JAMES R. BETTMAN*

A theoretical model and measurement system for perceived risk and its components is developed and empirically tested for nine product types. Regression analysis is used to consider both additive and multiplicative relationships. The results generally support the hypothesized model.

Perceived Risk and Its Components: A Model and Empirical Test

INTRODUCTION

Since the introduction in marketing of the concept of perceived risk by Bauer [2], much research has been carried out utilizing the ideas of risk and risk reduction processes in consumer decision making [7, 8, 17, 19, 22]. Despite the concern with the construct, however, little effort has been devoted to measuring risk and building a formal model of risk and its components. The problem of measuring perceived risk is discussed elsewhere [5]; it is sufficient to point out that most studies develop an arbitrarily defined measure of risk [8, 9, 19], and that there is little standardization in measures across studies.

In this article the primary concern is to model risk in terms of its components. The major previous study in this area is by Cunningham who points out, "an arbitrary method of constructing the perceived risk index was used" [9, p. 84]. Cunningham measured two dimensions of risk—consequences and certainty—and combined the ratings for these components arbitrarily to yield essentially a three-level ordinal risk scale. He had no independent measure of risk to which he could relate his component measures.

This study attempts to remedy some of the shortcomings of earlier studies. First, no other study has attempted to obtain values for both the dependent measure, perceived risk, and the component measures. Secondly, to measure the components in a nonarbitrary manner, a theoretical model of risk and its components is needed.

* James R. Bettman is Assistant Professor at the Graduate School of Management, UCLA. Funds for subjects were provided by the Division of Research of the Graduate School of Management. He would like to thank an anonymous referee for helpful comments.

A MODEL OF PERCEIVED RISK AND ITS COMPONENTS

To obtain more precision in models dealing with perceived risk, it will be helpful to partition risk into two slightly different constructs. A distinction should be made between inherent risk and handled risk, since different components should be relevant for each. Inherent risk is the latent risk a product class holds for a consumer—the innate degree of conflict the product class is able to arouse. Handled risk is the amount of conflict the product class is able to arouse when the buyer chooses a brand from a product class in his usual buying situation. That is, handled risk to a first approximation represents the end results of the action of information and risk reduction processes on inherent risk. This implies that in a case where a consumer has *no* information, handled and inherent risk should be the same. Handled risk thus includes the effects of particular brand information, whereas inherent risk deals with the riskiness a consumer feels if no information is assumed. For example, a consumer may feel there is a great deal of risk associated with the product class aspirin. However, she has a favorite brand which she buys with confidence. In this case, inherent risk is high, but handled risk may be low for aspirin. This partition has not been clearly made previously. Most studies seem to have dealt with inherent risk. (See [8, 22] for studies dealing with handled risk, however.)

Let us consider a model for inherent risk first.[1] From an information processing viewpoint, buyer brand choices within a product class are implemented in terms of decision rules. Also, different product classes have varying levels of salience or importance. Thus, the risk

[1] Measures for the specific variables considered are given in the methodology section below.

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inherent in a brand choice situation within a product class will depend upon the degree to which a buyer believes he can construct a reasonable decision rule for making a brand choice, and the importance to him of making a satisfactory choice within that product class. Further, the goodness of the buyer's decision rule is hypothesized to depend upon his perceived distribution of quality over the brands of the product class. In particular, several aspects of this distribution may be important. First, the higher the perceived variation in quality for the product class, the less the likelihood of constructing an effective brand choice decision rule. Variation is measured by the variance of the perceived quality distribution. However, variance may not be the only measure affecting the goodness of brand choice. A second measure is the percentage of brands that falls above an acceptable level of quality for the buyer. That is, the greater the size of the region of acceptable brands (similar to the evoked set concept of [14]) in terms of quality, the lower the risk. Finally, the mean level of the quality distribution might also be considered. The higher the mean level of quality, the greater the chance an effective brand choice decision rule can be developed, and hence the lower the risk. Two measures of importance are used: the degree to which the buyer desires a brand that performs satisfactorily, and the price the buyer perceives he pays when he buys a brand from the product class. Note that the three measures relating to goodness of decision rule and the two relating to importance are *not* purported to be multiple measures of single traits. Each measure is intended to examine *different* aspects of either goodness of decision rule or importance, which are conceived as many-faceted phenomena. This discussion is summarized in the following set of hypotheses:

H_1: Inherent risk for a product class will increase with (a) variation in perceived product quality; (b) importance of the brand choice for a product class; and (c) the perceived price paid when a brand from the product class is purchased.

