The University of Western Ontario

REPORT OF THE FACULTY PAY EQUITY COMMITTEE

August 2005

Committee Members:

Karen Campbell
Ruban Chelladurai
Regna Darnell
Paul Handford
John Koval
Sheila Macfie
Jennifer Schroeder

Table of Contents

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Introduction

Gender pay equity is addressed by The Pay Equity Act of 1987, and the most recent pay equity study at Western (in 1995) was, in part, a response to that legislation, although the report noted that the Act does not require such response. Pay equity on campus is widely seen as a central element in any well-ordered academic community, a perspective well expressed by a recently-enunciated policy of the Canadian Association of University Teachers (CAUT), and by CAUT Council's commentary upon that policy (see Appendix A). The present study was pursued in that spirit.

Letter of Understanding F of the 2002-2006 Collective Agreement between the University of Western Ontario and the University of Western Ontario Faculty Association (UWOFA) mandates a Faculty Pay Equity Committee charged to "review salary patterns of Probationary and Tenured Members and of Limited-Term Members … to investigate gender-based differences in Members' salaries" and to provide a report on its analysis (see Appendix B). This Letter of Understanding stipulates that this exercise be carried out following distribution of the 2004-05 Anomaly Fund.

The present study therefore seeks to make an analysis and description of the degree to which gender differences in compensation might persist at Western following the adjustments made by the 1995 Pay Equity exercise (see below) and the disbursement of Anomaly Fund monies between 2001 and 2005, as required by past and current Collective Agreements.

Pay Equity studies at Western

Studies of salary and gender have been carried out at Western in 1975, 1989-1991 and in 1995. As required by Letter of Understanding F, the present study is developed from the most recent of these. The 1995 report[1] notes, in a brief review of the field, that the multiple regression approach has become generally acknowledged as the preferred method in studies of gender equity in compensation, while other approaches (such as the peer-matching approach used at Western in 1974) are now understood as less desirable.

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[1] Available on line at: http://www.uwo.ca/uwofa/docs/UWO-Pay-Equity-Report-August-1995.pdf. Hereafter referred to as PE.1995

Our analytical approach is similar to that of the 1995 study, although it differs in two respects. First, we were able to include a measure of academic activity and achievement (PAI) among the variables possibly predictive of salary—a *desideratum* noted in the 1995 report. Second, while the 1995 analysis compared individual female salaries to the regression line calculated for the entire population (males plus females), our approach in addition uses predictions of female salaries from the male population regression equation ("what any given female would be earning if she were a male with the same credentials, experience etc."); this provides for the delineation of pay differentials at the individual level (see methods description, pp. 7-8).

Western's Salary Structure

Salary models in Canadian universities vary widely. They range from simple grids, where salaries are fixed by rank and by the number of years in a rank, to complex structures where, for example, starting salary and market adjustments are matters for individual bargaining and annual increments are derived from a mix of elements, often involving some measure of academic activities and achievements and the calculation of what is usually called "merit pay." Western's system[2] is one of this latter sort.

Before certification (of UWOFA as the legal bargaining agent for Western's faculty in 1998), salary increments were built of three components: a percentage, or *scale*, increase (sometimes referred to as the *cost-of-living* component, since it is nominally supposed to compensate for the effects of inflation), a fixed dollar *Progress Through The Ranks (PTR)* amount, and a *selective increase* component based on academic activity and achievements. According to the salary settlements produced by the two Collective Agreements (1998-2002, 2002-2006), the PTR component has been lost and its relative importance assumed by a "merit-based" component (PLCP: Performance Linked Career Progress; —see footnote 2 for source of its description and mode of calculation).

There are salary floors attached to the academic ranks, but now, as before, these usually have little impact on the salary trajectory of most individuals, the floors generally having been surpassed before any given promotion.

[2] see Collective Agreement: Compensation & Benefits:
http://www.uwo.ca/uwofa/CA02-06upd/Coll_agreement_02-06_complete.html#compensation

Methodology

Answering the Question: Preliminary Remarks on Analysis

Our task has been to analyse data on faculty salaries to discover the magnitude of any differential among the salaries of male and female faculty members ***by virtue of gender alone***. This final phrase is critical, since a wide range of other factors, some of which may be *correlated* with gender, can also affect salaries. Given this potential complexity, simple approaches are rarely capable of providing a proper answer to the question. To take the example from Western's last pay equity study (PE.1995): suppose we simply compare the average salaries of the male versus the female components of a faculty population (whether that of a single campus, of a province's universities or of a nation's); we might find that the average woman's salary is lower than that of the men. However, this is possibly highly misleading: suppose that, for whatever reason, most women are relatively newly-hired; that factor could, potentially, explain all the gender difference in average salaries, given that pay generally increases with years of service.

Opinion converges on the choice of some sort of multiple regression approach to answering our question (see discussion and references in PE.1995; see footnote, p.3) In such an analysis, all variables (the *independent* or *predictor* variables) that are suspected of influencing salary level (the *dependent* or *response* variable) are included, and the machinery of the analytical procedure generates measures of the importance of each of the predictors *independent of the influences of all others.* Thus we can discover, among other things, the impact of gender alone independent of—or *controlled for*—the effects of everything else that also influences salary. Of course, the analysis can only control for the effects of variables included in the analysis: there may be several, even many, other variables that affect salaries. If they are not included in the analysis (starting salary, for example, is a variable unavailable to us) their possible contributions cannot be evaluated.

In assessing the importance of each predictor, we are mainly interested in two things: are their effects *statistically significant* and, if so, what are the magnitudes of their *contributions* to the overall value of the dependent variable, in this case, salary. To assess the first of these we look at the probability attached to each predictor variable's influence on salary; this is the probability of observing the given (or greater) level of influence, *by chance alone.* If the probability is *below* some criterion value then the effect of the variable is considered to be statistically significant or, in common terms, real. The second item, the *contribution* of any given predictor variable to the value of the dependent variable (salary) is provided by its "parameter estimate"—the numerical "worth", as it were, of either the presence/absence of the factor (say rank of Associate Professor) or of incremental change in the value of the factor (say the number of years since earning a PhD). This exposition is enlarged upon below (p.7) and in the results section of this report (p.10); see also Appendix C.

The Populations

The populations for analysis comprise all Full Time Probationary and Tenured faculty Members and all Full Time Limited-Term Members (including "Permanents") who are eligible for membership in UWOFA. This group is defined in the Certificate issued by the Ontario Labour Relations Board in 1998, a copy of which is to be found as Appendix A to the 2002-2006 Collective Agreement between UWOFA and the University of Western Ontario. The relevant segment of this certificate reads:

> "… all persons employed as members of the academic staff at the University of Western Ontario … having full responsibility at least equivalent to that associated with teaching one full university degree credit course in any calendar year, save and except: (a) full voting members of the Board of Governors; (b) persons who hold any position in the University at, or equivalent to, or higher than the rank of Associate Dean or above, including but not limited to, Dean, Vice-Provost, Vice-Presidents, the President, and anyone who is appointed to act in these positions; (c) persons employed in a professional capacity as per Subsection 1 (3) [(a)] of the Labour Relations Act; (d) persons holding visiting appointments while on leave from another university, institution, firm or government agency … (e) persons seconded to positions providing confidential assistance to the President, the Provost, or a Vice-President of the University of Western Ontario; (f) persons seconded for a term of not less than one year to a non-academic administrative position, so long as it is the secondee's principal responsibility …"

In total, 46 individuals (33 males and 13 females) were excluded on these criteria, mostly through holding administrative positions of Associate Dean or above.

The Probationary/Tenured and Limited Term populations are distinct in several ways, some of which are plausibly related to compensation, and therefore must be analysed separately.

Our data for Probationary and Tenured Members are shown in Table 1a:

Table 1a: Probationary and Tenured Faculty* by rank and gender (as of February 28, 2005).

Rank	**Female**	**Male**	**Total**
Professor	34	260	294
Associate Professor	100	227	327
Assistant Professor	101	196	297
Total	235	683	**918**

* includes only UWOFA-eligible faculty.

The data for Limited-Term Members are shown in Table 1b:

Table 1b: Limited Term Faculty* by rank and gender (as of April 30, 2005).

Rank	**Female**	**Male**	**Total**
Associate Professor	3	1	4
Assistant Professor	16	32	48
Lecturer	48	37	85
Total	**67**	**70**	**137**

* includes only UWOFA-eligible faculty.

Outline of the Statistical Approaches Used in This Study

A full multiple linear regression model was fit to the data. This full model incorporated all available variables relating to individual faculty members that were thought to be possibly related to the outcome variable, salary. These variables were fit simultaneously so that their effects could be measured in the presence of the all other variables, and in particular, so that the difference (if any) due to gender could be estimated after adjusting for other important variables such as Rank, Years Since Highest Degree, etc.

