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Journal
Academy of Management Journal, 40(5)

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Publication Date
1997

Peer reviewed

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1997, Vol. 40, No. 5, 1063–1088.

DECISION MAKING IN AN ORGANIZATIONAL SETTING: COGNITIVE AND ORGANIZATIONAL INFLUENCES ON RISK ASSESSMENT IN COMMERCIAL LENDING

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Although management researchers would like to understand management decisions related to risk, almost all previous research on risk has used either experiments or aggregate corporate data rather than data from actual business decisions. In this initial research on risk in actual business decisions, we examined the risk assessments bankers assigned to commercial borrowers. We tested hypotheses derived from research in strategy, finance, and behavioral decision theory in order to assess the influence of both organizational and cognitive factors on the likelihood of risk assessment errors. Although we found that both organizational and cognitive factors influenced risky decision making, when both were present, organizational factors appeared to overwhelm cognitive biases.

Large literatures have developed to explain risk-related behaviors at the individual (behavioral decision theory), organizational, and corporate (finance and strategic management) levels. These literatures reveal a great deal about how people handle risk and uncertainty in experimental situations and how uncertainty influences corporate behavior and performance. Yet, despite these large and distinguished literatures, there is a dearth of statistical studies dealing with how managers and employees handle risk in making actual business decisions.

Drawing on experimental studies, the behavioral decision theory literature identifies many intriguing aspects of risk-related individual decision making. Although the research reported in this literature has relied heavily on experiments using student subjects, it also includes numerous experimental and survey studies using managers as subjects or respondents. Ex-

We would like to thank Norwest Banks and its employees, including William Stansifer, Jerry Thompson, and the many others who assisted us with data collection and commented on our findings. Thanks also to Kathleen Sutcliffe, Shawn Curley, Daniel Kahneman, Aks Zaheer, Paul Vaaler, and the behavioral science seminar at the University of Chicago for comments on an earlier draft. We retain responsibility for all analyses and conclusions reported here.

perimental or survey studies have been done in the accounting (see Libby and Fishburn [1977] for a review) and insurance industries (see, for instance, Hogarth and Kunreuther [1989, 1992] and Kunreuther, Hogarth, Meszaros, and Spranca [1994]) and in general management (MacCrimmon & Wehrung, 1986; Shapira, 1995). In addition, experimental studies of risk-related decision making have been done in nonbusiness settings (for example, medical practices; see Curley, Eraker, and Abrams [1984], Baron and Hershey [1988], and Li and Adams [1995]). This literature focuses largely on how individuals depart from normative decision rules—that is, on how they err.

However, although these studies provide insight into the cognitive processes decision makers use in experimental situations, we know of no studies that have directly examined the factors that bias decision makers making business decisions in their day-to-day environments. Business decisions seldom come solely from isolated individual information processing. Both cognitive heuristics and organizational contexts probably influence organizational decision makers. Several studies have indicated that the context in which a decision maker resides influences evaluation of risk-related decisions (Bromiley, 1987; March & Shapira, 1987; Shapira, 1995; Starbuck & Milliken, 1988).

Furthermore, in recent years researchers have begun to challenge many behavioral decision theory findings regarding errors in judgment. In a review, Schwarz (1994) argued that experimental subjects make many standard assumptions that underlie normal interpersonal communications. For example, the recipients of communication normally assume that the communication is coherent, provides relevant information, provides a message appropriate to the sender's communicative intent, and conveys the truth as the sender sees it. When researchers violate these assumptions by, for example, providing irrelevant information, subjects quite reasonably try to make sense out of the information provided and consequently use irrelevant information. Because subjects try to make sense of all the information provided by researchers, the subjects' responses show dramatic variation that depends on the order in which the researchers present information, the numbers associated with response scales, and even the typography of research instruments. Schwarz concluded the following: "The typical procedures used in social cognition research are likely to result in an overestimate of the size and pervasiveness of judgmental biases. . . . If we are to understand their operation in natural contexts, however, we need to ensure that their emergence in laboratory experiments does not reflect the operation of determinants that are unlikely to hold in other settings" (Schwarz, 1994: 134).

Consistent with Schwarz's concerns, in the findings of MacCrimmon and Wehrung's (1984, 1985, 1986, 1990) work on managerial risk, estimates of managerial risk attitudes varied widely depending on the measurement tool employed. MacCrimmon and Wehrung asked managers to complete paper-and-pencil exercises that assessed their risk preferences and behaviors in a variety of different ways (for instance, gambles in personal or business contexts, business gambles incorporated in an "in-basket" presentation, personality trait instruments, and normal life behaviors). MacCrimmon and Wehrung found that different measures of risk preferences were almost completely uncorrelated even within the same domain (e.g., business risks).

At the other end of the research spectrum, the corporate risk literature deals largely in corporate-level variables, such as the systematic risk of a firm's stock, income stream uncertainty, and bankruptcy risk. These studies consider, for example, how capital structure or liquidity influences aggregate risk and corporate performance, but they do not say much about how a corporate manager would deal with a normal risky business decision. With the sole exception of the measures used in some work on corporate diversification (Amit & Livnat, 1988; Bettis & Mahajan, 1985), the risk measures used cannot be related to specific corporate choices.

In this study, we extended the research on risk-related decision making to an organizational setting in order to explore both organizational and cognitive factors that may affect decision makers carrying out their normal responsibilities. By examining actual risk-related decisions, we could examine the effect of organizational context on decision makers. Using archival data on real business decisions prevented artificially controlling the information available to decision makers. Consequently, this setting alleviated Schwarz's (1994) concerns about experimenters' violating the rules of communication since the data pertained to decision makers using their normal rules of communication.

To summarize, both the behavioral decision theory literature and much of the managerial literature have emphasized ways in which managers deviate from rational, or expected, utility models of decision making with regard to risk (March & Shapira, 1987). Our study contributes to the management literature by examining the role and strength of both cognitive and organizational factors in leading to systematic errors using nonexperimental data and systematic statistical analysis.

THE DECISION CONTEXT: RISK ASSESSMENT IN COMMERCIAL LENDING

Unfortunately, few situations exist in which (1) managers frequently make and record risk assessments and (2) the correctness of such assessments can be evaluated. Many corporate investment decisions involve risk assessments, but often the assessments are not written down, the decisions are infrequent and unique, and data on the actual outcomes of the decisions are not retained. We studied an area in which these limitations do not hold: risk assessments made by commercial lending officers in a large bank.

Commercial lending by banks offers an appropriate area for the study of decision making since commercial lenders make judgmental assessments of risk and carefully track the outcomes related to such assessments. In addition, commercial lenders make repeated, similar decisions, which facilitates analysis. Commercial lending provides a setting in which decision makers receive feedback and have full information systems support. If managers can perform unbiased risk evaluations, researchers are more likely to find such evaluations here than in the context of more abstract, infrequent decisions, such as those about strategic choice.

