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810E23

Teaching Note

BRAND EQUITY

Jodie Whelan wrote this teaching note under the supervision of Professor Chris Higgins as an aid to instructors in the classroom use of the case Brand Equity, No. 9B10E023. This teaching note should not be used in any way that would prejudice the future use of the case.

Topics covered: brand equity; measuring intangible concepts; descriptive statistics; creating binary variables.

Statistical topics covered: Crosstabs; ANOVA; MANOVA.

Below are overviews of the statistical topics covered, sample answers to the case questions with teaching points, and suggested discussion questions with ideas for a response.

OVERVIEWS OF STATISTICAL TOPICS COVERED

Crosstabs (Questions 1 and 2)

Crosstabs, also known as contingency tables, are used to analyze the relationship between two categorical variables. In this case, the two categorical variables are brand (the airlines) and loyalty. (Recall that loyalty was converted into a binary variable with two categories: yes/high or no/low.) The null hypothesis in a crosstab is always the hypothesis of independence. In other words, the variables are not related to each other. A classic example of the hypothesis of independence is flipping two coins. The probability of getting heads on the first coin flip does not affect the probability of getting heads on the second flip.

Crosstabs work by computing expected frequencies assuming the hypothesis of independence is true. To calculate expected values, we first compute the probability of a joint event (i.e., A and B) assuming the hypothesis of independence is true. Under this assumption, P (A and B) = P (A) × P (B). To get the expected frequency, we then multiply this probability by the sample size. For example, the expected value of the respondent being a customer of CanAir and being loyal is calculated by multiplying the probability of being a customer of CanAir by the probability of the being loyal by the sample size. This will be true if the events are independent. If the null is true, the expected and observed frequencies will be close. If there is a dependent relationship, the expected and observed values will differ, the p-value will be less than .05

and the null hypothesis will be rejected. If there is no relationship between the two variables, the p-value will be greater than .05 and the null hypothesis will not be rejected.

ANOVA and MANOVA (Questions 4 and 5)

ANOVA (Analysis of Variance) is a statistical tool used to test differences in means across three or more groups. Because it tests means, the dependent variable must be interval or ratio data. ANOVAs work by comparing the random variance (within group variance that is not affected by the independent variable) to the non-random variance (between group variance that is due to the independent variable). When the non-random variance is much larger than the random variance, the ANOVA is significant, indicating that the independent variable affects the dependent variable.

MANOVAs (Multiple Analysis of Variance) are very similar to ANOVAs, except they contain multiple dependent variables. They essentially run multiple ANOVAs and provide an overall test of significance (the OMNIBUS test). If the overall test is significant, we know that at least one pair of means are different. The OMNIBUS test prevents an inflation of Type 1 error. Further protection against Type 1 error is obtained by using what is called the Bonferroni adjustment where you divide .05 (where you normally reject) by the number of dependent variables to get a more conservative rejection level. If you have two dependent variables, using the Bonferroni adjustment, you would reject at .025.

SAMPLE ANSWERS AND TEACHING POINTS

1. Run a crosstabs using the variables BRAND and LOYALBIN. What do the results tell you?

The null hypothesis for this test is the hypothesis of independence — whether a customer is loyal or not is not affected by the brand. More formally,

H_0: Loyalty is independent of brand.

Before looking at the Chi-Square test, students should examine the crosstab table. This is akin to examining descriptive statistics before jumping straight to tests of significance — something students should internalize! By comparing the observed values (“Count”) to expected values (“Expected Count”) for each cell, students will derive a better understanding of crosstabs as a statistical tool and a better understanding of the data they are working with. If, for each cell, the observed values are different from the expected values, it is likely there is a relationship between the two variables and the test will be significant. If, for each cell, the observed values are close to the expected values, it is likely there is no relationship between the two variables and the test will be insignificant.

