Product Testing in Financial Services: An Application

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Abstract: Credit Marketing has come a long way in today's economy of hard-hitting competition and diminishing customer loyalty. With the increasing level of cut-throat competition, decreasing customer loyalty and the increasing commoditization of banking products, it has become essential in today's sluggish economy for banks to proactively understand the changing customer preference. Understanding the changing customer preference can help build a value proposition for the Bank since banks today, are flexible enough to align their products towards the value needs of their customers. Traditional testing by the direct marketers has involved split groups, like an apple to apple, to compare customers' reaction to different offers. Therefore, with changing times, the traditional process of testing has become cumbersome. This study is aimed at demonstrating the benefits of product testing using experimental design to the bank's marketing team. We analyse a factorial model and demonstrates the results of incremental lifts in the market response rates. We conclude that incremental lifts in response rates are much higher against lower interest rates for home loans and lower late fees for credit cards. It also provides significant insights to the design of Banks' offers.

Keywords:
Fractional factorial, Incremental Lifts, Response Forecast

INTRODUCTION

Credit Marketing has come a long way in today's economy of hard-hitting competition and diminishing customer loyalty. With the increasing level of cut-throat competition, decreasing customer loyalty and the increasing commoditization of banking products, it has become essential in today's sluggish economy for banks to proactively understand the changing customer preference. Testing of the product before launching can help build a value proposition for the Bank since banks today, are flexible enough to align their products towards the value needs of their customers. This could actually need some effort by the Bank's marketers. This could mean understanding the response behavior of their customers against the features of a given product offer. A Bank typically offers a variety of products and each of these individual products can have multiple offer such that fixed, floating, joining fees, silver, platinum, etc. Further, such offers could vary by maturity, interest rate or other conditional rewards, etc. Behavioral psychologists explain that the human beings are highly influenced by the external competitive offers which are available in the market. Human behavior is to make rational economic decisions based on how much value they seek to derive from a bank's product terms as compared to the outside world. Therefore the Bank become needs to determine what to offer to its customer or customer segments. The entire process of determining product attributes and mapping it to the behavioral needs of a customer could be called customer value building. Thus, there exists a need to test for an expected customer response rather than simply designing a product offer in the hope that someone would buy it. This could improve efficiency and provide roll out opportunities for greater benefits within the bank. For example, the rapid launch of a new product within the customer base of savings account or credit cards would also require testing to understand the value of both the Bank and its customer accurately. This paper intends to highlight the issue of product testing in credit markets and proposes to adopt an innovative test strategy to credit markets using experimental design. This concludes that incremental lifts in customer response rates are much higher for product attributes such as lower floating rates, lower fixed rates and lower late fees. How does a bank conduct the testing its products to understand its customer preferences? Traditional testing by the direct marketers has involved split groups, like an apple to apple, to compare customers' reaction to different offers. For example, for one attribute of two levels, say home loan fixed rate 12% vs fixed rate 14%, we need two test groups when a base group (control group) is given a 12% offer vs the other group (test group) a 14% offer to conclusively say that 14% offer gives lower value to customers as compared to 12% offer by how much? Thus, split groups, as described here, are simple to understand and implement. In a second example, there could be 3 split groups where one group is offered floating 8.25%, another 9.25% and the third one 10.25%, etc. As the levels of an attribute increases such as floating 8.25%, 9.25%, 10.25%, etc, the bank needs a much larger number of test groups to establish its customers' value preferences due to the change in rates. Banks today have the flexibility to offer their products through multiple channels such as branch, the Web, and DSAs (Direct Sales Associates) or direct mails. Further, as competition increases, the competitive offers available in the market imply an innovative test plan with forward looking test offers. This practice of exhaustive testing is cumbersome. The test and control method which is the basis of Banks' market testing today, starts with a control cell for a base offer and and test cells for higher and lower prices. To test five price points and six promotions, one needs a control cell and thirty test cells. For a product with 'm' attributes having 'n' levels each, one actually needs more than 'm x n' test groups and also many control groups to objectively establish the incremental lifts in response rates for each of those levels. In products such as credit card marketing, the possible combinations of brands, co-brands, annual prices (APRs) and teaser rates (no joining fees), marketing messages and mail messages can quickly multiply up to hundreds of possible bundles of attributes. It will be impractical for a banker to test all of the above combinations. It is impossible to test for all possible incremental levels of the factors to be able to understand the response behavior of consumers, as mentioned earlier. Is it the lower price that prompts the higher response or is it the lower fees? It would be difficult to analyse them and implement the results. Therefore, an experimental design based method which seeks to provide a simpler solution to the problem is desired. The next section describes the literature on the application of experimental design in the industry and recommends the test strategy.

