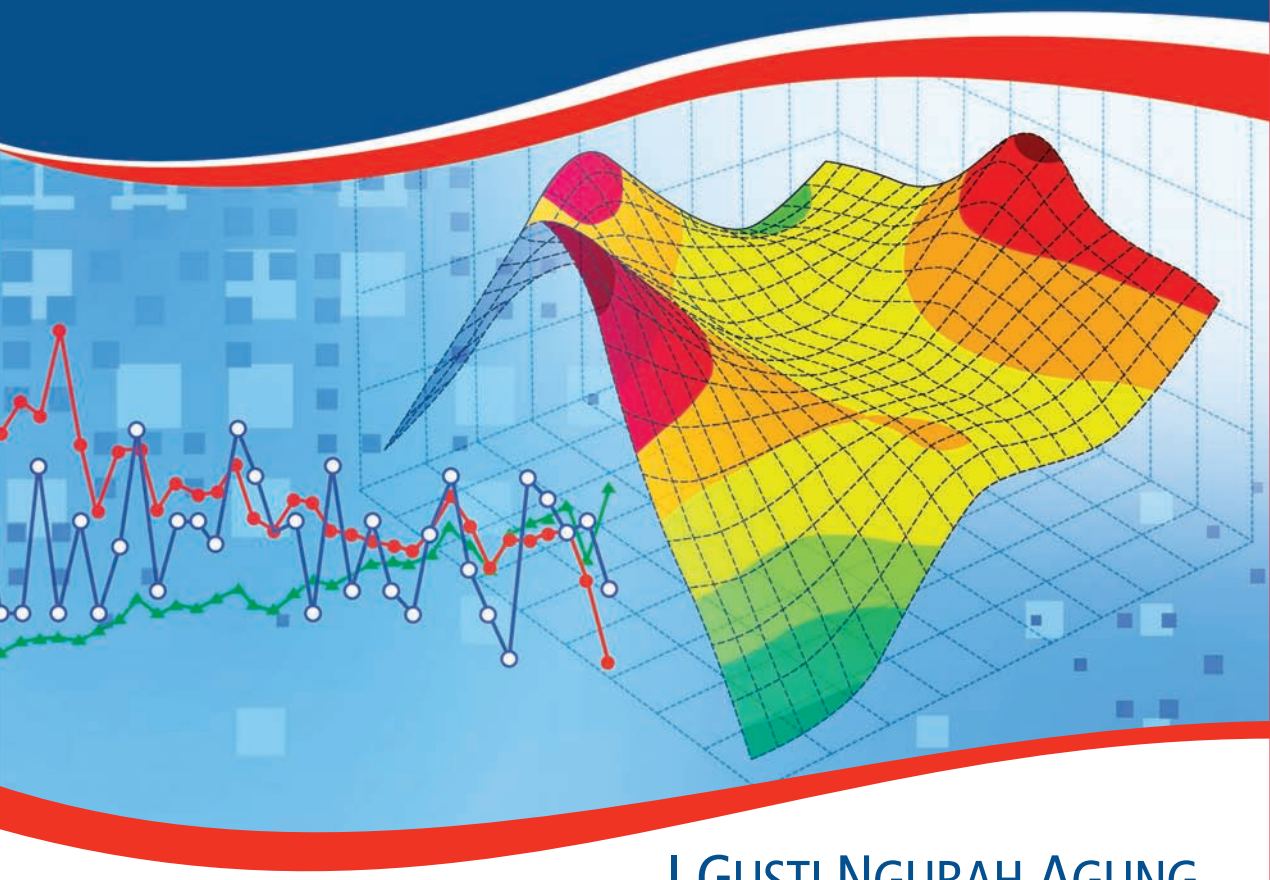
# Cross Section and Experimental Data Analysis Using Eviews



I Gusti Ngurah Agung

WILEY

# CROSS SECTION AND EXPERIMENTAL DATA ANALYSIS USING EVIEWS

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*Dedicated to my wife*
*Anak Agung Alit Mas,*
*my children*
*Martiningsih A. Chandra, Ratnaningsih A. Lefort, and Darma Putra,*
*my sons in law*
*Aditiawan Chandra, and Eric Lefort,*
*my daughter in law*
*Refiana Andries, and*
*all my grandchildren*
*Indra, Rama, Luana, Leonard,*
*Agung Mas Mirah, and Agung Surya Buana*

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# Preface

It is well known that EViews is excellent software for conducting time-series and panel data analyses. However, it has never been considered for doing cross-section data analysis. Based on my own experiences in writing several Indonesian books and papers on data analysis using SPSS, and doing a lot of experiments using EViews, I have found that EViews provides better programs or options for several statistical analysis methods than SPSS does.