H_2: Inherent risk for a product class will decrease with (a) the size of the acceptable set of brands in terms of quality; (b) the mean level of quality for the product class.

Note that this model has essentially a set of variables related to choice uncertainty (variation, size of acceptable set, mean quality) and a set related to choice importance. There is no claim that these sets are independent. Others have previously defined similar models. Cunningham [9] used certainty and consequences components. Berlyne [3], Sieber and Lanzetta [20], and Hansen [13], among others, have used an importance and uncertainty model. Finally, Myers and Alpert [16] used a related model for determinant product attributes based on variation and importance. However, this framework has not yet been applied to perceived risk in other than an arbitrary manner. The specific form of the relationship between inherent risk and the variables will be considered.

Handled risk, conceived as inherent risk modified by information, brand loyalty, etc., should increase with inherent risk, but decrease with amount of information held about the product class, with the perceived usefulness of that information and the confidence with which it is held, and with the mean familiarity with brands of the product class. In summary,

H_3: Handled risk for a product class will (a) increase with inherent risk for that product class; and decrease with (b) amount of information about the product class in general; (c) usefulness of that information; (d) confidence with which the information is held; and (e) mean familiarity with specific brands in the product class.

Note that H_3 in a sense is a hypothesis concerning under what conditions inherent risk and handled risk measure different phenomena. These models were empirically tested by measuring the necessary variables and using regression analyses.

METHODOLOGY

Data were collected from 123 housewives in the Los Angeles area, including members of a women's group and wives of students living in the married student housing complex at UCLA. Subjects were paid $5 for completing a one- to two-hour questionnaire measuring all of the constructs required by the models for nine grocery product types: paper towels, dry spaghetti, furniture polish, toothpaste, beer, instant coffee, aspirin, margarine, and fabric softener.

Many of the variables were measured by using a simple extended paired comparison method. For n stimuli, $n(n-1)/2$ ratings were needed. Here the stimuli were the nine product types. For an ordered stimulus pair (i, j), the subject chose which product type of the pair she believed was most risky (important, etc.), and then rated how much more risky (important, etc.) that product type was than the other on a 10-point scale, where 0 was indifference and 9 was much more risky (important, etc.). If this rating for pair (i, j) is called d_{ij}, then the sign convention used was $d_{ij} > 0$ if i is more risky than j, and $d_{ij} < 0$ if the reverse were true. Since only half of the pairs were collected, set $d_{ji} = -d_{ij}$. Then scale values were obtained by setting the scale value s_i for stimulus i to $s_i = \sum_{j=1}^{n} d_{ij}/n$, where $d_{ii} = 0$. Using this definition, the s_i sum to zero, and hence we have only a *relative* measure.

Measurement of inherent risk for a product class and handled risk is discussed in detail in [5]. In brief, the paired comparison method above was used where the subject was to rate which item would be most risky to shop for in an *imaginary* store, where all brand labels are covered and only product type and size information (not price or ingredients) are available. The scale ranged from -8 to $+8$. Handled risk for a product class was