MARKET TESTING STRATEGY

The science of experimental design can help project the impact of many stimuli by testing just a few of them. By selecting a subset of combinations of variables, such as in multivariate testing, that represent the complexity of all the original variables, marketer can model hundreds or even thousands of stimuli efficiently. Leading advertising experts like Claude Hopkins (1966), John Caples (1974), David Ogilvy (1983), and Bob Stone and Ron Jacobs (2001) have stressed the importance of testing new ideas in the global marketplace. Although factorial, fractional factorial, and related methods of The financial industry such as insurance, investment, credit card, and banking firms was among the first to use experimental design techniques for marketing testing. Although techniques on factorial design such as full factorial, fractional factorial, and various modifications of such designs have been widely applied to process improvements in the manufacturing industry, there have been few applications to the financial sector and also to direct mail, Internet, retail, and other market testing programs. Curhan (1974) used a fractional- factorial design to examine the effects of price, advertising, display space, and display location on the sales of fresh fruits and vegetables in a supermarket, while Barclay (1969) used a factorial design to evaluate the effect on profitability of raising the prices of two retail products manufactured by the Quaker Oats Company. Holland and Cravens (1973) presented the essential features of fractional-factorial designs and illustrated them with a hypothetical example concerning the effect of advertising and other factors on the sales of candy bars. Wilkinson, Wason, and Paksoy (1982) described a factorial experiment for assessing the impact of price, promotion, and display on the sales of selected items at Piggly Wiggly grocery stores. Factorial and fractional-factorial designs are well known and have been widely used in behavioral marketing experiments. Green, Krieger, and Wind (2001) describe a credit card study that illustrates how fractional-factorial designs may be used in conjoint analysis. Banks could make use of relatively low cost method of experimental design techniques. Bell et al (2006), have suggested the use of Placket-Burman design to the problem of credit card marketing to increase the speed, power and profitability of market testing programs. They conclude that efficient designs could enhance customer response rates, lower costs and profits. These studies establish that experimental design has given the industry the ability to quickly prove what sells and greatly improve the product performance. Full-factorial, fractional-factorial and Placket-Burman designs can provide a solid foundation for efficient and flexible multivariable testing in marketing. One can use modifications of these to test two or may be two dozen variables, analyse main effects alone or in combination with interactions and adjust the size and layout of the test design to meet the test objectives. An optimal design is the one where the volume of the confidence region of the effect estimates (main effects or interactions) is minimum. It is note easy to set up an optimal design because such designs are applicable only when the variables are continuous (like temperature and pressure). However, in case of discrete variables, such as in marketing tests, the design will be sub optimal. Optimal designs also assume some form for the model, relationship or range of influence for the variables being studied. In real life, such assumptions are not met and hence the design is sub optimal. Though sub optimal, multivariable testing is most effective as a strategic marketing tool. The next section describes the test layout and test strategy for two popular products of a Bank.

THE DESIGN

The simplest of all models are called two level full factorial models. Two level factorial experiments are factorial experiments in which each factor is investigated at only two levels. The early stages of experimentation usually involve the investigation of a large number of potential factors to discover the "vital few" factors. Two level factorial experiments are used to quickly filter out unwanted effects so that attention can then be focused on the important ones. Full factorial models comprise all the runs, alternatively, fractional factorial models are defined as the fraction of a full factorial that could resolve the complete experiment with a fraction of the total number of runs. It may be mentioned that marketer could not initiate a fractional factorial layout without realising the vital few factors which needs to be tested. The only problem in analysing a full factorial model is in the data values for response level because the response level data for all combinations may not be available in the Bank. Let’s describe the processes of testing for a typical home loan offer and a credit card offers in this section. Table 1 provides the test layout for the home loan offer for a Bank. For simplicity let's consider a 3 way 2 level design (also known as 3 factor 2 level design) such as 2 x 2 x 2 such as