Risk assessments of commercial borrowers are critical decisions for banks since they determine approval of new loans, renewal of existing lines of credit, the interest rates charged, which section of the bank manages the loans, and the levels of loan loss reserves that will be maintained. Thus, commercial banks need their risk assessments to accurately reflect the underlying risk borrowers present. Systematic biases in risk assessment will cause banks to accept or undercharge risky borrowers (or to do both) or to overcharge, and possibly lose, lower-risk customers.

If lending officers rely heavily on standardized, quantitative models to assess the riskiness of borrowers, their risk assessments may be relatively unaffected by individual cognitive forces. In consumer lending, formulas determine many decisions about risk; however, in commercial lending human judgment plays a large role in risk assessment. Although banks have attempted to standardize and routinize the decision process, commercial loan officers in many banks, including the bank studied here, are not bound by statistical decision rules. Therefore, we believe that commercial lending provides an appropriate setting for examining the factors that lead to biases in risk-related decision processes.

THEORETICAL FOUNDATIONS AND HYPOTHESES

Like much of the behavioral risk literature, this study examines the factors that lead bankers to over- or underestimate the risk presented by commercial borrowers. Obviously, an overwhelming number of potential factors could influence decision makers.

In reviewing the management and decision-making literatures, we tried to focus on the factors that (1) related to repetitive decision making, (2) had been hypothesized to bias decision makers, and (3) could be tested with the kind of archival data available. On the organizational side, two factors appeared most likely to affect decision makers: pressure for profitability, which influences evaluation and reward structures, and the degree of formalization of decision processes. On the sociocognitive side, we identified three factors: ambiguity avoidance, cognitive reactions to portfolio effects, and the fads-and-fashions effect. One hypothesis, concerning level of satisfaction with prior organizational performance, could be derived from both the organizational and cognitive literatures. Although many other cognitive variables could have been included, many of those related more closely to less routine, more idiosyncratic decisions. In addition, some cognitive variables, such as those related to the representativeness heuristic, are very difficult to measure using archival data.

In some cases, organizational and cognitive research suggested different hypotheses. In others, only an organizational or a cognitive hypothesis was available. From earlier organizational research (e.g., Bromiley, 1987; March & Shapira, 1987; Starbuck & Milliken, 1988), we suspected that when organizational and cognitive forces predicted opposite effects, organizational forces would tend to dominate. Therefore, when the two types of forces suggested competing hypotheses, we favored the organizational one.

The hypotheses to be presented are based, in some cases, on generalizing results of psychological research on individuals to decisions made in organizations. We would not argue that results obtained with organizational data can be used to reject a psychological phenomenon at the individual level, but rather that such results suggest whether the individual-level phenomenon appears to be influential at the organizational level. Such testing is particularly justified in the risk area, where numerous authors have attempted to use individual-level theories to justify hypotheses and findings at the organizational level (cf. Bowman, 1982, 1984; Fiegenbaum, 1990; Fiegenbaum & Thomas, 1985, 1986, 1988; Kahneman & Lovallo, 1993).

Duration of Relationship

How long a customer has been with a bank should influence risk assessment. Two conflicting arguments address the effect of the duration of a relationship. The first, based on the cognitive phenomenon of ambiguity avoidance, is that new customers will receive less favorable treatment. The second, based on organizational pressures for profitability, is that the treatment of new customers will be excessively favorable.

Ellsberg's (1961) experiments on *ambiguity avoidance* indicated that subjects generally avoided ambiguous choices. Curley, Yates, and Abrams (1986) tested six possible explanations for ambiguity avoidance. They found that if decision makers anticipate that others will evaluate decisions, they avoid ambiguous alternatives because they perceive them to be less justifiable than clear alternatives. Commercial lending fits this pattern extremely well in that lending officers must justify their decisions to both superiors and auditors. Perceived ambiguity about a borrower's worthiness should decrease as the length of the banking relationship increases. Therefore, the ambiguity avoidance concept indicates that the risk new borrowers represent should be overestimated, relative to how older borrowers are evaluated.

However, organizational pressures for profitability lead to an opposing hypothesis. Most organizational and strategy theorists (e.g., Cyert & March, 1963; Hofer & Schendel, 1978; Porter, 1980) have assumed that organizations strive for profitability and consequently create organizational pressure for profitability at the operating level. In many organizations, the planning process translates pressure for organizational profitability into pressure for subunit profitability (Bower, 1970). Consistent with this practice, the goal-setting process of the bank in which this research was set provided profit objectives for the bank's branches. Although the formal incentive system at work within this organization did not reward loan generation, both senior and branch managers informed us that branch managers commonly translated the branches' profitability goals into loan growth targets. Since profitability rises with increases in both sales of loans and services to borrowers, managers saw growth in loan portfolios as a primary way to improve performance.

Thus, subunit profitability goals translated into pressure to increase loan portfolios, which implied both keeping current borrowers and attacting new borrowers. Since the interest rates charged and loan approvals per se depended on risk ratings, the desire to increase loan portfolios influenced risk ratings. However, the degree of influence that profitability goals had on risk ratings varied systematically within the loan portfolios.

Banks need to be more accommodating to new customers than to old customers. New borrowers have few informal psychological ties to a given banker (Adams, 1976; Macauley, 1963), making it likely that they will switch to other banks if offered more favorable interest rates or terms. Indeed, some new customers actively compare rates among banks. Studies of relationship duration in areas such as auditing (Levinthal & Fichman, 1988) have shown that the likelihood of a customer's leaving decreases with the duration of a relationship. Information exchanges over the life of a lending relationship improve the efficiency of the relationship (Sharpe, 1990) and limit the likelihood that a borrower will want to change banks, since the borrower would have to invest time to develop a relationship with a new bank. Furthermore, an older customer generally has multiple ties to a bank via loans, trust services, credit cards, and so forth, making switching banks more difficult than it is for a new customer with fewer ties. As a result, although the competition for new customers is intense, once a firm (a customer) has been with a bank for a significant period of time, the bank develops a degree of monopoly power and can charge a higher rate of interest on loans to that firm. Finally, drawing an analogy to March and Simon's (1958) employment model, we suggest that a generally satisfied customer reduces efforts to search for alternatives to a current arrangement. The longer the relation endures, the less likely the customer is to shop around.

For all these reasons, new borrowers switch banks more readily than old borrowers. Given organizational pressures for profitability, bank branch managers will encourage growth in their loan portfolios. Consequently, loan officers will treat new borrowers more favorably than old borrowers to insure that the former do business with their bank.

