Statistical Methods for Assessment of Cooperative and Work-Integrated Education

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Abstract

While the effectiveness of Cooperative and Work-Integrated Education (CWIE) is well-recognized and well-documented by the persons directly concerned, it needs more convincing evidence to expand and popularize this programme. One of the ways to do so is to develop quantitative methods by which the effectiveness of CWIE can be described more objectively.

This paper introduces two types of statistical approaches to assess the effectiveness of CWIE, using an actual panel data on students' academic records and employment outcomes. Firstly, a simple comparison is made between students with and without CWIE on their academic performance as well as employment outcomes using t-tests, z-tests, and χ^2 tests, in which the process is explicitly shown rather than as a mere result of a statistical package. Secondly, Path analysis is used to focus on the interactive relationships among student's' attributes. For example, one suspects that even CWIE has a positive effect on academic performance, it may be, that those students with high pre-university performance tend to take CWIE as well as performing well academically. This would overvalue the effectiveness of CWIE on the academic performance. Path analysis can sort out such a complicated relationship to pinpoint the true effectiveness of CWIE. In this section, a regression analysis is used based on such models as linear, linear probability, logit, and probit models. For estimation, Ordinary Least Square (OLS) and Maximum Likelihood Estimation (MLE) methods are used, in which interpretation of the estimation results such as coefficients and testing criteria are explicitly described.

The aim of the paper is to make practitioners of CWIE familiar with these statistical methods so that the effectiveness of their own CWIE programmes can be presented in a persuasive manner.

1. Introduction

1. Introduction

While the effectiveness of CWIE is well-recognized and well-documented by the persons directly concerned (See, for example, a series of articles in International Handbook for Cooperative and Work-integrated Education (2011)), it may need more convincing evidence to expand and popularize this programme globally --- the popularity of the programme is still concentrated mostly in North America and the anglophone world at large. One of the ways to do so is to employ quantitative methods by which the effectiveness of CWIE programme can be described more objectively. The theoretical analysis of CWIE has been dealt with most extensively in Psychology and Education, where key concepts such as Kolb's experiential learning (Kolb, 1984), Dewey's learning model (Dewey, 1916), Lewin's action research and laboratory (Lewin, 1946), and Piaget's learning and cognitive development (Piaget, 1985) appear. Such theories can suggest mechanisms by which CWIE brings about its effects on educational outcome or job performance.

However, there is a need to know "to what extent it works" as much as "how it works." This has a practical implication. Often identifying the educational effect on an individual requires is a long process, as the effect is more likely to spread out over one's life time than just after graduation, which makes it difficult to pinpoint the causal relationship. In this respect, CWIE is no exception. At the same time, the practitioners of CWIE are well aware of its labour intensive nature. There is a need to show the bearers of CWIE, be it the university, the government fund or self-financing students, that the programme is worthwhile. In particular, it is imperative to prove its effectiveness as a system rather than a practice heavily depending on a particular group of students or outstanding talent and devotion of the practitioners.

There have been some quantitative analyses in CWIE literature. They can be divided into three categories. The first category consists of studies where the analysis is based on direct data comparisons (See, for example, Hartley and Smith (1999), Zegwaard and McCurdy (2008), Mendez (2008)). The focus is more on the nature of data and how to interpret the result than on the analytical procedures. The studies in the

second category use statistical tests of significance based on such tests as a t-test, a χ^2 test and an analysis of variance (ANOVA) (See, for example, Heller and Heinemann (1987), Duignan (2003), Van Gyn et al (1996)). And in the third category, the main framework of the analysis is a multiple regression analysis, by which causal relationships among factors are investigated (See, for example, Gomez et al (2004), Mendez and Rona (2010), Foster et al (2011), Mandilaras (2004)).

This paper attempts to show how these statistical approaches, i.e. the second and third categories, are constructed and employed to assess the effectiveness of CWIE, using panel data on students' academic performance and employment outcome. This will be done in five sections. Firstly, a simple comparison is made between students with and without CWIE on their academic performance as well as employment outcomes using t-tests, z-tests, χ^2 tests and ANOVA, in which the process is shown explicitly rather than as a mere result of a statistical package such as Excel, SPSS and SAS. Secondly, the path analysis is employed as an analytical framework to focus on the interactive relationships among student's' attributes. Thirdly, qualitative response models such as linear probability, logit, and probit models are called for to analyse who takes CWIE. Fourthly, a linear model is estimated to see if CWIE has a positive effect on academic performance of students. The final section concludes the paper with some outstanding issues.

2. Comparing the averages/proportions: t-tests, z-tests, χ^2 tests and ANOVA

Comparing averages --- a t-test and ANOVA

Consider examining the effect of CWIE on academic performance. Let Grade Point Average (GPA) in the final year represent the academic performance and pick up 100 students at random, who may or may not have taken CWIE. One can divide the students into those with and without CWIE to compare the difference in the final GPA between the two groups. As GPA is likely to vary within each group, the comparison would be about the characteristics of the distributions of GPA's, with the most popular measure being the distribution's average. Suppose we have a sample of 10 students with 4 students with CWIE (coop students) whose GPA's are 3.8, 3.5, 3.2, 2.4 and 6 students without CWIE (non-coop students) whose GPA's are 3.9, 3.5, 3.0, 2.9, 2.5, and 2.2 (See Table I) --- the example has a deliberately small size to show explicitly the calculation steps. This gives the average GPA's of 3.225 and 3.0 respectively. Is this difference large enough to conclude that CWIE contributes to improvement of academic performance?

Table I: GPA with and without CWIE

		Average	Sample size
With CWIE	3.8, 3.5, 3.2, 2.4	$\underline{Xc} = 3.225$	$Nc = 4$
Without CWIE	3.9, 3.5, 3.0, 2.9, 2.5, 2.2	$\underline{Xnc}= 3.0$	$Nnc = 6$
Total		$\underline{X} = 3.09$	$N =10$

Two statistical issues need to be clarified before evaluation --- namely, sampling and hypothesis testing. The 10 GPA marks do not come from the whole group of students (i.e. 100) but from a part of them or a "sample from the population." It follows then that it may not reflect the exact feature of the population depending on each pick. Consequently, an average out of the sample or a "sample mean" is not equivalent to the "population mean" of the entire students' body. Statistically, the sample means follow a distribution around the population mean but with its own variance. This implies that when the difference of average GPA between CWIE and non-CWIE groups is compared by using the samples in the present example, the sample size needs to be taken into consideration, as this affects the reliability of the sampling and the type of distribution used for the test. The larger the sample is, the more information it conveys and thus the more reliable it will be. The distribution used for the test is called a t-distribution but, as the sample size increases, it approaches a normal distribution. The rule of thumb is the sample size of 50 --- use a t-distribution table for a sample size below 50 and a normal distribution table for a sample size above 50.

The sample averages are compared to verify if there is a difference in the populations --- or equivalently if they come from the same population. Formally, a null hypothesis that "there is no difference in GPA between CWIE and non-CWIE groups" is tested against an alternative hypothesis, which negates the former in one of the following ways: the averages differ, the average with CWIE is better, the average with CWIE is smaller. Some may think CWIE raises the academic performance, while others may think it actually lowers it, so that in this case the appropriate alternative would be "the averages differ". A drawing line between accepting and rejecting the null hypothesis is expressed by a concept called a "significant level" or a "level of significance," which is generally set at 1%, 5% or 10%. This is the probability that the observed difference of sampling GPA averages is likely to accept the null hypothesis. So a significant level of, say, 5% or less, means the probability of accepting the null hypothesis is lower than 5% --- i.e. the GPAs for the CWIE and non-CWIE groups are different. In the past, a statistical table of a standard normal distribution was used to compare the observed result with benchmark results corresponding to major significant levels such as 1%, 5%, and 10%. But with the advancement in computer technology,

one can easily calculate the exact significant level known as P-value (For example, it is obtained by a statistical function “NORM.S.DIST” in Excel). Nowadays, statistical results are provided in either or both ways --- with asterisks to indicate if the results exceed the significant levels at 1%, 5%, and 10%, and/or with P-values. In this paper, both t-values and p-values are shown. .

The statistical testing of the effect of CWIE on academic performance for the above example would take the following steps.

(1) Set the null hypothesis (H0) and the alternative hypothesis (H1)
H0: GPAc = GPAnc, H1: GPAc $\neq$ GPAnc
where GPAc and GPAnc are the population averages for CWIE students and non-CWIE students respectively.

(2) Calculate the average of GPA’s of the sampled CWIE students (Xc) and the average of GPA’s of the sampled non-CWIE students (Xnc): Xc = 3.225, Xnc = 3.0

(3) Calculate s^2c and s^2nc
where $s^2c = \sum(Xci - Xc)^2$
$= (3.8 - 3.225)^2 + (3.5 - 3.225)^2 + (3.2 - 3.225)^2 + (2.4 - 3.225)^2 = 1.0875$
and $s^2nc = \sum(Xnci - Xnc)^2$
$= (3.9 - 3.0)^2 + (3.5 - 3.0)^2 + (3.0 - 3.0)^2 + (2.9 - 3.0)^2 + (2.5 - 3.0)^2 + (2.2 - 3.0)^2$
$= 1.960$

(4) Calculate the pooled variance of the two set of samples s^2:
where $s^2 = (s^2c + s^2nc) / (Nc + Nnc - 2) = (1.0875 + 1.96)/8 = 0.3809$

(5) Derive a value t (or statistic):
where $t = (Xc - Xnc)/s(\sqrt{(1/Nc + 1/Nnc)}$
$= (3.225 - 3.0)/\sqrt{0.3809}\sqrt{((1/4)+(1/6))} = 0.5648$
Use t to test H0 that the averages of GPAc and GPAnc are identical. The distribution to use for the test is a t-distribution with degree of freedom Nc + Nnc – 2 = 4 + 6 – 2 = 8. If t exceeds 1.86 (or 2.90), “the null hypothesis is rejected at a 5% (1%) significant level,” i.e. the CWIE students achieve a higher GPA than the non-CWIE students --- or CWIE raises the academic performance. (Note that more statistically rigorous phrase to express this result is “that CWIE has no effect in raising academic performance is rejected.”) Note that if t-value were negative it would imply CWIE education has a negative effect on academic performance. As t-value is well below 1.86 (or 2.90), H0 is not rejected at 5% (or 1%) significant level, i.e. the CWIE students do not achieve higher GPA’s than non-CWIE students.

The comparison of averages can also be performed by using ANOVA with the following steps:

(1) As for the t-test.
(2) As for the t-test and also derive the average of all samples, X.
(3) As for the t-test.
(4) As for the t-test.
(5) Calculate Nc $(Xc\text{-}X)^2$ + Nnc $(Xnc\text{-}X)^2$ = $4x(3.225\text{-}3.09)^2+6x(3.0\text{-}3.09)^2 = 0.1215$
(6) Derive a value F,
    Where F = Nc $(Xc\text{-}X)^2$ + Nnc $(Xnc\text{-}X)^2 / s^2 = 0.1215/0.3809 = 0.31898$
(7) Use F to test H0 that the averages of GPAc and GPAnc are identical. The distribution to use for the test is an F distribution with degrees of freedom 1 and Nc + Nnc – 2 = 4 + 6 – 2 = 8. If F exceeds 3.46 (or 8.41), "the null hypothesis is rejected at a 5% (1%) significant level," i.e. the achieved GPAs by the CWIE and the non-CWIE students differ. Note that an F value is always positive and on its own it does not show which is greater --- the inequality can be verified by comparing the average values themselves. As t is well below 3.46 (or 8.41), H0 is not rejected at 5% (0r 1%) significant level, i.e. the CWIE students do not achieve different GPA's from the non-CWIE students' GPA.

Note that this F value is equivalent to the t-value squared, i.e. F =0.31898 = $(0.5877)^2 = t^2$, where the t-distribution is with a degree of freedom 8 and ANOVA is equivalent to a two-tailed t-test.

Comparing proportions --- a z-test/ a χ^2 test

The effect of CWIE may also be measured by proportions as in the percentage of CWIE graduates in employment as opposed to being unemployed, in a full-time job as opposed to being in a part-time job, or in a listed-company as opposed to being in a non-listed company. As in the previous example, the null hypothesis that CWIE has no effect on employment outcome would be tested against the alternative hypothesis that CWIE shows the difference. The testing procedure is almost identical to what has been discussed for two average values, except for the distribution and the variances. When a choice is binary, the outcome follows a binomial distribution, and when the sample size is large enough i.e. a sample size n and proportion p satisfy np>5 and n(1-p)>5, it becomes a normal distribution with a mean np and a variance p(1-p), where p is the probability of occurrence, following the central limit theory.

As a numerical example, let the sample of 100 graduates consist of 40 with

CWIE experience and 60 without CWIE experience with both groups having 20 placed in full-time jobs. Let the sample size be N with Nc CWIE gradutess and Nnc non-CWIE graduates, and the proportions of those graduates in the sample with full-time jobs for CWIE graduates and non-CWIE graduates be Pc and Pnc, while those in population be πc and πnc (See Table II).

Table II

	CWIE graduates	Non-CWIE graduates	Total
Full-time job	20	20	40
(Proportion)	Pc = 0.5	Pnc = 0.33	P = 0.4
Sample size	Nc = 40	Nnc = 60	N = 100

The statistical testing of the effect of CWIE on a full-time job placement would take the following procedures. The steps are shown with the corresponding values for the above example.

(1) Set the null hypothesis (H0) and the alternative hypothesis (H1)
$H0{:}\pi c = \pi nc$, $H1{:}\pi c \neq \pi nc$

(2) Calculate the proportions of CWIE students and non-CWIE students at full-time jobs from the sample: Pc = 0.5 and Pnc = 0.33

(3) Calculate the total proportion of students at full-time jobs: P
where P = (PcNc + PncNnc) / (Nc + Nnc) = (0.5 x 40 + 0.33 x 60)/(40 + 60) = 0.4

(4) Derive a value z (or statistic):
where $z = (Pc - Pnc) / \sqrt{P(1-P)(1/Nc + 1/Nnc)}$
$= (0.5-0.33)/\sqrt{0.4(1-0.4)(1/40 + 1/60)} = 1.67$, given $H0{:}\pi c = \pi nc$

(4) Use z to test H0 that $\pi c = \pi nc$. The distribution to use is a normal distribution. If z exceeds 1.64 (or 2.33), "the null hypothesis is rejected at a 5% (1%) significant level," i.e. the CWIE students tend to be in full-time jobs more than the non-CWIE students.

In the numerical example above, z = 1.67 is greater than 1.64, implying H0 is rejected at a 10% significance level, i.e. the CWIE graduates have a higher chance of having full-time jobs than the no-CWIE graduates.

The comparison of proportions can also be tested using a χ^2 test, which is known as a "test of independence". Let the observed numbers of CWIE graduates with full-time jobs and part-time jobs be a and b, while those of non-CWIE graduates be c and d. Table III is what is called a "contingency table" for the observed numbers.

Table III: The contingency table for the observed numbers

	Full-time job	Part-time job	Total
CWIE graduates	a	b	a+b
Non-CWIE graduates	c	d	c+d
Total	a+c	b+d	a+b+c+d

Under the null hypothesis that there is no difference between the CWIE group and non-CWIE group --- the outcome is "independent" of the group type. So if the "expected contingency table" under the hull hypothesis has entries A, B, C, and D as in Table IV, then the following conditions have to be satisfied.

