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An Investigation of Factors Influencing Causal Attributions in Managerial Decision Making

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Abstract

This study investigates factors influencing causal attributions in managerial decision making. Three categories of factors are identified: (i) prior beliefs (ii) background frequencies, and (iii) covariation cues. The impact of factors in each of the above categories on causal attribution are studied in a marketing decision making context. Subjects demonstrated a bias toward assigning causality to variables that occurred infrequently or were controllable. Also, subjects were particularly influenced by the joint-occurrences of cause and effect variables.

Key words: Decision-making, casual inference

Marketing managers make marketing mix decisions in order to produce desirable changes in sales, market share and profits—decisions that are based on underlying assumptions of causality between the marketing mix variables and the expected outcomes. Therefore an understanding of how managers make causal inferences is central to the understanding of managerial decision making. Surprisingly, there is little work in marketing on how managers draw causal inferences. While there is research in other fields on general assessment of covariation, much of the research involves situations that, at least on the surface, differ from the situations that real-world managers face. This paper examines the issue of how managers make causal inferences in typical marketing situations, by drawing on and extending related work in psychology on covariation assessment.

Specifically, this paper assesses the role of causal cues in available data (such as joint occurrences and nonoccurrences of events, and violations of necessity and sufficiency conditions) on causal inferences. The paper also examines how one non-data based factor (controllability of the causal variable) impacts prior beliefs, and therefore assessments of causality. The effect on causal attributions of the amount (sample size) of information available and the incongruence of the information with prior beliefs is also investigated. We conclude by suggesting that if managers systematically mis-attribute causality, leading to non-optimal decisions, there is a need for training and decision support systems that reduce or compensate for their biases.

Background

This paper examines several factors that can impact causal judgments. First, it considers the cause and effect variables themselves. In the absence of data, managers would base their causal assessment on intuition or prior beliefs. While this assessment may and should be based on prior data (e.g., an analogous situation or the results of a meta-analysis), other factors are likely to enter the inference process. This paper considers two such factors: how unusual the cause variable is and whether or not it is controllable by the manager. Based on past studies, we expect that uncommon events are more likely to be seen as a cause (Weiner, 1985). Also, past studies (Kelley, 1973; Russell, 1982; Weiner, 1979) indicate that individual engage in causal attribution with the goal of controlling their environment. We therefore expect that managers will be biased by the controllability of the variable and consequently will perceive controllable variables (e.g., own price and advertising) to be more likely a cause than uncontrollable variables (e.g., competitive advertising and population growth).

This paper studies the effect of both prior beliefs and available data on managerial causal inferences. Consistent with past work, information is provided to subjects in the form of a 2×2 contingency table, where the cells represent the combinations of presence and absence of the potential cause and effect. We expect that joint-occurrences of events will be weighted the most, whereas joint non-occurrences of events will be weighted the least (Schustack and Sternberg, 1981). Further, we expect that the impact of data will depend both on its statistical power (in this study, sample size), and whether or not it is consistent with prior beliefs. Specifically, we anticipate that subjects will accept data more readily when it is congruent with their prior beliefs. Incongruent information will lead to weak causal attributions, particularly for small sample sizes (Nisbett, Krantz, Jepson, and Kunda, 1983). In essence, this suggests that managers are intuitively Bayesians in updating causal attributions.

Study 1

The basic task

A sample of 21 MBA students who had prior work experience and had taken at least one MBA level marketing course were each paid $8.00 for participating in the study. The subjects were each exposed to 64 scenarios in the form of contingency tables (see Appendix 1) where occurrences and non-occurrences of potential cause and effects were crossed, and were then asked to indicate, on a 100-point scale, the likelihood of a causal relationship between the two variables. The 64 scenarios varied in (i) the numbers in the four cells, and (ii) the potential causal variables (advertising expenditure, price, competitive advertising expenditure, and population growth).

While managers may not explicitly use contingency tables, causal inferences are based on recollections of instances. For example, in trying to assess whether advertising has paid off for his company, a manager may try to recall instances when he has increased advertising expenditures, and whether they led to a consequent increase in sales, thereby implicitly constructing a contingency table. Further, the increased availability of data, spreadsheet software, and decision support systems indicate that managers are increasingly being exposed to this type of data. This study focuses on managers' interpretations of data when it is available, thus ruling out faulty memory as a basis for interpretation.

