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ABSTRACT

To provide a strong motivation for students to learn multivariate statistics and the multivariate way of thinking, this paper uses an easily understandable example of ascertaining the effect of educational attainment on migration propensity in Japan. With cross-tabulations and a logistic model, we demonstrate the necessity of the multivariate approach by showing that the control for the effect of gender is indispensable for revealing the true effect of educational attainment. We further identify two conditions under which valid inference about the effect of a factor depends critically on the control for another factor. Finally, we identify an apparent contradiction between tabulated and logistic results and present a resolution to it.

Keywords: multivariate analysis, logistic model, odds ratios

1. INTRODUCTION

There are two kinds of data that are used for studying the relationships of the variables that are involved in real-world processes: *observational* and *experimental*. Observational data are obtained from observing real-world processes (e.g. the data collected from a survey that elicits answers to questions about the incidences and characteristics of migration from the time of birth to the date of survey). Experimental data are generated from experiments in which certain factors are controlled so that the relationships between key variables can be more easily ascertained (e.g. the data collected from an experiment in which the volume of an airmass is fixed so that the relationship between the temperature and pressure of the airmass can be more easily studied).

The data for studying a human behaviour (e.g. migration) and the consequent socioeconomic process (e.g. urbanization, suburbanization, or counter-urbanization) are usually of the observational type. Since many factors are likely to be involved and can not be practically controlled in the real-world, the usefulness of the observational data can be enhanced by collecting information on many relevant factors so that the relationship between a dependent variable and a specific explanatory factor of interest to a researcher can be properly assessed in the context of other influential factors via some multivariate model. Essentially, a well-specified multivariate model for analyzing observational data is analogous to a well-designed experiment for generating experimental data: both have the advantage of reducing the risk of making a misleading inference that results from the failure to control for the effect of one or more influential causal factors. In short, multivariate methodology tends to be particularly important in demography and other social sciences.

The main purpose of this paper is to use a simple real-world example to help students appreciate the importance of the multivariate perspective so that they can be motivated to learn multivariate statistics or at least a multivariate way of thinking. Our presentation consists of three parts. The first and most important part uses only *tabulations* of individual observations that can be easily understood by students who do not have any formal training in statistics. The tabulations will show that without a proper control for the effect of a related explanatory factor, the table showing the dependence of a variable on an explanatory factor of interest to a researcher can become very misleading. The second part introduces a *logistic model* that can not only reproduce the key informations of the tabulations but also provide additional informations for gaining a better understanding of the conditions under which the computed effect of an explanatory factor becomes misleading if the effect of another explanatory factor is not controlled for. This part should be easy to read for those with some background in regression analysis and can be used as a concrete example for learning the use of probability models. The third part introduces an *interaction term* into the logistic model in order to deal with questions about the interaction between two explanatory factors. This part will not be presented in the main text of the paper. Rather, it is done in an appendix, because it can probably be well understood only by those who are experienced users of multivariate models in their research. We hope that the three parts of this paper can be used by the instructors who appreciate the usefulness of substantively meaningful examples at both elementary and advanced levels of *applied* statistics.

Our real-world example is about an attempt at explaining the propensities to make interprefectural migration at the time of marriage in Japan by educational attainments. We hypothesize that the migration propensities tend to be higher for those with higher educational attainments. This hypothesis is based on the idea that those with better education tend to have greater information and contact fields so that their marital partners are more likely to be located outside of their own resident prefecture, especially in a prefecture with a good chance of getting a professional job. To test this hypothesis, we use the micro data of the 1986 national survey on migration history (IPP, 1988) and select the adults who are either college or university graduates. Typically, it takes two and four years to complete college and university education, respectively. According to our hypothesis, university graduates are expected to be more prone to make interprefectural migration at marriage than are college graduates.

2. DATA ANALYSIS USING TABULATIONS

We start our investigation by paying attention to only the dependent variable and the educational factor that are considered in our hypothesis. An interprefectural migration is said to have occurred if the prefecture of residence immediately before marriage is different from the prefecture of residence immediately after marriage. By cross-tabulating the individuals in the survey data according to migration status and educational attainment, we obtain the information shown in Table 1. Here the dependent variable is represented by a migration rate, which is obtained by dividing the number of interprefectural migrants by the size of the at-risk population.

For college graduates, the migration rate is 22.8% (i.e. 245/1,075*100%). For university graduates, it is 18.1%. Contrary to our hypothesis, these migration rates indicate that university graduates were less prone to make interprefectural migration than were college graduates. This finding is inconsistent with many other findings confirming the enhancing effect of educational attainment on long-distance migration in various countries (e.g. Long, 1988; Newbold & Liaw, 1994; Liaw & Kawabe, 1994; Liaw & Lin, 2001). What has gone wrong?

