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Exploring Profit Satisficing Approval Thresholds for Lending to the Underbanked

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Abstract This article describes a spreadsheet modeling approach to loan approval decisions supported by logistic regression models. The analysis supports the goals of lenders that seek to help underserved groups access capital with reasonable terms. Given scoring model results for loan applications, the approach utilizes a spreadsheet simulation model and data table of the profit implications of a full range of loan approval cutoffs to explore how lenient a cutoff policy could be while still maintaining some degree of profitability. The method supports an emphasis on prudently increasing the number of loans made and on the costs avoided by customers, who if rejected can access credit only at much higher cost.

Keywords Financial Wellness, Financial Services, Credit Scoring, Logistic Regression, Cutoff, Underbanked

1. Introduction

Organizations in the Financial Wellness industry offer financial education and loans to the underbanked, who lack the credit and banking history to borrow from conventional lenders, In contrast to other options available to the underbanked, financial wellness lenders feature reasonable payment and interest terms, and help their customers to build a credit history. In the United States, 20 percent of households comprise the underbanked market, who spend 30 billion USD per year on small-dollar loans from nonbank lenders, such as payday and auto title lenders (Pew 2018). For example, borrowers will typically pay a fee of $15 for a 2-week payday loan of 100, which implies a nominal annual interest of 390 percent. Borrowers very often are unable to overcome their cash constraints in two weeks and repeat the borrowing, which compounds the effective interest rate significantly (Robinson Schwartz 2017).

Correa Bahnsen et al. (2014) observe, consistent with my anecdotal observations, that in practice, decision makers base loan approval policy on predicting defaults correctly, rather than predicting profits. Accordingly, those researchers advocate example-specific modelling to account for cost and profit implications of credit approval policy. In a similar spirit, I show an approach to integrate logistic regression estimates of probability of loan performance into a spreadsheet model of the profit implications of various credit approval thresholds. To protect proprietary model and customer information, I illustrate the approach with a mock lender, Largo LLC who offers a loan product that competes with alternatives such as payday loans.

Largo LLC receives, through its referral network in the financial wellness space, about 1,500 applications per day for an $800, 8-month loan. The following section describes a spreadsheet simulation model that begins with logistic regression output from Largo's underwriting model. Specifically, the probability of a loan performing is estimated for the loan

applications received on one particular day, which is used here as an illustrative example. The steps below simulate, using MS Excel, the profit implications of Largo approval policy for the example loans.

2. Method: Modeling Loan Decisions and Performance.

Largos exploration of the profit implications of various cutoffs for approving loans proceeds in two phases. The first phase develops, for a specific approval cutoff, a working spreadsheet model that estimates the total profit from approving a batch of loans, in this case the applications received on the example day. Table 2 shows the progression across spreadsheet columns of the first phase of modelling. The second phase uses Excels Data Table tool to assess the estimated total profit, and number of customers served, for different cutoffs. Table 3 shows the results of the second phase of modelling.

2.1. Estimate the profitability of lending decisions

Utilizing the results of its scoring model, a logistic regression model, Largo assigns interest rates based on the probability that a loan would perform (versus default). Table 1 shows, by risk classification bounded by cutoff probabilities that a loan would perform the interest rates assigned and associated monthly loan payments. Largo used a VLOOKUP function to assign interest rates based on probability of a loan performing falling between thresholds in the leftmost column of Table 1.

Table 1. Interest Rates and Monthly Payments Based on Probability of Perform

Estimated Probability of Loan Performing	Interest Rate	Monthly Payment
0	35.00%	$113.56
0.25	32.00%	$112.37
0.45	30.00%	$111.57
0.65	28.00%	$110.78
0.85	23.00%	$108.82
0.95	18.00%	$106.87

Next, Largo simulates if each loan performs or defaults, as a binomially distributed random variable with a mean equal to the estimated probability that the loan would perform. Excels BINOM.INV function is used for this step. Time of default also influences revenues, so Largo uses the GAMMA.INV function, to simulate values from a gamma distribution with parameters, alpha = 1, and beta = 2. This is a way to simulate values from an exponential distribution with mean 0.5. The exponential function is a common hazard function, providing time between or time to some event with constant hazard (Wajid and Kahn 2006), which Largo assumes is reasonable for its borrowers. Largo needs to convert the results of the GAMMA.INV function into integers that represent number of payments received and does so with a combination of IF, MIN and FLOOR functions. If the BINOM.INV function simulates perform for a loan, then the value 8 would be returned, indicating that 8 payments are received. If the BINOM.INV function simulates default for a loan, then the smaller of 7 or the integer part of value from the GAMMA.INV function is returned, again, indicating the number of payments received.

