RESEARCH NOTE

What Are Degrees of Freedom?

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1 TRANSFER

s we were teaching a multivariate statistics course for doctoral students, one of the students in the class asked, "What are degrees of freedom? I know it is not good to lose degrees of freedom, but what are they?" Other students in the class waited for a clear-cut response. As we tried to give a textbook answer, we were not satisfied and we did not get the sense that our students understood. We looked through our statistics books to determine whether we could find a more clear way to explain this term to social work students. The wide variety of language used to define degrees of freedom is enough to confuse any social worker! Definitions range from the broad, "Degrees of freedom are the number of values in a distribution that are free to vary for any particular statistic" (Healey, 1990, p. 214), to the technical:

Statisticians start with the number of terms in the sum [of squares], then subtract the number of mean values that were calculated along the way. The result is called the degrees of freedom, for reasons that reside, believe it or not, in the theory of thermodynamics. (Norman & Streiner, 2003, p. 43)

Authors who have tried to be more specific have defined degrees of freedom in relation to sample size (Trochim, 2005; Weinbach & Grinnell, 2004), cell size (Salkind, 2004), the number of relationships in the data (Walker, 1940), and the difference in dimensionalities of the parameter spaces (Good, 1973). The most common definition includes the number or pieces of information that are free to vary (Healey, 1990; Jaccard & Becker, 1990; Pagano, 2004; Warner, 2008; Wonnacott & Wonnacott, 1990). These specifications do not seem to augment students' understanding of this term. Hence, degrees of freedom are conceptually difficult but are important to report to understand statistical analysis. For example, without degrees of freedom, we are unable to calculate or to understand any underlying population variability. Also, in a bivariate and multivariate analysis, degrees of freedom are a function of sample size, number of variables, and number of parameters to be estimated; therefore, degrees of freedom are also associated with statistical power. This research note is intended to comprehensively define degrees of freedom, to explain how they are calculated, and to give examples of the different types of degrees of freedom in some commonly used analyses.

DEGREES OF FREEDOM DEFINED

In any statistical analysis the goal is to understand how the variables (or parameters to be estimated) and observations are linked. Hence, degrees of freedom are a function of both sample size (N) (Trochim, 2005) and the number of independent variables (k)in one's model (Toothaker & Miller, 1996; Walker, 1940; Yu, 1997). The degrees of freedom are equal to the number of independent observations (N), or the number of subjects in the data, minus the number of parameters (k) estimated (Toothaker & Miller, 1996; Walker, 1940). A parameter (for example, slope) to be estimated is related to the value of an independent variable and included in a statistical equation (an additional parameter is estimated for an intercept in a general linear model). A researcher may estimate parameters using different amounts or pieces of information, and the number of independent pieces of information he or she uses to estimate a statistic or a parameter are called the degrees of freedom (df)(HyperStat Online, n.d.). For example, a researcher records income of N number of individuals from a community. Here he or she has Nindependent pieces of information (that is, N points of incomes) and one variable called income (k); in subsequent analysis of this data set, degrees of freedom are associated with both N and k. For instance, if this researcher wants to calculate sample variance to understand the extent to which incomes vary in this community, the degrees of freedom equal N - k. The relationship between sample size and degrees of freedom is

positive; as sample size increases so do the degrees of freedom. On the other hand, the relationship between the degrees of freedom and number of parameters to be estimated is negative. In other words, the degrees of freedom decrease as the number of parameters to be estimated increases. That is why some statisticians define degrees of freedom as the number of independent values that are left after the researcher has applied all the restrictions (Rosenthal, 2001; Runyon & Haber, 1991); therefore, degrees of freedom vary from one statistical test to another (Salkind, 2004). For the purpose of clarification, let us look at some examples.

A Single Observation with One Parameter to Be Estimated

If a researcher has measured income (k = 1) for one observation (N = 1) from a community, the mean sample income is the same as the value of this observation. With this value, the researcher has some idea of the mean income of this community but does not know anything about the population spread or variability (Wonnacott & Wonnacott, 1990). Also, the researcher has only one independent observation (income) with a parameter that he or she needs to estimate. The degrees of freedom here are equal to N - k. Thus, there is no degree of freedom in this example (1 - 1 = 0). In other words, the data point has no freedom to vary, and the analysis is limited to the presentation of the value of this data point (Wonnacott & Wonnacott, 1990; Yu, 1997). For us to understand data variability, N must be larger than 1.

