Risk plus Marketing equals profit – but not always what you expect
_by Murray Bailey

The conflict between risk and marketing can be summed up by the story, that if the boss sees the risk and marketing director having lunch together, the business is in trouble. The historical reason was because marketing were responsible for bringing in the sales and risk was responsible for selecting the better quality ones – or "sales-prevention" as marketers would often call the risk team.

During the 1980's Direct Marketing moved away from simply driving volume into the business, to using response models. Response models enabled the marketer to rank prospects and select the most responsive. In fact a break-even point could be found whereby additional selections would result in mailing prospects that would cost more money to mail then they would generate in income. The break-even point was therefore the response rate at which the cost of the mailing equalled the income.

One of the difficulties was that this still failed to take into account the likelihood of acceptance, since marketing and risk were still reluctant to share too much information. By the early 1990's some marketing agencies were touting "conversion scorecards". These ranked prospects based on the likelihood of acceptance following response. This seems like a reasonable compromise, but the subsequent models tended to be weak because the objectives of respond and risk are diametrically opposed. A linear model therefore finds that the predictiveness cancels each other out.

Profit Model

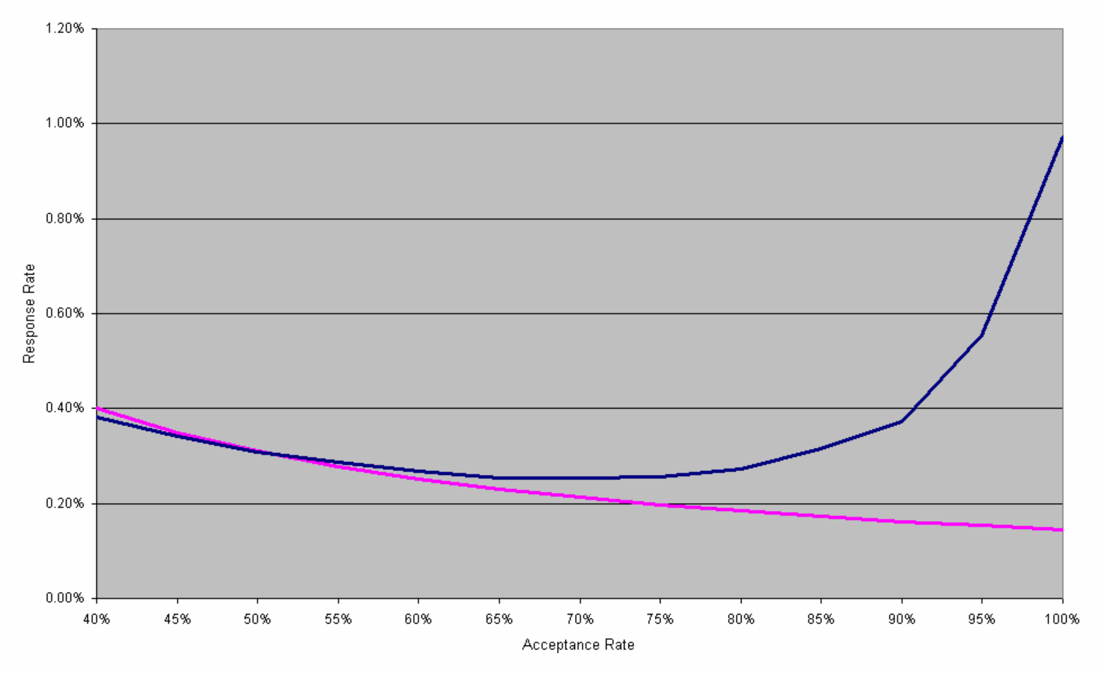
To calculate the break-even point, marginal profitability can be expanded beyond the simple elements of income and cost of the mailing. Such a model was discussed in Tony Masters' article in the launch issue of CRI[1].

Table 1: definitions and values

p	average proportion outstanding = 75%
T	loan term (yrs) = 2
m	interest rate margin = 2.5%
F	fee = 0
I	**commission on ins = £300**
i	proportion taking ins = 70%
E	early redemption charge = £150
e	proportion of early redeemers = 70%
A	advance = £5,000
b	bad rate = 3.5%/variable
Q	**take-up cost = £5**
C	mail cost per piece = £0.45
r	response rate = variable
a	acceptance rate = variable
P	processing cost = £20
t	take-up = 80%
NPV	Net Present value (discount) = 90%

For comparison, in this article we have used the same notation that Masters used. Table 1 shows the definitions and values assumed. Equation 1 is the break-even point where the left-hand side is the income and the right-hand side is the cost. Note that the advance of this approach over simpler models is that it incorporates acceptance rate and bad debt.

Figure 1: Break-even response rates



The blue line in figure 1 is the line of zero profit. In other words, this is the response rate required to break-even for any given acceptance rate. However, bad debt is not a fixed value. Risk people know that bad rate - and hence bad debt – increases with acceptance rate. Figure 2 is an example loss curve. When this additional variable is included in the model, the line of zero profit, is starkly different. This is shown as the pink line in figure 1: the zero profit line restated. The exponential nature of bad rate, causes the minimum response rate to shoot up for very high levels of acceptance.

