Inferential Statistics

CHAPTER

12

What You Should Know!

The purpose of inferential statistics is to acquire knowledge that can be used to make inferences or predictions about the data. The type of inferential statistic used largely depends on the variables' levels of measurement within the analysis. After completing this chapter, the reader should be able to:

1. Differentiate between descriptive, comparative, and inferential statistics.
2. Discuss measures of association, including lambda, gamma, and Pearson's r, and provide examples.
3. Explain what is meant by statistical significance, and describe how tests of significance are used.
4. Describe the commonly used comparative statistics techniques, including crime rates, crime-specific rates, percentage change, and trend analyses.
5. Discuss bivariate analysis and provide examples.
6. Discuss multivariate statistics, and provide an example of a multivariate technique for nominal- and ordinal-level data.
7. Describe the various multivariate techniques for ratio-level data.

Statistical Analysis

The previous chapter discussed the three types of statistics: descriptive, comparative, and inferential. Descriptive statistics describe the data being analyzed. A variety of descriptive statistics were presented in Chapter 11, including measures of central tendency and variability. Comparative statistics, whose function is to compare the attributes of two variables, were also introduced. Comparative statistics are within a "gray area" that moves from description to inference. As such, comparative statistics are often classified as either descriptive or inferential rather than as a separate category.

Inferential statistics were briefly touched on in Chapter 11. The purpose of inferential statistics is to make inferences, estimations, or predictions about the data. This chapter shows how comparative statistics may be used to begin making inferences about the data and provides an overview of inferential statistics. Criminal justice and criminological researchers use a variety of inferential techniques. The selection of the proper inferential technique is based on the characteristics of the data, including the variables' levels of measurement.

Overview of Inferential Statistics

Inferential statistics allow the researcher to develop inferences (predictions) about the data. If the sample is representative (Chapter 5), then these predictions may be extended to the population from which the data were drawn. Inferential statistics allow criminal justice and criminological researchers to conduct research that can be generalized to populations within society. When making inferences about datasets, researchers rely on measures of association to determine the strength and direction (if applicable) of the relationships between or among variables. Tests of significance are also used to determine whether the sample that was examined is representative of the population from which it was drawn.

Measures of Association

Measures of association are used to determine the strength of relationships and direction (if appropriate) among the variables that are being studied. The measure of association that is used is dependent on the type of analysis being conducted, the distribution of the data, and the level of data under analysis. Many measures of association are used in criminal justice and criminological research, but some measures are more commonly used and are considered to be standards, such as lambda, gamma, and Pearson's r and r^2. Lambda is commonly used for nominal-level data. Gamma is commonly used for ordinal-level research. Pearson's r and r^2 are commonly used for interval- and ratio-level data.

Measures of association for nominal-level data, such as lambda, tell researchers how strong the relationship is but do not indicate directionality. Lambda is based on a cross-tabulation (Chapter 11) and determines the strength of the relationship. The outcome of lambda will range from 0 (no relationship) to 1 (a perfect relationship). A 0.00001 indicates a very weak relationship. A 0.9999 indicates an extremely strong relationship. Researchers can assess the strength of the relationship as being weak, moderate, or strong. For example, a lambda score of 0.5367 indicates a moderate relationship, whereas a lambda score of

0.8249 is an indicator of a relatively strong relationship. Since nominal-level variables do not indicate direction, the lambda also does not indicate direction, and researchers have to assess the cross-tabulation (also known as a contingency table) to determine the structure of the relationship.

For ordinal-level data, measures of association, such as gamma, tell the researcher both the strength and the direction of the relationship. Gamma is based on a cross-tabulation and will range from −1.00 to +1.00. A zero (0) indicates no relationship; a negative one (−1) indicates a perfect negative relationship (as one variable increases, the other variable decreases); and a positive one (+1) indicates a perfect positive relationship (as one variable increases, the other variable increases). A score of −0.8790 indicates a strong, negative relationship, whereas a score of +0.2358 indicates a weak, positive relationship.

Measures of association for ratio-level data, such as Pearson's r and r^2, indicate both the strength and direction of the relationship. Keep in mind that for analysis purposes, interval-level data are treated as ratio-level data. The results for Pearson's r range from −1.00 to +1.00 and are interpreted the same as the results for gamma. Pearson's r^2 is determined by squaring (multiplying the number by itself) and indicates the percent of variance explained in the dependent variable by the independent variable. A higher percentage indicates a stronger relationship. In addition to the strength and direction of the relationship, statistical significance is also of importance.