The descriptive statistical methods that are very important to mention are specifically the option *Equality Tests by Classification*, which can easily be used to construct various descriptive statistical summaries, by using or inserting any sets of categorical and numerical variables. For inferential statistical methods, EViews provides the Wald test (which can easily be used to test various hypotheses using the model parameters), an object *System* (which can be used to represent a general linear model (GLM, either univariate or multivariate), a structural equation model (SEM), and a seemingly causal model (SCM) – refer to Agung (2009a)), several estimation settings to conduct analysis based on instrumental variables, and STEPLS (stepwise least squares), which has a unique method, namely the combinatorial selection method. Furthermore, EViews also provides many functions, so that anyone can easily generate new series or variables, such as the simplest function @Meansby(arg1, arg2 [ ,s]) for generating the mean of ARG1 by the categorical variable ARG2, and many advanced functions which are beyond the scope of this book.

Furthermore, I have found that all types of model and method for cross-section and experimental data presented in this book can easily be applied to panel data having a large number of observed individuals or objects, by taking into account an additional time *t*-variable. Take note that one of the categorical variables of any of the models presented in this book could be replaced by the categorical time *t* variable. If the panel data have a sufficient number of time-point observations, then the time *t* can be used as a numerical independent variable. Finally, with regard to the piecewise regression models, the models for panel data could have the numerical time *t* variable together with its defined dummy variables. Thus, this book would be an excellent complement or guide for doing analysis based on panel data having a large number of observed individuals or objects.

Each chapter in this book demonstrates the simplest possible data analysis of those presented in the whole chapter. I am very confident that the simplest data analysis (such as the one- and two-way tabulations of the proportions, means, and median), the simplest linear regression of a bivariate numerical variable, and the simplest binary choice model having a single categorical independent variable in particular, as well as simple graphs, can easily be understood by all

readers, especially the statistical users. Furthermore, special notes and comments are also presented for any unexpected or uncommon results. Hence, I would say that this book should be a good guide for undergraduate and graduate students in doing data analysis. And regarding this point, it is important to mention that I have advised many undergraduate students, including my children and grandsons, since 1960.

On the other hand, based on my observations, even graduate students and less-experienced researchers do not think that descriptive statistical analysis is the most useful analysis in an evaluation study. Refer to Chapter 2, specifically the illustrative empirical studies presented in Section 2.15.

It is recognized that all statistical models having numerical dependent variables and their estimation methods based on cross-section data can easily be derived from my first book (Agung, 2009a); thus, the application of those models will not be presented in detail in this book.

Furthermore, note that all models having numerical dependent variables based on any cross-section data, such as the additive and two- and three-way interaction SCMs, could easily be derived from all time-series models presented in Agung (2009a) by using two alternative methods or modifications. And similarly for the instrumental variable models (Chapter 7), nonlinear models (Chapter 10), and the nonparametric estimation methods (Chapter 11).

The first method is to delete the time $t$ variable as well as the lags of endogenous and exogenous variables from the time-series models, and then simpler models would be obtained containing fewer variables. The second method is to replace the time $t$ variable as well as the lags of endogenous and exogenous variables by a relevant set of numerical or dummy variables. Then, under the assumption that the corresponding path diagram is acceptable, in a theoretical sense, various cross-section models, either additive or two- and three-way interaction models, could easily be defined. However, in some cases the path diagrams should be modified to anticipate the structural relationship of the new variables. Many alternative path diagrams are presented in Agung (2009a), and additional illustrative path diagrams will be presented in this book. Finally, all methods for testing hypotheses, specifically the additional or advanced testing hypotheses presented in Agung (2009a: Chapter 9), can be applied directly.

For these reasons, the first book should be considered as a very important complement of this book. Hence, this book will mainly present illustrative data analyses based on models having categorical dependent variables, such as the binary and multinomial choice models, including the ordinal choice models, having categorical or numerical independent variables, as well as both types of independent variable. In addition, selected models having numerical dependent variables, such as the latent variable models and censored dependent variable models, are also presented.

This book contains 12 chapters.

Chapter 1 presents special notes and comments on selected theoretical concepts of statistics, which are misinterpreted by all students and less experienced researchers based on my own observations. Some of the theoretical concepts are the sample space, representative sample, statistic as a function or parameter estimator, hypothesis testing, and random variable and its theoretical normal distribution. In addition, notes on specific groups of variables and causal relationships between variables, in a theoretical sense, are presented, which should be considered even before doing data analysis. Finally, special notes and comments on the

reliability and validity of instruments or tests, as well as on forecasting and the misinterpretation of some sampled statistics, are presented.