As stated earlier, our view is that when organizational and psychological factors compete, the organizational factors are likely to be more powerful. Thus, our hypothesis draws on the organizational pressure for profitability argument rather than on ambiguity avoidance:

> *Hypothesis 1. The duration of a customer relationship has a positive association with the direction of risk-rating errors, increasing the likelihood of overrating and decreasing the likelihood of underrating borrowers.*

With these contrasting arguments, care must be taken in interpretation of results. Most commonly, researchers have a single argument, and their null hypothesis is the extreme position that a parameter specified by the argument is zero (Simon, 1977). Researchers attempt to reject the hypothesis that the parameter is zero and, if they can reject that hypothesis, conclude that the data agree with their theory. Our two contrary arguments present a slightly more complex situation. If the sign of the appropriate parameter supports Hypothesis 1 and is statistically significant, we can conclude that the data agree with Hypothesis 1. At the same time, we cannot conclude the data do not demonstrate support for the ambiguity avoidance argument. We must recognize that this effect might be present but is simply overshadowed by the effect of pressure for profitability. That is, organizational pressures for profits might be large enough to mask a small ambiguity avoidance effect.

Loan Size

Assessing the influence of loan size on risk errors leads to a similar pair of competing arguments. Both cognitive and profitability arguments pertain to loan size.

From a cognitive perspective, Kahneman and Lovallo (1993: 22) argued that, for decisions viewed in isolation, the willingness to take risks is approximately constant for decisions that vary greatly in size. Further, they argued that decision makers generally think of decisions as individual choices even when they could be viewed as instances of a category of similar decisions.

Our observations in the bank and discussions with its lenders indicated that the bankers did frame risks narrowly rather than as instances of a larger class. Commercial lending officers intentionally tried to evaluate each borrower as an individual case, and the information systems that were in place did not really provide information to the lending officers that would encourage them to do otherwise. The professionalism of a lending officer lay in the ability to evaluate borrowers. Given that the bankers viewed loan decisions in isolation, Kahneman and Lovallo's argument predicted that bias in risk assessments would not be related to loan size.

However, a banker facing organizational pressure for profitability will rate the risk of loans of differing sizes differently since the value of a loan to a bank depends on its size. Large loans generate a greater cash flow and increase the size of a loan portfolio, both of which relate to profitability in banking organizations. Furthermore, large loans cost less to administer per dollar borrowed than small loans; a portfolio of ten $100,000 loans costs much more to administer than one $1,000,000 loan. Consequently, a bank makes greater profits on the large loan than on the small ones, even given the same interest rate. Since the risk assessment constitutes the primary factor a lending officer can manage to encourage or discourage loans of a given size, we would expect excessively high risk assessments for small loans and excessively low risk assessments for large loans.

We hypothesize that the organizational effect will outweigh the cognitive effect when it comes to the influence of loan size on risk-rating biases.

Hypothesis 2. Loan size has a negative association with the direction of risk-rating errors, decreasing the likelihood of overrating and increasing the likelihood of underrating borrowers.

The Fads-and-Fashions Effect

Shiller (1984) argued that stock market investors react to fads and fashions. Information that has little real value can affect both the amount and the distribution of investment in the stock market. For example, investors have seen conglomerate mergers very favorably at certain times, and the stock prices of firms acquiring unrelated businesses have reflected this perception, but at other times such mergers have been seen unfavorably. Similarly, Black (1986) argued that noise information affects the valuation of stocks, making stock prices unpredictable. Noise information could result in the types of fashionable investing trends that Shiller envisioned. Banking may be subject to a similar phenomenon, as industries may be considered especially exciting at at a given time, and so lending to them becomes fashionable.

In general, the excitement an industry conveys should increase the difficulty of assessing the risk a borrower from that industry presents, whether that risk is high or low. Excitement comes from unanticipated events and the possibility or expectation that such events will occur. For example, many high-technology industries are exciting because people believe innovations will occur in them, but they cannot predict which firm in which year will have a successful innovation. In the earliest years of the personal computer industry, the industry was very exciting, but few could predict which firms would survive. Some commercial lenders told us that they avoided high-technology firms as overly risky.

However, the fashion argument predicts the opposite: bankers may prefer to lend to firms in exciting or innovative industries even if industry performance indicators suggest otherwise. Just as investors may gain some personal satisfaction by investing in exciting or otherwise desirable firms (for instance, a number of mutual funds provide socially concerned investors with socially "appropriate" investments), we believe that lenders will be influenced by the excitement value of the industry to which they lend. The overeagerness of commercial banks to lend to oil companies during the oil boom fits this picture; events like the Penn Square disaster, in which numerous banks overinvested in risky oil exploration loans, suggest that this eagerness was not justified. In another example, First Bank System of Minnesota decided to lend to the California movie industry, the ultimate exciting industry—and one in which First Bank had very poor returns. By this argument, customers in exciting industries will be more likely to receive lower risk ratings than customers in unexciting industries of the same actual riskiness.

Hypothesis 3. The excitement value of a borrower's industry has a negative association with the direction of *risk-rating errors, decreasing the likelihood of overrating and increasing the likelihood of underrating borrowers.*

Unlike the earlier constructs, the fads-and-fashions effect is predicted on a sociocognitive basis, and no countervailing organizational force is predicted.

The Influence of Prior Performance

Drawing from both behavioral decision research (Kahneman & Tversky, 1979) and organizational theory (Cyert & March, 1963), researchers have argued that when organizations perform at a level below performance targets, they attempt to make changes and take risks in hopes of getting back above target (Bowman, 1980, 1982, 1984; Bromiley, 1991; Fiegenbaum & Thomas, 1985, 1986, 1988; March & Shapira, 1987; Miller & Bromiley, 1990; Singh, 1986). Conversely, organizations that perform at levels above their performance targets tend to become more conservative in their risk taking. In the commercial banking field, the easiest way for a branch bank unit to take risks is by underestimating the risks inherent in its loans. Unit-level managers cannot simply assess risk correctly and still make riskier loans because central bank systems will quickly identify such loans as problems. Therefore, drawing on prior organizational research, which relies heavily on cognitive theories, we would expect that bankers in poorly performing branches will underestimate the riskiness of loans and that those in branches performing well will overestimate the riskiness of loans.

Hypothesis 4. Branch performance has a positive asssociation with the direction of risk-rating errors, increasing the likelihood of overrating and decreasing the likelihood of underrating borrowers.

The remaining hypotheses reflect organizational forces for which we identified no competing cognitive forces.