Multiple Observations (N) with One Parameter to Be Estimated

Suppose there are N observations for income. To examine the variability in income, we need to estimate only one parameter (that is, sample variance) for income (k), leaving the degrees of freedom of N - k. Because we know that we have only one parameter to estimate, we may say that we have a total of N - 1 degrees of freedom. Therefore, all univariate sample characteristics that are computed with the sum of squares including the standard deviation and variance have N-1 degrees of freedom (Warner, 2008).

Degrees of freedom vary from one statistical test to another as we move from univariate to bivariate and multivariate statistical analysis, depending on the nature of restrictions applied even when sample size remains unchanged. In the examples that follow, we explain how degrees of freedom are calculated in some of the commonly used bivariate and multivariate analyses.

Two Samples with One Parameter (or *t* Test)

Suppose that the researcher has two samples, men and women, or $n_1 + n_2$ observations. Here, one can use an independent samples t test to analyze whether the mean incomes of these two groups are different. In the comparison of income variability between these two independent means (or k number of means), the researcher will have $n_1 + n_2 - 2$ degrees of freedom. The total degrees of freedom are the sum of the number of cases in group 1 and group 2 minus the number of groups. As a case in point, see the SAS and SPSS outputs of a t test comparing the literacy rate (LITERACY, dependent variable) of poor and rich countries (GNPSPLIT, independent variable) in Table 1. All in all, SAS output has four different values of degrees of freedom (two of which are also given by SPSS). We review each of them in the following paragraphs.

The first value for degrees of freedom under t tests is 100 (reported by both SAS and SPSS). The two groups of countries (rich and poor) are assumed to have equal variances in their literacy rate, the dependent variable. This first value of degrees of freedom is calculated as $n_1 + n_2 - 2$ (the sum of the sample size of each group compared in the t test minus the number of groups being compared), that is, 64 + 38 - 2 = 100.

For the test of equality of variance, both SAS and SPSS use the F test. SAS uses two different values of degrees of freedom and reports folded F statistics. The numerator degrees of freedom are calculated as n_1 , -1, that is 64 - 1 = 63. The denominator degrees of *freedom* are calculated as $n_2 - 1$ or 38 - 1 = 37. These degrees of freedom are used in testing the assumption that the variances in the two groups (rich and poor countries, in our example) are not significantly different. These two values are included in the calculations computed within the statistical program and are reported on SAS output as shown in Table 1. SPSS, however, computes Levene's weighted Fstatistic (see Table 1) and uses k-1 and N-k degrees of freedom, where k stands for the number of groups being compared and N stands for the total number of observations in the sample; therefore, the degrees of freedom associated with the Levene's F statistic

		The SAS System	vstem		1					SPSS	SPSS SYSTEM	M			1
		The TTEST Procedure	rocedure				Group Statistics	ics							
		Statistics	ß					GNPSPLIT	LL	N	M		SD	SEM	
		Lower CL	Upper CL	CL	Lower CL	CL	LITERACY	0 (poor)		64	46.563	63	25.6471	3.2059	6
Variable GNI	GNPSPLIT N	Mean	Mean	Mean	Std Dev	Std Dev		1 (rich)	-	38	88.974	74	18.0712	2.9315	5
CY	poor(0) 64	40.156	46.563	52.969	21.846	25.647							1	[
	rich(1) 38	83.034		94.914	14.733	18.071						Lev Equal	Levene's Test for Equality of Variances	or inces	
	TC- (7-1) III	11.71	10.00-	(70.07	101.00							F	-	d	
		Statistics	S				LITERACY	Equ	Equal variances assumed	es assume	pa	14.266	-	000	
		Upper CL						Equ	Equal variances not assumed	es not ass	umed				
Variable	GNPSPLIT	Std Dev	Std Err	Minimum		Maximum		-						1	
LITERACY	poor(0)	31.062	3.2059	5		95					t test	for Equali	r test for Equality of Means	s	
LITERACY	Rich(1)	23.38	2.9315	25		100			F		p (2-	M	SE	95% C	95% CI of the
LITERACY	Diff (1-2)	26.854	4.7379						1	df	tailed) D	ifference	Difference Difference	Diffe	Difference
														Lower	Upper
		T-lests	cs				LITERACY	Equal				12	2		
Variable	Method	Variances	DF	t Value		$\Pr > t $		variances	0 051 1	100	000	C112 CA	4 7379	-51 8111	-33 0113
LITERACY	Pooled	Equal	100	-8.95		<.0001		Equal	1 1//.0-	-			1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1		
LITERACY	Satterthwaite	Unequal	76	-9.76		<.0001		variances							
		Equality of Variances	l'ariances					not assumed	-9.763	96.967	- 000	-42.4112	4.3441	-51.0331	-33.7892
Variable	Method	Num DF	Num DF Den DF	F Value		$\Pr > F$									
LITERACY	Folded F	63	37	2.01		0.0236									