To pursue the investigation further, we notice the fact that Japan is a male-oriented society in which brides are more likely to move to the location of grooms rather than the other way round. It seems likely that our hypothesis may be supported by the data, if we control for the strong effect of gender. Thus, we make a three-way cross-tabulation of the observations in the survey data and obtain the education-specific migration rates for each gender (Table 2). Among males, the migration rate turns out to be 6.9% for college graduates and 12.5% for university graduates. Among females, it is 29.9% for college graduates and 42.4% for university graduates. In other words, after controlling for the effect of gender, the empirical data indeed support our hypothesis that the higher the educational attainment, the greater the propensities to make interprefectural migration.

The above finding has two important implications. First, in designing the questions of a survey questionnaire, the researcher must not ask only the questions that are directly relevant to her/his specific theory or policy concerns. Rather, she/he should review the broad literature and ask questions about all factors that are shown in the literature to be highly influential factors. Our finding indicates that the chance of making valid inferences from survey data can be greatly enhanced if questions about such influential factors are included in the questionnaire. More specifically, a researcher who is not interested in gender issues must still ask a gender question in the survey, if he wants to understand the effect of educational attainment on the migration behavior at marriage in Japan. Second, compared with a bivariate perspective, a multivariate perspective is less prone to lead to a misleading inference from empirical data.

For the readers who have not taken any training in statistics and have no intention to do so, we wish that they would keep these two important implications in mind before leaving this paper behind at this point. For others, please continue reading.

3. DATA ANALYSIS USING A LOGISTIC MODEL

Although it is a very useful tool for uncovering the inherent relationship between two variables in the context of one or two more variables, multidimensional cross-tabulation becomes increasingly unwieldy when the researcher wants to control for the effects of two or more explanatory factors. Its unwieldiness is particularly severe when each of the explanatory factors is represented by a large number of categories, because the researcher may end up with the task of making an inference from an unreasonably large number of tables. A more abstract but analytically more effective way to study empirical data from the multivariate perspective is to use a multivariate statistical model. If the values of the dependent variable are not restricted to a particular range, and if the scatter diagrams suggest a linear relationship, a linear regression model may be used. When the values of the dependent variable are restricted to the range between zero and one (or 100%), it is common to use a logistic or a probit model (Cox, 1989).

In this section, we will show that a logistic model can be used (1) to generate the key informations obtained from the above cross-tabulations, (2) to yield the so-called p-values that can be used to assess whether certain computed effects are statistically significant (i.e. not likely the result of sampling errors), and (3) to identify the conditions under which the control for the effect of an extraneous factor becomes essential for avoiding the risk of making a misleading inference about a hypothesized relationship from empirical data.

The formulation of the logistic model for explaining a person's propensity to make interprefectural migration at marriage by educational attainment and gender is as follows. Let i be used to identify a person in question. We use P_i to represent her/his probability of making interprefectural migration, U_i to represent her/his educational attainment, and F_i to represent her/his gender. More specifically, U_i is a dummy variable that assumes the value of 1, if person i is a university graduate. Otherwise, it assumes the value of 0. F_i is another dummy variable that assumes the value of 1, if person i is female. Otherwise, it assumes the value of 0. Considering educational attainment and gender as two explanatory factors, we write down the logistic model as:

$$P_i = \exp(B_o + B_1 * U_i + B_2 * F_i) / \{ 1 + \exp(B_o + B_1 * U_i + B_2 * F_i) \},$$

where exp( ) is the exponential function, and B_o , B_1 and B_2 are unknown coefficients to be estimated. We expect both B_1 and B_2 to turn out as positive values, because the propensity to make interprefectural migration is expected to be enhanced by having a university education and being female. We use the Logistic procedure of SAS to fit various specifications of this model to the survey data. The estimation method used by this procedure is the maximum likelihood method.

By using educational attainment as the only explanatory factor, our first specification of the logistic model yields the estimation result shown in the top panel of Table 3. The estimated coefficient of U_i (-0.2924) turns out to have a “wrong” sign. The very large magnitude of the associated t-statistic (-16.8) and equivalently the very small p-value (0.0000) indicate that it is extremely unlikely that the perverse effect of education attainment revealed by the estimation result is due to sampling errors.