Chapter 2 presents simple descriptive statistical summaries which are considered as very important quantitative inputs for decision makers. The statistical summaries presented are frequency tables of the problem (endogenous) indicators by their relevant cause (exogenous) factors, since it is recognized that the causal relationship between variables can be studied using their tabulation based on the transformed categorical variables. In addition, unconditional and conditional measures of association based on *N*-way tabulation are presented. Since, with regard to *N*-way tabulation, EViews also provides the test statistics directly (namely chi-square and likelihood ratio statistics), then this chapter also presents the testing of hypotheses on the multiple associations, as well as on the conditional associations, between categorical variables. Furthermore, this chapter also presents special notes on the statistics-based frequency table with empty cells and incomplete tables. In addition, by defining a specific pattern of causal association between a set of categorical variables, in a theoretical sense, this chapter proposes that the *N*-way tabulation procedure can also be used to test their causal associations. Finally, this chapter demonstrates how to present a descriptive statistical summary based on any set of variables, with examples of empirical studies in various selected fields.

Chapter 3 presents various linear models which have a zero–one indicator as an endogenous variable and a set of dummy variables as exogenous variables generated by either a single or multiple categorical factors, called one-way proportion models. The alternative one-way proportion models presented are the regressions and the binary choice models, starting with the simplest models based on a $2 \times 2$ table. For the model having multiple categorical exogenous variables, it is proposed to generate a cell factor, namely CF, so that any multifactorial models can easily be presented as one-way proportion models. In addition, this chapter demonstrates that a lot of regressions and logistic functions can easily be written based on a cell-proportion tabulation, which are called subjective-regression and subjective-logistic functions. Special notes and comments on the three alternative binary choice models, namely the binary logit, probit, and extreme-value models, are presented. Finally, this chapter presents a one-way proportion model based on the *N*-way tabulation with empty cells and incomplete frequency tables.

Chapter 4 presents various two-way cell-proportion models or bi-factorial design models of a zero–one endogenous variable, in the form of multiple regressions of binary choice models, with categorical exogenous variables. The main objectives of these models are to test hypotheses on the main and interaction effects of categorical exogenous variables on zero–one endogenous variables. For illustration purposes, three types of nonhierarchical model, a full-factorial or hierarchical model, and an additive model are presented. To generalize, multifactorial design models are presented; however, they are treated as if they are bi-factorial design models. For example, based on factors $A$ and $B$, three alternative nonhierarchical models with designs $[A^*B]$, $[A + A^*B]$, and $[B + A^*B]$ and one hierarchical model with a design $[A + B + A^*B]$ can be presented. For the multifactorial designs, the factors $A$ or $B$ can represent two cell factors, namely CF1 or CF2, which are generated based on the subsets of the multifactors. Finally, this chapter presents special multifactorial binary choice models with unexpected statistical results, which are related to the special incomplete frequency tables.

Chapter 5 mainly presents *N*-way or multifactorial multivariate cell-mean models; however, for data analysis, the models would be considered or presented as one-, two-, or three-way

multivariate cell-mean models. In addition, the test for equality of means, variances, and medians of a single numerical variable by various types of categorical factor are presented.

Chapter 6 presents the application of two types of multinomial choice model. The first type of model is a set of one-way and multifactorial binary choice models, and the second type are the one-way and multifactorial ordered choice models. In addition, simple two- and three-level choice models are presented. Finally, special notes on the true multinomial logistic model are presented.

Chapter 7 presents the application of various binary and ordered choice models having numerical exogenous variables, or both numerical and categorical variables, called general choice models (GCMs), starting with various simple GCMs with a single numerical exogenous variable. The models can then easily be extended to a lot of choice or discrete models, both linear and nonlinear GCMs. Special notes and comments on the acceptability of estimates, in a statistical sense, are presented supported by residual analysis.

Chapter 8 demonstrates the applications of various statistical models based on an experimental data set by using the original measured variables and their transformed variables, such as the natural logarithm of the variables, and the zero–one indicators as well as ordinal variables (even though the data only have numerical variables), in addition to treatment factors. In fact, the models, such as the binary and ordered choice models, have been presented in previous chapters. Furthermore, the application of various causal models is also presented, such as MANOVA, homogeneous regression (MANCOVA), heterogeneous regressions, and the system equations, based on numerical variables.