Table IV: The expected contingency table

	Full-time job	Part-time job
CWIE graduates	A	B
Non-CWIE graduates	C	D

where $A = (a+b)(a+c)/(a+b+c+d)$ $B = (a+b)(b+d)/(a+b+c+d)$
$C = (a+c)(c+d)/(a+b+c+d)$ $D = (b+d)(c+d)/(a+b+c+d)$

The test statistic χ^2 is defined as the sum of squared differences between the "observed values" and the "expected values under the null hypothesis" divided by the "observed figures." That is

$$\chi^2 = (a - A)^2/A + (b - B)^2/B + (c - C)^2/C + (d - D)^2/D \quad (1)$$

In the above example,

$A = (a+b)(a+c)/(a+b+c+d) = (20+20)\ (20+20)/(20+20+20+40)) = 16$
$B = (a+b)(b+d)/(a+b+c+d) = (20+20)\ (20+40)/(20+20+20+40)) = 24$
$C = (a+c)(c+d)/(a+b+c+d) = (20+20)\ (20+40)/(20+20+20+40)) = 24$
$D = (b+d)(c+d)/(a+b+c+d) = (20+40)\ (20+40)/(20+20+20+40)) = 36$

Therefore, the observed and expected contingency tables for this example becomes as in Table V (a) and (b).

Table V (a)

Observed	Full-time job	Part-time job	Total
CWIE graduates	20	20	40
Non-CWIE graduates	20	40	60
Total	40	60	100

Table V (b)

Expected	Full-time job	Part-time job	Total
CWIE graduates	16	24	40
Non-CWIE graduates	24	36	60
Total	40	60	100

Therefore,

$$\chi^2 = (20–16)^2/16 + (20–24)^2/24 + (20–24)^2/24 + (40–36)^2/36 = 25/9 = 2.78 \quad (2)$$

The test for this type of contingency table with 2 rows and 2 columns is based on a χ^2 distribution with a “degree of freedom 1”, or “$\chi^2_{(1)}$”. The degree of freedom is 1, since fixing one of four entries in the contingency table i.e. A, B, C, and D, would determine all other entries given the observed numbers of CWIE graduates, non-CWIE graduates, those with full-time jobs and those with part-time jobs. With a $\chi^2_{(1)}$ distribution table, 2.78 is greater than 2.71 for a 10% significance level . Therefore, H0 is rejected at a10% significance level --- in other words, CWIE can be considered to improve the possibility of acquiring a full-time job.

Two tests can be used to verify the null hypothesis. In fact, the z test and the $\chi^2_{(1)}$ test are equivalent in the test for independence in a 2x2 contingency table, with $z^2 = \chi^2_{(1)}$ In the above example, $z^2 = 1.67^2 = 2.78 =\chi^2_{(1)}$. The difference is that when contingency table has more entries, z test cannot be used. Table VI summarises the ways these tests can be used.

Table VI

Quantity compared	Number of groups compared	Test & distribution used	Degree of freedom for 2 groups

Proportions	2	z-test (Normal)	Not applicable
Of groups	2 or more	χ^2 test (χ^2)	1
Averages	2	t-test (t)	n1+n2-2
Of groups	2 or more	ANOVA (F)	1, n1+n2-2

Note: (i) "Degree of freedom" only refer to cases when proportions or averages of 2 groups are compared --- for ANOVA, n1 and n2 are sample sizes of the 2 groups.
(ii) For comparing averages of 2 groups, a z-test and a χ^2 test are equivalent.
(iii) For comparing proportions of 2 groups, a t-test and ANOVA are equivalent.

The case of Kyoto Sangyo University

(The data set)

Kyoto Sangyo University is a private university in Kyoto, Japan, which was founded in 1965. It is a medium-sized university with 7 faculties, over 11,000 students and 800 academic and administrative staffs. Undergraduate course lasts for 4 years in Japan starting in April and ending in March. At the time of data collection, there were 773 universities, of which 178 were public and 595 were private in Japan.

The data has been collected from all 5473 undergraduate students who graduated in 2008 and 2009, --- 2739 and 2734 respectively. Of the total 5473, 3781 were male and 1692 were female from 7 faculties i.e. Economics, Business, Law, Foreign Languages, Culture, Science, and Engineering. From the original panel data of each student, we use annual GPAs, whether he/she has taken CWIE, and their employment outcome. Here is a brief description.

(i) The average annual GPAs for students in the 1st - and 3rd- year of undergraduate programme, GPA1 and GPA3, are 1.90 and 1.90, respectively taken from a total of 5160 students out of 5473, leaving out some with irregular registration patterns. GPA1 may be used to represent the student's academic ability before coming to university. This is because there is no standardized data on students' pre-university academic performance in Japan such as a national examination to cover every high school student and GPA1 is likely to depend on the pre-university achievement to great extent. GPA3 is used to identify the academic progress during the undergraduate years instead of the 4th year's GPA, due to a rather special circumstance of Japanese universities where many students manage to attain the necessary units to graduate by the end of 3rd year to spend almost

the entire 4th year to find a job, so that their 4th year's GPA does not reflect their ability.

(ii) CWIE: Of 5160 students considered in (i), CWIE was taken by 692 students or by13.4% (= 692/5160). This was much higher than the national average of 1.8% in 2007 and 2.2% in 2011. And 61.6% of work experience lasted less than two weeks in 2007 and there was a slight reduction to 61.6% in 2011, while 7.6% of work experience lasted over a month in 2007 and there was an increase to 11.5% in 2011, with the most of them unpaid (Ministry of Education, Japan, 2013). This shows Japan's CWIE is lagging behind other anglophone industrial nations.

(iii) Employment outcome: This was measured from two angles. Firstly, the students were asked whether they had obtained "provisional placement offers" of full-time employment, part-time employment or none. Out of 5160 students, 4195 obtained full-time employment offers while 421 obtained part-time employment offers. Secondly, 3965 offers students received were from private companies with 1354 listed companies and 2611 unlisted companies. It needs to be mentioned that KSU can be considered a typical Japanese private university, considering its history of almost 50 years, its medium size with over 11,000 students and 800 academic and administrative staffs in 7 faculties, and its location in a medium sized city of Kyoto. Thus, the result of statistical analysis of KSU may resemble what other universities would find if a similar analysis is made.

(Testing the effect of CWIE at KSU)

Given the above information, the following section illustrate how the effectiveness of CWIE at KSU could be tested. The statistical testing will be performed to compare the academic performance and employment placement of students with and without CWIE.

(1) Effect of career education on GPA1 and GPA3

5160 students were divided into two groups with and without CWIE and the average GPAs were found as in Table VII below.

Table VII: Average GPAs by group

Student	Average number	Average GPA1	GPA3
With CWIE	692	2.17	2.2
Without CWIE	4468	1.85	1.85

With the procedure illustrated earlier in this chapter, the existence of a significant difference in an academic performance level between students groups with and without CWIE is tested using a t-test and the following results are found (Although the original data base is huge and cannot be shown here, in order to show the calculation process the actual values used to derive t-value are provided in “Note” in parenthesis):

(a) Question: Are average GPA1s of groups with and without CWIE, 2.17 and 1.85, significantly different?
Answer: t = 11.59, which means they are significantly different at 1%. (P-value = 0)
(Note: $t = (2.17-1.85)/s(\sqrt{(1/692 + 1/4468)}$
where $s^2 = (274.52+ 2081.53) / (692+4468-2) = 0.457$)

(b) Question: Are average GPA3s of groups with and without CWIE, 2.2 and 1.85, significantly different?
Answer: t = 12.62, which means they are significantly different at 1%. (P-value = 0)
(Note: $t = (2.2-1.85)/s(\sqrt{(1/692 + 1/4468)}$
where $s^2 = (339.4+ 2037.38) / (692+4468-2) = 0.461$)

These test results seem to suggest that CWIE attracts better students, i.e. students with higher GPA1s, and makes students do better academically at university, i.e. students with higher GPA3.

(2) Effect of CWIE on obtaining a full-time/part-time job

4616 students were divided into two groups: those with and without CWIE and the number of students in each category is shown in Table VIII below.

Table VIII: Job placement status by group

	Full-time	Part-time	Full-time (%)
Total	4195	421	90.9%
With CWIE	621	20	96.9%
Without CWIE	3574	401	89.9%

With the procedure illustrated earlier, the existence of a significant difference in a job status between students groups with and without CWIE is tested using a z-test

and a $\chi^2(1)$ test --- as pointed earlier, they give the identical test result, and the following results are found (As before, the calculation process is shown in the parenthesis "Note").

Question: Does CWIE improve the chance of getting a full-time job?

Answer 1: Z-test

z = 5.67, which means CWIE significantly improves a chance of getting a full-time job.

(Note: $z = (0.969 - 0.899)/\sqrt{(0.909\,(1-0.909)(1/621+1/3574)} = 5.67$)

Answer 2: χ^2 with one degree of freedom

Table IX shows Contingency tables for observed values and expected vales:

Table IX: Contingency tables for observed values and expected vales

	Observed		Expected	
	Full-time/Part-time		Full-time/Part-time	
With CWIE	621	20	583	58
Without CWIE	3574	401	3612	363

Thus

$$\chi^2 = (621-583)^2/583 + (20-58)^2/58 + (3574-3612)^2/3612 + (401-363)^2/363 = 32.33 = 5.67^2 = z^2 \qquad (3)$$

In both cases, the effect is significant at 1% (P value = 0)

(3) Effect of CWIE on obtaining a job at a listed/unlisted company

4616 students were divided into two groups: those with and without CWIE and the number of students in each category is shown in Table X below.

Table X: Company status by group

	Listed	Unlisted	Listed(%)
Total	1354	2611	34.1%
With CWIE	221	372	37.3%

Without CWIE	133	2239	33.6%

Question: Does CWIE improve the chance of getting a job at a listed company?

Answer 1: Z-test

z = 1.74, which means CWIE significantly improves a chance of getting a full-time job.

(Note: $z = (0.372-0.336)/\sqrt{(0.341\ (1-0.341)(1/593+1/3372)} = 1.74$)

Answer 2: χ^2 with one degree of freedom

Table XI shows Contingency tables for observed values and expected vales:

Table XI: Contingency tables for observed values and expected vales

	Observed		Expected	
	Listed/Unlisted		Listed/Unlisted	
With CWIE	221	372	203	390
Without CWIE	1133	2239	1151	2221

Thus

$$\chi^2 = (221-203)^2/203 + (372-390)^2/390 + (1133-1151)^2/1151 + (2239-2221)^2/2221 = 3.02 = 1.74^2 = z^2 \quad (4)$$

In both cases, the effect is significant at 10% (P value = 0.08)

In sum, the following conclusion can be drawn:

(i) When students are grouped into those with and without CWIE, the averages of first year and third year GPA are both significantly higher for the former group.

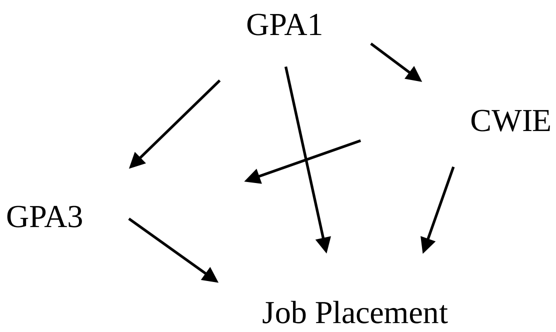
(ii) The overall academic performance for those with CWIE shows difference. One may conclude that CWIE has a positive effect on academic performance. However, it does suggest also that students who take WIL have high per-university academic performance. If this is true, then the value of CWIE is overestimated. The next section deals with this issue of singling out the effect of CWIE, by using a series of regression analyses.

3. Interactive framework of student's attributes: Path analysis/SEM/Recursive

form

It has been suspected that a student's attributes such as pre-university academic performance, academic performance at university, job placement, gender, faculty, together with whether CWIE is taken are interrelated and a simple comparison of values and proportions may not be adequate. Some researchers used a regression models to take care of such an interactive framework (See, for example, regression models used in Mendez and Rona (2010), Gomez et al (2004), Foster et al (2011)). But a more systematic approach often employed to solve such issues is a "path analysis". Path analysis is both a concept and a statistical tool to determine causal relationships among variables within a given structure and such relationships are often described by a "path diagram" as illustrated in Figure I for our analysis of CWIE. The concept is useful for disentangling causal relationships among the variables.

Figure.I: Path diagram



Path analysis was first introduced by Sewall Wright, a geneticist, who sought to disentangle genetic influences across generations (Wright, 1921). Wright's contribution to investigations in social science went further, when he subsequently wrote an article on an analysis of a corn market, where he applied his approach to economic analysis of supply and demand interaction (Wright, 1925), and an article on an identification problem of simultaneous equation system, where he discussed how to identify supply and demand from a set of given data (Wright, 1934). It is worth noting that his interests in simultaneity and identification appeared long before they started to be treated as a standard concepts in econometrics.

Today, the analysis is widely used in social science including psychology, sociology and economics. As a statistical or econometric tool, Path analysis is categorized as one type of a structural equation model (SEM) or a simultaneous equation model respectively.

A set of causal relationships in Fig. I can be expressed as:

GPA1 → CWIE (5-1)
GPA1 & CWIE → GPA3 (5-2)
GPA1 & CWIE & GPA3 → Job placement (5-3)

with → expressing the causal relationship

Or, if each causal relationship can be expressed as a linear equation with a constant term, coefficients, and an added error term uncorrelated to each other:

Equation 1 CWIE = a1 + a2 GPA1 + u1 (6-1)
Equation 2 GPA3 = b1 + b2 GPA1+b3 CWIE + u2 (6-2)
Equation 3 Job = c1 + c2 GPA1+ c3 CWIE + c4 GPA3 + u3 (6-3)

where Job implies a choice between full-time and part-time jobs, or a choice between listed and unlisted companies.

This hierarchical structure is called a “fully recursive model” and it is known that an ordinary least square (OLS) method may be used to estimate coefficients of each equation, i.e. a’s, b’s, and c’s, separately (See, for example, Greene (2008) or Wooldridge (2002) or (2009)). Equations 1 and 3 have “qualitative response” as a dependent variable on the left-hand side of the equations, i.e. 1 if CWIE taken and 0 otherwise for Equation 1 and 1 if full-time job or listed company or 0 otherwise, while Equation 2 has a usual cardinal value of GPA3 as its dependent variable. Estimation process differs between the two types. In the following two sections, the processes for Equations 1 and 2 are described in turn by using the KSU data. Equation 3 is not dealt with in this paper, as the procedure is the same as that of Equation 3.

4. Who takes CWIE programme?: Qualitative response models

Equation 1: CWIE = a1 + a2 GPA1 + u1 (7)

This equation estimates the effect of GPA1 on the decision to take CWIE. As pointed earlier, it is possible that those students who are interested in CWIE were

already academically motivated before starting university career. Higher school grades can be used to represent pre-university academic performance if any national data is available. If, however, no such exam exists or cannot be traced to cover all the students concerned, a best proxy would be their grades in the first term or first year at university, e.g. GPA1, since this result is more likely to be a reflection of pre-university achievement rather than what is achieved at university. The decision to take CWIE may also depend on the student's other personal attributes such as gender or the faculty that the student belongs to. Thus, the equation to estimate is:

$$\text{CWIE} = a1 + a2\ \text{GPA1} + a3\ \text{Gender} + a4\ \text{Faculty} + u1 \tag{8}$$

where the dependent variable CWIE is one or zero and for the independent variables GPA1 may be grades and Gender and Faculty are dummy variables, with a constant term a1 and an error term u1 with a standard normally distribution.

As CWIE is a 1-0 variable, this model is called "a binary (instead of qualitative) response model." This belongs to a family of "limited dependent variable models," in which the range of values of the dependent variable is substantially limited. In some cases, a straightforward use of OLS method on this linear equation may not be appropriate.

For the binary response models, researchers have been using several functional forms, namely, a linear probability model, a logit model, and a probit model, each with its own advantages and disadvantages (The discussion to follow can be found in most of standard textbooks of econometrics --- for example, see Wooldridge (2009)).