Organizational Standardization

According to the behavioral theory of the firm, routines act as the repository for organizational knowledge (Cyert & March, 1963; Nelson & Winter, 1982), and organizations' managers learn by observing outcomes and adjusting routines (Bromiley & Marcus, 1987; Cohen, 1991). Routines also increase the predictability of outcomes (March & Simon, 1958). We refer to increased specification of decision processes as standardization. The corporate management of the bank that was studied attempted both to increase the clarity of the rules for making loan decisions and to ensure that all branches conformed to the same set of routines.

Over the study period, the degree of standardization found in the bank's loan review process substantially increased. At the beginning of the study period, the bank branches acted fairly autonomously and utilized varying loan review processes. By the end of the period, the bank had a highly standardized loan review process across loans and across branches.

Management may change risk assessment processes to achieve two different objectives: to reduce bias (consistent tendencies to over- or underrate loans) and to increase reliability (as manifested by lower overall error rates). If management believed loan officers tended to make systematic errors by consistently over- or underassessing risk, standardization might change the overall tendency to over- or underrate risk in a portfolio. For example, if management believed risk assessments were insufficiently conservative, they might attempt to increase conservatism via explicit guidelines on what borrower characteristics implied what classification. However, if management believed assessments were on the average adequate but that the noise level in the assessments was unacceptably high, then standardization might attempt to simply reduce the frequency of errors by increasing the consistency of the procedures and risk-rating criteria used by lenders. Senior managers reported that the goals of the standardization process included increasing the predictability and consistency of risk ratings as well as increasing the level of conservatism in the bank.

Consequently, assuming that standardization has outcomes consistent with managerial intent, we expected that increased standardization of the loan review process would result in more overrated and fewer underrated risks and a decrease in the error variance in risk evaluations.

> *Hypothesis 5. Standardization has a positive association with the direction of risk-rating errors, increasing the likelihood of overrating and decreasing the likelihood of underrating borrowers.*

> *Hypothesis 6. Standardization has a positive association with the likelihood that a loan will receive an accurate risk rating.*

DATA AND METHODS

The Site

We obtained permission to interview individuals involved in the commercial lending process and to statistically analyze the lending decisions at the Community Banking Division of Norwest Banks. We collected data on loans, risk assessments, and borrowers from the loan files of borrowers at five branches of the bank. Norwest, a superregional bank-holding company, exhibited strong overall performance during the time period covered in the study, 1986–93. In 1992, IBCA Ltd. rated Norwest as one of the ten most profitable banks in the world.

We had complete access to all the bank's commercial loan files. The bank typically maintains ongoing relationships with commercial customers and reviews each borrower annually, evaluating the current creditworthiness of the borrower using a seven-point rating scale. We collected annual loan review data (including the beginning date of the lending relationship, the amount of existing loans, the borrower's risk rating, and more, and financial statement data from the loan files for all corporate borrowers who had loan balances of at least $100,000 (the minimum for full annual documentation). Most of this bank's branches maintained limited commercial loan activities. The five branches examined had the largest commercial loan portfolios in the target metropolitan area. The loan and financial data we obtained covered 223 firms. Because we had multiple years of data for each firm, the data set included 787 total observations.

We interviewed corporate managers involved in the commercial lending activity as well as branch managers, commercial lending supervisors, and commercial lending officers. The branch managers said that they operated with an extremely thin margin between the cost of funds and the rates they charged borrowers. Thus, they placed a heavy emphasis on avoiding bad loans. The bank had a rating system whereby 1 indicated low risk and 7 indicated, if not actual bankruptcy, a high probability of the bank's not recovering all the funds due. At the time of loan origination, the bank rated most small commercial borrowers as at risk level 3 or 4. If a borrower was later reclassified to risk level 6 or 7, the bank usually transferred the file from the branch that issued the loan to a separate organization that attempted to work out the loan—to recover the funds invested without loss of capital and try to get the interest owed.

Commercial loans are not usually isolated, single-period transactions; rather, most commercial loans go to ongoing customers. Indeed, this bank emphasized developing close relations with customers to encourage their purchases of other services that might be both lower risk and more profitable than the loans themselves. The bank's incentive system for commercial bankers rewarded sales of ancillary services but not origination of new loans.

Although the formal incentive system did not reward individuals' loan generation, the branch's performance evaluation criteria included profitability goals that branch managers informally translated into loan-growth-rate targets. One senior manager suggested that branches with extremely fast growth in loans outstanding probably underestimated borrower risk in order to have high performance.

The bank increasingly emphasized a high level of standardization. Risk rating followed a carefully defined process, and both the superiors of the commercial lending officers and internal loan reviewers/auditors often reviewed the ratings. Both branch and corporate managers said the extent of latitude granted branches had declined in recent years and that emphasis on avoiding losses or recognizing potential losses had increased.

The Model

To define risk assessments as errors, some criteria for correct risk assessments must be created. We began by developing a model of risk assessment based on the data available to loan officers at the times of the risk assessments.

In the first phase of the analysis, we used ordinal logistic regression analysis to develop a model to explain the annual risk ratings loan officers assigned to the borrowers. The model was estimated using data on borrowers in loan-rating categories 3 to 6, since very few borrowers fell in the other risk categories; only 13 of the 787 observations were in categories 1, 2, or 7. Drawing on the factors identified in the risk-rating-rationale section of the bank's loan review manual and also on discussions with bank managers, we selected six variables: the ratio of profit before interest and taxes to total assets, which measures profitability; the ratio of cash flow after debt amortization to total assets, which measures cash flow; the current ratio, which measures liquidity; the ratio of net worth to total assets, which measures leverage; the ratio of net working capital to total assets, which measures the collateral margin (an indicator of marketable collateral); and the logarithm of total assets, which measures size. These variables closely resemble those identified in earlier work on predicting bankruptcy or default risk (Altman, 1968, 1984; Beaver, 1966; Edmister, 1972; Hoeven, 1979; Ohlson, 1980).

For model development, the database was divided into two parts. Using random numbers, we selected approximately two-thirds of the data for model estimation and held out the remaining one-third for model validation. Thus, of the 787 total observations, 506 were selected for use in estimation, with the remaining 281 used for validation. Although the estimation database included 506 usable observations, the model was estimated using 76 observations since we needed to have equal numbers of observations in each risk rating to ensure that the resulting model would not be biased toward any particular risk rating. Thus, we estimated the model using a data set that contained 19 observations in each of the risk ratings included in the analysis, for a total of 76 data points.

A stepwise logistic regression analysis starting with the six variables resulted in a three-variable model that included net worth to total assets, net working capital to total assets, and profit before interest and taxes to total assets. The other three variables did not significantly add to the explanatory value of the three-variable model.