- Floating Interest Rate with 2 levels (8.25% and 9.25%)
- Fixed rate with 2 levels (12% and 14%)
- Processing Fees with 2 levels (0.5% and 1%)

Table 1: Response against Home Loan Offers across DSAs (2 x 2 x 2)

Run	Floating Rate (%)	Fixed rate (%)	Processing Fees (%)	Response Rate (%)
1	8.25	12	0.5	1.00%
2	9.25	14	1.0	1.00%
3	8.25	12	0.5	0.45%
4	9.25	14	1.0	0.5%
5	8.25	12	0.5	0.90%
6	9.25	14	1.0	0.90%
7	8.25	12	0.5	0.55%
8	9.25	14	1.0	0.6%

Source: Test data from DSAs on Home Loans (2009)

The total number of DSAs from where the bank has collected the response information is four. The bank intends to apply a design that is easier as well as cheaper to implement and also provide maximum information after the analysis. Table 2 summarises the explanations of the factors of the home loan.

Table 2: Summarising the Explanation of 3 factors

Main Effects	Description of the Effect

Floating Rate	Comparison of the Marginal Response Rate against Floating Rate, averaging over the levels of Fixed rate and Processing Fees
Fixed rate	Comparison of the Marginal Response Rate against Fixed rate, averaging over the levels of Floating Rate and Processing Fees
Processing Fees	Comparison of the Marginal Response Rate against Processing Fees, averaging over the the levels of Fixed rate and Floating Rate

Source: Hand Book of Statistics (www.itl.nist.gov)

A shown in Table 1 there exist eight combinations of the offers and all of these are solicited to the customers by four DSAs. The response rate column provides the response rate of customers who have responded against the solicitations. Which factor gives higher incremental lift to the response rate against home loans? Further, questions such as ;the incremental lift for a 100 basis points drop in fixed rate, the incremental lift for a 100 basis points drop in floating rate, and, the incremental lift for a 50 basis points drop in processing fees, etc? The results of the analysis are provided in the model observations section. Let's consider another example of a credit card offer for a leading Indian Bank. The base of credit card customers is considered a good channel to acquire customers and manage them during their life cycle through a variety of product offers as the credit card customers mature to become home loan, auto loan, CASA, investment and wealth management products, etc. Table 3 provides the test layout for the credit card offers for a Bank. For simplicity let's consider a 3 way 2 level design such as 2x2x2 such as

- Purchase Interest Rate with 2 levels (2.5%, 3.0%)
- Late Fees/ Renewal Fees with 2 levels (Rs.300/-, Rs. 600/-)
- Grace Period Days with 2 levels (48 days, 50 days)

Table 3: Response against Credit Card Offers across DSAs (2 x2 x 2)

Run	Purchase Interest Rate (%)	Late Fees (Rs	Grace Period (Days)	Response Rate (%)

1	2.5	300	48	1.00%
2	3.0	600	50	1.00%
3	2.5	300	48	0.45%
4	3.0	600	50	0.5%
5	2.5	300	48	0.90%
6	3.0	600	50	0.90%
7	2.5	300	48	0.55%
8	3.0	600	50	0.6%

Source: Test data on DSAs on Credit Cards on Indian Banks (2009)

The total number of DSAs from where the Bank has collected the response information is 4. Table 5 summarises the meaning of the factors of the credit card. There exists 8 runs and the customers are randomly offered all combinations by the 4 DSAs. The acceptance column provides the number of customer who have accepted the offer.

Table 4: Summarizing the Explanation of 3 factors in 2 x 2 x 2 Design

Main Effects	Description of the Effect
Purchase Interest Rate	Comparison of the Marginal Response Rate against Purchase Interest rate, averaging over the levels of Late Fees and Grace period
Late Fees	Comparison of the Marginal Response Rate against Late Fees , averaging over the levels of Purchase Interest Rate and Grace Period
Grace period	Comparison of the Marginal Response Rate against Grace Period, averaging over the levels of Purchase Interest Rate and Late Fees.

