Justifying Contingent IT Investments:
Balancing the Need for Speed of Action with Certainty before Action[1]

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Abstract

Executives need to master different mechanisms for analyzing their firms' investment opportunities in uncertain, difficult times. Rapidly changing business conditions require firms to move quickly, with total commitment and the rapid deployment of capital, resources, and management attention, often in several directions at the same time. However, high levels of strategic uncertainty and environmental risk, combined with limits on available funding, require firms to limit their commitment. In brief we require high levels of strategic commitment to numerous projects, while simultaneously preserving our flexibility and withholding commitment. While achieving both is clearly impossible, techniques exist that enable executives (1) to identify and to delimit their range of investment alternatives that must be considered, and to do so rapidly and reliably; (2) to divide investments into discrete stages that can be implemented sequentially; (3) to determine which chunks can safely and profitably be developed as strategic options, with value that can be captured when subsequent stage investments are made later; and (4) to quantify and to estimate the value of these strategic options with a significant degree of accuracy, so that selections can be made from a portfolio of investment alternatives. This paper also avoids restrictions of common option valuation models by providing a technique that is general enough to be used when the data required by common models are not available or the assumptions are not satisfied.

1. Introduction

Technological innovations in shopping, distribution, and entertainment that outstrip consumers' ability to adopt them, cultural and military conflicts polarized by recent events in the middle east, and unprecedented stock market volatility combine to create an increasing sense of strategic uncertainty. Executives are concerned about implementing the infrastructure that they may need

to take advantage of market opportunities as they arise. They are equally concerned with avoiding any unnecessary investments in technology infrastructure in support of market opportunities that do not arise. They are trading off the desire for speed (*"we have no time to waste"*) with the desire for certainty before acting (*"we have no resources to waste"*). This requires a methodology for justifying investments in assets that will be required only under specific sets of conditions, and for enabling rapid deployment of these assets when they are required. We call such investments contingent investments.

We develop a general framework that permits evaluation of a contingent IT investment; that is, we provide a technique that allows a firm to estimate the value on a technology investment that enables the future deployment of a strategy should conditions arise that make this strategy desirable. The set of conditions that may cause a strategy to become desirable includes environmental factors such as the behavior of customers, and game theoretic factors, such as the actions of competitors. The generality of this framework forces us to make a trade-off between deriving closed form solutions with overly demanding restrictions on the set of conditions and providing heuristic evaluations for general conditions without such restrictions. Since our intention is to provide business practitioners a useful tool for evaluating contingent investments and to make these tools sufficiently general to incorporate truly innovative applications of information technology, we find imposing arbitrary restrictions on business conditions inconsistent with our objectives. Instead, we establish an economic model for the general framework, within which it is possible to provide arbitrary complex sets of conditions as inputs and to use computer simulations and other numerical methods to evaluate *ex ante* values of contingent investment strategies given these conditions.

2. Maintaining Strategic Flexibility: Achieving Speed while Deferring Commitment

It is not too difficult in principle to determine the value that a firm may receive from obtaining in advance the resources that it would need to deploy a specific strategy at a future time. In order to determine such value, you would need to:

- Delineate your **set of alternative business contexts**. This entails determining what condition θ a firm might face in terms of regulation, customer preferences, technological advances, or new entrants at time t. The specific set of conditions revealed at time t will be represented by $\theta \in \Theta$ and the likelihood that a given condition θ happens is represented by $\pi_\theta \in \Pi$.[2]

- Delineate your **set of strategic responses**. This entails determining: (1) the set of possible strategies $s \in \Sigma$ to be pursued; and (2) the benefits, or the financial and competitive payoff, from selecting a particular strategy $\beta(\theta, s)$ at time t when θ is known.

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[2] Alternative contexts can be identified through scenario analysis. Actions may be needed in one scenario but unnecessary or even dangerous in another. These contingent possibilities, those things that we can identify now as possibly useful at a later time, yield the most interesting investment decisions. For example, it may be useful for an insurance company that will be operating in some future, fully deregulated environment to have detailed predictions of expected claims associated with individuals who have different family backgrounds, different ethnic backgrounds, and different individual genetic predisposition to expensive medical conditions. Even attempting to maintain such information today would be considered morally repugnant to most of western society and would produce significant loss of brand image and customer loyalty. Increasingly, scenario analysis is used to predict the range of possible future environments, so that the range of systems they will require can be determined in advance (e.g., Clemons [6], Schoemaker [24], Schwartz [25], Wack [28, 29]). Delimiting strategic alternatives through scenario analysis is the most subjective and least precise portion of our methodology. We are indeed aware that failure to identify a significant future state of the world can entirely preclude consideration of an entire class of strategies. Additionally, by ignoring some outcomes with non-zero probabilities it can cause us to overestimate the probabilities of other outcomes, and thus can result in substantial bias in our estimates of the value of some investments. However, scenario analysis at present appears to be among the best available mechanisms for delimiting θ and β.

- Determine the **optimal** strategy for each θ at time t and let this be

  $s^*(\theta) = \arg\max_s \beta(\theta, s)$ and determine the resources that must be deployed to implement

  that strategy.

- Calculate the difference between the returns from the best strategy (when the resources are available) and the returns from the best alternative strategy (when the resources are not available); both are evaluated for the same set of conditions represented by θ. This difference is the value $\upsilon(\theta)$ of having the appropriate resources for $s^*(\theta)$, given that θ actually describes the environment at time t. (Of course, if $s^*(\theta)$ does not require the resources, then $\upsilon(\theta)$ is zero.)

Thus, if (1) the set of future environments Θ and Π were known and (2) adequate models were available to determine the value of a strategy in each of these specific future environments, then we can calculate the value of the resources needed to deploy that strategy. This could be done simply by comparing the expected values created by the best strategies that could be deployed with and without those resources. This tells us the value of strategies once resources are known, but tells us little about preparing in advance, or developing a plan for committing resources. In this paper, we suggest that firms do not need to make full commitment of resources beforehand. Instead, firms can identify investment opportunities early, evaluate them accurately, and where justified commit resources that enable a fast response in case a given strategy needs to be implemented at some future time. That is, we provide a mechanism for enabling rapid response, with a set of actions we can take now, so that when θ is revealed at time t we are able to take the correct context-specific actions quickly.

Obtaining future flexibility while withholding expensive full commitment until requirements are known is facilitated by initially laying the groundwork for future actions through what we might

have called *strategy-enabling partial investments*. These partial investments cost less than complete acquisition of the full set of necessary resources. Importantly, they enable speed of action when the appropriate course of action can be determined and they allow delaying full spending on necessary investments until it is clear which investments are required. When future conditions become known and requirements become clear, contingent IT investments can now be made. The initial investments are properly viewed as **strategic options**, while completing the future contingent investments can best be seen as **exercising** the strategic options created by initial investments.

3. Review of the Literature

An option is simply the right to obtain an asset at later time, at a pre-specified price (call) or the right to sell an asset at a later time, at a pre-specified price (put). Different forms of options have been identified and studied in the literature.

3.1. Financial Options

A financial option is the right to trade a **financial asset** at a future time and at a predetermined price. These can be considered "context-independent" "common value" assets; the value of an option to buy shares of IBM or US Treasury bills at a specified price is the same for all investors, and this value is determined solely by the difference between the value of the shares and the strike price of the option when it is exercised. Valuation of financial options requires existence of arbitrage-free markets where the underlying assets are traded. Using market prices of the underlying assets and their return variances, a number of option price models have been proposed, among which are the commonly used binomial model in discrete time due to Cox and

Rubinstein [11] and Black-Scholes model in continuous time due to Fischer Black and Myron Scholes [4].[3]

3.2. Real Options

In its purest sense, a real option is the right to trade a physical asset, such as real estate or manufactured durables such as aircraft, at a future time and at a predetermined price.[4] These are not common value instruments, in the sense that an option to upgrade a fleet of aircraft will have different values to different airlines depending upon their size and the age of their fleets; likewise, the value of an option to build a hotel near an airport will have different values to different hotel chains depending upon their targeted market segments and the nature of their existing offerings near the airport.   This greatly complicates any effort at valuation. Like financial options, the greater the volatility in demand, the more valuable the option to take delivery without delay; these options are valuable because of the future flexibility of action that they confer, and thus the value of these options is dependent upon uncertainty in the cost and availability of assets and upon uncertainty in the value of their deployment. Myers introduced the concept of real options [21]. Trigeorigis [27] provides an excellent treatment of real options in investment decisions.

A large body of research on real options focuses on applying financial option pricing models to evaluating real options. However, real options differ from financial options in one critical aspect: there exist no arbitrage-free markets where underlying assets are traded. All applications

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[3] Since a financial option is an investment that supports flexibility — the right to trade an investment at a specified price at some future time — it is not surprising that the value of the option increases as a function of the value of flexibility. The value of flexibility naturally increases with the volatility of the underlying instrument — if shares of IBM **always** traded at $140 and US Treasuries were **always** $10,000 — an option conferring the right to trade them at $140 and $10,000 respectively would have no value.

[4] Many researchers also include in this category actions that enhance strategic flexibility, such as learning or initial experiments with early market entry; we find it useful to make a distinction between real options as we have defined them, and strategic options, which we introduce in the next section; we trust this will cause no confusion among our readers.

of option pricing models require identifying "twin assets" that is theoretically perfectly correlated with the underlying assets of the real options and use their prices and return variances in the pricing models. Critics to real options approach often dismiss such choice of "twin assets" arbitrary and useless. Indeed, twin assets are used as a quick way of forcing the applicability of traditional financial options valuation techniques by attempting to find a source of historical distributions that can be applied analogously to Black-Scholes. However, even were such assets to exist, this would fail to capture the firm-specific valuation essential to real options theory.

Significantly, real options theory, in fact, does not dictate use of any particular pricing models. It is simply an approach that recognizes the value of management flexibility in investment evaluation. This paper takes an alternative approach with regard to valuation while staying true to the principal of real options theory. Moreover, as Trigeorigis [27] points out, options pricing models usually provide a single risk-adjusted expected value that is consistent with the objective of maximizing firms' market capitalization. Project managers' decision criteria, however, are often not aligned with maximizing firms' market capitalization. Instead of providing managers merely a single expected value adjusted by market's risk acceptance level, our model provides managers with a distribution of the value of the investment and let the mangers make risk adjustments based on their preferences.