Following discussion, some of these initial variables were removed from the model. This is usually done where a) a variable is closely related to other variables in the model, yet these other variables are more useful in explaining the outcome, or b) a variable varies so little that it has little influence on the outcome. Such variables are removed because they fail to add to the explanation of the outcome variable (here, salary), and also because their inclusion needlessly adds to the variability of the parameter estimates, and makes the resulting statistical tests weaker. In the present case, two variables were removed as redundant: Age and Highest Degree. Age was found to be correlated with Years Since Highest Degree and Years Since First Degree, and these two variables explained salary more effectively. In the case of Highest Degree (possession of Ph.D), there were so few non-Ph.D. degrees in this population that the variable contributed practically nothing to salary variation. A regression model was fit with 21 variables, including Age and Highest Degree, but the regression coefficients were minimally different from those for the model that did not include these two variables. Age and Highest Degree were therefore seen as redundant, and excluded from further models.

Next, we applied a more complex statistical model that included *interaction terms* comprising a "multiplier" of gender by each of the other variables in the model (see Appendix C). These interaction terms measure how a difference in salary due to gender might be “modified” by the values of other variables. For example, if the interaction term were (Gender)*(Rank of Professor), and if, in the multiple regression model, this term were found to be statistically significant (see definition above), then one might argue that *the amount of* salary difference due to gender *itself differs* among the ranks. If this by-rank differential in gender salary differences were large, then one might want to split the data into two sets—in the present example, one of "Professor rank" individuals and one of "Other ranks"—and start again with a full regression model on each. On the other hand, if this difference in gender pay differentials due to rank were small, then one could argue instead that, on average, the effect of gender is significant across the board, but with some variation in that effect due to ranks. This would have the benefit of avoiding the difficulty of having to conduct analyses on two or more smaller data sets.

In an early analysis, we searched for statistically significant interactions between gender and the other explanatory factors shown in Table 2. This analysis revealed one statistically significant interaction. The Faculty of Health Sciences demonstrated a statistically significant interaction with gender, indicating that the relationship between gender and salary in that faculty is somewhat different from that found in other faculties. However, exclusion of this Faculty from the regression models resulted in only small changes to the model parameter estimates, and furthermore the population size of the Faculty of Health Sciences is too small to permit a reliable stand-alone analyses. Therefore we proceeded with analyses based upon the salaries of members of all faculties.

Next we decided to reduce the number of variables further using a statistical procedure called backward elimination (or backward stepwise elimination). Following the argument given above, the removal of variables whose effect on the outcome variable is not statistically significant will also reduce the variability in the regression estimates of all variables left in the model, particularly the estimate of the difference in salary due to gender. Variables are removed sequentially as long as the p-value of their regression estimate is greater than some fixed value, in this case 0.10 (see Appendix C, pp. 31 & 32).

Having finally decided on a "reduced" model with a smaller number of variables than the full model, we investigated whether there are any individuals whose salaries unduly affect the relationships established for the whole sample. Statistical procedures were run to look for these possible "influential cases"—sometimes (erroneously) called "outliers" (see Appendix D). Where any such influential cases are found, these cases are temporarily removed from the data set and the multiple regression re-calculated. Such new results are then checked for any changes in regression coefficients—in particular, the coefficient estimating the salary difference due to gender. If any coefficients change markedly through the exclusion of the influential case(s), then the case(s) would be permanently removed from the data set, and the model for the smaller data set considered to be the final model. In our analyses, as is usual, the supposed influential cases were not strongly influential, and so these cases were left in the data set, and the model remained as it was before the investigation of possible influential cases.

The final multiple regression model thus provided an estimate of the salary differences due to gender, after adjusting for all other useful explanatory variables (see Table 2 for a list of included variables). This is an overall, or average, measure of difference by gender. Such an average difference, however, perhaps constitutes only a part of the whole story: as well as there being an *average* difference in salary among men and women, it is also possible that their salaries are *distributed* differently around their respective average salaries.

We were therefore interested in looking at the *distribution* of individual salaries. In particular, we wished to calculate a predicted salary for any individual woman "as if she were a male". To do this, one has to take a multiple regression equation, with all the terms that relate the values of the predictor variables to that of the outcome (salary) and, for each individual woman, multiply those terms by her score on each variable. These predictions can then be compared with actual salaries, and the differences noted. There are at least two regression models that may be used to make these predictions:

- **The regression model calculated for males and females together, as described above.** Since this model contains no significant interaction terms, it could be argued that there are no significant differences in slope between males and females: therefore, one may use this "common" model. Use of such a model was proposed for determining serious anomalies in female salaries in the Pay Equity Report of 1995.
- **A regression model calculated for the males only, using the same variables as in the final "common" model** (see Appendix E). It could be argued that, although the

regression slopes from the common model are not significantly different between males and females (no interactions), it is a more conservative approach to use a regression equation derived from regression analysis on the male population only. This is the approach used in the present study.

Table 2: Explanations of the variables used in the multiple regression models.

Variable	***Code / Metric***	***Definition and / or Comments***
Dependent (response) variable: *The magnitude of this variable is determined by (is a function of) the magnitudes of the independent variables, plus others not in the analysis e.g. starting salary.*		
Annual salary	$	Nominal (i.e., full) annual salary for 2004-2005. Salaries were not reduced for unpaid leave, sabbatical leave, reduced responsibility contracts or other temporarily reduced salaries. Anomaly adjustments for 2004-2005 were included. Administrative stipends were not included.
Independent (predictor) variables: *Factors whose influence on the dependent variable is under investigation*		
Gender	Female=1 Male=0	The average difference between female salaries and the reference (male) salaries, all else being equal.
Years since highest degree	Years	Number of years since completing highest degree.
Years since first degree	Years	Number of years since completing first degree.
Years at Western	Years	Number of years of continuous employment as a regular full-time faculty member at Western.
Rank 1 (Professor)	Prof=1 Other ranks=0	The average difference between the salaries of Professors and those of the reference group (all other ranks), all else being equal.
Rank 2 (Associate Professor)	Assoc. Prof=1 Other ranks=0	The average difference between the salaries of Associate Professors and those of the reference group (all other ranks), all else being equal.
Rank 3[1] (Assistant Professor)	Lecturer=1 Other ranks=0	The average difference between the salaries of all other ranks and those of the reference group (Lecturers), all else being equal.
Years at current rank	Years	Number of years of continuous employment at Western at the current academic rank.
Relative performance		Individual PAI[2] divided by the average PAI of the department or faculty.
Department average salary	$	Total salary of Probationary and Tenured faculty members within each department or non-departmentalised faculty divided by the number of Probationary and Tenured members in that unit. Similarly, for Limited Term faculty: total salary of limited term faculty in the unit divided by the number of limited term faculty in that unit.
Faculty of ____	Fac. __ = 1-10 Fac. Soc. Sci.=0	The average differences between salaries in individual Faculties/Schools and the reference group (Social Science), all else being equal.

[1] This rank applies to the analysis of Limited Term members only, to assess those at Lecturer rank.

[2] PAI is the Performance Assessment Indicator, which is the weighted average of Performance Level Points assigned in each area of academic responsibilities.

Results & Discussion of Analyses

Probationary and Tenured faculty

We present the results of two sorts of regression analysis: a) a full regression model, where all variables are entered simultaneously (Table 3), and b) a backward elimination model (Table 4). Both tables show estimates of the nature of the contributions made by all the variables in accounting for all variation in salary, and of their statistical significance. The ANOVA results from both models show that the regressions are highly significant (Full: $F_{(19,898)} = 244.34$, $P < 0.001$; Backward Elimination: $F_{(14,903)} = 330.4$, $P < 0.001$). Both methods (and others not shown here) have their specific virtues, and we show both for completeness.

The backward elimination model would be expected to give the "best estimate" of regression effects because the non-significant variables are not in the model, but, as would be expected, the two approaches give similar results. Both models explain almost 84% of the total variance in faculty salaries ($R^2 = 0.838$ and 0.837). Such levels of explanatory value are very high indeed. The present R^2 values represent a slight improvement on the model developed in 1995, where the model explained 80% of the variation in salaries.

The reader may appreciate an overview of how to "read" Tables 3 and 4. Consider first the column headed "probability." The "full model" analysis in Table 3 tells us that the effects of the predictor variable "membership in the Faculty of Health Sciences" has an attached probability of 0.3995. This means that we can safely regard that "predictor" as of no real value at all in predicting salary, for such variation as may be attributed to it could easily be explained by chance alone. We make this determination because the probability value of 0.3995 means that there would be a 39.95% likelihood of getting this result (or one even more extreme) by chance alone. This falls far above the conventional criterion value of 0.05, (or 5% likelihood of chance alone) which is the criterion used for statistical testing. On the other hand, this same analysis shows a probability of <0.001 (less than one in 1000) attached to the predictor variable "Years at Current Rank"; thus we must infer that how long a member has worked at Western in their current rank is of very real importance in influencing salary—it is a ***statistically significant variable***. Consider next the *magnitude* of the influence of significant variables on salary. While statistical significance of the variables is indicated by the values in the "probability" column, the magnitude of the variables' effect is shown by those in the "parameter estimate" column. As described below, the interpretation of these values depends on whether the respective variables are continuous (assessed values in a continuum) or categorical (reflect one of a few categories).

