Analysis of Traditional Model			Bayesian Analysis of Modified Model		
	Estimate	SE	95% Confidence Interval	Posterior Mean	Posterior SD	95% Credibility Interval	Posterior Mean	Posterior SD	95% Credibility Interval
β_0	-2.54	1.93	(-6.41, 1.34)	-2.54	1.96	(-6.32, 1.31)	1.07	0.93	(0.03, 3.47)
β_1	0.66	0.17	(0.33, 0.99)	0.66	0.17	(0.33, 0.99)	0.40	0.12	(0.15, 0.63)
β_2	0.38	0.10	(0.18, 0.59)	0.38	0.10	(0.17, 0.58)	0.39	0.10	(0.18, 0.59)
σ_ε	1.95	0.28	(1.60, 2.37)	1.94	0.21	(1.59, 2.40)	1.98	0.21	(1.63, 2.43)
R^2	0.60			0.59	0.06	(0.45, 0.68)	0.48	0.05	(0.35, 0.56)

Discussion

The results of the Bayesian analysis of the traditional model—in terms of point estimates and intervals—closely mirrored those of the classical analysis, as expected given the use of diffuse priors. By contrast, the results of the Bayesian analysis of the modified model differed from those of the other analyses. These differences are highlighted by the results for β_1 and β_0. In terms of the latter, whereas the classical and Bayesian analysis of the traditional model allows β_0 to take on any real value, the use of the prior distribution in the modified model restricts the posterior distribution to be between zero and 15. This difference is summarized by the point estimates. The ML estimate and the posterior mean for β_0 for the traditional model is –2.54 and the posterior mean for β_0 for the modified model is 1.07. It is problematic to interpret the negative value for β_0 in the traditional model, as it is impossible for a student to score less than zero on the third exam. By construction, this is precluded in the modified model via the prior distribution for β_0.

Interestingly, the R^2 values for each model make it appear at first glance that the modified model (posterior mean of R^2 = 0.44) does not perform as well as the traditional models using ML or Bayesian analysis (R^2 = 0.60 and 0.59, respectively). This is a necessary result, as the ML solution to the traditional model maximizes R^2 in the sample on which the estimates are derived. However, to explore the difference in the quality of prediction, a second sample of 1950 students' tests scores was employed. For each student, the point estimates (ML estimates or posterior means in Table 1) from each of the models were used to generate a prediction. The squared correlations between these predictions and the true values were then calculated as R^2 statistics for this second dataset. When the regression model based on the original 50 sample scores are used to predict the 1950 scores in this dataset, the R^2 for each of the models is as follows: ML analysis of the traditional model, R^2 = 0.43, Bayesian analysis of the traditional model, R^2 = .43, Bayesian analysis of the modified model, R^2 = 0.44. These three R^2 values are not meaningfully different; the models performed equally well in predicting the outcome on the third exam in the larger sample. For all the models, using the prediction equation from the original sample to form predictions for new data naturally lowers each of these R^2 values relative to the values in the original sample. However, the differences in the amount of the reduction in R^2 when cross-validated with the second sample are revealing. The modified model displayed much less of this reduction than did the traditional models. This is interpreted as indicating that—in the original sample—the modified model provided the most realistic view of the predictive utility of the predictors in the population and future samples. Put another way, the traditional model capitalizes on variation in the sample data with which it is estimated and suffers when cross-validated on another dataset, whereas the modified model performs almost as well in estimating the cross-validating dataset as it does in the original sample. Note that using adjusted R^2 for the analyses of the original model yielded 0.58 and 0.57 for the classical and Bayesian analyses, respectively. Though these values are smaller than the values of R^2 reported in Table 1 (0.60 and 0.59), they still indicate considerably inflated predictive quality relative to the cross-validation. By incorporating existing substantive knowledge of the population, the modified model (necessarily) sacrifices predictive power in the original sample yet provides a more accurate estimate of the predictive accuracy for future samples.

For comparative purposes the traditional model using ML was fit on this cross-validation dataset; the results are given in Table 2. Viewing the results from this larger dataset as more representative of the population, note that the estimates from this model are quite close to those from the results from the modified model of the original data set. Additionally, for β_0, β_1, and R^2, the results are much closer to the modified model than the traditional model. From the perspective of the results from the second dataset, the estimates of the parameters (particularly β_0 and β_1) and the estimate of the quality of prediction (in terms of R^2) of the modified model of the original dataset yield more accurate results than those from the traditional model. This is because the modified model augments the data by incorporating known properties of the substantive problem into the model. On a criterion that ranges from zero to 15 in the population, it is intellectually unsatisfying if not contradictory to allow a predicted value outside this range for the range of possible values of the predictors. In the current context, the intercept represents such a prediction. Substantively, as researchers knowledgeable about the context, we know that it is impossible for a student to have a negative total score on the third exam, regardless of performance on the first two exams. Yet the traditional models do not allow us to incorporate this substantive knowledge. The fact that the model-implied intercepts for the traditional models were negative in the original data emphasizes the point that those models capitalized on chance when fitting the best line for the observed data. A Bayesian approach—supported by the flexibility of MCMC estimation—allows this prior knowledge to be brought to bear in modeling.

Table 2. Results of Classical Analysis for the cross-validation dataset.

	Estimate	SE	95% Confidence Interval
β_0	1.39	0.32	(0.76, 2.02)
β_1	0.39	0.03	(0.33, 0.45)
β_2	0.38	0.02	(0.34, 0.42)
σ_ε	2.17	0.00	(2.17, 2.17)
R^2	0.44		

In summary, this paper is intended to highlight an understudied advantage of a Bayesian approach to regression modeling, namely, the ease and flexibility with which substantive information may be incorporated to augment the information in the sample data when fitting models. We illustrate how that information can be modeled in the prior distribution (in the example, via the choice of the support of the prior distribution) and via the likelihood (in the example, by adjusting predicted values). The advantages manifest themselves in supporting inferences consistent with the population, which is particularly beneficial in the case of small sample analyses, in which sampling variability is more profound.

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Appendix

Annotated WinBUGS code for running the traditional model

```
model{

beta.0 ~ dnorm(0, .0001);          # prior for the intercept
beta.1 ~ dnorm(0, .0001);          # prior for coefficient 1
beta.2 ~ dnorm(0, .0001);          # prior for coefficient 2
tau.e ~ dgamma(.01, .01);          # prior for the error precision
sigma.e <- 1/sqrt(tau.e);          # standard deviation of the errors

for(i in 1:N){
    y.prime[i] <- beta.0 + beta.1*x1[i] + beta.2*x2[i];    # predicted value
    y[i] ~ dnorm(y.prime[i], tau.e);          # conditional distribution of y
}

}
```

Annotated WinBUGS code for running the modified model

```
model{

beta.0 ~ dunif(0, 15);          # prior for the intercept
beta.1 ~ dnorm(0, .001);        # prior for coefficient 1
beta.2 ~ dnorm(0, .001);        # prior for coefficient 2
tau.e ~ dgamma(1, 1);           # prior for the error precision
sigma.e <- 1/sqrt(tau.e);       # standard deviation of the errors

for(i in 1:N){
    y.prime[i] <- beta.0 + beta.1*x1[i] + beta.2*x2[i];    # predicted value, adjusted next
    y.prime.adj[i] <- step(y.prime[i] - 15)*15 + (1-step(y.prime[i] - 15))*y.prime[i]
    y[i] ~ dnorm(y.prime.adj[i], tau.e);          # conditional distribution of y
}

}
```

The SSER Method: Replicability Possibilities within the General Linear Model Extended to the Independent Samples *t*-Test, One-Way ANOVA, and Chi-Square

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The purpose of this examination was to extend the research pertaining to the idea of a statistically significant exact replication (SSER) method for estimating a study's replicability for the cases of the independent sample t-test, the one-way analysis of variance, and chi-square. A second intention of this study was to provide users with three programs that would calculate the SSER value when there was a statistically significant finding to assist in determining the chance that an exact replication would be statistically significant beyond 50%.

Over a 10 year period of applied and theoretical research pertaining to the statistically significant exact replication (SSER) technique, and other concepts affiliated with the SSER such as replication, power, and probability, the literature indicated that developmental work and scholarly debate in this area have resulted in an probability-based method for estimating a study's replicability (cf. Froman & Shneyderman, 2004; Greenwald, Gonzalez, Harris, & Guthrie, 1996; Macdonald, 2002, 2003; Newman, McNeil, & Fraas, 2004; Posavac, 2002, 2003; Walker, 2006). The SSER is premised on the idea that, "… the probability of a statistically significant exact replication (SSER) can be estimated from the probability of the statistical test" (Newman et al., p. 37). Within the idiom of the SSER, the concept of replication was operationalized as "…a test conducted with additional subjects sampled in the same fashion as those in the initial study and tested under conditions identical to those of the initial study" (Greenwald et al., p. 181). That is, the "…initial experiment and the replication differ only due to random variation (Posavac, 2002, p. 102). Because SSER probability is an estimate derived from a probability value of an observed test statistic that an exact replication will be statistically significant, it should be thought of as an upper bound value of replicability ranging between 0 and 1.00, with a benchmark of ≥ .80 to assure a demonstrable result of the likelihood of a finding being repeated successfully (Greenwald et al.). Ultimately, the SSER method poses the subsequent question: How much beyond a 50% chance is there of replicating a statistically significant finding for an observed sample statistic?

Purpose

This study had two purposes. The first intention was to expand on and add to the aforementioned scholarly literature in this area of research. The second goal was to provide users of the method with three programs in SPSS (Statistical Package for the Social Sciences) that would calculate the SSER value when there was a statistically significant finding extended to three cases all algebraically related: the independent samples t-test, the one-way analysis of variance (ANOVA), and chi-square (cf. Walker, 2006 for previous extension work with the t-test and ANOVA). In statistics, the issue of *power and sample size* is related to the Type I error rate, alpha level of significance, directional nature of the hypothesis, and population variance.

Method

Using the data provided in Newman et al. (2004) for the case of an independent samples t-test with an observed t value of 2.150, 38 df (degrees of freedom), and a two-tailed t critical value of 2.024 at the .05 alpha level, the concept of the SSER method was replicated and modified with the t-test example and extended to the one-way ANOVA and chi-square. For the t-test program, users need to supply within the program's syntax matrix the observed t value and the test's df, which is ascertained by n-2. For the ANOVA, users need to provide the observed F value, df1 for the numerator, df2 for the denominator, df3 for the R2 effect size, where df3 is determined via n-1, and the sample size. For the chi-square program, users need to supply the observed chi-square value, the df, and the sample size (see Appendices A – C for the programs' syntax). Once these sample-based, observed data are entered in the marked area of a particular program's syntax, users run the program to derive an SSER result. The programs' defaults are set for all of the critical values at the .05 level. If this default level needs to be changed a priori, due to theoretical assumptions and/or literature-based reasoning, users can follow the instructions embedded within the programs' syntax.