3.3 Strategic Options

The concept underlying our approach has been widely used in strategic management literatures in the form of strategic options. A strategic option represents a **capability to deploy a selected strategy**. Rather than being purchased, these capabilities are synthesized by making the investments that will be needed for rapid deployment of the strategy later, if and when it is

desired.[5] Deciding not to implement the strategy has much in common with choosing not exercise a real option, and much of the analysis used in real options theory is therefore applicable. Strategic options are context-specific rather than common-value. For example, a strategy based on customer relationship management and individualized service will have different value for chains like the Ritz Carlton or the Inter-Continental, whose clientele expect the most careful attention to their specific individual needs and preferences, than it would for more mass-market chains like Marriott Courtyard or Holiday Inn.

Financial options provide inspiration but do not directly suggest how strategic options might be valued. No "twin assets" are available to offer much guidance when attempting to value strategic options: the first airline to develop an online distribution strategy was not able to find any assets that mimic either the benefits from customer adoption or the potential losses from retaliation from travel agents concerned with the loss of business that online distribution might represent [8]. There were no traded assets that mimic the value for many strategic systems investments, nor were there reasonable surrogates (there was no known distribution, with known mean and variance, for the pricing strategies employed by Capital One [9] or for the regulation that could be applied to the insurance industry in the face of improved genetic testing capabilities by individuals [10]).[6] Moreover, unlike financial options where the value is determined by a large, anonymous, exogenous marketplace, the variance of value in strategic options at least to some extent is endogenous, and is heavily contingent on the timing of our actions and of the actions of competitors [16, 17]

3.4. Contingent IT Investments as Strategic Options

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[5] Other authors in the strategy area, particularly Bowman and Hurry [5], Mitchell and Hamilton [20], and Kogut [17] have used the term strategic option much as we have here.
[6] Capital One is the first credit card issuer in the US that uses differential pricing strategy in determining customers' interest rates. See Clemons and Thatcher [8] for more details.

MIS researchers have studied the idea that investments in IT need to be valued and justified since at least the early 1970s. Some systems could clearly be justified because they were necessary to the timely conduct of business. Others were more subjective, and required valuing the information produced by the systems [13]. Dos Santos [12] applies real options theory to making IT investments, dividing the investment into two stages and treating the first stage as an option on the speedy deployment of the second. He assumes distributions on both the benefits and costs of exercising the option (making the second stage investment). Kulatilaka and Perotti [18] study investment in technology options in the presence of competition, and determine that in the presence of competition options are exercised sooner (to achieve competitive benefits) but total benefits to innovators are reduced (due to competition). Benaroch and Kauffman [2, 3] provide an excellent example of applying option valuation model in real business environments. Zhu [30] studies IT options, rather than technological options more generally, and derives similar results. Huchzermeier and Loch [14] apply a sequential decision analysis framework to a multi-stage investment process, where additional information becomes available on five sources of risk (market payoff, project budget, product performance, market requirements, and project schedule) at each stage in the process and use dynamic programming to determine the options value. Tallon et. al. [26] provide an excellent overview of real options research in the IS field.

3.5. Sequential Decision Theory and Statistical Decision Theory

Perhaps the earliest work directly related to the valuation technique we use is statistical decision analysis, pioneered by Raiffa and Schlaifer in the 1960s [22, 23]. Their idea was simple but powerful: analyzing *ex ante* the effects of taking a sequence of decisions, and allowing the combination of actions made based on previous decisions and the evolving state of the world to create a decision tree. The end nodes of the tree could be evaluated, weighted by their *ex ante* probabilities, and summed, to determine the best initial course of action. Trigeorigis [26] shows that option valuation models are themselves special cases of decision tree analysis. Much of what we do below is based on this idea.

4. Sequential Decision Making and Strategic Chunkification

Some systems investments can be divided into segments, tasks, or chunks that can be implemented sequentially. To coin a term that is easy to remember, we call dividing a contingent IT investment opportunity into chunks **strategic chunkification**; the first chunk is made because the contingent investment **may** prove very useful, while the second chunk of investment is made only when it is known that the contingent investment **will** be useful. Development of the initial tasks can be undertaken early, perhaps immediately, and surely before there is certainty that the full project will be required. Later tasks can be undertaken when the state of the future (the emergent scenario) is clearer, or perhaps, is revealed with certainty. If the investment in the early tasks is limited, and if the investment in these tasks will result in a substantial reduction in time to complete the entire systems implementation process, then completing these early tasks can be viewed as creating strategic options. The cost of implementation of the early tasks can be viewed as paying an option premium; the benefits from rapid completion of systems development, such as early market share gains resulting from early deployment, can be considered the benefits from exercising an option that is in the money.

We can be more specific. Consider preparation for a future strategy, where the act of preparing requires two tasks, which require investments E_1 and E_2 respectively. Investment E_1 has duration of L_1 and investment E_2 has duration of L_2.

- The options premium, or the **cost of the option**, can be estimated by E_1, the cost associated with the investment needed to complete the first task.

- The **value of the option** will be more difficult to estimate in a meaningful fashion. It is determined by the value of the sequence of investments E_1 at t_1, E_2 at t_2, compared to the value of both investments made beginning at t_2. While this value cannot actually be determined, business simulation modeling can be most effective, when factors such as response time and adoption rate of customers, and the value of first mover advantages, can be incorporated. This will be explored in more detail in Sections 5 and 6.

Making first phase investment reduces firm's response time in case changes in environmental conditions make the overall investment necessary. The **reduction in time** will frequently be close to L_1, the time required to complete implementation of the first task and thus the duration of the first phase. (Assuming that both tasks would need be performed sequentially, the eventual completion of sequence $\{E_1, E_2\}$ when needed would be accelerated by L_1 if the first task were performed in advance, before it was required.) Thus, the value of advanced preparation can be determined by calculating the value of the difference between the optimal strategy $\beta(\theta, s^*)$ that would be pursued with the enabling investment E_1 completed in advance if the state of the world were revealed to be θ at time t_2 and the best alternative strategy s in θ that could pursued if E_1 had not been completed. This computation needs to be performed for all states of the world $\theta \in \Theta$, integrating over probability distributions for the state of the world π_θ and the time at which it is revealed.

5.   Model

We use the credit card industry to illustrate derivation of our model and its practical applications. Credit card companies' main revenue source is financial charges paid by customers who carry balance each month. The main costs of credit card companies include interest expense associated with the loans created by allowing customers to pay for their purchases after the issuer has paid the merchant, and charge-offs due to customers' defaulting on their debts. There exist substantial differences in profitability across customers. The best customers are those who carry large balances while the worst are those who pay balances in full each month or, worse yet, file for bankruptcy. In general, the best 20% customers of a credit card company generate more than 125% of the profits for the firm. We therefore use the following assumptions to model the difference across credit card users. Table 1 provides a summary of all variables used in these assumptions.

Assumption 1: Each individual customer carries a monthly balance of b_i, while the distribution of b_i in the population is $f(b)$.

Assumption 2: Each individual faces the possibility of bankruptcy or default at any time, which can be modeled as a Poisson process. The bankruptcy probability for individual i is λ_i (per quarter), while the distribution of λ over individuals in the population is $g(\lambda)$. Customer bankruptcy forms a major cost for credit card issuers. Appendix A calculates annual bankruptcy rate of the entire population C_y, quarterly bankruptcy rate of the entire population C_q, conditional quarterly bankruptcy rate of customers with bankruptcy history in the past year C_{q-} and conditional quarterly bankruptcy rate of customers without bankruptcy history in the past year C_{q+}.

Assumption 3: An individual's probability of bankruptcy is not correlated with the individual's outstanding card balance, and thus b_i and λ_i are independent. While this assumption is clearly not true for the population at large, Capital One argues convincingly that data did not contradict this assumption strongly during the initial attack period of their differential pricing strategy.

Assumption 4: There are a total number of N customers in the entire population.

Despite the differences across customers, credit card companies historically charged uniform financial charge across customers, because the companies do not know who are their most profitable customers.

Assumption 5: There are two identical incumbent banks (CB and OB) initially split the market by half. Both banks face capital cost r_f.

Assumption 6: Before implementing a differential pricing strategy, and in the absence of any information on which to base pricing decisions, both banks charge customers the same interest rate of r_s (per quarter).

5.1. An Attacker with Differential Pricing

Before Capital One transformed the industry through differential pricing, banks charged all their credit card customers the same interest rate for MasterCard and Visa balances, generally 19.8% annually. We now consider the possibility of an attacker with a differential pricing strategy, one that would enable it to identify high-balance revolvers, charge them lower rates, and attract them away from their current banks.[7]

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[7] *Revolvers* are credit card holders who use their cards, accrue large balances, and pay them off slowly over time, paying finance charges each month as long as they maintain outstanding balances. Revolvers are particularly attractive to monoline credit card issuers because they are their principal source of income. Issuers earn money when credit card users pay finance charges; they lose money when *transactors* use the cards but pay their balances off each month, enjoying free loans while paying no finance charges.

Assumption 7: Before implementing a differential pricing strategy, banks do not maintain information about individual customers. After the implementation, the bank knows each individual's b_i and bankruptcy history for the past year.

Assumption 8: The implementation of a differential pricing strategy by an incumbent bank has a defensive component aimed at reducing or eliminating loss of the most profitable customers to a new entrant attacker. For customers with a balance of more than k who have not filed for bankruptcy in the past year, the bank will offer an attractive rate of r_n. For customers with a bankruptcy filing in the past year, they are offered secured credit cards at a premium rate of r_p. For the rest of the customers, the rate will stay at r_s. The interest rate for high-balance customers is lower than the rate that was offered to all customers before differential pricing, which in turn is lower than the high-risk rate offered to customers who have had a recent bankruptcy filing.

Assumption 9: No all customers are aware of the best credit card offers. We use in-play ratio to represent percentage of customers that are actively comparing offers across credit card companies in a given quarter. The in-play ratio limits the speed with which customers will accept offers and switch banks, even when offers are as attractive as those being employed by the attackers here. Only I customers are considering switching in each quarter.

