Managing Consumer Credit Delinquency in the US Economy: A Multi-Billion Dollar Management Science Application

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GE Capital provides credit card services for a consumer credit business exceeding $12 billion in total outstanding dollars. Its objective is to optimally manage delinquency by improving the allocation of limited collection resources to maximize net collections over multiple billing periods. We developed a probabilistic account flow model and statistically designed programs to provide accurate data on collection resource performance. A linear programming formulation produces optimal resource allocations that have been implemented across the business. The PAYMENT system has permanently changed the way GE Capital manages delinquent consumer credit, reduced annual losses by approximately $37 million, and improved customer goodwill.

Retail consumer credit in the United States is a $220 billion industry (DRI McGraw Hill). More than this, it is a marketing tool used for essentially all retail business. Without it, the US economy would operate at much lower levels of production, sales, revenues, and profits.

During the last decade, however, American consumers have been living beyond their means. Consumer spending has actually surpassed disposable income (Figure 1). Consumer installment debt has grown even faster and currently amounts to almost 20 percent of disposable income (Figure 2). As a result, the average consumer is in a highly leveraged financial situation.
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The number of consumer bankruptcies more than doubled during the second half of the '80s (Figure 3). Even more significant, an increasing number of home owners are missing their mortgage payments, and mortgage defaults are rising (Figure 4). Normally, this is the payment consumers try to meet irrespective of the state of their finances.

This overleveraged state of consumer finance is a long-term issue that is not likely to be resolved soon. At the end of 1990, GE estimated retail consumer credit delinquency to be a $15-billion problem, with yearly write-offs amounting to approximately $8 billion. Despite numerous explanations for such behavior (see, for instance, Sullivan [1987]), the consumer credit grantor cannot afford to employ outdated delinquency management approaches in the 1990s.

General Electric's Consumer Credit Business

The General Electric Company is a global corporation with 1990 revenues of $58.8 billion and profits of $4.3 billion. GE Capital, a subsidiary of GE's financial services business, produces approximately 24 percent of GE's profits. GE Capital's retailer financial services (RFS) component is the largest provider of private label consumer credit in the nation. At the end of 1990, RFS was managing retail consumer credit outstandings (that is, total amounts owed by consumers) in excess of $12 billion from the US, Canada, and Europe. All indicators suggest that GE's share in the retail consumer credit industry will continue to grow at above market rates—RFS's volume has grown five fold in the last five years alone. Unfortunately, the
expression “the check is in the mail” has become well-worn humor. RFS’s delinquent balances approach the $1 billion mark. Despite RFS’s spending $150 million annually in collection efforts, write-offs were approximately $400 million for 1990.

**Delinquent Consumer Credit Collections**

RFS’s $12 billion in outstanding dollars is composed of more than 300 individual retail customer accounts or portfolios. The range of portfolios is varied and includes the lawn-and-garden, fine-fashion, hardware, furniture, computer, and department-store industries. Specific clients include Apple, Levitz, Mitsubishi, Macy’s, and Montgomery Ward.

Because of varying customer demographics and product lines, each portfolio experiences an individual delinquency rate, and has particular customer repayment characteristics.

The financial arrangements between GE and its clients vary. In general, GE underwrites the consumer’s card and assumes responsibility for collecting the outstanding amount. Although the arrangement with respect to credit losses also varies, typically some type of loss sharing exists between GE and its clients.

**Stages of Delinquency**

A consumer’s credit account can fall into one of several payment states. An account is termed **inactive or paid up** if it has no outstanding balance, while an account is labeled **current** if it is paying its monthly payments on schedule; these accounts are also termed **1-due** (they owe one monthly payment). Accounts can become **2-due, 3-due, ..., n-due**. Beyond the 10-due state, and often before then, an account is usually labeled a loss. RFS uses an entirely different approach in collecting such accounts compared to those in earlier stages of delinquency. Some proportion of the accounts escape collection attempts by filing for bankruptcy.

**Account Types**

Accounts sharing the same delinquency state are not all created equal. Individual customers have different demographics, monthly payments, balances, and other factors that contribute to differing repayment patterns. For our purposes, we segment a delinquent portfolio into groups of accounts that have similar outstanding balances and expected payment performances; together these two qualities determine an **account type**. An account’s expected repayment performance, or performance score, is an estimate of the probability that the customer will make one or more payments during the next billing period. Currently, RFS performance-scoring models are based on customer behavioral variables and determined using regression techniques, discriminant and cluster analyses, and independent approaches, such as CART (classification and regression trees), and neural networks. RFS develops performance-scoring models for individual due states and portfolios and updates them frequently.

**Resources and Strategies**

To collect delinquent accounts, RFS uses several types of approaches: mailed letters, interactive taped telephone messages, live telephone calls, and legal procedures. We refer to these collection devices as **collection resources**. Each resource is available in several variations and can be applied at different frequencies. For example, the taped phone message comes in two basic levels.
of severity (simple versus harsh reminder). Within each severity level are male and female voices, differently worded messages, and messages in different languages. These messages can be used as seldom as once per billing period or as frequently as every day. RFS also combines basic resources to produce new resources. For example, it might immediately follow the interactive taped phone message with a live telephone contact if the taped message inspired a promise to pay; the rationale being to reinforce the promise. Collection resources differ in cost and effectiveness; for example, the live telephone resource typically costs six times as much as the taped telephone resource and may be 150 percent as effective.