Table 1. SSER results

Test	*df*	Observed Statistic Value	Critical Value (.05)	*p*-Value	Effect Size	SSER Value
t-Test	38	2.150	2.024	.038	.698	.550
ANOVA	1,38	4.623	4.098	.038	.106	.527
Chi-Square	1	4.320	3.841	.038	.312	.511

Results and Discussion

To answer the SSER's question, how much beyond a 50/50 chance is there of replicating a statistically significant finding for an observed sample statistic?, the Newman et al. (2004) example calculated an SSER value for the *t*-test of .55 or just a little over half of the replications would be anticipated to generate an observed *t* value greater than 2.150 and a little less than half of the replications would be expected to yield an observed *t* value less than 2.150. In replication of said result, and extending the method to two other tests, data in Table 1 indicated that for all three of the statistically significant test results, there was just a slight likelihood of over a 50% chance of replication, with the upper bound of an exact statistically significant replication estimated at .55 for the *t*-test, .53 for the ANOVA, and .51 for chi-square; all of which were not very reliable. In addition, if we report the effect sizes affiliated with these statistically significant results that had just over a 50% chance of replication, we find that the *t*-test had a Cohen's $d = 0.70$, the ANOVA had an $R^2 = 0.11$, and chi-square had a coefficient of contingency = .31. Even though we had statistically significant results and effects sizes that ranged from small to bordering on large, the important information garnered from these data are that they had just over a 50% chance of replication.

In a second example using the ANOVA program, the probability value of the observed F was statistically significant at $p = .049$, but the SSER value was .001 or virtually no chance, beyond 50%, that an exact replication would be statistically significant at the .05 level. This outcome illustrates a caution noted by Newman et al. (2004) that a statistically significant result affiliated with an observed test value will not always generate an exact replication that will be statistically significant as well.

It should be noted that because a given SSER value is based on a sample test statistic, which in turn is related to a sample size, the 50/50 split of an exact replication being statistically significant beyond 50% is assumed via a normal distribution and predicated on the fact that "larger sample sizes… would give the researcher more statistical power and would increase the likelihood of rejecting null hypotheses in SSERs" (Posavac, 2002, p. 111). Given these assumptions, there is a possibility that an SSER value could be lower, in the sense of not reaching its maximum upper value, when affiliated with a small sample size (i.e., $n < 30$). Posavac (2002) determined that small samples had limited impact on SSER probabilities by showing, in the case of the *t*-test, that when a sample was as small as $n = 10$ or df = 8 with alpha established at the levels of .05, .01, and .005 for a two-tailed test, values for the SSER were .50 at the .05 level, ranging from .73 to .84 at the .01 level, and between .80 to .92 at the .005 level.

Although the SSER is a post-hoc viewpoint, it does not carry the same connotation as selective post-hoc analyses for data dredging since it would only be performed after a statistically significant result were found and gives one an indication if said result were replicable or not beyond 50%. Also, it should be emphasized that the terms of alpha level setting (i.e., to control against type I error) need to be determined by users of the programs *a priori* and based on theory and/or research, and that these programs, while undemanding to run, should only be employed when statistical significance has been realized. Finally, the SSER replication probability, like other probability indices, should be interpreted in its research context with attentiveness toward factors that may impact its value such as influential data points, sampling variability, or data distribution (Macdonald, 2002).

Conclusion

The purpose of this study was to extend the research pertaining to the idea of a statistically significant exact replication method. The current study continues the idea of the SSER method and provides users with programs that will calculate the SSER value when there is a statistically significant finding to assist in determining the chance that an exact replication will be statistically significant beyond 50%. A standard feature of science is replication and an extension of the SSER method within the general linear model should afford users with more data upon which to base their decisions pertaining to, for example, the reliability of particular variables in a model or result stability.

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Appendix A: SSER program for the independent samples *t*-test

```
*****************************************************************************
NOTE: During your initial research, if the probability value of the observed t-test is > .05, there
is NO need to run this program
*****************************************************************************.
DATA LIST LIST / TOBS (F9.3) DF (F8.0).
*****************************************************************************
Between BEGIN DATA and END DATA below, put your observed t value (TOBS) and degrees of
freedom (DF, which is n-2)
*****************************************************************************.
BEGIN DATA
2.150    38
END DATA.
*****************************************************************************
NOTE: Below in TDIFF for the critical value of t, choose the alpha level for a two-tailed test, either
TCRIT.05, TCRIT.01, or TCRIT.001 Currently, the program default is set at the .05 level
*****************************************************************************.
COMPUTE TCRIT.05 = ABS(IDF.T(.025,DF)).
COMPUTE TCRIT.01 = ABS(IDF.T(.005,DF)).
COMPUTE TCRIT.001 = ABS(IDF.T(.0005,DF)).
COMPUTE TDIFF = TOBS-TCRIT.05.
COMPUTE TREP = CDF.T(TDIFF,DF).
COMPUTE SIG1 = CDF.T(TOBS,DF).
COMPUTE D = 2*TOBS/SQRT(DF).
COMPUTE SIG = (1-SIG1)*2.
EXECUTE.
FORMAT TCRIT.05 TO SIG  (F9.3).
VARIABLE LABELS D 'Cohens d Effect Size (.20, .50, .80 are Suggested = Small, Medium, and Large
Effects)'/TOBS 'Your Observed t Value'/SIG 'The Probability of Your Observed t Value'/TCRIT.05 'For
Your DF, the Critical Value of t, Alpha=.05, Two-Tailed Test (Program Default Value)'/TCRIT.01 'For
Your DF, the Critical Value of t, Alpha=.01, Two-Tailed Test'/TCRIT.001 'For Your DF, the Critical
Value of t, Alpha=.001, Two-Tailed Test'/DF 'Degrees of Freedom'/TREP 'The Upper Limit of the SSER
Probability Value'/.
REPORT FORMAT=LIST AUTOMATIC ALIGN (CENTER)
  /VARIABLES= DF TOBS TCRIT.05 SIG D TCRIT.01 TCRIT.001
  /TITLE "Test Statistics".
REPORT FORMAT=LIST AUTOMATIC ALIGN (LEFT)
MARGINS (*,120)
  /VARIABLES= TREP
  /TITLE "How Much Beyond a 50/50 Chance Do You Have of Replicating Your Statistically Significant
Findings?".
************************************************
NOTE: A SSER value >= .80 is desired
************************************************.
```

Appendix B: SSER program for the one-way ANOVA

```
DATA LIST LIST / FOBS (F9.3) DF1 DF2 DF3 N (4F8.0).
***************************************************************************
Between BEGIN DATA and END DATA below, put your observed F value (FOBS), the degrees of
freedom (DF1 for the numerator, DF2 for the denominator, and DF3 for the R2 effect size where it is
always found through N-1) from your F test, and the sample size (N)
***************************************************************************.
BEGIN DATA
4.623 1 38 39 40
END DATA.
***************************************************************************
NOTE: Below in FDIFF for the critical value of F, choose the alpha level for a two-tailed test, either
FCRIT.05 or FCRIT.01. Currently, the program default is set at the .05 level
***************************************************************************.
COMPUTE FCRIT.05 = ABS(IDF.F(.95,DF1,DF2)).
COMPUTE FCRIT.01 = ABS(IDF.F(.99,DF1,DF2)).
COMPUTE FDIFF = FOBS-FCRIT.05.
COMPUTE FREP = CDF.F(FDIFF,DF1,DF2).
COMPUTE R2 = FOBS/(FOBS+DF3).
COMPUTE FSIG = SIG.F(FOBS,DF1,DF2).
EXECUTE.
FORMAT FCRIT.05 TO FSIG  (F9.3).
VARIABLE LABELS R2 'R2 Effect Size (.10, .25, .40 are Suggested = Small, Medium, and Large
Effects)'/FOBS 'Your Observed F Value'/FCRIT.05 'For Your DF1 and DF2, the Critical Value of F,
Alpha=.05 (Program Default Value)'/FCRIT.01 'For Your DF1 and DF2, the Critical Value of F,
Alpha=.01'/DF1 'Degrees of Freedom for the Numerator'/DF2 'Degrees of Freedom for the
Denominator'/FSIG 'The Probability of the Observed F Value'/FREP 'The Upper Limit of the SSER
Probability Value'/.
REPORT FORMAT=LIST AUTOMATIC ALIGN (LEFT)
MARGINS (*,150)
  /VARIABLES= DF1 DF2 FOBS FCRIT.05 R2 FSIG FCRIT.01
  /TITLE "Test Statistics".
REPORT FORMAT=LIST AUTOMATIC ALIGN (LEFT)
MARGINS (*,110)
  /VARIABLES= FREP
  /TITLE "How Much Beyond a 50/50 Chance Do You Have of Replicating Your Statistically Significant
Findings?".
```

Appendix C: SSER program for chi-square

```
DATA LIST LIST / CHIOBS (F9.3) DF N (2F8.0).
****************************************************************************
Between BEGIN DATA and END DATA below, put your observed chi-square value (CHIOBS), the
degrees of freedom (DF), and the sample size (N)
****************************************************************************.
BEGIN DATA
4.32 1 40
END DATA.
****************************************************************************
NOTE: Below in CHIDIFF for the critical value of chi-square, choose the alpha level for either
CHICRIT.05, CHICRIT.01, or CHICRIT.001 Currently, the program default is set at the .05 level
****************************************************************************.
COMPUTE CHICRIT.05 = ABS(IDF.CHISQ(.95,DF)).
COMPUTE CHICRIT.01 = ABS(IDF.CHISQ(.99,DF)).
COMPUTE CHICRIT.001 = ABS(IDF.CHISQ(.995,DF)).
COMPUTE CHIDIFF = CHIOBS-CHICRIT.05.
COMPUTE CHIREP = CDF.CHISQ(CHIDIFF,DF).
COMPUTE C = SQRT(CHIOBS/(N+CHIOBS)).
COMPUTE SIG = 1-CDF.CHISQ(CHIOBS,DF).
EXECUTE.
FORMAT CHICRIT.05 TO SIG  (F9.3).
VARIABLE LABELS  C 'Pearsons Coefficient of Contingency (C) Effect Size (.10, .30, .50 are
Suggested = Small, Medium, and Large Effects)'/CHIOBS 'Your Observed Chi Square Value'/SIG 'The
Probability of Your Observed X2 Value'/CHICRIT.05 'For Your DF, the Critical Value of X2, Alpha=.05
(Program Default Value)'/CHICRIT.01 'For Your DF, the Critical Value of X2, Alpha=.01'/CHICRIT.001
'For Your DF, the Critical Value of X2, Alpha=.001'/DF 'Degrees of Freedom'/CHIREP 'The Upper Limit
of the SSER Probability Value'/.
REPORT FORMAT=LIST AUTOMATIC ALIGN (LEFT)
MARGINS (*,150)
  /VARIABLES= DF CHIOBS CHICRIT.05 SIG C CHICRIT.01 CHICRIT.001
  /TITLE "Test Statistics".
REPORT FORMAT=LIST AUTOMATIC ALIGN (LEFT)
MARGINS (*,110)
  /VARIABLES= CHIREP
  /TITLE "How Much Beyond a 50/50 Chance Do You Have of Replicating Your Statistically Significant
Findings?".
```

Hope, Optimism and Self-Efficacy: A System of Competence and Control Enhancing African American College Students Academic Well-Being

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Competence and control beliefs are central constructs in understanding student motivation. However, most research has examined competence and control beliefs in isolation from each other, and little is known about how these beliefs function as a system in relationship to one another. Using Huberty's (2003) recommendation, multiple correlation analyses were used to examine the relationship of hope, self-efficacy, optimism and pessimism, as a cognitive set of competence and control beliefs, to the academic well-being of African-American college students at a historically black university in the Southeastern United States. Results suggest that the cognitive set was significantly related to multiple measures of academic well-being including increased academic achievement, positive emotion, adaptive coping strategies and life satisfaction, and decreased negative emotion and maladaptive coping strategies. Although the cognitive set was predictive of measures of academic well-being, the individual measures of hope, self-efficacy, optimism and pessimism predicted different aspects of academic well-being.

