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Perceiving Competitive Reactions: The Value of Accuracy (and Paranoia)

BRUCE H. CLARK
Marketing Group, College of Business Administration, 202 Hayden Hall, Northeastern University, Boston, MA 02115

DAVID B. MONTGOMERY
Graduate School of Business, Stanford University, Littlefield 339, Stanford, CA 94305; Marketing Science Institute, 1000 Massachusetts Ave., Cambridge, MA 02138

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Abstract

An assumption of much of the literature in marketing strategy is that a firm accurately knows the nature of its interaction with competitors. This study examines this assumption and explores the relationship between firm performance and accuracy in perception. Teams in the Markstrat2 simulation game reported their reactions to competitors, while simultaneously indicating their perceptions of whether competitors had reacted to their decisions in the past. Teams were in general inaccurate in identifying competitive reactions. Further, missing a competitive reaction (not perceiving a competitor's stated reaction) significantly reduced a team's performance. The data suggest that teams may benefit from being paranoid about their competitors; late in the game, the more competitive reactions a team perceived to its moves, the better the firm performed, regardless of accuracy.

Researchers in marketing and strategy have beomce increasingly interested in how the interaction between competitors plays out in the market. A particular focus of this work has been on how a given firm reacts to attack by competitors. Economic models have outlined patterns of competitive reaction through game theory (e.g., Wilson, 1989) and conjectural variations (Amit, Domowitz, and Fershtman, 1988). An empirical tradition has examined actual actions and reactions (Robinson, 1988; Gatignon, Anderson, and Helsen, 1989; Bowman and Gatignon, 1995).

The theory in this literature tends to assume, implicitly or explicitly, that actions and reactions are observable, and thus observed, by competitors, but empirical evidence on this point is scarce. Further, numerous researchers have suggested that the assumption that managers see their environment accurately is unlikely to be true. Theory in signaling argues that noisy environments can make perceiving information about competitors difficult, especially when the information is in some sense private (Moore, 1990). In the empirical literature on competitive reactions, Robinson (1988) observes that reactions may be especially difficult to detect.

Given that an action or reaction is perceived at all, the next question concerns the accuracy with which an action is perceived. Accuracy is important in two senses. First, it is an underlying assumption of many models of competitive interaction, as noted above. Second, accuracy in perceiving competitors is presumed to improve firm performance, as demonstrated by the attention virtually all strategy texts devote to analyzing competitors (e.g., Porter, 1980; Aaker, 1995).

This paper has two purposes. First, it tests the assumption that firms accurately know the nature of their interaction with competitors. Second, it examines whether accuracy has a positive effect on firm performance. Theoretically, we break down perceived accuracy into different underlying forms. We identify accuracy on these underlying forms by surveying participants in the simulation game Markstrat2 (Larreche and Gatignon, 1990) and relate accuracy to performance measures in the game.

1. Accuracy in perceiving competitive reactions

Consider a situation with a firm and a competitor, where the firm in time period t is considering whether the competitor reacted to the firm in time period $t - 1$. For the purposes of this research, we define a reaction as a behavior that the reactor reports was caused by competitive behavior. One of four outcomes can occur, as illustrated in Table 1.

In the first case, a competitor reacts to the firm, and the firm correctly perceives that a reaction has occurred. Following the analogy of a statistical test, we call this a *true positive*. Second, a competitor might react, but the firm might miss this reaction, what we will call a *false negative*. Third, we have a *false positive*, where the firm perceives a competitive reaction that the competitor does not report, and fourth, we have a *true negative*, where both firm and competitor agree nothing happened.

In general, one assumes that if the firm perceives a competitive reaction in time period $t - 1$, it takes that into account in its decisions for time period t. But each of these forms of accuracy or inaccuracy has different consequences for the firm's decisions.

In the case of a true positive, the firm makes plans reflecting a competitive reaction. The standard strategic prescription noted above is that this correct understanding of one's competitors should improve the quality of one's decisions and thus improve performance. True negatives should also improve the performance of one's firm, in that the firm does not waste economic or decision-making resources on competitors who are not reacting to the firm's plans.

The false cells represent riskier propositions. In the false positive cell, the firm takes into account a reaction that did not occur. This produces plans that may or may not react to the competitor. At best, the plans may use resources ineffectively, but at worst, a plan built on a false positive could actually provoke a previously benign competitor into engaging the firm.

Table 1. Different forms of accuracy in perceiving competitive reactions.

	Firm Perceives Reaction	Firm Perceives No Reaction
Competitor Reacts	True Positive	False Negative
Competitor Doesn't React	False Positive	True Negative

A false negative suggests the firm may be blind to a competitive threat. Zajac and Bazerman (1991) discuss a number of forms of "competitive blind spots" that may result in an unpleasant surprise for the myopic firm. With a false negative, the firm has missed something that is going on, and its decisions and performance may be the poorer for missing it.