Brand * Loyalty - Binary Crosstabulation

			Loyalty - Binary		Total
			No (Codes 1 - 7)	Yes (Codes 8 - 10)	
Brand	CanAir	Count	234	79	313
		Expected Count	264.0	49.0	313.0
		% within Brand	74.8%	25.2%	100.0%
		% within Loyalty - Binary	18.5%	33.6%	20.9%
		% of Total	15.6%	5.3%	20.9%
	Maple Leaf	Count	220	81	301
		Expected Count	253.8	47.2	301.0
		% within Brand	73.1%	26.9%	100.0%
		% within Loyalty - Binary	17.4%	34.5%	20.1%
		% of Total	14.7%	5.4%	20.1%
	Charter or Low Cost	Count	262	38	300
		Expected Count	253.0	47.0	300.0
		% within Brand	87.3%	12.7%	100.0%
		% within Loyalty - Binary	20.7%	16.2%	20.0%
		% of Total	17.5%	2.5%	20.0%
	UK	Count	286	21	307
		Expected Count	258.9	48.1	307.0
		% within Brand	93.2%	6.8%	100.0%
		% within Loyalty - Binary	22.6%	8.9%	20.5%
		% of Total	19.1%	1.4%	20.5%
	AirUSA	Count	263	16	279
		Expected Count	235.3	43.7	279.0
		% within Brand	94.3%	5.7%	100.0%
		% within Loyalty - Binary	20.8%	6.8%	18.6%
		% of Total	17.5%	1.1%	18.6%
Total		Count	1265	235	1500
		Expected Count	1265.0	235.0	1500.0
		% within Brand	84.3%	15.7%	100.0%
		% within Loyalty - Binary	100.0%	100.0%	100.0%
		% of Total	84.3%	15.7%	100.0%

In this crosstab, all the observed values are different from the expected values. For CanAir and Maple Leaf, there are more loyal customers than expected: CanAir has 79 loyal customers, 30 more than the expected 49; Maple Leaf Airlines has 81 loyal customers, 34 more than the expected 47.2. For the remaining brands, the number of loyal customers was fewer than expected. The observed count for Charter or Low Cost was 38 (versus the expected 47); the observed count for UK was 21 (versus the expected 48.1); and the observed count for AirUSA was 16 (versus the expected 43.7). It appears that brand and loyalty are related. (Surprise!)

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	91.486[a]	4	.000
Likelihood Ratio	94.331	4	.000
Linear-by-Linear Association	79.052	1	.000
N of Valid Cases	1,500		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 43.71.

The Chi-Square test (the test of significance) returns a significant p-value (X^2 (4 df) = 91.486; $p < .001$). This means that the null hypothesis is rejected — brand and loyalty are not independent of each other. The variables are somehow related. It is important to note, however, that causal direction cannot be inferred from a crosstab. Students cannot conclude that certain brands cause higher/lower loyalty.

2. Delete the brands associated with UK and AirUSA (use SELECT CASES). Rerun the crosstabs. What do the results tell you?

Because we have changed our sample for analysis, the *expected values* change (not the observed values). Expected values are calculated by multiplying the probability of each event and then computing an expected value based on this probability. For example, the expected value of the respondent being a customer of CanAir and being loyal is calculated by multiplying the probability of being a customer of CanAir by the probability of the being loyal times the overall sample size.

In the crosstab for question 1, the equation looks like this:

P (CanAir and loyal) = P (CanAir) × P (loyal) × sample size
= 313 ÷ 1500 × 235 ÷ 1500 × 1500
= 49.0

In the crosstab for this question, the equation looks like this:

P (CanAir and loyal) = P (CanAir) × P (loyal) × sample size
= 313 ÷ 914 × 198 ÷ 914 × 914
= 67.8

The total number of respondents (i.e., the denominator) has changed because we have reduced our sample size. Likewise, the total number of loyal respondents has also changed, affecting the probability of being loyal.

