

### **Assessing RFM at Tuscan Lifestyles**

Joan Beckman is increasingly confident that careful analysis of the *Tuscan Lifestyles* customer database will lead to more efficient and effective marketing decisions. As director of marketing for the upscale specialty catalog specializing in cookware, tableware, linens, and decorative home accessories in the spirit of the Tuscany region of Italy, Joan has been pursuing several initiatives in database marketing and customer relationship management.

*Tuscan Lifestyles* is proud of its track record in identifying prospects that become customers. Their historical response rate for direct mail to prospect lists is 2.3% – far above the industry average. However, Joan is convinced that there are opportunities to increase the effectiveness of subsequent catalog mailings. *Tuscan Lifestyles* typically mails catalogs eight times a year to their full customer list. Yet, as their customer list grows Joan wonders if it may be more effective to develop a portfolio of catalogs – and, through market tests, identify which subset of the full customer list to target.

Database marketers have a long history of success with using RFM (for Recency – Frequency – Monetary) analysis to target customers. The fundamental premise underlying RFM analysis is that customers who have purchased recently, have made more purchases and have made larger purchases are more likely to respond to your offering than other customers who have purchased less recently, less often and in smaller amounts. RFM analysis can also be used to target special offers to ‘welcome’ new customers, encourage small purchasers to spend more, to reactivate lapsed customers, or encourage other marketing initiatives.

#### **Decile Analysis**

Although there are several variations of RFM segmentation, they all begin by classifying customers based on the recency of their last purchase, the frequency of their purchases, and the amount spent. The typical first step is to conduct some decile analysis. Decile analysis classifies customers into deciles for each variable – recency, frequency and monetary. For example, for recency, the customer list is sorted in order – from the most recent purchasers to the least recent, then divided into ten equal (or nearly equal) groups. The 10% who comprise the most recent purchasers are grouped into one decile, the 10% who are the next most recent into the second decile, and so on. There is no uniform convention for the coding or labeling of deciles – the top or best decile can be labeled 1 or 10. Regardless of whether 1 or 10

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*Professor Charlotte Mason prepared this case to provide material for class discussion rather than to illustrate either effective or ineffective handling of a business situation. Names and data may have been disguised to assure confidentiality. The assistance of the Direct Marketing Educational Foundation in supplying the data used for this case is gratefully acknowledged.*

designates the best decile, the same convention should be used for all decile variables. That is, if the most recent customers are in recency decile 1, then frequency decile 1 should contain the most frequent customers, and monetary decile 1 the largest spenders.

Once customers are coded into deciles, the response rates, purchase amounts or other relevant variables can be compared across the 10 deciles. If recency is indicative of response to a marketing campaign, then the most recent decile will have a higher response rate than the deciles of less recent customers. The same analysis is repeated for frequency and monetary.

### **RFM Classification**

In combination, there would be 1000 (10 x 10 x 10) combinations for the recency, frequency and monetary deciles – ranging from customers who rank in the top decile for all three variables to those in the lowest decile for all three and all possibilities in between. To reduce the number of combinations it is typical to consider quintiles – or five groups – rather than deciles when looking at combinations of RFM. Thus, there are 125 (5 x 5 x 5) possible RFM groups or segments.

There are at least three variations of how RFM segments are determined:

- 'Independent n-tiles' Approach

This approach computes quintiles independently for recency, frequency and monetary. That is, the entire customer list is sorted based on recency and divided into recency quintiles. Then, the entire customer list is resorted based on frequency and divided into frequency quintiles. Finally, the entire customer list is sorted one more time based on monetary and divided into monetary quintiles. Then these three quintile variables are combined to form the RFM index. For example, a customer in the 1<sup>st</sup> recency quintile, 2<sup>nd</sup> frequency quintile and 4<sup>th</sup> monetary quintile – is assigned an RFM index of 124.

This approach typically yields unequal numbers of customers across the 125 combinations. For example, some combinations – such as customers who are very recent, very frequent, yet very low on monetary – are less common than others.

- 'Sequential n-tiles' Approach

This approach computes quintiles first for recency. Then, *within* each of the five quintiles for recency, quintiles for frequency are computed – resulting in a total of 25 recency/frequency combinations. Finally, *within* each of these 25 groups, quintiles for monetary are computed. This method produces approximately equal numbers of customers for each of the 125 RFM cells which is useful for running market tests since it is problematic to compare response rates across groups with widely varying numbers of customers – especially if some groups have very few (say only 5 or 10) customers.