The estimated coefficients in the top panel indicate that the estimated model is:

$\underline{P}_i$ = exp (-1.2202 -0.2924*U_i) / { 1 + exp(-1.2202 -0.2924*U_i) }

where $\underline{P}_i$ is the predicted probability. By letting U_i be 0 and 1 in turn, we find that $\underline{P}_i$ = 0.228 for a college graduate, and $\underline{P}_i$ = 0.181 for a university graduate. These predicted probabilities are identical to the corresponding migration rates in Table 1 that were generated by the method of cross-tabulation.

By using both educational attainment and gender as explanatory factors, our second specification of the logistic model yields the estimation result shown in the middle panel of Table 3. Now, we find that in the context of gender, the estimated coefficient of U_i (0.5764) indeed turns out to have a positive sign, as we have hypothesized. Based on the large t-statistic (4.5) and equivalently the very small p-value (0.0000) associated with this estimated coefficient, we are highly confident that the positive effect of educational attainment is not a spurious result from sampling errors.

The estimated coefficients of the second specification indicate that the estimated logistic model is:

$\underline{P}_i$ = exp(-2.5385 +0.5764*U_i +1.6785*F_i) / { 1 + exp(-2.5385 +0.5764*U_i+1.6785*F_i) }

By substituting all possible combinations of the values of U_i and F_i into the above equation, we get the following predicted probabilities:

$\underline{P}_i$ = 0.057 for a male college graduate,

$\underline{P}_i$ = 0.123 for a male university graduate,

$\underline{P}_i$ = 0.297 for a female college graduate,

$\underline{P}_i$ = 0.430 for a female university graduate.

These predicted probabilities are very similar to the corresponding migration rates in Table 2 that were generated by a three-dimensional cross-tabulation. This strong similarity suggests that there seems to be no need for using a "saturated" logistic model to study the effects of the two explanatory factors in question. Note that, as will be shown in the appendix, the saturated model for our empirical problem contains an additional term that is created by using the product of U_i and F_i as an additional explanatory variable. It has the ability of generating predicted probabilities that are exactly identical to the migration rates shown in Table 2.

From the methodological point of view, the most intriguing question is why the estimated effect of educational attainment becomes misleading when the effect of gender is not controlled for. The answer lies in two basic facts. First, U_i and F_i have a strong negative correlation. The simple correlation coefficient between them is -0.51, the magnitude of which is very great in light of the fact that it is computed from micro data. This strong negative correlation results from the fact that most college students were female, whereas most university students were male. This fact is a reflection of the domination of the Japanese society by a patriarchal value system that presumed that a two-year college education was good enough for a polished lady, whereas a four-year university education was essential for a successful household head.[1] Second, in terms of the impact on the propensities to make interprefectural migration at marriage, the gender effect is much stronger than the education effect. This is reflected by the fact that the coefficient of F_i (1.6785) is about three times the coefficient of U_i (0.5764). In other words, the effect of the male-oriented residential arrangement is much stronger than the effect of

[1] The university entrance rate for Japanese females increased substantially in the 1990s (from 15.2% in 1990 to 31.5% in 2000). However, the gender gap remains quite large, because during the same period, the corresponding rate for Japanese males increased from 33.4% to 47.5% (Statistics Association, 2001, p. 115).

educational attainment. As a consequence of these two basic facts, the omission of F_i from the logistic model forces U_i to become a perverse proxy for maleness and hence to assume a misleading negative coefficient.

Based on the above analysis, we now state the two general conditions under which the control for another explanatory factor (say, F_{2i}) should be seriously considered in order to avoid making a misleading inference about the effect of an explanatory factor of interest to the researcher (say, F_{1i}).

Condition 1: (i) F_{1i} and F_{2i} have a strong negative correlation; (ii) the effects of F_{1i} and F_{2i} on the dependent variable are in the same direction; and (iii) the effect of F_{2i} is much stronger than that of F_{1i}.

Condition 2: (i) F_{1i} and F_{2i} have a strong positive correlation; (ii) F_{1i} and F_{2i} have opposite effects on the dependent variable; and (iii) the effect of F_{2i} is stronger than that of F_{1i}.

To get a more concrete understanding of the problem, let us pretend that our research interest is in the gender effect rather than the education effect. Is it alright that we assess the effect of gender without controlling for the effect of education? By cross-tabulating the observations of the survey data only by gender and migration status, we find in Table 4 that the migration rate is much higher for females (32.9%) than for males (11.1%), which clearly supports the idea that the residential arrangement was strongly male-oriented. Similarly, using gender as the only explanatory factor, our third specification of the logistic model yields a positive coefficient for F_i (1.3688), which is significantly different from zero (see the bottom panel of Table 3). Thus, the effect of the male-oriented tradition on migration propensities can be easily detected without controlling for the effect of education. The reason for it is that the gender effect is much stronger than the education effect. In other words, the third part of Condition 1 does not apply here. However, it is important to point out that the strength of gender's effect has been understated when the effect of education is not controlled for: the coefficient of F_i has been reduced from 1.6785 in Specification 2 to 1.3688 in Specification 3. In other words, the failure to control for the effect of education has resulted in *somewhat* misleading information about the effect of gender.