Most collection resources are available in limited quantities. One, however, is available in unlimited quantities. RFS can choose to simply do nothing, that is, to mail the monthly bill but otherwise make no attempt to contact the consumer. Effective use of this no-action resource is very important in reducing collection costs and retaining customer goodwill.

**Historical Perspective**

GE Corporate Research and Development (CRD), located in Schenectady, New York is GE’s corporate-level think tank. It has a staff of approximately 1,800, including over 600 PhDs in various areas of science and engineering. CRD has produced inventions that have created entire new businesses in fields ranging from polymers to medical diagnostics. However, until it begin work in 1987, CRD had made relatively little contribution to GE’s financial services business. Because of the current significance of GE Capital to GE and its outstanding growth and future importance, upper management challenged CRD to do more for this very important business.

CRD’s management science and statistics program, a small group of operations researchers and statisticians, had past ties to GE Capital, having helped it develop a credit-scoring system to determine which

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**The taped phone message comes in two basic levels of severity.**

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credit applications to approve and which to reject. This group returned to the consumer credit business to take a long hard look at RFS’s National Collections and Support Center (NCSC) in Canton Ohio, which is responsible for collecting 40 percent of the 2-due and 3-due accounts managed by RFS. The NCSC is one of RFS’s three collection centers. These centers concentrate on managing the high volume, 2- and 3-due accounts. The NCSC can execute about 50,000 taped calls and 30,000 live calls per 15-hour day, seven days a week.

Fifteen business centers located across the continental US make more personalized collection attempts at lower volumes and concentrate on stages of delinquency between 3-due and 9-due. Unlike the collection and support centers, the business centers have multiple computer screens of information that allow collectors to review agreements reached in the past.

The collection centers and business centers have different physical locations, management policies, overhead rates, and
equipment. Implementing the same strategy at different locations often brings different results and incurs different costs, largely because of differing labor markets.

Accounts beyond 9-due, and often before, are handled by RFS's two recovery centers, which employ an entirely different set of collection rules.

The management information system associated with this physical hierarchy consists of the accounts-receivable system in Atlanta, Georgia, which maintains billing data on nondelinquent accounts, and the collection system in Stamford, Connecticut, which processes data on delinquent accounts. This data includes the demographic and financial information included on the application for credit, credit rating information from independent credit bureaus, and behavioral data accumulated during the life of the account.

Historically, seasoned collection managers had determined collection strategies. Successful management science applications are achieved by pooling the business knowledge of such managers with appropriate analytical techniques. Because we had the managers' enthusiastic commitment, we were able to develop and apply a greedy algorithm approach in 1987, entitled COPS (collections optimization software), for determining improved collection strategies. Although COPS met the goal of basic collection improvements for NCSC, it was a crude tool. It failed to model critical aspects of the business, such as long-term resource effects, and it was based on management "guesstimates" instead of measured results. Despite its shortcomings, COPS laid the groundwork for further investigating a problem of major interest to the credit industry.

We began a much larger effort in 1988. Our goal was to develop an accurate measurement and optimization system that satisfied the varied needs and constraints of RFS's more than 300 consumer credit card portfolios and yet could be implemented on a production basis. A team composed of CRD's management scientists and analysts from RFS headquarters made numerous visits to collection and business centers in such exotic locations as Atlanta, Canton, Charlotte, Chicago, Danbury, and Denver. The team strived to fully understand the requirements described by RFS's collection managers and staff and to offer them the opportunity to shape this work, thus promoting their ownership of the eventual system. It is critical to communicate with the eventual users frequently to insure their continued commitment and a solution that they can use. Our discussions with the field management and staff provided us with a working understanding of the problem on which to base our solution.

Both our preliminary investigations and the opinions of experienced collection managers convinced us that the effect of a collection resource is exhibited in multiple billing periods and not limited to the period in which it is applied; many believe the effect is more strongly felt in the following billing period, especially if the resource is applied late in the period. With these short- and long-term phenomena in mind, we broke from tradition and intro-
duced a revised, rigorous definition for collection strategy.

A collection strategy specifies a unique resource for each due state, balance range, and performance score category over multiple months (Figure 5). The repayment risk categories are determined by the performance score; for example, a score of 80 to 100 indicates a better than 0.8 probability of obtaining one or more payments during the next billing period. Such an account is regarded as a low risk. By measuring the performance of a strategy that has been employed over multiple billing periods, instead of a single billing period, we can obtain an accurate estimate of its true effect.

Using Delinquency Movement Matrices to Model Account Repayment Dynamics

Given that we can assess the stable performance of a sequence of resources, that is, a collection strategy, we can assume that the repayment performance of an account treated with the same strategy over numerous months will depend only on the account’s current delinquency state, outstanding balance, and performance score. Given this scenario, we can model the account repayment dynamics using a Markovian probability transition matrix, which we call a delinquency movement matrix (DMM). The entries of a DMM give the probabilities of a transition between the due state of an account last month and its due state this month. The Markovian assumption may at first seem inappropriate since the general process of delinquent account flow contains a certain degree of “account memory” with respect to collection resource. It is the vector definition of a strategy that allows us to treat the process as Markovian. By partitioning the population of delinquent accounts into test groups and treating each test group repeatedly over consecutive billing periods with an individual strategy to be evaluated, we provided equivalent past collection treatments and therefore insured identical account memory with respect to the collection resources used. Then, by estimating a strategy’s DMMs, we can accurately predict future performance.