For continuous variables (Years Since Highest Degree, Years Since First Degree, Years At Western, Years At Current Rank, Relative PAI, Department Average Salary), the parameter estimate represents the average impact, on salary, of a single unit change in the continuous variable. For example, in Table 3 we see a parameter estimate of 272.47 attached to the variable "Years Since Highest Degree". This can be interpreted as indicating that, after controlling for all other variables in the regression model, average salary is $272.47 greater for each additional year since completion of the highest degree. Similarly, after controlling for other variables in the regression model, average salary is: $379.86 greater for each additional year since completion of the first degree, $850.14 higher for each year at current rank, $486.28 lower for

Table 3: Summary of the full regression model for Probationary and Tenured Faculty. The dependent variable is annual salary. Model $R^2 = 0.838$.

Variable	Parameter estimate	t value	Prob. > |t|
Gender[a]	-2082.80	-2.30	0.0217
Years since highest degree	272.47	2.67	0.0076
Years since first degree	379.86	4.12	<0.001
Years at Western	-486.28	-5.72	<0.001
Rank 1 (Professor)[b]	26733.00	15.72	<0.001
Rank 2 (Associate Professor)[c]	11357.00	10.03	<0.001
Years at current rank	850.14	7.66	<0.001
Relative performance	12384.00	6.34	<0.001
Department average salary	0.62	10.64	<0.001
Richard Ivey School of Business[d]	27028.00	6.92	<0.001
Faculty of Medicine and Dentistry[d]	-3989.02	-2.99	0.0029
Non-significant variables:			
Faculty of Music[d]	-4041.53	-1.88	0.0603
Faculty of Engineering[d]	2675.21	1.73	0.0839
Faculty of Information and Media Studies[d]	3750.14	1.67	0.0955
Faculty of Education[d]	3156.50	1.51	0.1307
Faculty of Law[d]	3129.90	1.40	0.1617
Faculty of Arts and Humanities[d]	-1852.57	-1.36	0.1748
Faculty of Science[d]	-1207.78	-1.06	0.2896
Faculty of Health Sciences[d]	1295.84	0.84	0.3995

[a] Difference between female and male salary (female minus male).
[b] Difference between Professor and Assistant Professor salaries (Professor minus Assistant).
[c] Difference between Associate and Assistant Professor salaries (Associate minus Assistant).
[d] Difference between individual Faculty/School and the Faculty of Social Science.

Table 4: Summary of the backward elimination regression model for Probationary and Tenured Faculty. The dependent variable is annual salary. Model R^2 = 0.837.

Variable	**Parameter estimate**	**t value**	**Prob. > |t|**
Gender[a]	-2162.31	-6.05	0.0141
Years since highest degree	244.58	6.11	0.0136
Years since first degree	424.31	23.78	<0.001
Years at Western	-517.50	37.92	<0.001
Rank 1 (Professor)[b]	26777.00	250.32	<0.001
Rank 2 (Associate Professor)[c]	11379.00	101.23	<0.001
Years at current rank	863.79	60.99	<0.001
Relative performance	12396.00	40.33	<0.001
Department average salary	0.61	128.39	<0.001
Faculty of Arts and Humanities[d]	-3238.94	6.97	0.0084
Richard Ivey School of Business[d]	26151.00	52.39	<0.001
Faculty of Medicine and Dentistry[d]	-5268.21	18.89	<0.001
Faculty of Music[d]	-5430.22	6.93	0.0086
Faculty of Science[d]	-2480.86	6.16	0.0133
Variables removed from the model due to lack of significant effect:			
Faculty of Engineering[d]			0.1829
Faculty of Law[d]			0.2106
Faculty of Education[d]			0.2295
Faculty of Information and Media Studies[d]			0.2455
Faculty of Health Sciences[d]			0.3995

[a] Difference between female and male salary (female minus male).
[b] Difference between Professor and Assistant Professor salaries (Professor minus Assistant).
[c] Difference between Associate and Assistant Professor salaries (Associate minus Assistant).
[d] Difference between individual Faculty/School and the Faculty of Social Science.

each additional year spent at Western; $12,384.00 higher for every full point higher in relative PAI; and $0.62 greater for each $1.00 increase in departmental average salary. To estimate the overall effect of each additional year at Western, on must combine the four values involving years to give a value of $1015.16 per year; the negative value for "each additional year at Western" indicates that a premium is being paid, on average, to people recruited from outside Western, possibly from outside the country.

For categorical variables (gender, rank, faculty), the parameter estimate represents the average impact of the variable on salary, relative to some reference category (standard comparison group, coded as 0 in the analysis). For gender, the parameter estimate represents the impact of being female, relative to the male reference group, on salary. For example, Table 4 shows a parameter estimate of -2162.31 attached to the variable "gender". This can be interpreted as indicating that, after controlling for all other variables in the regression model, average annual salary is $2,162.31 lower for females relative to males. Similarly, after controlling for the other variables in the regression model, average salary is $26,777.00 higher for Professors and $11,379.00 higher for Associate Professors when compared with Assistant Professors (the reference category). Relative to the reference category of Faculty of Social Science, and after controlling for all other variables in the regression equation, salaries are, on average, higher by $26,151.00 in the Richard Ivey School of Business and lower by $3,238.94, $5,268.21, $5,430.22 and $2,480.86 in the Faculties of Arts, Medicine and Dentistry, Music and Science, respectively. Any salary differential in other Faculties was not statistically significant.

Influence of gender on salaries

As is clear from the full model (Table 3) and the backward elimination best-fit model (Table 4), women *on average* receive lower salaries than men. The statistically best estimate of this differential is given by the results shown in Table 4, indicating that women earn $2,162.31 less per year than men after controlling for all other statistically significant predictors of salary that were available for analysis. This is the differential remaining after accounting for Years Since Highest Degree, Years Since First Degree, Years At Western, Rank, Years At Current Rank, Relative PAI, Department Average Salary and Faculty, and is therefore not attributable to those factors. In other words, a woman earns, on average $2,162.31 less than a man who is employed at the same Rank in the same Faculty and who has the same number of Years Since Highest Degree, Years Since First Degree, Years at Western, Years At Current Rank, Relative PAI, and Departmental Average Salary.

To examine the *distribution* of salaries, we ran a full regression model for the male population only, using the variables shown in Table 4 (male plus female backward elimination model; see Appendix E). This gave us regression equation with which to predict women's salaries "as if they were men" (see Methods, p.8). We then plotted actual individual female salaries against their predicted salaries (Figure 1a). For comparison, we made corresponding predictions for individual male salaries, and their actual vs. predicted salaries are plotted in Figure 1b. This illustrates the difference between what individual males actually earn and what they would earn if their salaries were dictated solely by the variables in the regression analysis. There is evidently a wide range of remuneration both below and above the predicted salaries, in both females and males; however, more women receive salaries less than predicted than receive salaries higher than predicted (61.4 % of the dots (individuals) fall below the line). Male salaries are even more broadly distributed, especially at higher salary levels, but the numbers above and below the predicted line are equal (Figure 1b). We would not expect actual salaries to fall exactly on the line of predicted salaries because additional variables that probably contribute to salary (e.g., starting salary) were not included in the model.

To get a clearer picture of male/female differences in individual deviations from predicted salaries, the percentage of each population falling above and below the predicted salaries were calculated, by $2,500 classes. (Figure 2; the data are shown in Table 5). It is clear from Figure 2 that more females than males are paid less than predicted, while more males than females are paid more than predicted. For example, 53.6% of females as compared to 45.9% of males are paid up to $10,000 less than predicted. If the 1995 approach to increasing anomalously low salaries had been successful, then we would expect fewer very low female salaries; to some extent, this has been the case.

The reader is cautioned that Figure 2 does not show any information on actual salaries; it merely shows a frequency plot of *differences between* actual and predicted individual salaries, and a given differential can, in principle, apply to a salary at any level: high, average or low. It is of interest, however, to look at the way that (actual minus predicted) differences relate to actual salary, and we show this in Figure 3. Here it is readily apparent that negative salary differentials among females are concentrated among individuals earning less than $100,000, while among males, the higher negative differentials are concentrated in the above $100,000 salary range.

Taken as a whole, the analyses suggest a similar (though not identical) overall distribution of salaries for women and men with an "across the board" differential of $2162.31 in favour of men. Unless the analyses include all variables that do, in fact, influence salary, no regression-based approach can account for all the variability in salaries. In the present case, although only 16% of the variation in salaries remains unexplained, one might suppose that factors such as starting salary as well as factors arising during the career path might explain much of this remaining differential. Regardless of this limitation, our analyses consistently indicate that women's salaries are significantly lower than those of their male colleagues, even after accounting for the explanatory variables for which we have data; this suggests that there is a systemic differential across many individuals and many salary levels.

