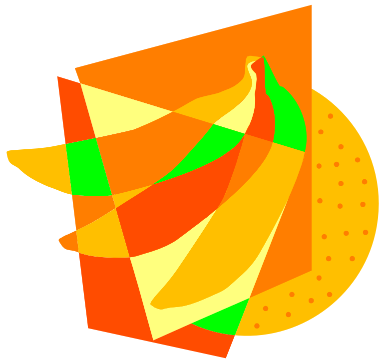
Kenan-Flagler Business School
The University of North Carolina



Assessing a Model's Performance: Lifts, Gains and Profits

Models are created to predict or classify – so one common way to assess a model's performance is to compare its performance to the results expected if no model was used. We can assess the value of a predictive model by using the model to rank or score a set of customers and then contacting or targeting them in that order.

Lifts and gains are commonly used performance measures. Lift indicates how much better a model performs than the 'no model' or average performance. For example, assume that BookBinders wanted to assess the effectiveness of targeting its customer list based on recency of last purchase. A sample of 50,000 customers is randomly selected from the customer list and mailed the offer. After all the orders have been received, the analysis begins. The 50,000 customers are divided into deciles with the most recent customers in decile 1 and the least recent customers in decile 10.

To show how lift is calculated, consider the results in Exhibit 1 that summarize the number of customers and number of buyers by recency decile for the BookBinders Book Club test involving the offer to purchase "The Art History of Florence." Exhibit 1 reports:

- Recency Decile: note there are nine rather than ten deciles as a result of large numbers of customers having the same value for months since last purchase close to the 'dividing line' between deciles

- # Customers: the number of customers in that decile

- # Buyers: the number of customers who bought "The Art History of Florence"

Professor Charlotte Mason prepared this note to provide material for class discussion rather than to illustrate either effective or ineffective handling of a business situation.

Exhibit 1 Recency Decile Summary

Recency Decile	# Customers	# Buyers
1 (top)	3748	670
2	7424	1058
3	3820	459
4	6254	638
5	6158	521
7	6229	474
8	6184	389
9	5346	203
10 (bottom)	4837	110
Total	50000	4522

Lift and Cumulative Lift

From these 'raw' numbers we can compute the following as shown in Exhibit 2:

- Cumulative # customers: the number of total customers up to and including that decile
- Cumulative % customers: the percent of total customers up to and including that decile
- Cumulative # Buyers: the number of buyers up to and including that decile
- Response Rate: the actual response rate for each decile, computed by the number of buyers divided by the number of customers for each decile
- Lift: (response rate for each decile) ÷ (overall response rate) ×100
- Cumulative Response Rate: cumulative # buyers ÷ cumulative # customers
- Cum(ulative) Lift: (cumulative response rate) ÷ (overall response rate) ×100

Exhibit 2 Lift Calculations

Decile	# Customers	Cumulative # customers	Cumulative % Customers	# Buyers	Cum # Buyers	Response Rate	Lift	Cum Response Rate	Cum Lift
1(top)	3748	3748	7.5%	670	670	17.88%	198	17.88%	198
2	7424	11172	22.3%	1058	1728	14.25%	158	15.47%	171
3	3820	14992	30.0%	459	2187	12.02%	133	14.59%	161
4	6254	21246	42.5%	638	2825	10.20%	113	13.30%	147
5	6158	27404	54.8%	521	3346	8.46%	94	12.21%	135
7	6229	33633	67.3%	474	3820	7.61%	84	11.36%	126
8	6184	39817	79.6%	389	4209	6.29%	70	10.57%	117
9	5346	45163	90.3%	203	4412	3.80%	42	9.77%	108
10	4837	50000	100.0%	110	4522	2.27%	25	9.04%	100
Total	50000	100%		4522		9.04%			

For example, below are the calculations leading to the numbers for decile 2:

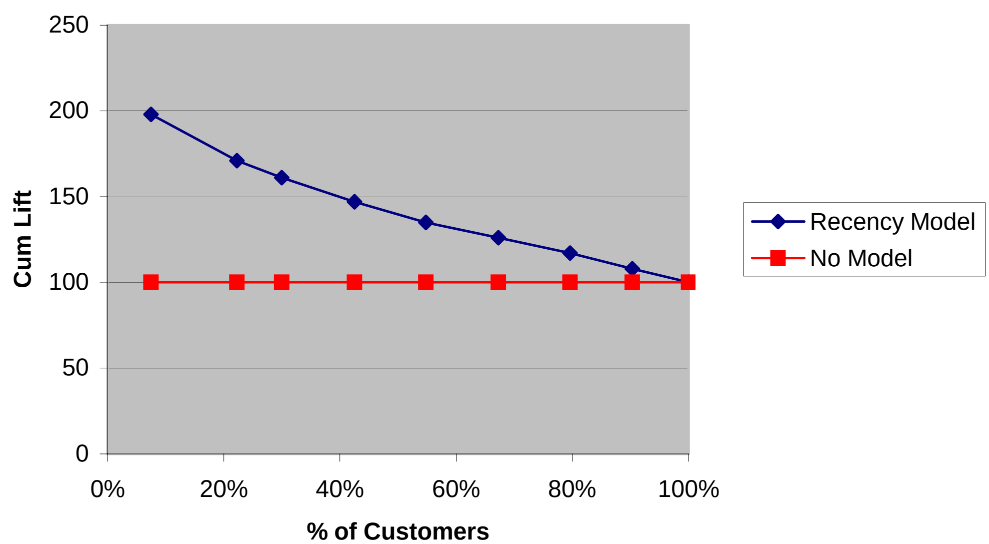
- Cumulative # customers = 3748 + 7424 = 11172
- Cumulative % customers = 11172/50000 = 0.223, or 22.3%.
- Cumulative # buyers = 670 + 1058 = 1728
- Response rate = 1058/7424 = 0.1424, or 14.24%
- Lift = 14.25/9.04*100 = 158
- Cumulative response rate = 1728/11172= 0.1547, or 15.47%
- Cumulative lift = 15.47/9.04*100 = 171

Lift is an index that indicates the model's ability to beat the 'no model' case or average performance. For example, from Exhibit 2 we see that the lift for the top decile is 198. This indicates that by targeting only these customers we would expect to yield 1.98 times the number of buyers found by randomly mailing the same number of customers. In contrast, the last decile (decile 10) has only one-quarter (.25 times) the number of buyers as one would expect in a random sample of the same size.

From the cumulative lift column we see that by targeting the top two deciles, we would expect to yield 1.71 times the number of buyers as compared with a random mailing. As a larger percent of the customers are included, cumulative lift will decrease – reaching 100 (or average response) when 100% of customers are included.

Lift indices that exceed 100 indicate better than average performance or response, whereas lift indices less than 100 indicate poorer than average performance or response. Note that lift is a relative index – a lift of 400 could refer to a predicted 8% response rate or a predicted 80% response rate – depending on whether the overall or average response rate is 2% or 20%. A chart depicting the cumulative lift is shown in Exhibit 3.

Exhibit 3 Cumulative Lift Chart : Recency Deciles



Note: Most standard spreadsheet or statistical programs contain options to create line charts and also scatter plots. Though the results may look similar, there is a key difference between these two. A scatter plot is appropriate for plotting two metric variables (such as sales and profits). A line chart is used to plot one metric variable (say, sales) against a categorical variable (say, month). With a line chart, the values for the categorical variable are equally spaced along the horizontal axis. With a scatter plot, the values for the horizontal axis variable are scaled by their value. So, if you use a line chart with a two metric variables, the values for the x-axis variable will be equally spaced regardless of their actual value. For lift (cumulative lift on the y-axis versus cumulative % of customers on the x-axis) and gains (cumulative gains on the y-axis versus cumulative % of customers on the x-axis) charts, a scatter plot is the appropriate choice.

Gains and Cumulative Gains

A different way to summarize a model's performance is with *gains* and *cumulative gains.* Again, we begin with the raw numbers in Exhibit 1 and create the following shown in Exhibit 4:

- Gains: the proportion of responders in each decile
- Cum(ulative) Gains: the proportion of responders up to and including the decile, or simply the sum of the gains up to that decile.

Exhibit 4 Gains and Cumulative Gains

Decile	# Customers	Cumulative # customers	Cumulative % Customers	# Buyers	Cum # Buyers	Gains	Cum Gains
1(top)	3748	3748	7.5%	670	670	15%	15%
2	7424	11172	22.3%	1058	1728	23%	38%
3	3820	14992	30.0%	459	2187	10%	48%
4	6254	21246	42.5%	638	2825	14%	62%
5	6158	27404	54.8%	521	3346	12%	74%
7	6229	33633	67.3%	474	3820	10%	84%
8	6184	39817	79.6%	389	4209	9%	93%
9	5346	45163	90.3%	203	4412	4%	98%
10	4837	50000	100.0%	110	4522	2%	100%
Total	50000	100%		4522			