Factors manipulated

Seven factors were each manipulated at two levels. The seven factors were (1) controllability of the cause (controllable or non-controllable), (2) joint occurrences of the cause and effect (high or low), (3) violations of sufficiency conditions, where the cause occurred but the effect did not (high or low), (4) violations of necessity conditions, where the effect occurred but the cause did not (high or low), (5) joint non-occurrences of the cause and effect (high or low), (6) congruence between prior causal beliefs and the covariance information presented (incongruent or congruent), and (7) total sample size, the total number of instances reported in the four cells (high or low).

The manipulation of the seven factors at two levels each resulted in a fractional design of 64 scenarios that allowed all two-factor interactions to be estimated independently of the main effect.

Construction of the 64 scenarios

Determining the numbers in the four cells. The numbers in the four cells were determined based on the levels of the total sample size and the four information factors (both cause-and-effect-occurring, cause-occurring-but-not-effect, effect-occurring-but-not-cause, and both cause-and-effect-not-occurring). The actual numbers in the four cells were randomly generated from a uniform distribution, with the range of the distribution as given below.

Level of sample size	*Level of the information factors*	*Range*
High	High	38–42
High	Low	13–17
Low	High	7–9
Low	Low	2–4

For example, in Appendix 1 the number corresponding to cause-and-effect-occurring is 8. This lies between 7–9, and therefore corresponds to a scenario where the level of sample size is low, but the level of cause-and-effect-occurring is high. Similarly, the number corresponding to cause-occurring-but-not-effect is 3. This is between 2–4 in the above table and corresponds to a scenario where the levels of sample size and cause-occurring-effect-not-occurring are both low. This procedure insured that the total number of instances (sum of the four cells in the contingency table) was over 50 for the high level of sample-size, and below 50 for the low level of sample-size.

Determining the causal variable in each scenario. Once the numbers in the four cells were determined, it resulted in 64 contingency tables where the covariation between the cause and effect were either positive or negative. The next step was to determine the causal variable in each scenario. This was done by linking the covariation between the cause and the effect (positive or negative) to the levels of the remaining two factors; controllability of the causal variable, and congruence between the prior beliefs (obtained from pretest of a similar sample) and covariation information, in the following manner:

Level of Controllability	*Level of Congruence*	*Covariation in the Contingency Table*	*Causal Variable Used*
Controllable	Congruent	Positive	Advertising
Controllable	Congruent	Negative	Price
Controllable	Incongruent	Positive	Price
Controllable	Incongruent	Negative	Advertising
Uncontrollable	Congruent	Positive	Population Growth
Uncontrollable	Congruent	Negative	Competitive Advertising
Uncontrollable	Incongruent	Positive	Competitive Advertising
Uncontrollable	Incongruent	Negative	Population Growth

Let us refer to Appendix 1 once again. We see that the covariation is positive. Also, it corresponds to a scenario where the causal variable is controllable and congruent with prior beliefs. Therefore we use advertising expenditure as the causal variable as it is the only one among the four that is both controllable by the marketing manager and congruent with a positive covariation. Twenty four of the scenarios had a zero covariation, and in these scenarios, the causal variable was randomly selected, so that each of the four causal variables appeared in six such scenarios.

Measures

Based on the information in the contingency tables, subjects indicated, on a 100 point scale, the likelihood that a change in the potential causal variable would cause a change in the Sales. Prior causal beliefs for each of the four variables (Advertising, Price, Competitive Advertising and Population Growth) were also obtained from each respondent. As the perceived frequency of the cause occurring will be high when the relative frequencies of both joint occurrences and violations of sufficiency conditions are high, the product CAUSE-AND-EFFECT-OCCURRING*CAUSE-AND-NO-EFFECT-OCCURRING was used as an measure of the perceived frequency of the cause occurring. Similarly, as the perceived frequency of the effect occurring will be high when the relative frequencies of both joint occurrences and violations of necessity conditions are high, the product CAUSE-AND-EFFECT-OCCURRING*EFFECT-AND-NO-CAUSE-OCCURRING was used as a measure of the perceived frequency of the effect occurring.