A linear probability model expresses the probability of response as a linear function of independent variables. However, as the observed dependent variable can only take 1 or 0 --- the unobserved probability is called a "latent variable", a linear relation is not theoretically appropriate, i.e. predicted values of the dependent variable may lie outside of the 0-1 range (See Figure.II). The binary nature of the dependent variable also implies heteroskedastic errors. In this case, OLS estimators are not biased but for t and F statistics the usual standard errors need to be replaced by "heteroskedasticity-robust standard errors", since the error terms are not normally distributed. In practice, however, these error values are not far from each other. The estimation procedure for this model is simple as OLS is used for the linear equation directly and the interpretation of the coefficients is intuitive --- an increase in a unit values of a variable would raise the probability of taking CWIE by the estimated coefficient.

Unlike a linear probability model, a logit model keeps the dependent variable between 0 and 1. The term “logit” comes from “a logistic curve” (See Figure. III). If the probability of response p depends on x linearly i.e. ax + b, then a logistic curve is expressed by

$$p = \exp(ax+b) / (1+ \exp(ax+b)) \tag{9}$$

It can be easily verified that if ax+b approaches ∞ (or-∞). p approaches 1 (or 0). The equation can be rearranged in a linear form by a “logit transformation” as:

$$\ln p/(1-p) = ax+b \tag{10}$$

This could be estimated by a least square method if p takes values other than 1 or 0. In the present case, where the dependent variable takes 1 or 0, it is not feasible, but when the probability is replaced by an observed percentage such as the average percentage of those who have taken the choice for each group, the least square method can be used and it is known as a “minimumχ^2 method”.

A probit model is based on the standard normal cumulative distribution and can be expressed as

$$p = (2\pi)^{-1/2}\int_{-\infty}^{ax+b} \exp(-z^2/2)dz \tag{11}$$

It can be verified that, as in the logit model above, if ax+b approaches ∞ (or-∞), p approaches 1 (or 0) (See Figure. III).

Unlike a linear probability model, both logit model and probit models are non-linear in ax+b and some cautions are needed for the estimation process. Firstly, a straightforward least square method would not work because of the non-linearity. For the non-linear estimation, the most commonly used method today is the “maximum likelihood estimation (MLE)”. Secondly, the estimated coefficients do not give a straightforward interpretation of the least square estimation, since a unit increase of an independent variable will cause a marginal change in the dependent variable through the non-linear forms of the logit and probit equations. This means that the estimated coefficients of the linear probability, logit, and probit models cannot be directly compared. There is a further complication that for the logit and probit models these values depends on the values of independent variables --- note that for the linear probability model, the marginal effect is constant over the values of independent variables. As a rule of thumb, Wooldridge (2002) suggests using “scale factors” to multiply the coefficients for the logit and probit models of 0.4 and 0.25 respectively, to compare the coefficients among the three models. Also as a statistic for goodness-of-fit, i.e. R^2 in the least square method, McFadden (1974) suggested a statistic known as “Pseudo R^2” for the maximum likelihood method, which is often found in statistical packages.

Testing the causes of CWIE at KSU

As explained above, a qualitative response model was estimated using a linear probability model, a logit model, and a probit model, where independent variables include student’s gender, graduation year, and faculty as dummy variables.

$$\text{CWIE} = a1 + a2\ \text{GPA1} + a3\ \text{Gender} + a4\ \text{Faculty} + a5\ \text{GraduationYear} + u1 \tag{12}$$

Table XII shows the estimation results. Both a and b are the identical result of least square method based on a linear probability model. The difference is the treatment of errors. As explained earlier, the correct version is a with heteroskedasticity-robust t-values, which also gives a different set of P-values. However, the difference is not that large. Comparing the four sets of results, the tendency of signs, relative magnitudes, and significance among the independent variables is alike. Note, however, the coefficients for the same variables in the linear probability, logit, and probit models differ because of the way coefficients affects the dependent variable. On the whole, the linear probability model gives reasonable results and one may sacrifice the theoretical rigour of logit and probit models for the simple and intuitive nature of linear probability models.

5. Does CWIE have a positive effect on academic performance? : Least square models

Equation 2

$$\text{GPA3} = b1 + b2\ \text{GPA1} + b3\ \text{CWIE} + b4\ \text{Gender} + b5\ \text{Faculty} + u2 \tag{13}$$

A dependent variable is GPA3 and this is determined by what one came with to university with, i.e. GPA1, and what one took at university, i.e. CWIE. Also as in Equation 1, other attributes of students are included such as gender, faculty, and year of

graduation as dummy variables. As GPA3 is a quantitative variable, the equation can be estimated in a linear form.

Testing the effect of CWIE on academic performance at KSU

For applying the equation to the KSU case, a graduation dummy is included as in Equation 1, so that we estimate the following equation:

Equation 2 $$GPA3 = b1 + b2\ GPA1 + b3\ CWIE + b4\ Gender + b5\ Faculty + b6\ Graduation\ year + u2 \quad (14)$$

The estimation procedure for this equation is simple, as the dependent variable is not a qualitative response. OLS estimation may be used straight away. The result is shown in Table XIII. Apart from faculty discrepancies affecting GPA3, both GPA1 and CWIE do have positive and significant effects on GPA3.

6. Conclusion

This paper has attempted to show how statistical methods can be used on available data for CWIE as a useful tool to explain to those who are not aware of the effectiveness of CWIE at university, in the government or among potential students. In the choice of method, there is a trade-off between “simple intuitive appeal” and “theoretical rigour.” Simple comparisons of averages and proportions are easy to work with but would be more persuasive if statistical sampling and testing are used. When causal relationships are considered, an econometric approach of path analysis is a better choice. Using the path analysis on the KSU student data, it was shown that CWIE does raise academic performance at university, i.e.GPA3, but its magnitude may be overestimated as students with higher academic marks, i.e. GPA1, tend to take CWIE. As for binary response models, the estimated results of a linear probability model with OLS method and logit and probit models with MLE method were compared and it was suggested that the simplicity and intuitive appeal of the former outweighs the theoretical rigour of the latter.

Finally, it is important to emphasize that this type of quantitative analysis based on statistical and econometric methodologies should be taken to complement and not substitute qualitative analysis based on psychological and sociological methodologies. The former can explain how effective CWIE is but cannot explain how such a mechanism works.

Bibliography

Blalock, H. M. (1985): “Causal Models in the Social Sciences,” Second Edition, New York: Aldine.

Dewey, J.(1916): “Democracy of Education: An introduction to the philosophy of education,” New York, NY: The Free Press.

Duignan, J. (2003): “Placement and adding value to the academic performance of undergraduates: Reconfiguring the architecture - an empirical investigation,” Journal of Vocational Education and Training, 55 (3), pp.335-350.

Foster, H., Green, P., Houston, P., McAree, D., McCann, C., McCulloch, D. and Pogue, M. (2011): “Are sandwiches better? The impact of work placement upon degree performance,” Perspective on Pedagogy and Practice, University of Ulster, Vol. 2, pp53-64.

Goldberger, A. S. (1972): “Structural Equation Methods in the Social Sciences,” Econometrica, vol.40, No.6, pp.979-1001.

Gomez, S., Lush, D. and Clements, M. (2004): “Work placements enhance the academic performance of bioscience undergraduates,” Journal of Vocational Education and Training, 56 (3), pp.373-386.

Greene, W. H. (2008): “Econometric Analysis,” Sixth Edition, Pearson Prentice Hall.

Hartley, J.L. and Smith, B.W. (2000): “Strengthen academic ties by assessment of learning outcomes,” Journal of Cooperative Education, 35(1), pp.41-47.

Heller, B. and Heinemann, H.N. (1987): “The impact of structured and non-structured work experiences on college students' attitude, values and academic performance,” Journal of Cooperative Education, 23 (3), pp.19-32.

Kaplan, D. W. (2000): “Structural Equation Modeling: Foundations and Extensions,” Sage Publications, Inc.

Kolb, D.A.(1984): “Experiential Learning: Experience as the source of learning and development,” Engelwood Cliffs, NJ: Prentice Hall.

Lewin, K. (1946): “Action research and minority problems,” Journal of Social Issues, 2(4), pp.34-46.

Lleras, C. (2005): “Path Analysis, “ in Kempf-Leonard, K.L. (ed.) “Encyclopedia of Social Measurement,” Elsevier Academic Press.

Mandilaras, A. (2004): “Industrial placement and degree performance: Evidence from a British higher institution,” International Review of Economics Education, 3(1), pp.39-51.

Maruyama, G. M. (1997): “Basics of Structural Equation Modeling,” Sage Publications, Inc.

Mendez, R. (2008): "The correlation between industrial placements and final degree results: A study of Engineering Placement Students," Paper presented it the ASET conference, Plymouth.

Mendez, R. and Rona, A. (2010): "The Relationship between Industrial Placements and Final Degree Results: a study of engineering placement students," Learning and Teaching in Higher Education, Issue 4-2, pp.46-61.

Ministry of education, culture, sports, science and technology, Japan (2013): "The report on internships at higher education institutions"

Ott, R. and Longnecker, M. (2010): "An Introduction to Statistical Methods and Data Analysis, International Edition," sixth Edition, Brooks/Cole, Cengage Learning.

Piaget, J.(1985): "The equilibrium of cognitive structures," Chicago, IL: University of Chicago Press.

Silberston, Z. A. (1987): "Path Analysis," in Eatwell, J., Milgate, M. and Newman, P. (ed.) "The new Palgrave: a dictionary of economics," Macmillan.

Van Gyn, G., Cutt, J., Loken, M. and Ricks, F. (1996): "Investigating the educational benefits of cooperative education: A longitudinal study," Journal of Cooperative Education, 32 (2), pp.70-85.

Wonnacott, T.H. and Wonnacott, R. J. (1990): "Introductory Statistics for Business and Economics (Wiley series in probability and mathematical statistics)," John Wiley & Sons.

Wooldridge, J. M. (2009): "Introductory Econometrics," fourth Edition, South Western.

Wooldridge, J. M. (2010: "Econometric Analysis of Cross Section and Panel Data," (2nd ed.), The MIT Press, Cambridge, Massachusetts.

Wright, S. (1921): "Correlation and Causation," Journal of Agricultural Research, 20, pp.557-585.

________ (1925): Corn and Hog Correlations, Washington: U.S. Department of Agriculture Bulletin 1300.

________ (1934): "The Method of Path Coefficients," Annals of Mathematical Statistics, 5, pp.161-215.

Zegwaard, K.E. and McCurdy, S. (2008): "Value of work placements for students and its influence on student performance: Faculty perceptions," In Coll, R.K. and Hoskyn, K. (Eds): "Proceedings from the Annual Conference for the New Zealand Association for Cooperative Education," New Plymouth, New Zealand.

Statistical Methods for Assessment of Cooperative and Work-Integrated Education

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Abstract

While the effectiveness of Cooperative and Work-Integrated Education (CWIE) is well-recognized and well-documented by the persons directly concerned, it needs more convincing evidence to expand and popularize this programme. One of the ways to do so is to develop quantitative methods by which the effectiveness of CWIE can be described more objectively.

This paper introduces two types of statistical approaches to assess the effectiveness of CWIE, using an actual panel data on students' academic records and employment outcomes. Firstly, a simple comparison is made between students with and without CWIE on their academic performance as well as employment outcomes using t-tests, z-tests, and χ^2 tests, in which the process is explicitly shown rather than as a mere result of a statistical package. Secondly, Path analysis is used to focus on the interactive relationships among student's' attributes. For example, one suspects that even CWIE has a positive effect on academic performance, it may be, that those students with high pre-university performance tend to take CWIE as well as performing well academically. This would overvalue the effectiveness of CWIE on the academic performance. Path analysis can sort out such a complicated relationship to pinpoint the true effectiveness of CWIE. In this section, a regression analysis is used based on such models as linear, linear probability, logit, and probit models. For estimation, Ordinary Least Square (OLS) and Maximum Likelihood Estimation (MLE) methods are used, in which interpretation of the estimation results such as coefficients and testing criteria are explicitly described.

The aim of the paper is to make practitioners of CWIE familiar with these statistical methods so that the effectiveness of their own CWIE programmes can be presented in a persuasive manner.

1. Introduction

1. Introduction

While the effectiveness of CWIE is well-recognized and well-documented by the persons directly concerned (See, for example, a series of articles in International Handbook for Cooperative and Work-integrated Education (2011)), it may need more convincing evidence to expand and popularize this programme globally --- the popularity of the programme is still concentrated mostly in North America and the anglophone world at large. One of the ways to do so is to employ quantitative methods by which the effectiveness of CWIE programme can be described more objectively. The theoretical analysis of CWIE has been dealt with most extensively in Psychology and Education, where key concepts such as Kolb's experiential learning (Kolb, 1984), Dewey's learning model (Dewey, 1916), Lewin's action research and laboratory (Lewin, 1946), and Piaget's learning and cognitive development (Piaget, 1985) appear. Such theories can suggest mechanisms by which CWIE brings about its effects on educational outcome or job performance.

However, there is a need to know "to what extent it works" as much as "how it works." This has a practical implication. Often identifying the educational effect on an individual requires is a long process, as the effect is more likely to spread out over one's life time than just after graduation, which makes it difficult to pinpoint the causal relationship. In this respect, CWIE is no exception. At the same time, the practitioners of CWIE are well aware of its labour intensive nature. There is a need to show the bearers of CWIE, be it the university, the government fund or self-financing students, that the programme is worthwhile. In particular, it is imperative to prove its effectiveness as a system rather than a practice heavily depending on a particular group of students or outstanding talent and devotion of the practitioners.

There have been some quantitative analyses in CWIE literature. They can be divided into three categories. The first category consists of studies where the analysis is based on direct data comparisons (See, for example, Hartley and Smith (1999), Zegwaard and McCurdy (2008), Mendez (2008)). The focus is more on the nature of data and how to interpret the result than on the analytical procedures. The studies in the

second category use statistical tests of significance based on such tests as a t-test, a χ^2 test and an analysis of variance (ANOVA) (See, for example, Heller and Heinemann (1987), Duignan (2003), Van Gyn et al (1996)). And in the third category, the main framework of the analysis is a multiple regression analysis, by which causal relationships among factors are investigated (See, for example, Gomez et al (2004), Mendez and Rona (2010), Foster et al (2011), Mandilaras (2004)).

This paper attempts to show how these statistical approaches, i.e. the second and third categories, are constructed and employed to assess the effectiveness of CWIE, using panel data on students' academic performance and employment outcome. This will be done in five sections. Firstly, a simple comparison is made between students with and without CWIE on their academic performance as well as employment outcomes using t-tests, z-tests, χ^2 tests and ANOVA, in which the process is shown explicitly rather than as a mere result of a statistical package such as Excel, SPSS and SAS. Secondly, the path analysis is employed as an analytical framework to focus on the interactive relationships among student's' attributes. Thirdly, qualitative response models such as linear probability, logit, and probit models are called for to analyse who takes CWIE. Fourthly, a linear model is estimated to see if CWIE has a positive effect on academic performance of students. The final section concludes the paper with some outstanding issues.

2. Comparing the averages/proportions: t-tests, z-tests, χ^2 tests and ANOVA

Comparing averages --- a t-test and ANOVA

Consider examining the effect of CWIE on academic performance. Let Grade Point Average (GPA) in the final year represent the academic performance and pick up 100 students at random, who may or may not have taken CWIE. One can divide the students into those with and without CWIE to compare the difference in the final GPA between the two groups. As GPA is likely to vary within each group, the comparison would be about the characteristics of the distributions of GPA's, with the most popular measure being the distribution's average. Suppose we have a sample of 10 students with 4 students with CWIE (coop students) whose GPA's are 3.8, 3.5, 3.2, 2.4 and 6 students without CWIE (non-coop students) whose GPA's are 3.9, 3.5, 3.0, 2.9, 2.5, and 2.2 (See Table I) --- the example has a deliberately small size to show explicitly the calculation steps. This gives the average GPA's of 3.225 and 3.0 respectively. Is this difference large enough to conclude that CWIE contributes to improvement of academic performance?