We discuss perception of competitive reactions in terms of accuracy, but another way to think of this is to consider a signal detection analogy.[1] Signal detection theory examines how difficult it is for subjects to correctly identify a signal (in our case, a competitive reaction) broadcast in a noisy environment (in our case, general dynamics of the marketplace). See Macmillan and Creelman (1991) for a review. Rather than say "a firm is inaccurate" in its perceptions, the signal detection approach would say "a firm finds it difficult to see the signal amid the noise."

Perceiving competitive reactions may be particularly difficult for firms, as it requires them to infer something about the implicit intentions of a competitor. This may be a subtle signal amid the noise of the market. It may be quite straightforward for a firm to recognize that a competitor has introduced a new product, but much more difficult to say that the new product was intended to react to the firm, absent public statements of intentions (see Moore, 1990).

While there is no quantitative evidence of the exact degree of difficulty this presents in competitive interactions, work in social psychology and communications suggests that individuals may be fairly inaccurate in their inferences about the internal state of others with whom they interact. In person perception, for example, correlations between a person's self-ratings on personality measures and others' ratings of that person, while statistically significant, range only from .30 to .60 even for self-other pairs that know each other well, suggesting explained variance of between .09 and .36 (Funder, 1987).

Communications researchers have examined the accuracy with which an individual can tell whether another person is lying. An exhaustive review of findings in this area suggests that percentage accuracy in determining whether another person is lying ranges from 45 to 70 percent, and that it may be especially difficult for participants in an interaction—as opposed to observers—to detect deception (Kalbfleisch, 1992).

Since our research is in a little-known area empirically, we do not state a research hypothesis that accuracy will be at a specific level (e.g., 50 percent). However, given the evidence above, it seems reasonable to expect that the accuracy with which firms can judge competitors' reactions will be low.

2. Research hypotheses on accuracy and performance

While it is possible that accuracy matters in firm performance, we first examine more basic hypotheses about competitive reactions that could affect a firm's performance, regardless of the firm's accuracy in perceiving the reactions.

First, it is likely that if competitive reactions are of sufficient quality and magnitude, then the more reactions experienced by a firm, the lower the firm's performance. Competitive reactions may hurt a firm regardless of the accuracy with which the reactions are perceived; indeed, one of the practical implications of much of the research on competitive reactions is to better understand how a competitor can best react to hurt a firm. Sizable reactions, in particular, may allow the firm no defense. A small firm might realize, for example, that a large competitor is undercutting its price but have little recourse. One can argue that flanking strategies and niche strategies are often designed precisely to avoid provoking competitive reactions that would damage the attacking firm.

As it is necessary to account for the impact of competitive reactions in general, we therefore test the following hypothesis:

Hypothesis 1: *The more competitive reactions experienced by a firm, the lower the firm's performance, regardless of how accurately these reactions are perceived.*

A second possibility we explore is what we call the paranoia hypothesis. There is much discussion in the popular business press of the virtue of competitive paranoia in business. Perhaps the most avid proponent of view is Andrew Grove, the CEO of Intel Corporation, whose Grove's law proposes that "only the paranoid survive" (Schlender, 1995). Similarly, the CEO of Hewlett-Packard claims part of his management style is to maintain a "healthy paranoia" about IBM within his organization (*Bloomberg Business News*, 1995). In a broader sense, much of the rhetoric surrounding continuous improvement and total quality management reflects the belief that somewhere out there is a competitor waiting to catch the firm unawares. Bernie Marcus, cofounder of the successful Home Depot retail chain, remarks, "We're always looking for someone to crawl over our backs, to destroy us" (Seller, 1995, p. 62).

The word *paranoid* suggests that the beliefs noted above are in some sense irrational or excessive—that is, they may be inaccurate. It may be that these firms perceive threats from competitors when none exist. It is possible, however, that even irrational beliefs about competitors may have performance benefits. First, paranoia may be highly motivating. If a firm believes it is constantly under competitive threat, it will work hard to defend itself. Second, paranoia may lead to more detailed competitive analysis, reducing the possibility of bad competitive surprises in the future.

Formally, we state the paranoia hypothesis here as follows:

Hypothesis 2: *The more competitive reactions a firm perceives, the higher the firm's performance, regardless of how accurate these perceptions are.*

If accuracy in perception of competitive reactions matters, then we will be able to reject Hypothesis 1 and/or 2 in favor of one or more of the following specific hypotheses, in line with the logic above:

Hypothesis 3: *The more competitive reactions a firm correctly perceives (true positives), the higher the firm's performance.*

Hypothesis 4: *The more competitive reactions a firm does not perceive (false negatives), the lower the firm's performance.*

Hypothesis 5: *The more competitive nonreactions a firm erroneously perceives as reactions (false positives), the lower the firm's performance.*

Note that we ignore true negatives here on the grounds that the important focus here is on situations where (1) a reaction occurred and/or (2) a reaction was perceived. True negatives had no significant effects on any of the results reported below.

