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Interfaces with Other Disciplines

Developing a measure of risk adjusted revenue (RAR) in credit cards market: Implications for customer relationship management

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ABSTRACT

Current models of customer lifetime value (CLV) consider the discounted value of profits that a customer generates over an expected lifetime of relationship with the firm. This practice can be misleading in the financial services markets because it ignores the risk posed by the customer (such as delinquency and default). Specifically, in the credit card market, the correlation between revenue and risk is positive. Therefore, firms need to adjust a customer's profits for the associated risk before developing a measure of customer lifetime value. We propose a new measure, risk adjusted revenue (RAR), that can incorporate multiple sources of risk and demonstrate the usefulness of the proposed measure in correctly assessing the value of a customer in the credit card market. The model can be extended to compute risk adjusted lifetime value (RALTV). We use the RAR metric to understand the effectiveness of different modes of acquisition, and of retention strategies such as affinity cards and reward cards. We find that both reward- and affinity-cardholders generate higher RAR than non-reward and non-affinity cardholders respectively. The ordering of different modes of acquisition with respect to RAR (in decreasing order) is as follows: Internet, direct mail, telesales, and direct selling.

1. Introduction

There is a growing interest in customer relationship management (CRM) and customer lifetime value (CLTV) among researchers and practitioners alike. This trend is partly attributable to the availability of an overwhelming amount of customer transaction data and the necessary data-mining tools to obtain managerially useful insights. Also, as costs of acquisition and retention increase, firms attempt to find ways of targeting desirable customers in an efficient manner. One important metric used to assess the desirability of a customer is customer lifetime value, which computes the discounted value of a stream of profit generated by a customer over an expected lifetime of association with a firm. These models have become increasing popular and have been the subject of much research (Berger and Nasr, 1998).

However, most of these models have been applied to consumer goods and services where the notion of risk is not well defined and is possibly less important. In contrast, the financial sector poses new challenges. The correlation between risk and return is both positive and high. This means that profitable customers are also associated with higher risk. For example, in the credit card industry a customer who carries a large balance on the card is highly profitable, but such a customer may also be more likely to default on payments and expose the bank to a greater risk of bad debt. Therefore, there is a need to develop a risk adjusted lifetime value model. Given the recent financial meltdown in the credit markets, the notion of accurately adjusting for risk assumes even greater relevance. While we develop our model in the context of the credit card industry, the model can be easily applied to other industries.

There is very limited research on risk adjusted lifetime value models. In one of the first papers, Dhar and Glazer (2003) coin the term risk adjusted lifetime value (RALTV) to remedy this limitation and suggest that one should account for *beta risk* or the contribution that a given customer makes to the volatility, and therefore, the predictability, of the entire portfolio of customers. They employ concepts developed in finance literature to propose a measure of RALTV. However, they describe a conceptual model without any application to empirical data.

Another paper that accounts for customer risk while computing customer lifetime value is by Ryals and Knox (2005). Using data from the insurance industry, the authors consider two types of risk – the probability of retention and the probability of a customer filing a claim. They account for the risks by multiplying the expected profit with the two probability measures to obtain a measure of

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risk adjusted customer lifetime value. Thus we see that when the risks are measured using a probability measure the expected profit from the customer is easy to compute. However, if there are other measures of risk such as volatility, it is not clear how to adjust the profit to obtained risk adjusted lifetime value. We provide a solution to this problem which has not been addressed before.

Recent papers emphasize the need to develop models to optimize customer portfolios using well known principles from finance literature (Hopkinson and Lum, 2001; Buhl and Heinrich, 2008; Tarasi et al., 2011). Hogan et al. (2002) suggest that customers should be treated as risky assets since they vary significantly in their lifetime value. The above papers advocate the use of the CAPM model of financial portfolio theory to compute a risk adjusted discount rate in customer valuation. The papers suggest using beta risk, a measure of the covariance of an individual customer's return (or lifetime value) with that of the entire portfolio of customers.

We build on these studies to develop a comprehensive measure of risk adjusted revenue (RAR) in which we control for different types of risk that are posed by a customer. Note that we use the term RAR and not RALTV because we do not have data on the costs of providing credit card services (e.g., acquisition costs, retention costs and costs of borrowing capital) and so we employ the model on revenues and not discounted profits. Given the right data, our model can be used to compute RALTV. We adjust for different types of risk such as the beta risk, the probability of default, and the volatility of revenue streams and apply our model to data from a credit card firm. In contrast to Ryals and Knox (2005), our proposed model allows us to adjust for multiple risks including those that cannot be measured using a probability measure.