Once perform versus default and the number of payments are simulated, Largo estimates the profit (loss) on a loan as the number of payments received times the monthly payment amount as shown in Table 1 by risk class, less the $800 loaned. Initially, an arbitrary cutoff value is applied to the estimated probability that each loan performs to model approving versus denying loans. Then Largo sums the loan-by-loan estimated contribution to profit (loss) across all cases (down the rightmost column of Table 2) to give an estimate of total profits on loans approved for a given cutoff value for approve versus deny decisions.

Table 2. Spreadsheet Columns of Phase 1

Probability of Perform	Interest Rate	Perform or Default	Inverse Gamma	Payments Received	Estimated Profit if Approved	Approve	Profit on Approved
0.0288	35%	0	1.433977	1	(686.44)	0	0.00
0.5306	30%	1	0.481297	8	92.59	0	0.00
0.9310	23%	1	3.165013	8	70.53	1	70.53
0.8420	28%	0	1.771337	1	(689.22)	1	(689.22)
0.9897	18%	1	1.647559	8	54.94	1	54.94

2.2. Create a data table showing estimated total profit by cutoff

In the second phase of modeling, Largo creates a data table, which has as its outputs, the estimated total profit for approved loans and the number of loans approved, given a particular cutoff value. Column inputs for the data table range from zero to one to explore the profitability of the full range of approval policies in increments of 0.05. Table 3 shows the data table results for one realization of the random numbers in the simulation. Recalculating the random numbers allows Largo to observe simulated variation in profits according to cutoff policies for approving a batch of loans.

Table 3. Data Table from Phase 2

Cutoff	Estimated Profit	Number of Loans Approved
0	($430,007)	1500
0.05	($345,013)	1295
0.10	($215,459)	1142
0.15	($151,036)	1022
0.20	($131,889)	954
0.25	($116,012)	909
0.30	($95,363)	848
0.35	($60,421)	800
0.40	($46,346)	765
0.45	($34,949)	722
0.50	($31,118)	685
0.55	($9,213)	654
0.60	($4,289)	621
0.65	($3,213)	585
0.70	($5,005)	547
0.75	$2,653	507
0.80	$10,346	461
0.85	$10,299	412
0.90	$7,320	347
0.95	$10,730	242
1.00	$0	0

3. Results and Discussion

The modelling of profit implications by approval cutoffs suggests that there is substantial opportunity for Largo to increase the number of loans it would approve above the

profit-maximizing cutoff while still realizing some contribution to profit. Specifically, Largo could consider more than doubling the number of applications who receive loans, increasing that number from the profit-maximizing 242 approved applications to 507 by decreasing its approval cutoff from 0.95 to 0.75. Also noteworthy is that Largo could increase the number of customers who receive loans by 70 percent with only a small decrease, from the maximum estimated contribution to profit, by decreasing its approval cutoff from 0.95 to 0.80.

4. Conclusion

This article showed an example approach, which lenders in the financial wellness industry could employ, to explore the potential to serve more borrowers while satisficing profit requirements. The spreadsheet simulation modeling approach utilizes logistic regression credit scoring results to consider the how the choice of cutoff policy for loan approval decisions can affect the number of borrowers who gain access to credit at relatively reasonable terms compared their other options. For the mock (but realistic) batch of loans considered, the opportunity to expand credit beyond the profit-maximizing choice is rather substantial. The example lender could serve 70 percent more borrowers with minimal decrease in profits. If the lender can accept the lowest positive profit contributions, they could double the number of customers served.

Future work on this topic could quantify the savings to borrowers who receive credit from reduced approval cutoffs and test the approach with other datasets though there seem to be few publicly available (Louzada et al. 2016).

5. References

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