Note: CL (SAS out;

are the same (that is, k-1 = 2-1 = 1, N-k = 102 - 2 = 100) as the degrees of freedom associated with "equal" variance test discussed earlier, and therefore SPSS does not report it separately.

If the assumption of equal variance is violated and the two groups have different variances as is the case in this example, where the folded F test or Levene's F weighted statistic is significant, indicating that the two groups have significantly different variances, the value for degrees of freedom (100) is no longer accurate. Therefore, we need to estimate the correct degrees of freedom (SAS Institute, 1985; also see Satterthwaite, 1946, for the computations involved in this estimation).

We can estimate the degrees of freedom according to Satterthwaite's (1946) method by using the following formula:

df Satterthwaite =

$$\frac{(n_1 - 1) (n_2 - 1)}{(n_1 - 1) \left[1 - \frac{S_1^2 n_2}{(S_1^2 n_2 + S_2^2 n_1)}\right]^2 + (n_2 - 1) \left[\frac{S_1^2 n_2}{(S_1^2 n_2 + S_2^2 n_1)}\right]^2}$$

where $n_1 = \text{sample size of group 1}$, $n_2 = \text{sample size of group 2}$, and S_1 and S_2 are the standard deviations of groups 1 and 2, respectively. By inserting subgroup data from Table 1, we arrive at the more accurate degrees of freedom as follows:

Because the assumption of equality of variances is violated, in the previous analysis the Satterthwaite's

value for degrees of freedom, 96.97 (SAS rounds it to 97), is accurate, and our earlier value, 100, is not. Fortunately, it is no longer necessary to hand calculate this as major statistical packages such as SAS and SPSS provide the correct value for degrees of freedom when the assumption of equal variance is violated and equal variances are not assumed. This is the fourth value for degrees of freedom in our example, which appears in Table 1 as 97 in SAS and 96.967 in SPSS. Again, this value is the correct number to report, as the assumption of equal variances is violated in our example.

Comparing the Means of g Groups with One Parameter (Analysis of Variance)

What if we have more than two groups to compare? Let us assume that we have $n_1 + \ldots + n_g$ groups of observations or countries grouped by political freedom (FREEDOMX) and that we are interested in differences in their literacy rates (LITERACY, the dependent variable). We can test the variability of g means by using the analysis of variance (ANOVA). The ANOVA procedure produces three different types of degrees of freedom, calculated as follows:

- The first type of degrees of freedom is called the between-groups degrees of freedom or model degrees of freedom and can be determined by using the number of group means we want to compare. The ANOVA procedure tests the assumption that the g groups have equal means and that the population mean is not statistically different from the individual group means. This assumption reflects the null hypothesis, which is that there is no statistically significant difference between literacy rates in g groups of countries $(\mu_1 = \mu_2 = \mu_3)$. The alternative hypothesis is that the g sample means are significantly different from one another. There are g - 1 model degrees of freedom for testing the null hypothesis and for assessing variability among the g means. This value of model degrees of freedom is used in the numerator for calculating the F ratio in ANOVA.
- The second type of degrees of freedom, called the *within-groups degrees of freedom* or *error degrees of freedom*, is derived from subtracting the model degrees of freedom from the corrected total degrees of freedom. The within-groups

degrees of freedom equal the total number of observations minus the number of groups to be compared, $n_1 + \ldots + n_g - g$. This value also accounts for the denominator degrees of freedom for calculating the *F* statistic in an ANOVA.