The break-even point in Master's article, assumed a fixed bad debt expense. Equation 1 shows the profit equation based on variable acceptance rate and bad rate. The break-even point is when this equals.

equation 1: Profit equation

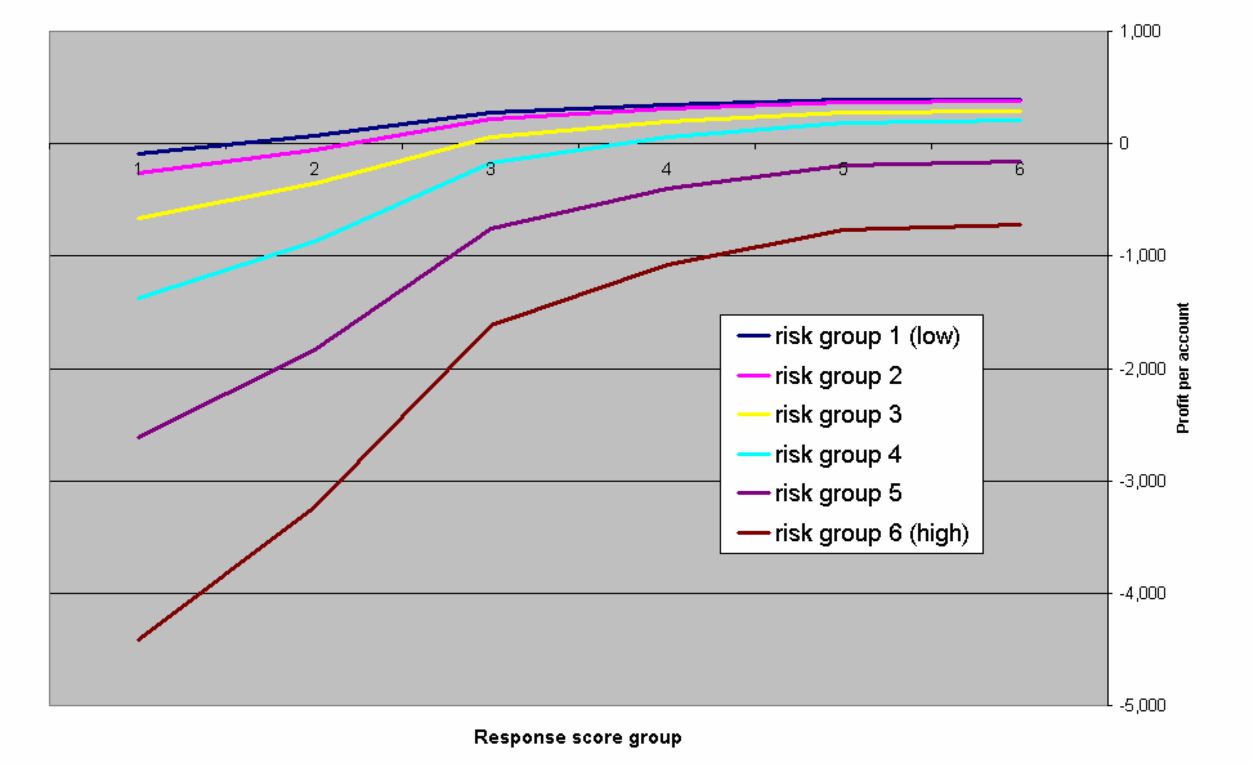
Profit = Income – costs = NPV (**ApTm** + **F** + **Ii** +**Ee**) – (**bA** + **Q** + **C/rat** + **P/at)**

Putting the equation into practice
Rather than use a conversion score, the benefit of the model is that it can be applied to a matrix of risk scores verses response. Figure 2 shows the profit by risk and response where the interest rate is not varied nor is the loan amount. Each line represents a risk score band.

The profit matrix is shown in table 2. Score bands 5 and 6 never make money and should therefore be excluded from the mailing. The other risk groups make more money as risk fall and response increases. Response group 1 – the lowest responders – also never make enough profit and should be excluded.

For these results, the model could have been any profit-based calculation. However, using the equation that links response and quality, we have the opportunity to test alternative scenarios.

figure 2: Profit by risk and response groups



Risk Based pricing
Using the two-dimensional score matrix we can determine which cells we wish to encourage and which to discourage. The approach of targeting prospects based on a score matrix was covered by Dan Dierker in January-February's 2003's issue of CRI[2]. In his article he proposed two matrices: firstly application risk versus premailing risk – this ensures the alignment of the premailing risk score and secondly response propensity versus conversion propensity.

In our example we simply have risk score versus response score, but the principle is the same. The high response high reward prospects are the 'Golden group', the historical core of the business. The low quality should be excluded. The low response high quality group, could perform like our golden group if we could get them to respond and so marketers encourage these prospects with incentives.