As noted in the introduction, the idea that perceiving past competitive reactions accurately will help performance (Hypotheses 3, 4, and 5) is commonplace in marketing strategy. Clearly, knowing how a competitor will behave in a market in the *future* is useful to the perceiving firm in that it identifies likely combinations of firm-competitor behavior. In a simple game theory sense, knowledge that a competitor will behave in one manner allows a player to eliminate from consideration all cells in the payoff matrix that arise from a competitor behaving in another manner. This is cognitively efficient; rather than contemplate the payoffs from a wide range of competitive behaviors, one can focus on understanding the consequences of a much smaller range of behaviors. A deeper understanding of likely competitive behavior leads to better decisions, which in turn should improve performance.

The assumption underlying analysis of *past* competitor behavior is that this will allow the firm to predict future competitor behavior. Deshpande and Gatignon (1994), for example, suggest that managers can use historical data to identify the consistent reaction patterns of competitors and can then use these behaviors to predict future competitive responses. One can argue, however, that a competitor's past behavior should be irrelevant to future behavior. The rational competitor will look at conditions in the future market and make the best decision for those conditions, regardless of past behavior. Returning to our simple game theory analogy, the competitor will always look at all possibilities in the payoff matrix for the future period.

Why then, should understanding past competitor behavior improve firm performance? While past competitive behavior should not predict future competitive behavior normatively, it may be used to predict future competitive behavior probabilistically when either of two conditions are met. First, if market and competitive conditions have not changed, then the competitor presumably faces the same choices and payoffs in the future as in the past. Thus, the optimal decision for the future remains the same as it was in the past.

In the more likely situation that market and competitive conditions do change, future behavior patterns will be associated with past behavior patterns if past behavior patterns are "irrationally" unchanging despite changes in the environment. There is much evidence in the strategy literature that this kind of unchanging behavior is very common. It is variously referred to as "persistence" (Lant, Milliken, and Batra, 1992), "inertia" (Miller and Chen, 1994), or "momentum" (Miller and Friesen, 1980) and can arise from a number of sources. For example, past success can encourage inertia (Miller and Chen, 1994). One may have made a commitment to a particular course of action that one must fulfill (Staw, 1981). An organization may face constraints on its ability to change due to its size, internal structure, or external constituencies (Hannan and Freeman, 1984). Culture can drive a firm's behavior in ways that may or may not match market conditions (Deshpande, Farley, and Webster, 1993). This evidence suggests that past competitive behavior may indeed be used to predict future competitive behavior even in changing environments, meaning firms can use the cognitive shortcut of analyzing past behavior as a proxy for future behavior. To the extent that firms are accurate in this endeavor, then the shortcut will result in sound decisions and superior performance. Our research will test this relationship.

3. Method and data

The empirical setting for this study was the Markstrat2 simulation game (Larreche and Gatignon, 1990). The Markstrat2 simulation places teams of subjects in the position of managing the marketing and research and development strategy of one of five firms in a hypothetical consumer durable goods industry. A given team's performance is governed by its own decisions and competitors' decisions as they interact with underlying trends in the Markstrat economy. (For more detail on the Markstrat environment, see Glazer, Steckel, and Winer, 1992.)

A particular advantage of this setting is that it allows us to observe all sides of a complex, repeated competitive interaction. We can then relate management decisions in this interaction to performance in the game, following in a growing tradition of Markstrat research (Lant and Montgomery, 1987; Glazer, Steckel, and Winer, 1987, 1992; Glazer and Weiss, 1993). Regarding our particular research problem, Markstrat is a setting in which competitive reactions are likely to occur and in which many of the drivers of strategic inertia noted above are likely to exist.

Subjects in the study came from two samples. The first consisted of a sample of MBA students at Stanford University taking an elective in marketing strategy. Sixty-one students were randomly assigned to fifteen teams across three Markstrat industries and played an eight-period game over the course of a month. The second sample consisted of 100 executives of a European multinational, grouped by the company into twenty teams across four Markstrat industries, who played a seven-period game as part of a six-day executive education program. There were no empirical differences regarding our hypotheses across these two subject pools, so all results below reflect a pooled analysis.

In each period, beginning with period three, teams filled out a "competitive reaction form." The form asked them to discuss their decisons and strategy for the coming period. The form also asked a series of open-ended questions about whether teams were attacking or reacting to competitors in their decisions and whether they had observed reactions by competitors to their decisions.

Answers to these questions were coded to indicate the actions and reactions teams reported making against competitors, and the actions and reactions teams reported perceiving by competitors. Answers were coded by three independent judges in the MBA sample and two in the Executive sample. Perrault and Leigh (1989) interjudge reliability indices for answers where at least one coder believed an action or reaction occurred or was perceived averaged .79 for the MBA sample and was .86 for the Executive sample.[2] Disagreements were resolved by discussion among the coders. For a given team in a given period, forms were coded to indicate whether the team was or was not reacting to each of its four competitors in its decisions for that period and whether the team had or had not perceived reactions in previous periods by each of its four competitors.

Once all teams were coded on reactions or perceptions, accuracy counts were tallied by comparing perceived reactions in period t to reported reactions in period $t - 1$ and calculating true positives, true negatives, false positives, and false negatives accordingly. So, for example, if team 1 stated in period 5 that it perceived that team 2 had reacted to its previous moves, and team 2 reported in period 4 that it was reacting to team 1, this was coded as a true positive. These counts are used as the independent variables in the analysis reported below.