Calculating the third type of degrees of freedom is straightforward. We know that the sum of deviation from the mean or Σ(Y_i - Y) = 0. We also know that the total sum of squares or Σ(Y_i - Y)² is nothing but the sum of N² deviations from the mean. Therefore, to estimate the total sum of squares Σ(Y_i - Y)², we need only the sum of N - 1 deviations from the mean. Therefore, with the total sample size we can obtain the total degrees of freedom, or corrected total degrees of freedom, by using the formula N - 1.

In Table 2, we show the SAS and SPSS output with these three different values of degrees of freedom using the ANOVA procedure. The dependent variable, literacy rate, is continuous, and the independent variable, political freedom or FREEDOMX, is nominal. Countries are classified into three groups on the basis of the amount of political freedom each country enjoys: Countries that enjoy high political freedom are coded as 1 (n = 32), countries that enjoy moderate political freedom are coded as 2 (n = 34), and countries that enjoy no political freedom are coded as 3 (n = 36). The mean literacy rates (dependent variable) of these groups of countries are examined. The null hypothesis tests the assumption that there is no significant difference in the literacy rates of these countries according to their level of political freedom.

The first of the three degrees of freedom, the between-groups degrees of freedom, equals g - 1. Because there are three groups of countries in this analysis, we have 3 - 1 = 2 degrees of freedom. This accounts for the numerator degrees of freedom in estimating the *F* statistic. Second, the within-groups degrees of freedom, which accounts for the denominator degrees of freedom for calculating the *F* statistic in ANOVA, equals $n_1 + \ldots + n_g - g$. These degrees of freedom are calculated as 32 + 34 + 36 - 3 = 99. Finally, the third degrees of freedom, the total degrees of freedom, are calculated as N - 1 (102 - 1 = 101). When reporting *F* values and their respective degrees of freedom, researchers should report them as follows: The independent and the dependent variables are significantly related [F(2, 99) = 16.64, p < .0001].

Degrees of Freedom in Multiple Regression Analysis

We skip to multiple regression because degrees of freedom are the same in ANOVA and in simple regression. In multiple regression analysis, there is more than one independent variable and one dependent variable. Here, a parameter stands for the relationship between a dependent variable (Y) and each independent variable (X). One must understand four different types of degrees of freedom in multiple regression.

The first type is the *model* (*regression*) *degrees* of *freedom*. Model degrees of freedom are associated with the number of independent variables in the model and can be understood as follows:

A null model or a model without independent variables will have zero parameters to be estimated. Therefore, predicted Y is equal to the mean of Y and the degrees of freedom equal 0.

A model with one independent variable has one predictor or one piece of useful information (k = 1) for estimation of variability in Y. This model must also estimate the point where the regression line originates or an intercept. Hence, in a model with one predictor, there are (k + 1) parameters—k regression coefficients plus an intercept—to be estimated, with k signifying the number of predictors. Therefore, there are [(k + 1) - 1], or k degrees of freedom for testing this regression model.

Accordingly, a multiple regression model with more than one independent variable has some more useful information in estimating the variability in the dependent variable, and the model degrees of freedom increase as the number of independent variables increase. The null hypothesis is that all of the predictors have the same regression coefficient of zero, thus there is only one common coefficient to be estimated (Dallal, 2003). The alternative hypothesis is that the regression coefficients are not zero and that each variable explains a different amount of variance in the dependent variable. Thus, the researcher must estimate k coefficients plus the intercept. Therefore, Table 2: Analysis of Variance (ANOVA) of Literacy Rates According to Countries' Levels of Freedom with Reported Degrees of Freedom (N = 102)

SAS SYSTEM

Dependent Variable: LITERACY perct of adult population literate b The ANOVA Procedure