Brand * Loyalty - Binary Crosstabulation

			Loyalty - Binary		
			No (Codes 1 - 7)	Yes (Codes 8 - 10)	Total
Brand	CanAir	Count	234	79	313
		Expected Count	245.2	67.8	313.0
		% within Brand	74.8%	25.2%	100.0%
		% within Loyalty - Binary	32.7%	39.9%	34.2%
		% of Total	25.6%	8.6%	34.2%
	Maple Leaf	Count	220	81	301
		Expected Count	235.8	65.2	301.0
		% within Brand	73.1%	26.9%	100.0%
		% within Loyalty - Binary	30.7%	40.9%	32.9%
		% of Total	24.1%	8.9%	32.9%
	Charter or Low Cost	Count	262	38	300
		Expected Count	235.0	65.0	300.0
		% within Brand	87.3%	12.7%	100.0%
		% within Loyalty - Binary	36.6%	19.2%	32.8%
		% of Total	28.7%	4.2%	32.8%
Total		Count	716	198	914
		Expected Count	716.0	198.0	914.0
		% within Brand	78.3%	21.7%	100.0%
		% within Loyalty - Binary	100.0%	100.0%	100.0%
		% of Total	78.3%	21.7%	100.0%

The results of this crosstab indicate CanAir has more loyal customers than expected (79 versus 67.8); Maple Leaf has more loyal customers than expected (81 versus 65.2); and Charter or Low Cost has fewer loyal customers than expected (38 versus 65).

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	21.551[a]	2	.000
Likelihood Ratio	23.086	2	.000
Linear-by-Linear Association	14.005	1	.000
N of Valid Cases	914		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 64.99.

This test is significant (X^2 (2 df) = 21.551; $p < .001$). The null hypothesis is rejected, and we conclude that there is a significant relationship between brand and loyalty.

Though the differences for CanAir and Maple Leaf are smaller than the ones discussed in question 1 (30 versus 11.2 and 34 versus 15.8, respectively), the gap between expected and observed for Charter or Low Cost is greater than the one presented in question 1 (-11 versus -27). *Discuss with the students how this result could be interpreted.* Perhaps customers are not especially loyal to either CanAir or Maple Leaf but are highly disloyal to Charter or Low Cost. This can be further explored by running a crosstab with just CanAir and Maple Leaf. There is no longer a significant relationship between brand and loyalty.

3. How can you measure brand equity with the collected data?

For this question, students must return to the case handout. Recall that "Ariel created a multi-dimensional measure of brand equity with five main variables: *familiarity* of the product, perceived *uniqueness* of the product, *popularity* of the product, *relevancy* of the product to lifestyle, and customer *loyalty* to the product." Consequently, brand equity should be calculated by computing a mean score of all five measures. When computing this variable, it is important that students use the interval data, not the categorical (binary) data. Using the binary data sacrifices a lot of information.

4. What statistical analysis is suitable to compare brand equity across brands? Why? Compare brand equity across brands for your chosen category.

A one-way ANOVA should be used to compare brand equity across brands. This is the appropriate analysis because there is one independent variable with multiple levels (brand) and a dependent variable that contains interval data (brand equity).

When running ANOVAs, students should always begin by calculating and looking at descriptive statistics so they can understand their data.

Descriptives

brand_equity

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
A&W	283	5.6774	1.81645	.10798	5.4648	5.8899	1.00	9.00
Burger King	291	5.7463	1.89416	.11104	5.5277	5.9648	1.00	9.00
Harvey's	316	5.2737	2.25731	.12698	5.0239	5.5236	1.00	9.00
McDonald's	308	6.8527	1.41580	.08067	6.6940	7.0114	1.00	9.00
Wendy's	302	5.5384	2.20984	.12716	5.2882	5.7886	1.00	9.00
Total	1,500	5.8191	2.01980	.05215	5.7168	5.9214	1.00	9.00

For fast food, it appears that McDonald's has the highest brand equity (M = 6.8527). A&W, Burger King, and Wendy's seem to all be in the middle of the pack (Ms = 5.6774, 5.7463, 5.5384, respectively). Harvey's has the lowest brand equity (M = 5.2737). However, it is interesting to note that, if we were using Ariel's split between high and low (high > 8), none of these companies would be considered to have high brand equity.