Beyond this basic coding, we split our pooled sample into early- and late-game groups, as described below.[3] We argue that teams can learn from history; it is also reasonable to assume that learning may have different effects at different points in the game as the industry evolves (cf. Moore, 1992). Further, previous Markstrat research has revealed that significant time-based effects can occur in the simulation (Glazer, Steckel, and Winer, 1992).

4. Results

4.1. Overall accuracy rates

Table 2 reports summary counts of true positives, false negatives, false positives, and true negatives for the entire sample. We attempted a time analysis by dividing the sample into early and late groups, where early observations are from periods 4 and 5, while later observations are from periods 6, 7, and 8 (52 percent of all observations were late under this scheme, while 48 percent were early). There were no significant differences in accuracy rates between early and late periods.

Overall team accuracy is significantly better than zero. A chi-squared test of association suggests that perceived and actual reactions are significantly associated ($\chi^2 = 5.35$, $df = 1$, $p < .025$). Total accuracy, as reflected by the number of true positives and true negatives (26 + 338) over the total sample (510), is passable but hardly sterling at 71 percent.

Focusing on cases where a reaction occurred or was perceived, we can look at accuracy on reactions in two ways; the numbers are low under either scheme. First, we can look at the number of true positives over the total number of actual reactions. This answers the question of how many actual reactions were perceived correctly. The rate here is 21 percent (=26/123). Second, we can divide the number of true positives over the number of reactions teams perceived. This answers the question of how many of the positive perceptions teams held were correct. The rate here is a marginally more encouraging 35 percent (=26/75).

Table 2. Summary accuracy counts.

Number (Row%) (Col%)	Firm Perceives (time t) Reaction	Firm Perceives (time t) No Reaction	Totals
Competitor (time $t - 1$) Reacts	True Positives 26 (21%) (35%)	False Negatives 97 (79%) (22%)	123 (100%) (24%)
Competitor (time $t - 1$) Doesn't React	False Positives 49 (13%) (65%)	True Negatives 338 (87%) (78%)	387 (100%) (76%)
Totals	75 (15%) (100%)	435 (85%) (100%)	510 (100%) (100%)

A final way of considering the level of accuracy is to examine two standard measures from signal detection theory (see Macmillan and Creelman, 1991, for a discussion of these measures). The first, d', measures the difficulty of detecting signal amid noise. Assuming two normally distributed levels of psychological stimulation, d' indicates the number of standard deviations separating the mean level of psychological stimulation when the signal is present and the mean level when the signal is absent. When d' equals zero, the subject is unable to distinguish signal from noise. As a subject is better and better able to distinguish signal from noise, d' rises. Levine and Parkinson (1994) suggest it is likely to vary between 0 and 1 in most situations.

For our sample, $d' = .32$. Cohen (1988) suggests that a difference of .5 standard deviations between two normal distributions ($d' = .5$) is a medium effect size, "one large enough to be visible to the naked eye" (p. 26). By contrast, he considers .2 a "small" effect size. One can convert this difference measure to a correlation using the method described in Cohen (1988, pp. 23–24). In this case the correlation is .135 suggesting an R^2 of .018 (recall Funder's, 1987, findings of correlations between .30 and .60). While accuracy is statistically significant, all analyses suggest that the level of accuracy in this setting is low.[4]

A second measure from signal detection theory, c, measures any general bias subjects have to report signals or nonsignals independent of how difficult the detection task is. Positive values of c suggest that subjects have a bias against reporting seeing signals, while negative values suggest a bias for reporting signals. For our sample, $c = .97$, indicating teams have a general conservative bias such that they report few signals. This agrees with an examination of the raw data in Table 2, where teams report few reactions (75) relative to the number of reactions that actually occur (123).

4.2. *The effect of accuracy on performance*

Given relatively low levels of accuracy overall, did firms with higher accuracy perform better than those with lower accuracy? We test this hypothesis by using multiple regression.

The dependent variable in the analysis is a summed two-item scale of the two performance measures emphasized in these game administrations: net marketing contribution, a profit measure, and unit market share of the Sonite industry, a market share measure. Each of these two measures was standardized, and then the two standardized measures were summed and standardized again for interpretive ease to create a performance variable with a mean of zero and a standard deviation of one. The Cronbach coefficient alpha of this two-item scale is .87, indicating the two make a reliable single measure of performance. The regression analysis examines performance in time period t as a function of accuracy about competitive reactions in time period $t - 1$. Correspondingly, we regress performance observations in periods 4 through 8 on team accuracy about reactions in periods 3 through 7.

We use the total true positive, false positive, and false negative numbers for each team in each time period for which data are available as independent variables, along with total reactions (the sum of true positives and false negatives, as illustrated in Table 2) and total perceived reactions (the sum of true positives and false positives). Descriptive statistics for these variables are reported in Table 3. Table 4 reports fit, coefficients, standard errors, and p-values for regression models discussed below.