F Value 16.64 Mean Square 12126.74142 728.84945 24253.48284 72156.09559 Sum of Squares DF 66 2 Source Model Error

96409.57843

101

Corrected Total

 $P_{\Gamma} > F$ LITERACY Mean 62.36275 F Value Mean Square Root MSE 26.99721 Anova SS Coeff Var £3.29061 DF R-Square 0.251567 Source

16.64 12126.74142 24253.48284 2 FREEDOMX

Duncan's Multiple Range Test¹ for LITERACY 0.05 The ANOVA Procedure Alpha

33.92148 728.8495 66 Harmonic Mean of Cell Sizes Error Degrees of Freedom Error Mean Square

3 2 Number of Means² Critical Range

13.69

13.01

2 (=partly free) FREEDOMX 1 (=free) Z 32 34 84.313 57.529 Mean³ Duncan Grouping A B

LITERACY

SPSS SYSTEM

	Sum of				
	Squares	df	M ²	F	d
Between Groups	24253.483	2	12126.741	16.638	000.
Within Groups	72156.096	66	728.849		
Total	96409.578	101			

<,0001

 $\Pr > F$

Homogeneous Subsets Post Hoc Tests LITERACY

Duncan ab

<.0001

		Subset ($\alpha = .05$)	α = .05)
FREEDOMX	N	1	2
3 (=not free)	36	47.417	
2 (=partly free)	34	57.529	1
(=free)	32		84.313
		.126	1.000

Means for groups in homogeneous subsets are displayed. ^aUses Harmonic Mean Sample Size = 33.921.

⁶The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

is error rate, not the experimentwise error rate. ²Cell sizes are not equal. ³Means with the same letter are not significantly different. Perct = percentage. Coeff Var = coefficient of Note: 'Duncan's multiple range test for literacy controls the Type I con variation. SS =Sum of Squares.

3 (=notfree)

36

47.417

B 8 there are (k + 1) - 1 or k degrees of freedom for testing the null hypothesis (Dallal, 2003). In other words, the model degrees of freedom equal the number of useful pieces of information available for estimation of variability in the dependent variable.

- The second type is the residual, or error, degrees of freedom. Residual degrees of freedom in multiple regression involve information of both sample size and predictor variables. In addition, we also need to account for the intercept. For example, if our sample size equals N, we need to estimate k + 1 parameters, or one regression coefficient for each of the predictor variables (k) plus one for the intercept. The residual degrees of freedom are calculated N - (k +1). This is the same as the formula for the error, or within-groups, degrees of freedom in the ANOVA. It is important to note that increasing the number of predictor variables has implications for the residual degrees of freedom. Each additional parameter to be estimated costs one residual degree of freedom (Dallal, 2003). The remaining residual degrees of freedom are used to estimate variability in the dependent variable.
- The third type of degrees of freedom is the *total*, or *corrected total*, *degrees of freedom*. As in ANOVA, this is calculated N 1.
- Finally, the fourth type of degrees of freedom that SAS (and not SPSS) reports under the parameter estimate in multiple regression is worth mentioning. Here, the null hypothesis is that there is no relationship between each independent variable and the dependent variable. The degree of freedom is always 1 for each relationship and therefore, some statistical software, such as SPSS, do not bother to report it.

In the example of multiple regression analysis (see Table 3), there are four different values of degrees of freedom. The first is the regression degrees of freedom. This is estimated as (k + 1) - 1 or (6 + 1) - 1 = 6, where k is the number of independent variables in the model. Second, the residual degrees of freedom are estimated as N - (k + 1). Its value here is 99 - (6 + 1) = 92. Third, the total degrees of freedom are calculated N - 1 (or 99 - 1 = 98). Finally, the degrees of freedom shown under parameter estimates for each parameter always equal

1, as explained above. F values and the respective degrees of freedom from the current regression output should be reported as follows: The regression model is statistically significant with F(6, 92) = 44.86, p < .0001.