Note, however, that with this approach it is not possible to say in an absolute sense whether a '221' customer or a '411' customer has made more purchases. This is because the frequency quintiles are created *within* each recency group – as an analogy, consider sorting consumers into quintiles based on salary *separately* for males and females. A male in the second salary quintile may have a higher salary (in absolute terms) than a female in the top salary quintile. Similarly a customer in the 2<sup>nd</sup> recency and 2<sup>nd</sup> frequency quintile may have made more purchases than a customer in the 4<sup>th</sup> recency but 1<sup>st</sup> frequency quintile.

- ‘Intuitive Groupings’ Approach

This approach uses intuitive splits rather than quintiles to form the groups. For example, customers may be grouped into recency groups determined by: (1) purchase in last 6 months, (2) last purchase 6-12 months ago, (3) last purchase 12-24 months ago, (4) last purchase 24-36 months ago, and (5) last purchase more than 36 months ago. This approach is ‘intuitive’ in that it is easy to know what is meant by a customer in the second recency group, but relies on judgment to know where to ‘draw the lines.’

**Testing RFM at Tuscan Lifestyles**

Following is an outline of what Joan proposes for using RFM analysis for targeting mailings to current *Tuscan Lifestyles* customers:

1. Compile the catalog offering.
2. Select a random sample from the full customer database and mail the catalog.
3. Track the response (% who respond, \$ orders) by RFM classification or ‘cell.’
4. Assess response across recency, frequency and monetary deciles and RFM cell.
5. Use results of the test mailing to determine which customers from the remaining customer list (i.e. those not in the test) to mail.

To test the RFM approach for targeting mailings, Joan had a research analyst compile data from a random sample of 96,551 customers who received this recent mailing. Exhibits 1 and 2 show that 2.5% of customers of customers responded to this mailing, ordering an average amount of \$104.24.

**Exhibit 1:** Percent who ordered from last catalog

**Bought from last catalog?**

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid no	94180	97.5	97.5	97.5
yes	2371	2.5	2.5	100.0
Total	96551	100.0	100.0	

**Exhibit 2:** Average Order Size

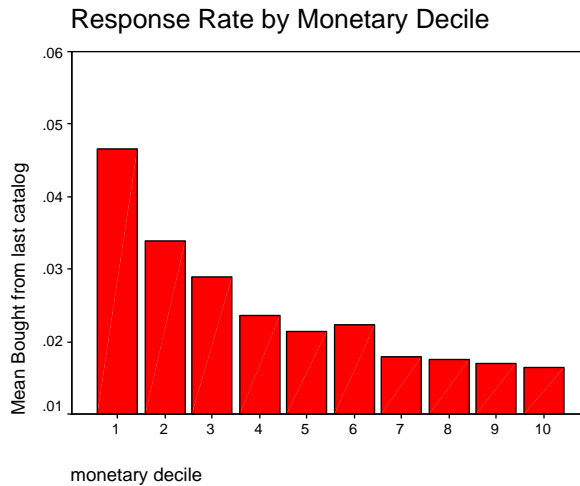
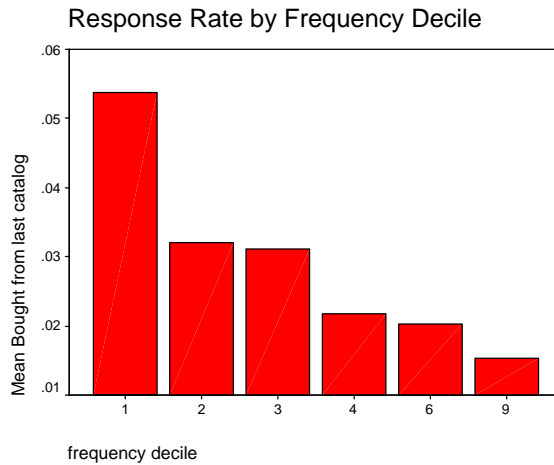
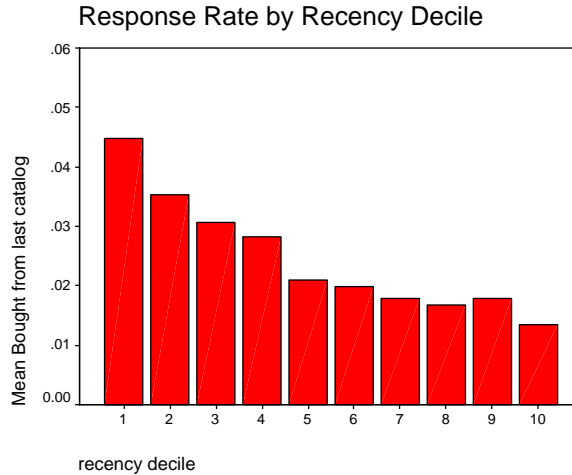
Dollars ordered from last catalog

Bought from last catalog?	N	Mean	Minimum	Maximum
no	94180	.00	0	0
yes	2371	104.24	5	6249
Total	96551	2.56	0	6249

Exhibit 3 charts response rate (% who ordered anything) by recency, frequency and monetary deciles. The charts show that more recent, more frequent and higher spending customers had higher response rates to this mailing with the greatest variation in response rate across the different frequency groups. Among those who responded, Exhibit 4 charts the average \$ order amount by recency, frequency and monetary deciles. Among the customers who placed orders, there was relatively little variation in the average \$ order amount across recency and frequency deciles. Across the monetary deciles, the top decile’s average \$ order amount was noticeably

higher. Overall recency, frequency and monetary are most helpful for predicting the likelihood of response, but are of limited value for predicting the magnitude of response among those who do buy.