Table I: GPA with and without CWIE

		Average	Sample size
With CWIE	3.8, 3.5, 3.2, 2.4	$\underline{Xc}$ = 3.225	Nc = 4
Without CWIE	3.9, 3.5, 3.0, 2.9, 2.5, 2.2	$\underline{Xnc}$= 3.0	Nnc = 6
Total		$\underline{X}$ = 3. 09	N =10

Two statistical issues need to be clarified before evaluation --- namely, sampling and hypothesis testing. The 10 GPA marks do not come from the whole group of students (i.e. 100) but from a part of them or a "sample from the population." It follows then that it may not reflect the exact feature of the population depending on each pick. Consequently, an average out of the sample or a "sample mean" is not equivalent to the "population mean" of the entire students' body. Statistically, the sample means follow a distribution around the population mean but with its own variance. This implies that when the difference of average GPA between CWIE and non-CWIE groups is compared by using the samples in the present example, the sample size needs to be taken into consideration, as this affects the reliability of the sampling and the type of distribution used for the test. The larger the sample is, the more information it conveys and thus the more reliable it will be. The distribution used for the test is called a t-distribution but, as the sample size increases, it approaches a normal distribution. The rule of thumb is the sample size of 50 --- use a t-distribution table for a sample size below 50 and a normal distribution table for a sample size above 50.

The sample averages are compared to verify if there is a difference in the populations --- or equivalently if they come from the same population. Formally, a null hypothesis that "there is no difference in GPA between CWIE and non-CWIE groups" is tested against an alternative hypothesis, which negates the former in one of the following ways: the averages differ, the average with CWIE is better, the average with CWIE is smaller. Some may think CWIE raises the academic performance, while others may think it actually lowers it, so that in this case the appropriate alternative would be "the averages differ". A drawing line between accepting and rejecting the null hypothesis is expressed by a concept called a "significant level" or a "level of significance," which is generally set at 1%, 5% or 10%. This is the probability that the observed difference of sampling GPA averages is likely to accept the null hypothesis. So a significant level of, say, 5% or less, means the probability of accepting the null hypothesis is lower than 5% --- i.e. the GPAs for the CWIE and non-CWIE groups are different. In the past, a statistical table of a standard normal distribution was used to compare the observed result with benchmark results corresponding to major significant levels such as 1%, 5%, and 10%. But with the advancement in computer technology,

one can easily calculate the exact significant level known as P-value (For example, it is obtained by a statistical function “NORM.S.DIST” in Excel). Nowadays, statistical results are provided in either or both ways --- with asterisks to indicate if the results exceed the significant levels at 1%, 5%, and 10%, and/or with P-values. In this paper, both t-values and p-values are shown. .

The statistical testing of the effect of CWIE on academic performance for the above example would take the following steps.

(1) Set the null hypothesis (H0) and the alternative hypothesis (H1)
H0: GPAc = GPAnc, H1: GPAc $\neq$ GPAnc
where GPAc and GPAnc are the population averages for CWIE students and non-CWIE students respectively.

(2) Calculate the average of GPA’s of the sampled CWIE students (Xc) and the average of GPA’s of the sampled non-CWIE students (Xnc): Xc = 3.225, Xnc = 3.0

(3) Calculate s^2c and s^2nc
where $s^2c = \sum(Xci - Xc)^2$
$= (3.8 - 3.225)^2 + (3.5 - 3.225)^2 + (3.2 - 3.225)^2 + (2.4 - 3.225)^2 = 1.0875$
and $s^2nc = \sum(Xnci - Xnc)^2$
$= (3.9 - 3.0)^2 + (3.5 - 3.0)^2 + (3.0 - 3.0)^2 + (2.9 - 3.0)^2 + (2.5 - 3.0)^2 + (2.2 - 3.0)^2$
$= 1.960$

(4) Calculate the pooled variance of the two set of samples s^2:
where $s^2 = (s^2c + s^2nc) / (Nc + Nnc - 2) = (1.0875 + 1.96)/8 = 0.3809$

(5) Derive a value t (or statistic):
where $t = (Xc - Xnc)/s(\sqrt{\ }(1/Nc + 1/Nnc)$
$= (3.225 - 3.0)/\sqrt{0.3809}\sqrt{((1/4)+(1/6))} = 0.5648$
Use t to test H0 that the averages of GPAc and GPAnc are identical. The distribution to use for the test is a t-distribution with degree of freedom Nc + Nnc – 2 = 4 + 6 – 2 = 8. If t exceeds 1.86 (or 2.90), “the null hypothesis is rejected at a 5% (1%) significant level,” i.e. the CWIE students achieve a higher GPA than the non-CWIE students --- or CWIE raises the academic performance. (Note that more statistically rigorous phrase to express this result is “that CWIE has no effect in raising academic performance is rejected.”) Note that if t-value were negative it would imply CWIE education has a negative effect on academic performance. As t-value is well below 1.86 (or 2.90), H0 is not rejected at 5% (or 1%) significant level, i.e. the CWIE students do not achieve higher GPA’s than non-CWIE students.

The comparison of averages can also be performed by using ANOVA with the following steps:

(1) As for the t-test.

(2) As for the t-test and also derive the average of all samples, X.

(3) As for the t-test.

(4) As for the t-test.

(5) Calculate Nc $(Xc-X)^2$ + Nnc $(Xnc-X)^2 = 4x(3.225-3.09)^2+6x(3.0-3.09)^2 = 0.1215$

(6) Derive a value F,

Where F = Nc $(Xc-X)^2$ + Nnc $(Xnc-X)^2 / s^2 = 0.1215/0.3809 = 0.31898$

(7) Use F to test H0 that the averages of GPAc and GPAnc are identical. The distribution to use for the test is an F distribution with degrees of freedom 1 and Nc + Nnc – 2 = 4 + 6 – 2 = 8. If F exceeds 3.46 (or 8.41), "the null hypothesis is rejected at a 5% (1%) significant level," i.e. the achieved GPAs by the CWIE and the non-CWIE students differ. Note that an F value is always positive and on its own it does not show which is greater --- the inequality can be verified by comparing the average values themselves. As t is well below 3.46 (or 8.41), H0 is not rejected at 5% (0r 1%) significant level, i.e. the CWIE students do not achieve different GPA's from the non-CWIE students' GPA.

Note that this F value is equivalent to the t-value squared, i.e. $F = 0.31898 = (0.5877)^2 = t^2$, where the t-distribution is with a degree of freedom 8 and ANOVA is equivalent to a two-tailed t-test.

Comparing proportions --- a z-test/ a χ^2 test

The effect of CWIE may also be measured by proportions as in the percentage of CWIE graduates in employment as opposed to being unemployed, in a full-time job as opposed to being in a part-time job, or in a listed-company as opposed to being in a non-listed company. As in the previous example, the null hypothesis that CWIE has no effect on employment outcome would be tested against the alternative hypothesis that CWIE shows the difference. The testing procedure is almost identical to what has been discussed for two average values, except for the distribution and the variances. When a choice is binary, the outcome follows a binomial distribution, and when the sample size is large enough i.e. a sample size n and proportion p satisfy np>5 and n(1-p)>5, it becomes a normal distribution with a mean np and a variance p(1-p), where p is the probability of occurrence, following the central limit theory.

As a numerical example, let the sample of 100 graduates consist of 40 with

CWIE experience and 60 without CWIE experience with both groups having 20 placed in full-time jobs. Let the sample size be N with Nc CWIE gradutess and Nnc non-CWIE graduates, and the proportions of those graduates in the sample with full-time jobs for CWIE graduates and non-CWIE graduates be Pc and Pnc, while those in population be πc and πnc (See Table II).

Table II

	CWIE graduates	Non-CWIE graduates	Total
Full-time job	20	20	40
(Proportion)	Pc = 0.5	Pnc = 0.33	P = 0.4
Sample size	Nc = 40	Nnc = 60	N = 100

The statistical testing of the effect of CWIE on a full-time job placement would take the following procedures. The steps are shown with the corresponding values for the above example.

(1) Set the null hypothesis (H0) and the alternative hypothesis (H1)
H0:$\pi c = \pi nc$, H1:$\pi c \neq \pi nc$

(2) Calculate the proportions of CWIE students and non-CWIE students at full-time jobs from the sample: Pc = 0.5 and Pnc = 0.33

(3) Calculate the total proportion of students at full-time jobs: P
where P = (PcNc + PncNnc) / (Nc + Nnc) = (0.5 x 40 + 0.33 x 60)/(40 + 60) = 0.4

(4) Derive a value z (or statistic):
where z = (Pc –Pnc) /√P(1－P)(1/Nc + 1/Nnc)
= (0.5－0.33)/√0.4(1－0.4)(1/40 + 1/60) = 1.67, given H0:$\pi c = \pi nc$

(4) Use z to test H0 that$\pi c = \pi nc$. The distribution to use is a normal distribution. If z exceeds 1.64 (or 2.33), “the null hypothesis is rejected at a 5% (1%) significant level,” i.e. the CWIE students tend to be in full-time jobs more than the non-CWIE students.

In the numerical example above, z = 1.67 is greater than 1.64, implying H0 is rejected at a 10% significance level, i.e. the CWIE graduates have a higher chance of having full-time jobs than the no-CWIE graduates.

The comparison of proportions can also be tested using a χ^2 test, which is known as a “test of independence”. Let the observed numbers of CWIE graduates with full-time jobs and part-time jobs be a and b, while those of non-CWIE graduates be c and d. Table III is what is called a “contingency table” for the observed numbers.

Table III: The contingency table for the observed numbers

	Full-time job	Part-time job	Total
CWIE graduates	a	b	a+b
Non-CWIE graduates	c	d	c+d
Total	a+c	b+d	a+b+c+d

Under the null hypothesis that there is no difference between the CWIE group and non-CWIE group --- the outcome is “independent” of the group type. So if the “expected contingency table” under the hull hypothesis has entries A, B, C, and D as in Table IV, then the following conditions have to be satisfied.

Table IV: The expected contingency table

	Full-time job	Part-time job
CWIE graduates	A	B
Non-CWIE graduates	C	D

where $A = (a+b)(a+c)/(a+b+c+d)$ $B = (a+b)(b+d)/(a+b+c+d)$

$C = (a+c)(c+d)/(a+b+c+d)$ $D = (b+d)(c+d)/(a+b+c+d)$

The test statistic χ^2 is defined as the sum of squared differences between the “observed values” and the “expected values under the null hypothesis” divided by the “observed figures.” That is

$$\chi^2 = (a - A)^2/A + (b - B)^2/B + (c - C)^2/C + (d - D)^2/D \qquad (1)$$

In the above example,

$A = (a+b)(a+c)/(a+b+c+d) = (20+20)\ (20+20)/(20+20+20+40)) = 16$

$B = (a+b)(b+d)/(a+b+c+d) = (20+20)\ (20+40)/(20+20+20+40)) = 24$

$C = (a+c)(c+d)/(a+b+c+d) = (20+20)\ (20+40)/(20+20+20+40)) = 24$

$D = (b+d)(c+d)/(a+b+c+d) = (20+40)\ (20+40)/(20+20+20+40)) = 36$

Therefore, the observed and expected contingency tables for this example becomes as in Table V (a) and (b).

Table V (a)

Observed	Full-time job	Part-time job	Total
CWIE graduates	20	20	40
Non-CWIE graduates	20	40	60
Total	40	60	100

Table V (b)

Expected	Full-time job	Part-time job	Total
CWIE graduates	16	24	40
Non-CWIE graduates	24	36	60
Total	40	60	100

Therefore,

$$\chi^2 = (20–16)^2/16 + (20–24)^2/24 + (20–24)^2/24 + (40–36)^2/36 = 25/9 = 2.78 \quad (2)$$

The test for this type of contingency table with 2 rows and 2 columns is based on a χ^2 distribution with a “degree of freedom 1”, or “$\chi^2_{(1)}$”. The degree of freedom is 1, since fixing one of four entries in the contingency table i.e. A, B, C, and D, would determine all other entries given the observed numbers of CWIE graduates, non-CWIE graduates, those with full-time jobs and those with part-time jobs. With a $\chi^2_{(1)}$ distribution table, 2.78 is greater than 2.71 for a 10% significance level . Therefore, H0 is rejected at a10% significance level --- in other words, CWIE can be considered to improve the possibility of acquiring a full-time job.

Two tests can be used to verify the null hypothesis. In fact, the z test and the $\chi^2_{(1)}$ test are equivalent in the test for independence in a 2x2 contingency table, with $z^2 = \chi^2_{(1)}$ In the above example, $z^2 = 1.67^2 = 2.78 =\chi^2_{(1)}$. The difference is that when contingency table has more entries, z test cannot be used. Table VI summarises the ways these tests can be used.

Table VI

Quantity compared	Number of groups compared	Test & distribution used	Degree of freedom for 2 groups

Proportions	2	z-test (Normal)	Not applicable
Of groups	2 or more	χ^2 test (χ^2)	1
Averages	2	t-test (t)	n1+n2-2
Of groups	2 or more	ANOVA (F)	1, n1+n2-2

Note: (i) "Degree of freedom" only refer to cases when proportions or averages of 2 groups are compared --- for ANOVA, n1 and n2 are sample sizes of the 2 groups.
(ii) For comparing averages of 2 groups, a z-test and a χ^2 test are equivalent.
(iii) For comparing proportions of 2 groups, a t-test and ANOVA are equivalent.

The case of Kyoto Sangyo University

(The data set)

Kyoto Sangyo University is a private university in Kyoto, Japan, which was founded in 1965. It is a medium-sized university with 7 faculties, over 11,000 students and 800 academic and administrative staffs. Undergraduate course lasts for 4 years in Japan starting in April and ending in March. At the time of data collection, there were 773 universities, of which 178 were public and 595 were private in Japan.

The data has been collected from all 5473 undergraduate students who graduated in 2008 and 2009, --- 2739 and 2734 respectively. Of the total 5473, 3781 were male and 1692 were female from 7 faculties i.e. Economics, Business, Law, Foreign Languages, Culture, Science, and Engineering. From the original panel data of each student, we use annual GPAs, whether he/she has taken CWIE, and their employment outcome. Here is a brief description.

(i) The average annual GPAs for students in the 1st - and 3rd- year of undergraduate programme, GPA1 and GPA3, are 1.90 and 1.90, respectively taken from a total of 5160 students out of 5473, leaving out some with irregular registration patterns. GPA1 may be used to represent the student's academic ability before coming to university. This is because there is no standardized data on students' pre-university academic performance in Japan such as a national examination to cover every high school student and GPA1 is likely to depend on the pre-university achievement to great extent. GPA3 is used to identify the academic progress during the undergraduate years instead of the 4th year's GPA, due to a rather special circumstance of Japanese universities where many students manage to attain the necessary units to graduate by the end of 3rd year to spend almost

the entire 4th year to find a job, so that their 4th year's GPA does not reflect their ability.
(ii) CWIE: Of 5160 students considered in (i), CWIE was taken by 692 students or by13.4% (= 692/5160). This was much higher than the national average of 1.8% in 2007 and 2.2% in 2011. And 61.6% of work experience lasted less than two weeks in 2007 and there was a slight reduction to 61.6% in 2011, while 7.6% of work experience lasted over a month in 2007 and there was an increase to 11.5% in 2011, with the most of them unpaid (Ministry of Education, Japan, 2013). This shows Japan's CWIE is lagging behind other anglophone industrial nations.
(iii) Employment outcome: This was measured from two angles. Firstly, the students were asked whether they had obtained "provisional placement offers" of full-time employment, part-time employment or none. Out of 5160 students, 4195 obtained full-time employment offers while 421 obtained part-time employment offers. Secondly, 3965 offers students received were from private companies with 1354 listed companies and 2611 unlisted companies. It needs to be mentioned that KSU can be considered a typical Japanese private university, considering its history of almost 50 years, its medium size with over 11,000 students and 800 academic and administrative staffs in 7 faculties, and its location in a medium sized city of Kyoto. Thus, the result of statistical analysis of KSU may resemble what other universities would find if a similar analysis is made.