DMMs Based on Account Types

In addition to constructing individual DMMs for specific strategies, we estimate DMMs for differing account-balance-range

![Diagram](image_url)

Figure 5: This simplified department store strategy indicates which resource to use for each due stage, balance range, and performance category.
and performance-score segments; this allows us to further distinguish the different levels of account repayment performance. We use the subscript notation shown in Figure 6 to denote such a dependency.

Categorizing accounts by balance range, performance score, and strategy allows us to work with homogeneous groups within which the repayment characteristics are, for all practical purposes, identical. Thus, the transition probabilities for accounts that have the same balance range and performance score and are treated by the same strategy depend only on their current due state, which again suggests a Markovian model. Thus, given a group of delinquent accounts with a particular balance-range and performance-score combination, we can use the DMM information to determine the most effective strategy for collections.

Frequent updating of DMMs is essential since changes in the types of accounts approved for credit, economic factors, and seasonality all affect the information contained. For example, DMMs for many clients indicate strong seasonal behavior. January is traditionally a difficult collections month, whereas November collections require less effort as consumers strengthen their financial standings for the holiday shopping season.

We developed an elaborate computerized system that RFS now uses to estimate the DMMs for competing strategies and named it the Champion-Challenger program.

**Optimizing Delinquent Collections**

Several interpretations exist as to the goal of optimizing delinquent collections. One interpretation suggests that RFS wishes to maximize the net delinquent dollar amount collected subject to collection resource constraints. Here, net implies that collection costs are to be considered. Ignoring collection resource constraints would typically produce an answer that would be infeasible in actual practice. In general, increasing collection resources is economically beneficial because of the increased amount collected relative to the additional cost. This has its limit since some people will never pay. A point of diminishing returns does exist.

An alternative RFS objective might be to minimize the amount of delinquent credit losses. If RFS is successful at collecting an interest charge on the delinquent accounts along with the monthly payments, then avoiding losses (that is, write-offs and account bankruptcy) might be considered the real objective. For several reasons, however, delinquency is regarded as an unpredictable and undesirable state that should be minimized. Accounts that are more than 2-due typically have their available credit

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**Figure 6:** The delinquency movement matrix (DMM) contains the probabilities of an account, in a specified balance range and performance category, transitioning between the various possible due stages over a one-month period when treated with a specified strategy.

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**Interfaces 22:1** 96
lines terminated; other differences, as compared to nondelinquent accounts, also exist.

Still a third alternative is to minimize losses and to employ strategies that move the currently delinquent accounts to less delinquent (and eventually to current) states.

Subtle yet important differences exist among the three alternatives. We believe that successfully managing a delinquent portfolio by maximizing the net collections over time results in achieving all three objectives. An important associated benefit is that we improve customer goodwill by correctly identifying those customers who do not require collection efforts.

**Managing a Delinquent Portfolio**

The true effect of a strategy can be measured only by considering what happens to an account over multiple billing periods. Novice collection managers often believe erroneously that maximizing the net amount collected in a single billing period is the goal. This practice, known as *creaming*, makes the collections manager look like a superstar that month but can leave the portfolio with a poor repayment potential in the following months, resulting in dismal overall collections over a multiple month period.

Creaming also erodes customer goodwill. The reasons for poor subsequent collections are easily understood. In any delinquent portfolio, (1) some accounts pay without any collection efforts, (2) some take small amounts of coaxing to pay, (3) some need large amounts of coaxing, (4) some require large amounts of coaxing plus time to assemble payments, and (5) some seldom pay. By creaming, the collections manager concentrates the most effective strategies on categories 1 and 2 while not working the accounts in categories 3, 4, and 5. Thus, he or she realizes an excellent return for one month’s efforts, but the next month the creaming strategy will be less effective; the accounts in categories 3 and 4 will not have positioned themselves (juggled finances or saved) to make any type of payment.

Other multiple-billing-period phenomena exist; some understood, others not. All indicate the importance of considering the multiple-billing-period effect in managing delinquency.

**Application Dynamics**

To manage delinquency effectively, one must both understand and successfully model delinquency dynamics. The collection strategy assigned to a particular account can probabilistically determine the due state of the account at the beginning of the next billing period. Thus, once a collection manager assigns strategies to different account types, the distribution of the account portfolio for the next billing period can be determined, at least in a stochastic sense. Following different strategy assignments would result in different account portfolio distributions for the next billing period. In addition, the distribution of the account portfolio should also be viewed as a constraint in the optimization problem since one cannot collect on more accounts of a certain type than exist. Thus, strategy decisions not only contribute to the objective function for the current period but also stochastically affect feasibility for the next period (Figure 7).

In this initial description, we do not consider the addition of new accounts in sub-
sequent billing periods. Instead the optimization presented here is concerned with maximizing the net collections over time from the account portfolio available at the beginning of the first billing period. The inclusion of additional account volume is easily modeled and has been implemented.

Any realistic attempt to optimize delinquent collections must model the interdependencies between strategy assignments during the current month and the resulting account distribution for the following month for a multiple month period. It must also model the collection resource constraints for each period considered. This is a formidable task, considering RFS's more than 300 individual retail company portfolios, each of which has specific customer interface and constraint requirements. All of this illustrates the need for flexibility in the formulation.