There is no better incentive than interest rate. By offering a lower interest rate to this group, we may be able to increase profitability. Traditionally this may be done by trial and error – or if the company has better control – champion / challenger testing. The attraction of the profit equation that we have been using is that it enables the marketer to run what-ifs on the data.

To assess the optimal interest rate, we need an additional relationship: how response varies with interest rate. We would like to show the input for this, but such models are proprietary. Learning this relationship costs considerable money and effort and it is understandable that our client would not wish to publish the information.

What we can say is that generally there is an inverse trend: as the interest rate increases, the response decreases. This trend becomes faster as the interest rate is increased. However, the curve is not smooth. There are 'windows' of interest rates over which the response does not vary significantly. For example, if the rate is not the best in the market, but almost, that band just below the best is between 0.5% and 1%. There are other steps and each step is larger than the previous.

Since response to interest rates depends on the competition, we considered looking at a model of interest rate margin. Alternatives could have been the interest rate movement from the norm or rate relative to bank base rate.

Applying the rate-response model to the matrix enabled us to find the optimum interest rate. The combination of the models could have been by using a technique such as Monte-Carlo simulation. However, with a simple six by six matrix and handful of variables it was just as easy to test each cell by iteratively stepping the interest rate up or down to find the maximum profit. Not very technical, but it works and it's easy to explain!

Table 2 shows the final margins. The standard interest rate margin was 2.5% and we derived optimum rates between 1.5% and 5%. 1.5% meant that the interest rate offered to the lowest responders, highest quality group would be 6.5% if the bank's cost of funds was 5%. The high responders, worst risk prospects that still made profit (response groups 5 and 6 and risk group 5) would be offered a rate of 10%. Neither of these cells would have been acceptable without risk based pricing. Similarly the response group 1/risk group 1 and response group 2/risk group 2 are now acceptable mailing groups.

Table 2: interest rate matrix

	Profit	LOW	Response Score			HIGH		
		1	**2**	**3**	**4**	**5**	**6**	
	1	-86	67	276	346	387	393	230
Risk Score	**2**	-267	-60	222	317	372	379	160
	3	-663	-358	58	197	278	290	-33
	4	-1,373	-867	-176	55	190	209	-327
	5	-2,619	-1,831	-756	-397	-187	-158	-991
	6	-4,415	-3,233	-1,621	-1,082	-768	-724	-1,974
		-1,570	-1,047	-333	-94	45	65	

Lending limits

So far we have assumed that the average amount lent is fixed. The model enables this to be modified as well. Traditionally risk managers set low lending limits for higher risk applicants and higher limits for low risk applicants. The problem with this is that higher risk people tend to want to borrow more.

What we tend to do is restrict the higher risk applicants and find that the low risk applicants don't borrow enough. However, when analysis by income is performed, we find that affordability is playing a part in the lending calculation (or at least should be). The credit score is predicting stability rather than affordability, however there is a close relationship between the two.

Therefore, if we restrict lending by score and income we may be missing an opportunity. What the model shows is that - provided there is not an affordability issue - the more you lend the more profit is made.

In the example, if we had a maximum loan amount of £7,500, the profitability was maximised for each cell of the matrix at £7,500! This challenges the paradigm that most risk managers apply today. However, what it says is let the affordability calculation take care of the loan amount rather than the score. It also supports something that we have long argued for larger ticket value lending – leave income and affordability out of the scorecard and handle it separately (for an example see reference 3).

Summary of results

If we mailed everyone without consideration of pre-selecting the best risk or response groups, with a response rate of under 1% we would acquire 2,549. By applying the two scores and selecting only the prospects who would generate profit, the number of loans acquired falls to 2,172 but the profit per loan increases from £198 to £323 – a 63 percent improvement.

Maximising the loan amount had little impact on the umber acquired, but the profit per loan increased to £411. Combining this with risk based pricing, the most significant impact was seen. The number acquired was 2,581 and the profit per loan increased to £443. Overall, using intelligent selection and marketing the profit from the same prospect pool could be increased by 125%.

Finally, we recommend that when applying the model, you maintain a control group. The problem with prospects is that they are not just driven by interest rates, they are also affected by the competitive market place. This is in a constant state of flux and so we advise that a control group is maintained to test the rate-response assumptions.

Additionally, the modelling and actual results may through up some unexpected figures. In our case, we found a test cell of prospects in the middle of the matrix that seemed to justify a lower rate. However, it was not consistent with the other rates and we suggest that the matrix of rates should have a logical progression. If cells have unusual results, we recommend that you re-evaluate assumptions and check cell counts (for significance) before concluding that the results are correct. If they still seem to be right, perhaps do a champion/challenger test on the cell just to make sure – after all you are supposed to be risk-averse!

Reference

1. Masters, T. “Modelling Personal Loan profitability”, Credit Risk International March-April 2002, Blue Moon Publishing.
2. Deiker, D. “Credit Marketing: Working with Propensity and Risk”, Credit Risk International January-February 2003, Blue Moon Publishing.
3. Betts, J and Emery B. “Scorecards and underwriters – is there a middle way?” Credit Risk International September-October 2003, Blue Moon Publishing.

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