Degrees of Freedom in a Nonparametric Test

Pearson's chi square, or simply the chi-square statistic, is an example of a nonparametric test that is widely used to examine the association between two nominal level variables. According to Weiss (1968) "the number of degrees of freedom to be associated with a chi-square statistic is equal to the number of independent components that entered into its calculation" (p. 262). He further explained that each cell in a chi-square statistic represents a single component and that an independent component is one where neither observed nor expected values are determined by the frequencies in other cells. In other words, in a contingency table, one row and one column are fixed and the remaining cells are independent and are free to vary. Therefore, the chi-square distribution has $(r-1) \times (c-1)$ degrees of freedom, where r is the number of rows and *c* is the number of columns in the analysis (Cohen, 1988; Walker, 1940; Weiss, 1968). We subtract one from both the number of rows and columns simply because by knowing the values in other cells we can tell the values in the last cells for both rows and columns; therefore, these last cells are not independent.

As an example, we ran a chi-square test to examine whether gross national product (GNP) per capita of a country (GNPSPLIT) is related to its level of political freedom (FREEDOMX). Countries (GNPSPLIT) are divided into two categories-rich countries or countries with high GNP per capita (coded as 1) and poor countries or countries with low GNP per capita (coded as 0), and political freedom (FREEDOMX) has three levels-free (coded as 1), partly free (coded as 2), not free (coded as 3) (see Table 4). In this analysis, the degrees of freedom are $(2-1) \times (3-1) = 2$. In other words, by knowing the number of rich countries, we would automatically know the number of poor countries. But by knowing the number of countries that are free, we would not know the number of countries that are partly free and not free. Here, we need to know two of the three components-for instance, the number of countries that are free and partly free-so that we will know the number of countries

SAS SYSTEM SPSS SYSTEM			S	SPSS SYSTEM			
The REG Procedure	Model Summary	mmary					
Model: MODEL1 Dependent Variable: LITTERACY perct of adult population literate b	Model	R	R	Adjusted R ²	SE of the Estimate		
	1	.863ª	.745	.729	16.1919		
Number of Observations Kead 192 Number of Observations Used 99	^a Predictor	s: (Constant), G	VP80, partfree,	EDFUND84	Predictors: (Constant), GNP80, partfree, EDFUND84, SCHOOL80, PUPILS80, free	JPILS80, free	0
Number of Observations with Missing Values 93	Analysis o	Analysis of Variance: Dependent Variable = Literacy	endent Variable	: = Literacy			
	Model		Sum of Squares	df	W	H	9
Surree DF Survess Rusters RVAlue Dev E	1	Regression	70569.721	9	11761.620	44.861	±000°
6 70570 11762 44.86		Residual	24120.239	92	262.177		-
92 24120 262.17651		Total	94689.960	98	+		1
Corrected Total 98 94690	^a Predictor	s: (Constant), Gl	VP80, partfree,	EDFUND84	^a Predictors: (Constant), GNP80, partfree, EDFUND84, SCHOOL80, PUPILS80, free	JPILS80, free	
Root MSE 16.19187 R-Square 0.7453	Coefficien	Coefficients: Dependent Variable = Literacy	ariable = Litera	tcy			
Dependent Mean 62.02020 Adj R-Sq 0.7287 Coeff Var 26.10741			Unstandardized Coefficients	ardized cients	Standardized Coefficients		
Parameter Estimates	Model		В	SE	β	t	b
	1	(Constant)	29.725	9.276	3.204	.002	
Standard		free	5.396	5.000	.082	1.079	.283
Intercent 1 20 73514 0		partfree	-1.628	4	025	394	.694
Free Countries 1 5 20550 5 00005 1 00		EDFUND84	4.83E-005	000	.034	.584	.561
ree Partly Free Countries 1 -1 67820 4 13821	1	PUPILS80	-697	.154	310	4.522	000.
D84 education expenditures 1984 h 1 0.00009 0.00008 0.58		SCHOOL80	.583	.068	.524	8.615	000.
SD 1 -0.69716 0.15416 -4.52		GNP80	100.	.001	.158	1.917	.058
1 0 58254 0 06767							
10'0 70/00'0 1/70/00 1							

Note: Perct = percentage. Coeff Var = coefficient of variation. Adj. = adjusted. GMP = gross national proc

GNP PER CAPITA 1980 ISD

GNP80

<.0583

1.92

0.00119 0.00062

Table 4: Chi Square of GNPSPLIT and Level of Freedom in Countries with Reported Degrees of Freedom (N = 124)