We segmented the account portfolios, investigated various dynamic, linear, and quadratic programming formulations, compared them with respect to utility, accuracy, and efficiency. After an extensive modeling and verification effort, we developed a stochastically constrained, multi-period linear-programming formulation. We incorporated this novel approach, capable of accurately and efficiently identifying improved strategies, in a user-friendly software system called PAYMENT.

Converting concepts into formal mathematical models, implementing these as user-friendly, graphics-oriented software,
and developing documentation involved a long period of applied research, continued interactions, brainstorming, and experimentation.

**PAYMENT**

PAYMENT's functionality can be divided into two parts: strategy evaluation and optimization. The first involves systematically evaluating the short- and long-term effects of current strategies or strategies put into practice on an experimental basis using the champion-challenger program. Optimization is based on a multiple time period linear programming formulation that allows collection managers to determine improved allocations of collection resources to accounts segmented by due state, balance range, and performance score. (We present the details of this formulation in the appendix.)

**Implementing the Prototype**

In May 1989, the PAYMENT system was ready for a test drive! Because the team had been so comprehensive in working with the field, numerous portfolios wanted to apply the PAYMENT approach to optimize collections. Since the new program affected millions of dollars, we proceeded cautiously and resisted the temptation to move forward with all the portfolios simultaneously. After careful consideration, we selected a discount department store chain as the initial "beneficiary" of the PAYMENT technology. Because it reflects, more or less, the process we used subsequently at various other RFS business centers, we will describe this prototype implementation in some detail.

**Champion-Challenger Strategy Comparisons—A Global Approach**

PAYMENT determines an improved collection strategy composed of the optimal components from strategies on which it has information. The improved strategy can be only as good as the best components from the strategies that have been evaluated and the information available on them. We obtained this information from field evaluations of the alternative strategies via the champion-challenger program. We have placed a great deal of emphasis on testing comprehensively, that is, employing all possible combinations of viable collection resources across the differing account segments to determine which performs best and where. As obvious as it may seem, this testing was an important contribution; collection managers have over the years converged to using their favorite strategies on specific account types; yet they will openly admit this selection is based largely on "gut feel." By clearly communicating the benefits of the approach, we persuaded this hardened bunch of experts to be receptive to an idea that initially seemed ludicrous—to conduct an experiment with a potential multi-million dollar consequence for even the smallest portfolio (Figure 8).

We called the strategy currently employed for collections "the champion"—this obviously made things interesting for the collection managers. We assigned accounts randomly to each of the strategies using the last two digits of the account number as the randomizing factor (account numbers are based on the order in which credit applications are processed). We did not assign the same proportion of accounts to each strategy. We allocated fewer accounts to long-shot strategies that could conceivably provide worse rather than im-

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January–February 1992 99
Figure 8: A comprehensive champion-challenger program implements all viable side by side comparisons of collection resources.

proved results.

We initiated the champion-challenger study formally in July, 1989. At the end of each month, we generated DMMs for the different balance range, performance score, and strategy segments. The data were used by PAYMENT and the results reviewed with collection management.

It soon became apparent that in many of the balance-range and performance-score segments, the challengers were outperforming the champion. However, to capture the long-term effects we needed, we postponed further action until we had accumulated data for four months. In December, we used the DMMs from the champion-challenger studies for July through November in PAYMENT to find an improved strategy.

We began implementation of this new strategy right away, hastened partly by the fact that PAYMENT’s suggestions made good intuitive sense, at least in hindsight! In fact, the collection managers were so
convinced of the merits of PAYMENT’s suggested new strategy that they wanted to totally replace the existing strategy. This is typical in studies of this type. Once a winner is identified, people are naturally impatient to fully capitalize on the gains. However, for comparison purposes, the team negotiated with collection management to leave the old champion in place on 20 percent of the portfolio as a control group while applying the PAYMENT strategy to 60 percent of the portfolio. The remaining 20 percent of the accounts were dedicated to a pure live strategy, that is, collection managers contacted all accounts live by telephone, as opposed to using prerecorded messages. This strategy had long been acknowledged by collection managers to be the most effective strategy possible. However, its use is typically restricted by its prohibitive cost and the limited availability of the live resource. Our rationale for running a side-by-side verification was to insure against possible changes in the relative effectiveness of the strategies, to obtain rigorous evidence of improvement, to quantify this improvement, and to further evaluate the pure live strategy.

The Discount Department Store Chain Results

We applied all three strategies for a five-month period during which we monitored the results monthly; we conducted a detailed analysis at the end of April.

We submitted a production SAS job to sum the actual dollars collected per account during the April billing period for each of the competing strategies and used the results as an indicator of the performance associated with the individual strategies. We tracked more than 100,000 2-due accounts. The PAYMENT-suggested strategy had been applied to 63,200 2-due accounts while the previous champion strategy, the control group, had been used on 20,764 2-due accounts, with the remaining 21,143 2-due accounts receiving the pure live strategy. The mean dollar amounts collected during this period for the PAYMENT, champion, and pure live strategies were $31.56, $29.44, and $29.79 respectively. This performance difference represents an approximate 7.2 percent collections improvement for the 2-due accounts. We realized an 8.9 percent improvement on the 2-due accounts identified as good by performance score; approximately one half of all 2-due accounts fell in this category. When we considered the cost of implementing the strategies, the percent improvement exceeded nine percent for the 2-due good accounts alone. We also calculated the associated variances for each strategy group and found that the group of accounts treated with the PAYMENT strategy also had less variability. Using this variance information, we can construct a confidence interval (CI) for the difference between the PAYMENT and champion population means. The 95 percent CI, assuming unequal variances, is ($9.7, $3.27) per account, indicating a statistically significant improvement.