Using parameter estimates from the resulting logistic regression equations to predict the riskiness of loans in the hold-out sample, we found the model predicted the exact rating assigned by the bankers 53 percent of the time. This percentage significantly exceeds the 25 percent that would result by chance ($p < .01$). Furthermore, the model disagreed with the bank by more than one risk-rating level only 7 percent of the time, compared to the 38 percent that would result by chance. A detailed discussion of the model's development and validation appears in an earlier publication (McNamara & Bromiley, 1993).

Dependent variable. The hypotheses concern whether the bankers' risk ratings erred by being too high or too low. If the model and a banker's assessment agreed, we assumed the rating was correct. If the model and the banker disagreed, we had to evaluate whether the banker's rating was correct or incorrect. We determined this in the following manner: If the assessment in year t for a banker and the model differed, we asked whether the banker's assessment changed in future years. If the banker's assessment did not change, we could not determine whether the banker was incorrect.[1] Similarly, if the banker's assessment moved away from the model's, we were fairly certain that the model was incorrect. We defined the banker as in error when (1) the predictions of the model differed from the banker's assessment and (2) the banker's assessment moved toward the model's assessment within the next two years. For example, if the model predicted a loan's risk as a 4 in year t and the banker assessed the risk as a 3 in year t but changed the assessment to a 4 in year $t + 1$ or $t + 2$, we considered the banker's assessment in year t as incorrect and coded the risk of the borrower as underrated.

The hypotheses in the study relate to understanding cases in which the bankers erred. Consequently, we took all the observations with two subsequent years of assessments for those customers and classified them as (1) overrated: a banker assessed the risk as higher than the model did, and the banker moved toward the model's assessment within two years; (2) underrated: the banker assessed the risk as lower than the model did and the banker moved toward the model's assessment within two years; and (3) other: the model and the banker agreed, or they disagreed but the banker did not move toward the model. The cases were coded as overrated (1), other (0), and underrated (−1). Therefore, our analysis explicitly tested whether the hypothesized variables explained which types of loans received over- or underestimated risk ratings.

We used each firm-year combination as an observation, which resulted in 523 observations that could be categorized into one of the three groups. The rest of the observations were not included since we did not have the two years of subsequent information needed to determine the direction of change in the bankers' risk ratings. Most of the observations (73%) for which we did not have three years of data were for loan reviews conducted in the last two years for which we collected data, 1990 and 1991. The remainder were for

[1] Given that these are ongoing relationships, inertia may delay changes in risk ratings. Although it is possible to argue that if a loan's risk rating is not changed within two years, the bank is correct and the model incorrect, it is equally possible to argue that for many of these loans, inertial effects will not have been overcome within two years even though the loan risk is over- or underrated. Three factors indicate to us that the latter argument is often true. First, the bank did not maintain an information system that would have allowed bankers to learn from earlier mistakes in rating the riskiness of loans. Consequently, there was no information-system-based learning taking place that would lead to the "debiasing" of risk ratings. Second, the publication of research (McNamara & Bromiley, 1993) in which we discuss the development of the risk-rating model sparked significant interest from several regional banks. This indicates that commercial lenders are less than fully confident in the risk ratings they apply to their loans. Third, we discussed the meaning of these persistent differences between the model's estimate of risk and the bank's estimate with senior managers at Norwest, and they were in agreement that we could not conclude whether the bank or the model was more accurate.

TABLE 1
Distribution of Observations across Borrowers

Number of Observations per Borrower	Frequency
1	23
2	59
3	45
4	53
5	7

borrowers who paid off their loans, left the bank, or dropped below the $100,000 cutoff for full documentation within two years. Of the 523 observations, 82 were identified as underrated, 24 were identified as overrated, and 417 were identified as other. These 523 observations came from 187 borrowers. The remaining 36 borrowers had less than the three years of reports necessary to be included in the analysis. Table 1 shows the distribution of observations.

Independent variables. The number of years the bank had loaned to a given customer measured the duration of the relationship. The outstanding amount of a loan in millions of dollars measured its size. We measured the performance of a branch as its profitability in the prior year. Since the bank changed its profitability measures during the span of the study, we used an ordinal variable that reflected the relative profitability of each branch in each year.

Although a series of actions taken by the bank indicated that the degree of standardization in the loan review process increased over the life of the study, we were unable to objectively measure standardization. Consequently, we measured it using perceptual measures. We asked three senior managers who had been in management roles throughout the study to complete a short questionnaire in which they assessed the degree of standardization by year using four questions rated on a seven-point Likert scale. Three of the questions were modified versions of questions used by Van de Ven and Ferry (1980: 161–162) for measuring unit standardization. We added a fourth question designed to measure the degree of standardization across units (branches). The Cronbach's alpha across the four measures exceeded .98 for each respondent. We averaged the responses across questions and respondents to get an overall indication of the degree of standardization by year. As we expected, the responses indicated that the degree of standardization increased over the time period of the study.

Because industry excitement value is inherently a perceptual construct, we measured three industry characteristics using perceptual measures. Three banking industry experts asssociated with a major midwestern university, all with practical experience in the banking sector, rated the profitability, volatility, and interest/excitement of all industries (defined by four-digit Standard Industrial Classification [SIC] code) represented in the sample on a scale of 1 to 5, with 5 being high profitability, volatility, and excitement.[2] Because the bank questioned the accuracy of its categorization of borrowers at the four-digit SIC code level, we averaged each rater's responses to obtain estimates at the two-digit SIC code level. Cronbach alpha coefficients for the profitability, volatility, and excitement variables were .51, .56, and .57, respectively. For use in the analysis, we averaged the ratings of the three experts for each two-digit SIC code industry.

Analytic methods. Because the dependent variable could take on three discrete but ordered values, we used multinomial ordinal logistic regression analysis to test Hypotheses 1 through 5. Hypothesis 6 (change in accuracy over time) was tested using binomial logistic regression with the standardization variable as the only independent variable. Overrated and underrated loans were combined in order to test the hypothesis that the number of misrated loans decreased as standardization increased.

Test for regression to the mean. We tested whether our results could be affected by regression to the mean. Of the 106 observations in which the bankers' risk ratings erred, 41 had risk ratings that moved toward the mean risk rating (4), and 65 moved away. In contrast, of the 29 observations for which we concluded that the model erred, 11 moved toward the mean risk rating, and 18 moved away. These results suggest that error corrections in the data do not reflect regression to the mean (i.e., extreme estimates later being closer to the mean) for either the bankers or the model.

RESULTS

How Good Is the Model?

To evaluate the quality of the predictive model, we compared its quality of prediction to that of the bankers themselves. Over the past three decades, studies have found that decisions previously considered to be extremely complex judgments could be readily modeled (cf. Clarkson, 1962). Indeed, many of these studies have shown that models based on individuals' decisions can subsequently make better decisions than the individuals (cf. Dawes, 1971; Goldberg, 1970). In the case of commercial lending, this finding suggests that a good model of the bankers' risk assessments might predict a borrower's creditworthiness better than the actual risk assessments themselves. If that were so, it would lend credibility to our experimental model.