(Testing the effect of CWIE at KSU)

Given the above information, the following section illustrate how the effectiveness of CWIE at KSU could be tested. The statistical testing will be performed to compare the academic performance and employment placement of students with and without CWIE.

(1) Effect of career education on GPA1 and GPA3

5160 students were divided into two groups with and without CWIE and the average GPAs were found as in Table VII below.

Table VII: Average GPAs by group

Student	Average number	Average GPA1	GPA3
With CWIE	692	2.17	2.2
Without CWIE	4468	1.85	1.85

With the procedure illustrated earlier in this chapter, the existence of a significant difference in an academic performance level between students groups with and without CWIE is tested using a t-test and the following results are found (Although the original data base is huge and cannot be shown here, in order to show the calculation process the actual values used to derive t-value are provided in "Note" in parenthesis):

(a) Question: Are average GPA1s of groups with and without CWIE, 2.17 and 1.85, significantly different?
Answer: $t = 11.59$, which means they are significantly different at 1%. (P-value = 0)
(Note: $t = (2.17 - 1.85)/s(\sqrt{(1/692 + 1/4468)}$
where $s^2 = (274.52 + 2081.53) / (692+4468-2) = 0.457$)

(b) Question: Are average GPA3s of groups with and without CWIE, 2.2 and 1.85, significantly different?
Answer: $t = 12.62$, which means they are significantly different at 1%. (P-value = 0)
(Note: $t = (2.2 - 1.85)/s(\sqrt{(1/692 + 1/4468)}$
where $s^2 = (339.4 + 2037.38) / (692+4468-2) = 0.461$)

These test results seem to suggest that CWIE attracts better students, i.e. students with higher GPA1s, and makes students do better academically at university, i.e. students with higher GPA3.

(2) Effect of CWIE on obtaining a full-time/part-time job

4616 students were divided into two groups: those with and without CWIE and the number of students in each category is shown in Table VIII below.

Table VIII: Job placement status by group

	Full-time	Part-time	Full-time (%)
Total	4195	421	90.9%
With CWIE	621	20	96.9%
Without CWIE	3574	401	89.9%

With the procedure illustrated earlier, the existence of a significant difference in a job status between students groups with and without CWIE is tested using a z-test

and a $\chi^2(1)$ test --- as pointed earlier, they give the identical test result, and the following results are found (As before, the calculation process is shown in the parenthesis "Note").

Question: Does CWIE improve the chance of getting a full-time job?

Answer 1: Z-test

z = 5.67, which means CWIE significantly improves a chance of getting a full-time job.

(Note: $z = (0.969-0.899)/\sqrt{(0.909\ (1-0.909)(1/621+1/3574)} = 5.67$)

Answer 2: χ^2 with one degree of freedom

Table IX shows Contingency tables for observed values and expected vales:

Table IX: Contingency tables for observed values and expected vales

	Observed		Expected	
	Full-time/Part-time		Full-time/Part-time	
With CWIE	621	20	583	58
Without CWIE	3574	401	3612	363

Thus

$$\chi^2 = (621-583)^2/583 + (20-58)^2/58 + (3574-3612)^2/3612 + (401-363)^2/363 = 32.33 = 5.67^2 = z^2 \quad (3)$$

In both cases, the effect is significant at 1% (P value = 0)

(3) Effect of CWIE on obtaining a job at a listed/unlisted company

4616 students were divided into two groups: those with and without CWIE and the number of students in each category is shown in Table X below.

Table X: Company status by group

	Listed	Unlisted	Listed(%)
Total	1354	2611	34.1%
With CWIE	221	372	37.3%

Without CWIE	133	2239	33.6%

Question: Does CWIE improve the chance of getting a job at a listed company?

Answer 1: Z-test

z = 1.74, which means CWIE significantly improves a chance of getting a full-time job.

(Note: $z = (0.372－0.336)/\sqrt{(0.341\ (1－0.341)(1/593+1/3372)} = 1.74$)

Answer 2: χ^2 with one degree of freedom

Table XI shows Contingency tables for observed values and expected vales:

Table XI: Contingency tables for observed values and expected vales

	Observed		Expected	
	Listed/Unlisted		Listed/Unlisted	
With CWIE	221	372	203	390
Without CWIE	1133	2239	1151	2221

Thus

$$\chi^2 = (221－203)^2/203 + (372－390)^2/390 + (1133－1151)^2/1151 + (2239－2221)^2/2221 = 3.02 = 1.74^2 = z^2 \quad (4)$$

In both cases, the effect is significant at 10% (P value = 0.08)

In sum, the following conclusion can be drawn:

(i) When students are grouped into those with and without CWIE, the averages of first year and third year GPA are both significantly higher for the former group.

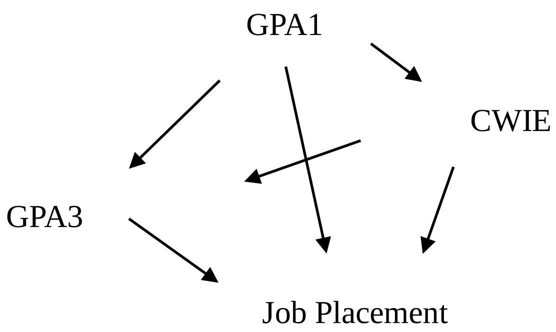
(ii) The overall academic performance for those with CWIE shows difference. One may conclude that CWIE has a positive effect on academic performance. However, it does suggest also that students who take WIL have high per-university academic performance. If this is true, then the value of CWIE is overestimated. The next section deals with this issue of singling out the effect of CWIE, by using a series of regression analyses.

3. Interactive framework of student’s attributes: Path analysis/SEM/Recursive

form

It has been suspected that a student's attributes such as pre-university academic performance, academic performance at university, job placement, gender, faculty, together with whether CWIE is taken are interrelated and a simple comparison of values and proportions may not be adequate. Some researchers used a regression models to take care of such an interactive framework (See, for example, regression models used in Mendez and Rona (2010), Gomez et al (2004), Foster et al (2011)). But a more systematic approach often employed to solve such issues is a "path analysis". Path analysis is both a concept and a statistical tool to determine causal relationships among variables within a given structure and such relationships are often described by a "path diagram" as illustrated in Figure I for our analysis of CWIE. The concept is useful for disentangling causal relationships among the variables.

Figure.I: Path diagram



Path analysis was first introduced by Sewall Wright, a geneticist, who sought to disentangle genetic influences across generations (Wright, 1921). Wright's contribution to investigations in social science went further, when he subsequently wrote an article on an analysis of a corn market, where he applied his approach to economic analysis of supply and demand interaction (Wright, 1925), and an article on an identification problem of simultaneous equation system, where he discussed how to identify supply and demand from a set of given data (Wright, 1934). It is worth noting that his interests in simultaneity and identification appeared long before they started to be treated as a standard concepts in econometrics.

Today, the analysis is widely used in social science including psychology, sociology and economics. As a statistical or econometric tool, Path analysis is categorized as one type of a structural equation model (SEM) or a simultaneous equation model respectively.

A set of causal relationships in Fig. I can be expressed as:

GPA1 → CWIE (5-1)

GPA1 & CWIE → GPA3 (5-2)

GPA1 & CWIE & GPA3 → Job placement (5-3)

with → expressing the causal relationship

Or, if each causal relationship can be expressed as a linear equation with a constant term, coefficients, and an added error term uncorrelated to each other:

Equation 1	CWIE = a1 + a2 GPA1 + u1	(6-1)
Equation 2	GPA3 = b1 + b2 GPA1+b3 CWIE + u2	(6-2)
Equation 3	Job = c1 + c2 GPA1+ c3 CWIE + c4 GPA3 + u3	(6-3)

where Job implies a choice between full-time and part-time jobs, or a choice between listed and unlisted companies.

This hierarchical structure is called a "fully recursive model" and it is known that an ordinary least square (OLS) method may be used to estimate coefficients of each equation, i.e. a's, b's, and c's, separately (See, for example, Greene (2008) or Wooldridge (2002) or (2009)). Equations 1 and 3 have "qualitative response" as a dependent variable on the left-hand side of the equations, i.e. 1 if CWIE taken and 0 otherwise for Equation 1 and 1 if full-time job or listed company or 0 otherwise, while Equation 2 has a usual cardinal value of GPA3 as its dependent variable. Estimation process differs between the two types. In the following two sections, the processes for Equations 1 and 2 are described in turn by using the KSU data. Equation 3 is not dealt with in this paper, as the procedure is the same as that of Equation 3.

4. Who takes CWIE programme?: Qualitative response models

Equation 1: CWIE = a1 + a2 GPA1 + u1 (7)

This equation estimates the effect of GPA1 on the decision to take CWIE. As pointed earlier, it is possible that those students who are interested in CWIE were

already academically motivated before starting university career. Higher school grades can be used to represent pre-university academic performance if any national data is available. If, however, no such exam exists or cannot be traced to cover all the students concerned, a best proxy would be their grades in the first term or first year at university, e.g. GPA1, since this result is more likely to be a reflection of pre-university achievement rather than what is achieved at university. The decision to take CWIE may also depend on the student's other personal attributes such as gender or the faculty that the student belongs to. Thus, the equation to estimate is:

$$\text{CWIE} = a1 + a2\ \text{GPA1} + a3\ \text{Gender} + a4\ \text{Faculty} + u1 \tag{8}$$

where the dependent variable CWIE is one or zero and for the independent variables GPA1 may be grades and Gender and Faculty are dummy variables, with a constant term a1 and an error term u1 with a standard normally distribution.

As CWIE is a 1-0 variable, this model is called "a binary (instead of qualitative) response model." This belongs to a family of "limited dependent variable models," in which the range of values of the dependent variable is substantially limited. In some cases, a straightforward use of OLS method on this linear equation may not be appropriate.

For the binary response models, researchers have been using several functional forms, namely, a linear probability model, a logit model, and a probit model, each with its own advantages and disadvantages (The discussion to follow can be found in most of standard textbooks of econometrics --- for example, see Wooldridge (2009)).

A linear probability model expresses the probability of response as a linear function of independent variables. However, as the observed dependent variable can only take 1 or 0 --- the unobserved probability is called a "latent variable", a linear relation is not theoretically appropriate, i.e. predicted values of the dependent variable may lie outside of the 0-1 range (See Figure.II). The binary nature of the dependent variable also implies heteroskedastic errors. In this case, OLS estimators are not biased but for t and F statistics the usual standard errors need to be replaced by "heteroskedasticity-robust standard errors", since the error terms are not normally distributed. In practice, however, these error values are not far from each other. The estimation procedure for this model is simple as OLS is used for the linear equation directly and the interpretation of the coefficients is intuitive --- an increase in a unit values of a variable would raise the probability of taking CWIE by the estimated coefficient.

Unlike a linear probability model, a logit model keeps the dependent variable between 0 and 1. The term “logit” comes from “a logistic curve” (See Figure. III). If the probability of response p depends on x linearly i.e. ax + b, then a logistic curve is expressed by

$$p = \exp(ax+b) / (1+ \exp(ax+b)) \tag{9}$$

It can be easily verified that if ax+b approaches ∞ (or-∞). p approaches 1 (or 0). The equation can be rearranged in a linear form by a “logit transformation” as:

$$\ln p/(1-p) = ax+b \tag{10}$$

This could be estimated by a least square method if p takes values other than 1 or 0. In the present case, where the dependent variable takes 1 or 0, it is not feasible, but when the probability is replaced by an observed percentage such as the average percentage of those who have taken the choice for each group, the least square method can be used and it is known as a “minimumχ^2 method”.

A probit model is based on the standard normal cumulative distribution and can be expressed as

$$p = (2\pi)^{-1/2}\int_{-\infty}^{ax+b} \exp(-z^2/2)dz \tag{11}$$

It can be verified that, as in the logit model above, if ax+b approaches ∞ (or-∞), p approaches 1 (or 0) (See Figure. III).

Unlike a linear probability model, both logit model and probit models are non-linear in ax+b and some cautions are needed for the estimation process. Firstly, a straightforward least square method would not work because of the non-linearity. For the non-linear estimation, the most commonly used method today is the “maximum likelihood estimation (MLE)”. Secondly, the estimated coefficients do not give a straightforward interpretation of the least square estimation, since a unit increase of an independent variable will cause a marginal change in the dependent variable through the non-linear forms of the logit and probit equations. This means that the estimated coefficients of the linear probability, logit, and probit models cannot be directly compared. There is a further complication that for the logit and probit models these values depends on the values of independent variables --- note that for the linear probability model, the marginal effect is constant over the values of independent variables. As a rule of thumb, Wooldridge (2002) suggests using “scale factors” to multiply the coefficients for the logit and probit models of 0.4 and 0.25 respectively, to compare the coefficients among the three models. Also as a statistic for goodness-of-fit, i.e. R^2 in the least square method, McFadden (1974) suggested a statistic known as “Pseudo R^2” for the maximum likelihood method, which is often found in statistical packages.

Testing the causes of CWIE at KSU

As explained above, a qualitative response model was estimated using a linear probability model, a logit model, and a probit model, where independent variables include student’s gender, graduation year, and faculty as dummy variables.

$$\text{CWIE} = a1 + a2\ \text{GPA1} + a3\ \text{Gender} + a4\ \text{Faculty} + a5\ \text{GraduationYear} + u1 \tag{12}$$

Table XII shows the estimation results. Both a and b are the identical result of least square method based on a linear probability model. The difference is the treatment of errors. As explained earlier, the correct version is a with heteroskedasticity-robust t-values, which also gives a different set of P-values. However, the difference is not that large. Comparing the four sets of results, the tendency of signs, relative magnitudes, and significance among the independent variables is alike. Note, however, the coefficients for the same variables in the linear probability, logit, and probit models differ because of the way coefficients affects the dependent variable. On the whole, the linear probability model gives reasonable results and one may sacrifice the theoretical rigour of logit and probit models for the simple and intuitive nature of linear probability models.

5. Does CWIE have a positive effect on academic performance? : Least square models

Equation 2

$$\text{GPA3} = b1 + b2\ \text{GPA1} + b3\ \text{CWIE} + b4\ \text{Gender} + b5\ \text{Faculty} + u2 \tag{13}$$

A dependent variable is GPA3 and this is determined by what one came with to university with, i.e. GPA1, and what one took at university, i.e. CWIE. Also as in Equation 1, other attributes of students are included such as gender, faculty, and year of

graduation as dummy variables. As GPA3 is a quantitative variable, the equation can be estimated in a linear form.

Testing the effect of CWIE on academic performance at KSU

For applying the equation to the KSU case, a graduation dummy is included as in Equation 1, so that we estimate the following equation:

Equation 2

$$GPA3 = b1 + b2\ GPA1 + b3\ CWIE + b4\ Gender + b5\ Faculty + b6\ Graduation\ year + u2 \qquad (14)$$

The estimation procedure for this equation is simple, as the dependent variable is not a qualitative response. OLS estimation may be used straight away. The result is shown in Table XIII. Apart from faculty discrepancies affecting GPA3, both GPA1 and CWIE do have positive and significant effects on GPA3.