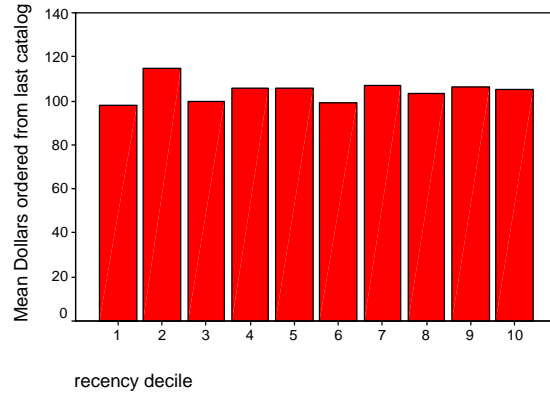
**Exhibit 3:** Bar Charts of Response Rate by Recency, Frequency and Monetary Decile



**Exhibit 4: Bar Charts of Average \$ Order by Recency, Frequency and Monetary Decile**

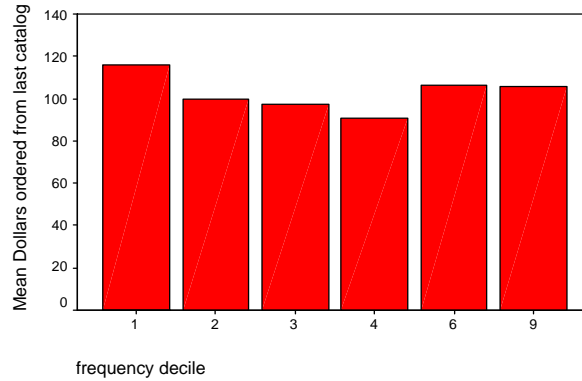
Average \$ Order Amount by Recency Decil

(across customers who placed orders)



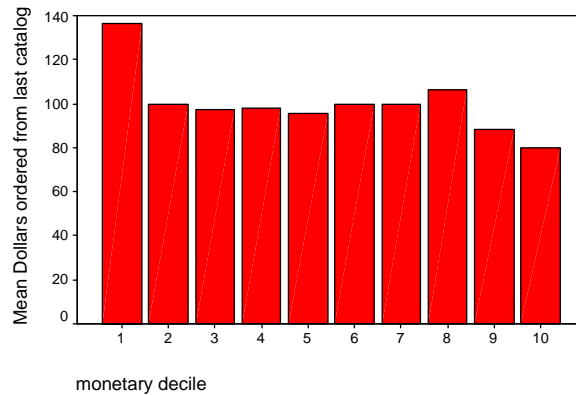
Average \$ Order Amount by Frequency Decile

(across customers who placed orders)



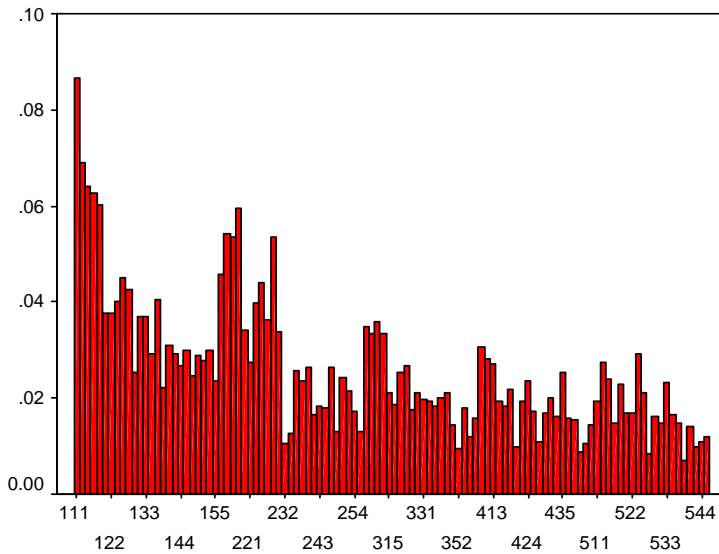
Average \$ Order Amount by Monetary Decile

(across customers who placed orders)



The RFM values using the sequential approach were computed for each customer in the dataset. For the RFM classification, again a '1' reflects the 'best' customers and a '5' the 'worst'. Exhibit 5 plots the average response rate by RFM cell. As expected there is a great deal of variation across RFM cell – indicating that this approach can be helpful in identifying which customers to target (i.e. those in cells with a higher response rate).