Source: Hand Book of Statistics (www.itl.nist.gov)

Therefore, a simple (2 x 2 x 2) design gives the unique benefit of conducting an experiment to understand the preference of customers willing to buy the credit cards. The specific questions which are examined include; the incremental lift of purchase APR 2%

over 2.5%, the incremental lift of Rs. 600/- late fees over Rs. 300/-, is the comparision between a grace period of 48 days vs a grace period of 50 days,etc? Hence the test layout intends to obtain the maximum information about the sensitivities of the offer attributes from the minimum offer combinations. We analyse these models using the Main Effects alone, ignoring the presence of any interactions for simplification in understanding in the next section.

OBSERVATIONS

In practice there exist two methods of analysing the test layout, namely, the logistic regression method and the ANOVA method. The logistic regression method could used when the sample size is larger. The ANOVA method is used here since it is simpler to understand and can be used in smaller samples. The results of the analysis on the response level test data for both the home loan and credit cards are interesting to note. One needs to use his marketing experience to interpret the results, then the statistical output should be implemented with care. We describe the results of the analysis of our test data in Chart 1 & Chart 2 for the first analysis on Home Loan and Chart 3 & Chart 4 for the second analysis on Credit Cards. The first analysis on home loan offers response provides critical insights into the value of home loan products. The analysis on home loan response level captures factors such as Fixed rate and floating rate as the most significant attributes of this model. A customer prefer floating rate over Fixed rate and so does lower price points over a higher price points. We also find that processing fees is insignificant here which could be because of a sample issue. The charts display an incremental lift of 24% over a 200 basis point drop in the fixed rate. Further, it shows a lift of 30% over a 100 basis points drop in the floating rate. The next analysis on the response level against the attributes of credit cards throws significant marketing insights. Both the APR and late fees amount are significant as both purchase APR and late fees jointly determine the decision to accept a credit card offer. A 50 basis point increase in APR results in a drop in the response rate over 26% and similarly a Rs. 300 increase in late fees results in the drop in response rate by 19%. As mentioned earlier, both the models depict stronger value statements on the incremental benefits in response rates by reading only the data from 8 test cells, which are very easy to collect and compile by a Bank. The quantum of incremental lifts for a given 100 basis points rise or fall in the price point is important information to the marketer. Therefore, these results have significant implications in understanding the preference of a bank's customers. This would mean the Bank has an opportunity adjust the design of their home loan offer to shift the response design of their home loan offer to raise the response of their offers. A financial analysis of the net income impact due to unit drop in price points is critical to decide on the offer levels, which has not been discussed here on account of data limitations. Financials would include historical data on cost of funds, segment riskiness, net cash flows over time, etc. A lower price point could hit the bottom line of the Bank since the increase in business income due to the increased number of converted accounts, say at a rate (below 8.25%) of 7.25% would not justify the reduced interest income. However there exists a benefit of lowered Net Credit Losses at floating 7.25% vs floating 8.25% (or higher). In the second analysis, it is easier to attract credit card customers at lower APR say (purchase APR below 2%) at 1.75%. However, similar to the above argument the increased number of credit card accounts may not set forth the reduction in interest income even if it is true that lower APR means lower Net Credit Losses. Therefore, these conclusions are not easy to make and these results needs to be substantiated with richer financials to be able to take a comprehensive decision. A critical discussion on these specific findings on incremental lifts in response rates against a product attribute level changes is necessary to be able to obtain innovations in product offers. Implementation of our model could result in forecast response rates which are critical to the design of offers. For example, a 200 basis point drop in Fixed rate results in a lift of 24% over response rate, this means a 100 basis point drop could cause an interpolated lift of 12 % in response rate and so on. This means the bank need not test for a fixed rate home loan offer of 13%. Similarly, a 50 basis point rise in purchase APR causes a drop of 26% in response rate, this means a 100 basis points rise in purchase APR could be extrapolated to drop on 52% in response rate and so on. The bank obtains these insights without necessarily testing for a 3.5% purchase APR offer and interpolating the forecast. All of these discussions point to the fact that there exists opportunity of cost savings using experimental design approach. Many a times bank's marketing team assumes that a particular product attribute such as renewal fees or processing fees are important for a product. However, such analysis will help the Bank understand the fact that the critical and important attributes are pricing and late fees compared to others factors.