We also found significant improvements for the 3-due accounts and for the billing periods prior to April. When considering the five-month period from December 1989 to April 1990, we found that the average collection improvement per billing period due to the PAYMENT strategy was greater than $185,000. This portfolio currently represents less than one percent of
RFS's total volume.

The benefits of the PAYMENT strategy did not stop there! Despite its improved effectiveness, PAYMENT's strategy actually cost less to implement than the control strategy. Although this may not be true for all portfolios, it does indicate PAYMENT's consideration of resource cost when determining an improved collection strategy. This reduced cost phenomenon is a result of PAYMENT's accurate allocation of collection resources to the account segments. In particular, PAYMENT suggested much greater use of the no-action resource.

Beyond the improvement in collections and the savings in strategy cost was yet another benefit. Collection management saw an increase in customer goodwill. This results from PAYMENT's allocation of just enough collection muscle to the appropriate customers. This increase in goodwill was indicated by a significant reduction in calls to the call-back center. The call-back center receives customers' calls to the 800 numbers listed on their monthly statements and handles various complaints. These include the ever popular "I'm a good customer and do not appreciate being reminded to pay my monthly payment. . . . I'm using my Visa card from this point on. . . ." They imply that in the future the department store will lose the revenue associated with the use of its card and possibly the customer's business as well. PAYMENT is able to identify this "good" customer and suggest the appropriate no-action treatment. Reducing such calls to the call-back center is the tip of the iceberg. A customer pleased with the quality of his or her credit services is more likely to make additional purchases on credit—a result strongly desired by both the department store chain and RFS. In fact, although the benefit in goodwill is difficult to quantify accurately, many collection managers agree that the long-range benefits of increased customer goodwill can far outweigh near-term improvements in the dollars collected.

Implementation for a $12-Billion Business

The PAYMENT program realized significant benefits during the spring of 1990. We began its implementation for other portfolios at their request. Their individual collection managers monitored the benefits. The results, in general, were quite positive, and the level of interest in PAYMENT escalated throughout RFS. The focal point for PAYMENT moved from CRD to RFS headquarters, and we initiated a PAYMENT newsletter to improve communication of PAYMENT experiences. Moreover, our description of PAYMENT was the lead presentation at the 1990 annual GE Capital collection managers meeting, which was attended by approximately 150 managers and members of their staffs from throughout GE Capital. This meeting also provided another first—a GE Capital management award was presented to CRD for "outstanding contributions . . . and remarkable responsiveness to our needs through the development of PAYMENT."

The need for a general rollout plan, which allowed for participation of the entire $12-billion business, soon became apparent. True to expectations, this turned out to be a major undertaking, involving hundreds of managers and staff throughout GE Capital; an undertaking that still undergoes refinement today. One product
of this effort was a day-long PAYMENT workshop offered repeatedly to train collection managers and their staffs. We prepared a PAYMENT text, conducted classroom training, and began individual champion-challenger studies. Over time, PAYMENT was installed at more and more RFS facilities.

The champion-challenger computer hardware and software system is now capable of assigning, tracking, and measuring the results from the specific strategy to be used for each of RFS's approximately 50 million consumer accounts from more than 300 portfolios. The system allows strategies to be changed as often as desired and makes performance results available on a daily basis. Collection managers can make strategy changes from any of the collection and support centers and business centers and have them take effect the next day. Performance data is provided by personnel at the three collection and support centers and downloaded over the computer network to centers across the country.

We held an initial PAYMENT workshop for the collection managers from the $4.5-billion portfolio of a national department store chain—RFS's largest portfolio. It is more than 50 times the size, in terms of outstanding credit volume, of the department store used in the prototype application. Using a similar approach, this chain developed comprehensive test strategies that we implemented during the period from May to August 1990. By the end of this period, the collection managers were soundly convinced of PAYMENT's findings. At the beginning of September, we undertook the largest and most comprehensive collection strategy switch in RFS history—a 100 percent replacement using the significantly different strategy suggested by PAYMENT.

As with the department store portfolio, the new strategy for the national chain called for more no-action and live resources (displacing tape resources). In this

A customer pleased with the credit services is more likely to make additional purchases on credit.

application, however, these changes involved hundreds of thousands of accounts. We asked GE Capital's upper management for greatly increased funding to cover the additional equipment and training needed to implement the new strategy. We were able to defend our requests and achieve success in the implementation because of the reputation of PAYMENT.