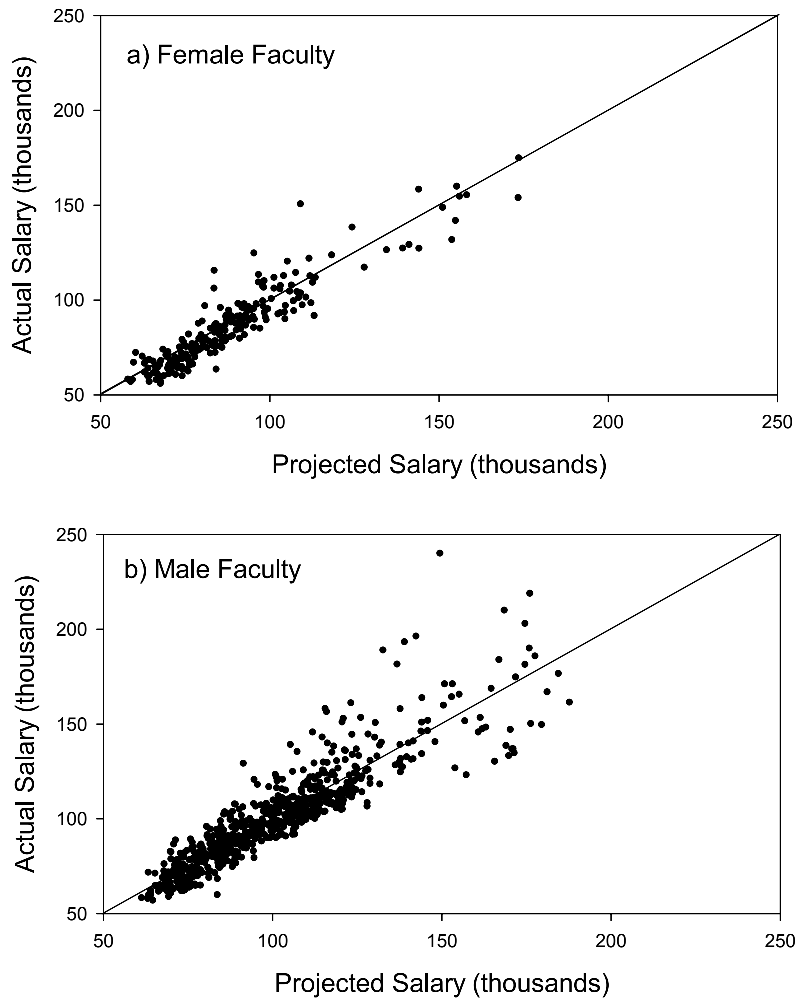


Figure 1. Scatter plot of (a) female and (b) male actual vs. predicted salaries.
See Methods p.8 and Results p.13.

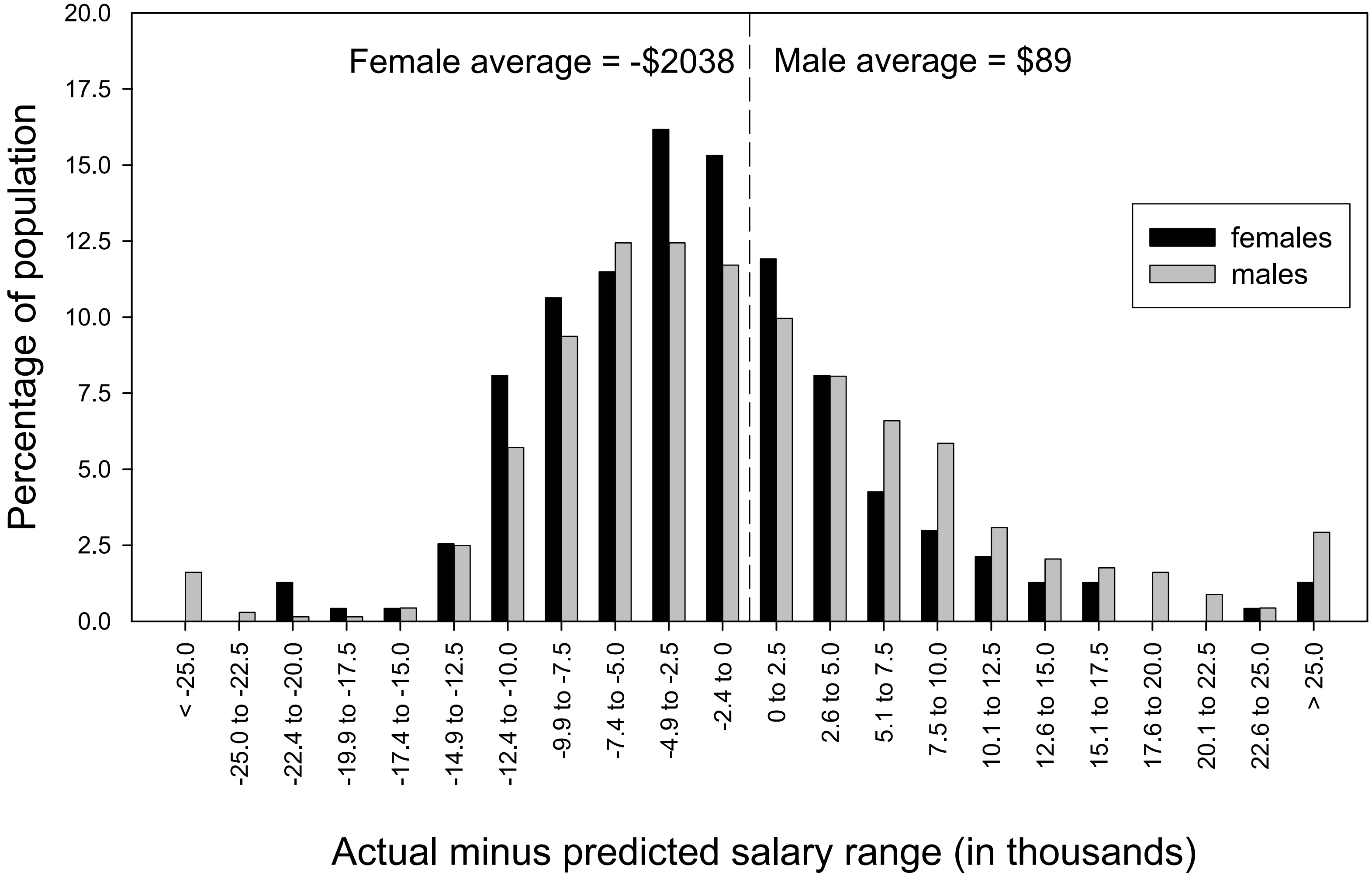


Figure 2. Distribution of the differential between actual and predicted individual salaries among male and female Probationary and Tenured faculty.

Table 5: Tabular summary of the data plotted in Figure 3. Predicted salaries are based on a backward elimination model using male salaries only. All variables with p≤0.10 in the “all faculty” model (Table 4) were kept in the “male only” model.

Range[a]	Females	%	Males	%
< -25	0	0	11	1.6
-25 to -22.5	0	0	2	0.3
-22.4 to -20.0	3	1.3	1	0.1
-19.9 to -17.5	1	0.4	1	0.1
-17.4 to -15.0	1	0.4	3	0.4
-14.9 to -12.5	6	2.6	17	2.5
-12.4 to -10.0	19	8.1	39	5.7
-9.9 to -7.5	25	10.6	64	9.4
-7.4 to -5.0	27	11.5	85	12.4
-4.9 to -2.5	38	16.2	85	12.4
-2.4 to 0.0	36	15.3	80	11.7
0.1 to 2.5	28	11.9	68	10.0
2.6 to 5.0	19	8.1	55	8.1
5.1 to 7.5	10	4.3	45	6.6
7.6 to 10	7	3.0	40	5.9
10.1 to 12.5	5	2.1	21	3.1
12.6 to 15.0	3	1.3	14	2.0
15.1 to 17.5	3	1.3	12	1.8
17.6 to 20.0	0	0	11	1.6
20.1 to 22.5	0	0	6	0.9
22.6 to 25.0	1	0.4	3	0.4
> 25	3	1.3	20	2.9
Totals	**235**	**100.0**	**683**	**100.0**

[a] actual salary minus predicted salary (in thousands of dollars).