Statistical Significance

The presence of statistical significance indicates that the sample findings are representative of the population being studied. If a researcher is using a complete enumeration (the entire population is studied rather than just a sample from that population), then determining statistical significance is unnecessary because it is already known that the population is accurately represented. However, complete enumerations are rare because studying entire populations is too costly and time consuming.

Statistical significance is based on probability sampling and is used when trying to determine a nomothetic explanation for a phenomenon (Chapter 6). It is this use of probability that enables researchers to make inferences based on relatively few observations. Generally, social science researchers require a statistical significance of 0.05 or better, which indicates that they are 95% confident that the findings from the sample represent the population, to state that a result is statistically significant.

Comparative Statistics

Several comparative techniques are available to criminal justice researchers. Briefly discussed here are crime rates, crime-specific rates, percentage change, and trend analyses. These examples of comparative statistics are widely used within the field of criminal justice and provide the basis for the FBI's Uniform Crime Reports (Chapter 11).

Crime Rates

Crime rates are perhaps the most frequently presented data within criminal justice and criminological research and are simply the number of crimes that occurred in an area (e.g., city, county, state) divided by the population for that area and then typically multiplied by 100,000. The purpose of calculating crime rates is to allow the comparison of the occurrence of crime between places with different population sizes. Crime rates for index crimes (i.e., murder and nonnegligent homicide, forcible rape, robbery, aggravated assault, burglary, motor vehicle theft, larceny-theft, and arson) are commonly displayed in the Uniform Crime Reports. **Table 12-1** provides an example of violent crime rates. By viewing the rates presented in that table, the reader may easily compare the rates among the various states even though the states have different populations.

Crime-Specific Rates

Crime-specific rates differ from crime rates in that they use a different base than population within the computations. For example, one could look at motor vehicle thefts by number of registered vehicles, burglaries by number of households, or gun-related crimes by number of registered guns. This method can also be used to calculate victimization rates, arrest rates, and clearance rates.

TABLE 12-1

Violent Crime Rates per 100,000 Population for Select States, 2014

State	Population	Violent crime	Murder and nonnegligent manslaughter	Rape	Robbery	Aggravated assault
Arizona	6,731,484	399.9	4.7	50.2	92.8	252.1
California	38,802,500	396.1	4.4	29.7	125.5	236.6
Hawaii	1,419,561	259.2	1.8	31.3	78	148.1
Nevada	2,839,099	635.6	6	47.8	209.7	372.1
Texas	26,956,958	405.9	4.4	42.3	115.7	243.6
Washington	7,061,530	285.2	2.5	38.2	79.9	164.7
Wyoming	584,153	195.5	2.7	29.8	9.1	153.9

urce: Data from "Crime in the United States, 2014: Violent Crime," Federal Bureau of Investigation, 2015.

Percentage Change

Percentage-change statistics allow researchers to compare data over time. The computation is straightforward: Subtract the earlier number from the later number, and then divide the difference by the earlier number. This statistic allows one to determine whether there has been an increase or decrease in particular crimes between the two points in time. The bottom of Table 12-2 demonstrates this statistic for three index crimes in the United States for three different sets of years.

Trend Analyses

Trend analyses are yet another way of comparing differences over time. Researchers may use a visual representation, such as a histogram, to show how rates have increased for a particular offense. Trend analyses are quite useful in assessing the impact of crime prevention strategies. The reader should refer to Table 12-2, which shows the number of specific crimes from 1998 to 2007. From this table, one can determine what trends may have existed for these crimes during the reported time frame.

TABLE 12-2

Specific Crimes in the United States by Volume, Rate per 100,000, and Percent Changes, 1998–2007

Year	Population	Forcible rape volume	Forcible rape rate	Robbery volume	Robbery rate	Aggravated assault volume	Aggravated assault rate
1998	270,296,000	93,144	34.5	447,186	165.4	976,583	361.3
1999	272,691,000	89,411	32.8	409,371	150.1	911,740	334.3
2000	281,421,906	90,178	32	408,016	145	911,706	324
2001	284,796,887	90,491	31.8	422,921	148.5	907,219	318.5
2002	287,973,924	95,235	33.1	420,806	146.1	891,407	309.5
2003	290,788,976	93,883	32.3	414,235	142.5	859,030	295.4
2004	293,656,854	95,089	32.4	401,470	136.7	847,381	288.6
2005	296,507,061	94,347	31.8	417,438	140.8	862,220	290.8
2006	299,398,484	92,757	31	447,403	149.4	860,853	287.5
2007	301,621,157	90,427	30	445,125	147.6	855,856	283.8
Percent change in volume and rate per 100,000 inhabitants for 2, 5, and 10 years							
2007/2006		−2.5	−3.2	−0.5	−1.2	−0.6	−1.3
2007/2003		−3.7	−7.1	+7.5	+3.6	−0.4	−3.9
2007/1998		−2.9	−13	−0.5	−10.8	−12.4	−21.5

Inferential Statistics

Inferential statistics make inferences, estimations, or predictions about the data. Because of the nature of inferential statistics, to do justice in explaining them requires a text of its own. Extensive explanations are left for statistics courses, but brief descriptions of selected statistics follow.