Table 1
MEAN VALUES FOR PRODUCT CLASS VARIABLES

Variable	Paper towels	Dry spaghetti	Furniture polish	Toothpaste	Beer	Instant coffee	Aspirin	Margarine	Fabric softener
	Product classes								
Inherent risk	−2.083	−1.552	−.759	1.760	.607	1.356	.487	1.181	−.996
Handled risk	−1.118	−1.277	.396	.331	.829	.946	.022	−.096	−.032
Mean quality	11.162	10.746	11.068	9.154	10.687	10.675	11.494	10.603	10.083
Percentage acceptable	.741	.625	.611	.362	.574	.487	.603	.518	.523
Relative variance	.499	.410	.425	.725	.544	.539	.431	.501	.394
Importance	−1.567	−.813	−1.734	2.694	−.842	1.278	1.578	1.651	−2.244
Perceived price	.330	.381	1.013	.796	1.373	1.135	.880	.416	.888
Mean familiarity	5.557	3.368	3.780	4.157	3.814	4.092	4.910	4.072	2.862
Information	.198	−1.428	−1.753	2.117	−.867	.645	1.985	1.286	−2.183
Usefulness	5.146	3.463	3.675	6.423	4.171	5.455	6.073	5.618	3.228
Confidence	5.675	3.732	3.634	6.000	4.512	5.171	6.333	5.488	3.195

measured in the same manner as inherent risk, except that the subject was asked to rate risk in terms of shopping in her own usual grocery store, not the imaginary store. This scale also ranged from −8 to +8.

Several measures were then developed based on the subject's perceived distribution of quality over brands. The subject was given a 20-point quality scale for each product type, where 0 was labeled very low quality, 10 to 11 average quality, and 19 very high quality. The subject was given a reasonable sample of brand names (eight to twelve, varying across product classes but the same for all subjects) for each product type and asked to locate each brand on the quality line. To measure mean quality, the sample mean of these ratings was computed. On this same quality line, the subject was asked to place an X on the quality line at the lowest level of quality for the product type that would be just acceptable if she were going to use the product. The number of brands above this level was then counted. Note that this is similar to the Howard-Sheth concept of evoked set [14]. This measure was then divided by the total number of brands given the subject for that product class to obtain the measure of percentage of acceptable brands. The variable thus ranges from 0 to 1.

Finally, again based on the quality line results, a variance was computed and then divided for each subject by the maximum variance she perceived across all nine product classes to obtain a relative measure of variation. This variable ranges from 0 to 1. Note that this and the mean quality and acceptable set measures above are direct measures of the properties of the perceived quality distribution rather than indirect (e.g., 'Rate how much quality variation you feel there is among brands of aspirin'). Scott's [18] suggestion of such direct measures for cognitive variables is the rationale for using aided recall questions rather than unaided questions. Since the subject saw brand names in placing the brands on the quality scale, an unaided question about percentage of acceptable brands, for example, would not have been appropriate. Of course, all quality scale measures could have been recall. However, this would hinder analysis of results, since subjects might have very different sets of recalled brands.

Importance of the choice within a product type was measured using the extended paired comparison method. The subject was asked to rate for which product type it was more important to choose a satisfactory brand. The resultant scale ranged from −8 to +8. Perceived price was measured by asking the subject how much was paid for the brand normally bought within the product class. Note that this is a recall measure and may also include effects due to package size.

An aided measure of mean familiarity with brands in a product type resulted from subjects' ratings of each brand used for the quality line from 0 (extremely unfamiliar) to 9 (extremely familiar). The mean of these numbers was then calculated. Amount of information held about the product class was rated using the extended paired comparisons. Usefulness of information and confidence in information held were rated on 0 to 9 scales.

Mean levels for the variables are given in Table 1 for each product class. Several aspects of these measures should be noted, however: (a) The risk measures are *relative* measures. The mean level has been removed. Since relative degree of risk is measured for each product class, *relative* variation was measured. (b) An attempt was made to distinguish between inherent and handled risk by means of the *choice situation* that would evoke each construct (i.e., the imaginary store setting vs. the normal store setting).

Several of the measures defined above are reasonably unusual. Some discussion of the validity of these measures is necessary. Certainly there was an attempt to achieve face validity for the risk and other measures. More can be said, however. The measures of certainty and danger used by Cunningham [9] were also collected in the questionnaire, adapted to a 10-point rating scale format. The correlations of certainty with inherent risk for the nine product types ranged from −.10 to −.53, with a value of −.37 for the data pooled over product types. The correlations of Cunningham's danger measure with inherent risk ranged from .26 to .57, with the pooled data yielding a correlation of .45. These correlations give some support to the validity of the inherent risk measure, although Cunningham never directly measured risk, but simply the two components.