Table 3. Descriptive statistics ($n = 138$).

	Mean	Standard Deviation	Minimum	Maximum
Performance	0.000	1.000	−1.939	2.399
Total reactions	0.891	0.941	0.000	4.000
Total perceived reactions	0.543	0.821	0.000	4.000
True positives	0.188	0.476	0.000	2.000
True negatives	2.449	1.088	0.000	4.000
False positives	0.355	0.589	0.000	3.000
False negatives	0.703	0.823	0.000	3.000
Budget	17,134.000	5,409.965	7,387.000	24,545.000

Table 4. Regression results ($n = 138$) (dependent variable: performance).

Independent Variables[a]	Base	Model 1	Model 2	Model 3	Model 4	Model 5
Late period dummy	−0.119 (0.124) $p = .169$	−0.261 (0.171) $p = .065$	−0.314 (0.141) $p = .014$	−0.215 (0.170) $p = .104$	−0.405 (0.185) $p = .015$	−0.312 (0.139) $p = .013$
Total reactions		−0.174 (0.097) $p = .037$				
Late X total reactions		0.152 (0.130) $p = .120$				
Total perceived reactions			−0.099 (0.102) $p = .168$		−0.163 (0.105) $p = .061$	−0.149 (0.103) $p = .075$
Late X total perceived reactions			0.401 (0.149) $p = .004$		0.426 (0.148) $p = .002$	0.412 (0.146) $p = .003$
True positives				−0.045 (0.168) $p = .394$		
Late X true positives				0.472 (0.263) $p = .038$		
False negatives				−0.208 (0.108) $p = .028$	−0.249 (0.110) $p = .012$	−0.197 (0.086) $p = .012$
Late X false negatives				0.049 (0.150) $p = .372$	0.114 (0.149) $p = .223$	
Number of independent variables	12	14	14	16	16	15
R^2	.5627	.5740	.5901	.5953	.6090	.6071

a. Budget variable and team and industry dummy variables not reported; for total number of variables in the model, see "Number of independent variables." Entries in table report coefficient (standard error in parentheses, and one-tailed p value.

Four other sets of variables were included in the performance regressions. First, we included the total budget figure for time period t, since budget represents the monetary resources available for a team to spend on marketing and generally has a positive effect on performance. Second, we included dummy variables for the team starting positions, as it has been demonstrated that in the standard Markstrat scenario used here, team starting position has an influence on profitability (Ross, 1987). Third, we included dummy variables for industry to allow for individual industry effects. Finally, we added a dummy variable for time period, late versus early, dividing observations as previously described (variable = 1 for periods 6, 7, and 8). A regression using budget alone accounts for 44.34 percent of the variance in the performance measure. Adding team and industry dummy variables significantly increases R^2 to 55.95 percent. We finally add the late period dummy variable, which does not significantly improve the model fit ($R^2 = 56.27$ percent) but is included to test for time effects. This last regression represents the "base" model reported in Table 4.[5] All regressions reported here include these control variables, so we test how much accuracy affects performance given the team's industry, starting position, time period, and how much money it has to spend in the period. If a regression including accuracy variables has a significantly improved fit over the base model, this suggests that accuracy has a significant effect on performance.

We first test our two baseline hypotheses, Hypotheses 1 and 2. In this empirical analysis, Hypothesis 1 suggests that performance in time period t should be negatively affected by the number of competitive reactions in time period $t - 1$. Adding total actual reactions and the corresponding time interaction term to the baseline regression model, reported as Model 1 in Table 4, does not significantly improve fit ($R^2 = .5740$, $F_{2,123} = 1.61$, ns). It is worth noting, however, that the coefficient on total reactions is negative and significant, as expected ($t_{123} = -1.80$, $p = .037$ one-tailed). Thus it appears that Hypothesis 1 is supported in Model 1.

Hypothesis 2, the paranoia hypothesis, suggests that performance in time period t should be positively affected by the number of competitive reactions the team perceives in time period $t - 1$, regardless of whether the perceptions are accurate. Adding the total perceived reactions variable and the corresponding time interaction term significantly improves fit over the base model ($R^2 = .5901$, $F_{2,123} = 4.15$, $p < .05$). This regression is reported as Model 2 in Table 4. Examining the individual coefficients reveals a pattern opposite of that in Model 1. The main effect for total perceived reactions is not significant, but the late game interaction term is positive, as expected, and significant ($t_{123} = 2.70$, $p = .004$, one-tailed). Hypothesis 2 is supported, but only late in the game.

Given these two regressions, we now want to explore whether true positives, false negatives, or false positives makes any difference in overall performance.