We examined cases in which the banks and the model disagreed and compared the likelihood that subsequent bankers' risk ratings moved in the direction of the model's predicted risk rating to the likelihood that they moved away.[3] For the 56 borrowers for which a banker's risk rating was

[2] Profitability and volatility were measured in order to check that the measure of excitement did not act as a proxy for either of these other two factors. The actual wordings of the questions were: (1) "How profitable on average is this industry?" (2) "What is the variability in profitability in this industry over time?" and (3) "To what degree is this industry exciting or interesting?"

[3] To make the observations in the test independent, each borrower could only enter this test as one observation. Thus, if the bank erred on a given customer for two years, it would only be counted once in the analysis.

lower than the model's and was adjusted within two years, the banker adjusted the risk rating in the direction of the model's rating 48 times. We could clearly reject the hypothesis that when the banker's risk assessment was lower than the model's, the likelihood of moving toward the model's assessment was 0.5 (binomial test, $p < .0001$). Of the 30 times when a banker's risk rating exceeded the model's and the rating was adjusted in subsequent years, the banker adjusted the risk rating in the direction of the model's 21 times. Again, we could reject the hypothesis that the probability of moving toward the model's assessment was 0.5 (binomial test, $p < .05$). Thus, we could conclude that when the model and the bankers' assessments differed and we could discern which was correct, the model was correct more often than the bankers. This finding provides additional confidence in the model.

The Main Analyses

Table 2 presents the results of the three-level ordinal multinomial logistic regression analysis.[4] We could reject the hypothesis that the nonintercept parameters were zero ($p < .0001$) and therefore concluded that the behavioral variables, as a set, aided in distinguishing among the three categories of loans.

Given the existence of organizational pressure for profitability, we hypothesized that lenders underestimate the risk newer borrowers present (Hypothesis 1). In contrast, the ambiguity avoidance argument implies newer borrowers should receive overestimated risk ratings. Consistent with Hypothesis 1, the length of the bank's association with a customer significantly ($p < .01$) and positively influenced risk-rating errors; as the duration of the relationship increased, the likelihood that a loan's risk would be underrated decreased, and the likelihood that the loan risk would be overrated increased. As noted above, this finding does not demonstrate that ambiguity avoidance has no influence but that, if it does have influence, it was overwhelmed by the organizational pressure for profitability.

Organizational pressure for profitability was also the basis for the hypothesis that lenders overestimate the riskiness of small loans and underestimate the riskiness of large loans (Hypothesis 2). In contrast, Kahneman and Lovallo's (1993) cognitive argument implies size should have no effect on risk-rating errors. Consistent with Hypothesis 2, we found marginal support ($p < .10$) for the hypothesis that loan size has a negative influence on rating

[4] We tested whether sample selection (i.e., losing observations with insufficient subsequent data) influenced these results. Using a sample selection estimate routine from LIMDEP Version 6.0 (Econometric Software, 1992), we attempted to estimate the sample selection model with a "logit" analysis but found it did not converge. Consequently, we used multinomial "probit" analysis, which did converge. The results from multinomial probit analyses with and without sample selection were identical to two decimal places. Probit results differed from the logit analysis in only one way: the statistical significance of loan amount declined from $p = .09$ to $p = .15$. Given that we had chosen logit initially, we present and interpret logit results, recognizing the weakness of the estimate on loan amount.

TABLE 2
Results from Three-Level Ordinal Logistic Regression Analysis[a, b] for Risk Assessment Error

Independent Variable	Parameter Estimate	Standard Error	Wald Chi-Square	Probability
Intercept 1	−2.13	1.31	2.66	0.10
Intercept 2	2.93	1.32	4.96	0.03
Duration of relationship	0.03	0.01	12.39	0.00
Loan amount	−0.22	0.13	2.78	0.10
Industry profitability	0.64	0.38	2.75	0.10
Industry volatility	0.45	0.31	2.12	0.15
Industry excitement	−0.95	0.24	15.29	0.00
Branch performance	−0.03	0.08	0.14	0.71
Standardization	−0.21	0.10	4.58	0.03

[a] The dependent variable was coded as follows: risk assessment erred by being too low = −1; risk assessment erred by being too high = +1; other = 0.

[b] $N = 523$. For the test that all covariates except the intercepts equal zero, $\chi^2 = 34.63$, 7 *df*, $p < .0001$.

errors, reducing the likelihood of overrating and increasing the likelihood of underrating.

One might argue that this bias toward large loans simply means that large loans go to larger customers, who are less likely to fail. The data do not support this relationship. When we developed the model to predict risk, firm size was included in the stepwise logistic regression procedure but did not significantly aid in predicting a loan's risk rating. We also conducted an additional logistic regression analysis using risk-rating errors in which we replaced loan size with firm size; the firm size parameter was statistically insignificant ($p = .55$). Loan size had a marginally significant ability to predict errors in ratings even though firm size did not help predict either firm risk ratings or errors in risk rating. The effect of loan size clearly does not come from being a proxy for firm size.

On the basis of a cognitive phenomenon labeled the fads-and-fashions effect, we hypothesized that the excitement value of an industry negatively influences risk-rating errors, decreasing the likelihood of overrating and increasing underrating (Hypothesis 3). As noted above, in testing this hypothesis, we included two control variables (judgments of industry profitability and volatility) along with the judgment of industry interest/excitement. The two control variables provided judgmental measures of industry factors that quite plausibly could impact the creditworthiness of firms. The remaining variable, industry excitement, reflects the excitement construct from Hypothesis 3 and should not influence creditworthiness positively. Consistent with Hypothesis 3, the more exciting an industry was perceived to be, the less likely it was that a firm's loan risk would be overrated and the more likely it was that it would be underrated ($p < .001$). Note that in addition to industry excitement, the parameter on industry profitability was marginally significant ($p < .10$). The remaining industry perceptual measure (volatility) had no significant influence on errors in risk ratings. Therefore, the data support Hypothesis 3.

Drawing on both organizational and cognitive arguments, we hypothesized that prior performance levels have a negative influence on risk-rating errors: that bankers in branches with lower performance (risk-seeking) would underrate the risk of loans and that bankers in branches with higher performance (risk-avoiding) would overrate the risk. Contrary to Hypothesis 4, branch performance level did not appear to influence the risk ratings of loans. Thus, we conclude that Hypothesis 4 was not supported.