Assumption 10: The implementation of a differential pricing strategy — either by a new entrant bank or by one of the incumbent banks following an aggressive differential pricing strategy — calls for the bank to offer r_l as the balance transfer rate for a year to a new customer, followed by r_n for subsequent periods.[8] The balance transfer interest rate is lower than the rate for subsequent periods, which in turn is less than the rate that was

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[8] A balance transfer is a transfer of money a customer owes another creditor to a new credit card account.

offered to all customers before differential pricing. However, if a customer goes bankrupt after switching banks, the customer's rate will be raised to the high-risk rate of r_p. Balance transfer products are offered to solicited new customers with a balance of more than k. The bank only solicits customers from incumbents that have not implemented differential pricing strategy. Once an incumbent implements information systems for differentiation pricing, it acquires profitability information on individual customers. It can therefore use this information to selectively retain good customers and leave unprofitable customers to the attacker. In equilibrium, the attacker stops soliciting customers from the incumbent due to the information disadvantage.

Assumption 11: Differential pricing cannot be implemented immediately. It takes a bank L_1 periods to develop the infrastructure needed to implement a differential pricing strategy and E_1 is the cost of doing so. L_2 is the time taken to deploy this strategy once E_1 has been completed and E_2 is the cost of doing so. For simplicity, we assume that L_2 is almost instantaneous and cost E_2 almost zero. The option value of investing E_1 is the incremental value of being ready to deploy differential pricing if attacked, conditioned by the timing and likelihood of attack.

This is precisely the situation faced by Capital One in the mid-1990s. With the benefit of hindsight, Capital One's success can readily be explained: a bank's most profitable credit card customers are those who pay their card balances off slowly, and these are precisely the customers who would be attracted by lower annual interest rates and the resulting lower monthly finance charges. Unfortunately for competitors' management teams, the nature of their appropriate response is significantly less intuitive. Any actions that reduced the finance charges paid by the most attractive revolvers would greatly reduce profits unless accompanied by offsetting increases

in finance charges for other customers (prohibited by state usury laws in most cases) or by reductions in the number of unprofitable customers being carried by the bank.

 We consider the credit card industry at the time at which data mining and precision pricing was first introduced. The **Attacking Bank** (AB) launches its precision pricing strategy and begins to attract high balance revolvers. **Creative Bank** (one of two dominant players) has various strategic responses available to it. The **Other Bank** (OB) simply ignores changes in the industry and maintains the status-quo. We compare the strategies that CB may follow, and, in particular we compare them to the profits enjoyed by OB.

6. Analysis

6.1. Analysis of Alternative Strategies for Defenders — The *Status Quo* and the Value of Preserving It

A casual analysis suggests that neither incumbent bank would want to move to differential pricing; with all customers initially being charged the maximum allowed under usury laws, cutting prices for some customers would not be matched by offsetting increases for others, and thus should inevitably reduce the profits for the entire industry.

Case 1: Status Quo

In the base case or *status quo* scenario, before the entry of AB, CB and OB split the entire market with total outstanding credit card debt of $N\int_{0}^{\infty} bf(b)db$. Each bank earns revenue from financial charges r_s, and faces capital cost r_f and charge-offs due to customer bankruptcy C_q. The profit of each firm can be calculated as $\dfrac{N}{2}\left(\int_{0}^{\infty} bf(b)db\right)\left(r_s - r_f - C_q\right)$. We use $P^s{}_{X,j}$ to represent firm X's earning in quarter j if it uses strategy s. Therefore, we have

$$P^1_{CB,j} = P^1_{OB,j} = \frac{N}{2}\left(\int_0^\infty bf(b)db\right)\left(r_s - r_f - C_q\right)$$

$$P^1_{AB,j} = 0$$

Assuming 200,000 customers in a market with monthly credit card balances uniformly distributed between $0 and $3000, quarterly bankruptcy rates uniformly distributed between 0% and 2%, quarterly financial charge of 4% and capital cost of 1%, status quo brings 5-year earning streams with NPV of $16.943 million.

Case 2: CB Initiates Preemptive Pricing Strategy

Consider what happens if CB engages in data mining and differential pricing, changing its pricing strategy for its existing customer base but not offering a balance transfer product to attract new customers away from OB. We assume that since they receive no immediate reward for doing so, customers do not transfer from OB to CB. OB's profit therefore remains the same as in Case 1. CB, however, categorizes customers into three groups and charges them different rates: 1) customers that went bankrupt in the past year are offered secured credit cards with premium rate r_p and collateral requirement for their credit card debts. There are $\dfrac{NC_y}{2}$ customers in this category with average balance of $\int_0^\infty bf(b)db$, producing a profit of

$\dfrac{NC_y}{2}\left(\int_0^\infty bf(b)db\right)(r_p - r_f);$[9] 2) customers with monthly balance over k are offered a preferential

rate of r_n. $N\left(\dfrac{1-C_y}{2}\right)\left(\int_k^\infty f(b)db\right)$ customers are in this category with average balance B_{k+} and

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[9] There is no charge-offs because the credit card debts are secured by customers' collaterals.

bankruptcy rate C_{q-}. They bring a profit of $N\left(\dfrac{1-C_y}{2}\right)\left(\displaystyle\int_k^\infty f(b)db\right)B_{k+}\left(r_n - C_{q-} - r_f\right)$ to CB. 3)

The remaining customers do not see any changes in their credit card term. The $N\left(\dfrac{1-C_y}{2}\right)\displaystyle\int_0^k f(b)$ customers in this category carry an average balance B_{k-} and have an average bankruptcy rate C_{q-}. Total profit from this group of customers is $N\left(\dfrac{1-C_y}{2}\right)\left(\displaystyle\int_0^k f(b)db\right)B_{k-}\left(r_s - C_{q-} - r_f\right)$.

Therefore, we have

$$P^2{}_{CB,j} = \frac{NC_y}{2}\left(\int_0^\infty bf(b)db\right)\left(r_p - r_f\right) + N\left(\frac{1-C_y}{2}\right)\left\{\begin{array}{l}\left(\displaystyle\int_k^\infty f(b)db\right)B_{k+}\left(r_n - C_{q-} - r_f\right)+\\[2mm] \left(\displaystyle\int_0^k f(b)db\right)B_{k-}\left(r_s - C_{q-} - r_f\right)\end{array}\right\}$$

$$P^2{}_{OB,j} = \frac{N}{2}\left(\int_0^\infty bf(b)db\right)\left(r_s - r_f - C_q\right)$$

$$P^2{}_{AB,j} = 0$$

Using the same example as in Case 1, we calculate that NPV of CB's 5-year earning stream becomes reduced to $15.24 million while OB remains at $ 16.94 million. Continuation of the *status quo* strategy of Case 1 is therefore preferable, and this strategy offers no reason for either bank to disturb the *status quo*.

Case 3: CB Initiates Aggressive Pricing Strategy

We now consider CB's introducing defensive differential pricing to protect its own best accounts along with an aggressive balance transfer product to attract the best customers from OB, just the strategy that AB would have pursued if left an opening in the market. However, any attack on OB's customers base by a major incumbent competitor, following a strategy that looked like the initiation of a price war, would have received an immediate response. As both firms are

implementing aggressive pricing strategy, they once again split the market. Each firm adopts

exactly the same strategy as CB does in Case 2, except that for the $N\left(\dfrac{1-C_y}{2}\right)\left(\displaystyle\int_k^\infty f(b)db\right)$

customers with balance over k, they are offered a one-year promotional rate r_l for balance

transfer followed by a preference rate r_n. Each firm therefore has two types of customers with

balance over k: those who are still in promotion period and those who are not. To calculate

number of customers that need to be charged at the promotion rate r_l, firms need to know number

of customers switched during the last four quarters. This number can be calculated as the

difference between cumulative number of switched customers by the end of current quarter and

that of a year ago. Given in-play ratio of I, we therefore have $\left[(1-I)^{\max(0,j-4)} - (1-I)^j\right]$

customers (in percentage) receive the promotional rate r_l in the current quarter, while the rest are

charged at the preferential rate r_n. Profit from customers with balance over k is therefore

$$\left[(1-I)^{\max(0,j-4)} - (1-I)^j\right]\left(\int_k^\infty f(b)db\right)B_{k+}\left(r_l - C_{q-} - r_f\right)+$$
$$\left[1 - (1-I)^{\max(0,j-4)} + (1-I)^j\right]\left(\int_k^\infty f(b)db\right)B_{k+}\left(r_n - C_{q-} - r_f\right).$$

In total, the profits of three firms are:

$$P^3{}_{CB,j} = \frac{NC_y}{2}\left(\int_0^\infty bf(b)db\right)\left(r_p - r_f\right)+$$

$$N\left(\frac{1-C_y}{2}\right)\left\{\begin{array}{l}\left[(1-I)^{\max(0,j-4)} - (1-I)^j\right]\left(\int_k^\infty f(b)db\right)B_{k+}\left(r_l - C_{q-} - r_f\right)+\\[2mm] \left[1 - (1-I)^{\max(0,j-4)} + (1-I)^j\right]\left(\int_k^\infty f(b)db\right)B_{k+}\left(r_n - C_{q-} - r_f\right)+\\[2mm] \left(\int_0^k f(b)db\right)B_{k-}\left(r_s - C_{q-} - r_f\right)\end{array}\right\}$$

$$P^3{}_{OB,j} = \frac{NC_y}{2}\left(\int_0^\infty bf(b)db\right)(r_p - r_f) +$$

$$N\left(\frac{1-C_y}{2}\right)\begin{bmatrix}\left[(1-I)^{\max(0,j-4)} - (1-I)^j\right]\left(\int_k^\infty f(b)db\right)B_{k+}(r_l - C_{q-} - r_f) + \\ \left[1 - (1-I)^{\max(0,j-4)} + (1-I)^j\right]\left(\int_k^\infty f(b)db\right)B_{k+}(r_n - C_{q-} - r_f) + \\ \left(\int_0^k f(b)db\right)B_{k-}(r_s - C_{q-} - r_f)\end{bmatrix}$$

$$P^3{}_{AB,j} = 0$$

Not surprisingly, both banks earned more under the *status quo* scenario than they do when either attempts to introduce the strategy pursued by AB.

6.2. Inevitability of Attack and the Need for Careful Response

Case 4: CB and OB Do Nothing in Response to Attack

This comfortable oligopoly enjoyed by CB and OB could not continue. Figure 1 shows what happens when AB enters the industry with a strategy based upon data mining and differential pricing, effectively targeting the most attractive customers in the credit card portfolios of its competitors; neither CB nor OB is prepared to respond immediately. The competitive situation of both CB and OB deteriorates after AB's entry and the results are unacceptable for both defending banks. Figure 1 was done under conditions favorable to defenders, with customers exhibiting only slow response to the attacker's offers; even under conservative assumptions, failure to respond to AB's attack is unacceptable for CB.