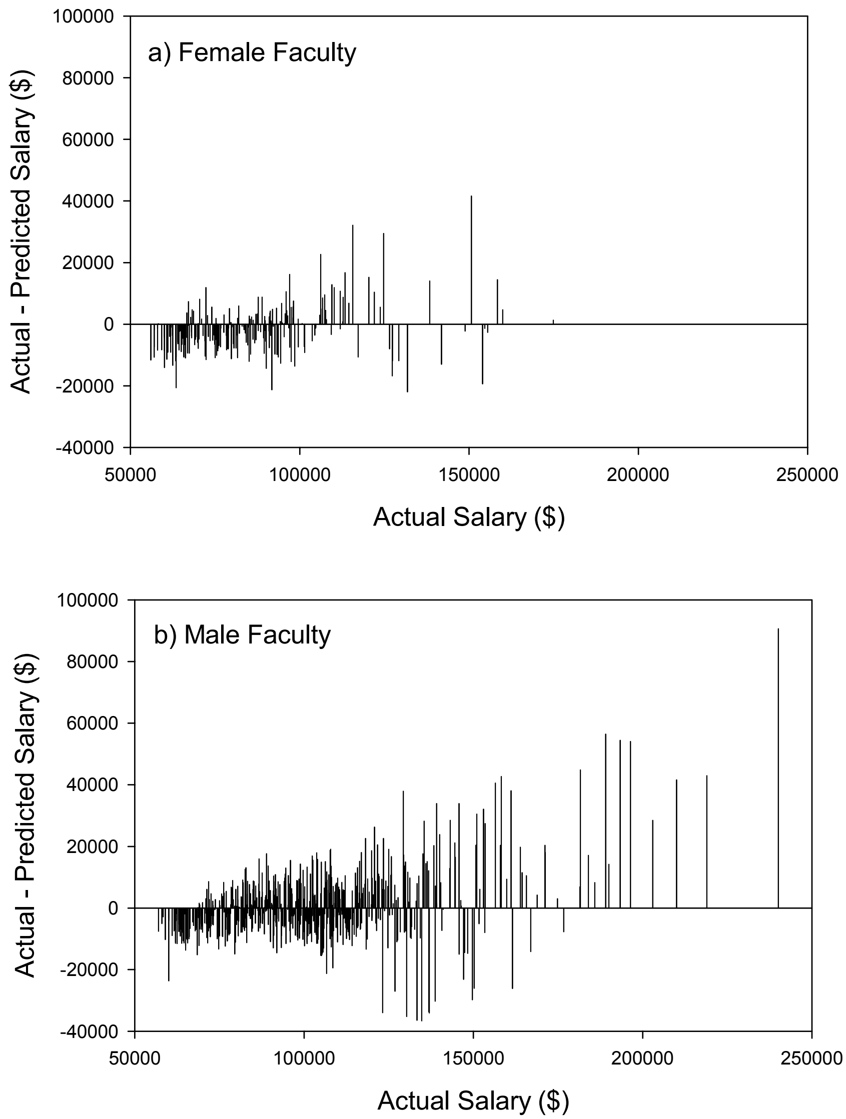


Figure 3. Plot of corresponding (actual minus predicted) salaries vs. actual individual salaries in (a) female and (b) male populations. Each vertical line represents an individual; its position along the x-axis shows the actual salary, and its extent along the y-axis represents the salary differential.

Limited Term faculty

Our analyses provided no evidence of any significant salary differential among men and women Limited Term faculty (see Tables 6 & 7).

Table 6: Summary of the full regression model for Limited-term Faculty. The dependent variable is annual salary. Model $R^2 = 0.656$.

Variable	Parameter estimate	t value	Prob. > |t|
Years since first degree	745.28	4.12	<0.001
Years at Western	505.08	2.43	0.0166
Years at current rank	1682.31	2.55	0.0120
Department average salary	0.74	5.56	<0.001
Richard Ivey School of Business[d]	12498.00	3.26	0.0015
Non-significant variables:			
Gender[a]	112.55	-1.25	0.2126
Years since highest degree	-164.48	-0.88	0.3833
Rank 2 (Associate Professor)[b]	3003.71	0.46	0.6431
Rank 3 (Assistant)[c]	4810.07	1.92	0.0574
Relative performance	7598.04	1.33	0.1845
Faculty of Music[d]	8379.33	1.17	0.2437
Faculty of Health Sciences[d]	-3365.94	-1.04	0.3007
Faculty of Science[d]	-2839.03	-0.94	0.3480
Faculty of Education[d]	-6140.91	-0.71	0.4795
Faculty of Information and Media Studies[d]	-2546.18	-0.47	0.6409
Faculty of Medicine and Dentistry[d]	-266.74	-0.51	0.6409
Faculty of Engineering[d]	4591.97	0.41	0.6825
Faculty of Arts and Humanities[d]	799.06	0.21	0.8328
Faculty of Law[d] – no members in this category			

[a] Difference between female and male salary (female minus male).
[b] Difference between Associate Professor and Lecturer.
[c] Difference between Assistant Professor and Lecturer.
[d] Difference between individual Faculty/School and the Faculty of Social Science.

Table 7: Summary of the backward elimination regression model for Limited-term Faculty. The dependent variable is annual salary. Model $R^2 = 0.6359$

Variable	**Parameter estimate**	**t value**	**Prob. > |t|**
Years since first degree	576.04	26.12	<0.001
Years at Western	418.31	4.77	0.0307
Rank 3 (Assistant Professor)[a]	5442.69	7.18	0.0083
Years at current rank	1922.34	10.71	0.0014
Department average salary	0.64	35.27	<0.001
Richard Ivey School of Business[b]	13478.00	16.54	<0.001
Variables removed from the model due to lack of significant effect:			
Gender[c]			0.9571
Years since highest degree			0.3938
Rank 2 (Associate Professor)[d]			0.6332
Relative performance			0.1485
Faculty of Arts and Humanities[b]			0.8342
Faculty of Engineering[b]			0.6846
Faculty of Education[b]			0.4933
Faculty of Information and Media Studies[b]			0.5930
Faculty of Health Sciences[b]			0.5384
Faculty of Medicine and Dentistry[b]			0.5635
Faculty of Music[b]			0.2085
Faculty of Science[b]			0.4154
Faculty of Law[b] – no members in this category			

[a] Difference between Assistant Professor and all other ranks.
[b] Difference between individual Faculty/School and the Faculty of Social Science.
[c] Difference between female and male salary (female minus male).
[d] Difference between Associate Professor and Lecturer.

Summary and Conclusions

We have used regression techniques to address the question: To what degree are salaries of Full Time faculty at the University of Western Ontario influenced by gender, independent of the influences of all other identified variables? Data for our populations were collected after the disbursement of the 2004-05 Anomalies Fund and of similar funds in earlier years.

Our results show:

- Probationary and Tenured faculty

    - Despite earlier pay equity exercises and the Anomalies Funds, gender remains a statistically significant predictor of the salaries of Probationary and Tenured faculty.

    - Across the population, and independently of all other measured variables, there is a gender-based salary differential best estimated as $2,162 p.a.

    - Although our models account for an impressive 84% of the variation in salaries there remains unaccounted salary variation among individuals (both male and female); this indicates that there are further dimensions to salary determination that remain to be analysed.

We further note that:

- It is probable that starting salary is an important predictor of at least some of this remaining salary variation.

- With 235 Probationary and Tenured female faculty, the cost of complete elimination of this differential would be $508,070, or, to put this in some context, about half of the total amount in the 2002-2006 Anomalies Fund.

Limited Term Full-time faculty

- There is no evidence of a gender-based differential between male and female salaries among Limited Term faculty.

Recommendations

- We recommend the gathering of systematic data on starting salaries so that future analyses can include that variable. This recommendation was made in the 1995 PEC Report, but was not acted upon. We feel that it is worth repeating since it remains an obvious candidate as an important explanatory variable;

- We recommend the regular review of equity in compensation, on a cycle of at most 5 years, and perhaps associated with renewals of the Collective Agreement;

- We recommend broadening the mandate of subsequent Salary Equity Committees to include all Designated Groups[3], in addition to gender;

- We recommend that future salary equity analyses should use the most appropriate statistical techniques available at the time, that is, methods should not be restricted to multiple regression;

- We recommend that the gender inequity in faculty salaries be addressed immediately or, in any case, before the commencement of negotiations for the next contract.

[3] In the Employment Equity Act, Designated Groups comprise: women, aboriginal peoples, persons with disabilities and members of visible minorities,

Possible Approaches to Addressing the Salary Inequity

We make no specific recommendation on how the gender-based salary inequity should be addressed. However, we provide below commentary on two possible methods for approaching the redress of the gender-based salary differential:

A. Across-the-board awards of $2,162 to all female faculty.

Advantages:

- Such an approach would acknowledge and account for the systemic dimension of the gender salary differential.

- Such an approach is both simple to conceptualise and implement.

Disadvantages:

- Such an approach would ignore the fact that individual women differ substantially in the degree to which they depart from a predicted salary; indeed, some fall well below the predicted level by amounts well in excess of $2,162.

- The treatment of females who earn well in excess of their predicted salary remains problematic using an across-the-board increase. On the one hand, some may perceive that a further increase in salary for these females is unwarranted. On the other hand, an increase of only $2,162 may be insufficient because a much smaller proportion of females, as compared to males, are paid substantially more than predicted (>$10K: 6.4% of females and 12.7% of males; >$20K: 1.7% of females and 4.2% of males).

- While such an approach would eliminate the *mean* salary differential, it would not address the gender differential in the *distribution* of individual salaries (the difference in the *shapes* of the curves shown in Figure 2).

- An across the board approach would mean that future regression analytical investigation of gender pay equity would, at least in the short term, suggest that gender is not a significant determinant of salary, even though a significant *distributional* differential may remain. We regard this as a substantial problem.

B. A combination of systemic and variable individual awards derived from some version of the prediction analyses, with a mean value of $2,162.

Advantages:

- Such an individual-based approach would address the gender-differential in both the mean and the distribution of salaries.
- Such an approach would permit equitable compensation for all females regardless of salary level.

Disadvantages:

- Such an approach would be relatively difficult to implement.
- Such an approach would leave unattended the fact that there are similar salary-distribution issues also needful of attention among the male, as among the female, population.

Appendix A.