One goal of schooling is to motivate students to do well, where *doing well* usually translates into academic achievement. However, focusing solely on academic achievement overlooks *being well* academically. Academic well-being includes academic achievement, but expands the idea of doing well to also include adaptively coping with life's daily challenges, experiencing positive emotions and increasing life satisfaction.

Focusing on the larger issue of academic well-being expands measures of academic success from the acquisition and recall of knowledge (National Research Council, 2005) to the development of students' personal sense of agency that motivates them to take control of their life, challenge themselves and persevere through difficulties (Bandura, 1986; Snyder, Shorey, Cheavens, et al., 2002; Scheier & Carver, 1985). A personal sense of agency develops through an evolving system of competence and control as individuals begin to discover who they are by identifying their capabilities and realizing their potential to achieve goals (Little, Snyder, & Wehmeyer, 2006; Schunk & Zimmerman, 2006).

This system of competence and control is based on the dual theory of motivation, which links competence and control beliefs to actions and outcomes (Schunk & Zimmerman, 2006; Snyder, Harris, Anderson, et al., 1991; Snyder et al., 2002). Competence beliefs link to actions as perceptions one has about their ability to achieve goals. Control beliefs link to actions and outcomes as perceptions one has about available means and processes to pursue goals. Together, action and outcome perceptions interact to increase the energy to initiate goal pursuit (because of competence beliefs) and to utilize different means to sustain goal pursuit when obstacles arise (because of control beliefs), therefore increasing the likelihood of persevering and attaining one's goals.

Previous research has established that competence and control beliefs are related, but distinct constructs (Arnau, Rosen, Finch, Rhudy, & Fortunato 2007; Brouwer, Meijer, Weekers, & Baneke, 2008; Bryant & Cvengros, 2004; Magaletta & Oliver, 1999; Steed, 2002). Previous research has also demonstrated that competence and control beliefs are powerful predictors of student achievement (Onweugbuzie & Snyder, 2000; Parjares, 2002; Snyder et al., 2002), coping, and well-being (Chang, 1996, 1998; Pajares, 2002). However, most research highlights single constructs that are focused on either competence or control beliefs; more research is needed to examine how competence and control beliefs function in relationship to each other (Schunk & Zimmerman, 2006). Additionally, most competence and control beliefs research has used predominantly White Americans as research participants. As such, "there is a need to test the influence of competence and control beliefs with diverse student populations" (Schunk & Zimmerman, 2006, p. 362).

In this paper, we address both gaps in the literature. Specifically, we examine how three measures of competence and control beliefs— hope (Snyder et al., 2002), optimism (Scheier & Carver, 1985), and self-efficacy (Bandura 1977, 1986)—function as a cognitive set to form a system of competence and control beliefs that influences academic well-being among African-American college students.

Hope.

Hope is a motivation construct that initiates and sustains one's progress in goal pursuit through the combination of pathways and agency perceptions (Snyder, 2000). The pathways component of hope is a control belief defined as the perception that one can plan and strategize various routes needed to progress toward a goal (Snyder, 2002; Snyder, et al., 1991). The agency component of hope is a competence belief defined as the perception that one has the energy and ability to successfully utilize viable pathways during goal pursuit. The joint effect of agency and pathways is necessary for goal attainment, and it is through the reciprocal interaction of the two hope subcomponents that goal-directed thinking is sustained. Once goals are achieved, positive emotions cycle back to increase pathways and agency perceptions.

Hopeful perceptions positively affect multiple life domains. Hope is positively related to healthy outcomes in patients coping with psychological (Snyder, 2004) and physical health problems (Moon & Snyder, 2000). Adults with high hope utilize more adaptive problem solving and coping behaviors (Chang, 1998). Hope is predictive of student achievement across all educational levels (Curry, Maniar, Sondag & Sandstedt, 1999; Curry, Snyder, Cook, Ruby & Rehm, 1997; Lopez, Bouwkamp, Edwards & Teramoto-Pedrotti, 2000; McDermott & Snyder, 2000; Snyder et al., 1991; Snyder, Hoza, Pelham, et al., 1997). Hope also predicts better study skills (Onweugbuzie & Snyder, 2000) and the maintenance of goals in adverse academic situations (Yoshinobu, 1989). Although the relationship between hope and academic achievement is well established, research examining hope theory beyond white populations is largely non-existent and requires additional research (c.f., Chang & Banks, 2007; Danoff-Burg, Prelow, & Swenson, 2004).

Optimism.

Optimism is a control belief involving thought processes associating positive thinking and maintaining a positive attitude to life events and situations (Scheier & Carver, 1985, 1992; Seligman, 1991). Optimists have a general expectancy of positive results that is associated with greater success in attaining goals (Shepperd, Maroto, & Pbert, 1996), and optimism is viewed as a cornerstone for well-being across life domains (Peterson, 2000). Optimistic thinkers strategize differently than pessimists and prepare for the best outcome verses preparing for the worst. The role of expecting positive outcomes is associated with greater mental and physical health (Scheier & Carver, 1985, 1988). It is also influential in educational, occupational, and psychological adjustment (Chang, 1998), and is related to positive outcomes in achievement, coping strategies, and adjustment in college (Chang, 1996; Aspinwall & Taylor, 1992). As with hope, more research is needed to understand the role of optimistic thinking and African-Americans (c.f., Baldwin, Chambliss, & Towler, 2003; Jones, O'Connell, Gound, Heller, & Forehand, 2004).

Self-Efficacy.

Self-efficacy is a competence belief about one's "judgments of their capabilities to organize and execute courses of action required to attain designated types of performances" (Bandura, 1986, p. 391). There are multiple sources of self-efficacy beliefs, but mastery experiences—how one interprets, evaluates, and judges their competence—is the most powerful source (Bandura, 1997). Self-efficacy is an essential thought referencing process for students' success in the academic environment (Bandura, 1997). Efficacy beliefs are highly predictive of academic goal setting and achievement (Bandura, 1997; Zimmerman, 2000; Zimmerman et al., 1992), and self-regulatory coping strategies and effort (Pajares, 2002). Although more research is needed (Schunk & Zimmerman, 2006), existing research suggests the importance of self-efficacy among African American students for achievement and well-being (Jonson-Reid, Davis, Saunders, Williams, & Williams, 2005).

Hope, Self-Efficacy, and Optimism as a System of Competence and Control.

We propose that hope, optimism, and self-efficacy are expectancy beliefs that form a cognitive set because each focuses on different aspects of competence and control. Self-efficacy is the perception one has about their capability to perform certain tasks, and is a competence belief characterized by the statement "I think I can" (Bandura, 1977, 1986, 1997). Control beliefs are important within self-efficacy theory, but are conceptualized as an outcome of competence beliefs (Bandura, 1986). Optimism is a general disposition to expect positive, rather than negative, results in circumstances and situations (Scheier & Carver, 1985). Optimism is a control belief characterized by the statement "good things happen to me." Competence beliefs are important within optimism theory, but are conceptualized as an outcome of control beliefs (Scheier & Carver, 1985). Hope represents competence and control beliefs, but in different ways than self-efficacy or optimism. Hope agency is a competence belief characterized by the statement "I will achieve my goals." Self-efficacy focuses on the belief that goals can be achieved, but hope agency focuses on the belief that goals will be achieved. Hope pathways is a control belief characterized by the statement "I can think of many ways to achieve my goals." Optimism focuses on the general positive outcome beliefs, but pathways identify specific routes to achieve the outcomes.

We argue that the overlap and difference between these constructs form a system of competence and control (McBride, Robinson, Rose, & Turner, 2007). Specifically, we argue that students who think they can achieve goals (self-efficacy); have the will to achieve goals (hope agency); identify alternative routes when obstacles arise during goal pursuit (hope pathways); and are generally positive that things work out the way they plan (optimism) have an interactive system of beliefs that lead to actions which result in increased academic achievement, greater positive emotions, more adaptive coping strategies, and higher overall life satisfaction. In short, we predict that hope, optimism and self-efficacy form a system of competence and control that is related to increased academic well-being among African-American college students.

Method

Participants.

Two hundred five (122 females, 83 males) self-identified African Americans from a public historically black university in the southeast United States participated in this study. All students were enrolled in an Introductory Psychology course and received no incentive to participate. The students ranged in age from 17 to 28, with a mean of age 19.6 and a standard deviation 1.8.

Materials.

Demographic Information. Students were asked to provide information about their ethnicity, age, gender and academic achievement. Academic achievement was measured using the scale adapted from Dombusch, Ritter, Leiderman, Roberts and Fraleigh (1987), which asked participants to respond whether they make mostly As, Bs, or Cs in different subject areas. Dornbusch et al., (1987) indicate that this method provides valid responses and the tendency to inflate grades is typical only when one is near the bottom of the distribution, having grades below a C.

Hope. The Academic Hope Scale (AHS; Campbell & Kwon, 2001) is one measure within the Domain Specific Hope Scale-Revised, a 48 item scale that assesses hope in six life domains (academics, family life, leisure, romantic relationships, social relationships, and work). The AHS is a 6-item measure of hopeful thinking, and consists of three agency items (e.g., "I actively pursue my school work") and three pathway items (e.g., "I can think of many ways to make good grades"). Students are asked to rate items across an 8-point Likert-type scale ranging from 1 (*definitely false*) to 8 (*definitely true*). AHS scores can range from 6 to 48, with higher scores reflecting greater agency and pathways to obtain a goal. The AHS demonstrates moderately high reliability, with Cronbach's alpha reliability coefficients of .89 and higher, and a mean score of 39.8 (Campbell & Kwon, 2001, McBride et al., 2007).

Self-efficacy. The Academic Self-Efficacy Scale (ASES) is one measure within the Multidimensional Self-Efficacy Scale (Zimmerman, Bandura, & Martinez-Pons, 1992). It is a 13-item scale that measures student perceptions of ability to perform various academic tasks (e.g., "How well can you learn science?" "How well can you participate in class discussions?"). Students rate their response to each item on a 6-point Likert-type scale ranging from 1 (*definitely not well*) to 6 (*definitely very well*). ASES scores can range from 13 to 78, with higher scores reflecting greater ability to successfully perform academic tasks. The ASES has moderately high reliability, with a reported Cronbach's alpha reliability coefficient of .89, and reported mean score of 60.5 (Zimmerman et al., 1992).