For example, below are the calculations leading to the numbers for decile 2:

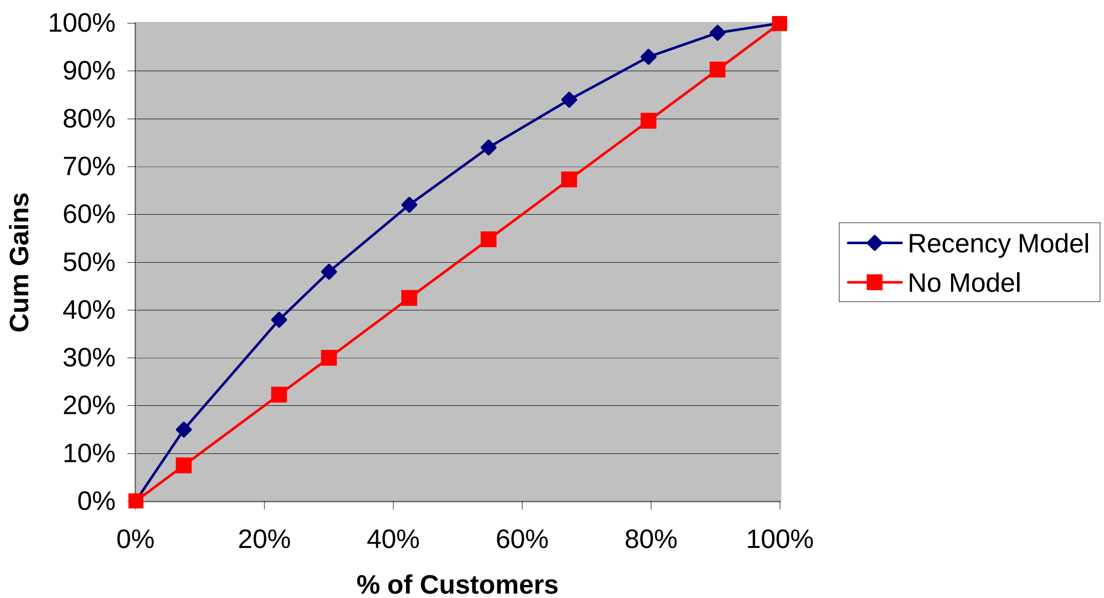
- Gains = 1058/4522 = 0.23, or 23%
- Cum(ulative) gains = 1728/4522 = 0.38, or 38%

The cumulative gains chart in Exhibit 5 is a useful visual representation for comparing a model to the 'no model' case or average performance. All models start at the 0-0 point – if 0% of the customers are mailed or targeted, then we will yield 0% of buyers. Similarly, all models end at the 100-100 point – if 100% of the customers are targeted then we will yield 100% of buyers.

The diagonal line represents the no model or baseline case – for example, if we randomly select 10% to mail or target, then we would expect to get 10% of the buyers. Similarly, if we randomly select 50% to target, then we would expect to get 50% of the buyers, and so on. The cumulative gains for the model reveal what proportion of responders we can expect to gain from targeting a specific percent of customers using the model. For example, results of using a recency model to target customers for “The Art History of Florence” show that by targeting the 7.5% most recent customers, we would gain 15% of total buyers. By targeting the top 22.3% most recent customers, we would gain 38% of customers.

Cumulative gains charts are sometimes known as ‘banana’ charts because of their banana-like shape. The larger the distance between the model and no model lines (i.e., the fatter the banana), the stronger or more powerful the model is.