-- Figure 1 --

With the entry of AB, both CB and OB start to lose customers. But there are two types of customers staying with the incumbent firms. The first type is customers who have not consider

switching. In quarter j, $(1-I)^j$ of CB and OB's customers (in percentage) are in this category.

These customers are charged with standard rate r_s, and have average quarterly bankruptcy rate of

C_q and average monthly balance of $\int_0^\infty bf(b)db$. They generate a profit of

$$(1-I)^j \frac{N}{2}\left(\int_0^\infty bf(b)db\right)\left(r_s - C_q - r_f\right)$$ for CB and OB respectively. The second type is customers

who have considered switching credit card issuers, but are not eligible for balance transfer offers.

In Quarter j, $1-(1-I)^j$ of incumbents' customers (in percentage) have considered switching and

$\int_0^k f(b)db$ of them (in percentage) are not eligible for balance transfer. This group of customers is

charged with standard rate r_s, and has average quarterly bankruptcy rate of C_q and average

monthly balance of B_{k-}. CB and OB's profits on this group are therefore

$$\left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)\left(r_s - C_q - r_f\right).$$ Profits of AB can be calculated likewise. We

therefore have

$$P^4{}_{CB,j} = (1-I)^j\frac{N}{2}\left(\int_0^\infty bf(b)db\right)\left(r_s - C_q - r_f\right)+\left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)\left(r_s - C_q - r_f\right)$$

$$P^4{}_{OB,j} = (1-I)^j\frac{N}{2}\left(\int_0^\infty bf(b)db\right)\left(r_s - C_q - r_f\right)+\left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)\left(r_s - C_q - r_f\right)$$

$$P^4{}_{AB,j} = N\left[(1-I)^{max(0,j-4)} - (1-I)^j\right]B_{k+}\left(\int_k^\infty f(b)db\right)\left(r_l - C_q - r_f\right)+$$

$$N\left[1-(1-I)^{max(0,j-4)}\right]B_{k+}\left(\int_k^\infty f(b)db\right)\left(r_n - C_q - r_f\right)$$

6.3. Analysis of Alternative Strategies for Defenders — The Range of Alternatives and Conditions Determining Success

CB does have a range of strategies available to it:

- **DP** — (Differential Pricing only) Roll out data mining and differential pricing as quickly as possible (8 quarters), but do nothing in the short term to protect market share until data mining is available;

- **CPDP** — (Cut Prices immediately while preparing for Differential Pricing) Cut prices for all accounts now to halt erosion of market share, while once again implementing data mining as quickly as possible, within 8 quarters; and

- **MODP** — (Match Offers while preparing for Differential Pricing) Do not cut prices for any customers initially, but match the offers customers have received, for any customers who call to transfer their balances to AB, while once again implementing data mining as quickly as possible.

A number of factors influence the attractiveness of each of these strategies. Principal among them are the following two:

- The **in-play ratio I**, that is, the rate at which customers consider switching their balances among banks simply because they have been offered a better rate. As we discussed in Assumption 7, not all customers will considering switching credit card issuers at all time. For a given quarter, we assume only I (in percentage) customers will switch to a new credit card issuers if they are offered better rates.

- The **retention-effectiveness ratio R**, that is, the percentage of customers who cancel their planned balance transfers from CB to AB when CB matches the offers that they have received.

    Assumption 12: Retention-effectiveness is limited. When a bank matches the interest rate that a competitor offered one of its high-balance customers as an incentive to

motivate a balance transfer, the matching counter-offer will be effective only R (in percentage) of the time. Retention-effectiveness is assumed to be the same across all players.

6.4. Analysis of Alternative Strategies for Defenders — Examination of Specific Scenarios

We will initially consider only strategies for defenders that are not based on their developing the infrastructure or performing the advanced training or other forms of preparation that are required to launch differential pricing. We make this assumption since both incumbents were able to determine that their own deployment of differential pricing and their competitor's inevitable response to it would damage both of them; thus, an investment in preparing for differential pricing would have negative value.

We consider profitability of the three strategies mentioned in the previous section.

Case 5: CB Does Nothing Until Ready to Replicate Strategy

Given that CB does nothing until ready and the initial investment E_1 takes L_1 quarters to implement, its profits in the first L_1 quarters will be exactly the same as in Case 4:

If $j < L_1$,

$$P^4{}_{CB,j} = (1-I)^j \frac{N}{2}\left(\int_0^\infty bf(b)db\right)(r_s - C_q - r_f) + \left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)(r_s - C_q - r_f)$$

$$P^4{}_{OB,j} = (1-I)^j \frac{N}{2}\left(\int_0^\infty bf(b)db\right)(r_s - C_q - r_f) + \left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)(r_s - C_q - r_f)$$

$$P^4{}_{AB,j} = \left[(1-I)^{\max(0,j-4)} - (1-I)^j\right]B_{k+}N\left(\int_k^\infty f(b)db\right)(r_l - C_q - r_f) +$$

$$\left[1-(1-I)^{\max(0,j-4)}\right]B_{k+}N\left(\int_k^\infty f(b)db\right)(r_n - C_q - r_f)$$

After L_1, CB joins AB in attracting customers from OB. Comparing it with the situation before L_1, when AB gets customers from both CB and OB, it becomes obvious that AB's incremental increase in its customer base after L_1 is equivalent to one-fourth of what AB would have received without CB's involvement, i.e.

$$\left[(1-I)^{\max(L_1,j-4)} - (1-I)^j\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{4}(r_l - C_q - r_f)+$$
$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{4}(r_n - C_q - r_f)$$

. CB receives the same incremental increase as AB does. The outflow of customers from OB remains unchanged. We therefore have,

If $j \geq L_1$,

$$P^4{}_{CB,j} = (1-I)^{L_1} \frac{NC_y}{2}\left(\int_0^\infty bf(b)db\right)(r_p - r_f) + (1-I)^{L_1} N\left(\frac{1-C_y}{2}\right)\left\{\begin{array}{l}\left(\int_k^\infty f(b)db\right)B_{k+}(r_n - C_{q-} - r_f)+\\ \left(\int_0^k f(b)db\right)B_{k-}(r_s - C_{q-} - r_f)\end{array}\right\}+$$

$$\left[1-(1-I)^{L_1}\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)(r_s - C_q - r_f)+$$

$$\left[(1-I)^{\max(L_1,j-4)} - (1-I)^j\right]B_{k+} \frac{N\int_k^\infty f(b)db}{4}(r_l - C_q - r_f)+$$

$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+} \frac{N\int_k^\infty f(b)db}{4}(r_n - C_q - r_f)$$

$$P^4{}_{OB,j} = (1-I)^j \frac{N}{2}\left(\int_0^\infty bf(b)db\right)(r_s - C_q - r_f) + \left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)(r_s - C_q - r_f)$$

$$P^4{}_{AB,j} = \left[(1-I)^{\min(L_1,\max(0,j-4))} - (1-I)^{L_1}\right]B_{k+}N\int_k^\infty f(b)db\left(r_l - C_q - r_f\right)+$$

$$\left[1-(1-I)^{\min(L_1,\max(0,j-4))}\right]B_{k+}N\int_k^\infty f(b)db\left(r_n - C_q - r_f\right)+$$

$$\left[(1-I)^{\max(L_1,j-4)} - (1-I)^j\right]B_{k+}\frac{N\int_k^\infty f(b)db}{4}\left(r_l - C_q - r_f\right)+$$

$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+}\frac{N\int_k^\infty f(b)db}{4}\left(r_n - C_q - r_f\right)$$

Case 6: CB Drops Rates for All Existing Customers Until Ready to Replicate Strategy.

In this case, CB drops all customers' rates to AB's promotional rate during L_1. This strategy helps CB keep all its customers until it implements data mining technology and gets more information about individual customers. During L_1, the $\dfrac{N}{2}$ customers of CB will be charged with promotional rate r_l. It indicates a profit of $\dfrac{N}{2}\left(\int_0^\infty bf(b)db\right)\left(r_l - r_f - C_q\right)$ for CB. During the same period, AB gets all its customers from OB, which is half of what AB gets in Case 4, i.e.

$$\left[(1-I)^{\max(L_1,j-4)} - (1-I)^j\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{2}\left(r_l - C_q - r_f\right)+$$

; and OB's customer outflow remains

$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{2}\left(r_n - C_q - r_f\right)$$

unchanged. We therefore have

If $j < L_1$,

$$P^6{}_{CB,j} = \frac{N}{2}\left(\int_0^\infty bf(b)db\right)\left(r_l - r_f - C_q\right)$$

$$P^6{}_{OB,j} = (1-I)^j \frac{N}{2}\left(\int_0^\infty bf(b)db\right)\left(r_s - C_q - r_f\right) + \left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)\left(r_s - C_q - r_f\right)$$

$$P^6{}_{AB,j} = \left[(1-I)^{\max(0,j-4)} - (1-I)^j\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{2}\left(r_l - C_q - r_f\right) +$$

$$\left[1-(1-I)^{\max(0,j-4)}\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{2}\left(r_n - C_q - r_f\right)$$

After L_1, CB implements differential pricing strategy to its own customers and joins AB in attracting customers from OB. As calculated in Case 2, CB gets a profit of

$$\frac{NC_y}{2}\left(\int_0^\infty bf(b)db\right)\left(r_p - r_f\right) + N\left(\frac{1-C_y}{2}\right)\left\{ \begin{array}{l} \left(\int_k^\infty f(b)db\right)B_{k+}\left(r_n - C_{q-} - r_f\right)+ \\ \left(\int_0^k f(b)db\right)B_{k-}\left(r_s - C_{q-} - r_f\right) \end{array} \right\}$$ from its original customer

base. In addition, it also attracts half of switching customers from OB. Case 5 has calculated that these new customers contribute a profit of

$$\left[(1-I)^{\max(L_1,j-4)} - (1-I)^j\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{4}\left(r_l - C_q - r_f\right)+$$

$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{4}\left(r_n - C_q - r_f\right)$$

to CB. Like CB, AB also gets half of

switching customers from OB after L_1, receiving a profit of

$$\left[(1-I)^{\max(L_1,j-4)}-(1-I)^j\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{4}(r_l-C_q-r_f)+$$