The total reactions variable in the Hypothesis 1 regression, as noted in Table 2, simply represents the sum of true positives and false negatives for a given observation. By specifying a single sum variable, we are defining a linear constraint such that true positives and false negatives have the same coefficient. The constraint may be illustrated in equation form:

$$\text{Performance} = \text{Intercept} + \text{Control variables} + \beta_1 \text{ (Total reactions)}$$

$$\text{where } \beta_1 \text{ (Total reactions)} = \beta_1 \text{ (True positives + False negatives)}$$

$$= \beta_2 \text{ True positives} + \beta_3 \text{ False negatives if } \beta_2 = \beta_3.$$

A similar constraint operates for the time interaction terms. We can test whether different forms of accuracy in perceiving positive reactions matters by relaxing these linear constraints. We do this by specifying a model with separate parameters for true positives and false negatives and their respective interaction terms, allowing them to have different coefficients. This regression is reported as Model 3 in Table 4. If the unconstrained model significantly improves fit over the constrained model, we can reject $\beta_2 = \beta_3$ and correspondingly reject Hypothesis 1.

The unconstrained model does precisely that. R^2 improves to .5953 to .5740 in the constrained model ($F_{2,121} = 3.24, p < .05$). Examining the individual coefficients in Model 3 reveals that while the main effect for true positives has no significant effect, the late game interaction term is significant and positive as expected ($t_{121} = 1.793, p = .038$ one-tailed). Meanwhile, the main effect for false negatives is significant and negative as expected ($t_{121} = -1.932, p = .028$ one-tailed), while the interaction term is not. Thus, false negatives have the expected negative effect on performance, supporting Hypothesis 4, while late in the game, true positives have the expected positive effect on performance, partially supporting Hypothesis 3. Further, we can reject Hypothesis 1; not all reactions matter equally in terms of firm performance. Rather, a firm's performance is affected by true positives and false negatives differently at different points in the game. At least in this analysis, both accuracy and type of accuracy matter.

We apply a similar technique to relaxing the linear constraint on the Hypothesis 2 regression. The simple sum of total perceived reactions had a significant effect on performance late in the game, but we wish to test whether it makes a difference if a given perceived reaction is correct or incorrect. In equation form, we examine the following:

$$\text{Performance} = \text{Intercept} + \text{Control variables} + \beta_1\ (\text{Total perceived reactions})$$

$$\text{where } \beta_1\ (\text{Total perceived}) = \beta_1\ (\text{True positives} + \text{False positives})$$

$$= \beta_2\ \text{True positives} + \beta_3\ \text{False positives if } \beta_2 = \beta_3.$$

Again, similar constraints apply to the late game interaction terms. Here, an unconstrained model (not reported) does not significantly improve fit over Model 2, the Hypothesis 2 model (R^2 improves from .5901 to .5971, $F_{2,121} = 1.06$, ns). Because relaxing the constraints does not improve fit over Model 2, it appears that true positives and false positives have statistically similar effects on performance.

Given this, we test a further model. If false positives and true positives have similar effects, suggesting total perceived reactions is the important variable to consider, then it seems reasonable to test total perceived reactions in conjunction with the false negative variable from Model 3. Model 4 in Table 4 reports this regression. While we cannot hierarchically compare Model 4 to Model 3, it does significantly improve fit over both Models 1 and 2 and has the highest R^2 of any model.

In examining coefficients in Model 4, the false negative variable remains significant and negative ($t_{121} = -2.27, p = .012$ one-tailed), while its late game interaction term is insignificant, therefore continuing to support Hypothesis 4. Regarding paranoia, the total perceived reaction variable is marginally negative ($t_{121} = -1.56, p = .061$ one-tailed), while its late game interaction is positive and significant ($t_{121} = 2.88, p = .002$ one-tailed).

Early in the game, total perceived reactions has a modest negative effect on performance, while late in the game it has a positive effect on performance. The latter finding again supports Hypothesis 2: late in the game, the more reactions a team sees, regardless of accuracy, the better that team's performance.

One can ask whether there might be accuracy effects underlying this total perceived reaction finding. As we did above, we can decompose total perceived reactions into its underlying components, true positives and false positives, and see if an unconstrained model allowing true positives and false positives to have separate effects improves on the constrained model where all perceived reactions have the same effect. An unconstrained model of this type does not significantly improve fit over Model 4 ($R^2 = .6177$, $F_{2,119} = 1.38$, ns). This again supports Hypothesis 2.

To get at more exact effect sizes, we eliminate the insignificant late game interaction term for false negatives from Model 4 and report Model 5 as a final model. Not surprisingly, R^2 barely drops. The false negative main effect remains significant and negative, supporting Hypothesis 4 ($t_{122} = -2.30, p = .012$ one-tailed), and the total perceived reactions variable is marginally negative ($t_{122} = -1.45, p = .075$ one-tailed), while its interaction term remains positive ($t_{122} = 2.82$, $p = .003$ one-tailed).

Given the marginal negative total perceived reactions variable in Model 5, we should check to see whether it cancels out the significant positive interaction term's effect late in the game. We can do this by testing whether the sum of the main effect and the interaction term ($-.149 + .412 = .263$) differs significantly from zero. Using Kmenta's test for the joint significance of coefficients (Kmenta, 1986, p. 420), we confirm that the sum is significantly positive ($t_{122} = 2.23, p < .05$). Paranoia has a positive effect on performance late in the game.