Optimism. Optimism was assessed using the Life Orientation Test-Revised (LOT-R; Scheier, Carver, & Bridges, 1994), a 10-item measure consisting of three optimism items ("In uncertain times, I usually expect the best"), three pessimism items ("If something can go wrong for me, it will") and four filler items. Students rated their response to each item on a 7-point Likert-type scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The three pessimism items were negatively worded and thus reverse coded to attain the total scale score. LOT-R scores can range from 6 to 42, with higher scores reflecting greater optimism. The LOT demonstrates moderate reliability, with a reported Cronbach's alpha reliability coefficient of .78, test-retest reliability ranging from .56 to .79 over 28 months, and a reported mean score of 25.1 (Scheier & Carver, 1985; Scheier, Carver, & Bridges, 1994).

Coping. Coping was assessed using the Brief Cope Scale (Carver, 1997), a 28-item measure consisting of fourteen subscales (two items per subscale) that assess different adaptive (e.g., active coping, planning, positive reframing) and maladaptive coping strategies (e.g., venting, substance use, denial). Students rated items that asked how they cope when confronted with difficult or stressful events across a 4-point Likert-type scale ranging from 1 (*I usually don't do this at all*) to 4 (*I usually do this a lot*). Brief Cope Scale scores can range from 2 to 8 within each subscale, with higher scores reflecting greater adaptive or maladaptive coping, depending upon the context of the subscale. The limited number of items in each subscale is evident with the low to moderate reliabilities of each subscale; reported Cronbach's alpha reliability coefficients range from .50 to .90 (Carver, 1997).

Positive and negative affect. Positive and negative emotion was assessed using the Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988), a 20-item measure with 10 items assessing positive affect ("Excited") and 10 items assessing negative affect ("Irritable"). Students rated the extent to which they have felt positive and negative emotional affects over the past week for each item on a 5-point Likert-type scale ranging from 1 (*very slightly*) to 5 (*extremely*), with higher scores reflecting higher positive and negative affect. Previous research reports mean scores of 32.4 for positive affect and 20.4 for negative affect, and moderately high reliability, with a reported Cronbach's alpha reliability coefficient of .85 and higher among college students (Watson & Clark, 1994).

Life satisfaction. The Satisfaction with Life Scale (SWLS; Diener, Emmons, Larsen, & Griffin, 1985) is a five-item measure that assesses general life satisfaction ("In most ways my life is close to my ideal"). Students rated items across a 7-point Likert-type scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). SWLS scores can range from 5 to 35, with higher scores reflecting greater overall satisfaction with life. Previous research reports mean scores of 20.67 to 24 and moderately high reliability, with a Cronbach's alpha reliability coefficient of .82 and higher among diverse college students (Diener et al., 1985; Utsey, Ponterotto, Reynolds, & Cancelli, 2000).

Procedures.

Student participants were recruited from an Introduction to Psychology course and received no incentive to participate. Course instructors administered the survey packets in class. Students read and signed the informed consent forms, completed the survey and returned the survey packet to their instructor. After completing the survey, students received a debriefing statement. Survey packets were collected from the course instructor by the primary researcher.

Analysis

The purpose of the study is to explain the relationship of hope, optimism and self-efficacy—as a system of competence and control—with measures of academic well-being among African-American college students. As such, we conducted multiple correlation analyses (MCA) because it is ideal for explanatory research that seeks to explain a *Y* variable using a set of *X* variables that go together to form a linear composite system based on relevant substantive theory (Huberty, 2003). To do so, we employed the following analytic strategy.

All data were entered into and analyzed using SPSS 17.0. All records were inspected for missing data and outliers. Records with missing data and outliers were deleted from the analysis, reducing the initial sample size from 242 to the reported *N* of 205. Descriptive statistics (mean, standard deviation, Cronbach's alpha reliability coefficients, correlations) were computed and compared to previous research studies to establish the reliability and validity of the measures.

Next, estimations of the correlations between the *Y*s and the linear composite of the *X*s, ρ, were computed. As recommended by Huberty (2003), ρ was estimated using an adjusted R^2 formula proposed by Ezekiel (1930) to control for the positive estimation bias of the derivation of the weights of the *X*s: $R^2_{adj} = R^2 - [p / (N - p - 1)](1 - R^2)$, where p denotes the number of X variables and N denotes the sample size. The resulting estimations were then examined whether they were greater than chance outcomes using effect size indices calculated as: $ES = R^2_{adj} - p / (N - 1)$ (Huberty, 1994).

If the estimators and effect sizes indicated a relationship between the *Y*s and the linear composite of the *X*s, then the next step was to define the construct underlying the composite of the *X*s. To do so, we considered the *p* structure *r*s, where the structure *r* for X_j is the correlation between X_j and the linear composite of the *p* Xs (which includes X_j) (Courville & Thompson, 2001; Thompson & Borrello, 1985, as cited in Huberty, 2003). X variables with high structure *r*s were jointly considered in labeling the construct underlying the linear composite.

Finally, since multiple Y variables were measured to assess academic well-being, multiple regression analysis (MRA) was used to compute the strongest X predictor from the linear composite to develop a better understanding of how hope, optimism and self-efficacy function as a system across a different measures.

Results

Descriptive Data.

The reported mean scores and standard deviations of hope and self-efficacy were consistent with previous research, and each measure had adequate reliability (see Table 1). The measure of optimism, Life Orientation Test-Revised (LOT-R), had a higher mean scale score and low reliability when compared to previous research (Scheier & Carver, 1985, 1994). Other researchers have argued the LOT-R may not represent the single construct optimism; instead, they argue the LOT-R should be treated as two orthogonal constructs, positively worded items representing optimism and negatively worded items representing pessimism (Bryant & Cvengros, 2004). A principle components factor analysis with varimax rotation indicated that the two-factor solution was preferable over the single factor solution, accounting for 58% of the total variance. Using two scores for optimism and pessimism, the means were consistent with previous research, and Cronbach's alpha reliability coefficients demonstrated adequate reliability (see Table 1). Given these findings, and based on previous research, the two-factor solution is used for the remainder of the paper.

The mean scores and Cronbach's alpha reliability coefficients for positive and negative affect and life satisfaction were adequate and consistent with previous research (Chang & Banks, 2007; Diener et al., 1985; Watson, et al., 1988). Cronbach's alpha reliability coefficients for coping strategies were low, but consistent with previous research (Carver, 1997). Low reliability is not surprising given that each coping strategy is only measured with two scale items.

Correlation analyses provided evidence about the convergent validity of the measures (see Table 2). As expected, hope, optimism and self-efficacy were positively correlated with each other and with positive affect, life satisfaction, and academic achievement. Pessimism was not correlated with hope, optimism and self-efficacy, and was positively correlated with negative affect, lending evidence regarding the discriminant validity of optimism and pessimism.

Correlations among hope, optimism and self-efficacy with coping strategies were also as expected. Hope, optimism and self-efficacy were positively correlated with adaptive coping strategies: active coping, planning, positive reframing, acceptance, religion, emotional support, instrumental support, and self-distraction. Hope *r*s ranged from .21 to .39 (*p*s < .01). Optimism *r*s ranged from .16 ($p < .05$) to .31 ($p < .01$). Self-efficacy *r*s ranged from .17 ($p < .05$) to .44 ($p < .01$). The three measures were not correlated to maladaptive coping strategies: denial, venting, substance use, behavioral disengagement or self-blame, with the exception of hope and self-blame ($r = -.15$, $p < .05$), and self-efficacy and substance use ($r = -.13$, $p < .05$). Correlations among pessimism and coping strategies were also as expected. In contrast with the other measures, pessimism was not correlated to adaptive coping strategies, with the exception of religion ($r = -.19$, $p < .01$). Further, pessimism was positively correlated with maladaptive coping strategies: denial, substance use, behavioral disengagement and self-blame; *r*s ranged from .21 to .29 (*p*s < .01). These results lend additional evidence regarding the discriminant validity of optimism and pessimism.

Academic Achievement

Multiple correlation analysis indicates that the cognitive set explained a significant amount of the variance of academic achievement ($R^2_{adj} = .17$) beyond a chance outcome ($ES = .15$; see Table 3).

Table 1. Means, Standard Deviations, and Reliabilities of Competence and Control and Academic Well-Being Measures (N = 205)

	M	*SD*	α
Hope	39.0	5.9	0.86
Self Efficacy	61.6	10.0	0.89
Life Orientation	28.4	5.3	0.50
Optimism	16.6	3.3	0.64
Pessimism	12.2	4.4	0.70
Grade Point Average	3.4	0.5	---
Satisfaction with Life	26.4	6.0	0.82
Positive Affect	39.1	8.0	0.89
Negative Affect	23.8	8.3	0.85
Coping			
Active Coping	6.6	1.3	0.63
Planning	6.5	1.3	0.61
Positive Reframing	6.6	1.4	0.67
Acceptance	6.5	1.5	0.61
Humor	5.5	1.9	0.81
Religion	6.6	1.7	0.84
Emotional Support	6.2	1.6	0.70
Instrumental Support	6.3	1.6	0.80
Self Distraction	6.4	1.4	0.57
Denial	4.3	1.9	0.77
Venting	5.0	1.7	0.38
Substance Use	3.5	1.9	0.83
Behavioral Disengagement	4.0	1.8	0.64
Self Blame	4.6	1.9	0.64

Table 2. Correlations of Optimism, Pessimism, Hope, Self-Efficacy, Affect, Life Satisfaction, and Average Grade.

	Optimism	Pessimism	Hope	Self-Efficacy	Positive Affect	Negative Affect	Life Satisfaction	Average Grade
Optimism	1.00							
Pessimism	.04	1.00						
Hope	$.51^{***}$	-.03	1.00					
Self-efficacy	$.39^{***}$	.02	$.60^{***}$	1.00				
Positive Affect	$.46^{***}$	.00	$.37^{***}$	$.45^{***}$	1.00			
Negative Affect	-.09	$.19^{**}$	$-.21^{**}$	-.02	-.05	1.00		
Life Satisfaction	$.54^{***}$	-.05	$.56^{***}$	$.35^{***}$	$.41^{***}$	-.11	1.00	
Average Grade	.10	-.08	$.36^{***}$	$.37^{***}$	$.14^{*}$	.10	$.19^{**}$	1.00

Multiple regression analysis indicates that hope, self-efficacy, and optimism were significant predictors of academic achievement, and that hope was the strongest predictor within the cognitive set. An inverse relationship was found between optimism and academic achievement. Although not consistent with optimism research, in general, the relationship is consistent with previous research among African-American students (McBride, Robinson, Rose, & Turner, 2007).