A second question concerns the difference between inherent and handled risk. Do they measure different constructs? In a sense, Hypothesis 3 specifies under what conditions these constructs should differ. Since handled risk is seen as a derivative of the level of inherent risk, there certainly should be some relationship between the two. The correlations between inherent and handled risk range from .46 to .81 over the nine product types, with a pooled data value of .62. The pooled data correlations with Cunningham's measures are −.20 for certainty and .26 for danger. This brief discussion certainly does not exhaust the possibilities. Further research might include multiple methods of measuring risk and the other constructs of the model to further examine issues of reliability and validity (see [6]).

Given these variables, regression equations were developed to test the relationships hypothesized by the risk models. For the inherent risk model, three major variations were tried. Several researchers have suggested a multiplicative model for the components of risk [9, 13, 20]. Hence, both linear and multiplicative regression models were run. If we denote by Y the dependent variable and by X_i the predictor variables, then the general form of these relationships is given in (1) and (2) below:[2]

(1) Linear model: $Y = \sum_i b_i X_i$.

(2) Multiplicative model: $Y = \prod_i X_i^{b_i}$.

Equation (2) can of course be estimated by taking logarithms of both sides, yielding $\log Y = \sum_i b_i \log X_i$.

In addition, a second nonlinear model was used for the inherent risk measure. This model, called the disjunctive model, was suggested by Einhorn [10]. Whereas the multiplicative model states that all components must be high in the appropriate direction for risk to be high, the disjunctive model says that any one component's being high can lead to high risk, regardless of the values of the other components. The disjunctive model is given in (3).

Disjunctive model:

(3) $$Y = \prod_i (a_i - X_i)^{-b_i}$$

This model is estimated by $\log Y = -\sum_i b_i \log (a_i - X_i)$. Here the constant a_i is chosen so that $\log (a_i - X_i)$ is defined for all values of X_i. This brings up a methodological problem with the disjunctive and multiplicative models. Since some values of the measured variables are negative, transformations need to be made before the models can be applied so that logarithms may be taken. For example, since inherent risk could be as low as −8 on the scale used, the transformation inherent risk equals inherent risk +9 was used to insure a minimum value of one and hence a minimum logarithm of zero for the multiplicative and disjunctive models.[3] However, such transformations change the results of these two models. Ratio scale variables are necessary, rather than interval scales. Thus, as pointed out by Goldberg [12], such models are only crude approximations.

Finally, linear models were used for handled risk. All of the models were run for each of the nine product classes separately, with some missing cases in each class where subjects did not buy within a product class, and hence had no measure for perceived price.

Before these regressions were run, analyses of possible multicollinearity existing in the systems of independent variables were performed, using the ideas of Farrar and Glauber [11]. They present a three-step hierarchy of tests for diagnosing multicollinearity: (1) a test for the severity of multicollinearity for the entire variable set, based on the determinant of the sample correlation matrix; (2) a test for the collinearity of each variable with others in the set; and (3) a test for *patterns* of interdependence among variables. The detailed calculations underlying these steps were performed for the five variables used in the inherent risk models and the five variables used in the handled risk models. The major results of these tests were that substantial multicollinearity existed in both sets of variables. For the inherent risk models, the analysis showed the major problems to be among the three variables measuring goodness of decision rule: mean quality, percentage acceptable, and relative variance. This is not surprising, since these three measures were all derived from the same subjective quality distribution over brands. For the handled risk models, all four of the informational measures (amount of information, usefulness, confidence, and mean familiarity) were the major problem, being highly intercorrelated.