From September through December 1990, we monitored the chain's strategy performance daily. We compared the results with those from the same time period the previous year, which had been an easier collection year because the national economy had been healthier. A summary of the results provided by collection management over this four-month period indicates an average three percent collections improvement due to the PAYMENT-suggested strategy. In terms of absolute dollars, this amounted to an average $1.6-million improvement per month. This was especially remarkable in light of the 1990 recession. This result probably gave a conservative impression of PAYMENT's true
benefit. During January 1991, after careful investigation, upper collection management documented an annual $19-million projected reduction in losses due to the implementation of the PAYMENT strategy. **Improved Collections Provide Reduced Losses**

Although delinquent dollars and the associated interest charges not collected in the earlier stages of delinquency (the 2-due and 3-due stages) can still be pursued at later stages of delinquency, collection effectiveness (CE) decreases dramatically. CE is defined as the proportion of outstanding dollars that do not become any more delinquent during the current month. For example, for a department store portfolio, 2-due CEs may average 0.85 while the 3-due and 4-due CEs fall to 0.65 and 0.45. At the 7-due stage, the CE is typically less than 0.2—more than 80 percent of these accounts will not make any payment and become 8-due. Clearly, it is best to collect an account during the front end (while it is 2-due or 3-due) irrespective of the interest charge applied. Middle- and back-end collections simply cost too much and are ineffective. In addition, once an account becomes 4-due, the customer's available credit limit is typically reduced to zero, causing two important consequences: The card loses all utility and the customer becomes even less interested in making payments. Second, potential business income from this card is also lost. This has a negative impact both on RFS and on the retail consumer business for which the card is offered. In essence, the longer RFS is unsuccessful at collecting a delinquent payment, the larger the amount lost will be both in dollars written off and in lost business.

The relationship between front-end collections and back-end losses is well understood and forms the basis for accurate yearly write-off projections. The department store chain collection management used this relationship to provide the annual $19-million loss reduction figure.

With the widespread, successful implementation of PAYMENT throughout RFS, we established a momentum for further management science applications. The first new application deals with handling long overdue accounts and write-offs. Current policy calls for writing off an overdue account after about nine months and then turning it over to a collections agency or to a lawyer. This, like other aspects of the business, is the result of tradition rather than scientific evidence. We are conducting a management science effort to identify optimum ways to handle long overdue accounts that is already pointing to an improved approach.

The second application brings new management science tools to GE Capital corporate headquarters. We developed a tool, called PAYMENT-HQ (to differentiate it from the original PAYMENT, which is now called PAYMENT-Field). While PAYMENT-Field improves collection strategies subject to resource constraints, PAYMENT-HQ helps determine what the optimum resource levels should be in the first place. The new tool is now in use for longer-term forecasting and for assessing the value of potential new portfolios.

The most recent effort is a joint undertaking between CRD and GE Capital to develop a comprehensive business model that ties the collections effort to other aspects of the business, such as granting
CONSUMER CREDIT

credit initially and managing credit lines—the dynamic determination of how much credit to make available to a particular account. When it is complete, we expect that this model will permit a dynamic flow of information from the collection operation to other parts of the business, with associated mechanisms for improving each of the ingredient processes.

An Annual $37-Million Business Impact

In light of the overleveraged consumer and the current state of the US economy, optimal management decisions are clearly necessary if GE Capital is to remain prosperous. The PAYMENT approach to managing consumer debt delinquency utilizes a wide spectrum of advanced management science techniques to provide superior insights. It aims to optimally manage delinquency for the benefit of the consumer, GE’s private label business partner, and GE Capital. The resulting collections technology has now been implemented on over 80 percent of GE Capital’s total volume, with a stated goal of 100 percent.

PAYMENT has permanently changed the way GE Capital handles delinquent consumer credit collections for its 300 retail business portfolios. This novel application of management science methodology is conservatively credited with a $37-million total annual reduction in the ongoing rate of losses for the entire RFS portfolio! Remarkably, these collection improvements often come with reduced collection resource expenditures. With PAYMENT, it actually costs less to collect more!

The improvements in collections and strategy-cost savings are only part of the story. To many, of greater importance is the improved customer goodwill. Eliminating possible harassment of good, but sometimes forgetful, customers insures the retention of these accounts as satisfied customers. At the same time, we all gain from the fact that those who should not be using credit are identified and discouraged early. Moreover, the approach we developed has obvious applicability in many collection environments; in particular, for the collection of home mortgage and auto loan payments. GE Capital is also investigating possible application to leasing debt.

As a result of PAYMENT’s unqualified success, management science concepts are being applied comprehensively throughout the business; for example, to enable top management to determine the optimal overall collection resource levels, to assess the value of prospective portfolio additions, and to identify portfolio profitability indicators.

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APPENDIX: PAYMENT

Mathematical Programming Formulation

The multiple time period linear pro-
gramming formulation determines how to best use collection resources to maximize net collections over time. Solution of the model yields an improved strategy that specifies what resource should be employed for each due state and account type. Delinquency movement matrices (DMMs) are used to measure the effects of the collection strategies and to define the objective function and constraints.

**Decision Variables and Notation**

In the real-world application of this work, we partitioned the accounts by specifying the balance range and the performance score. Due to the prediction significance of these variables, such partitioning benefits the implementation and leads to an improved strategy. However, in describing the model we refer to a balance range and performance score combination as an account type, which we denote using the symbol $r$; specifying a particular account type uniquely identifies a balance range and performance score category. The decision variables in the model are defined as

$$X_t(j, r) = \text{fraction of accounts of type } r, \text{ treated with collection strategy } j, \text{ during period } t.$$ 

In the formulation we let

- $T = \text{number of time periods under consideration}$;
- $J = \text{number of collection strategies } j$;
- $K = \text{number of collection resources } k$;
- $R = \text{number of account types } r$; and
- $S = \text{number of delinquent states}$ (paid up, current, 2-due, . . . , loss).