From organizational arguments concerning standardization, we hypothesized that bias in the ratings (i.e., the likelihood of overrating risk) in loan portfolios would change as the degree of standardization in the loan review process increased (Hypothesis 5). Given statements top managers in the bank made to us and to the popular press, we specifically expected to find that as standardization increased, the bank would become more conservative and more likely to overrate the risk of loans. In fact, we found modest evidence that as standardization increased, the likelihood that a loan would be underrated increased and the likelihood that it would be overrated decreased ($p < .05$).

This finding may have reflected changes in the bank's willingness to admit under- or overratings. Managers told us that the emphasis on avoiding losses or recognizing potential losses had increased over the last few years. This suggests that as standardization increased, lending officers may have become more willing to admit that a loan should be downgraded and more reluctant to argue that a borrower should be upgraded. To assess this question, we took all observations in which the bank's and the model's risk ratings disagreed and divided them into two groups: cases of the bank's risk ratings moving toward the model's and cases of the bank's risk ratings not doing so. We then conducted two binomial logistic regression analyses, one with the observations in which the bank's risk ratings were initially higher than the model's and one with the opposite cases. We found that as standardization increased, the likelihood that the bankers would move their risk ratings toward the model's increased for observations that were initially rated more favorably ($\chi^2 = 3.83$, $p = .05$) but decreased for observations that were initially rated less favorably ($\chi^2 = 2.73$, $p = .10$). Therefore, the evidence suggests that the standardization efforts did not cause lenders to become more conservative in their risk ratings, but it did increase the likelihood that they would admit that loan risk ratings needed to be downgraded.

Our final hypothesis was that standardization should reduce the prevalence of errors (Hypothesis 6). The results of the binomial logistic regression used to test this hypothesis appear in Table 3. Standardization had no significant influence on the prevalence of risk-rating errors ($p = .44$).

Supplementary Analysis

One concern about the results presented above derives from the construction of the dependent variable. Its reliance on the predictive model and

TABLE 3
Results from the Two-Category Logistic Regression Analysis[a]

Independent Variable	Parameter Estimate	Standard Error	Wald Chi-Square	Probability
Intercept	1.66	0.44	14.31	0.00
Standardization	−0.07	0.09	0.60	0.44

[a] $N = 523$. For the test that all covariates except the intercept equal zero, $\chi^2 = .61$, $p = .44$, n.s.

a somewhat complex categorization raises concerns. Furthermore, classifying observations as nonerrors when the model and bank disagreed but the bank did not change might have resulted in underestimation of the number of errors. Consequently, we conducted additional analyses using different dependent variables to examine the robustness of our findings.

Above all, the bank wanted to avoid classifying a loan as acceptable when it really should have been unacceptable. As noted above, the bank rated loans on a scale of 1 to 7, with risk ratings of 1 through 4 deemed acceptable and ratings of 5 through 7 deemed unacceptable. A rating of 5 to 7 resulted in additional monitoring and additional loan loss reserves, which directly reduce income. If a loan switched from acceptable to unacceptable between time t and time $t + 1$, there was a reasonable probability that the bank had underrated its riskiness at time t. Therefore, in this analysis, we took all loans in risk categories 1 to 4 (acceptable) at time t and tested whether the variables used in the primary analysis could differentiate between those that remained acceptable and those that moved to unacceptable at time $t + 1$.

Table 4 presents the results from this analysis. These results support those of the primary analysis. Duration of the relationship, loan size, indus-

TABLE 4
Discriminating between Good and Bad Loans: Results from the Logistic Regression Analysis[a, b]

Independent Variable	Parameter Estimate	Standard Error	Wald Chi-Square	Probability
Intercept	1.19	2.19	0.29	0.59
Duration of relationship	−0.06	0.02	9.21	0.00
Loan amount	0.49	0.17	7.87	0.01
Industry profitability	−2.11	0.59	12.83	0.00
Industry volatility	0.12	0.45	0.07	0.79
Industry excitement	0.78	0.37	4.57	0.03
Branch performance	−0.11	0.13	0.72	0.40
Standardization	0.57	0.21	7.13	0.01

[a] The dependent variable is the appropriateness of acceptable risk ratings at time t; loan risk too low = 1, loan risk appropriate = 0.

[b] $N = 459$, with 418 observations in category 0 and 41 observations in category 1. For the test that all covariates except the intercept equal zero, $\chi^2 = 41.91$, 7 *df*, $p < .0001$.

try excitement, and the degree of standardization in the loan review process all have the same significant results as in the prior analysis. Thus, by looking at loans that appear to have received underratings of risk, we find additional support for the effect of organizational pressure for profitability, the fads-and-fashions effect, and the effect of increased standardization.

This additional support can be bolstered by further analysis. Loans that switched from acceptable to unacceptable might have been underrated at time *t* or might have been correctly rated at time *t* but increased in risk within the next year for some reason. We divided observations that switched from acceptable to unacceptable into two groups: loans that the model had rated acceptable at time *t* and loans that the model had rated unacceptable at time *t*. If both a banker and the model rated the loan acceptable at time *t*, we could not assume the loan was misrated; the real risk the borrower presented probably changed from time *t* to $t + 1$. But for loans the model classified as unacceptable, we have additional confidence that the change reflected correction of an error.

We conducted two additional analyses. First, we defined a binary dependent variable that equaled 1 for loans that changed from acceptable to unacceptable between times *t* and $t + 1$ and that the model identified as *unacceptable* at time *t*. The variable equaled 0 for all other observations. Estimating the same explanatory variables as in previous analyses, we found the duration, loan size, and industry excitement variables were all significant ($p < .05$) in differentiating between loans that remained acceptable and loans that we strongly believed were underrated by the bank at time *t*.

For the second analysis, we defined a binary dependent variable that equaled 1 for loans that changed from acceptable to unacceptable between times *t* and $t + 1$ and that the model identified as *acceptable* at time *t*. The variable equaled 0 for all other observations. Estimating the same explanatory variables as in the previous analyses, we found only the standardization variable was significant ($p < .05$). The other variables of interest were all insignificant ($p > .10$).

These analyses demonstrate the robustness of the findings of the earlier analysis. These two additional ways of identifying loan rating "errors" (using all changes from acceptable to unacceptable, and using changes from acceptable to unacceptable that had been identified by the model as unacceptable) both agree with the original results based on the model. In all three measures of errors, we found consistent support for duration, loan size, industry excitement, and standardization effects. We also found some additional support for the contention that the standardization effort within the bank had caused lenders to become more open to admitting deterioration in borrowers' risk levels.

DISCUSSION

This study extends previous work examining the factors that affect risky decision making by testing their influence in nonexperimental data generated by actual business activities—actual managers conducting their normal business. Our study of commercial lenders' risk assessments of borrowers suggests that both cognitive and organizational factors influence the degree of error found in risk assessments in commercial lending.