Table 3. Summary of Multiple Correlation and Multiple Regression Analyses for Hope, Self-Efficacy, Optimism and Pessimism on Measures of Academic Well-Being (N = 205)

				βs			
	R^2	R^2_{adj}	ES	Hope	Self-Efficacy	Optimism	Pessimism
Grade Point Average	.19***	.17	.15	.31***	.24**	-.19*	-.04
Life Satisfaction	.40***	.39	.37	.35***	.01	.37***	-.02
Positive Affect	.29***	.28	.26	.03	.31***	.31***	.00
Negative Affect	.11***	.09	.07	-.29**	.17	-.09	.16*
Active Coping	.22***	.20	.18	.16	.29***	.11	-.06
Planning	.21***	.19	.17	.12	.33***	.08	-.02
Positive Reframing	.17***	.15	.13	.14	.18*	.18*	-.08
Religion	.13***	.11	.09	.04	.22*	.11	-.19**
Emotional Support	.09***	.07	.05	.07	.01	.24**	-.08
Instrumental Support	.10***	.08	.06	.03	.15	.21**	.02
Self Distraction	.08**	.06	.04	-.01	.13	.22**	-.02
Acceptance	.13***	.11	.09	.06	.20*	.16*	.14*
Humor	.07**	.05	.03	-.09	.15	.16	.18*
Denial	.11***	.09	.07	.03	-.08	.07	.32***
Substance Use	.07**	.05	.03	-.02	-.11	.04	.23***
Behavioral Disengagement	.09***	.07	.05	-.05	-.07	-.01	.27***
Self Blame	.12***	.10	.08	-.04	-.05	-.11	.30***
Venting	.02	.01	.00	-.05	.08	.02	.14

Note: *** $p < .001$; ** $p < .01$; * $p < .05$

Affect

The cognitive set explained a significant amount of the variance of positive affect beyond a chance outcome (see Table 3). Self-efficacy and optimism were significant predictors of positive affect, and both constructs contributed equally within the cognitive set. The cognitive set also explained a significant amount of the variance of negative affect beyond a chance outcome. Hope and pessimism were significant predictors of negative affect, and hope was the strongest predictor within the cognitive set. As expected, decreased hope was related to increased negative affect whereas increased pessimism was related to increased negative affect.

Life Satisfaction

The cognitive set explained a significant amount of the variance of life satisfaction beyond a change outcome (see Table 3). Hope and optimism were significant predictors of life satisfaction, and both constructs contributed equally within the cognitive set.

Coping Skills

The cognitive set significantly explained thirteen of the fourteen coping strategies beyond a chance outcome. The only coping strategy that the cognitive set did not significantly explain was venting (See Table 3). Analyses of the significant predictors within the cognitive set indicate that self-efficacy and optimism were significant predictors of adaptive coping strategies. Although both constructs were significant predictors, each was predictive of a different set of adaptive coping strategies. Self-efficacy was the strongest predictor of active coping, planning, religion, and acceptance within the cognitive set. Optimism was the strongest predictor of emotional support, instrumental support, and self-distraction. Both were equally predictive of positive reframing. These results indicate that positive perceptions of academic performance capability and anticipation of positive outcomes increase positive coping among students when difficult or stressful situations occur. By contrast, pessimism was a significant predictor of maladaptive coping strategies within the cognitive set. Pessimism was the strongest predictor of humor, denial, substance use, behavioral disengagement, and self-blame. These results indicate that anticipation of negative outcomes increases negative coping skills. Although hope is positively correlated with adaptive coping strategies, multiple regression analyses indicate it was not a significant predictor of any of the coping strategies within the cognitive set.

Hope, Optimism and Self-Efficacy as a System of Competence and Control

With the exception of venting, the cognitive set was significantly related to all outcome variables beyond a chance outcome. Therefore, the correlation structure of the linear composite of the cognitive set was computed to identify which constructs within the cognitive set should be considered when describing a system of competence of control. Results indicate that all constructs were significantly correlated to the linear composite of the cognitive set: hope (r = .82, p < .001), self-efficacy (r = .89, p < .001), optimism (r = .62, p < .001), and pessimism (r = .29, p < .001). Therefore, as predicted, all variables should be considered as a component of the cognitive set that forms a motivational system of competence and control related to African-American college students' academic well-being.

Discussion

Competence and control beliefs are central constructs in understanding student motivation (Schunk & Zimmerman, 2006). However, most research has examined competence and control beliefs in isolation from each other, and little is known about how these beliefs function as a system in relationship to one another. The results of this study suggest that hope, self-efficacy, optimism and pessimism form a robust cognitive set of competence and control that is significantly related to multiple measures of academic well-being. Specifically, increases to the cognitive set were related to increased academic achievement, positive emotion, adaptive coping strategies and life satisfaction, and decreases to the cognitive set were related to increased negative emotion and maladaptive coping strategies. These results confirm Schunk and Zimmerman's (2006) contention that measures of competence and control should be studied together as a cognitive set rather than individually, and that these cognitive sets can be used to inform educational activities. For example, educators could develop: goal-setting activities to create future mindedness to anchor hope, self-efficacy and optimism perceptions; curricular structuring that builds on demonstrated competence and attained skills to foster the development self-efficacy and hope-agency beliefs; learning strategies that are inclusive of metacognition, self-regulation, and time management skills to support the development of hope-pathways perceptions; and learning activities that require planning and leadership to foster self-efficacy and optimism and decrease pessimism.

The results of this study also confirm the importance of understanding how different constructs function within the cognitive set. Although the set, as a whole, was related to measures of academic well-being, the individual measures of hope, self-efficacy, optimism and pessimism predicted different aspects of academic well-being. Hope was a strong predictor of academic achievement and life satisfaction, and decreased negative affect. Self-efficacy was a strong predictor of positive affect and the adaptive coping strategies (active coping, planning, positive reframing, religion and acceptance). Optimism was a strong predictor of life satisfaction, positive affect, and adaptive coping strategies (emotional and instrumental support, and self-distraction). Pessimism was a strong predictor of maladaptive coping strategies (denial, substance use, behavioral disengagement, and self-blame). These results provide insight into the way these constructs function a system of competence and control. The results confirm Snyder's (2000) claim that competence and control beliefs interact to positively influence academic achievement, life satisfaction and positive emotion, and act as a buffer against negative emotion. But the results also suggest that competence and control beliefs differentially affect coping strategies. Whereas competence self-efficacy beliefs positively influence the active, cognitively oriented coping strategies of active coping, planning and positive reframing, control beliefs influenced the external strategies of emotional and instrumental support, substance use and behavioral disengagement.

Understanding how the measures within the cognitive set function allows educators to create more focused plans to foster positive student development. The results highlight that hopeful thinking, which consists of both competence (agency) and control (pathways) perceptions, may be sufficient to promote academic achievement and life satisfaction, and buffer against negative emotion. As such, activities that promote hopeful thinking may be incorporated most readily into learning environments. However, if a student is struggling to cope with difficult material or life events in general, then it may be more effective to focus on building self-efficacy beliefs to promote active coping strategies and optimistic beliefs to foster external coping strategies and buffer against pessimistic beliefs and maladaptive coping strategies.

In addition to adding to the achievement motivation literature, this paper also took up Huberty's (2003) recommendation to make a distinction between multiple correlation analysis (MCA) and multiple regression analysis (MRA), as explanation versus prediction methods. This paper demonstrated the methodological adjustments to R-squared and effect size indices needed for MCA when examining a theoretically driven group of variables that hang together to form a cognitive set. This paper also demonstrated how MCA and MRA could be used in conjunction with one another. MCA was utilized to examine whether the cognitive set was related to outcome measures of academic well-being. Once the relationship was established, MRA was utilized to identify which constructs within the set were most predictive of the different outcome measures to understand how the system of competence and control functioned within this population. Although these distinctions are subtle, this paper provides a practical example of the application of these methods.

Conclusions

The cognitive set of hope, self-efficacy, optimism and pessimism form a system of competence and control that is related to a diverse set of measures of African-American college students' academic well-being, including increased academic achievement and life satisfaction, enhanced adaptive and reduced maladaptive coping, and increased positive emotion and decreased negative emotion. Each of the constructs within the cognitive set uniquely contributed to these outcomes, which has implications for educators and researchers who want to foster positive student development. Although more research is needed to replicate these results within and across cultural groups, these findings point to a fertile line of future research that explores how existing constructs are related to, instead of better or worse than, each other and how these relationships can be used to foster students' academic well-being.

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Can Money Buy You Playoff Spots and Championships in Major League Baseball?

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The New York Yankees have long been thought of as the 800 lbs gorilla in the room when it comes to baseball payrolls. For years the Yankees have out spent every other team in major league baseball to "buy championships". Sometimes it has paid off (championships in 2000 and 2009); other times it has not.

How much have they spent? In 2009, the Yankees offered contracts to C.C. Sabathia (7 years, $161 million), A.J. Burnett (5 years, $82.5 million), and Mark Teixeira (8 years, $180 million) on top of the contracts already offered to Alex Rodriguez (10 years, $275 million) and Derek Jeter (10 years, $189 million). These were staggering amounts even by the New York Yankees standard.

The question to be asked by the rest of the teams in major league baseball is "does money buy playoff spots and championships?" This research argues that big dollar team payrolls do give an unfair advantage to some teams in major league baseball. The data from 2000-2009 seems to support that claim.

Methodology

Opening day team payrolls and the number of wins a team obtained in a season were collected for 2000-2009 from http://www.stevetheump.com/Payrolls.htm and http://www.baseball-reference.com/. A simple linear regression model from Montgomery and Peck (1992), shown in Equation 1, was fit to the data for each year.

$$Y = \beta_0 + \beta_1 X + \varepsilon \qquad (1)$$

The results are shown in Figures 1-10 below. Teams that made the playoffs are denoted with white diamonds, while teams that did not make the playoffs are denoted with black diamonds. The World Series champion is denoted by a white triangle.