Analysis and results

Both prior and posterior beliefs were averaged across the 21 respondents for each of the 64 scenarios. A regression was performed with the posterior beliefs as the dependent variable, and the seven factors as the independent variables (Table 1). The overall R^2 of the regression is 0.35. Prior beliefs are not significantly related to posterior beliefs. CAUSE-AND-EFFECT-OCCURRING*CAUSE-AND-NO-EFFECT-OCCURRING was significantly negatively related to posterior beliefs, showing that a variable is more likely to be considered a cause when it occurs infrequently. Also, CAUSE-AND-EFFECT-OCCURRING*EFFECT-AND-NO-CAUSE-OCCURRING was significantly negatively related to posterior beliefs, showing that a variable is more likely to be considered a cause when the effect associated with it occurs infrequently.

An examination of the four information factors showed that CAUSE-AND-EFFECT-OCCURRING was weighted the most, followed by CAUSE-AND-NO-EFFECT-OCCURRING, EFFECT-AND-NO-CAUSE-OCCURRING and finally NO-CAUSE-AND-NO-EFFECT-OCCURRING. Only CAUSE-AND-EFFECT-OCCURRING and CAUSE-AND-NO-EFFECT-OCCURRING were significantly related to posterior beliefs. The impact of CAUSE-AND-EFFECT-OCCURRING was significantly greater than the other three variables ($p < 0.05$). CAUSE-AND-NO-EFFECT-OCCURRING was significantly greater than NO-CAUSE-AND-NO-EFFECT-OCCURRING ($p < 0.05$), but not

Table 1: Determinants of posterior causal beliefs
dependent variable = posterior causal belief
(Standardized Regression Coefficients)

Independent variable	Standardized coefficients
PRIOR BELIEFS	0.0
CAUSE-AND-EFFECT-OCCURRING	0.71[a]
CAUSE-AND-NO-EFFECT-OCCURRING	0.26[c]
EFFECT-AND-NO-CAUSE-OCCURRING	0.17
NO-CAUSE-AND-NO-EFFECT-OCCURRING	0.06
CAUSE-AND-EFFECT-OCCURRING* CAUSE-AND-NO-EFFECT-OCCURRING	−0.72[a]
CAUSE-AND-EFFECT-OCCURRING* EFFECT-AND-NO-CAUSE-OCCURRING	−0.54[a]
INCONGRUENCE	−0.18
INCONGRUENCE*SAMPLE-SIZE	0.35[a]
R^2	0.35[a]

a = $p < 0.01$
c = $p < 0.10$

significantly greater than EFFECT-AND-NO-CAUSE-OCCURRING. EFFECT-AND-NO-CAUSE-OCCURRING was not significantly greater than NO-CAUSE-AND-NO-EFFECT-OCCURRING.

The incongruence between prior beliefs and the covariation (INCONGRUENCE) is negative, but not significant. Also, INCONGRUENCE*SAMPLE-SIZE is positive and significant. Finally, regressing prior beliefs as a function of CONTROLLABLE produced a significant R^2 of 0.08 ($p < 0.05$), indicating that the controllability of a variable significantly affects its likelihood of being considered a cause.

Discussion

Post-test discussions with subjects revealed one reason for some of the weaker results. Respondents found it difficult to use their prior beliefs about any causal relationship (negative or positive) while responding to the question. They indicated that they usually considered a directional causal relationship (either positive or negative) while giving responses. For example, in the question, "How likely will a change in advertising cause a change in sales?" some respondents interpreted change to mean an "increase," while others interpreted change to mean a "decrease." Therefore, a second study was conducted where directional (positive) causal beliefs were measured. Further, to rule out the explanation that results could be due to an order effect (that is, the relative positions of the four cells in the contingency table), Study 2 counterbalanced the positions of the four cells.

Study 2

Method

Fifty MBA students who had either completed or were enrolled in the MBA program and had taken at least one marketing course were recruited for the study. Forty-eight of the fifty subjects had previous work experience. Each subject was paid $7.00 and participated in a lottery for $500.

Twenty five subjects received one set of stimuli, while the other twenty five received the other. The two sets differed in the location of the four cells. One set was similar to that in the first study with joint occurrences being provided at top-left and joint nonoccurrences at bottom-right. In the other set, joint occurrences were provided at the bottom-right and nonoccurrences at top-left. Subsequent analysis showed no differences in the results across the two sets, and the results were combined for the two conditions.