Exhibit 5 Cumulative Gains Chart: Recency Deciles

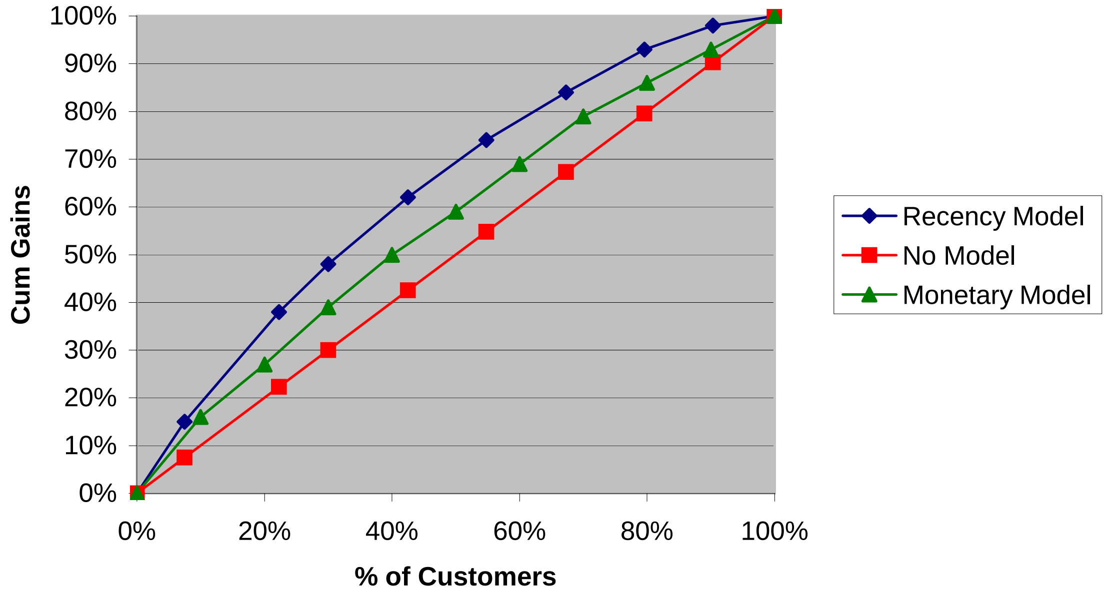


Comparing Models

Lifts and gains can also be used to compare two or more alternative models, to track a model’s performance over time, or to compare a model’s performance on different samples. A cumulative gains chart comparing the recency model to a model using monetary value for the BookBinders Book Club “The Art History of Florence” mailing is shown in Exhibit 6.

Clearly, the recency model is a more powerful predictor of response compared with the monetary model.

Exhibit 6 Cumulative Gains for Recency and Monetary Decile Models



Lifts and Gains for BookBinders RFM test

So far we have computed lifts and gains using deciles. However, when using RFM to target customers, we have many more groups than 10 – as many as 125 if using quintiles for each of the recency, frequency and monetary variables. The calculations are exactly as before – except they are done by RFM index or group rather than by decile. Excerpts of the computations are shown below:

RFM	# buyers	# cust	Response Rate	cumulative # customers	cumulative % customers	cum. # buyers	Lift	Cum Lift	Gains	Cum gains
111	109	450	0.24	450	0.90%	109	268	268	2.41%	2.41%
114	107	451	0.24	901	1.80%	216	262	265	2.37%	4.78%
113	103	454	0.23	1355	2.71%	319	251	260	2.28%	7.05%
112	102	452	0.23	1807	3.61%	421	250	258	2.26%	9.31%
211	83	395	0.21	2202	4.40%	504	232	253	1.84%	11.15%
214	82	396	0.21	2598	5.20%	586	229	249	1.81%	12.96%
115	91	455	0.20	3053	6.11%	677	221	245	2.01%	14.97%
212	75	388	0.19	3441	6.88%	752	214	242	1.66%	16.63%
213	75	388	0.19	3829	7.66%	827	214	239	1.66%	18.29%
124	84	437	0.19	4266	8.53%	911	213	236	1.86%	20.15%
…	…	…	…	…	…	…	…	…	…	…
555	9	605	0.01	48793	97.59%	4508	16	102	0.20%	99.69%
535	9	611	0.01	49404	98.81%	4517	16	101	0.20%	99.89%
554	5	596	0.01	50000	100.00%	4522	9	100	0.11%	100.00%

Note that table is sorted from highest to lowest response rate – and not by numerical order of the RFM cells. After all, one cannot say, in general, whether a 114 is better or worse than a 211. When using RFM indices for testing a marketing campaign, what matters is the response rate of each group. For some campaigns less recent or smaller spenders may have a higher response rate than more recent or bigger spenders – and for other campaigns the reverse may be true. Exhibits 7 and 8 chart the cumulative lifts and gains, respectively, for the RFM model.