Finally, to demonstrate the consistency between the cross-tabulation and logistic results, we show that the estimated model for the third specification is

$\underline{P}_i = \exp(-2.0837 + 1.3688 * F_i) / \{ 1 + \exp(-2.0837 + 1.3688 * F_i) \}$,

which implies that the predicted migration probabilities are

$\underline{P}_i = 0.111$ for a male, and $\underline{P}_i = 0.329$ for a female. Both of these predicted probabilities correspond exactly to the migration rates shown in Table 4.

Experienced users of probability models, please continue to read the appendix about the usefulness of *odds ratio* as a means to resolve an apparent contradiction between tabulated and logistic results.

4. CONCLUSION

In order to provide a strong motivation for students to learn multivariate statistics and the multivariate way of thinking, we have used an easily understandable example of an attempt at ascertaining the enhancing effect of educational attainment on the propensities to make interprefectural migration at marriage in Japan. The example shows that the failure to control for the effect of gender leads to a misleading inference about the effect of educational attainment. Such a misleading inference from empirical data represents not only a waste of the researcher's time and effort but also a serious hindrance to the development of sound theories.

An important implication of our result is that it is very important to make a *broad* literature review before starting an empirical research and designing a survey questionnaire. In other words, the researcher should become familiar with the literature outside his specific schools of thought and policy concerns. Otherwise, he may miss the information on a factor that has to be controlled for in order to reduce the risk of making a misleading inference from empirical data.

One of our contributions is the identification of two conditions under which the chance of making a valid inference about the effect of an explanatory factor (say, F_{1i}) is enhanced by controlling for another explanatory factor (say, F_{2i}):

Condition 1: (i) F_{1i} and F_{2i} have a strong negative correlation; (ii) the effects of F_{1i} and F_{2i} on the dependent variable are in the same direction; and (iii) the effect of F_{2i} is much stronger than that of F_{1i}.

Condition 2: (i) F_{1i} and F_{2i} have a strong positive correlation; (ii) F_{1i} and F_{2i} have opposite effects on the dependent variable; and (iii) the effect of F_{2i} is stronger than that of F_{1i}.

It is worth noting that our advice to include two highly correlated explanatory factors into a multivariate model goes against the common advice that such explanatory factors should not be included in the same model (Hair **et al**, 1992, p. 36; Johnson & Wichern, 1992, p. 313). The common advice is based on the concern that the standard errors of the estimated coefficients of such explanatory factors may become too large. But, our example has demonstrated that the basis for the common advice is overly simplistic.

Finally, our inquiry about whether the education effect is stronger for females than for males (see the appendix) has uncovered two important points about measurement: (1) *odds* is better than *probability* as a measure of *propensity*, although the latter is intuitively more appealing than the former; and (2) *odds ratio* is better than the *difference between two probabilities* as a measure of *the effect of a change in an explanatory factor*. By using these better measures, the apparent contradiction between the result of cross-tabulation and the estimated result of a multivariate statistical model vanishes.

APPENDIX

IS THE EDUCATION EFFECT ON MIGRATION PROPENSITIES STRONGER FOR FEMALES THAN FOR MALES?

In this appendix, we enquire about whether the effect of educational attainment on the propensities to make interprefectural migration is stronger for females than for males. In pursuing this enquiry, we first encounter an apparent contraction between the results of different approaches and then find a way to resolve the contradiction. Since the contradiction is likely to be encountered by other users of multivariate statistics, our finding should be of interest to researchers in various fields.

We see in the left panel of Appendix Table 1 that the change in educational attainment from college to university raises the migration rate by 12.4 % (i.e. 42.4% minus 29.9%) for females and 5.6% (i.e. 12.5% minus 6.9%) for males. Does this empirical finding indicate that the education effect is stronger for females than for males? One way to answer this question is to introduce the interaction variable "U_i * F_i" into the second specification of the logistic model and to see if it has an estimated coefficient that is positive and significantly different from zero. If so, the answer is "yes". Otherwise, the answer may be "no". In the left panel of Appendix Table 2, we see that the estimated coefficient of this interaction variable turns out to be a small negative value (-0.11) that is not significantly difference from zero (p-value = 0.7021). In other words, the logistic analysis does not provide any support for the idea that the education effect is stronger for females than for males.