Chapter 9 presents SCMs based mainly on numerical variables, which are most likely do not have pure causal relationships, since the data used is cross-section data. The SCMs presented start with the simplest linear regression in a two-dimensional space, namely SLR_2, based on a pair of numerical variables, and the patterns of their possible relationships are graphically presented in a two-dimensional coordinate system. This is then extended to the simplest linear regression in three-dimensional space, namely SLR_3, and SLR in the $k$-dimensional space, namely SLR_$k$, for $k > 3$, called a *hyperplane* in an abstract space. Finally, various SCMs are presented that correspond to specific path diagrams which represent the causal relationships defined theoretically based on a set of numerical variables.

Chapter 10 presents illustrative examples on how to develop a latent variable based on a set of defined measurable or observable variables or attributes, by using the object *Factor* or *Factor Analysis*, which is available only in EViews 6, and the principal component method for previous versions of EViews. However, this chapter will not present the application of latent variable models in detail, since they can be considered exactly the same as all models based on numerical variables, which are presented in previous chapters and in Agung (2009a). Hence, this chapter only presents single-stage and multistage factor analysis in generating latent variables, selected latent variable models with special notes and comments, and the evaluation or policy analysis based on latent variables.

Chapter 11 demonstrates various acceptable and unexpected regressions obtained based on the same set of three search regressors, in particular based on a larger number of search regressors, by using a multistage stepwise selection method. Since it is well known that the effect of an exogenous (cause, source, upstream, or independent) variable on an endogenous (downstream, impact, or dependent) variable, in general, is theoretically dependent on other exogenous variables, then a two-way interaction model should be applied, and selected or limited three-way interactions may be used as additional independent variables if and only if

the corresponding three main factors are completely correlated or associated, in a theoretical sense. As an extension of all the regressions presented, various similar regressions can easily be developed using transformed variables, such as the semilog and translog linear or nonlinear models, as well as the bounded regression models having $\log[(Y-L)/(U-Y)]$ as an dependent variable, where $L$ and $U$ are the lower and upper bounds of any numerical endogenous variable $Y$.

Finally, Chapter 12 presents unexpected empirical findings based on various Tobit and censored regression models, starting from the simplest models, such as the censored mean and cell-mean models, and censored regression models with one and two numerical variables, are introduced by using the fitted or index values variables, either as dependent or independent variables. Finally, it is found that ARCH and GARCH/TARCH models should be applied based on a switching censored regression.

In addition, I present special notes and comments, most of which are not presented in statistical books as well as research methods. Thus, it is expected that readers will have a better picture of the limitations of the various models, as well as the problems found in doing data analysis, specifically in obtaining alternative acceptable or good-fit models based on sampled data that happen to be selected or are available for the researcher. Refer to the notes and comments about a sample presented in Chapter 1. Furthermore, the advice to readers is to read the special notes and comments presented in Agung (2009a).

I wish to express my gratitude to the Graduate School of Management, Faculty of Economics, University of Indonesia, and the Ary Suta Center, Jakarta, for providing a rich intellectual environment and facilities that were indispensable for the writing of this text. In the process of writing the draft of this book using the PC, I would like to thank the staff of the Graduate School of Management, specifically Tridianto Subagio and Asep Saepul Hayat, who gave great help if I had problems with the software.

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# 1

# Misinterpretation of Selected Theoretical Concepts of Statistics

## 1.1 Introduction

It is recognized that most undergraduate and graduate students do not have sufficient knowledge of the basic theoretical concepts of statistics or mathematical statistics in general, such as the concepts of sample space, representative sample, a statistic as a parameter estimator, testing hypothesis, and random variable and its theoretical (normal) distribution. Thus, they think that they have to prove the theoretical concepts of statistics by using only a sample data set, for instance, error terms of statistical models should have independent and identical normal distributions. In fact, some of them even think that the cross-section data of a numerical variable should be tested whether or not it has a normal distribution, before doing further data analysis.

On the other hand, they think that they have to select a representative sample for their theses or dissertations. This does not have a clear meaning, as in fact there is no sampling method or guide on how to select a representative sample. Agung (1992a) states that it is better not to use the term "representative sample" anymore, since it can be misleading. It is well known that researchers will most likely select a nonprobability sample, specifically a convenient sample where each respondent has a convenient time in giving "good" responses. In other words, most sample survey researches do not use pure random samples, since researchers never take into account a complete list of the population. On the other hand, a random sample is basically defined as a sample where each individual in the population has an equal probability of being selected. In fact, even some of my graduate students for their theses and dissertations should be using a special sampling method, called the *friendship sampling method* (Agung, 2008a), since they should interview managers or high-ranking persons, who have very limited time and most likely do not want to participate in the study, or they are using their friends as the research objects.