. The outflow of customers from OB

$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{4}(r_n-C_q-r_f)$$

remains unchanged. We therefore have,

If $j\geq L_1$,

$$P^6{}_{CB,j}=\frac{NC_y}{2}\left(\int_0^\infty bf(b)db\right)(r_p-r_f)+N\left(\frac{1-C_y}{2}\right)\left\{\begin{array}{l}\left(\int_k^\infty f(b)db\right)B_{k+}(r_n-C_{q-}-r_f)+\\\left(\int_0^k f(b)db\right)B_{k-}(r_s-C_{q-}-r_f)\end{array}\right\}+$$

$$\left[(1-I)^{\max(L_1,j-4)}-(1-I)^j\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{4}(r_l-C_q-r_f)+$$

$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{4}(r_n-C_q-r_f)$$

$$P^6{}_{OB,j}=(1-I)^j\frac{N}{2}\left(\int_0^\infty bf(b)db\right)(r_s-C_q-r_f)+\left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)(r_s-C_q-r_f)$$

$$P^6{}_{AB,j}=\left[(1-I)^{\min(L_1,\max(0,j-4))}-(1-I)^{L_1}\right]B_{k+}\frac{N\int_k^\infty f(b)db}{2}(r_l-C_q-r_f)+$$

$$\left[1-(1-I)^{\min(L_1,\max(0,j-4))}\right]B_{k+}\frac{N\int_k^\infty f(b)db}{2}(r_n-C_q-r_f)+$$

$$\left[(1-I)^{\max(L_1,j-4)}-(1-I)^j\right]B_{k+}\frac{N\int_k^\infty f(b)db}{4}(r_l-C_q-r_f)+$$

$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+}\frac{N\int_k^\infty f(b)db}{4}(r_n-C_q-r_f)$$

Case 7: CB Matches Offers for Customers Attempting to Defect Until Ready to Replicate

Rather than dropping rates for all customers, CB can choose to match rates if a customer receives a better offer from a rival firm. This strategy does not affect rates charged to two types of customers discussed in Case 4. The profit from customers who have not considered switching remains at $(1-I)^j \frac{N}{2} \left(\int_0^\infty bf(b)db \right) (r_s - C_q - r_f)$. Likewise, the profit from customers who have considered switching credit card issuers, but are not eligible for balance transfer offers, stays at $\left[1 - (1-I)^j \right] \frac{N}{2} B_{k-} \left(\int_0^k f(b)db \right) (r_s - C_q - r_f)$. However, the strategy does affect rates charged to those customers who have monthly balancer over k and who are aware of offers from other firms. For these $\frac{N}{2} \left(\int_k^\infty f(b)db \right)$ customers, they are offered by CB a promotional rate r_l for the first year and a preferential rate r_n for the remaining years if they receives offer from AB. R customers (in percentage) choose to stay with the incumbent bank, while the remaining (1-R) choose to take AB's offer. These customers bring a profit of

$$R \left[(1-I)^{\max(0, j-4)} - (1-I)^j \right] B_{k+} \frac{N \left(\int_k^\infty f(b)db \right)}{2} (r_l - C_q - r_f) + \quad \text{to CB.}$$

$$R \left[1 - (1-I)^{\max(0, j-4)} \right] B_{k+} \frac{N \left(\int_k^\infty f(b)db \right)}{2} (r_n - C_q - r_f)$$

AB, on the other hand, gets all switching customers from OB, in addition to the (1-R) switching customers from CB, resulting in a profit of

$$
(2-R)\left[(1-I)^{\max(0,j-4)}-(1-I)^j\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{2}(r_l-C_q-r_f)+
$$

$$
(2-R)\left[1-(1-I)^{\max(0,j-4)}\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{2}(r_n-C_q-r_f)
$$

We therefore have

If $j < L_1$,

$$
P^7{}_{CB,j} = (1-I)^j\frac{N}{2}\left(\int_0^\infty bf(b)db\right)(r_s-C_q-r_f)+\left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)(r_s-C_q-r_f)+
$$

$$
R\left[(1-I)^{\max(0,j-4)}-(1-I)^j\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{2}(r_l-C_q-r_f)+
$$

$$
R\left[1-(1-I)^{\max(0,j-4)}\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{2}(r_n-C_q-r_f)
$$

$$
P^7{}_{OB,j} = (1-I)^j\frac{N}{2}\left(\int_0^\infty bf(b)db\right)(r_s-C_q-r_f)+\left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)(r_s-C_q-r_f)
$$

$$
P^7{}_{AB,j} = (2-R)\left[(1-I)^{\max(0,j-4)}-(1-I)^j\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{2}(r_l-C_q-r_f)+
$$

$$
(2-R)\left[1-(1-I)^{\max(0,j-4)}\right]B_{k+}\frac{N\left(\int_k^\infty f(b)db\right)}{2}(r_n-C_q-r_f)
$$

After L_1, CB splits with AB of switching customers from OB. As we have seen in previous cases, this group of customers generates a profit

$$\left[(1-I)^{\max(L_1,j-4)} - (1-I)^j\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{4}\left(r_l - C_q - r_f\right) +$$

to CB and AB respectively. We

$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{4}\left(r_n - C_q - r_f\right)$$

therefore have

If $j \geq L_1$,

$$P^7{}_{CB,j} = (1-I)^L \left\{ \frac{NC_y}{2}\left(\int_0^\infty bf(b)db\right)\left(r_p - r_f\right) + N\left(\frac{1-C_y}{2}\right)\left[\begin{array}{l}\left(\int_k^\infty f(b)db\right)B_{k+}\left(r_n - C_{q-} - r_f\right) + \\ \left(\int_0^k f(b)db\right)B_{k-}\left(r_s - C_{q-} - r_f\right)\end{array}\right]\right\}$$

$$\left[1-(1-I)^L\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)\left(r_s - C_q - r_f\right) +$$

$$R\left[(1-I)^{\min(L_1,\max(0,j-4))} - (1-I)^L\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{2}\left(r_l - C_q - r_f\right) +$$

$$R\left[1-(1-I)^{\min(L_1,\max(0,j-4))}\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{2}\left(r_n - C_q - r_f\right) +$$

$$\left[(1-I)^{\max(L_1,j-4)} - (1-I)^j\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{4}\left(r_l - C_q - r_f\right) +$$

$$\left[1-(1-I)^{\max(L_1,j-4)}\right]B_{k+} \frac{N\left(\int_k^\infty f(b)db\right)}{4}\left(r_n - C_q - r_f\right)$$

$$P^7{}_{OB,j} = (1-I)^j \frac{N}{2}\left(\int_0^\infty bf(b)db\right)\left(r_s - C_q - r_f\right) + \left[1-(1-I)^j\right]\frac{N}{2}B_{k-}\left(\int_0^k f(b)db\right)\left(r_s - C_q - r_f\right)$$

$$P^7{}_{AB,j} = (2-R)\left[(1-I)^{\min(L_1,\max(0,j-4))} - (1-I)^L\right]B_{k+} \frac{N\left(\int\limits_k^\infty f(b)db\right)}{2}(r_l - C_q - r_f) +$$

$$(2-R)\left[1 - (1-I)^{\min(L_1,\max(0,j-4))}\right]B_{k+} \frac{N\left(\int\limits_k^\infty f(b)db\right)}{2}(r_n - C_q - r_f) +$$

$$\left[(1-I)^{\max(L_1,j-4)} - (1-I)^j\right]B_{k+} \frac{N\left(\int\limits_k^\infty f(b)db\right)}{4}(r_l - C_q - r_f) +$$

$$\left[1 - (1-I)^{\max(L_1,j-4)}\right]B_{k+} \frac{N\left(\int\limits_k^\infty f(b)db\right)}{4}(r_n - C_q - r_f)$$

Assigning specific values for the model parameters described in Case 1 allows us to calculate the implications for CB of each of the three strategies that could be used in response to attack from AB. Assuming initially that in-play ratio I is a relatively high 50%, retention effectiveness R is only 25% and L_1 is 8 quarters, Figures 2-4 illustrate the results of deploying each of these three strategies for these specific values. Clearly, for these parameter values CB's best strategy would be CPDP; that is, it should cut prices for all its existing customers immediately, to avoid losing its most profitable accounts to AB, and it should then implement informed differential pricing when it is able to do so, after 8 quarters.

--- Figure 2 ---

--- Figure 3 ---

--- Figure 4 ---

The selection of CB's best strategy depends upon the values assumed for in-play ratio I and retention ratio R. Reducing I to 25% and increasing R to 75% changes the value of CB's earnings. Under DP, CB begins to prepare to match AB's strategy, but does nothing until its

infrastructure is available. Over the long term CB does better with this strategy than OB, but it does reduce CB's profits and the NPV of 5-year earnings are $14.43 million for CB and $11.77 million for OB. AB earns $4.22 million. Alternatively, CB can employ CPDP in response to AB's attack, immediately dropping its prices for all customers to avoid any loss of its good accounts to AB. With low in-play ratio and high retention ratio, this is unnecessarily costly, and reduces NPV of 5-year earnings to $14.00 million, below those available to CB with strategy DP. OB continues to earn $11.77 and AB earns $2.53 million. Finally, CB can employ MODP, matching the offers that its best customers receive from AB.   With NPV of 5-year earnings of $15.70 million this strategy is more profitable than DP or CPDP, and is better than the strategy followed by OB, which continues to earn $11.77 million. AB earns $1.95 million. Under low in-play ratio and high retention ratio, MODP is the preferred strategy. With slow loss of accounts, there is limited pressure for CB to act immediately. Moreover, with a high probability that matching offers will be effective, CB should cut prices only for those customers who begin to initiate the process to transfer their card balances to AB.