Should we base our inference on the result of the logistic analysis? To answer this question, we will take two approaches. First, we replace the migration rate by the odds of migration as a measure of migration propensity and then use *odds ratio* as a measure of the impact of a change in the value of an explanatory factor. Second, we replace the logistic model by a probit model, which is another widely used probability model (Cox, 1989).

In the right panel of Appendix Table 1, we see that among males, the odds of migration is 0.0742 for college graduates and 0.1424 for university graduates so that the impact of the change from college to university is represented by an odds ratio of 1.9. Among females, the odds of migration is 0.4269 for college graduates and 0.7348 for university graduates, yielding an odds ratio of 1.7 for representing the effect of the educational improvement. Thus, in terms of odds ratio, the education effect is about the same for the two sexes. Since it is actually slightly higher for males than for females, the use of the odds ratio also does not provide any support for the idea that the education effect is greater for females than for males.

To apply a probit model to the survey data, we use the SAS Logistic procedure with the "Link = Normit" option. The estimation result is shown in the right panel of Appendix Table 2. The estimated coefficient of the interaction $U_i * F_i$ turns out to be a slightly positive value (0.0037) that is not significantly different from zero (p-value = 0.9805). Thus, the probit analysis again does not provide any support for the idea that the education effect is stronger for females than for males.

In sum, we conclude that the effect of education on the migration propensity does not differ between the two sexes. In reaching this conclusion, we have found two important points about measurement: (1) *odds* is better than *probability* as a measure of *propensity*, although the latter is intuitively more appealing than the former; and (2) *odds ratio* is better than the *difference between two probabilities* as a measure of the effect of a change in an explanatory factor.

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Table 1. Misleading information about the effect of edudational attainment on the propensities to make interprefectural migration at marriage in Japan.

Educational attainment	Number of migrants (persons)	Size of at-risk population (persons)	Migration rate (%)
College	245	1,075	22.8
University	221	1,224	18.1
Total	466	2,299	20.3

Data Souce: The 1986 national survey on migration history.

Table 2. Meaningful information about the effect of educational attainment on the propensities to make interprefectural migration at marriage in Japan.

Educational attainment	Number of migrants (persons)	Size of at-risk population (persons)	Migration rate (%)
	Male		
College	23	333	6.9
University	124	995	12.5
	Female		
College	222	742	29.9
University	97	229	42.4

Table 3. Estimation results of different specifications of a logistic model for explaining the propensities of making interprefectural migration at marriage in Japan.

Variable	Coefficient	t-statistic	P-value
Specification 1: Gender is ignored.			
Intercept	-1.2202	-16.8	0.0000
University	-0.2924	-2.8	0.0049
Specification 2: Both educational attainment and gender are considered.			
Intercept	-2.5385	-18.4	0.0000
University	0.5764	4.5	0.0000
Female	1.6785	12.6	0.0000
Specification 3: Educational attainment is ignored.			
Intercept	-2.0837	-23.8	0.0000
Female	1.3688	12.3	0.0000

Note: The simple correlation between "University" and "Female" is -0.508 implying a tolerance level of 0.742 in Specification 2.

Table 4. Somewhat misleading information about the effect of gender on the propensities to make interprefectural migration at marriage in Japan.

Educational attainment	Number of migrants (persons)	Size of at-risk population (persons)	Migration rate (%)
Male	147	1,328	11.1
Female	319	971	32.9
Total	466	2,299	20.3

Appendix Table 1. Is the effect of educational attainment on inter-prefectural migration propensities stronger for females than for males?

Educational attainment	Migration rate (%)		Odds of migration	
	Male	Female	Male	Female
College	6.9	29.9	0.0742	0.4269
University	12.5	42.4	0.1424	0.7348
Difference in migration rate	5.6	12.4	----	----
Odds ratio	----	----	1.9	1.7

Appendix Table 2. Estimation results of the logit and probit models with an interaction term between educational attainment and gender.

Explanatory	Logistic model			Probit model		
variable	Coef.	t-statistic	P-value	Coef.	t-statistic	P-value
Constant	-2.6011	-12.0	0.0000	-1.4825	-14.2	0.0000
University	0.6517	2.8	0.0059	0.3303	2.8	0.0045
Female	1.7499	7.6	0.0000	0.9557	8.3	0.0000
University * Female	-0.1087	-0.4	0.7012	0.0037	0.0	0.9805

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