ANOVA

brand_equity

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	454.055	4	113.514	29.976	.000
Within Groups	5661.280	1495	3.787		
Total	6115.335	1499			

The ANOVA table above tells you that there is at least one pair of means that are different (p < .001). To determine which means are different, a follow-up test is needed. I have selected the Bonferroni test – others are equally good.

Multiple Comparisons

brand_equity
Bonferroni

(I) Brand	(J) Brand	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
A & W	Burger King	-.06889	.16246	1.000	-.5256	.3878
	Harvey's	.40365	.15926	.114	-.0441	.8514
	McDonalds	-1.17532*	.16024	.000	-1.6258	-.7249
	Wendy's	.13897	.16100	1.000	-.3136	.5916
Burger King	A&W	.06889	.16246	1.000	-.3878	.5256
	Harvey's	.47254*	.15810	.028	.0281	.9170
	McDonalds	-1.10643*	.15908	.000	-1.5536	-.6592
	Wendy's	.20787	.15985	1.000	-.2415	.6572
Harvey's	A & W	-.40365	.15926	.114	-.8514	.0441
	Burger King	-.47254*	.15810	.028	-.9170	-.0281
	McDonald's	-1.57897*	.15582	.000	-2.0170	-1.1409
	Wendy's	-.26468	.15660	.912	-.7049	.1756
McDonald's	A&W	1.17532*	.16024	.000	.7249	1.6258
	Burger King	1.10643*	.15908	.000	.6592	1.5536
	Harvey's	1.57897*	.15582	.000	1.1409	2.0170
	Wendy's	1.31430*	.15759	.000	.8713	1.7573
Wendy's	A&W	-.13897	.16100	1.000	-.5916	.3136
	Burger King	-.20787	.15985	1.000	-.6572	.2415
	Harvey's	.26468	.15660	.912	-.1756	.7049
	McDonald's	-1.31430*	.15759	.000	-1.7573	-.8713

*. The mean difference is significant at the 0.05 level.

From the above output, we see that, the brand equity for McDonald's is significantly different from all other brands. The only other significant difference in brand equity is between Harvey's and Burger King.

5. Compare loyalty, relevance, familiarity, uniqueness and popularity for the brands of your chosen category using the appropriate statistical analysis.

This question requires a MANOVA because there are multiple dependent variables. Recall that a MANOVA essentially runs multiple ANOVAs at once. For the most part, this question follows the same format as question 4; however, there are two notable changes. First, there is an overall test of significance called the OMNIBUS test. Second, when looking at the individual ANOVAs, the level of significance should be adjusted. (I recommend the Bonferroni procedure — more on this later.)

Multivariate Tests[c]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.905	2796.096[a]	5.000	1476.000	.000
	Wilks' Lambda	.095	2796.096[a]	5.000	1476.000	.000
	Hotelling's Trace	9.472	2796.096[a]	5.000	1476.000	.000
	Roy's Largest Root	9.472	2796.096[a]	5.000	1476.000	.000
brand	Pillai's Trace	.180	13.968	20.000	5916.000	.000
	Wilks' Lambda	.823	14.807	20.000	4896.288	.000
	Hotelling's Trace	.211	15.550	20.000	5898.000	.000
	Roy's Largest Root	.190	56.184[b]	5.000	1479.000	.000

a. Exact statistic

b. The statistic is an upper bound on F that yields a lower bound on the significance level.

c. Design: Intercept + brand

The first output we get is the OMNIBUS test. If it is significant, we know that at least one null hypothesis has been rejected (i.e., at least one pair of means are different). Because our OMNIBUS test is significant ($p < .05$), the next step is to look at the individual ANOVAs.