Bivariate Analysis

Bivariate analysis is the examination of the relationship between two variables. Usually this analysis involves attempting to determine how a dependent variable is influenced by an independent variable. The more commonly used bivariate techniques are contingency tables and bivariate (simple linear) regression. Assessing the relationship between two variables addresses the strength of the relationship, the direction of the relationship (if applicable), and the level of significance.

Contingency Tables (or Cross-Tabulations)

With nominal- and ordinal-level data, two popular statistical techniques are contingency tables (cross-tabulations) and chi-square, which is a common statistic for a contingency table. A contingency table is a set of interrelated cells that displays the relationship between two variables. Each cell can display a variety of data (**Table 12-3**), such as frequencies or percentages. From these data, a chi-square (χ^2) statistic can be calculated. Chi-square is one test of statistical significance that is popular because it can be used with data at any level of measurement. The contingency tables (cross-tabulations) and chi-square measure offer an analysis of the statistical relationship from which one might make an inference.

Bivariate Regression

Bivariate regression, also known as *simple linear regression*, is based on the principle that over time things tend to regress toward the mean. For example, if one were to measure the heights of female students enrolled at a school, one would find that they range from well above average to well below average height for women. Assuming a normal population, most of the heights would tend to cluster around the mean (average) height.

Bivariate regression is appropriate to examine the relationship between two variables when using ratio-level data with data that are normally distributed (Chapter 11) and have a linear relationship. If two variables have a linear relationship, then as the independent variable (X) increases, so does the dependent variable (Y). Conversely, if a negative relationship exists (e.g., a crime prevention strategy), then as X (the strategy used) increases, Y (the specific crime targeted) is expected to decrease.

TABLE 12-3

Example of Contingency/Cross-Tabulations: Overall Job Satisfaction by Level of Education/Degree

	Count Exp Val Row Pct Col Pct Tot Pct	EDUCATION H.S. Diploma 1	Assoc. Deg. 2	Bach. Deg. 3	Master's Deg. 4	Row Total
Overall	2	1 .5 100.0% 4.5% 2.3%	0 .2 .0% .0% .0%	0 .3 .0% .0% .0%	0 .0 .0% .0% .0%	1 2.3%
Neutral	3	11 10.2 55.0% 50.0% 25.6%	4 4.2 20.0% 44.4% 9.3%	4 5.1 20.0% 36.4% 9.3%	1 .5 5.0% 100.0% 2.3%	20 46.5%
	4	9 9.2 50.0% 40.9% 20.9%	3 3.8 16.7% 33.3% 7.0%	6 4.6 33.3% 54.5% 14.0%	0 .4 .0% .0% .0%	18 41.9%
Extremely Satisfied	5	1 2.0 25.0% 4.5% 2.3%	2 .8 50.0% 22.2% 4.7%	1 1.0 25.0% 9.1% 2.3%	0 .1 .0% .0% .0%	4 9.3%
Column Total		22 51.2%	9 20.9%	11 25.6%	1 2.3%	43 100%

Chi-Square	Value	DF	Significance
Pearson's	5.12525	9	.82326
Likelihood Ratio	5.53040	9	.78584
Linear-by-Linear Association	.61069	1	.43453

Minimum Expected Frequency—.023

Cells with Expected Frequency < 5 – 13 of 16 (81.3%)

Approximate Statistic	Value	ASE1	Val/ASEO	Significance
Phi	.34524			.82326
Cramer's V	.19933			.82326
Contingency Coefficient	.32634			.82326

Multivariate Analysis

Multivariate analysis is the examination of the relationship between three or more variables. Usually this involves attempting to determine how a dependent variable is influenced by more than one independent variable. This methodology offers more insights than bivariate analysis, in that it is possible to study the relationships among several variables at one time. The more commonly used multivariate techniques are Student *t* test, correlation, analysis of variance (ANOVA), and multiple regression (Frankfort-Nachmias & Leon-Guerrero, 2008; Gavin, 2008; Walker & Maddan, 2009; Weisburd & Britt, 2007). Again, the purpose here is not to teach how to compute these measures but rather to provide a brief overview of how these tools might be used in criminal justice and criminological research and what to discuss with a statistician if using this strategy.