Exhibit 7 Cumulative Lift by RFM Indices

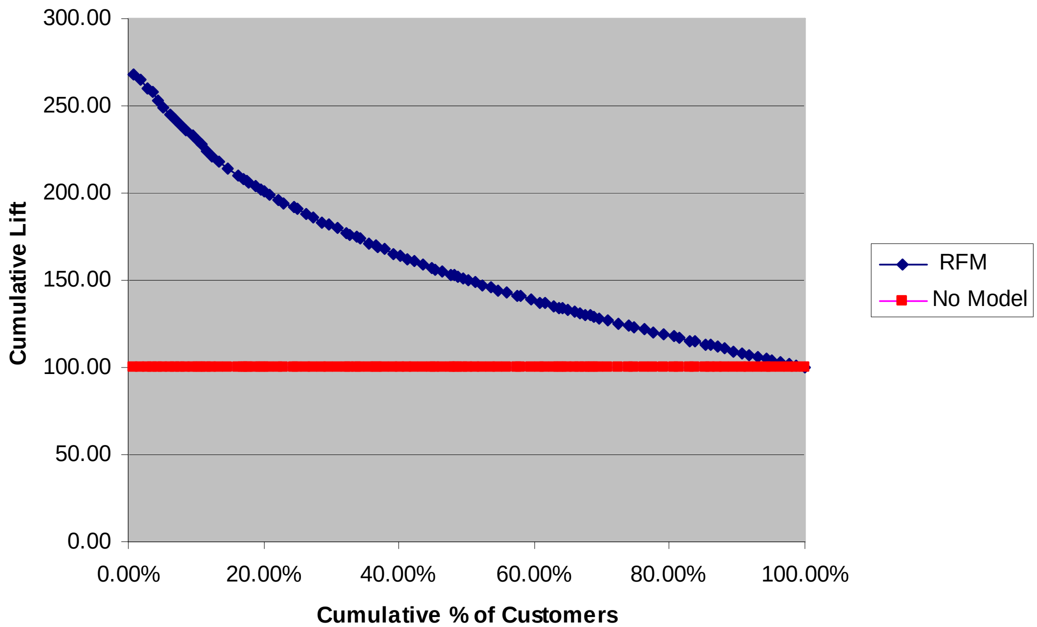
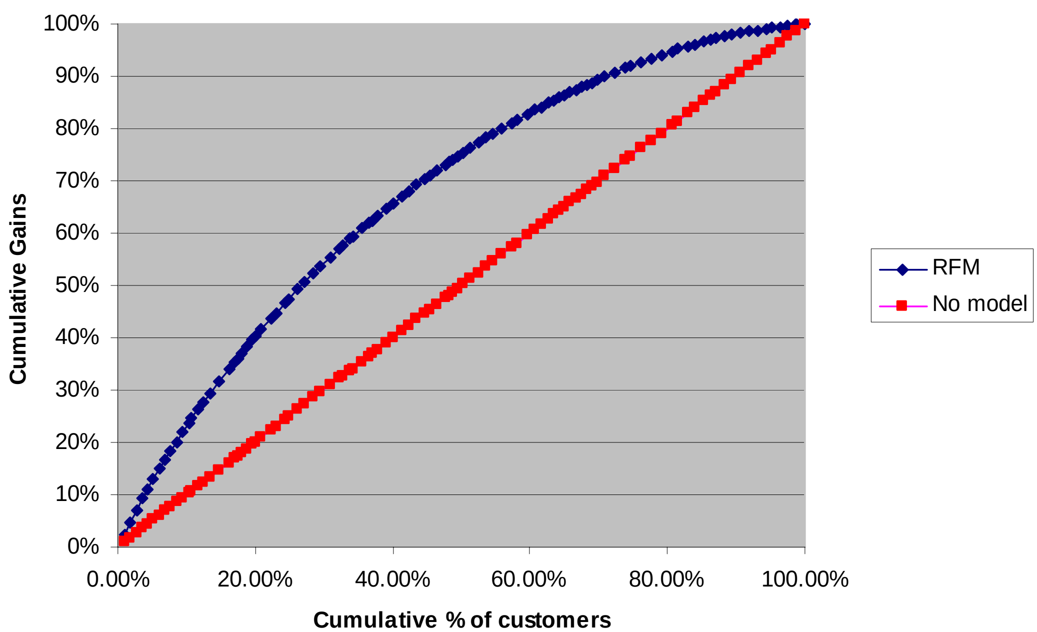