Furthermore, it is recognized that most books in applied statistics do not present or discuss the sample space with simple and detailed illustrations. Hence, students or readers never clearly know the limitation of a sample data set for estimating the true value of population parameters. On the other hand, several sampled statistics can be misinterpreted, such as a causal relationship between a pair of variables should be proven using a simple regression,

*Cross Section and Experimental Data Analysis Using EViews*, First Edition. I Gusti Ngurah Agung.

the standard error of a variable, a sample size has to be estimated using a statistical formula, the reliability Crownbach $\alpha$, which in fact is a consistency coefficient, and validity of an instrument data collection, which are in fact computed based on a sample of individuals that happen to be selected by the researchers.

For this reason, the following sections present some notes and comments on selected theoretical concepts of statistics, as well as sampled statistical values, which are considered as very important supporting knowledge in giving values to the statistical results based on a sample data set.

## 1.2 What is a Population?

It has been recognized that a population can be thought of as a complete set of individuals, a complete set of characteristics or variables, or as a complete set of scores, values, or measurements of variables. For these reasons, the following alternative definitions of a population are proposed. On the other hand, a hypothetical population will be introduced later, corresponding to any nonrandom samples which have been used in most or almost all sample survey researches.

**Definition 1.1**

A population is defined as a complete set of all individuals having specific characteristics defined by a researcher, such that each individual can be perfectly classified into whether or not the individual is a member of the population.

**Definition 1.2**

A population is defined as a complete set of all possible characteristics or variables of the observed individuals.

**Definition 1.3**

A variable is a characteristic of a set of individuals, which can have different scores/values/measurements for different individuals in the set.

**Definition 1.4**

A population is a complete set of multidimensional quantitative and qualitative scores, values, or measurements of all possible variables, which could give a complete data or information to a researcher. In other words, a population is a complete set of quantitative and qualitative scores/values/measurements of all possible defined variables.

## 1.3 A Sample and Sample Space

### *1.3.1 What is a Sample?*

**Definition 1.5**

A sample is a finite subset of a defined population. According to Definition 1.4, then, the sample data set, which will be called "sample" for short, will be defined as a finite set of quantitative

and qualitative scores, values, or measurements which happen to be selected by or are available for a researcher.

Take note that in any statistical data analyses, researchers or analysts would always consider a very small set of scores/values/measurements for a limited number of all possible variables or indicators. Researchers will never be observing or measuring a whole population, either as the complete sets of individuals, variables or characteristics, as well as scores/values/measurements. For this reason, every reader should be very confident that researchers will never have the total or complete information of a population, in general.

Corresponding to a sample survey, the population could be classified as a *sample population* and a *target population.* A sample population is defined as the population, from which a sample will directly be selected, by using a specific selection method, such as a multistage sampling method and others (see Kish (1975)). The target population is defined as a much larger population than the sample population for which the statistical results are predicted, estimated, or assumed to be applicable, in a statistical sense. Take note that this statement on the target population is an abstract or theoretical statement, which cannot be proven empirically. Refer to the notes presented in the following sections, as well as the notes in Agung (2009a: Section 2.14).

### *1.3.2 What is the Sample Space?*

**Definition 1.6**

*A sample space* is a set of all possible samples having a fixed size, say $n$, which could be selected from a defined population.

Note that a researcher will never observe a sample space; thus, a sample space should be considered as an *abstract theoretical concept*. Corresponding to the population as a set of a complete individuals, then, any samples of size $n$ would generate or have a sample space consisting of all possible sets of $n$ individuals in the population of size $N > n$. In this case, then, *the sample space of n individuals from the population of size N* can be presented as follows:

$$\Omega(n|N) = \{S_i(n);\ i = 1, \ldots, C(n,N)\} \tag{1.1a}$$

with

$$C(n,N) = \frac{N!}{n!(N-n)!} \tag{1.1b}$$

where $S_i(n)$ indicates the $i$th sample of $n$ individuals, $C(n,N)$ indicates a combination of $n$ out of $N$ individuals, and $k!$ (i.e. $k$-factorial) equals $(1 \times 2 \times 3 \times \ldots \times k)$, and it is defined that $0! = 1! = 1$.

In general, a sample space would have such a large number of elements. The following examples present the concepts of sample space and statistic, with simple illustrations.