Chart 1: ANOVA of Response rate on Home Loans

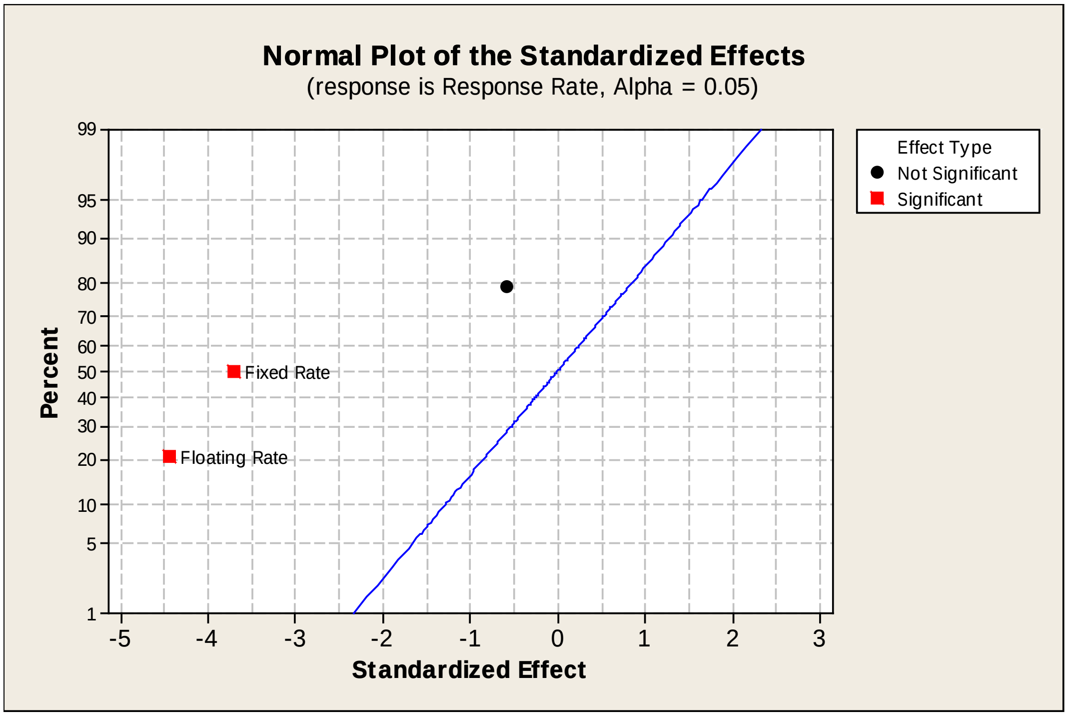


Chart 2: Effects Plot for ANOVA

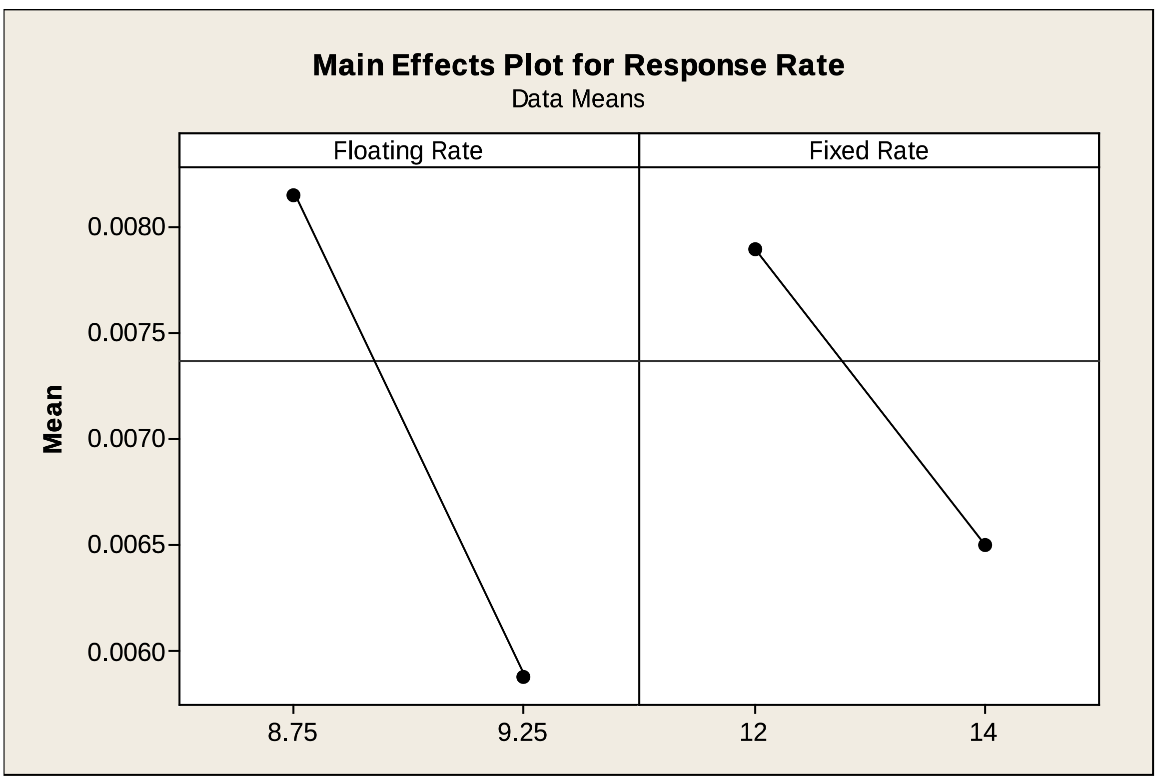