6.5. Investing in Strategic Flexibility: Calculating the Value of Advance Preparation for Differential Pricing

Case 8: CB implements differential pricing immediately after attack

Ignoring attack would be unacceptable for CB, while premature deployment of differential pricing dramatically reduces CB's profitability. There is another strategy, investing in preparation for data mining, and deploying it rapidly if and when a new entrant attacks. In this case, CB splits with AB of all switching customers from day 1. That is, both firms receive a

profit of
$$\left[(1-I)^{\max(0,j-4)}-(1-I)^{j}\right]B_{k+}\frac{N\left(\int_{k}^{\infty}f(b)db\right)}{4}\left(r_{l}-C_{q}-r_{f}\right)+$$
. In addition, CB also applies

$$\left[1-(1-I)^{\max(0,j-4)}\right]B_{k+}\frac{N\left(\int_{k}^{\infty}f(b)db\right)}{4}\left(r_{n}-C_{q}-r_{f}\right)$$

differential pricing to its current customers, generating a profit of

$$\frac{NC_{y}}{2}\left(\int_{0}^{\infty}bf(b)db\right)\left(r_{p}-r_{f}\right)+N\left(\frac{1-C_{y}}{2}\right)\left\{\begin{array}{l}\left(\int_{k}^{\infty}f(b)db\right)B_{k+}\left(r_{n}-C_{q-}-r_{f}\right)+\\\left(\int_{0}^{k}f(b)db\right)B_{k-}\left(r_{s}-C_{q-}-r_{f}\right)\end{array}\right\}.$$ We therefore have

$$P^{8}{}_{CB,j}=\frac{NC_{y}}{2}\left(\int_{0}^{\infty}bf(b)db\right)\left(r_{p}-r_{f}\right)+N\left(\frac{1-C_{y}}{2}\right)\left\{\begin{array}{l}\left(\int_{k}^{\infty}f(b)db\right)B_{k+}\left(r_{n}-C_{q-}-r_{f}\right)+\\\left(\int_{0}^{k}f(b)db\right)B_{k-}\left(r_{s}-C_{q-}-r_{f}\right)\end{array}\right\}+$$

$$\left[(1-I)^{\max(0,j-4)}-(1-I)^{j}\right]B_{k+}\frac{N\left(\int_{k}^{\infty}f(b)db\right)}{4}\left(r_{l}-C_{q}-r_{f}\right)+$$

$$\left[1-(1-I)^{\max(0,j-4)}\right]B_{k+}\frac{N\left(\int_{k}^{\infty}f(b)db\right)}{4}\left(r_{n}-C_{q}-r_{f}\right)$$

$$P^{8}{}_{OB,j}=(1-I)^{j}\frac{N}{2}\left(\int_{0}^{\infty}bf(b)db\right)\left(r_{s}-C_{q}-r_{f}\right)+\left[1-(1-I)^{j}\right]\frac{N}{2}B_{k-}\left(\int_{0}^{k}f(b)db\right)\left(r_{s}-C_{q}-r_{f}\right)$$

$$P^{8}{}_{AB,j}=\left[(1-I)^{\max(0,j-4)}-(1-I)^{j}\right]B_{k+}\frac{N\left(\int_{k}^{\infty}f(b)db\right)}{4}\left(r_{l}-C_{q}-r_{f}\right)+$$

$$\left[1-(1-I)^{\max(0,j-4)}\right]B_{k+}\frac{N\left(\int_{k}^{\infty}f(b)db\right)}{4}\left(r_{n}-C_{q}-r_{f}\right)$$

The value of this strategy-enabling partial investment can only be determined by examining the situation that would have obtained had the investment not been made. Let us do a specific calculation before presenting the general framework, and let us assume that as in Figures 2-4 the in-play ratio is 50% and retention ratio is 25%. The best alternative available to CB if it were to be attacked without advance preparation was shown to be the deployment of CPDP. Let us examine one more strategy, CB's early investment in preparation for data mining (PDP), to enable rapid deployment of differential pricing **if and when** CB is attacked. This strategy is shown in Figure 5; clearly, this is vastly preferable to the three alternatives shown in Figures 2-4.

-- Figure 5 --

With NPV of 5-year earnings of $16.63 million and acceptable short term profitability this is clearly the best strategic choice, better than those shown in Figures 2-4, and better than the corresponding figure of $10.94 million earned by OB. The incremental value of the investment in preparation is $4.25 million — the difference between the value of this strategy and the value of the best alternative, which was shown in Figure 2.

Comparison of NPV(PDP) to the alternatives under each combination of parameter values allows us to calculate the value of advance preparation, assuming these parameter values and assuming that an attack does materialize.

However, we do not know in-play ratio or retention ratio, and we cannot be sure if or when an attack will materialize. The timing of attack is determined by AB, a hostile opponent. The values of in-play ratio and retention ratio will only be known at the time of attack, and will be determined in part by environmental conditions and in part by strategic business decisions made by AB. Consequently, calculating the value of advance preparation as a strategic option requires

developing and using probability distributions for in-play ratio I, retention ratio R, and the time at which attack occurs.

Assuming that I and R were known, the value of advance preparation as a function of probability of attack at time t could be computed from the following:

---

(1) Value (Advance Preparation) =

$$\int_{t_o}^{t_n} p(t)\{NPV(PDP,t) - \max[NPV(DP,t), NPV(CPDP,t), NPV(MODP,t)]\}dt$$

Here, p(t) represents the probability of new entrant AB's attack at time t, and NPV(s, t) represents the NPV, at the present time, of strategy s, if attack occurs at time t. The integral is over time, from the lower to the upper bounds of the time period under consideration. $s \in \Sigma =$ {DP, CPDP, MODP}

Of course the values of NPV(DP,t), NPV(CPDP,t), and NPV(MODP,t) depend upon the values of I and R. Hence, the complete functional form becomes:

---

(2) Value (Advance Preparation) =

$$\int_{t_o}^{t_n} \int_{I_l}^{I_u} \int_{R_l}^{R_u} p(t)p(I)p(R)\left\{ NPV(PDP,t) - \max\begin{bmatrix} NPV(DP,t,I,R), \\ NPV(CPDP,t,I,R), \\ MONPV(DP,t,I,R) \end{bmatrix} \right\} dR\,dI\,dt$$

Here, p(I) and p(R) represent the probability distributions assumed for these variables, which must be integrated over the bounds of their distribution. The functional forms of NPV(*s,t,I,R*) have been extended to incorporate the dependence of the value of each strategy s upon the environmental context in which it is deployed, for s in {DP, CPDP, MODP}.

For example, let us assume the following:

- The probability of attack is 90%, with a distribution that places greater weight on early entry

- In-play ratio has a discrete distribution that places 25% probabilities on the values of 25% and 75% and the remaining 50% probability on 50%.

- Retention ratio has a discrete distribution that places 25% probabilities on the values of 25% and 75% and the remaining 50% probability on 50%.

This enables us to calculate an expected value $1.88 million for the strategic option created by advance preparation. (These calculations are described in Appendix C.) Comparing the value of this strategic option to the cost of advance preparation allows us to determine if the investment is worth making.

7.   Conclusions

This paper makes a modest contribution to our ability to evaluate strategic options in information technology infrastructure. It shows how a systematic determination of sources of strategic uncertainty can lead to a general framework for valuation, which can be solved numerically even if it is not amenable to closed form analysis. While this may not appear much like more formalistic approaches to options valuation, which are able to draw on a history of variance in

the valuation of some traded instrument, it is entirely faithful to the spirit of options valuation, and indeed to the mathematics that underlies the more formal approaches.

No simple, general, closed-form solution exists for the class of strategic options that we are exploring here. Our technique is as general as we have been able to derive and, perhaps, as general as any likely to be developed. Whether our technique is labeled sequential decision analysis for the value of strategy-enabling partial investments, or analysis of IT investments as strategic options, is of little importance. This technique makes a modest contribution to allowing the decision maker to structure what he or she does know about the impact of an expected strategy, even in the complete absence of historical data on the value of the payoff from the investment. Consequently, this technique makes a modest contribution towards allowing decision makers to employ strategic options theory as a technique to evaluate a wider class of investments intended to support future strategy.

Our future plans for this work entail multiple lines of research:

- Working with corporate IS managers to determine the extent to which the concept of strategy enabling partial investments is useful to them in their planning. Preliminary discussions suggest that this work is indeed helpful. For example, it was pointed out to us that much of the functionality of an information system innovation can be provided for much less than the total expected development cost. If this initial investment is made soon enough, it provides some functionality as soon as users need it, and the rest of the functionality can be provided later if demand justifies it.

- Working with corporate strategic planning officers to explore the extent to which scenario analysis can actually delimit the range of contexts in which an application may be deployed and the accuracy with which simulation can predict the value of specific initial investments

under varying scenarios. Again, preliminary experience with the several dozen times we have used scenario analysis suggests that it can be very effective in describing the full range of future environments. Decades of professional experience of numerous OR professionals supports the idea that if we understand a phenomenon we can model it, at least in terms of the underlying parameters that determine valuation. Of greater concern is the skepticism with which simulation modeling has been greeted any time it contradicted a decision maker's prior plans, unsupported intuitions, or agenda.

- Working to develop a broader range of case-based examples and experience with this combination of scenarios and simulations to produce an understanding of strategy enabling partial investments and real options.

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Appendix A

A.1.　Bankruptcy Rate

Lemma 1: (bankruptcy rate of the general population)

Individual i, with bankruptcy arrival-rate λ_i , has the probability of avoiding bankruptcy in a

given quarter of $e^{-\lambda i}$. Integrating across the general population, the expected rate of customer

bankruptcy in any given quarter is $C_q = 1 - \int_0^\infty e^{-\lambda} g(\lambda) d\lambda$. The annual bankruptcy rate can be

similarly calculated as $C_y = 1 - \int_0^\infty e^{-4\lambda} g(\lambda) d\lambda$

Lemma 2: (bankruptcy rate of customers with and without bankruptcy history in the past year)

We first calculate the conditional distribution of λ for customers who have avoided bankruptcy

in the past year $P_-(\lambda) = \dfrac{\int_0^\lambda e^{-4x} g(x) dx}{\int_0^\infty e^{-4x} g(x) dx}$.　Let its density function be $p_-(\lambda)$.　The conditional

quarterly bankruptcy rate of customers without bankruptcy in the past year is

therefore $C_{q-} = 1 - \int_0^\infty e^{-\lambda} p_-(\lambda) d\lambda$.