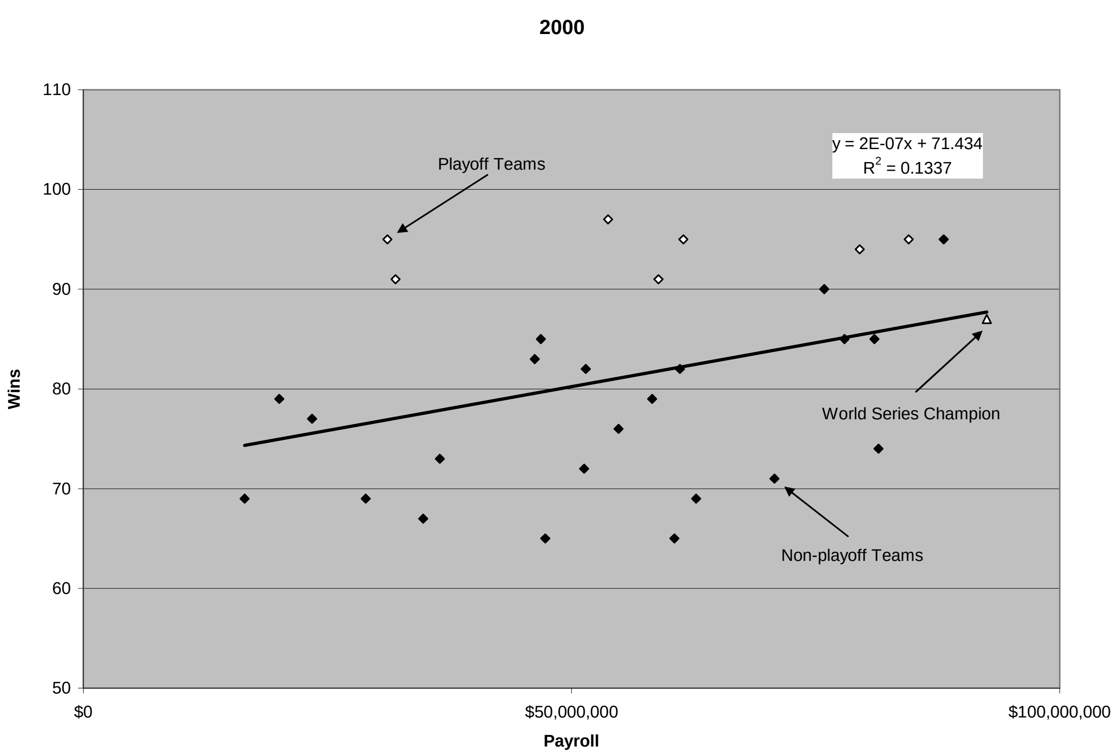

Figure 1. 2000 Season

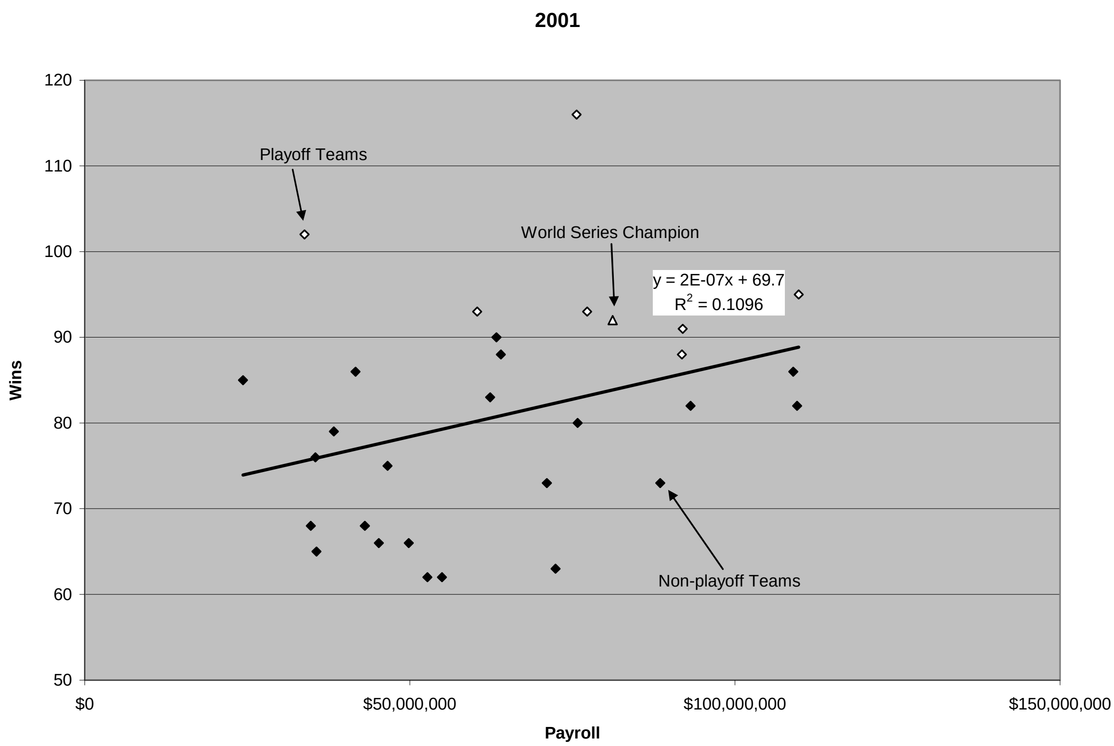

Figure 2. 2001 Season

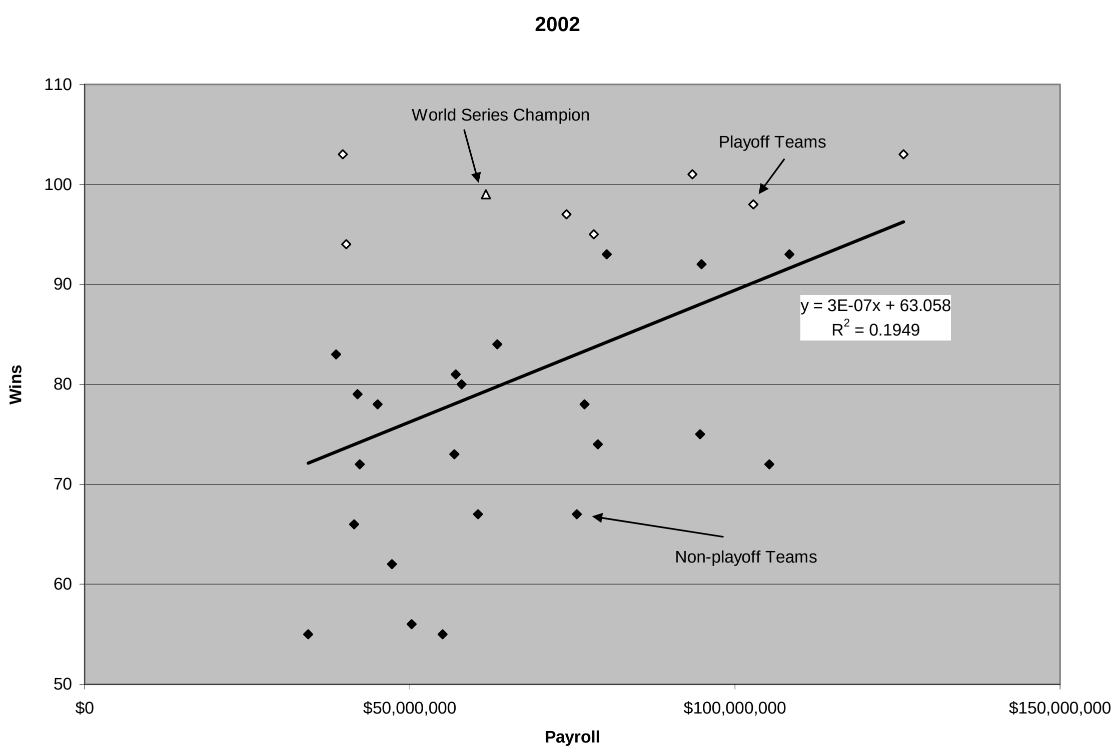

Figure 3. 2002 Season

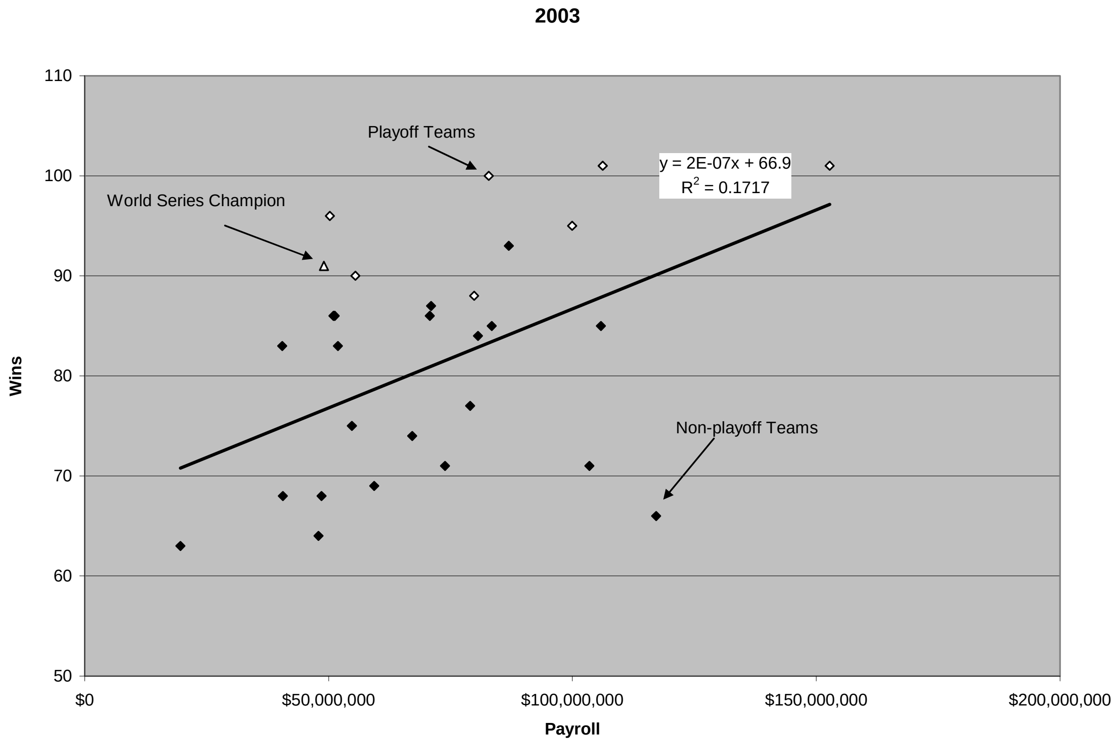

Figure 4. 2003 Season

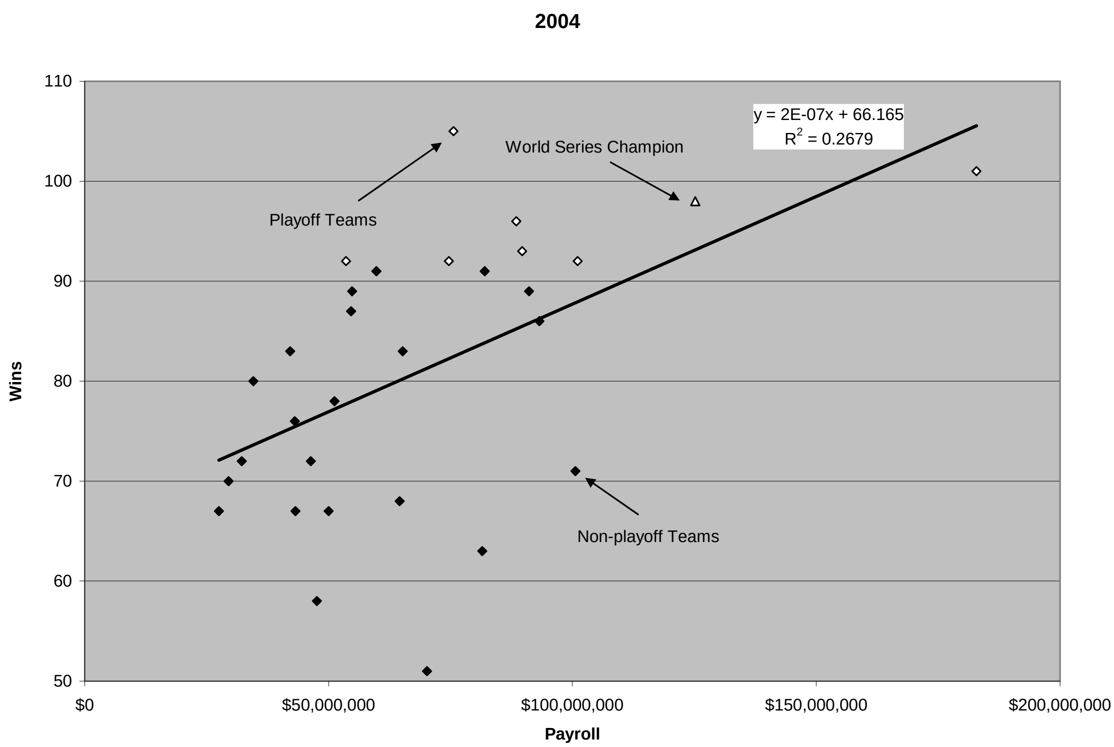

Figure 5. 2004 Season

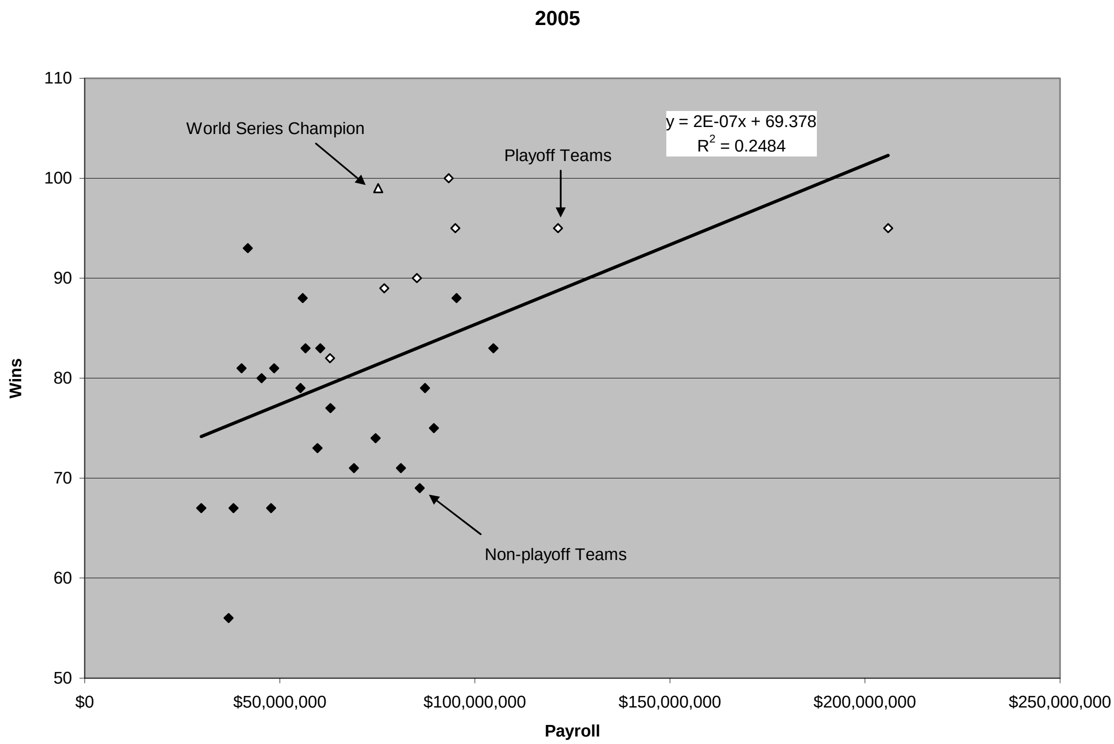

Figure 6. 2005 Season

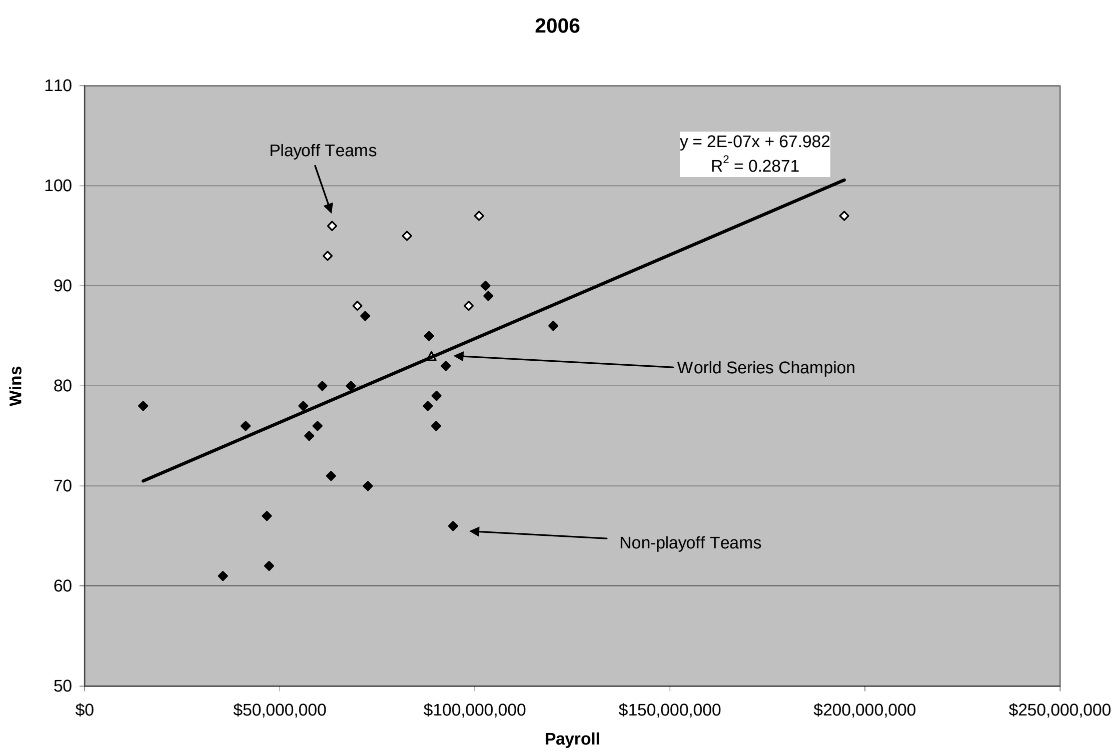

Figure 7. 2006 Season

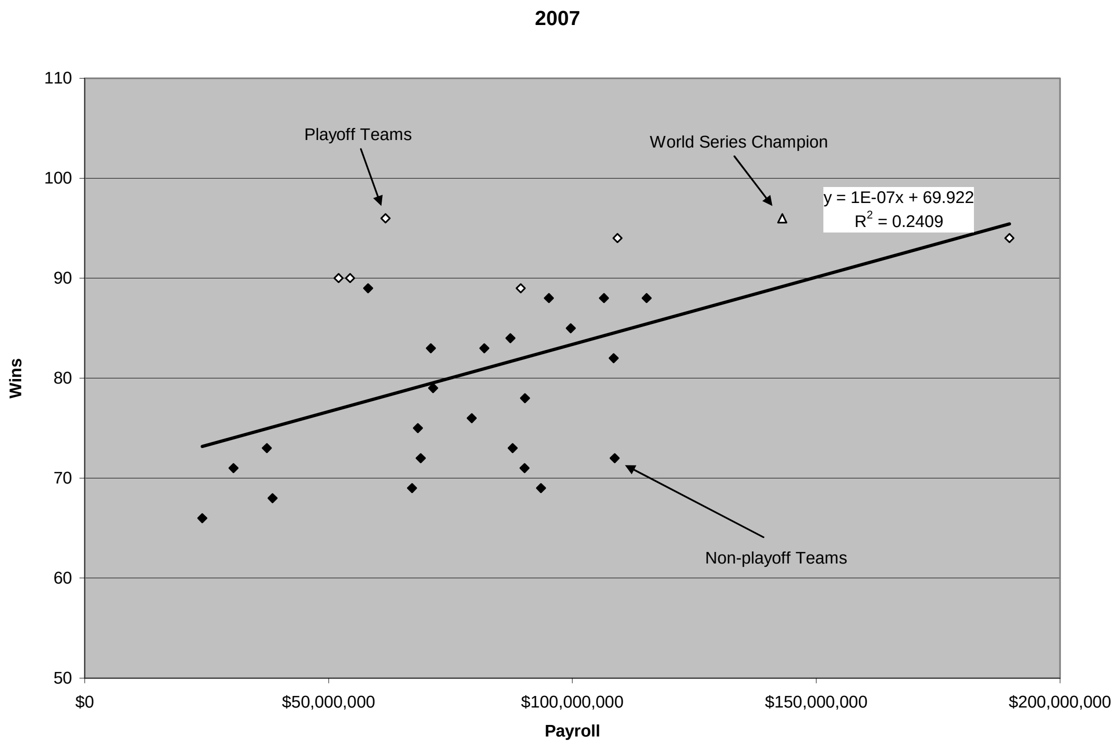

Figure 8. 2007 Season

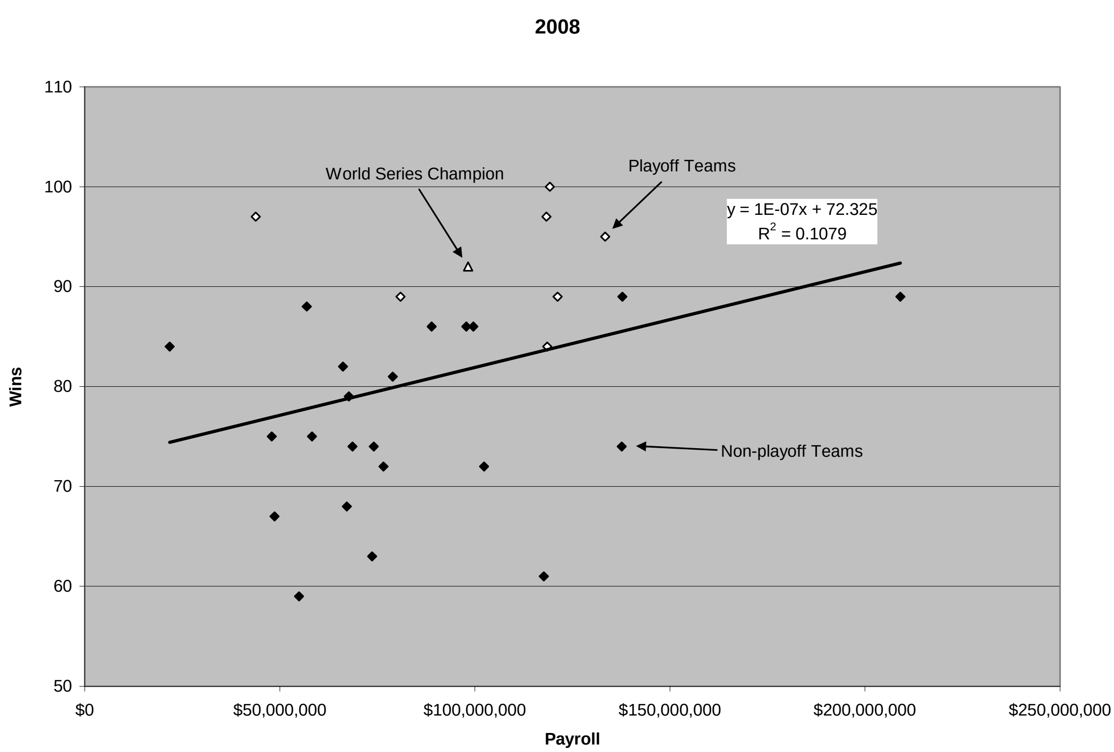

Figure 9. 2008 Season

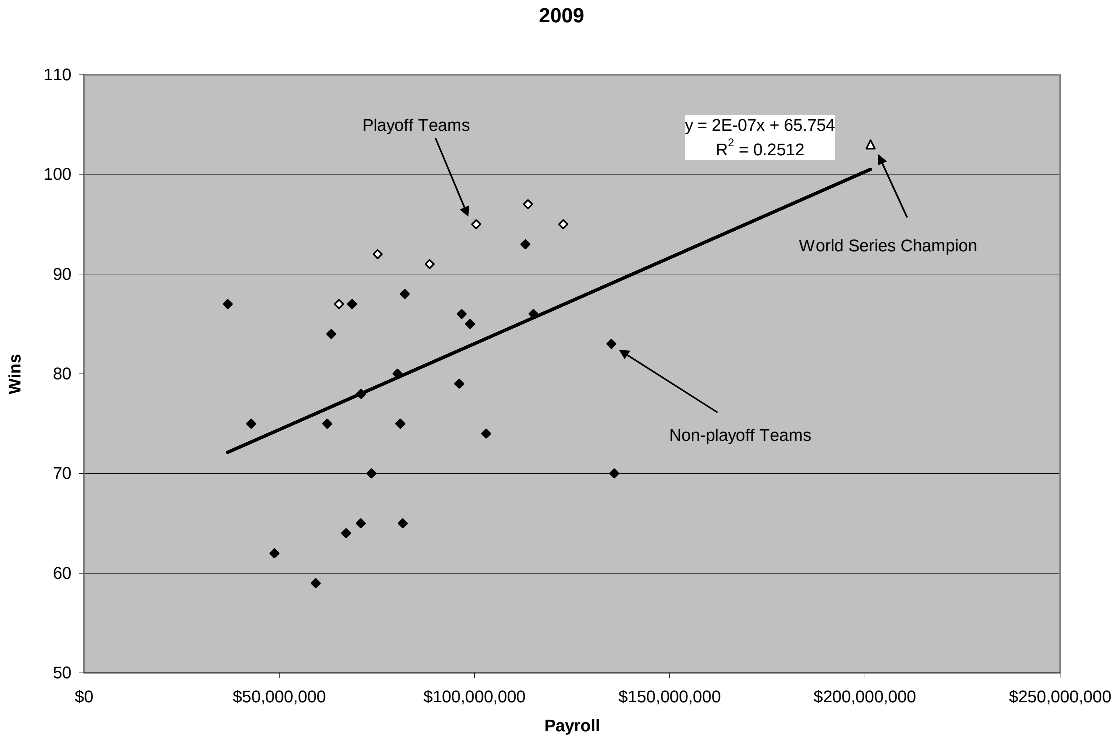

Figure 10. 2009 Season

Table 1. Coefficients of Determination, Regression Parameter Estimates, and p-values for H_0: $\beta_1 = 0$.

Season	r^2	b_0	b_1	p
2000	0.1337	71.43	$1.76\text{x}10^{-7}$	0.0469
2001	0.1096	69.69	$1.74\text{x}10^{-7}$	0.0740
2002	0.1949	63.06	$2.63\text{x}10^{-7}$	0.0146
2003	0.1717	66.90	$1.98\text{x}10^{-7}$	0.0228
2004	0.2679	66.16	$2.15\text{x}10^{-7}$	0.0034
2005	0.2484	69.38	$1.60\text{x}10^{-7}$	0.0051
2006	0.2871	67.98	$1.67\text{x}10^{-7}$	0.0023
2007	0.2409	69.92	$1.34\text{x}10^{-7}$	0.0059
2008	0.0803	72.98	$7.99\text{x}10^{-8}$	0.1292
2009	0.2512	65.75	$1.72\text{x}10^{-7}$	0.0048

Table1 contains the coefficients of determination, regression parameter estimates, and *p*-values for H_0: $\beta_1 = 0$ obtained from Equation 1 for each season. It should be noted that a statistically significant slope (i.e. relationship between team payroll and wins) was found in eight of the ten seasons using $\alpha = 0.05$.

In addition, it should be noted that the average r^2 for the 10 seasons is 0.1986 meaning that nearly 20% of the variation in wins is being explained by team payroll. It also appears that in recent years (2004-2009), the relationship between team payroll and wins has grown stronger (e.g. 2006 season $r^2 = 0.2871$, 2009 season $r^2 = 0.2512$). While these r^2 values appear small, low r2 values have been common in previous baseball studies. Schaffer and Heiny (2006) analyzed major league baseball data from the 2003 season. They were attempting to measure the effect of elevation on slugging percentage. They used slugging percentage as a dependent variable and elevation, ballpark, and ball player effects as independent variables. The r^2 for their model was 0.21. Hofacker (1988) analyzed major league baseball data from the 1982 season. He was attempting to measure a team's offensive ability independent of opponent and ballpark. He used runs scored as the dependent variable and opponent, park, league and home vs. away as independent variables. The r^2 for his model was 0.267 and he had the following

Table 2. Number of Playoff Teams from (max-Q_3), (Q_3-Q_2), (Q_2-Q_1), (Q_1-min) for each season.

Season	Max-Q_3	Q_3-Q_2	Q_2-Q_1	Q_1-Min
2000	3*	2	1	2
2001	4*	2	1	1
2002	3	3*	0	2
2003	3	2	1	2*
2004	5*	2	1	0
2005	4	3*	1	0
2006	3	2*	3	0
2007	4*	1	0	3
2008	5	2*	0	1
2009	4*	2	1	1
Totals	38	21	9	12
Percentage	0.4750	0.2625	0.1125	0.1500

Table 3. Number of Playoff Teams with the Highest Team Payroll, 2nd Highest Team Payroll, etc. Within Each Division

Playoff Team Payroll Rank within Divsion	1	2	3	4	5
Observed	30	20	15	8	7