CAUT Policies

<http://www.caut.ca/en/policies/pay_equity.asp>

Policy Statement on Pay Equity

The Canadian Association of University Teachers is committed to equity in pay for all members of the academy. Pay equity and human rights legislation compliance is inadequate to ensure the elimination of continuing discriminatory pay differentials between academic staff. Equity in pay is critical to the realization of overall equity in employment. Pay inequity continues to have adverse impacts on individuals from historically disadvantaged groups including women, disabled persons, aboriginal peoples, people from ethnic minorities, people of colour, gays, lesbians, bisexuals and trans-gendered peoples, and religious minorities. Pay inequity is discrimination.

1. All discriminatory pay differentials must be eliminated.

2. Pay discrimination can only be remedied by the periodic implementation of comprehensive pay equity studies within each university, using non-discriminatory measures in order to identify the internal inequities and equalize compensation. Academic staff participation in a pay equity study is required in order to enhance understanding and acceptance of the process, goals and outcomes.

3. Pay determined by market differentials may be inherently discriminatory against women and members of the other protected groups. It must be scrutinized and, where necessary, remediated.

4. Definition and practice of merit increases may be discriminatory.

5. It is the responsibility of the employer to ensure complete and timely remediation of pay inequity.

Approved by the CAUT Council, April 2004

Pay Equity in this policy statement is a broader term than that used in provincial Pay Equity legislation. The latter is restricted to pay equity for women only, and as well is aimed at the comparison of equal pay for work of equal value. This policy statement is more expansive in its purpose and goals, permitting the remediation of inequity in pay for other equity-seeking groups, and enabling the comparison of pay between employees within the same job class / occupational group. Under Pay Equity legislation faculty would ordinarily be treated as being in one job class or group and therefore no comparison of wages for male and female faculty within the group or class would be allowed.

The term "pay" in this policy statement includes all aspects of compensation including salary, benefits and pension.

Appendix B.

Letter of Understanding—F

PAY EQUITY STUDY

The Parties agree that this Letter of Understanding forms part of the Collective Agreement for the life of the Collective Agreement.

1. The Parties agree to establish a Pay Equity Committee. This Committee shall consist of three representatives appointed by the Association, at least one of whom shall be female, and three representatives appointed by the Employer, at least one of whom shall be female; the Director of Equity Services shall also be a member of the Committee, but without vote.

2. This Committee shall review salary patterns of Probationary and Tenured Members and of Limited-Term Members using regression analysis to investigate gender-based differences in Members' salaries.

3. The methodology shall be developed from that used in the 1995/1996 Pay Equity Study, namely, Annual Salary shall be the dependent variable, and independent variables may include but need not be limited to: Gender, Highest Degree, Years Since Highest Degree, Years Since First Degree, Years Employed as a Faculty Member at The University of Western Ontario, Age, Rank, Years in Rank, Home Faculty, Department Average Salary.

4. This analysis shall be conducted following distribution of the 2004-05 Anomaly Fund established by the Article *Compensation & Benefits.* The Committee shall provide a report on this analysis to the Association and the Employer within six months of distribution of the Anomaly Fund. The Parties shall have two months to review the report before it is published.

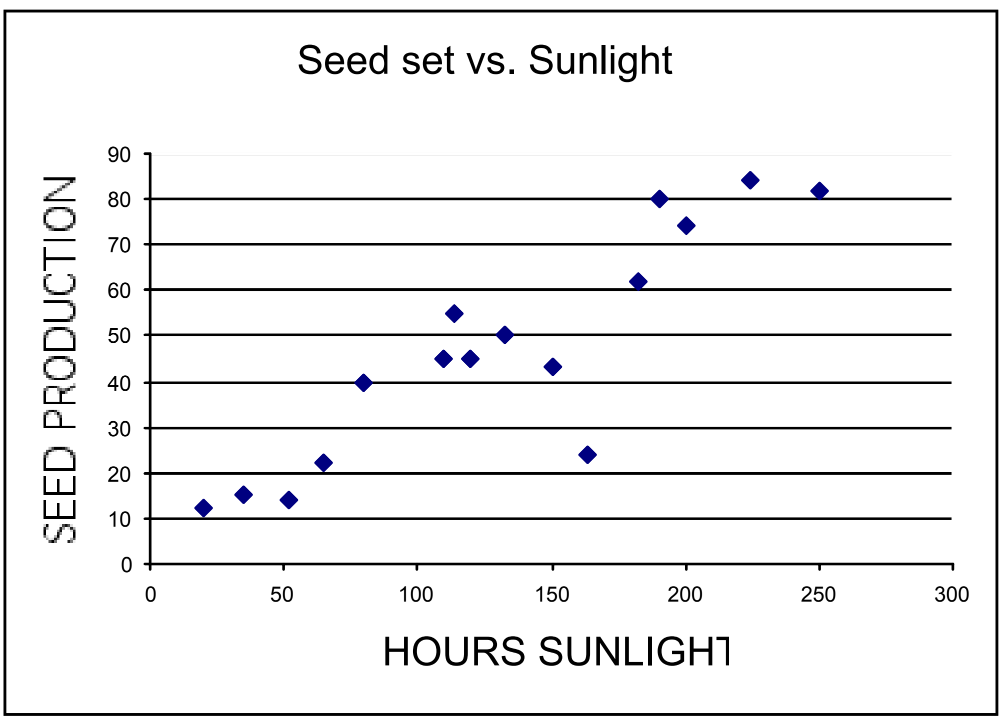
Appendix C.

An Introduction to Multiple Regression

Regression analysis is a way of exploring and describing the functional relationship(s) that may exist between two or more variables. If we have some *a priori* notions (albeit provisional, and subject to later investigation) about the causality of the relationship(s)—that one of the variables is affected by the other(s), rather than the other way around—then we can label the variables to reflect this. Thus, we can explore the way that variation in one variable (the *dependent* or *response* variable) is affected by variation in one or more other variables (the *independent* or *predictor* variable(s)).

In **simple regression**, we are dealing with a single predictor variable, and the regression analysis procedure provides a description of the way that variation in the dependent variable is related to variation in the predictor; another way to say this is that the analysis tells us how values of the dependent variable may be *predicted by* those of the independent variable. For example, we might be interested in the relationship between how many seeds plants produce in a season and how much direct sunlight those plants receive in that season—how seed production may be *predicted by* exposure to sunlight; it is obvious *a priori* that sunlight exposure cannot be influenced by seed production.

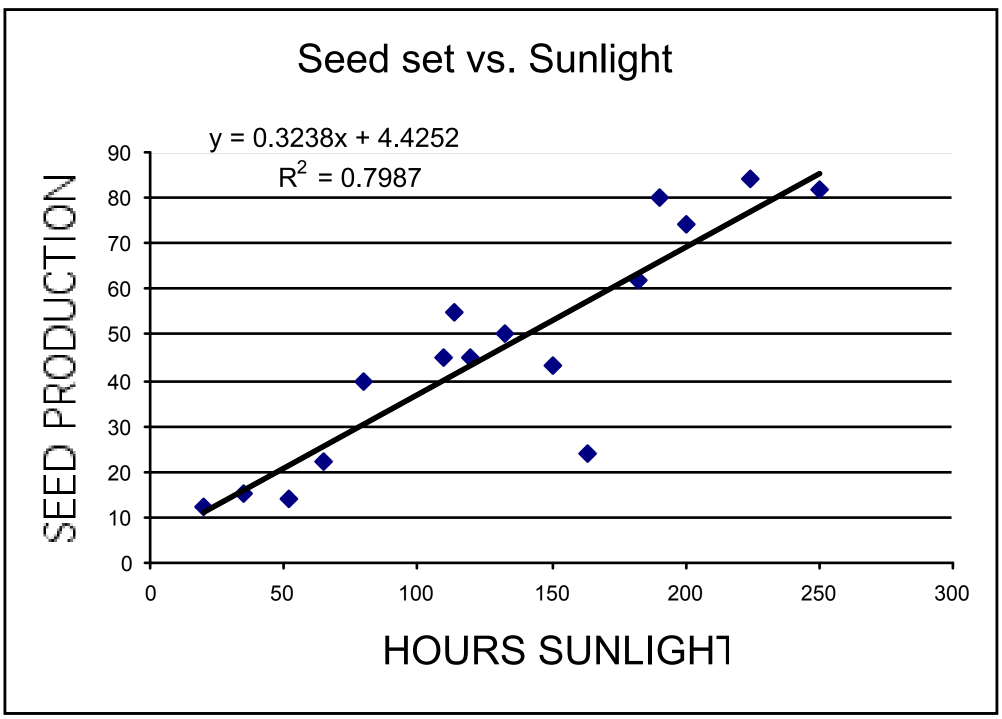
If we had data on these two factors for a number of different plants, we could plot these data out in a graph, called a scatter plot. Such a graph has two scaled axes, and by convention the dependent variable is represented on the vertical axis—the ordinate, while the predictor variable is represented on the horizontal axis—the abscissa. The data are shown as points in the body of the plot, with each point corresponding to the values of the two variables for each plant in the sample. Below is a scatter plot showing data of this sort, for 16 hypothetical plants:



What does this plot tell us—or at least suggest? A positive relationship seems apparent—the more sunlight a plant has experienced, the more seeds are produced by that plant. It indeed looks as though received sunlight *does* predict seed production, at least to some degree. However, it is also apparent that the relationship is not strict, or perfect—if it were, all the data points would lie on a line, and hours of sunlight would predict seed set perfectly. If seed production were *unrelated* to the amount of sunlight a plant receives, how would the plot then look? In such a case, there would be no perceptible trend in the distribution of the data points—high, moderate or low values of seed production would be associated equally often with high, moderate or low values of sunlight received. So these data do seem to show a positive functional relationship, albeit not a perfect one.