Organizational pressure for profitability appeared to influence the risk ratings that borrowers received. Newer borrowers were more likely to receive overly favorable risk ratings than borrowers with longer relationships with the bank, and larger loans tended to receive overly favorable assessments. Both of these factors relate to the organizational pressure to generate loan volume and thus to meet profit goals. Interestingly, the finding for duration contradicts the idea of ambiguity avoidance (Ellsberg, 1961), and the finding for loan size is inconsistent with Kahneman and Lovallo's (1993) argument regarding constant risk aversion across loan size. Therefore, our findings support the contention that organizational effects can sometimes overcome psychological effects in normal business decision making. This finding agrees with earlier studies' (Bromiley, 1987; March & Shapira, 1987) findings that organizational pressures significantly influence managers' assessments of risky decisions. These findings also suggest that although profit motives are ubiquitous and necessary within organizations, they may also unintentionally bias organizational decision-making processes.

Finding that organizational effects appear to dominate cognitive ones supports Schwarz's (1994) concern that biases found in behavioral decision theory studies reflect artifacts of experimental design. Schwarz (1994) implicitly assumed that once artifacts are eliminated, people will respond quite reasonably to risk situations. But much of what Schwarz called artifactual (e.g., the order of presentation of information and its typographical layout) may really matter in organizations. For example, standard budget forms that display years across the top and expenditure items in rows invite the reader to compare expenditures on specific items across years. In other words, Schwarz could be correct in arguing that people respond quite reasonably to the situations they face, but since their organizations largely define that situation, organizational effects could still result in substantial biases in risk-related decision making.

We also found, to our surprise, that although the standardization of the loan review process influenced the distribution of risk-rating errors, it did not have the expected effects. As standardization increased, the decision makers did not become more conservative, nor did they become more accurate in their risk assessments. In fact, the initial analysis suggested that lenders became more likely to underestimate the risk of loans as standardization increased. However, further analyses suggested that this result may in fact reflect a greater willingness of the lenders studied to admit underestimations of risk and more reluctance to admit overestimations once the process they used became more standardized. Thus, the standardization effort appeared to have the intended effect of increasing the sensitivity of lenders to the risk their borrowers presented, but it did not do so as directly as we had first expected.

In addition to these organizational effects, the data also support our hypothesis that fads and fashions related to the degree of excitement an industry conveys influence the distribution of risk errors. The lenders tended to underrate the riskiness of loans to firms in exciting industries and to overrate the riskiness of loans to firms in unexciting industries. This pattern demonstrates how the addition of complex and subjective analysis by an expert (the banker) actually hurt the quality of the judgment. The sociocognitive effect of industry excitement might have been influential because no organizational effects existed to counter it. Furthermore, this effect occurred despite statements made by many loan officers that they avoided exciting industries because they were risky!

Finally, we found no support for the effect of organizational unit profitability differences on willingness to assume risk (Bowman, 1980, 1982, 1984; Bromiley, 1991; Fiegenbaum & Thomas, 1985, 1986, 1988; March & Shapira, 1987; Singh, 1986). Lending officers in branches with poorer performance appeared to be no more risk seeking than lenders in better-performing branches. Thus, the corporate effects relating to the risk propensity of poorly performing firms found in earlier studies do not appear to neatly transfer to the actual decisions made within this organization.

CONCLUSION

This article begins to address the gap between the experimental studies conducted by behavioral decision theorists and the studies of macro-organizational phenomena found in strategic management. We found that risk assessments in commercial lending were influenced by pressures for organizational subunit profitability (the length of the lending relationship and the size of the loan), the degree of standardization in the loan review process, and the fads-and-fashions effect (the degree of excitement a firm's industry conveyed), but not by branch performance levels. Although both cognitive and organizational variables influenced decision making in commercial lending, when the two forces appeared to compete, the organizational effects appeared to be more powerful than the cognitive effects. Thus, we can conclude that scholarly understanding of managerial behavior regarding risk-related decisions must include organizational influences in addition to the more commonly studied cognitive effects.

Interestingly, the primary organizational effect found resulted from informal rather than formal organizational influences. Branches informally translated branch-level profit goals into loan-growth rate targets. The bank's top management discouraged such translations, but branch managers continued to make them. In contrast, we observed modest effects from the formal organizational changes that occurred during the time period covered by the study. These findings suggest that some of the most powerful forces that affect decisions on risk in organizations arise from the informal practices that permeate those organizations.

Combined, these findings emphasize the complexity and difficulty of developing procedures to guide decision behavior. Organizational actions do influence decision behavior and can overcome individual cognitive biases, but organizational actions also have unintended effects. Specifically, the emphasis on profitability led to unwanted decisions. These findings relate to a question identified by Kahneman and Lovallo (1993): should top managers attempt to improve risk-related decision processes or accept such biases and attempt to develop counterbiasing forces? Our very tentative results suggest that either incentive systems or standardization can reduce organizational or cognitive biases, but managers must be very aware of unintended consequences.

Also, our findings demonstrate that organizational risk assessment differs from optimal assessment and is subject to biases. We would expect risk assessment to be more accurate in commercial lending than in the realm of strategic choice. Commercial lenders face similar well-structured problems repeatedly and receive relevant feedback, which means they should learn to assess more accurately than strategic decision makers, who face relatively few and highly idiosyncratic major strategic choices with very noisy and long-delayed feedback. If commercial lenders exhibit behavioral biases, we would certainly expect similar or stronger biases in more abstract strategic choices. Thus, the range of variables used to explain corporate risk taking may need to be expanded. We find it quite plausible, for example, that corporate decision makers underestimate the riskiness of exciting businesses and make systematic errors in comparing the riskiness of familiar and new businesses, just as our bankers did.

Although this study had the advantage of examining real and important business decisions, limitations clearly remain. First, as in all nonexperimental studies, the controls commonly available in experiments were unavailable here. Second, unlike a general large-sample financial study, this study used data from multiple branches of a single bank, which may limit its generalizability. Finally, having examined a very specific kind of risk assessment, we may lack the ability to generalize to risk assessment in the larger business population. However, we believe the positive aspects of the design compensate for these three drawbacks: the study uses real decisions by real employees, the risk measures come from managers rather than from secondary data, and, by studying a single organization, we control for "risk culture" effects that might otherwise cloud the results.

The results from this study constitute a tentative, early step into examining competing influences on organizational decision making. Future research should address additional cognitive and organizational effects in additional business environments. This study suggests that understanding managerial risk assessment requires examination of actual risk assessments made by managers and demonstrates the feasibility of such studies. This study represents a first step toward investigating the effect that behavioral factors have on actual decision makers doing their normal business tasks.

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