The design was the same as the previous study with two main changes. First, both prior and posterior measures were phrased so as to measure the likelihood of an *increase* in sales. Also, the word 'substantial' was included in the question in order to provide for a more conservative test of the results. The second change was in the scenarios (see Appendix 2). The scenarios now provided for high and normal levels of sales and the four causal variables, unlike the previous study where increases and decreases were provided, in order to make the scenarios consistent with the new dependent variable. On average, the respondents took approximately 45 minutes to complete the task.

Analysis and results

Aggregate analysis. Both prior and posterior beliefs were aggregated across the 50 respondents for each of the 64 scenarios. A series of regressions were performed (Table 2). The simplest model assumes that posterior beliefs are solely a function of prior beliefs. This model produced an R^2 of 0.06 ($p < 0.10$), suggesting that posterior beliefs are weakly related to prior beliefs. When the regression was run with only the four covariation factors (CAUSE-AND-EFFECT-OCCURRING, CAUSE-AND-NO-EFFECT-OCCURRING, EFFECT-AND-NO-CAUSE-OCCURRING, NO-CAUSE-AND-NO-EFFECT-OCCURRING), it produced an R^2 of 0.78 (Regression 1). In this regression, all covariation factors except NO-CAUSE-AND-NO-EFFECT-OCCURRING are significant. This suggests subjects were heavily influenced by the data. When the regression was run with prior beliefs and the four covariation factors as the independent factors (Regression 2), the R^2 increases significantly to 0.84. When INCONGRUENCE, the interaction term INCONGRUENCE*SAMPLE-SIZE and the two estimates of the frequencies (CAUSE-AND-EFFECT-OCCURRING*CAUSE-AND-NO-EFFECT-OCCURRING and CAUSE-AND-EFFECT-OCCURRING*EFFECT-AND-NO-CAUSE-OCCURRING) were added (Regression 3), the R^2 increases significantly to 0.91.

Regression 3 provides stronger results than those found in the first study. The coefficient for PRIOR-BELIEFS is significant ($p < 0.01$), showing that prior causal beliefs influence causal attributions. CAUSE-AND-EFFECT-OCCURRING*CAUSE-AND-NO-EFFECT-OCCURRING is significantly negative ($p < 0.01$) showing that infrequent

Table 2: Determinants of posterior causal beliefs
dependent variable = posterior causal belief
(Standardized Regression Coefficients) Regression

Independent variable	1	2	3
PRIOR BELIEFS	—	0.27^a	0.25^a
CAUSE-AND-EFFECT-OCCURRING	0.72^a	0.73^a	1.05^a
CAUSE-AND-NO-EFFECT-OCCURRING	-0.42^a	-0.42^a	-0.23^a
EFFECT-AND-NO-CAUSE-OCCURRING	-0.27^a	-0.27^a	-0.15^a
NO-CAUSE-AND-NO-EFFECT-OCCURRING	0.07	0.07	0.08^c
CAUSE-AND-EFFECT-OCCURRING* CAUSE-AND-NO-EFFECT-OCCURRING	—	—	-0.33^a
CAUSE-AND-EFFECT-OCCURRING* EFFECT-AND-NO-CAUSE-OCCURRING	—	—	-0.22^a
INCONGRUENCE	—	—	-0.11^b
INCONGRUENCE*SAMPLE-SIZE	—	—	0.12^b
R^2	0.78^a	0.84^a	0.91^a

a = $p < 0.01$; b = $p < 0.05$; c = $p < 0.10$

events are more likely to be seen as causes. The frequency of the effect occurring (CAUSE-AND-EFFECT-OCCURRING*EFFECT-AND-NO-CAUSE-OCCURRING) is also significantly negative ($p < 0.01$) suggesting that infrequent events are likely to result in increased causal attributions. Also, all covariation factors but NO-CAUSE-AND-NO-EFFECT-OCCURRING are significant ($p < 0.01$). The pattern of coefficients for the four covariation factors show that joint occurrences (CAUSE-AND-EFFECT-OCCURRING) was weighted the most, followed by violations of sufficiency conditions (CAUSE-AND-NO-EFFECT-OCCURRING), then by violations of necessity conditions (EFFECT-AND-NO-CAUSE-OCCURRING) and finally by joint nonoccurrences (NO-CAUSE-AND-NO-EFFECT-OCCURRING). Joint occurrences and nonoccurrences increased the attribution of a positive causal relationship between the variables, whereas violations of sufficiency and necessary conditions reduced the attribution of a positive causal relationship between the variables.