Given a pattern like that in the figure above, we would then be interested in two questions: a) is the relationship real or only apparent—is our perception trustworthy?; and b) if the relationship is real, what is the quantitative nature of the relationship—how much does seed production go up or down for some given increase or decrease in sunlight received? This we find out through applying our regression analysis.

The analysis provides us, among other things (see below), with a mathematical statement of the nature of the functional relationship between the dependent and predictor variables. This statement is in the form of an equation: $Y = bX + c$, where Y is the dependent variable, X is the predictor variable, b is a parameter which, as it were, converts values of X to values of Y by a constant scaling factor, and c is a constant, which may assume any value, positive or negative, including zero. Some will recognise this equation as that for a straight line of gradient b and intercept c. The figure below shows the regression equation relating the values of Y, seed production, to X, hours of sunlight, together with the line expressing that equation.



The equation is such that the line it defines has a slope and position that minimises the total departure of all the data points from itself: we say that the line is "fit" to the data in this way, and the equation expresses the line that provides for that best fit.

How does this analysis help us to answer our questions a & b above about the "reality" and quantitative nature of the relationship between the variables? Let's begin with the second question, since it relates directly to the regression equation we have just considered. This equation tells us that, over the ranges of seed production and sunlight exposure for which we have data, for every further hour of sunshine we may expect a plant to produce, on average, 0.3238 more seeds. The intercept, *c*, tells us that, if this relationship remains true down to zero hours of sunlight (an unlikely proposition), a plant exposed to no direct sunlight would be expected to produce 4-5 seeds. Usually, we are not much interested in *c*.

But we should only take these quantitative estimates seriously to the extent that the data actually may be said to fit the equation well. This issue is addressed by the quantity R^2 (=0.7987 in our example). R^2 measures the degree to which the values of Y are predicted—or constrained, to look at it another way—by values of X. Thus R^2 measures the "goodness of fit" of the data points to the regression line. In fact it provides a measure of the total departure of all the data points from the line: it tells us how much of the variation in values of Y is "explained by" variation in values of X. If $R^2 = 1.0$, then *all* variation in Y is explained by variation in X, and all the data would lie perfectly on the regression line; if $R^2 = 0.00$, then Y is utterly unrelated to X—the amount of direct sunlight received by a plant would tell us nothing about how many seeds the plants will produce—any values of both X and Y might co-occur. As we have noted, in our case $R^2 = 0.7987$, and this may be interpreted as meaning that 79.87%—almost 80%—of all the variation in seed production is explained by variation in exposure to sunlight. This is a very high value of R^2, and we should be content to suppose that the relationship is therefore real[4]. This of course does not necessarily mean that sunlight exposure is the ***only*** factor that relates positively to seed production: there could be many other factors that predict seed production. Some of these might be correlated with sunlight, and therefore might contribute to an explanation of part—or even most of—that 80% figure. There might also be other variables that could account for some of the remaining 20% of unexplained variation in seed production. To look at this sort of multi-determination possibility, we must turn to multiple regression.

Thus we might further suspect that seed production is also influenced by the levels of nitrogen in the soil, by the amount of rainfall, by the degree of crowding of the plants and by the abundance of herbivorous insects. Nitrogen availability is unlikely to be correlated with sunlight levels, but the others plausibly could be. Thus, it might turn out that this more far-reaching analysis, while explaining more of the total variation in seed production, might also show us that sunlight levels have a much reduced impact, once rainfall, crowding and insect damage are taken into account.

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[4] In fact, the "reality" of an apparent relationship is assessed by computing an F- or t-statistic for the data set which then permits a specification of the probability of the relationship's being in the data by chance alone. Where the probability, P, is low, say <0.05, then the chance, in this case, would be less than one in twenty that the particular set of values in the data set is giving a misleading picture of the real relationships in the entire population from which the data are drawn.

So, if we can collect good, numerous, data on all of these factors as well as on seed production and levels of sunlight received, then we can conduct a more complex regression analysis with these several predictor variables. This is **multiple regression**, and it is a straightforward mathematical extension of simple regression (described above). Effectively, in doing such an analysis, one is exploring the relationships among the variables by expressing one of them (the dependent variable) in terms of mathematical functions of all the others—the predictor variables. Each predictor variable will have a *b*-parameter attached to it, as above, providing an estimate of how much an incremental change of one unit of that predictor variable will affect—on average, and controlling for the effects of all the other variables—the value of the dependent variable. Similarly, each variable will have associated (partial) R^2- and P-values; finally, the entire model equation, with terms representing all the predictor variables, will have corresponding (model) R^2- and P-values. In the present study of faculty salaries our multiple regression used the variables shown in Table 2, p. X. Tables 3 and 5 show the parameter estimates and P-values associated with each variable in our two versions of multiple regression analysis, Tables 4 and 6 show the corresponding total (model) F- and P-values, and the model R^2-values are reported in the text.

In addition to the simple effect of two variables, say sunlight and amount of rainfall, one might be interested in the multiplicative effect of the two variables together, often referred to as the *interaction* of the two variables. This multiplicative effect is put into a regression model by create a new variable, defined by the term (Sunlight*Rain). The effect of this interaction on the outcome would be measured, as for any other variable, by the parameter estimate of the coefficient of this term in the regression model.

If one of the variables in an interaction term is dichotomous, then the interaction term measures how the effect of the other variable changes over the levels of the dichotomous variable. For example, if the second variable is planting after May 24, then the interaction term may be written as (Sunlight)*(Plant > May 24). The coefficient of the interaction term measures the difference in the effect of sunlight on seed production between plants planted before and after May 24.

Moreover, if the values of this dichotomous variable are coded in a special way, then the parameters estimated by the regression coefficients have special meanings. If the variable (Plant > May 24) is coded as 0 for planting before or on May 24, and coded as 1 for planting after May 24, and a regression equation fit with the variables Sunlight, (Plant > May 24) and the interaction (Sunlight)*(Plant > May 24), then the coefficient of the variable Sunlight measures the effect of sunlight on seed production ONLY for those seeds sown before or on May 24, and the coefficient of the interaction (Sunlight)*(Plant > May 24) measures the effect of sunlight on seed production ONLY for those seeds sown after May 24.

Given that one has measured a number of variables on the subjects in a study, one is tempted to fit a regression model that includes all these variables. However, there are reasons for not including some variables, for example:

- one variable is highly correlated with one or more other variables, and the other variables have a more meaningful relationship with the outcome
- a variable varies little over the sample (in the preceding example, if most seeds were planted before May 24), that variable will have little chance of affecting the outcome.

These are examples of the types of variables discussed by Rao(1971) and Hocking (1974) and others. They concluded that:

- If a variable is “irrelevant” in that, in the presence of other variables, it has NO effect on the outcome, it should be excluded from the regression model because its inclusion will produce wider confidence intervals for the other regression coefficients, and statistical tests with smaller values of t-test statistics (or equivalent F-test statistics) and larger corresponding p-values, in other words, not including it will lead to smaller confidence intervals, and larger test statistics and smaller p-values;
- Even if the variable is NOT “irrelevant”, but has a small effect on the outcome variable, not including it in the regression model will still lead to smaller confidence intervals, and larger test statistics and smaller p-values. However, not including it will lead to a small bias in the estimates of the regression coefficients of the variables left in the regression model. There is a trade-off between bias and standard error of the regression coefficient. This is measured by the “mean square error” of the estimate, written as:

$$\text{mean square error} = \text{bias}^2 + (\text{standard error})^2$$

Rao and Hocking gave conditions for determining when variables could be not included in regression models, but these require knowing the true values of the regression parameters.

Given that there are good reasons for not including some variables in a multiple regression model, several ways of selecting the variables to be “not included” have been proposed. The most popular of these is called *backward elimination*, or sometimes the backward stepwise elimination procedure. The backward elimination procedure is a procedure with (possibly) repeating steps:

1. Start with the full regression model, such as shown in Table 3;
2. For each variable currently in the model, a t-statistic (and corresponding p-value) is calculated;
3. The variable with the lowest value of the t-statistic (and hence largest value of the corresponding p-value) is considered for removal from the model;
4. Decision time:

    4.1 If the t-statistic is not large (that is, its p-value is above the significance level for staying in the model, SLSTAY, also called the significance for removal) then that variable is removed from the model, and we have a “reduced” model. We then go back to step 2 but use this reduced model to calculate our new t-statistics, etc;

    4.2 If the t-statistic is large, then no variables are removed from the equation and the procedure stops with a final (“best”) model.