**Example 1.1** Sample spaces of a population of size $N = 5$

Suppose a sample of size $n$ is to be selected from a population of size $N = 5$ having identification numbers 1, 2, 3, 4, and 5; then, the following alternative sample spaces, namely the *sample space of individuals*, could be obtained.

1. For $n = 1$, the sample space is

$$\Omega(n = 1|N = 5) = \{1, 2, 3, 4, 5\}$$

   which is equal to the population. Note that the sample of size $n = 1$ can only provide 20% of the total information (i.e., one out of five) individuals in the population, which happen to be selected.
2. For $n = 2$, the sample space is

$$\Omega(n = 2|N = 5) = [\{1,2\}, \{1,3\}, \{1,4\}, \{1,5\}, \{2,3\}, \{2,4\}, \{2,5\}, \{3,4\}, \{3,5\}, \{4,5\}]$$

   where $\{i, j\}$ indicates a set of two individuals in the population, which will be written or presented as

$$\Omega(n = 2|N = 5) = \{12, 13, 14, 15, 23, 24, 25, 34, 35, 45\}$$

   Note that this sample space has $C(2, 5) = 10$ members, namely pairs of individuals, or a set of 10 observation pairs, which is larger than the population size $N = 5$. A member of this sample space could provide information only 40% out of the five individuals in the population. Compared with a sample size of $n = 1$, each member of this sample space can provide more information.
3. For $n = 3$, the sample space of size $C(3, 5) = 10$ will be

$$\Omega(n = 3|N = 5) = \{123, 124, 125, 134, 135, 145, 234, 235, 245, 345\}$$

   Similar to the previous sample size of $n = 2$, each member of this sample space can provide more information, compared with each member of the sample space $\Omega(n = 2|N = 5)$.
4. For $n = 4$, the sample space of size $C(4, 5) = 5$ will be

$$\Omega(n = 4|N = 5) = \{1234, 1235, 1245, 1345, 2345\}$$

   Compared to the previous sample spaces, each member of this sample space can provide a lot more information, since only one individual is not counted or observed.
5. For $n = 5$, the sample space of size $C(5, 5) = 1$ will be

$$\Omega(n = 5|N = 5) = \{12345\}$$

   In this case, the sample is in fact the whole population. In practice, however, one will never observe the whole population, especially for a large population size, since it will be very expensive and time consuming. □

**Example 1.2** A sample as a member of the sample space

For illustration purposes, Table 1.1 presents the sizes of sample spaces by selected population and sample sizes. Based on this table, the following notes and comments are presented.

**Table 1.1** Illustration of the size of sample spaces by population and sample sizes

| $N$ | 25 | 25 | 50 | 50 | 100 | 100 | 100 |
|---|---|---|---|---|---|---|---|
| $n$ | 2 | 4 | 2 | 4 | 2 | 4 | 5 |
| $\Omega$ size | 300 | 12 650 | 1225 | 230 300 | 4950 | 3 921 225 | 75 287 520 |

Table 1.1 demonstrates that, by increasing the sample size, the sizes of the sample spaces are increasing by a very large quantity. For example, by taking a sample of size $n = 2$ (or 2%) from a population of size $N = 100$, a sample space of size 4950 should be considered; by taking a sample of size $n = 4$ (4%), a sample space of size 3 921 225 should be considered; and by taking a sample of size 5%, a sample space of size more than 75 million should be considered. □

**Example 1.3** The mean-sample-space

Corresponding to the sample space $\Omega(n = 2|N = 5)$ in Example 1.1, let $Y_i$, $i = 1, 2, 3, 4, 5$ be the scores for the $i$th individual; then, it will be considered a sample space of the means or average values, called the *mean-sample-space*, as follows:

$$\begin{aligned}\Omega_{\mathrm{m}}(n = 2|N = 5) &= \{(Y_1 + Y_2)/2, (Y_1 + Y_3/2, \ldots, (Y_4 + Y_5)/2\} \\ &= \{(Y_i + Y_j)/2 | i < j = 1, 2, 3, 4, 5\}\end{aligned}$$

If a sample were to be selected, then the sampled mean selected will be one out of the 10 elements in the sample space, which, most likely, will not be equal to the population mean or the *mean parameter*. However, it is easy to derive that the average value of these 10 average values would equal to the mean parameter, as follows:

$$\{(Y_1 + Y_2)/2 + (Y_1 + Y_3)/2 + \cdots + (Y_4 + Y_5)/2\}/10 = \sum_{i=1}^{5} Y_i/5$$