To allow more reasonable tests of the hypotheses, the following alternatives were chosen. For inherent risk, the mean quality and relative variance variables were not included in the regressions. For handled risk, the usefulness, confidence, and mean familiarity variables were not included. Based on the analyses of patterns of multicollinearity reported above, these exclusions should remove many of the problems. The reduced set of hy-

[2] For notational convenience, constant terms are not included in the formulae below, although these terms were included in the actual regressions.

[3] All variables except price are transformed so that the lowest value is one before taking logarithms for the multiplicative model. Hence the smallest logarithm is 0. Such transformations are left implicit in the tables depicting the results of fitting the multiplicative models.

Table 2
VARIABLE DEFINITIONS AND EXPECTED SIGNS FOR REDUCED MODELS[a]

Variables	*Expected regression coefficient signs* — *Inherent risk*	*Handled risk*
Inherent risk		+
Handled risk		
Percentage of acceptable brands	−	
Importance	+	
Perceived price paid	+	
Information		−

[a] A blank means that variable does not appear in the indicated regression.

potheses to be tested is then shown in Table 2, with expected signs for the regression coefficients (in terms of the original hypotheses, H1(b), H1(c), H2(a), H3(a), and H3(b) will be examined).

RESULTS

Inherent Risk Models

The results for the linear and multiplicative inherent risk models for each product class are given in Table 3. The results for the disjunctive models were similar, with smaller R^2 values, and hence are not presented in detail. The pattern of results is very similar for both sets of models. In each model, all nine product type coefficients for importance are as hypothesized; for percentage of acceptable brands eight of nine are as hypothesized, with the one exception being not significantly different from zero at $p = .10$. These results lend confidence to the theory. However, for price the picture is less favorable to the hypothesis. Four of the nine coefficients have the wrong sign, with several being statistically significant. As Bass argues [1], this leads to rejection of the hypothesis. Two possible reasons for this rejection are that (1) price is confounded with package size bought, so that lower risk and larger package sizes (and hence higher prices) may be associated; and (2) perceived price may be related to perceived quality, with higher perceived price thus leading to lower risk. It is clear that additional mediating variables would need to be added to this part of the model, as price seems to bear no simple relation to inherent risk. Note finally that importance is the most explanatory variable for these inherent risk results, the R^2 values are quite good; and the linear model does slightly better than the multiplicative model in most cases.

Handled Risk Models

The handled risk regression results are presented in Table 4. All nine of the coefficients for inherent risk and eight of the nine for information have the predicted signs. The single offending coefficient for information is not easily explainable. On the whole, the hypotheses are upheld, however. Inherent risk is the major explanatory variable.

Table 3
INDIVIDUAL PRODUCT CLASS INHERENT RISK REGRESSION COEFFICIENTS[a]

Product class (N)	*Percentage acceptable*	*Importance*	*Perceived price*	R^2
Linear models				
Paper towels (122)	−.016	.584[b]	.096	.363[b]
Dry spaghetti (123)	−.228[b]	.487[b]	−.075	.334[b]
Furniture polish (119)	−.254[b]	.603[b]	−.032	.468[b]
Toothpaste (123)	−.089	.581[b]	−.122[c]	.402[b]
Beer (109)	.132	.579[b]	.125	.341[b]
Instant coffee (114)	−.059	.567[b]	.035	.348[b]
Aspirin (122)	−.117	.622[b]	.042	.470[b]
Margarine (122)	−.195[b]	.597[b]	.029	.460[b]
Fabric softener (114)	−.130	.433[b]	−.210[d]	.206[b]
Multiplicative models				
Paper towels (122)	−.001	.655[b]	.071	.440[b]
Dry spaghetti (123)	−.239[b]	.443[b]	−.104	.301[b]
Furniture polish (119)	−.258[b]	.602[b]	−.038	.469[b]
Toothpaste (123)	−.144[c]	.507[b]	−.159[d]	.334[b]
Beer (109)	.080	.452[b]	.082	.208[b]
Instant coffee (114)	−.089	.454[b]	.119	.269[b]
Aspirin (122)	−.066	.567[b]	.145[c]	.433[b]
Margarine (122)	−.195[b]	.533[b]	.150[d]	.427[b]
Fabric softener (114)	−.095	.433[b]	−.179[d]	.191[b]

[a] For the multiplicative models, logarithms of the variables transformed as described in the text were used. The entries in the table are standardized coefficients (beta weights).
[b] $p < .01$.
[c] $p < .10$.
[d] $p < .05$.