6. Conclusion

This paper has attempted to show how statistical methods can be used on available data for CWIE as a useful tool to explain to those who are not aware of the effectiveness of CWIE at university, in the government or among potential students. In the choice of method, there is a trade-off between “simple intuitive appeal” and “theoretical rigour.” Simple comparisons of averages and proportions are easy to work with but would be more persuasive if statistical sampling and testing are used. When causal relationships are considered, an econometric approach of path analysis is a better choice. Using the path analysis on the KSU student data, it was shown that CWIE does raise academic performance at university, i.e.GPA3, but its magnitude may be overestimated as students with higher academic marks, i.e. GPA1, tend to take CWIE. As for binary response models, the estimated results of a linear probability model with OLS method and logit and probit models with MLE method were compared and it was suggested that the simplicity and intuitive appeal of the former outweighs the theoretical rigour of the latter.

Finally, it is important to emphasize that this type of quantitative analysis based on statistical and econometric methodologies should be taken to complement and not substitute qualitative analysis based on psychological and sociological methodologies. The former can explain how effective CWIE is but cannot explain how such a mechanism works.

Bibliography

Blalock, H. M. (1985): “Causal Models in the Social Sciences,” Second Edition, New York: Aldine.

Dewey, J.(1916): “Democracy of Education: An introduction to the philosophy of education,” New York, NY: The Free Press.

Duignan, J. (2003): “Placement and adding value to the academic performance of undergraduates: Reconfiguring the architecture - an empirical investigation,” Journal of Vocational Education and Training, 55 (3), pp.335-350.

Foster, H., Green, P., Houston, P., McAree, D., McCann, C., McCulloch, D. and Pogue, M. (2011): “Are sandwiches better? The impact of work placement upon degree performance,” Perspective on Pedagogy and Practice, University of Ulster, Vol. 2, pp53-64.

Goldberger, A. S. (1972): “Structural Equation Methods in the Social Sciences,” Econometrica, vol.40, No.6, pp.979-1001.

Gomez, S., Lush, D. and Clements, M. (2004): “Work placements enhance the academic performance of bioscience undergraduates,” Journal of Vocational Education and Training, 56 (3), pp.373-386.

Greene, W. H. (2008): “Econometric Analysis,” Sixth Edition, Pearson Prentice Hall.

Hartley, J.L. and Smith, B.W. (2000): “Strengthen academic ties by assessment of learning outcomes,” Journal of Cooperative Education, 35(1), pp.41-47.

Heller, B. and Heinemann, H.N. (1987): “The impact of structured and non-structured work experiences on college students' attitude, values and academic performance,” Journal of Cooperative Education, 23 (3), pp.19-32.

Kaplan, D. W. (2000): “Structural Equation Modeling: Foundations and Extensions,” Sage Publications, Inc.

Kolb, D.A.(1984): “Experiential Learning: Experience as the source of learning and development,” Engelwood Cliffs, NJ: Prentice Hall.

Lewin, K. (1946): “Action research and minority problems,” Journal of Social Issues, 2(4), pp.34-46.

Lleras, C. (2005): “Path Analysis, “ in Kempf-Leonard, K.L. (ed.) “Encyclopedia of Social Measurement,” Elsevier Academic Press.

Mandilaras, A. (2004): “Industrial placement and degree performance: Evidence from a British higher institution,” International Review of Economics Education, 3(1), pp.39-51.

Maruyama, G. M. (1997): “Basics of Structural Equation Modeling,” Sage Publications, Inc.

Mendez, R. (2008): “The correlation between industrial placements and final degree results: A study of Engineering Placement Students,” Paper presented it the ASET conference, Plymouth.

Mendez, R. and Rona, A. (2010): “The Relationship between Industrial Placements and Final Degree Results: a study of engineering placement students,” Learning and Teaching in Higher Education, Issue 4-2, pp.46-61.

Ministry of education, culture, sports, science and technology, Japan (2013): “The report on internships at higher education institutions”

Ott, R. and Longnecker, M. (2010): “An Introduction to Statistical Methods and Data Analysis, International Edition,” sixth Edition, Brooks/Cole, Cengage Learning.

Piaget, J.(1985): “The equilibrium of cognitive structures,” Chicago, IL: University of Chicago Press.

Silberston, Z. A. (1987): “Path Analysis,” in Eatwell, J., Milgate, M. and Newman, P. (ed.) “The new Palgrave: a dictionary of economics,” Macmillan.

Van Gyn, G., Cutt, J., Loken, M. and Ricks, F. (1996): “Investigating the educational benefits of cooperative education: A longitudinal study,” Journal of Cooperative Education, 32 (2), pp.70-85.

Wonnacott, T.H. and Wonnacott, R. J. (1990): “Introductory Statistics for Business and Economics (Wiley series in probability and mathematical statistics),” John Wiley & Sons.

Wooldridge, J. M. (2009): “Introductory Econometrics,” fourth Edition, South Western.

Wooldridge, J. M. (2010: “Econometric Analysis of Cross Section and Panel Data,” (2nd ed.), The MIT Press, Cambridge, Massachusetts.

Wright, S. (1921): “Correlation and Causation,” Journal of Agricultural Research, 20, pp.557-585.

________ (1925): Corn and Hog Correlations, Washington: U.S. Department of Agriculture Bulletin 1300.

________ (1934): “The Method of Path Coefficients,” Annals of Mathematical Statistics, 5, pp.161-215.

Zegwaard, K.E. and McCurdy, S. (2008): “Value of work placements for students and its influence on student performance: Faculty perceptions,” In Coll, R.K. and Hoskyn, K. (Eds): “Proceedings from the Annual Conference for the New Zealand Association for Cooperative Education,” New Plymouth, New Zealand.

Statistical Methods for Assessment of Cooperative and Work-Integrated Education

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Abstract

While the effectiveness of Cooperative and Work-Integrated Education (CWIE) is well-recognized and well-documented by the persons directly concerned, it needs more convincing evidence to expand and popularize this programme. One of the ways to do so is to develop quantitative methods by which the effectiveness of CWIE can be described more objectively.

This paper introduces two types of statistical approaches to assess the effectiveness of CWIE, using an actual panel data on students' academic records and employment outcomes. Firstly, a simple comparison is made between students with and without CWIE on their academic performance as well as employment outcomes using t-tests, z-tests, and χ^2 tests, in which the process is explicitly shown rather than as a mere result of a statistical package. Secondly, Path analysis is used to focus on the interactive relationships among student's' attributes. For example, one suspects that even CWIE has a positive effect on academic performance, it may be, that those students with high pre-university performance tend to take CWIE as well as performing well academically. This would overvalue the effectiveness of CWIE on the academic performance. Path analysis can sort out such a complicated relationship to pinpoint the true effectiveness of CWIE. In this section, a regression analysis is used based on such models as linear, linear probability, logit, and probit models. For estimation, Ordinary Least Square (OLS) and Maximum Likelihood Estimation (MLE) methods are used, in which interpretation of the estimation results such as coefficients and testing criteria are explicitly described.

The aim of the paper is to make practitioners of CWIE familiar with these statistical methods so that the effectiveness of their own CWIE programmes can be presented in a persuasive manner.

1. Introduction

1. Introduction

While the effectiveness of CWIE is well-recognized and well-documented by the persons directly concerned (See, for example, a series of articles in International Handbook for Cooperative and Work-integrated Education (2011)), it may need more convincing evidence to expand and popularize this programme globally --- the popularity of the programme is still concentrated mostly in North America and the anglophone world at large. One of the ways to do so is to employ quantitative methods by which the effectiveness of CWIE programme can be described more objectively. The theoretical analysis of CWIE has been dealt with most extensively in Psychology and Education, where key concepts such as Kolb's experiential learning (Kolb, 1984), Dewey's learning model (Dewey, 1916), Lewin's action research and laboratory (Lewin, 1946), and Piaget's learning and cognitive development (Piaget, 1985) appear. Such theories can suggest mechanisms by which CWIE brings about its effects on educational outcome or job performance.

However, there is a need to know "to what extent it works" as much as "how it works." This has a practical implication. Often identifying the educational effect on an individual requires is a long process, as the effect is more likely to spread out over one's life time than just after graduation, which makes it difficult to pinpoint the causal relationship. In this respect, CWIE is no exception. At the same time, the practitioners of CWIE are well aware of its labour intensive nature. There is a need to show the bearers of CWIE, be it the university, the government fund or self-financing students, that the programme is worthwhile. In particular, it is imperative to prove its effectiveness as a system rather than a practice heavily depending on a particular group of students or outstanding talent and devotion of the practitioners.

There have been some quantitative analyses in CWIE literature. They can be divided into three categories. The first category consists of studies where the analysis is based on direct data comparisons (See, for example, Hartley and Smith (1999), Zegwaard and McCurdy (2008), Mendez (2008)). The focus is more on the nature of data and how to interpret the result than on the analytical procedures. The studies in the

second category use statistical tests of significance based on such tests as a t-test, a χ^2 test and an analysis of variance (ANOVA) (See, for example, Heller and Heinemann (1987), Duignan (2003), Van Gyn et al (1996)). And in the third category, the main framework of the analysis is a multiple regression analysis, by which causal relationships among factors are investigated (See, for example, Gomez et al (2004), Mendez and Rona (2010), Foster et al (2011), Mandilaras (2004)).

This paper attempts to show how these statistical approaches, i.e. the second and third categories, are constructed and employed to assess the effectiveness of CWIE, using panel data on students' academic performance and employment outcome. This will be done in five sections. Firstly, a simple comparison is made between students with and without CWIE on their academic performance as well as employment outcomes using t-tests, z-tests, χ^2 tests and ANOVA, in which the process is shown explicitly rather than as a mere result of a statistical package such as Excel, SPSS and SAS. Secondly, the path analysis is employed as an analytical framework to focus on the interactive relationships among student's' attributes. Thirdly, qualitative response models such as linear probability, logit, and probit models are called for to analyse who takes CWIE. Fourthly, a linear model is estimated to see if CWIE has a positive effect on academic performance of students. The final section concludes the paper with some outstanding issues.

2. Comparing the averages/proportions: t-tests, z-tests, χ^2 tests and ANOVA

Comparing averages --- a t-test and ANOVA

Consider examining the effect of CWIE on academic performance. Let Grade Point Average (GPA) in the final year represent the academic performance and pick up 100 students at random, who may or may not have taken CWIE. One can divide the students into those with and without CWIE to compare the difference in the final GPA between the two groups. As GPA is likely to vary within each group, the comparison would be about the characteristics of the distributions of GPA's, with the most popular measure being the distribution's average. Suppose we have a sample of 10 students with 4 students with CWIE (coop students) whose GPA's are 3.8, 3.5, 3.2, 2.4 and 6 students without CWIE (non-coop students) whose GPA's are 3.9, 3.5, 3.0, 2.9, 2.5, and 2.2 (See Table I) --- the example has a deliberately small size to show explicitly the calculation steps. This gives the average GPA's of 3.225 and 3.0 respectively. Is this difference large enough to conclude that CWIE contributes to improvement of academic performance?

Table I: GPA with and without CWIE

		Average	Sample size
With CWIE	3.8, 3.5, 3.2, 2.4	$\underline{Xc}$ = 3.225	Nc = 4
Without CWIE	3.9, 3.5, 3.0, 2.9, 2.5, 2.2	$\underline{Xnc}$= 3.0	Nnc = 6
Total		$\underline{X}$ = 3. 09	N =10

Two statistical issues need to be clarified before evaluation --- namely, sampling and hypothesis testing. The 10 GPA marks do not come from the whole group of students (i.e. 100) but from a part of them or a "sample from the population." It follows then that it may not reflect the exact feature of the population depending on each pick. Consequently, an average out of the sample or a "sample mean" is not equivalent to the "population mean" of the entire students' body. Statistically, the sample means follow a distribution around the population mean but with its own variance. This implies that when the difference of average GPA between CWIE and non-CWIE groups is compared by using the samples in the present example, the sample size needs to be taken into consideration, as this affects the reliability of the sampling and the type of distribution used for the test. The larger the sample is, the more information it conveys and thus the more reliable it will be. The distribution used for the test is called a t-distribution but, as the sample size increases, it approaches a normal distribution. The rule of thumb is the sample size of 50 --- use a t-distribution table for a sample size below 50 and a normal distribution table for a sample size above 50.

The sample averages are compared to verify if there is a difference in the populations --- or equivalently if they come from the same population. Formally, a null hypothesis that "there is no difference in GPA between CWIE and non-CWIE groups" is tested against an alternative hypothesis, which negates the former in one of the following ways: the averages differ, the average with CWIE is better, the average with CWIE is smaller. Some may think CWIE raises the academic performance, while others may think it actually lowers it, so that in this case the appropriate alternative would be "the averages differ". A drawing line between accepting and rejecting the null hypothesis is expressed by a concept called a "significant level" or a "level of significance," which is generally set at 1%, 5% or 10%. This is the probability that the observed difference of sampling GPA averages is likely to accept the null hypothesis. So a significant level of, say, 5% or less, means the probability of accepting the null hypothesis is lower than 5% --- i.e. the GPAs for the CWIE and non-CWIE groups are different. In the past, a statistical table of a standard normal distribution was used to compare the observed result with benchmark results corresponding to major significant levels such as 1%, 5%, and 10%. But with the advancement in computer technology,

one can easily calculate the exact significant level known as P-value (For example, it is obtained by a statistical function “NORM.S.DIST” in Excel). Nowadays, statistical results are provided in either or both ways --- with asterisks to indicate if the results exceed the significant levels at 1%, 5%, and 10%, and/or with P-values. In this paper, both t-values and p-values are shown. .

The statistical testing of the effect of CWIE on academic performance for the above example would take the following steps.

(1) Set the null hypothesis (H0) and the alternative hypothesis (H1)
H0: GPAc = GPAnc, H1: GPAc $\neq$ GPAnc
where GPAc and GPAnc are the population averages for CWIE students and non-CWIE students respectively.

(2) Calculate the average of GPA’s of the sampled CWIE students (Xc) and the average of GPA’s of the sampled non-CWIE students (Xnc): Xc = 3.225, Xnc = 3.0

(3) Calculate s^2c and s^2nc
where $s^2c = \sum(Xci - Xc)^2$
$= (3.8 - 3.225)^2 + (3.5 - 3.225)^2 + (3.2 - 3.225)^2 + (2.4 - 3.225)^2 = 1.0875$
and $s^2nc = \sum(Xnci - Xnc)^2$
$= (3.9 - 3.0)^2 + (3.5 - 3.0)^2 + (3.0 - 3.0)^2 + (2.9 - 3.0)^2 + (2.5 - 3.0)^2 + (2.2 - 3.0)^2$
$= 1.960$

(4) Calculate the pooled variance of the two set of samples s^2:
where $s^2 = (s^2c + s^2nc) / (Nc + Nnc - 2) = (1.0875 + 1.96)/8 = 0.3809$

(5) Derive a value t (or statistic):
where t = (Xc – Xnc)/s(√（1/Nc + 1/Nnc）
= (3.225 – 3.0)/√0.3809√((1/4)+(1/6)) = 0.5648
Use t to test H0 that the averages of GPAc and GPAnc are identical. The distribution to use for the test is a t-distribution with degree of freedom Nc + Nnc – 2 = 4 + 6 – 2 = 8. If t exceeds 1.86 (or 2.90), “the null hypothesis is rejected at a 5% (1%) significant level,” i.e. the CWIE students achieve a higher GPA than the non-CWIE students --- or CWIE raises the academic performance. (Note that more statistically rigorous phrase to express this result is “that CWIE has no effect in raising academic performance is rejected.”) Note that if t-value were negative it would imply CWIE education has a negative effect on academic performance. As t-value is well below 1.86 (or 2.90), H0 is not rejected at 5% (or 1%) significant level, i.e. the CWIE students do not achieve higher GPA’s than non-CWIE students.