Data necessary for the formulation is given below:

$$p_{r,t}(u, v) = \text{probability of an account of type } r, \text{ in due state } u, \text{ transitioning to due state } v, \text{ when treated with collection strategy } j;$$

$$EFT_k = \text{number of accounts that can be handled per billing period by the available resources of type } k;$$

$$C(j, u) = \text{cost of collecting a single account (independent of type) using the collection resource for due state } u \text{ specified by collection strategy } j;$$

$$R_{j,u,k} = \text{number of units of collection resource } k \text{ required when implementing collection strategy } j \text{ on accounts in due state } u;$$

$$I(r, u, v) = \text{average income collected per account of type } r, \text{ when it transitions from delinquency state } u \text{ to delinquency state } v; \text{ and}$$

$$N_t(u, r) = \text{number of accounts of type } r, \text{ in due state } u \text{ at the start of billing period } 1.$$

Finally, intermediate quantities in the formulation that depend on the decision variables and the above data are

$$E(j, u, r) = \text{net income expected from a single account of type } r, \text{ in delinquency state } u, \text{ when treated with collection strategy } j;$$

$$N_t(u, r) = \text{number of accounts of type } r, \text{ in delinquency state } u, \text{ available at the start of time period } t, \text{ (} t \geq 2); \text{ and}$$

$$n_t(j, u, r) = \text{number of accounts of type } r, \text{ in delinquency state } u, \text{ that will be treated via strategy } j \text{ during time period } t.$$

**Objective Function**

The objective is to maximize the sum of expected net collections over a specified number of time periods $T$. Using the DMMs we can calculate the expected net income for a single account of type $r$, in due state $u$, when treated with strategy $j$ as

$$E(j, u, r) = \sum_{v=0}^{S} p_{r,t}(u, v)[I(r, u, v) - C(j, u)].$$

Once the DMMs have been estimated, the $E(j, u, r)$ values are completely determined; these values are calculated before conducting the optimization. From the decision
CONSUMER CREDIT

variables, we see that the product

\[ X(j, r)N_i(u, r) = \text{number of accounts of type } r, \text{ in due state } u, \]

\[ \text{treated by strategy } j \text{ in billing period } t. \]

Thus, the quantity \( X(j, r)N_i(u, r)E(j, u, r) \) will represent the expected net collections from accounts of type \( r \) in due state \( u \) when treated by strategy \( j \) in period \( t \). The objective function, \( Z \), is then obtained by summing this expected net collections expression over all account types, due states, strategies, and billing periods; thus we wish to maximize

\[
Z = \sum_{t=1}^{T} \sum_{j=1}^{J} \sum_{s=2}^{S} \sum_{r=1}^{R} X(j, r)N_i(u, r)E(j, u, r).
\]

At first glance, \( Z \) appears to be a linear function of the decision variables \( X_i(j, r) \). However, the quantity \( N_i(u, r) \) will depend on the value of the decision variables of the previous billing period, \( X_{i-1}(j, r) \). Substituting this dependency into the objective function for \( N_i(u, r) \) and expanding, produces a two-factor product of decision variables from consecutive time periods. Recursive substitution shows that the objective function is actually a polynomial function in the decision variables with degree which will depend on the number of time periods considered in the optimization.

If we assume that an account does not change its type between two consecutive billing periods, we can determine a closed form expression for the expected value of \( N_i(u, r) \) for \( t \geq 2 \). The assumption is justified because balance range categories are large compared to monthly payments and an account rarely changes its repayment performance except for situations such as product dissatisfaction or unexpected economic hardship. However, the greater the number of billing periods considered, the less reliable this assumption becomes. The assumption is considered realistic for three billing periods. Limiting the optimization to a three-billing-period horizon will assure the validity of the assumptions.

\[
N_i(u, r) = \sum_{j=1}^{J} \sum_{s=2}^{S} p_{i,s}(v, u)N_{i-1}(v, r)X_{i-1}(j, r)
\]

where \( N_i(u, r) \) is known data.

This equation is an expected value calculation where the probability weights are the elements of the corresponding DMMs. Assuming an account retains the same type category between consecutive billing periods allows us to determine the expected number of accounts of type \( r \) in a particular due state \( u \) by considering the accounts of type \( r \) in all other due states \( v \) during the previous time period, and the probability of transitioning into due state \( u \), given that strategy \( j \) was used.

Substituting the expression for \( N_i(u, r) \) into \( Z \) above, incorporating the fact that \( N_i(u, r) \) is known, and considering only two billing periods produces the following quadratic objective function:

\[
Z = \sum_{j=1}^{J} \sum_{u=2}^{S} \sum_{r=1}^{R} X_i(j, r)N_i(u, r)E(j, u, r)
\]

\[
+ \sum_{j=1}^{J} \sum_{u=2}^{S} \sum_{r=1}^{R} E(j, u, r) \sum_{i=1}^{I} \sum_{v=2}^{S} p_{i,s}(v, u)
\]

\[
\times N_i(v, r)X_i(i, r)X_{i-1}(j, r).
\]

Although it is not obvious, Makuch [1990] demonstrates that this quadratic formulation actually represents a nonconvex problem as defined by Luenberger [1984].