Incongruent information reduces causal attributions ($p < 0.05$). Finally, the coefficient for INCONGRUENCE*SAMPLE-SIZE is significantly positive ($p < 0.05$) suggesting that subjects' stickiness with respect to their priors for incongruent information based on small sample sizes was overcome by information based on large sample sizes. The above results are consistent with the earlier study.[1]

Finally, regressing prior beliefs as a function of the controllability of the cause variable produced a significant R^2 of 0.09 ($p = 0.02$). Further tests (Baron and Kenny, 1986) showed that the effect of controllability on posterior beliefs was mediated by prior beliefs.

Individual level analysis. The full model in Table 2 was run individually for each of the 50 respondents (i.e., the prior and the posterior beliefs were not aggregated across the respondents). The results show that CAUSE-AND-EFFECT-OCCURRING is the most important variable for the respondents as measured by its size and its significance. CAUSE-AND-EFFECT-OCCURRING is positive for 48 of the 50 respondents (significantly positive for 43 respondents). Also, CAUSE-AND-NO-EFFECT-OCCURRING and EFFECT-AND-NO-CAUSE-OCCURRING are negative for most of the respondents; CAUSE-AND-NO-EFFECT-OCCURRING is negative for 38 of the 50 respondents (significant for 19 respondents), while EFFECT-AND-NO-CAUSE-OCCURRING is negative for 41 respondents (significant for 8 respondents). However, NO-CAUSE-AND-NO-EFFECT-OCCURRING is positive for 24 respondents (significant for 15), and negative for 26 respondents (significant for 8). PRIOR-BELIEFS and INCONGRUENCE*-SAMPLE-SIZE are positive for 35 and 37 respondents and significantly positive for 19 and 4 respondents respectively. INCONGRUENCE, CAUSE-AND-EFFECT-OCCURRING*CAUSE-AND-NO-EFFECT-OCCURRING and CAUSE-AND-EFFECT-OCCURRING*EFFECT-AND-NO-CAUSE-OCCURRING are negative for 39, 36 and 37 respondents and significantly negative for 3, 18 and 10 respondents respectively. Forty-seven of the fifty individual regressions were significant at $p < 0.01$. The results of the individual level analysis are consistent with the aggregate results. All variables, except NO-CAUSE-AND-NO-EFFECT-OCCURRING, are directionally consistent with the aggregate results for a majority of the respondents. Since NO-CAUSE-AND-NO-EFFECT-OCCURRING is almost evenly split between positive and negative parameters, it explains why it was not significant at the aggregate level. It is interesting that subjects appear to be inconsistent in how they utilize nonoccurrences of events.

Discussion

Simplifying the cognitive requirements of the task in Study 2 resulted in stronger results. Interestingly, subjects did not have a common strategy of utilizing joint nonoccurrences. For roughly half the subjects, joint nonoccurrences led to a greater attribution of positive causality whereas for the other half, joint nonoccurrences led to a lower attribution of positive causality. One possible explanation could be that subjects did not find information on joint nonoccurrences to be diagnostic. Alternatively, since individuals do not normally observe nonoccurrences of events in a real world environment, they may not have a clear strategy for utilizing such information when it is presented to them. This explanations is consistent with Einhorn and Hogarth's (1978) argument, in a different context, that biases in inferential learning may arise when information on non occurrences of events are not available.

Summary

The findings of the two studies have implications for two main areas: managerial judgment per se and likely biases/patterns of marketing decisions. Regarding managerial judgment, individuals paid more attention to joint occurrences than to joint nonoccurrences while making judgments of probable cause when both types of information were available. In real world situations, there may be a tendency to observe only occurrences of events, which may increase the tendency to ignore nonoccurrence of events, mis-estimate relations among variables, and therefore lead to inferior decisions.