The comparison of averages can also be performed by using ANOVA with the following steps:

(1) As for the t-test.
(2) As for the t-test and also derive the average of all samples, X.
(3) As for the t-test.
(4) As for the t-test.
(5) Calculate Nc $(Xc-X)^2$ + Nnc $(Xnc-X)^2 = 4x(3.225-3.09)^2+6x(3.0-3.09)^2 = 0.1215$
(6) Derive a value F,
    Where F = Nc $(Xc-X)^2$ + Nnc $(Xnc-X)^2 / s^2 = 0.1215/0.3809 = 0.31898$
(7) Use F to test H0 that the averages of GPAc and GPAnc are identical. The distribution to use for the test is an F distribution with degrees of freedom 1 and Nc + Nnc – 2 = 4 + 6 – 2 = 8. If F exceeds 3.46 (or 8.41), "the null hypothesis is rejected at a 5% (1%) significant level," i.e. the achieved GPAs by the CWIE and the non-CWIE students differ. Note that an F value is always positive and on its own it does not show which is greater --- the inequality can be verified by comparing the average values themselves. As t is well below 3.46 (or 8.41), H0 is not rejected at 5% (0r 1%) significant level, i.e. the CWIE students do not achieve different GPA's from the non-CWIE students' GPA.

Note that this F value is equivalent to the t-value squared, i.e. F =0.31898 = $(0.5877)^2 = t^2$, where the t-distribution is with a degree of freedom 8 and ANOVA is equivalent to a two-tailed t-test.

Comparing proportions --- a z-test/ a χ^2 test

The effect of CWIE may also be measured by proportions as in the percentage of CWIE graduates in employment as opposed to being unemployed, in a full-time job as opposed to being in a part-time job, or in a listed-company as opposed to being in a non-listed company. As in the previous example, the null hypothesis that CWIE has no effect on employment outcome would be tested against the alternative hypothesis that CWIE shows the difference. The testing procedure is almost identical to what has been discussed for two average values, except for the distribution and the variances. When a choice is binary, the outcome follows a binomial distribution, and when the sample size is large enough i.e. a sample size n and proportion p satisfy np>5 and n(1-p)>5, it becomes a normal distribution with a mean np and a variance p(1-p), where p is the probability of occurrence, following the central limit theory.

As a numerical example, let the sample of 100 graduates consist of 40 with

CWIE experience and 60 without CWIE experience with both groups having 20 placed in full-time jobs. Let the sample size be N with Nc CWIE gradutess and Nnc non-CWIE graduates, and the proportions of those graduates in the sample with full-time jobs for CWIE graduates and non-CWIE graduates be Pc and Pnc, while those in population be πc and πnc (See Table II).

Table II

	CWIE graduates	Non-CWIE graduates	Total
Full-time job	20	20	40
(Proportion)	Pc = 0.5	Pnc = 0.33	P = 0.4
Sample size	Nc = 40	Nnc = 60	N = 100

The statistical testing of the effect of CWIE on a full-time job placement would take the following procedures. The steps are shown with the corresponding values for the above example.

(1) Set the null hypothesis (H0) and the alternative hypothesis (H1)
$H0{:}\pi c = \pi nc$, $H1{:}\pi c \neq \pi nc$
(2) Calculate the proportions of CWIE students and non-CWIE students at full-time jobs from the sample: Pc = 0.5 and Pnc = 0.33
(3) Calculate the total proportion of students at full-time jobs: P
where P = (PcNc + PncNnc) / (Nc + Nnc) = (0.5 x 40 + 0.33 x 60)/(40 + 60) = 0.4
(4) Derive a value z (or statistic):
where $z = (Pc - Pnc) / \sqrt{P(1-P)(1/Nc + 1/Nnc)}$
$= (0.5-0.33)/\sqrt{0.4(1-0.4)(1/40 + 1/60)} = 1.67$, given $H0{:}\pi c = \pi nc$
(4) Use z to test H0 that $\pi c = \pi nc$. The distribution to use is a normal distribution. If z exceeds 1.64 (or 2.33), "the null hypothesis is rejected at a 5% (1%) significant level," i.e. the CWIE students tend to be in full-time jobs more than the non-CWIE students.

In the numerical example above, z = 1.67 is greater than 1.64, implying H0 is rejected at a 10% significance level, i.e. the CWIE graduates have a higher chance of having full-time jobs than the no-CWIE graduates.

The comparison of proportions can also be tested using a χ^2 test, which is known as a "test of independence". Let the observed numbers of CWIE graduates with full-time jobs and part-time jobs be a and b, while those of non-CWIE graduates be c and d. Table III is what is called a “contingency table” for the observed numbers.

Table III: The contingency table for the observed numbers

	Full-time job	Part-time job	Total
CWIE graduates	a	b	a+b
Non-CWIE graduates	c	d	c+d
Total	a+c	b+d	a+b+c+d

Under the null hypothesis that there is no difference between the CWIE group and non-CWIE group --- the outcome is “independent” of the group type. So if the “expected contingency table” under the hull hypothesis has entries A, B, C, and D as in Table IV, then the following conditions have to be satisfied.

Table IV: The expected contingency table

	Full-time job	Part-time job
CWIE graduates	A	B
Non-CWIE graduates	C	D

where $A = (a+b)(a+c)/(a+b+c+d)$ $\quad$ $B = (a+b)(b+d)/(a+b+c+d)$

$C = (a+c)(c+d)/(a+b+c+d)$ $\quad$ $D = (b+d)(c+d)/(a+b+c+d)$

The test statistic χ^2 is defined as the sum of squared differences between the “observed values” and the “expected values under the null hypothesis” divided by the “observed figures.” That is

$$\chi^2 = (a - A)^2/A + (b - B)^2/B + (c - C)^2/C + (d - D)^2/D \qquad (1)$$

In the above example,

$A = (a+b)(a+c)/(a+b+c+d) = (20+20)\ (20+20)/(20+20+20+40)) = 16$
$B = (a+b)(b+d)/(a+b+c+d) = (20+20)\ (20+40)/(20+20+20+40)) = 24$
$C = (a+c)(c+d)/(a+b+c+d) = (20+20)\ (20+40)/(20+20+20+40)) = 24$
$D = (b+d)(c+d)/(a+b+c+d) = (20+40)\ (20+40)/(20+20+20+40)) = 36$

Therefore, the observed and expected contingency tables for this example becomes as in Table V (a) and (b).

Table V (a)

Observed	Full-time job	Part-time job	Total
CWIE graduates	20	20	40
Non-CWIE graduates	20	40	60
Total	40	60	100

Table V (b)

Expected	Full-time job	Part-time job	Total
CWIE graduates	16	24	40
Non-CWIE graduates	24	36	60
Total	40	60	100

Therefore,

$$\chi^2 = (20–16)^2/16 + (20–24)^2/24 + (20–24)^2/24 + (40–36)^2/36 = 25/9 = 2.78 \quad (2)$$

The test for this type of contingency table with 2 rows and 2 columns is based on a χ^2 distribution with a "degree of freedom 1", or "$\chi^2_{(1)}$". The degree of freedom is 1, since fixing one of four entries in the contingency table i.e. A, B, C, and D, would determine all other entries given the observed numbers of CWIE graduates, non-CWIE graduates, those with full-time jobs and those with part-time jobs. With a $\chi^2_{(1)}$ distribution table, 2.78 is greater than 2.71 for a 10% significance level . Therefore, H0 is rejected at a10% significance level --- in other words, CWIE can be considered to improve the possibility of acquiring a full-time job.

Two tests can be used to verify the null hypothesis. In fact, the z test and the $\chi^2_{(1)}$ test are equivalent in the test for independence in a 2x2 contingency table, with $z^2 = \chi^2_{(1)}$ In the above example, $z^2 = 1.67^2 = 2.78 =\chi^2_{(1)}$. The difference is that when contingency table has more entries, z test cannot be used. Table VI summarises the ways these tests can be used.

Table VI

Quantity compared	Number of groups compared	Test & distribution used	Degree of freedom for 2 groups

Proportions	2	z-test (Normal)	Not applicable
Of groups	2 or more	χ^2 test (χ^2)	1
Averages	2	t-test (t)	n1+n2-2
Of groups	2 or more	ANOVA (F)	1, n1+n2-2

Note: (i) "Degree of freedom" only refer to cases when proportions or averages of 2 groups are compared --- for ANOVA, n1 and n2 are sample sizes of the 2 groups.
(ii) For comparing averages of 2 groups, a z-test and a χ^2 test are equivalent.
(iii) For comparing proportions of 2 groups, a t-test and ANOVA are equivalent.

The case of Kyoto Sangyo University

(The data set)

Kyoto Sangyo University is a private university in Kyoto, Japan, which was founded in 1965. It is a medium-sized university with 7 faculties, over 11,000 students and 800 academic and administrative staffs. Undergraduate course lasts for 4 years in Japan starting in April and ending in March. At the time of data collection, there were 773 universities, of which 178 were public and 595 were private in Japan.

The data has been collected from all 5473 undergraduate students who graduated in 2008 and 2009, --- 2739 and 2734 respectively. Of the total 5473, 3781 were male and 1692 were female from 7 faculties i.e. Economics, Business, Law, Foreign Languages, Culture, Science, and Engineering. From the original panel data of each student, we use annual GPAs, whether he/she has taken CWIE, and their employment outcome. Here is a brief description.

(i) The average annual GPAs for students in the 1st - and 3rd- year of undergraduate programme, GPA1 and GPA3, are 1.90 and 1.90, respectively taken from a total of 5160 students out of 5473, leaving out some with irregular registration patterns. GPA1 may be used to represent the student's academic ability before coming to university. This is because there is no standardized data on students' pre-university academic performance in Japan such as a national examination to cover every high school student and GPA1 is likely to depend on the pre-university achievement to great extent. GPA3 is used to identify the academic progress during the undergraduate years instead of the 4th year's GPA, due to a rather special circumstance of Japanese universities where many students manage to attain the necessary units to graduate by the end of 3rd year to spend almost

the entire 4th year to find a job, so that their 4th year's GPA does not reflect their ability.
(ii) CWIE: Of 5160 students considered in (i), CWIE was taken by 692 students or by13.4% (= 692/5160). This was much higher than the national average of 1.8% in 2007 and 2.2% in 2011. And 61.6% of work experience lasted less than two weeks in 2007 and there was a slight reduction to 61.6% in 2011, while 7.6% of work experience lasted over a month in 2007 and there was an increase to 11.5% in 2011, with the most of them unpaid (Ministry of Education, Japan, 2013). This shows Japan's CWIE is lagging behind other anglophone industrial nations.
(iii) Employment outcome: This was measured from two angles. Firstly, the students were asked whether they had obtained "provisional placement offers" of full-time employment, part-time employment or none. Out of 5160 students, 4195 obtained full-time employment offers while 421 obtained part-time employment offers. Secondly, 3965 offers students received were from private companies with 1354 listed companies and 2611 unlisted companies. It needs to be mentioned that KSU can be considered a typical Japanese private university, considering its history of almost 50 years, its medium size with over 11,000 students and 800 academic and administrative staffs in 7 faculties, and its location in a medium sized city of Kyoto. Thus, the result of statistical analysis of KSU may resemble what other universities would find if a similar analysis is made.

(Testing the effect of CWIE at KSU)

Given the above information, the following section illustrate how the effectiveness of CWIE at KSU could be tested. The statistical testing will be performed to compare the academic performance and employment placement of students with and without CWIE.

(1) Effect of career education on GPA1 and GPA3

5160 students were divided into two groups with and without CWIE and the average GPAs were found as in Table VII below.

Table VII: Average GPAs by group

Student	Average number	Average GPA1	GPA3
With CWIE	692	2.17	2.2
Without CWIE	4468	1.85	1.85

With the procedure illustrated earlier in this chapter, the existence of a significant difference in an academic performance level between students groups with and without CWIE is tested using a t-test and the following results are found (Although the original data base is huge and cannot be shown here, in order to show the calculation process the actual values used to derive t-value are provided in “Note” in parenthesis):

(a) Question: Are average GPA1s of groups with and without CWIE, 2.17 and 1.85, significantly different?
Answer: $t = 11.59$, which means they are significantly different at 1%. (P-value = 0)
(Note: $t = (2.17-1.85)/s(\sqrt{(1/692 + 1/4468)}$
where $s^2 = (274.52+ 2081.53) / (692+4468-2) = 0.457$)

(b) Question: Are average GPA3s of groups with and without CWIE, 2.2 and 1.85, significantly different?
Answer: $t = 12.62$, which means they are significantly different at 1%. (P-value = 0)
(Note: $t = (2.2-1.85)/s(\sqrt{(1/692 + 1/4468)}$
where $s^2 = (339.4+ 2037.38) / (692+4468-2) = 0.461$)

These test results seem to suggest that CWIE attracts better students, i.e. students with higher GPA1s, and makes students do better academically at university, i.e. students with higher GPA3.

(2) Effect of CWIE on obtaining a full-time/part-time job

4616 students were divided into two groups: those with and without CWIE and the number of students in each category is shown in Table VIII below.

Table VIII: Job placement status by group

	Full-time	Part-time	Full-time (%)
Total	4195	421	90.9%
With CWIE	621	20	96.9%
Without CWIE	3574	401	89.9%

With the procedure illustrated earlier, the existence of a significant difference in a job status between students groups with and without CWIE is tested using a z-test

and a $\chi^2(1)$ test --- as pointed earlier, they give the identical test result, and the following results are found (As before, the calculation process is shown in the parenthesis "Note").

Question: Does CWIE improve the chance of getting a full-time job?

Answer 1: Z-test

z = 5.67, which means CWIE significantly improves a chance of getting a full-time job.

(Note: $z = (0.969-0.899)/\sqrt{(0.909 (1-0.909)(1/621+1/3574)} = 5.67$)

Answer 2: χ^2 with one degree of freedom

Table IX shows Contingency tables for observed values and expected vales:

Table IX: Contingency tables for observed values and expected vales

	Observed		Expected	
	Full-time/Part-time		Full-time/Part-time	
With CWIE	621	20	583	58
Without CWIE	3574	401	3612	363

Thus

$$\chi^2 = (621-583)^2/583 + (20-58)^2/58 + (3574-3612)^2/3612 + (401-363)^2/363 = 32.33 = 5.67^2 = z^2 \qquad (3)$$

In both cases, the effect is significant at 1% (P value = 0)

(3) Effect of CWIE on obtaining a job at a listed/unlisted company

4616 students were divided into two groups: those with and without CWIE and the number of students in each category is shown in Table X below.

Table X: Company status by group

	Listed	Unlisted	Listed(%)
Total	1354	2611	34.1%
With CWIE	221	372	37.3%

Without CWIE	133	2239	33.6%

Question: Does CWIE improve the chance of getting a job at a listed company?

Answer 1: Z-test

z = 1.74, which means CWIE significantly improves a chance of getting a full-time job.

(Note: $z = (0.372 - 0.336)/\sqrt{(0.341\ (1 - 0.341)(1/593+1/3372)} = 1.74$)

Answer 2: χ^2 with one degree of freedom

Table XI shows Contingency tables for observed values and expected vales:

Table XI: Contingency tables for observed values and expected vales

	Observed		Expected	
	Listed/Unlisted		Listed/Unlisted	
With CWIE	221	372	203	390
Without CWIE	1133	2239	1151	2221

Thus

$$\chi^2 = (221 - 203)^2/203 + (372 - 390)^2/390 + (1133 - 1151)^2/1151 + (2239 - 2221)^2/2221 = 3.02 = 1.74^2 = z^2 \qquad (4)$$

In both cases, the effect is significant at 10% (P value = 0.08)

In sum, the following conclusion can be drawn:

(i) When students are grouped into those with and without CWIE, the averages of first year and third year GPA are both significantly higher for the former group.