SAS SYSTEM The FREQ Procedure Table of GNPSPLIT by FREEDOMX FREEDOMX(FREEDOM INDEX ISD) Statistics for Table of GNPSPLIT by FREEDOMX Prob <,0001 <.0001 0.0001 Total 61.29 124 100.00 76 48 38.71 Frequency Missing = 68 Value 0.4219 22.0708 22.0179 14.8569 13 , 27.08 , 3. 10.48 , ffffff*fffffffffffffff 28.23 46.05 72.92 27.08 38.71 35 48 2, 31, 10 , 75.61 , 8.06 , 24.39 . 25.00 , 40.79 , 20.83 33.06 DF 41 N 1 , 25 , 10, 8.06 , 13.16 , 20.16 , 52.08 , 71.43 , 28.57 . Ffffffff 35 28.23 ikelihood Ratio Chi-Square Mantel-Haenszel Chi-Square "ffffffff" GNPSPLIT Frequency 0 Row Pct Col Pct Percent Total Phi Coefficient Chi-Square Statistic

Effective Sample Size = 124 Frequency Missing = 68

0.4219

0.3887

Contingency Coefficient

Cramer's V

ree.

Case Processing Summary

SPSS SYSTEM

	Valid	%	Ca Mis N	Vissing %	To	Total %
NPSPLIT * FREEDOMX	124	64.6	68	35.4	192	100.0

GNPSPLIT * FREEDOMX Crosstabulation

	1		F	FREEDOMX	X	Total
			1	2	3	
GNPSPLIT	0	Count	10	31	35	26
		% of Total	8.1%	25.0%	28.2%	61.3%
	1	Count	25	10	13	48
		% of Total	20.2%	8.1%	10.5%	38.7%
Total		Count	35	41	48	124
		% of Total	28.2%	33.1%	38.7%	100.0%

Chi-Square Tests

	Value	df	Asymptotic. p (2-tailed)
Pearson χ^2	22.071*	2	000
Likelihood Ratio	22.018	2	000
Linear-by-Linear Association	14.857	1	000*
Valid Cases (N)	124		

Note: For the SAS, 35% of data are missing. GNPSPLIT = Countries divided into rich (1) and poor (0) based on their GNP per capita in 1980. FREEDOMX = countries divided into three categories based on their level of political freedom—1=free; 2=partly free; 3=not

that are not free. Therefore, in this analysis there are two independent components that are free to vary, and thus the degrees of freedom are 2.

Readers may note that there are three values under degrees of freedom in Table 4. The first two values are calculated the same way as discussed earlier and have the same values and are reported most widely. These are the values associated with the Pearson chi-square and likelihood ratio chi-square tests. The final test is rarely used. We explain this briefly. The degree of freedom for the Mantel-Haenszel chisquare statistic is calculated to test the hypothesis that the relationship between two variables (row and column variables) is linear; it is calculated as $(N-1) \times r^2$, where r^2 is the Pearson product-moment correlation between the row variable and the column variable (SAS Institute, 1990). This degree of freedom is always 1 and is useful only when both row and column variables are ordinal.

CONCLUSION

Yu (1997) noted that "degree of freedom is an intimate stranger to statistics students" (p. 1). This research note has attempted to decrease the strangeness of this relationship with an introduction to the logic of the use of degrees of freedom to correctly interpret statistical results. More advanced researchers, however, will note that the information provided in this article is limited and fairly elementary. As degrees of freedom vary by statistical test (Salkind, 2004), space prohibits a more comprehensive demonstration. Anyone with a desire to learn more about degrees of freedom in statistical calculations is encouraged to consult more detailed resources, such as Good (1973), Walker (1940), and Yu (1997).

Finally, for illustrative purposes we used World Data that reports information at country level. In our analysis, we have treated each country as an independent unit of analysis. Also, in the analysis, each country is given the same weight irrespective of its population size or area. We have ignored limitations that are inherent in the use of such data. We warn readers to ignore the statistical findings of our analysis and take away only the discussion that pertains to degrees of freedom. SWR

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