In sum, the results of our best model suggest that false negatives have a significant negative effect on performance throughout the game, supporting Hypothesis 4, while paranoia has a positive effect on performance only late in the game, partially supporting Hypothesis 2.

5. Discussion

We began this research with two objectives. First, we wanted to test the assumption that firms accurately know the nature of their interaction with competitors. Second, we wanted to test the posited positive relationship between accuracy in perceiving competitive reactions and performance.

Regarding the first objective, we find that accuracy rates are low. Teams in this empirical setting underestimate the number of competitive reactions and are wrong in the majority of judgments they make, either as a percentage of total reactions (21 percent of total reactions perceived correctly) or as a percentage of total perceived reactions (35 percent of reactions perceived are correct). Compared to analogous interpersonal perception tasks, the detection rate seems low. The effect size, as measured by d', appears modest at best. In this empirical setting for this type of accuracy, we found no support for the assumption that firms accurately know the nature of their interaction with competitors. In particular, the finding that subjects have a bias to underreport reactions suggests that firms may not be aware of the impact of their actions on competitors.

Regarding our second research objective, testing the accuracy-performance relationship, we find that only certain forms of accuracy matter regarding performance in this setting. Notably, correct perceptions, in the form of true positives and true negatives, had little effect on performance. Rather, it was misperceptions where a team *missed* a reaction (false negative) that hurt performance. The effect is not large—reducing the number of false negatives by one increases performance by about 20 percent of one standard deviation in Model 5—but is statistically significant and consistent across all models tested. Recalling Zajac and Bazerman (1991), we can say that in this setting competitive blind spots matter: not perceiving a competitor's reaction hurts performance.

If missing competitive reactions is the problem, then it appears logical that one should err on the side of overperceiving reactions. This is the reasoning behind the paranoia hypothesis, which suggests that simply perceiving many reactions should improve one's decisions and performance, regardless of the accuracy of the perceptions. Late in our game, paranoia helped performance, resulting in an improvement of 26 percent of a standard deviation for each reaction perceived, regardless of accuracy. The pattern of early versus late game coefficients across all models suggest that the punishing effects of early false negatives in the game led players to learn to be paranoid later in the game, to their benefit.

Academically speaking, this research adds to the evidence that investigating perception and inference in competitive decision making is important; in this setting, misperception was common and had significant performance consequences. The time-of-game effects confirm the importance of understanding how managers learn about the markets in which they compete.

Further, examining the effect of type of competitive reaction on both the size of the benefit and loss from accuracy, and on accuracy rates themselves, would be very worthwhile. While we cannot address this in our data, we would speculate that magnitude of reaction will make a difference in both areas, such that large reactions are more likely to be seen and are more likely to make a difference in performance if accurately or inaccurately seen. Magnitude may provide an alternate account for the bias finding above: perhaps teams underreport total reactions because they only report the large ones despite the fact that smaller ones matter. It also seems likely that the speed and effectiveness of a given reaction will affect both accuracy rates and the accuracy-performance link.

Practically speaking, this research provides data to support the anecdotes suggesting that competitive paranoia matters and that the oft-repeated advice to analyze one's competitors intensely is valuable. Firms may underestimate the impact of their actions on competitors and may benefit from an attitude of heightened competitive vigilance. Companies may have a bias against noticing reactions, as suggested by the finding on the variable c above. Regarding perceiving competitive reactions in general, this research suggests that a firm may benefit from adopting the following decision rule: when in doubt, assume a competitor did react. A little paranoia may help performance!

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Notes

1. We are grateful to the editor for recommending this literature to us.
2. As it was relatively easy to agree when no competitive reaction was perceived or occurred—nothing was written on the form about a particular team—these nonreactions are excluded from the reliability indices to give a better indication of the actual reliability of the coding scheme for reactions. Were these nonstatements included, interrater reliability would be well over .9 for all judges.
3. We are grateful to an anonymous reviewer for suggesting a more detailed time analysis than we originally presented.
4. As a final test of accuracy, we conducted a simple binomial test against a null hypothesis of 50 percent accuracy (the "tossing a coin test" of accuracy). For both the percentage of total reactions perceived correctly (21 percent) and the percentage of total perceived reactions that are correct (35 percent), we can handily reject the hypothesis that teams are accurate at the 50 percent level for this task.
5. Note that to improve readability, we do not report coefficients for the budget variable and team and industry dummy variables in Table 4. The coefficients are available upon request from the first author. In general, the budget and dummy variable coefficients and significance levels are quite stable across all analyses.

References

Aaker, David A. (1995). *Strategic Market Management* (4th ed.). New York: John Wiley.

Amit, Raphael, Ian Domowitz, and Chaim Fershtman. (1988). "Thinking One Step Ahead: The Use of Conjectures in Competitor Analysis." *Strategic Management Journal* 9, 431–442.

Bloomberg Business News. (1995). "Company Spotlight: Hewlett-Packard Soars on 'Paranoia' " (May 15), 1-3.

Bowman, Douglas, and Hubert Gatignon. (1995). "Determinants of Competitor Response Time to a New Product Introduction." *Journal of Marketing Research* 32 (February), 42–53.