This simple illustration can directly be generalized to the sample space of the means $\Omega_{\mathrm{m}}(n|N)$, for the population of size $N$ with a fixed sample size $n$. This general mean-sample-space will be presented as

$$\begin{aligned}\Omega_{\mathrm{m}}(n|N) = \Omega_{\mathrm{m}}(n) &= \left\{ \sum_{i=1}^{n} Y_i/n | N \right\} \\ &= \left\{ \sum_{i=1}^{n} y_i/n | \forall Y_j, j = 1, 2, \ldots, N \right\}\end{aligned} \tag{1.2}$$

A special case of this mean-sample-space is the sample space of the proportions called the *proportion-sample-space*, which is obtained if and only if $Y_j$ has a value of zero or one for all $j = 1, 2, \ldots, N$. This proportion-sample-space can be written in a simple form as

$$\Omega_{\mathrm{p}}(n|Y_j = \{0, 1\}, j = 1, \ldots, N) = \{0, 1/n, 2/n, \ldots, (n-1)/n, 1\} \tag{1.3}$$

where $\Omega_p = 0$ indicates that all individuals in the sample have zero scores, and $\Omega_p = 1$ indicates that all individuals in the sample have scores of ones, under the condition the numbers of zeros ($N_0$) and ones ($N_1$) in the population are greater than $n$, namely $N_0 > n$ and $N_1 > n$.

These sample spaces have a $C(n, N)$ total number of element, as presented in (1.1); however, many or a lot of subsample spaces have identical average observed values. Note that the proportion-sample-space $\Omega_p(n|N)$ has only $(n + 1)$ possible values from a set of $C(n, N)$ possible samples. This condition indicates that the sample space of the means, as well as the sample space of the proportion, has a distribution. □

### *1.3.3 What is a Representative Sample?*

In a sample survey, in general, a very large size of sample space should be considered. Refer to the sample space of the sample of size $n = 5$, which could be selected from a population of size $N = 100$, presented in the previous example. So this is what a sample is, a representative sample in particular. An illustration is provided in the following example.

**Example 1.4** A member of the proportion-sample-space

With regard to the proportion-sample-space in (1.3), a sample of any sample size will provide only a single value of proportion, say $k/n$, for a fixed value of $k$, out of the $(n + 1)$ possible proportions. How could you know (or be sure) that the observed proportion is equal to the proportion in the population?

For illustration purposes, let us refer to the sample space $\Omega(n = 2|N = 5)$ presented in Example 1.3. In this case, the sample of size 40% of the population should be considered as a relatively large sample size. Even though the sample is large, every reader should be confident that the 40% selected individuals cannot be representing the other 60% in all of their characteristics. Then by considering a zero–one population of size $N = 5$, namely {1, 1, 1, 0, 0}, the proportion-sample-space is $\Omega_p(n = 2) = \{0, 1/2, 1\}$, as presented above. Note that the proportion of 1 (ones) in the population is 0.60 (i.e., the population mean or the value of the mean parameter), which does not in the sample space. In fact even, by taking a random sample of size $n = 4$, the proportion-sample-space will be $\Omega_p(n = 4|N = 5) = \{1/2, 3/4\}$, since there are only two zeros and three ones in the population, and this sample space also does not contain the value of 0.60. Hence, it is very clear that a sample cannot be representing the population.

Finally, by considering the sample space $\Omega_p(n = 5|N = 100)$, a sample of size 5% should be selected out of more than 75 million possible samples, as presented in Table 1.1. Whatever the sampling method applied, it should be realized that there will never be a representative sample, especially if a sample of size less than 5% were to be selected from a population of size greater than 100. □

On the other hand, the term "representative sample" is, in fact, not an operational statement or terminology, since there is no method or guide on how to select a representative sample. In other words, the term "representative sample" is an abstract statement, which could be misleading. For this reason, Agung (1992a) suggested no longer using this terminology. Furthermore, it is suggested to use any sampling methods which are considered feasible for the study, such as snowball, purposive, convenience, and friendship (*kekerabatan*, in Agung (2008a)). The friendship sampling method should be applied by my students for their dissertations, since they

have to interview managers or high-ranking persons, who are most likely not willing to participate in a study, particularly in Indonesia.

Even though a random sample is required for the inferential statistical analysis, as well as for the statistical theory in general, it has been recognized that a pure random sampling method can never be applied in practice. Note that the pure random sampling method can be applied only if a complete list of individuals in the population is known. However, in practice, a complete list of the individuals in a population is never taken into account by a researcher, then it is suggested the term "random sampling method" should not be used any more in a research proposal. Every reader should be very confident in using any nonprobability sampling method, such as quota, snowball, and convenient sampling methods. For this reason, I propose the following definitions.