For the salary data under consideration, the backward elimination procedure would work as follows:

First iteration:

1. Start with the full regression model
2. For each variable currently in the model, a t-statistic (and corresponding p-value) is calculated; these are shown in Table 3;
3. The variable with the lowest value of the t-statistic (and hence largest value of the corresponding p-value) is considered for removal from the model; in this case, this would be the variable Faculty of Health Sciences.
4. Decision:
   4.1 If the t-statistic is not large then that variable is removed from the model, and we have a "reduced" model. In this case, the t-value is 0.84 with p-value 0.3995. We are working with SLSTAY = 0.10 (see below). Since 0.3995> 0.10, we remove the variable Faculty of Health Sciences from the model and go to step 2;

Second iteration:

2. Recalculate t-statistics (and p-values) with reduced model (that is, model not including Faculty of Health Sciences variable);
3. The largest p-value is 0.2455, which is for the variable faculty of Information and Media Studies (FIMS);
   4.1. Since this p-value is greater than 0.10, we remove the variable FIMS, and go to step 2;

Third iteration:

2. Recalculate t-statistics (and p-values) with reduced model (that is, model not including Faculty of Health Sciences or FIMS variable);
3. The largest p-value is 0.2295, which is for the variable Faculty of Education;
   4.1 Since this p-value is greater than 0.10, we remove the variable Faculty of Education, and go to step 2;

Fourth iteration:

2. Recalculate t-statistics (and p-values) with reduced model (that is, model not including Faculty of Health Sciences or FIMS or Faculty of Education or Faculty of Law or Faculty of Engineering variables);
3. The largest p-value is 0.0133, which is for the variable Faculty of Science;
   4.2 Since this p-value is less than 0.10, we do NOT remove the variable Faculty of Science, and stop the backward elimination model with the resulting "best" model shown in Table 4;

Since, in backward elimination, we have been performing a sequential procedure, the p-values calculated are not the same as for the full model (see Table 3). Given that we have been doing a sequential procedure, with the sequence being based in the data, the question is: at what value, or level, should we be stopping the procedure; in other words, what is a reasonable value for SLSTAY? Kennedy and Bancroft (1971) using a criterion similar to the mean square error (see above), and Hoerl et al. (1986), using the criterion of minimization of the mean square error of a particular variable of interest, suggested that, on average, a value of SLSTAY of 0.10 would be best. Hence we have used SLSTAY=0.10 to stop at the model indicated in Table 4. The backward elimination procedure is also discussed in Kleinbaum et al (1999).

Influential Cases:

Determining whether a case (observation) is influential can be done by using three criteria, namely diff-betas, diff-fits and/or Cook's distance.

- **diff-beta**:
  The diff-beta criterion is defined as the difference between the parameter estimate for a variable, say gender, in the regression model using all the cases, and the parameter estimate when a particular case is removed from the calculations. This difference is standardized for by the expected standard of such a difference.
  A diff-beta statistic is statistically significant when its value is greater than 2 or less than -2; however, it is generally conceded that values greater than 1 or less that –1 are "important" and should be looked at more closely (see below). The number of diff-beta statistics is the number of variables times the number of cases; in this study, this is (14*918=)12852. Because of the large number of such statistics, summary statistics such as diff-fits and Cook's distance are often calculated (see below);

- **diff-fits:**
  The diff-fit statistic for each case is the differences between the value of the outcome variable for that case and the predicted outcome (from the multiple regression equation) calculated WITHOUT that observation in the regression equation.
  A diff-fit statistic is statistically significant when its value is greater than 2 or less that -2; however, it is generally conceded that values greater than 1 or less that –1 are "important" and should be looked at more closely (see below). The number of diff-fit statistics is equal to the number of cases, in this case, 918.

- **Cook's distance:**
  Cook's distance for a case can be computed as a summary of the diff-beta statistics for that case. A value of Cook's distance greater that 1 is considered "important". The number of Cook's distance statistics is equal to the number of cases, in this case, 918.

The general approach to "influence diagnosis" is the following:

1. Look at the diff-fits and Cook's distance statistics; if any of these are significant or important, note the case(s) which are exerting influence;
2. Look at the diff-beta statistics to see which cases are influencing which variables;
3. Remove the supposedly influential cases, and refit the multiple regression. Look at the regression parameter estimates of this model and seen if removing the influential cases does indeed change the estimates by a great amount;
4. Then decide:

4.1 If the influential cases don't affect the parameter estimates to a large extent, go back to the original model containing these cases;
4.2 If the influential cases DO affect the parameter estimates, remove these cases from the dataset, stating very clearly that this is being done, and continue on with the statistical analysis using this new, smaller dataset.

References:

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Appendix D.

Glossary of statistical terms

Dependent or Response Variable. The outcome that we are trying to explain in a regression analysis. Any change in the dependent variable is viewed as a function of changes in the independent variable(s).

Distribution. The collection of numbers (the data) available for a particular independent or dependent variable, displayed in sequential order.

F-test. A statistical test used to determine whether or not a particular independent variable accounts for changes in a dependent variable beyond chance levels. Technically, an F test is the ratio of (systematic variance plus error variance) divided by error variance. If an independent variable has no effect at all, the calculated value of F will be 1.0.

Independent or Predictor Variable. The factor that is used as a predictor in a regression analysis. The independent variable is conceptualised as accounting for changes in the dependent variable.

Influential Case. A case, or observation, which affects greatly a regression equation; usually the influence is measured by how much the case affects the estimates of one or more regression parameters.

Mean. A descriptive statistic indicating the central tendency of a distribution. The mean is defined as the arithmetic average of the values (the numbers) in a distribution. Thus, to obtain the mean, simply add up all the values and divide by the number of values in the distribution.

Outlier. A case, or observation, which differs greatly from its expected value. For a set of observations on one variable, an outlier is an observation very much larger, or very much smaller, than the mean of the all the observations. For regression, an outlier is an observation on a dependent variable which differs greatly from its predicted score based on the fit regression equation.

Population. The entire group of individuals under consideration in a statistical analysis.

R^2. The proportion of variance in the dependent variable accounted for by considering changes in the independent variable(s). This value is expressed as a percentage, and the higher the value, the better the level of prediction in a regression equation. In a multiple regression analysis, partial R^2 describes the proportion of variance in the dependent variable accounted for by any given independent variable. The model R^2 describes the proportion of variance in the dependent variable accounted for by all the independent variables in the regression model or equation.

Regression. A statistical technique that uses the association between the independent variable(s) and the dependent variable as means of prediction. May be either simple linear (one independent variable) or multiple regression (more than one independent variable).

Scatter Plot. A graph showing the relationship between a particular independent variable and a dependent variable.

Significance Level (Level of Statistical Significance). The result of a statistical test does not guarantee that any changes accounted for in the dependent variable will reflect the "truth". A certain amount of error is always present and results must be interpreted in light of the potential error (or noise) in the measurements. Thus, a level of statistical significance is adopted for any statistical test. This level is a probabilistic statement about the likelihood of the results of the test occurring by chance alone. The commonly accepted level is 5%, which is denoted as $P < 0.05$. By this criterion, any result which has a probability of occurring by chance that is lower than 5% (0.05) is accepted as an accurate finding.

Variance. A descriptive statistic indicating how the numerical values of a variable are distributed around their mean. If the numbers are relatively close to one another, the distribution will have a low variance. If the numbers are widely different from one another, the distribution will have a high variance.

Appendix E.

Results of Regression analysis on Males only.

The multiple regression equation from this analysis was used to estimate the predicted salaries appearing in Figures 1, 2 & 3 and in Table 5.

Table E.1: Summary of the regression model for Male Probationary and Tenured Faculty. The dependent variable is annual salary. With the exception of Gender, all variables that were significant in the "all faculty" model (Table 4) were forced to stay in this model. Model R^2 = 0.8165 (F=229.00, p<0.0001).

Variable	**Parameter estimate**	**t value**	**Prob. > |t|**
Years since highest degree	222.15	1.70	0.0888
Years since first degree	361.56	2.88	0.0041
Years at Western	-509.61	-5.08	<0.001
Rank 1 (Professor)[a]	27589.00	13.29	<0.001
Rank 2 (Associate Professor)[b]	10859.00	7.51	<0.001
Years at current rank	898.79	6.94	<0.001
Relative performance	10432.00	4.37	<0.001
Department average salary	0.66	9.62	<0.001
Faculty of Arts and Humanities[c]	-2058.91	-1.26	0.2066
Richard Ivey School of Business[c]	24106.00	5.31	<0.001
Faculty of Medicine and Dentistry[c]	-4973.99	-3.44	0.0006
Faculty of Music[c]	-4553.65	-1.78	0.0753
Faculty of Science[c]	-2737.58	-2.31	0.0212
Variables kept out of the model due to lack of significant effect in the "all faculty" model:			
Faculty of Engineering[c]			
Faculty of Law[c]			
Faculty of Education[c]			
Faculty of Information and Media Studies[c]			
Faculty of Health Sciences[c]			

[a] Difference between Professor and Assistant Professor salaries (Professor minus Assistant).
[b] Difference between Associate and Assistant Professor salaries (Associate minus Assistant).
[c] Difference between individual Faculty/School and the Faculty of Social Science.