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Familiar	1167.585[a]	4	291.896	36.767	.000
	Unique	417.503[b]	4	104.376	14.326	.000
	Relevant	207.117[c]	4	51.779	6.177	.000
	Loyalty	427.777[d]	4	106.944	12.110	.000
	Popular	1457.354[e]	4	364.339	57.421	.000
Intercept	Familiar	75664.306	1	75664.306	9530.722	.000
	Unique	58912.180	1	58912.180	8085.985	.000
	Relevant	51321.003	1	51321.003	6122.127	.000
	Loyalty	49604.092	1	49604.092	5616.936	.000
	Popular	78931.659	1	78931.659	12439.851	.000
brand	Familiar	1167.585	4	291.896	36.767	.000
	Unique	417.503	4	104.376	14.326	.000
	Relevant	207.117	4	51.779	6.177	.000
	Loyalty	427.777	4	106.944	12.110	.000
	Popular	1457.354	4	364.339	57.421	.000
Error	Familiar	11749.705	1480	7.939		
	Unique	10782.858	1480	7.286		

	Relevant	12406.650	1480	8.383		
	Loyalty	13070.126	1480	8.831		
	Popular	9390.695	1480	6.345		
Total	Familiar	88752.000	1485			
	Unique	70285.000	1485			
	Relevant	64065.000	1485			
	Loyalty	63210.000	1485			
	Popular	89991.000	1485			
Corrected Total	Familiar	12917.290	1484			
	Unique	11200.361	1484			
	Relevant	12613.767	1484			
	Loyalty	13497.903	1484			
	Popular	10848.050	1484			

a. R Squared = .090 (Adjusted R Squared = .088)
b. R Squared = .037 (Adjusted R Squared = .035)
c. R Squared = .016 (Adjusted R Squared = .014)
d. R Squared = .032 (Adjusted R Squared = .029)
e. R Squared = .134 (Adjusted R Squared = .132)

Instead of using the standard p-value as the criteria for significance (i.e., $p < .05$), students should divide it by the number of dependent variables and use this as the criteria for significance. Here, it would be .05 divided by five dependent variables. Thus, our criteria for significance would be $p < .01$. This is known as the *Bonferroni adjustment*. We use the Bonferroni adjustment to reduce our p-value to protect against Type 1 error.

With our adjusted cut-off of .01, it appears that brand has a significant effect on all five of our dependent variables. For more information, students could proceed to run Bonferroni posthoc tests. These are interpreted just as they are for ANOVAs.

DISCUSSION QUESTIONS

1. Ariel created binary variables for familiarity, uniqueness, relevance, loyalty and popularity by splitting responses into "yes" and "no." Do you agree with their decision to split the data at 7/8? Why or why not?

The key point to be made here is that Ariel's decision to split the data into no (1-7) and yes (8-10) is completely arbitrary. There is no hard and fast rule, and a number of approaches could be taken. The important thing is to consider your research purpose.

Some students may suggest that a median split is a better alternative. However, considering that we are interested in yes and no, splitting the data at 7/8 seems more aligned with the purpose at hand. Another method may be to split the data into multiple categories (i.e., yes, indifferent, no). Again, however, this is removed from the purpose. We were simply interested in yes or no. If we were going to split into multiple categories, we might as well just leave the data as interval data. Other students may suggest split the data into yes and no but leave out the middle ground (i.e., no = 1-3; yes = 8-10). This approach, however, would drastically reduce our sample size.

The split at 7/8 was a wise choice because it uses the data available to us and it errs on the side of caution. Though some people may consider 6 or 7 high, this is a conservative approach.

2. Do you agree with Ariel's measure of brand equity?

The takeaway here is that measures should match our definition of the concept. Since Ariel defined brand equity as being a compilation of relevance, familiarity, loyalty, uniqueness and popularity, it makes perfect sense that they would measure it that way. However, you could begin an interesting discussion by asking your students whether they can think of any other ways to measure brand equity or the constructs that contribute to it. Be creative. For example, could logo or slogan recognition be a measure of familiarity? What about just colours? Could repeat purchasing be an indicator of loyalty? Could website fans be an indicator of popularity?

The goal here is to get your students thinking about how survey data and other sources of data can be used together, especially when dealing with intangible constructs.