Chart 3: ANOVA of Credit Card Response Rate

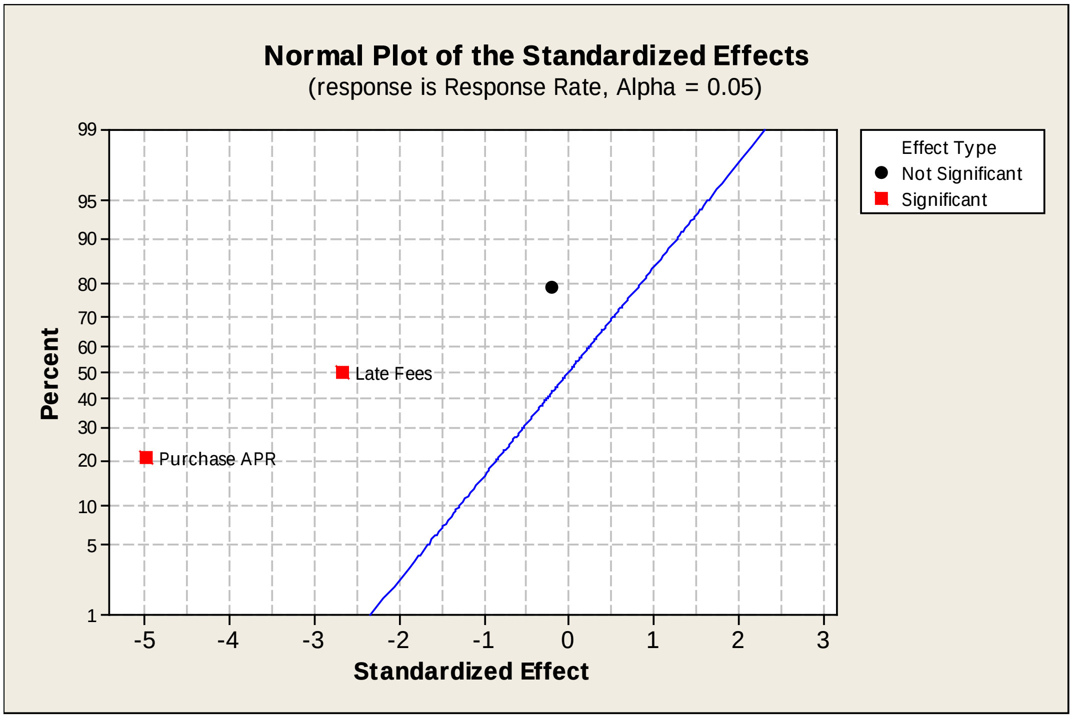
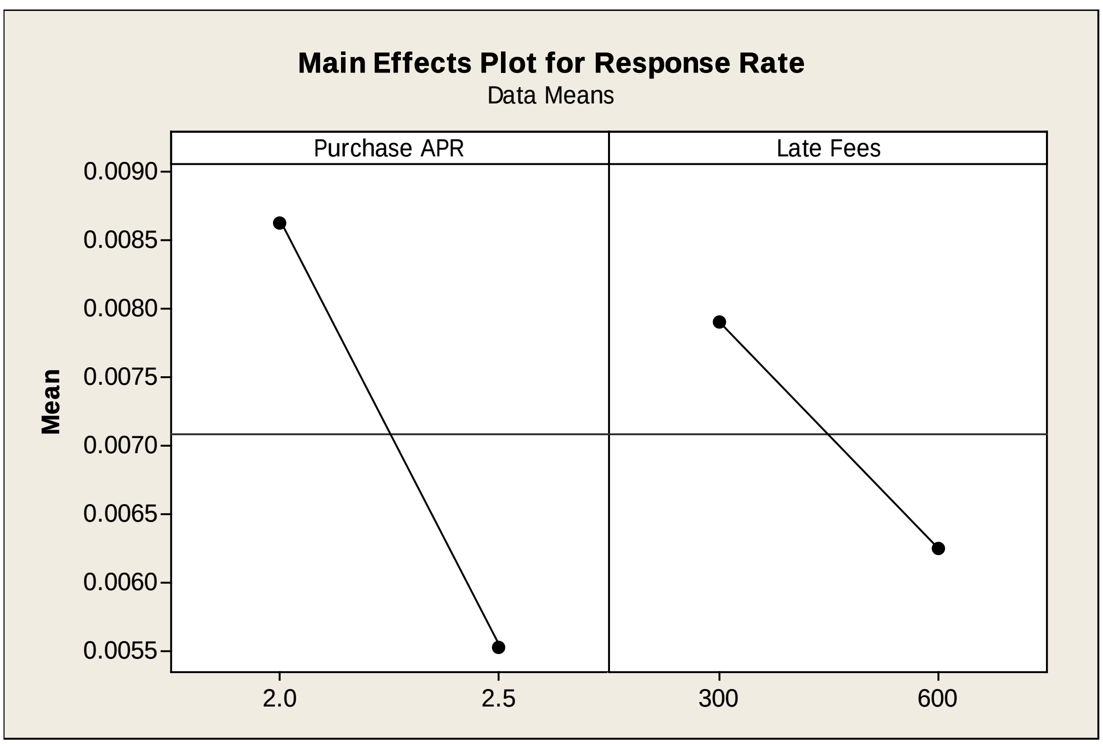