**Definition 1.7**

A sample is an element of a sample space *which happens to be selected* from the corresponding sample space.

**Definition 1.8**

A sample data set is a set of multidimensional scores, values, or measurements of a finite number of variables *which happen to be selected by* or *are available for* a researcher.

Under these definitions, every reader should be very confident that sample data cannot provide complete information on the corresponding population, such as the true values of the basic parameters, as well as the true population models. Refer to the notes and comments presented in the following sections and in Agung (2009a: Section 2.14).

### *1.3.4 Relationship between the Sample Space, Population, and a Sample*

Based on the characteristics of the sample space, population, and a sample previously presented, Figure 1.1 illustrates their relationships. This figure shows that the sample space

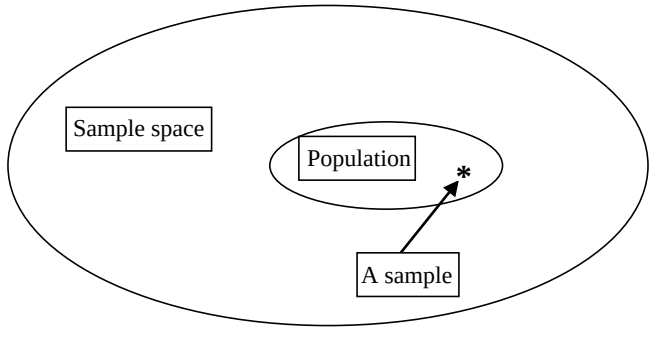


**Figure 1.1** Relationship between of the number of elements in a sample space and its corresponding population and a selected sample.

has a much greater number of elements than the population, and a sample is an *element* (or a *point*) of the sample space which happens to be selected by a researcher. Refer to the illustrative examples presented in Table 1.1, specifically the sample space of size 75 287 520 corresponding to a sample of size on $n = 5$ selected from a population of size $N = 100$. Thence, it is not right to say that a sample is a representative of the corresponding population or, moreover, the sample space.

In empirical statistics, the data analysis is done based on a sample only. On the other hand, the theoretical statistics derive all theorems, statistics, and their distributions based on the sample space, specifically the sample space of a random sample, namely the *random sample space*. See the following sections.

## 1.4 Distribution of a Random Sample Space

In probability or statistical theory, if the sample is a pure random sample, then the proportion-sample-space $\Omega_p$ in (1.3) has the *binomial probability distribution function*:

$$\Pr(\Omega_p = k/n) = C(k,n)p^k q^{n-k} \tag{1.4}$$

where $p$ is the proportion of ones and $q$ is the proportion of zeros in the population, such that $p + q = 1$.

Furthermore, Conover (1980: 544) stated that the binomial probability distribution function can be approximated by a normal distribution for $n > 20$. For illustration purposes, suppose we have the set of values {1, 1, 1, 0, 0} for the population of size $N = 5$ presented above; then, based on the sample space $\Omega_p(n = 2|N = 5)$, the sample space of proportions is $\Omega_p(n = 2|N = 5) = \{0, 1/2, 1\}$, where the number of the zero-proportion is only one $= C(2, 2)$, the proportion of 0.50 is a multiple of $C(1, 3) \times C(1, 2) = 3 \times 2 = 6$, and the proportion of ones is a multiple of $C(2, 3) = 3$. Hence, there are $10 = C(2, 5)$ possible samples of individuals, but three possible proportions. In this case, the sample space has a distribution {0.1, 0.6, 0.3}, which can presented as

$$\Pr(\Omega_p = 0) = 0.1,\ \Pr(\Omega_p = 1/2) = 0.6, \quad \text{and} \quad \Pr(\Omega_p = 1) = 0.3$$

with the following general equation or restriction, based on a random sample of size $n$ from the population of size $N$:

$$\begin{aligned} &\Pr(\Omega_p = k/n) = p_k,\ k = 0, 1, \ldots, n \\ &\sum_{i=0}^{n} \Pr(\Omega_p = k/n) = \sum_{i=0}^{n} p_k = 1,\ p_k \geq 0,\ \forall k \end{aligned} \tag{1.5}$$

Similarly, for the mean-sample-space in (1.2) we will have

$$\sum_i \Pr(\Omega_m = m_i) = 1,\ \infty < m_i < \infty,\ \forall i \tag{1.6}$$

where $m_i$ indicates the $i$th mean or element in the mean-sample-space. In this case, however, the number of distinct mean values cannot be identified.