Likewise, we calculate the conditional distribution of λ for customers who have filed bankruptcy

in the past year $P_+(\lambda) = \dfrac{1 - \int_0^\lambda e^{-4x} g(x) dx}{1 - \int_0^\infty e^{-4x} g(x) dx}$.　Let its density function be $p_+(\lambda)$.　The conditional of

quarterly bankruptcy rate for customer with bankruptcy in the past year is therefore

$$C_{q+} = 1 - \int_0^\infty e^{-\lambda} p_+(\lambda) d\lambda.$$

A.2. Average Size of Balance Transfers

Lemma 3: (average monthly credit card balance of customers who are eligible (ineligible) for balance transfer)

The threshold of balance transfer is k. The average monthly credit card balance of customers

who are eligible for balance transfer offer is therefore $B_{k+} = \dfrac{\int_k^\infty b f(b) db}{\int_k^\infty f(b) db}$. The average of

customers who are ineligible for balance transfer is therefore $B_{k-} = \dfrac{\int_0^k b f(b) db}{\int_0^k f(b) db}$.

A.3. NPV Calculations

The NPV of each bank (CB, OB, or AB) for each of the seven strategies s described in the paper

can be calculated as following $NPV^s{}_X(L_1) = \sum_{j=1}^\infty \dfrac{P^s{}_{X,j}(L_1)}{(1+r_f)^j}$, where X $\in$ {CB, OB, AB} and s $\in$

{1, 2, 3, 4, 5, 6, 7, 8}. The profit each bank earns from a strategy is a function of L_1, the delay

required to complete and install systems before its implementation. The option value for

enabling immediate implementation of a strategy s, instead of waiting for L_1 periods before

deploying it can thus be valued as $V_X(L_1) = \max_s NPV^s{}_X(0) - \max_s NPV^s{}_X(L_1)$

Appendix B presents the results of performing these calculations for specific values of interest rates, bankruptcy rates, balances, in-play ratios and retention-effectiveness ratios. Appendix C uses the results of appendix B to perform the calculations over probability distributions for in-play ratios, retention-effectiveness ratios, and timing of AB's attack.

Appendix B: NPV Analysis

NPV Analysis	25% In Play 75% Retention	50% In Play 25% Retention	50% In Play 75% Retention
Case 1: Status Quo			
Creative Bank	$ 16,943,262	$ 16,943,262	$ 16,943,262
Other Bank	$ 6,943,262	$ 16,943,262	$ 16,943,262
Attacking Bank	$ -	$ -	$ -
TOTAL	$ 3,886,525	$ 33,886,525	$ 33,886,525
Case 2: CB initiates preemptive pricing strategy			
Creative Bank	$ 5,244,307	$ 15,244,307	$ 15,244,307
Other Bank	$ 16,943,262	$ 16,943,262	$ 16,943,262
Attacking Bank	$ -	$ -	$ -
TOTAL	$ 32,187,569	$ 32,187,569	$ 32,187,569
Case 3: CB initates aggressive pricing strategy			
Creative Bank	$ 8,597,366	$ 19,153,777	$ 19,153,777
Other Bank	$ 11,772,576	$ 10,943,265	$ 10,943,265
Attacking Bank	$ -	$ -	$ -
TOTAL	$ 30,369,942	$ 30,097,042	$ 30,097,042
Case 4: CB and OB do nothing in response to attack			
Creative Bank	$ 11,772,576	$ 10,943,265	$ 10,943,265
Other Bank	$ 11,772,576	$ 10,943,265	$ 10,943,265
Attacking Bank	$ 6,706,118	$ 7,818,941	$ 7,818,941
TOTAL	$ 30,251,271	$ 29,705,471	$ 29,705,471
Case 5: CB does nothing until ready to replicate strategy			
Creative Bank	$ 14,428,075	$ 12,942,986	$ 12,942,986
Other Bank	$ 11,772,576	$ 10,943,265	$ 10,943,265
Attacking Bank	$ 4,223,827	$ 6,130,713	$ 6,130,713
TOTAL	$ 30,424,478	$ 30,016,965	$ 30,016,965
Case 6: CB drops rates for all exisitng customers until ready to replicate strategy			
Creative Bank	$ 13,999,291	$ 13,734,603	$ 13,734,603
Other Bank	$ 11,772,576	$ 10,943,265	$ 10,943,265
Attacking Bank	$ 2,525,629	$ 3,346,728	$ 3,346,728
TOTAL	$ 28,297,496	$ 28,024,596	$ 28,024,596
Case 7: CB matchs offers for customers attempting to defect until ready to replicate strategy			
Creative Bank	$ 15,701,723	$ 13,638,983	$ 15,030,975
Other Bank	$ 11,772,576	$ 10,943,265	$ 10,943,265
Attacking Bank	$ 2,950,178	$ 5,434,717	$ 4,042,724
TOTAL	$ 30,424,478	$ 30,016,965	$ 30,016,965

Appendix C: Option Value Calculation

Option Valuation ($ million) In-Play/Retention	Lag 8	7	6	5	4	3	2	1	No Entry	
25/25	$2.07	$1.88	$1.67	$1.45	$1.21	$0.94	$0.65	$0.34	$0.00	
25/50	$1.64	$1.49	$1.33	$1.15	$0.96	$0.75	$0.52	$0.27	$0.00	
25/75	$1.22	$1.11	$0.99	$0.85	$0.71	$0.55	$0.38	$0.20	$0.00	
50/25	$3.46	$3.12	$2.76	$2.37	$1.97	$1.53	$1.06	$0.55	$0.00	
50/50	$2.86	$2.67	$2.43	$2.17	$1.85	$1.49	$1.06	$0.55	$0.00	
50/75	$2.17	$2.02	$1.84	$1.64	$1.40	$1.13	$0.81	$0.43	$0.00	
75/25	$3.80	$3.47	$3.11	$2.72	$2.30	$1.82	$1.29	$0.69	$0.00	
75/50	$3.63	$3.45	$3.11	$2.72	$2.30	$1.82	$1.29	$0.69	$0.00	
75/75	$2.77	$2.63	$2.45	$2.23	$1.96	$1.62	$1.20	$0.67	$0.00	

Probability In-Play/Retention	8	7	6	5	4	3	2	1	No Entry	Marginal Probability
25/25	1.25%	1.09%	0.94%	0.78%	0.63%	0.47%	0.31%	0.16%	0.63%	**6.25%**
25/50	2.50%	2.19%	1.88%	1.56%	1.25%	0.94%	0.63%	0.31%	1.25%	**12.50%**
25/75	1.25%	1.09%	0.94%	0.78%	0.63%	0.47%	0.31%	0.16%	0.63%	**6.25%**
50/25	2.50%	2.19%	1.88%	1.56%	1.25%	0.94%	0.63%	0.31%	1.25%	**12.50%**
50/50	5.00%	4.38%	3.75%	3.13%	2.50%	1.88%	1.25%	0.63%	2.50%	**25.00%**
50/75	2.50%	2.19%	1.88%	1.56%	1.25%	0.94%	0.63%	0.31%	1.25%	**12.50%**
75/25	1.25%	1.09%	0.94%	0.78%	0.63%	0.47%	0.31%	0.16%	0.63%	**6.25%**
75/50	2.50%	2.19%	1.88%	1.56%	1.25%	0.94%	0.63%	0.31%	1.25%	**12.50%**
75/75	1.25%	1.09%	0.94%	0.78%	0.63%	0.47%	0.31%	0.16%	0.63%	**6.25%**
Marginal Probability	**20.00%**	**17.50%**	**15.00%**	**12.50%**	**10.00%**	**7.50%**	**5.00%**	**2.50%**	**10.00%**	**100.00%**

Option Value	**$1.89**
Option Variance	**$1.03**

Table 1: Definition of Variables

| Variables	Descriptions
b_i	Average unpaid monthly credit card balance carried by customer i.
B_{k+}	Average unpaid monthly balance of all customers who are eligible for balance transfer offer
B_{k-}	Average unpaid monthly balance of all customers who are not eligible for balance transfer offer
λ_i	Quarterly bankruptcy rate of customer i (modeled as arrival rate in a Poisson process)
C_y	Annual bankruptcy rate among the entire population
C_q	Quarterly bankruptcy rate among the entire population
C_{q+}	Quarterly bankruptcy rate among customers with bankruptcy history in the past year
C_{q-}	Quarterly bankruptcy rate among customers without bankruptcy history in the past year
I	In-play ratio: percentage of customers considering switching credit cards in any given quarter
R	Retention ratio: percentage of customers staying with their current credit card issuers if the issuers match rates offered by rivals
k	For new customers: threshold of monthly balance that eligible for balance transfer
	For existing customers: threshold of monthly balance to quality for preferential rate r_n.
	Before implementing differential pricing strategy: standard rate charged to all credit card customers
r_s	After implementing differential pricing strategy: standard rate charged to customers with monthly balance of less than k.
r_l	12-month special promotional rate for balance transfer customers.
r_p	Premium rate charged to secured credit card customers (customers who defaulted in the past year)
r_n	Preferential rate for customers with monthly balance over k.
L_l	The delay required to complete and install systems before its implementation
N	Number of customers
j	Quarter index

Figure 1: CB does nothing in response to AB's attack
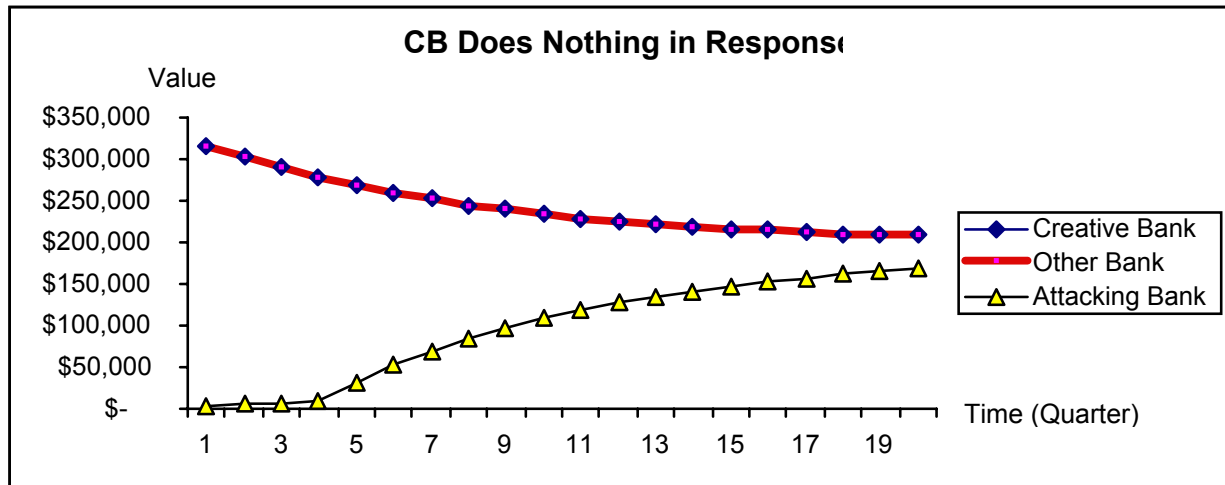
AB begins its attack. Neither CB nor OB responds. NPV of profits of both incumbent banks are reduced to $10.94 million, while AB enjoys profits of $7.82 million.