Chart 4: Effects Plot for ANOVA



CONCLUSIONS

We presented a simple and easily implementable product testing model using experimental methods. These results can have critical business implications. Experimental design, which quantifies the effects of independent stimuli on behavioral responses, can help marketing analyse how the various attributes of a product marketing campaign influence consumer behavior. The bank finally has an objective and informed decision making process to devising customer value proposition. The bank has the flexibility to compare the expected customer preferences across various product offers, which actually leads to a value statement. Therefore, such approach is much more precise and cost effective than traditional market testing. The specific findings of these experiments led to immediate and substantial improvements, increased response rates, lower costs, and may be higher profits. When the Bank knows how customers will respond to what you have to offer, it can target marketing programs directly to their needs and boost the bottom line in the process. Therefore experimental design can go a long way to identify, develop and manage industry leading products, propositions to enable Banks to further penetrate the consumer markets. With the advent of information technology, test and learn framework is easy to adopt and implement in a bank. To a bank's marketer, there always exist very limited opportunity to choose and pick across a variety of offers while targeting. Thus the method to test more offers around competition and build efficient tools to identify and match customer needs better. All of this can actually go a long way in building a better product for the Bank. We learnt that the experimental design is particularly helpful in product markets where large number of customers and that face rapid and constant change in their markets, such as retail banking markets. Banks spend enormous amount on attracting the customer and then converting them. Getting the right first time is difficult and therefore experimentation is critical. The adoption of such models by marketing teams across foreign bank, private banks and public sector banks have been mixed. Wider adoption of this new marketing science will take more time. To be specific, public sector banks and Indian private sector banks are lagging behind the foreign banks who have implemented these best practices from their central offices abroad. The questions around implementation of this model could happen in a series of steps such as, planning a series of tests so as to build upon the results from each test, testing many combinations around price points or channels or around the lead offer in the market, and finally not repeating past mistakes.

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