In the financial sector, credit card companies have to constantly search for more effective ways to attract new profitable customers who are good risks, and at the same time, try and minimize their expected loss from customers who are bad risks. Increased competition and aggressive marketing efforts have led to a deeper penetration of the pool of high risk customers. Therefore, it is imperative that banks and card issuers use more sophisticated analyses to better target their customers. The current institutional practice for evaluating and targeting customers relies on the use of scorecards. Customers are divided into deciles based on their profitability and risk profiles (credit scores). These scorecards are then employed by the firm to decide the credit limit and the annual percentage rate (APR) for a given customer. While simple to implement and use, these scorecards focus on only one type of risk, namely, the probability of default.

Managers currently use measures such as customer lifetime value to decide the amount of resources to spend on acquiring and retaining a given customer. The number and type of solicitations and other communications that are sent to a customer are influenced by the value that the customer is expected to bring to the firm. In the financial sector, a new measure that also adjusts for the riskiness of the customer would be useful in better targeting and retaining profitable, but less risky, customers.

We use data from a major credit card issuing company to develop and estimate our model and also make inferences about the impact of RAR on a customer's overall value to the firm. There are three sources of revenue for the credit card company: interchange income, interest income, and fee income. Interchange income is the percentage (typically between 1.5% and 2%) that the bank gets from the retailer for each customer purchase transaction amount. Interest income is generated whenever a customer carries an unpaid balance to the next period or takes a short term cash loan. Firms charge different kinds of fees for negative customer behavior such as over-the-limit fees, late payment fees, and returned check fees. Americans paid an estimated $22.9 billion in penalty fees from credit cards in 2009 (creditcard.com). Approximately 78% of total credit card revenues are derived from interest income (Min and Kim, 2003). In our dataset, approximately 72% of the bank's revenue comes from interest income. Based on this discussion, banks would like to increase the three sources of income streams from customers. On the other hand, banks would like to minimize several kinds of risk posed by customers. We identify seven measures of risk in this paper: probability of default, volatility in interchange income, volatility in interest income, volatility in fee income, beta risk in interchange income, beta risk in interest income, and beta risk in fee income.

We employ a data envelopment analysis (DEA) model to compute the risk adjusted revenue measure for each individual customer. DEA is commonly used to evaluate the efficiency of a business unit and has been applied in several contexts such as the analysis of hospitals, schools, mutual funds and a host of other areas (Charnes et al., 1994). DEA is an extreme point method that compares each customer with the "best set of customers" and provides a metric that reflects the risk adjusted value of each customer relative to a group of best customers. DEA is especially useful in our context due to its ability to handle multiple inputs and outputs and it does not require an assumption about the functional form relating inputs to outputs (Charnes et al., 1994). The model can accommodate additional input and output variables as well.

How can the RAR scores help in customer relationship management? We use the RAR scores to segment customers into 'most profitable' and 'least profitable' after adjusting for the risk they pose to the firm. We then identify the factors that discriminate between the two segments. Specifically, we focus on the value of programs such as reward cards and affinity cards and on the effect of the mode of channel used to acquire customers. By understanding the differences between highly profitable customers and less profitable customers, managers can better utilize their limited resources for targeting and retaining profitable customers.

The credit card industry uses two common metrics to measure customer risk – the probability of default and the expected loss resulting from a customer who defaults. Numerous papers have focused on the methodology to be used to calculate the default probability (Crook et al., 2007) or on factors affecting default (Dunn and Kim, 1999). We demonstrate the added benefit of accounting for additional measures of risk apart from the standard measures used in the financial industry.

In light of the recent global financial meltdown, portfolio profitability and risk management have been receiving increased attention not only from firms but also in the popular press. Our research provides financial service firms with strategic guidance with respect to two critical functions of customer relationship management: customer acquisition and ongoing retention efforts. We provide empirical evidence of the relationship between both customer acquisition methods and retention strategies using risk adjusted revenue. Firms must balance the challenge of attracting new customers against maintaining an acceptable level of overall portfolio profitability and risk. We find that customers acquired through direct mail are less likely to default (and expose the firm to financial risk), which suggests that firms concerned with portfolio risk management should reallocate customer acquisition spending into this channel. Our research also provides support for firm investment in affinity and reward programs since these programs assist firms in attracting less risky customers. Finally, RAR in the credit card market has implications for the long-term growth and sustainability of the firm. Financial institutions themselves obtain access to funds based, in part, on an evaluation of their own overall portfolio risk. Using RAR, firms can lower their overall risk by targeting and retaining less risky and more profitable customers, which then allows them to borrow at competitive rates.

Since the results from DEA can be susceptible to outliers, we perform a bootstrapping analysis as in Simar and Wilson (1998).