Exhibit 8 Cumulative Gains by RFM Indices



Profits

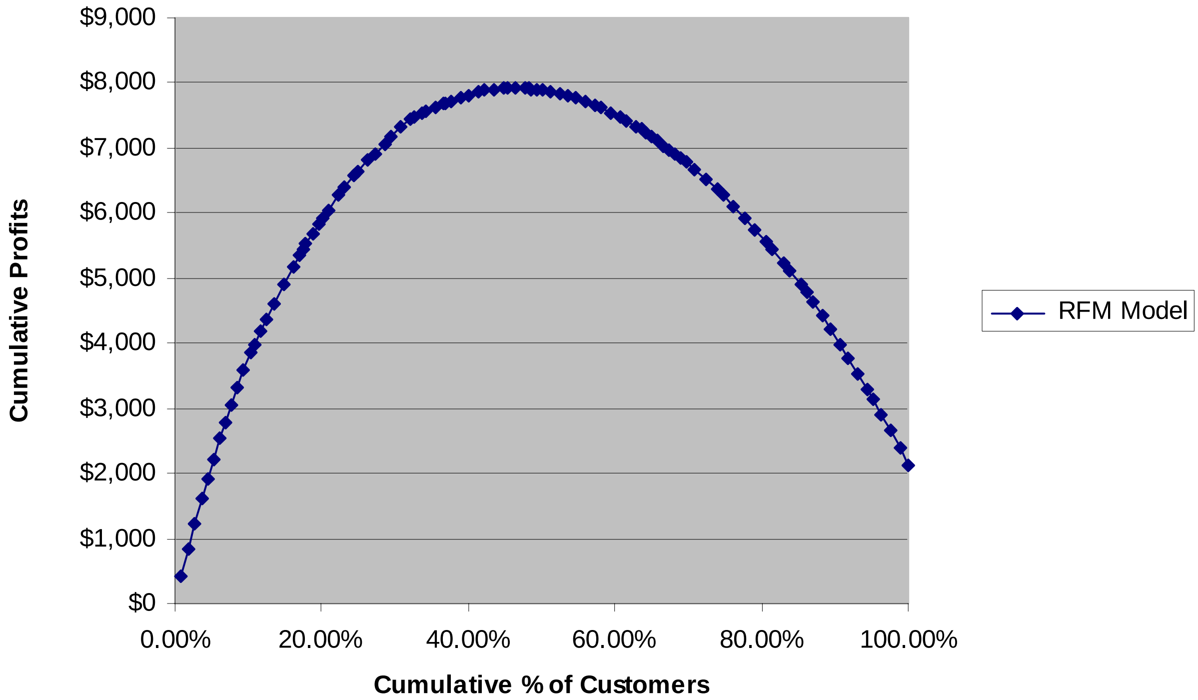
Using the number of customers and buyers in each RFM cell, it is straightforward to compute profits and cumulative profits for each group. Using the following information

Cost of Mailing the Offer	$0.50
Selling price (including shipping) paid by customer	$18.00
Wholesale price paid by BookBinders	$9.00
Shipping costs	$3.00

we compute the profits as ($18 - $9 - $3) times the number of buyers minus $0.50 times the number of customers in each cell. Excerpts of the computations are shown below. Note that profits are positive and cumulative profits increase as long as the response rate exceeds the breakeven response rate (8.33% in this instance). Once RFM cells with response rates lower than the breakeven are included, cumulative profits drop. Exhibit 9 charts cumulative profits for the RFM model.

RFM Index	# buyers	# customers	Response Rate	Profits	Cum Profits
111	109	450	24.22%	$429	$429
114	107	451	23.73%	$417	$846
113	103	454	22.69%	$391	$1,237
112	102	452	22.57%	$386	$1,623
211	83	395	21.01%	$301	$1,923
214	82	396	20.71%	$294	$2,217
115	91	455	20.00%	$319	$2,536
…	…	…	…	..	
235	54	607	8.90%	$21	$7,901
232	52	601	8.65%	$12	$7,913
331	32	372	8.60%	$6	$7,919
425	42	508	8.27%	-$2	$7,917
252	50	607	8.24%	-$4	$7,913
323	19	236	8.05%	-$4	$7,909
325	19	238	7.98%	-$5	$7,904
			…		
553	11	608	1.81%	-$238	$2,900
555	9	605	1.49%	-$249	$2,652
535	9	611	1.47%	-$252	$2,400
554	5	596	0.84%	-$268	$2,132

Exhibit 9 Cumulative Profits for the RFM Model



Summary

In summary, lift is a relative measure of the effectiveness of a predictive model. It is computed as the ratio between the results obtained with the model to the results with no model. For a model predicting response, lift reveals how much more likely we are to get responders if we use the model than if we contact a random sample of customers.

For a model predicting response, gains show the percent of total possible responders gained by targeting a specific percent of the customers scored or ranked by a model. Cumulative lift and gains charts are useful visual tools for measuring and comparing a model's performance. Both charts include a baseline or no model case – the greater the difference between the lift or gains curve and the baseline, the better the model.