In general, subjects focused on situations where the potential cause occurred. This might be facilitated by linguistic structures that typically represent causation in memory as '*X* causes *Y*' rather than '*Y* is caused by *X*.' It is possible that the question determines whether managers put more emphasis on violations of necessity or sufficiency conditions. If the question is "why did sales change?" then there may be more emphasis on situations where sales changed (including violations of necessity). On the other hand, if the question is "what will happen if we increase advertising?" then the emphasis may be on situations where advertising was increased (including violations of sufficiency conditions). The phrasing of the instructions in this study was consistent with the latter question. However, McKenzie (1992) found that changing the order of information and instructions to reflect an effect-followed-by-cause order did not change the cause-to-effect order in which causal knowledge was organized.

Subjects also exhibited the 'control bias', that is, the controllability of the variable influenced their prior causal beliefs. In the real world, managers may not be asking themselves the question, "What could have caused this event?" but rather the question, "What event that I can control could have caused this event?" As a result, uncontrollable events may not be even considered as causal candidates. In other words, managers may create a consideration set of controllable causes and then proceed to pick the most likely candidate out of this set.

Prior beliefs were weakly related to posterior beliefs, consistent with findings in covariation assessment that prior beliefs influence sampling of information (Roedder John, Scott and Bettman, 1986), but not assessment of covariation (Bettman, Roedder John and Scott, 1986). In this case, all the information were easily available to managers. In situations where all the information is not available, prior beliefs may play a stronger role in a manager's search for information and causal attributions.

The results have at least two important implications. First, in building decision aids, it is important to focus attention on events other than joint occurrences as well as a large number of variables and to train marketing managers to utilize this information. Mere presentation of the information appears to be inadequate. The observation that receiving market research information in a market simulation did not improve players' performance (Glazer, Steckel and Winer, 1992) may be due to their inaccurate (biased) processing of the information. Second, it is important to understand how managers retrieve covariation factors from memory or distill it from complex environments. It seems likely that managers, particularly if they are hypothesis testers (Lalljee, 1981), will search for information consistent with their priors, biasing covariation assessment and hence causal assessments. Studying how managers retrieve information and how they can be trained to do so most appropriately is another important direction for future research.

Some specific marketing phenomenon are also explainable based on the results. For example, when sales increase, there is a tendency to attribute this to variables they control such as advertising rather than environmental factors such as competition. The consequence of this is a likelihood of over-advertising, evidence of which is found in some econometric studies. Given the saliency of short term promotion successes and the prevalence of scanner data, we expect a strong tendency toward over-promotion, a state of affairs which many in industry now acknowledge exists.

In summary, managers, due to biases in information recall and use, as well as a preference for attributing causality to variables they can control, will tend to overestimate the impact of their marketing mix elements on sales and profits compared to competitive or environmental factors. As a consequence, they will overspend on advertising and promotion, which will in turn be matched by competitors. Developing training aids and decision support systems which counteract the biases should be an important and useful direction for research.

Appendix 1

A sample scenario

In this market, information is available from 23 instances.

	SALES	
	INCREASED	DECREASED
ADVERTISING EXPENDITURES INCREASED	8	3
ADVERTISING EXPENDITURES DECREASED	3	9

Based on the above information, answer the following question on a scale from 0 to 100.
In this market, how likely would a change in your advertising *cause* a change in your sales?

Appendix 2

Sample scenario

In this market, information is available from *160* instances.

	SALES	
	HIGH	NORMAL
ADVERTISING LEVELS HIGH	42	38
ADVERTISING LEVELS NORMAL	39	41

Based on the above information answer the following question on a scale from 0 to 100.
In this market how likely would an increase in your advertising *cause* an increase in your sales?

Notes

1. A number of alternative models were also run. When the correlation from the available information (in the four cells of the contingency table) was computed and used in conjunction with prior beliefs, the R^2 was 0.52, suggesting that subjects combined data in a way other than by forming a simple correlation (when the correlation was used alone, R^2 was 0.44). Also running logistic regressions to account for ceiling effects, where the dependent variable POSTERIOR was converted to LOG((POSTERIOR/(1-POSTERIOR)) showed that the standardized parameters changed only marginally and the overall results were essentially the same. Therefore, only the more interpretable results for linear regressions are reported.

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