Figure 2: CB does nothing until Ready to Replicate Strategy
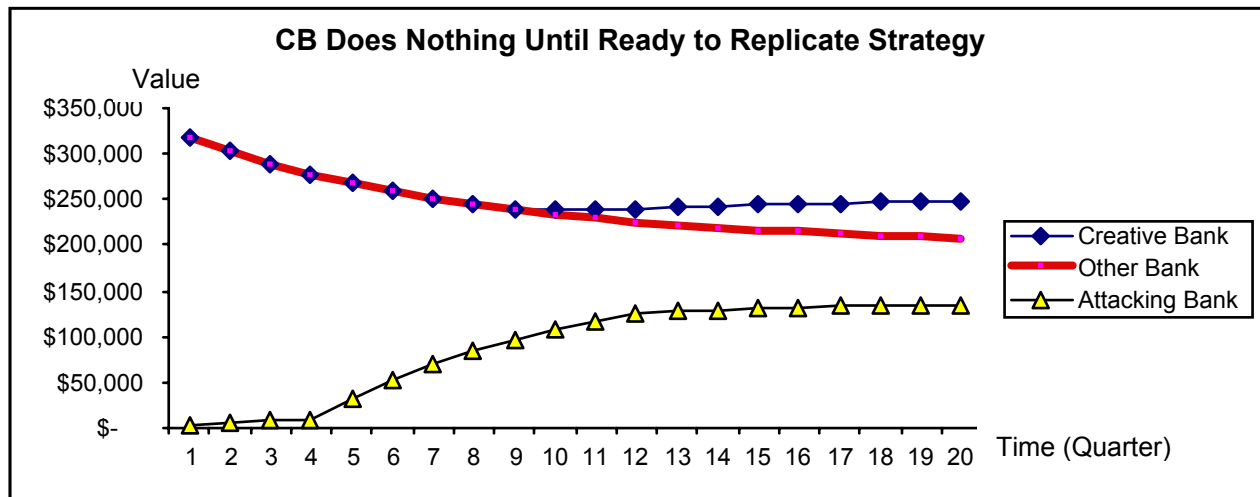

AB begins its attack. OB does nothing. CB begins to prepare to match AB's strategy, but does nothing until its infrastructure is available. Clearly this works better than OB's strategy, but with high in-play ratio it results in the loss of too many good accounts to AB before CB is ready to implement differential pricing. The NPV of CB's 5-year earnings is reduced to $12.94 million. This is better than OB's strategy of doing nothing, which results in NPV of earnings being reduced to $10.94 million, but CB still loses too many good accounts before it is ready to act .

**Figure 3: CB drops rates for all until ready to replicate strategy**
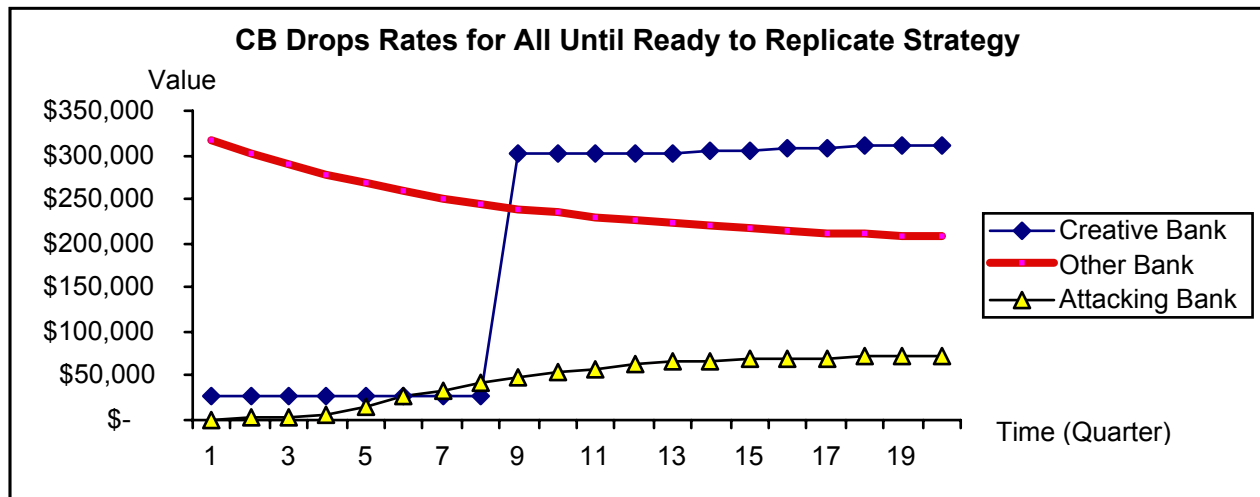
AB begins its attack. CB responds by dropping its prices for all customers to avoid any loss of its good accounts to AB. With high in-play ratio the large majority of CB's best accounts would have left in the two years it takes CB to replicate AB's strategy and this defensive move preserves all of these accounts. The NPV of CB's earnings is preserved and CB earns $13.74 million, but the short-term impact may be unacceptable. Once again, OB earns $10.94 million. AB earns $3.35 million.

Figure 4: CB matches offers until ready to replicate strategy

CB Matches Offers Until Ready to Replicate Strategy
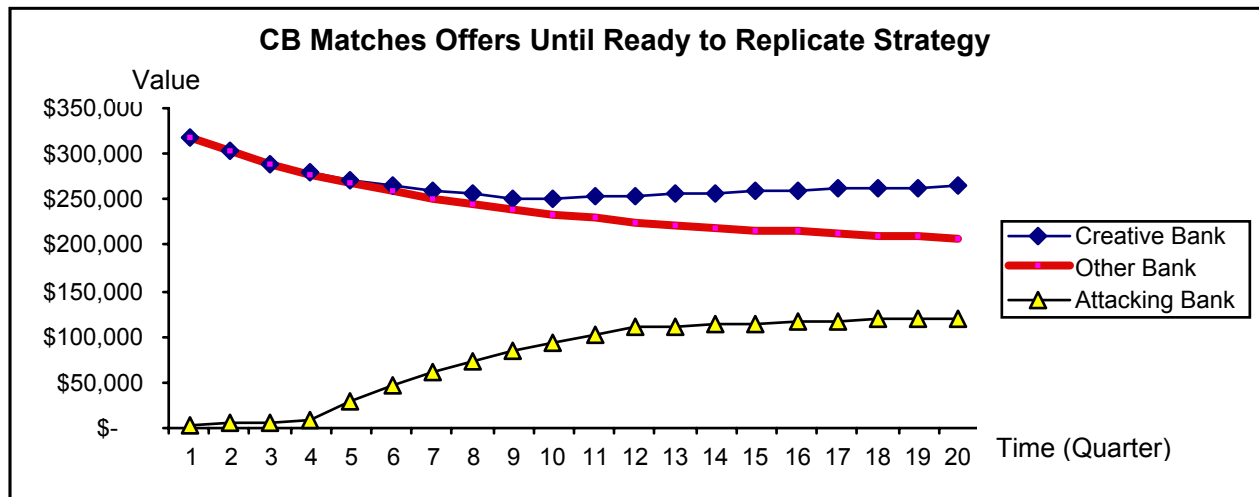
AB begins its attack. CB responds by attempting to match the offers that its best customers receive from AB. With high in-play ratio, many of CB's accounts are at risk each month, but with low retention ratio matching their offers is rarely effective in persuading customers to remain with CB. CB earns $13.63 million, while OB once again earns $10.94 million. This strategy is less profitable for CB than dropping rates for all customers but the short-term effects are better.

Figure 5: CB implements differential pricing immediately after attack

CB Implements Differential Pricing Immediately after Attack
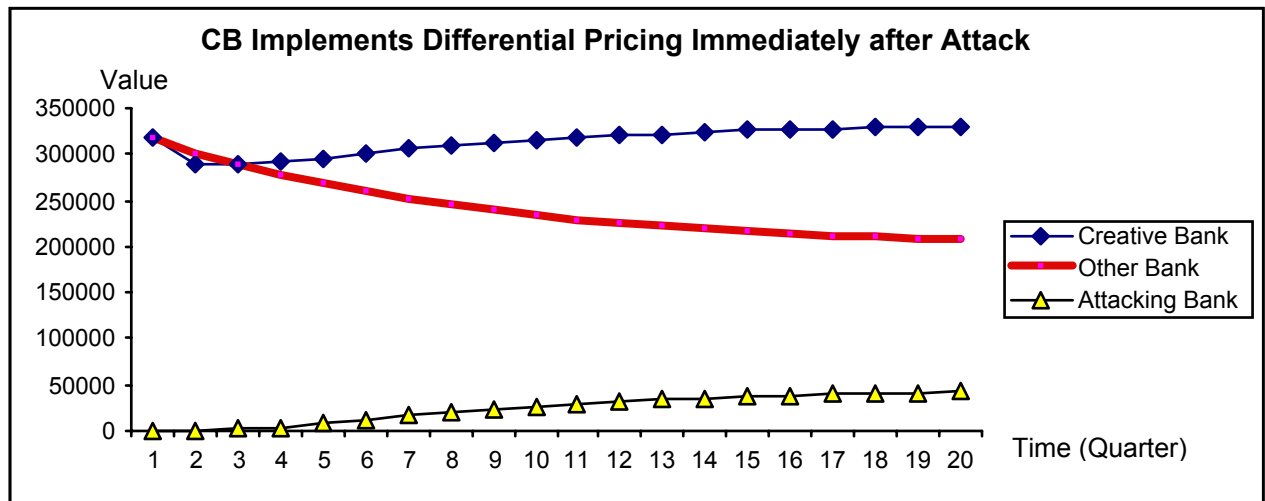
Rapid deployment of differential pricing enables CB to respond to attack from AB.