Table 4
INDIVIDUAL PRODUCT CLASS HANDLED RISK LINEAR REGRESSION COEFFICIENTS[a]

Product class (N)	*Inherent risk*	*Information*	R^2
Paper towels (122)	.488[b]	−.062	.225[b]
Dry spaghetti (123)	.775[b]	.097[c]	.664[b]
Furniture polish (119)	.619[b]	−.133[c]	.386[b]
Toothpaste (123)	.534[b]	−.150[c]	.233[b]
Beer (109)	.740[b]	−.169[d]	.503[b]
Instant coffee (114)	.727[b]	−.259[b]	.414[b]
Aspirin (122)	.690[b]	−.011	.472[b]
Margarine (122)	.509[b]	−.066	.238[b]
Fabric softener (114)	.678[b]	−.192[b]	.446[b]

[a] Entries in the table are standardized coefficients (beta weights).
[b] $p < .01$.
[c] $p < .10$.
[d] $p < .05$.

IMPLICATIONS

The Model and Its Components

The hypothesized models are supported reasonably well by the data, except for the perceived price variable in the inherent risk models. For the inherent risk models, importance is the dominant variable, with percentage of acceptable brands being the variable relating to the goodness of the buyer's brand decision rule. For the handled risk models, inherent risk is the dominant variable, with information seen as a corrective variable.

Importance seems to be very heavily weighted in all of the inherent risk equations. Slovic and Lichtenstein, using a linear model to examine choices in betting situations, found the consequences portion of the bet to be more important in some situations than the probability component [21]. Perhaps for grocery products, uncertainty is fairly low, and hence importance takes the dominant role. It is also possible that the specific wording of the importance question was such that it was measuring essentially the same phenomenon as the inherent risk measure.

Additive and Multiplicative Models

Most work in the risk area has proposed some sort of multiplicative formulation [3, 9, 13, 20]. However, here the linear models fit slightly better which could be accounted for in several ways. First, the methodological problems discussed above may be downgrading the performance of the multiplicative model. Second, the models really deal with *relative* risk, as the mean has been removed in the measurement process. This could affect the performance of the multiplicative model. Finally, other research has supported a linear model. In particular, Lanzetta and Driscoll [15] suggest that positive correlation between importance and uncertainty might lead to such an effect. In this study the correlation between importance and percentage acceptable is $-.252$ (because of the way this variable is scaled, the negative sign is correct here). Thus the phenomena suggested by Lanzetta and Driscoll may be operating. However, the R^2 values are quite close for the two models, and the model coefficients have very similar patterns, so no definitive statements about model form can be made.

Marketing Implications

If perceived risk is an important factor in consumer choices [4], then understanding perceived risk is of some benefit to the marketer. The model of risk shown here suggests that if the marketer desires to reduce risk, he can attempt to influence either the buyer's decision rule or his importance for the product class. Since importance is likely to be hard to affect, the major leverage would seem to be in influencing variables related to the buyer's goodness of decision rule, in particular by emphasizing that his brand is in the acceptable set. Also, information about the brand is useful in reducing handled risk. However, note that when risk was low in the consumer choice models in [4], price became more important in brand choice. Hence, if the marketer has a high price, he may wish to emphasize the riskiness of the product class by stressing importance and a small number of acceptable brands, while at the same time promoting the quality of his own brand.