**Exhibit 5:** Response Rate by Sequential RFM Cell



Joan has asked you to compute the lifts, gains and profits to be expected as a result of this RFM approach. Exhibit 6 contains an excerpt of an Excel file that contains the number of customers and the number of buyers for each RFM cell from this test mailing to 96,551 customers. For example, there were 796 customers classified into the '111' cell (1's are most recent, frequent and highest in monetary) and 69 of them placed an order from the catalog. A full listing of the file is included in the Appendix and can be found in the file *gains and lifts.xls*.

**Exhibit 6:** Excerpt from Excel file with Number of Customers and Buyers per RFM cell

RFM	# customers	# Buyers
111	796	69
112	796	55
113	798	51
114	796	50
115	796	48
121	798	30
122	795	30
123	796	32
124	797	36
125	799	34
131	786	20
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Use the information in the spreadsheet (*lifts and gains.xls*) to complete the following analyses:

1. Create a cumulative lift chart plotting cumulative lift versus % of customers mailed for the RFM segmentation model approach. To do this you will need to compute the response rate, lift and cumulative lift for each RFM cell – then plot vs. cumulative % of customers using a scatterplot.

Hint #1: Once you have computed the response rate – you should sort by response rate (descending). This will put the RFM cells with the highest response rate at the top. Then go ahead and compute lift and cumulative lift for each cell – and then chart cumulative lift.

2. Create a cumulative gains chart plotting cumulative gains versus % of customers mailed for the RFM segmentation model approach. Similar to (1) above, you will need to compute the gains and cumulative gains for each RFM cell (sorted in order of decreasing response rate) – and then plot vs. cumulative % of customers.
3. Create a chart that plots total (i.e. cumulative) gross profit on the y-axis vs. % of customers targeted on the x-axis. Assume that the most profitable RFM cells (i.e. those with the highest response rate) are targeted first – working down the list to the lowest response rate. Note that you would expect gross profit to continue to increase as long as profitable RFM cells are included in the mailing. Then, however, gross profits will peak and decline as unprofitable RFM cells are included in the mailing (in other words, your cumulative gross profit chart should look like an inverted-U)

To determine gross profit, use the following numbers:

Cost to produce and mail a catalog = \$1

COGS and variable costs on orders = 50% (of sales revenues)

Average order (of those who order) = \$104.24

4. What is the breakeven response rate?
5. What would the profit from this mailing have been if only the profitable RFM cells had been targeted? How does this compare with the actual profit as a result of mailing to all 96,551 customers?

**Appendix**  
**Listing of spreadsheet**  
**(gains and lifts.xls)**

<b>RFM</b>	<b># customers</b>	<b># Buyers</b>
111	796	69
112	796	55
113	798	51
114	796	50
115	796	48
121	798	30
122	795	30
123	796	32
124	797	36
125	799	34
131	786	20
132	788	29
133	781	29
134	784	23
135	789	32
141	634	14
142	615	19
143	653	19
144	633	17
145	634	19
151	806	20
152	934	27
153	751	21
154	937	28
155	808	19
211	789	36
212	792	43
213	787	42
214	790	47
215	789	27
221	724	20
222	731	29
223	725	32
224	715	26
225	729	39
231	471	16
232	475	5
233	471	6
234	468	12
235	468	11
241	719	19



242	720	12
243	716	13
244	724	13
245	722	19
251	1152	15
252	1114	27
253	1210	26
254	1159	20
255	1144	15
311	805	28
312	807	27
313	806	29
314	807	27
315	801	17
321	747	14
322	745	19
323	750	20
324	740	13
325	753	16
331	766	15
332	768	15
333	772	14
334	746	15
335	806	17
351	1522	22
352	1564	15
353	1678	30
354	1343	16
355	1564	25
411	885	27
412	886	25
413	885	24
414	883	17
415	882	16
421	412	9
422	413	4
423	412	8
424	425	10
425	407	7
431	826	9
432	836	14
433	794	16
434	857	14
435	833	21
441	1838	29
442	1884	29

443	1490	13
444	1903	20
445	1719	25
511	875	17
512	877	24
513	874	21
514	877	13
515	874	20
521	476	8
522	478	8
523	478	14
524	473	10
525	478	4
531	805	13
532	813	12
533	814	19
534	791	13
535	810	12
541	1672	12
542	1710	24
543	1599	16
544	1738	19
545	1675	20