Fortunately, we have yet to consider an additional real-world requirement. When dealing with account portfolios of this size all strategies must be implemented through an elaborate computerized system of detailed routing instructions. Although such a computerized system is easily changed, reconfiguration of the physical resources is difficult. Thus, in order for a solution to be implemented practically it must be a steady state solution, that is, the strategy
assigned to an account type should be the same for all billing periods. By incorporating this requirement, we can replace the above quadratic objective function with a linear function. The two period objective function which reflects constant strategy assignments for account types is given below. Once we have decided on the values for the decision variables during the first time period, we can then determine the number of accounts to be treated by a strategy during the second time period, that is, \( n_2(j, u, r) \), and thereby calculate the second time period’s contribution to the objective function. This is done by making use of the constant strategy requirement, which states that once we know an account type, we also know the strategy to use. Incorporating this requirement yields the following objective function:

\[
Z = \sum_{j=1}^{J} \sum_{u=2}^{S} \sum_{r=1}^{R} X_1(j, r)N_1(u, r)E(j, u, r) \\
+ \sum_{j=1}^{J} \sum_{u=2}^{S} n_2(j, u, r)E(j, u, r).
\]

Just as we derived the expected value for \( N_1(u, r) \) above, we can derive an expression for the expected number of accounts that we will be collecting via strategy \( j \) during the second time period; namely,

\[
n_2(j, u, r) = \sum_{v=1}^{S} p_{j,v}(v, u)N_1(v, r)X_1(j, r)
\]

where \( N_1(v, r) \) is known.

Substituting this expression for \( n_2(j, u, r) \) in the previous objective function expression produces the following two-period objective function. Here we have dropped the time period subscript on the decision variable since in this formulation the decision variables do not depend on the time period.

\[
Z = \sum_{j=1}^{J} \sum_{r=1}^{R} X(j, r) \sum_{u=2}^{S} N_1(u, r)E(j, u, r)
++ \sum_{j=1}^{J} \sum_{r=1}^{R} \sum_{u=2}^{S} E(j, u, r)
\times \sum_{v=2}^{S} p_{j,v}(v, u)N_1(v, r).
\]

A three-period objective function can be constructed in an analogous manner by considering the accounts that result from actions taken during the second period; the resulting objective function is given below.

\[
Z = \sum_{j=1}^{J} \sum_{r=1}^{R} X(j, r) \sum_{u=2}^{S} N_1(u, r)E(j, u, r)
++ \sum_{j=1}^{J} \sum_{r=1}^{R} \sum_{u=2}^{S} E(j, u, r) \sum_{v=2}^{S} p_{j,v}(v, u)
\times N_1(v, r) + \sum_{j=1}^{J} \sum_{r=1}^{R} \sum_{u=2}^{S} E(j, u, r)
\sum_{v=2}^{S} p_{j,v}(v, u)N_1(v, r).
\]

**Constraints**

The constraints in this maximization problem consist of collection resource constraints, which prevent the allocation of more resources than exist in a particular billing period, and account constraints, which prevent the collection of more accounts of a certain type than are delinquent at the beginning of each billing period.

The collection resources available are measured by the number of accounts that can be collected per month. For example, the amount of type \( k \) resource is given by the number of accounts that can be collected per month using only type \( k \) resources. For a particular collection strategy \( j \), we use the conversion factor, \( R_{j,u,k} \), which indicates the quantity of type \( k \) resource needed to implement strategy \( j \) for collecting a single account currently in due state \( u \). Since we cannot exceed the amount of available resources, the resource constraints for the first time period can be
CONSUMER CREDIT

written as

\[ \sum_{j=1}^{I} \sum_{r=1}^{R} \sum_{u=2}^{S} X(j, r)N_j(u, r)R_{j,u,k} \leq EFT_k \]

for \( k = 1, \ldots, K. \)

The EFT notation stands for “effective full time equivalent units” and is the unit of resource measurement employed by RFS. Resource constraints for the second time period are given in the next equation. The quantity inside the brackets is the number of accounts of type \( r \) one can expect to have in due state \( u \), at the beginning of the second period; these accounts will be collected via strategy \( j \).

\[
\sum_{j=1}^{I} \sum_{r=1}^{R} \sum_{u=2}^{S} \left[ \sum_{l=2}^{S} p_{j,r}(v, u)X(j, r)N_j(v, r) \right] \times R_{j,u,k} \leq EFT_k \quad \text{for} \quad k = 1, \ldots, K.
\]

Resource constraints for the third period are similarly derived.

The account constraints arise because we cannot attempt to collect on more accounts of a certain due state and type than actually exist at the beginning of each billing period. We can express the account constraints as

\[
\sum_{j=1}^{I} X(j, r) \leq 1 \quad \text{for} \quad r = 1, \ldots, R.
\]

Lastly, it is necessary to include non-negativity constraints. Without such constraints it is conceivable that by making certain \( X(j, r) \) negative (others proportionally positive) we could infeasibly increase the objective function. A likely scenario would be to increase the allowable proportion of high-payment accounts, while decreasing the proportion (to a negative value) of low-payment accounts, and still satisfy resource and account constraints. Non-negativity can be modeled as

\[
X(j, r) \geq 0 \quad \text{for} \quad j = 1, \ldots, J
\]

\[
r = 1, \ldots, R.
\]

References


Sullivan, A. Charlene, 1987 “Economic factors associated with delinquency rates on consumer installment debt,” working paper no. 55, Credit Research Center, Purdue University.