REFERENCES

1. Bass, Frank M. "Application of Regression Models in Marketing: Testing versus Forecasting," Institute Paper 265, Krannert Graduate School of Industrial Administration, Purdue University, 1969.
2. Bauer, Raymond A. "Consumer Behavior as Risk Taking," in Donald F. Cox, ed., *Risk Taking and Information Handling in Consumer Behavior.* Boston: Graduate School of Business Administration, Harvard University, 1967, 23–33.
3. Berlyne, D. E. *Conflict, Arousal, and Curiosity.* New York: McGraw-Hill, 1960.
4. Bettman, James R. "Information Processing Models of Consumer Behavior," *Journal of Marketing Research,* 7 (August 1970), 370–6.
5. ———. "Perceived Risk: A Measurement Methodology and Preliminary Findings," in M. Venkatesan, ed., *Proceedings of the 3rd Annual Conference of the Association for Consumer Research.* 1972, in press.
6. Campbell, Donald T. and Donald W. Fiske. "Convergent and Discriminant Validation by the Multitrait-Multimethod Matrix," *Psychological Bulletin,* 56 (March 1959), 81–105.
7. Cox, Donald F., ed., *Risk Taking and Information Handling in Consumer Behavior.* Boston: Graduate School of Business Administration, Harvard University, 1967.
8. ——— and Stuart U. Rich. "Perceived Risk and Consumer Decision Making—The Case of Telephone Shopping," in Donald F. Cox, ed., *Risk Taking and Information Handling in Consumer Behavior.* Boston: Graduate School of Business Administration, Harvard University, 1967, 487–506.
9. Cunningham, Scott M. "The Major Dimensions of Perceived Risk," in Donald F. Cox, ed. *Risk Taking and Information Handling in Consumer Behavior.* Boston: Graduate School of Business Administration, Harvard University, 1967, 82–108.
10. Einhorn, Hillel J. "The Use of Nonlinear, Noncompensatory Models in Decision Making," *Psychological Bulletin,* 73 (March 1970), 221–30.
11. Farrar, Donald E. and Robert R. Glauber. "Multicollinearitv in Regression Analysis: The Problem Revisited," *Review of Economics and Statistics,* 49 (February 1967), 92–107.
12. Goldberg, Lewis R. "Five Models of Clinical Judgment: An Empirical Comparison Between Linear and Nonlinear Representations of the Human Inference Process," *Organizational Behavior and Human Performance,* 6 (July 1971), 458–79.
13. Hansen, Flemming. *Consumer Choice Behavior: A Cognitive Theory.* New York: Free Press, 1972.
14. Howard, John A. and Jagdish N. Sheth. *The Theory of Buyer Behavior.* New York: John Wiley and Sons, 1969.
15. Lanzetta, John T. and James M. Driscoll. "Effects of Uncertainty and Importance on Information Search in Decision Making," *Journal of Personality and Social Psychology,* 10 (December 1968), 479–86.
16. Myers, James H. and Mark I. Alpert. "Determinant Buying Attitudes: Meaning and Measurement," *Journal of Marketing,* 32 (October 1968), 13–20.
17. Perry, Michael and B. Curtis Hamm. "Canonical Analysis of Relations Between Socio-Economic Risk and Personal

Influence in Purchase Decisions," *Journal of Marketing Research*, 6 (August 1969), 351–4.
18. Scott, William A. "Conceptualizing and Measuring Structural Properties of Cognition," in O. J. Harvey, ed., *Motivation and Social Interaction-Cognitive Determinants*. New York: Ronald Press, 1963, 266–88.
19. Sheth, Jagdish N. and M. Venkatesan. "Risk-Reduction Processes in Repetitive Consumer Behavior," *Journal of Marketing Research*, 5 (August 1968), 307–10.
20. Sieber, Joan E. and John T. Lanzetta. "Conflict and Conceptual Structure as Determinants of Decision Making Behavior," *Journal of Personality*, 32 (December 1964), 622–41.
21. Slovic, Paul and Sarah Lichtenstein. "Relative Importance of Probabilities and Payoff in Risk Taking," *Journal of Experimental Psychology Monograph*, 78 (November 1968), 1–18.
22. Spence, Homer E., James F. Engel, and Roger D. Blackwell. "Perceived Risk in Mail-Order and Retail Store Buying," *Journal of Marketing Research*, 7 (August 1970), 364–9.