comments. "While it is true that researchers in some fields might scoff at such a low r^2, perhaps the better way to think about the current result is that it offers insight into just how stochastic baseball must be. Such considerations necessarily imply that the analysis presented be considered exploratory." Another explanation might be that additional variability in the model is lost when players get injured or teams underperform during the season independent of team payroll. The important item to note is that these studies had several independent variables in their models while the current study has but one independent variable, yet explains just as much, and sometimes more, variability.

Additional evidence seems to indicate that team payroll influences the number of wins. For each season, the team payroll quartiles (Q1, Q2, Q3) were obtained and the number of teams that made the playoffs from (max-Q3), (Q3-Q2), (Q2-Q1), and (Q1-min) were determined. Table 2 below displays the quartile data. The World Series champion is denoted by (*).

From Table 2, it should be noted that 38 of the 80 playoff teams came from the (max-Q_3) quartile while only 12 came from the (Q_1-min) quartile. In addition, 9 of the 10 World Series champions came from the (max-Q_3) or (Q_3-Q_2) quartiles. The lone exception was the 2003 World Series champion Florida Marlins.

A Chi-squared Goodness of Fit Test from Conover (1999) was conducted to examine the question of equal dispersion of playoff teams from (max-Q_3), (Q_3-Q_2), (Q_2-Q_1), and (Q_1-min). If there was an equal dispersion of playoff teams, one would expect to find 20 playoff teams from each quartile. Equation 2 below displays the Chi-squared Goodness of Fit statistic and corresponding calculations where O_i is the observed number of playoff teams from (max-Q_3), (Q_3-Q_2), (Q_2-Q_1), and (Q_1-min), E_i is the expected number of playoff teams, and N is the total number of playoff teams.

$$\chi^2 = \sum_{i=1}^{4} \frac{O_i^2}{E_i} - N = \left(\frac{38^2}{20} + \frac{21^2}{20} + \frac{9^2}{20} + \frac{12^2}{20} \right) - 80 = 25.5 \qquad (2)$$

The corresponding *p*-value of the Chi-squared Goodness of Fit statistic is less than 0.001 indicating that too many teams come from above the median and too few from below the median.

Investigating the imbalance further, team payrolls of playoff teams were ranked within baseball divisions. Table 3 shows how many teams made the playoffs with the highest payroll, 2nd highest payroll, etc within divisions.

A Chi-squared Goodness of Fit Test from Conover (1999) was conducted to examine the question of equal dispersion of playoff teams within team payroll rank. If there was an equal dispersion of playoff teams, one would expect to find 16 playoff teams from each level. Equation 3 below displays the Chi-squared Goodness of Fit statistic and corresponding calculations where O_i is the observed number of playoff teams from each division rank, E_i is the expected number of playoff teams, and N is the total number of playoff teams.

$$\chi^2 = \sum_{i=1}^{4} \frac{O_i^2}{E_i} - N = \left(\frac{30^2}{16} + \frac{20^2}{16} + \frac{15^2}{16} + \frac{8^2}{16} + \frac{7^2}{16} \right) - 80 = 22.4 \qquad (3)$$