Student *t* Test

The Student *t* test is used to compare groups' means for a particular variable and hypothesis testing. Computing Student *t* is a fairly complex process that contrasts expected outcomes with observed outcomes. The differences among the means of the variables are then assessed. The Student *t* indicates whether the relationship between the groups is statistically significant. As seen in **Table 12-4**, the differences between the means are obvious. The *t*-values do not mean anything at this point, but indicate the values used by the computer to calculate the significance.

Correlation

Correlation is a commonly used technique for evaluating ratio-level data. The previous discussion of bivariate regression explained how relationships between two variables are examined based on the assumption of a linear relationship. In correlation, relationships are assessed based on covariation. Covariation simply means that as changes occur in one variable, X, there will also be changes in another variable, Y. Assessing correlations is based on how the variation in one variable corresponds to variation in the other variable.

The means of assessing the correlation of ratio-level data is Pearson's r, which is used to determine the strength of the association among variables by dividing the covariance of X and Y by the product of the standard deviation of X and Y. The statistical software packages calculate these numbers. Of interest here is the strength, direction (recall one is looking at a number between −1 and +1), and level of significance. **Table 12-5** is an example of the use of correlations in analyzing ratio-level data.

Analysis of Variance

ANOVA is another means of examining ratio-level data. Where correlation uses Pearson's r to determine the nature of relationships among variables, ANOVA

TABLE 12-4

Student's *t* for Student's Perceptions of Policing Comparison of Selected Means Scores, by Time

Variable	Mean (t_1)	Mean (t_2)	*t*-value
Primary Role	.554	−.458	5.49*
Level of Competency	−.747	−1.289	4.29*
Serve and Protect	−1.000	−.800	−1.27
Corrupt Act	−.598	−.390	−1.33
Strike a Minority	−.171	−.500	2.37*
Ignore Needs	−1.000	−1.060	.55
Preventing Crime	−.476	−.951	2.97*
Harass or Help	−1.374	−1.470	.96
Unknown Reaction	.482	.716	−1.65
Professionalism	.183	.598	−3.38*
Help Society	.627	.928	−1.84
Benefit of Doubt	.256	.646	−2.39*

* = $p < .05$

Note: t_1 and t_2 represent the distribution of the questionnaire. t_1 was at the beginning of the semester, and t_2 was the end of the semester.

Source: Modified from Dantzker, M. L., & Ali-Jackson, N. (1998). Examining students' perceptions of policing and the effect of completing a police-related course. In M. L. Dantzker, A. J. Lurigio, M. J. Seng, & J. M. Sinacore (Eds.), *Practical Applications for Criminal Justice Statistics* (pp. 195–210). Boston, MA: Butterworth-Heinemann. Copyright Elsevier 1998.

uses something known as an *F ratio* to compare the means of three or more groups. This technique helps avoid committing errors that might occur when using multiple *t* tests (Frankfort-Nachmias & Leon-Guerrero, 2008). ANOVA allows statisticians to determine significance by assessing the variability of group means. Therefore, it is a useful method for evaluating grouped data (e.g., the outcomes of correctional treatments on inmate groups). Table 12-6 is an example of ANOVA findings.

Multiple Regression

Multiple regression, which is also known as *ordinary least squares*, is another means of analyzing ratio-level data. It is based on the same assumptions as bivariate regression. However, instead of assessing the relationship between only two variables, multiple regression usually examines the associations between several variables at once. This popular technique enables researchers to look not only at how the independent variables predict the outcome of the dependent variable, but also at the relationships among the independent variables. Multiple regression goes beyond bivariate analysis by also assessing variance among the independent variables (Keith, 2005). Researchers can use multiple regression to see how the

TABLE 12-5

Correlation

Variable(s)	Incomp	Motto	Corrupt	College
Role				
Pearson's r	.119	.133	.058	−.145
Sig. (2-tailed)	.013	.006	.230	.003
N	439	435	437	413
Incomp				
Pearson's r	1.000	.346	.308	−.054
Sig. (2-tailed)		.000	.000	.277
N	440	436	438	414
Motto				
Pearson's r	.346	1.000	.349	−.085
Sig. (2-tailed)	.000		.000	.086
N	436	436	434	410
Corrupt				
Pearson's r	.308	.349	1.000	−.106
Sig. (2-tailed)	.000	.000		.032
N	438	434	438	412
College Years				
Pearson's r	−.054	−.085	−.106	1.000
Sig. (2-tailed)	.277	.086	.032	
N	414	410	412	414

variables interact, and then they can use this knowledge to add relevant independent variables or to remove irrelevant independent variables (variables that do not impact the analysis) from the regression equation. An example of multiple regression results is shown in **Table 12-7**. However, to determine whether to use multiple regression and how to deal with problems that may arise, one should consult with a statistician or someone experienced in using regression.