Cohen, Jacob. (1988). *Statistical Power Analyses for the Behavioral Sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum.

Deshpande, Rohit, John U. Farley, and Frederick E. Webster, Jr. (1993). "Corporate Culture, Customer Orientation, and Innovativeness in Japanese Firms: A Quadrad Analysis." *Journal of Marketing* 57(1), 23–37.

Deshpande, Rohit, and Hubert Gatignon. (1994). "Competitive Analysis." *Marketing Letters* 5(3), 271–287.

Funder, David C. (1987). "Errors and Mistakes: Evaluating the Accuracy of Social Judgment." *Psychological Bulletin* 101(1), 75–90.

Gatignon, Hubert, Erin Anderson, and Kristiaan Helsen. (1989). "Competitive Reactions to Market Entry: Explaining Interfirm Differences." *Journal of Marketing Research* 26 (February), 44–55.

Glazer, Rashi, Joel H. Steckel, and Russell S. Winer. (1987). "Group Process and Decision Performance in a Simulated Marketing Environment." *Journal of Business Research* 15, 545–557.

Glazer, Rashi, Joel H. Steckel, and Russell S. Winer. (1992). "Locally Rational Decision Making: The Distracting Effect of Information on Managerial Performance." *Management Science* 38 (February), 212–226.

Glazer, Rashi, and Allen M. Weiss. (1993). "Marketing in Turbulent Environments: Decision Processes and the Time-Sensitivity of Information." *Journal of Marketing Research* 30(4), 509-521.

Hannan, Michael T., and John H. Freeman. (1984). "Structural Inertia and Organizational Change." *American Sociological Review* 49, 149–164.

Kalbfleisch, Pamela J. (1992). "Deceit, Distrust and the Social Milieu: Application of Deception Research in a Troubled World." *Journal of Applied Communication Research* 20, 308–334.

Kmenta, Jan. (1986). *Elements of Econometrics* (2nd ed.). New York: Macmillan.

Lant, Teresa K., Frances J. Milliken, and Bipin Batra. (1992). "The Role of Managerial Learning and Interpretation in Strategic Persistence and Reorientation: An Empirical Exploration." *Strategic Management Journal* 13(8), 585–608.

Lant, Teresa K., and David B. Montgomery. (1987). "Learning from Strategic Success and Failure." *Journal of Business Research* 15, 503–517.

Larreche, Jean-Claude, and Hubert Gatignon. (1990). *Markstrat2: A Marketing Strategy Simulation*. Redwood City, CA: Scientific Press.

Levine, Gustav, and Stanley Parkinson. (1994). *Experimental Methods in Psychology.* Hillsdale, NJ: Lawrence Erlbaum.

Macmillan, Neil A., and C. Douglas Creelman. (1991). *Detection Theory: A User's Guide.* Cambridge, UK: Cambridge University Press.

Miller, Danny, and Ming-Jer Chen. (1994). "Sources and Consequences of Competitive Inertia: A Study of the U.S. Airline Industry." *Administrative Science Quarterly* 39 (March), 1-23.

Miller, Danny, and Peter H. Friesen. (1980). "Momentum and Revolution in Organizational Adaptation." *Academy of Management Journal* 24, 591-614.

Moore, Marian Chapman. (1990). "Signaling and Screening: Tactics in Negotiations Across Organizations." *Research on Negotiation in Organizations* 2, 77-93.

Moore, Marian Chapman. (1992). "Signals and Choices in a Competitive Interaction: The Role of Moves and Messages." *Management Science* 38(4), 483-500.

Perrault, William D., and Lawrence E. Leigh. (1989). "Reliability of Nominal Data Based on Qualitative Judgments." *Journal of Marketing Research* 26 (May), 135-148.

Porter, Michael E. (1980). *Competitive Strategy.* New York: Free Press.

Robinson, William T. (1988). "Marketing Mix Reactions to Entry." *Marketing Science* 7 (Fall), 368-385.

Ross, William T. (1987). "A Re-examination of the Results of Hogarth and Makridakis, 'The Value of Decision Making in a Complex Environment: An Experimental Approach.' " *Management Science* 33 (February), 288-296.

Schlender, Brent. (1995). "Why Andy Grove Can't Stop." *Fortune* 132 (July 10), 88-98.

Sellers, Patricia. (1995). "So You Fail. Now Bounce Back!" *Fortune* 131 (May 1), 48-66.

Staw, Barry M. (1981). "The Escalation of Commitment to a Course of Action." *Academy of Management Review* 6, 577-587.

Wilson, Robert. (1989). "Deterrence in Oligopolistic Competition." In P.C. Stern, R. Axelrod, R. Jervis, and R. Radner (eds.), *Perspectives on Deterrence* (pp. 157-190). New York: Oxford University Press.

Zajac, Edward J., and Max H. Bazerman. (1991). "Blind Spots in Industry and Competitor Analysis: Implications of Interfirm (Mis)perceptions for Strategic Decisions." *Academy of Management Review* 16(1), 37-56.