The corresponding p-value of the Chi-squared Goodness of Fit statistic is less than 0.001 indicating that too many teams come from teams with the highest team payroll within a division and too few from the lowest team payroll with a division. It would appear if one was to bet on playoff spots, simply bet on the team with highest payroll within the division. An example of this is the 2003 Minnesota Twins. They had the 18th highest team payroll overall, but had the highest team payroll within the American League Central Division and made the playoffs.

Some would argue that the luxury tax (or competitive balance tax) was supposed to level the playing field. However, according to http://www.stevetheump.com/luxury_tax.htm, the New York Yankees are essentially the only team to ever exceed the luxury tax salary cap. For example, in 2008, the Yankees were charged a 40% penalty for exceeding the team cap of $155 million dollars. The Yankees final payroll of the season was $222.2 million and had to pay $26.9 million in tax that was distributed to the other major league teams. However, when $26.9 million is divided up by the 29 remaining teams, less than $1 million is being added to their respective payrolls. $1 million barely covers two players making the league minimum ($400,000). According to the regression models discussed above, adding $1 million to a team's payroll will not generate many additional wins or playoff spots. So it would appear that the luxury tax is a failure.

Others would argue that the current revenue sharing agreement was supposed to create a better competitive balance among the 30 teams. According to Ray (2007), "In 1997, major league baseball created a new revenue sharing system that requires successful teams to pay millions of dollars every year to unsuccessful teams." Unfortunately Ray states, "The revenue sharing agreement doesn't require recipients to spend the "shared" revenue on actual ballplayers. All that is required by teams is that they use the money "to improve the product on the field." That vague requirement, however, has not been enforced by the League. In reality, the money can go anywhere. It can even go into the owner's pockets." Ray adds "From 2002 through 2006, Tampa Bay took in an average of $32 million per year in revenue sharing money. During that same period, the Rays had an average payroll of just $27 million, which was the lowest in baseball. They also had the worst five year record on the field, winning an average of just 70 games per season. Yet the team turned an average profit of more than $20 million during those years." So it would appear the revenue sharing agreement needs to be revisited.

Conclusion

It would appear from the evidence presented that team payrolls unduly influences the number of wins obtained in any given season, playoff spots obtained, and championships won. Money can improve a team's chance of obtaining a playoff spot and shot at a championship. The data seems to support that a more equitable system for team payrolls must be put in place. Either a salary cap needs to be imposed or a minimum team payroll must be enforced by Major League Baseball under the current revenue sharing rules. The inequities in the data are obvious. Big payroll teams like the New York Yankees or Los Angles Angels are over represented in the playoffs while small payroll teams like the Pittsburgh Pirates, Kansas City Royals, or Florida Marlins are not competitive under the current system.

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