Other Multivariate Techniques

In addition to the multivariate techniques discussed previously, several other methods are popular among criminologists. All of them require a solid understanding of the statistical procedures involved. Further explanations are left for statistics courses, and only brief descriptions of selected additional statistics are offered here.

TABLE 12-6

Selected ANOVA Results from a Perceptions Study

Value Label	Mean	Std Dev	Sum of Sq	d.f.	F
AVOID					
Springfield Acad	−1.3750	.5310	13.2500		
MA Regional Acad	−1.7500	.4935	9.5000	1	11.60*
CORRUPT					
Springfield Acad	−1.4375	.7693	27.8125		
MA Regional Acad	−1.4000	.9282	33.6000	1	04
DRUGS					
Springfield Acad	.0625	1.4790	102.8125		
MA Regional Acad	.4500	1.4313	79.9000	1	1.54
EXPECTATIONS					
Springfield Acad	.1702	1.2036	66.6383		
MA Regional Acad	−.2500	1.0801	45.5000	1	2.89
HELP SOCIETY					
Springfield Acad	1.3750	.7889	29.2500		
MA Regional Acad	1.4000	.8412	27.6000	1	.02
IGNORE					
Springfield	1.3958	.8440	33.4792		
MA Regional Acad	−1.6500	.6222	15.1000	1	2.50

*p-.01

TABLE 12-7

Multiple Regression: Regressions of County Population Against Crime and Arrests in Montgomery County, 1970–1990

Variable	bo	b1	R2	F	Sig F
Part I Crimes	1,810.7	38.3	.50	18.7	.000
Part II Crimes	3,029.4	56.4	.29	7.8	.012
Total Crimes	4,840.1	94.7	.50	18.6	.000
Part I Arrests	3,177.5	2.6	.40	12.6	.002
Part II Arrests	−1,059.8	11.9	.47	16.9	.001
Total Arrests	2,117.7	14.6	.60	28.0	.000

Source: Modified from Guynes, R., & McEwen, T. (1998). Regression analysis applied to local correctional systems. In Dantzker, M. L., et al. *Practical Applications for Criminal Justice Statistics* (pp. 149–168). Boston, MA: Butterworth-Heinemann. Copyright Elsevier 1998.

Probit and logistic regression can be used to complete multivariate regression for analyses with nominal- or ordinal-level dependent variables. Multiple regression assumes the dependent variable is a ratio-level variable, which is not always the case; that the data distributions will be normal; and that the relationship between the independent and dependent variables will be linear, which is not the case if the dependent variable is a nominal- or ordinal-level variable. Like multiple regression, both logistic and probit results are assessed using r^2 as the measure of association (Keith, 2005). Probit and logistic regression, as well as chi-square, are examples of nonparametric techniques that have been designed to address the issue of analyzing data with distributions that are not normal.

Discriminate analysis is a favorite technique of some authors. It is appropriate when the analysis consists of ratio-level independent variables and a nominal-level dependent variable. A discriminate analysis focuses on being able to classify observations into the nominal categories of the dependent variable based on their values on a set of independent variables. Factor analysis also categorizes data. It is used to determine patterns among the variation of values of the variables being studied. Variables that are highly correlated are clustered together based on computer-generated factors (Keith, 2005). This is an extremely complex procedure that must later be interpreted by the researcher to determine whether the factor loadings (the outcomes) have logical meaning. Finally, path analysis seeks to provide a graphic depiction of the causal relationships among the independent variables to explain their influences on the dependent variable. Like factor analysis, it is a complex procedure that is best left to statisticians.

Summary

This chapter provides an overview of several statistical techniques that should aid the reader in understanding research and preparing their own. The authors do not claim to provide the knowledge needed for in-depth data interpretation (which is provided in statistics textbooks and courses), but one should be able to grasp the principles involved in conducting inferential statistics. The reality of modern research is that researchers do not really need to be expert statisticians. Many statistical analyses can be completed through a variety of user-friendly software packages. Often, all the researcher needs to do is be able to code and enter data, choose what statistical techniques should be run, interpret the results, and report the findings.