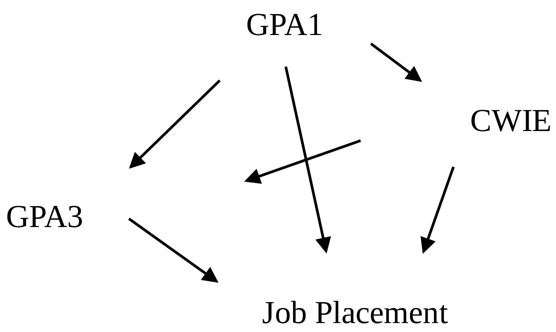
(ii) The overall academic performance for those with CWIE shows difference. One may conclude that CWIE has a positive effect on academic performance. However, it does suggest also that students who take WIL have high per-university academic performance. If this is true, then the value of CWIE is overestimated. The next section deals with this issue of singling out the effect of CWIE, by using a series of regression analyses.

3. Interactive framework of student's attributes: Path analysis/SEM/Recursive

form

It has been suspected that a student's attributes such as pre-university academic performance, academic performance at university, job placement, gender, faculty, together with whether CWIE is taken are interrelated and a simple comparison of values and proportions may not be adequate. Some researchers used a regression models to take care of such an interactive framework (See, for example, regression models used in Mendez and Rona (2010), Gomez et al (2004), Foster et al (2011)). But a more systematic approach often employed to solve such issues is a "path analysis". Path analysis is both a concept and a statistical tool to determine causal relationships among variables within a given structure and such relationships are often described by a "path diagram" as illustrated in Figure I for our analysis of CWIE. The concept is useful for disentangling causal relationships among the variables.

Figure.I: Path diagram



Path analysis was first introduced by Sewall Wright, a geneticist, who sought to disentangle genetic influences across generations (Wright, 1921). Wright's contribution to investigations in social science went further, when he subsequently wrote an article on an analysis of a corn market, where he applied his approach to economic analysis of supply and demand interaction (Wright, 1925), and an article on an identification problem of simultaneous equation system, where he discussed how to identify supply and demand from a set of given data (Wright, 1934). It is worth noting that his interests in simultaneity and identification appeared long before they started to be treated as a standard concepts in econometrics.

Today, the analysis is widely used in social science including psychology, sociology and economics. As a statistical or econometric tool, Path analysis is categorized as one type of a structural equation model (SEM) or a simultaneous equation model respectively.

A set of causal relationships in Fig. I can be expressed as:

GPA1 → CWIE (5-1)
GPA1 & CWIE → GPA3 (5-2)
GPA1 & CWIE & GPA3 → Job placement (5-3)

with → expressing the causal relationship

Or, if each causal relationship can be expressed as a linear equation with a constant term, coefficients, and an added error term uncorrelated to each other:

Equation 1 CWIE = a1 + a2 GPA1 + u1 (6-1)
Equation 2 GPA3 = b1 + b2 GPA1+b3 CWIE + u2 (6-2)
Equation 3 Job = c1 + c2 GPA1+ c3 CWIE + c4 GPA3 + u3 (6-3)

where Job implies a choice between full-time and part-time jobs, or a choice between listed and unlisted companies.

This hierarchical structure is called a "fully recursive model" and it is known that an ordinary least square (OLS) method may be used to estimate coefficients of each equation, i.e. a's, b's, and c's, separately (See, for example, Greene (2008) or Wooldridge (2002) or (2009)). Equations 1 and 3 have "qualitative response" as a dependent variable on the left-hand side of the equations, i.e. 1 if CWIE taken and 0 otherwise for Equation 1 and 1 if full-time job or listed company or 0 otherwise, while Equation 2 has a usual cardinal value of GPA3 as its dependent variable. Estimation process differs between the two types. In the following two sections, the processes for Equations 1 and 2 are described in turn by using the KSU data. Equation 3 is not dealt with in this paper, as the procedure is the same as that of Equation 3.

4. Who takes CWIE programme?: Qualitative response models

Equation 1: CWIE = a1 + a2 GPA1 + u1 (7)

This equation estimates the effect of GPA1 on the decision to take CWIE. As pointed earlier, it is possible that those students who are interested in CWIE were

already academically motivated before starting university career. Higher school grades can be used to represent pre-university academic performance if any national data is available. If, however, no such exam exists or cannot be traced to cover all the students concerned, a best proxy would be their grades in the first term or first year at university, e.g. GPA1, since this result is more likely to be a reflection of pre-university achievement rather than what is achieved at university. The decision to take CWIE may also depend on the student's other personal attributes such as gender or the faculty that the student belongs to. Thus, the equation to estimate is:

$$\text{CWIE} = \text{a1} + \text{a2 GPA1} + \text{a3 Gender} + \text{a4 Faculty} + \text{u1} \qquad (8)$$

where the dependent variable CWIE is one or zero and for the independent variables GPA1 may be grades and Gender and Faculty are dummy variables, with a constant term a1 and an error term u1 with a standard normally distribution.

As CWIE is a 1-0 variable, this model is called "a binary (instead of qualitative) response model." This belongs to a family of "limited dependent variable models," in which the range of values of the dependent variable is substantially limited. In some cases, a straightforward use of OLS method on this linear equation may not be appropriate.

For the binary response models, researchers have been using several functional forms, namely, a linear probability model, a logit model, and a probit model, each with its own advantages and disadvantages (The discussion to follow can be found in most of standard textbooks of econometrics --- for example, see Wooldridge (2009)).

A linear probability model expresses the probability of response as a linear function of independent variables. However, as the observed dependent variable can only take 1 or 0 --- the unobserved probability is called a "latent variable", a linear relation is not theoretically appropriate, i.e. predicted values of the dependent variable may lie outside of the 0-1 range (See Figure.II). The binary nature of the dependent variable also implies heteroskedastic errors. In this case, OLS estimators are not biased but for t and F statistics the usual standard errors need to be replaced by "heteroskedasticity-robust standard errors", since the error terms are not normally distributed. In practice, however, these error values are not far from each other. The estimation procedure for this model is simple as OLS is used for the linear equation directly and the interpretation of the coefficients is intuitive --- an increase in a unit values of a variable would raise the probability of taking CWIE by the estimated coefficient.

Unlike a linear probability model, a logit model keeps the dependent variable between 0 and 1. The term "logit" comes from "a logistic curve" (See Figure. III). If the probability of response p depends on x linearly i.e. ax + b, then a logistic curve is expressed by

$$p = \exp(ax+b) / (1+ \exp(ax+b)) \tag{9}$$

It can be easily verified that if ax+b approaches ∞ (or-∞). p approaches 1 (or 0). The equation can be rearranged in a linear form by a "logit transformation" as:

$$\ln p/(1-p) = ax+b \tag{10}$$

This could be estimated by a least square method if p takes values other than 1 or 0. In the present case, where the dependent variable takes 1 or 0, it is not feasible, but when the probability is replaced by an observed percentage such as the average percentage of those who have taken the choice for each group, the least square method can be used and it is known as a "minimumχ^2 method".

A probit model is based on the standard normal cumulative distribution and can be expressed as

$$p = (2\pi)^{-1/2}\int_{-\infty}^{ax+b} \exp(-z^2/2)dz \tag{11}$$

It can be verified that, as in the logit model above, if ax+b approaches ∞ (or-∞), p approaches 1 (or 0) (See Figure. III).

Unlike a linear probability model, both logit model and probit models are non-linear in ax+b and some cautions are needed for the estimation process. Firstly, a straightforward least square method would not work because of the non-linearity. For the non-linear estimation, the most commonly used method today is the "maximum likelihood estimation (MLE)". Secondly, the estimated coefficients do not give a straightforward interpretation of the least square estimation, since a unit increase of an independent variable will cause a marginal change in the dependent variable through the non-linear forms of the logit and probit equations. This means that the estimated coefficients of the linear probability, logit, and probit models cannot be directly compared. There is a further complication that for the logit and probit models these values depends on the values of independent variables --- note that for the linear probability model, the marginal effect is constant over the values of independent variables. As a rule of thumb, Wooldridge (2002) suggests using “scale factors” to multiply the coefficients for the logit and probit models of 0.4 and 0.25 respectively, to compare the coefficients among the three models. Also as a statistic for goodness-of-fit, i.e. R^2 in the least square method, McFadden (1974) suggested a statistic known as “Pseudo R^2 ” for the maximum likelihood method, which is often found in statistical packages.

Testing the causes of CWIE at KSU

As explained above, a qualitative response model was estimated using a linear probability model, a logit model, and a probit model, where independent variables include student’s gender, graduation year, and faculty as dummy variables.

$$\text{CWIE} = a1 + a2\ \text{GPA1} + a3\ \text{Gender} + a4\ \text{Faculty} + a5\ \text{GraduationYear} + u1 \quad (12)$$

Table XII shows the estimation results. Both a and b are the identical result of least square method based on a linear probability model. The difference is the treatment of errors. As explained earlier, the correct version is a with heteroskedasticity-robust t-values, which also gives a different set of P-values. However, the difference is not that large. Comparing the four sets of results, the tendency of signs, relative magnitudes, and significance among the independent variables is alike. Note, however, the coefficients for the same variables in the linear probability, logit, and probit models differ because of the way coefficients affects the dependent variable. On the whole, the linear probability model gives reasonable results and one may sacrifice the theoretical rigour of logit and probit models for the simple and intuitive nature of linear probability models.

5. Does CWIE have a positive effect on academic performance? : Least square models

Equation 2

$$\text{GPA3} = b1 + b2\ \text{GPA1} + b3\ \text{CWIE} + b4\ \text{Gender} + b5\ \text{Faculty} + u2 \quad (13)$$

A dependent variable is GPA3 and this is determined by what one came with to university with, i.e. GPA1, and what one took at university, i.e. CWIE. Also as in Equation 1, other attributes of students are included such as gender, faculty, and year of

graduation as dummy variables. As GPA3 is a quantitative variable, the equation can be estimated in a linear form.

Testing the effect of CWIE on academic performance at KSU

For applying the equation to the KSU case, a graduation dummy is included as in Equation 1, so that we estimate the following equation:

Equation 2 $$\text{GPA3} = b1 + b2\ \text{GPA1} + b3\ \text{CWIE} + b4\ \text{Gender} + b5\ \text{Faculty} + b6\ \text{Graduation year} + u2 \quad (14)$$

The estimation procedure for this equation is simple, as the dependent variable is not a qualitative response. OLS estimation may be used straight away. The result is shown in Table XIII. Apart from faculty discrepancies affecting GPA3, both GPA1 and CWIE do have positive and significant effects on GPA3.

6. Conclusion

This paper has attempted to show how statistical methods can be used on available data for CWIE as a useful tool to explain to those who are not aware of the effectiveness of CWIE at university, in the government or among potential students. In the choice of method, there is a trade-off between “simple intuitive appeal” and “theoretical rigour.” Simple comparisons of averages and proportions are easy to work with but would be more persuasive if statistical sampling and testing are used. When causal relationships are considered, an econometric approach of path analysis is a better choice. Using the path analysis on the KSU student data, it was shown that CWIE does raise academic performance at university, i.e.GPA3, but its magnitude may be overestimated as students with higher academic marks, i.e. GPA1, tend to take CWIE. As for binary response models, the estimated results of a linear probability model with OLS method and logit and probit models with MLE method were compared and it was suggested that the simplicity and intuitive appeal of the former outweighs the theoretical rigour of the latter.

Finally, it is important to emphasize that this type of quantitative analysis based on statistical and econometric methodologies should be taken to complement and not substitute qualitative analysis based on psychological and sociological methodologies. The former can explain how effective CWIE is but cannot explain how such a mechanism works.

Bibliography

Blalock, H. M. (1985): “Causal Models in the Social Sciences,” Second Edition, New York: Aldine.

Dewey, J.(1916): “Democracy of Education: An introduction to the philosophy of education,” New York, NY: The Free Press.

Duignan, J. (2003): “Placement and adding value to the academic performance of undergraduates: Reconfiguring the architecture - an empirical investigation,” Journal of Vocational Education and Training, 55 (3), pp.335-350.

Foster, H., Green, P., Houston, P., McAree, D., McCann, C., McCulloch, D. and Pogue, M. (2011): “Are sandwiches better? The impact of work placement upon degree performance,” Perspective on Pedagogy and Practice, University of Ulster, Vol. 2, pp53-64.

Goldberger, A. S. (1972): “Structural Equation Methods in the Social Sciences,” Econometrica, vol.40, No.6, pp.979-1001.

Gomez, S., Lush, D. and Clements, M. (2004): “Work placements enhance the academic performance of bioscience undergraduates,” Journal of Vocational Education and Training, 56 (3), pp.373-386.

Greene, W. H. (2008): “Econometric Analysis,” Sixth Edition, Pearson Prentice Hall.

Hartley, J.L. and Smith, B.W. (2000): “Strengthen academic ties by assessment of learning outcomes,” Journal of Cooperative Education, 35(1), pp.41-47.

Heller, B. and Heinemann, H.N. (1987): “The impact of structured and non-structured work experiences on college students' attitude, values and academic performance,” Journal of Cooperative Education, 23 (3), pp.19-32.

Kaplan, D. W. (2000): “Structural Equation Modeling: Foundations and Extensions,” Sage Publications, Inc.

Kolb, D.A.(1984): “Experiential Learning: Experience as the source of learning and development,” Engelwood Cliffs, NJ: Prentice Hall.

Lewin, K. (1946): “Action research and minority problems,” Journal of Social Issues, 2(4), pp.34-46.

Lleras, C. (2005): “Path Analysis, “ in Kempf-Leonard, K.L. (ed.) “Encyclopedia of Social Measurement,” Elsevier Academic Press.

Mandilaras, A. (2004): “Industrial placement and degree performance: Evidence from a British higher institution,” International Review of Economics Education, 3(1), pp.39-51.

Maruyama, G. M. (1997): “Basics of Structural Equation Modeling,” Sage Publications, Inc.

Mendez, R. (2008): “The correlation between industrial placements and final degree results: A study of Engineering Placement Students,” Paper presented it the ASET conference, Plymouth.

Mendez, R. and Rona, A. (2010): “The Relationship between Industrial Placements and Final Degree Results: a study of engineering placement students,” Learning and Teaching in Higher Education, Issue 4-2, pp.46-61.

Ministry of education, culture, sports, science and technology, Japan (2013): “The report on internships at higher education institutions”

Ott, R. and Longnecker, M. (2010): “An Introduction to Statistical Methods and Data Analysis, International Edition,” sixth Edition, Brooks/Cole, Cengage Learning.

Piaget, J.(1985): “The equilibrium of cognitive structures,” Chicago, IL: University of Chicago Press.

Silberston, Z. A. (1987): “Path Analysis,” in Eatwell, J., Milgate, M. and Newman, P. (ed.) “The new Palgrave: a dictionary of economics,” Macmillan.

Van Gyn, G., Cutt, J., Loken, M. and Ricks, F. (1996): “Investigating the educational benefits of cooperative education: A longitudinal study,” Journal of Cooperative Education, 32 (2), pp.70-85.

Wonnacott, T.H. and Wonnacott, R. J. (1990): “Introductory Statistics for Business and Economics (Wiley series in probability and mathematical statistics),” John Wiley & Sons.

Wooldridge, J. M. (2009): “Introductory Econometrics,” fourth Edition, South Western.

Wooldridge, J. M. (2010: “Econometric Analysis of Cross Section and Panel Data,” (2nd ed.), The MIT Press, Cambridge, Massachusetts.

Wright, S. (1921): “Correlation and Causation,” Journal of Agricultural Research, 20, pp.557-585.

________ (1925): Corn and Hog Correlations, Washington: U.S. Department of Agriculture Bulletin 1300.

________ (1934): “The Method of Path Coefficients,” Annals of Mathematical Statistics, 5, pp.161-215.

Zegwaard, K.E. and McCurdy, S. (2008): “Value of work placements for students and its influence on student performance: Faculty perceptions,” In Coll, R.K. and Hoskyn, K. (Eds): “Proceedings from the Annual Conference for the New Zealand Association for Cooperative Education,” New Plymouth, New Zealand.