

Predicting Customer Value by Product: From RFM to RFM/P

Track: Marketing Management

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### **Abstract**

Recency, frequency, and monetary (RFM) models are widely used to estimate customer value. However, they are based on the customer perspective, not taking into account the product perspective. Furthermore, when recency, frequency, and monetary values vary among product categories, predictability becomes lower. A RFM by product (RFM/P) is proposed to first estimate customer values by product and then aggregate them to get the overall customer value. Empirical applications for a financial services company and a supermarket demonstrate that RFM/P prediction accuracy is similar or greater than traditional RFM. Additionally, RFM/P unleashes the possibility to combine customer and product perspectives.

### **1. Introduction**

The growing availability of customer transaction data has enabled marketing managers to better understand the firm customer base. Although the data collecting process has gone through a lot of improvements in the last years, data analysis remains a challenge for companies. Executives and academics are committed in building a data analytics orientation to be capable of connecting customer and competitor data to marketing strategy (Venkatesan, 2016). The process of analysis consists in extracting useful information from a huge amount of data, including unstructured data. In this sense, the first step would be to check if the data already available is well explored by the firm before spending efforts to collect even more data.

The advances in technology have driven other changes to marketing management, such as shifts in perspectives: from transaction to relationship with customers, from product-centric to customer-centric marketing strategies. This evolution has led to emergence of new marketing metrics: brand equity and customer equity (measured as a sum of customer lifetime values), since they are more appropriate for the contemporary marketing management orientation which is also concerned with the companies' intangibles assets and long term returns of investments. The adoption of these forward-looking metrics enables managers to compute more accurately the expected cash flow. In line with the product-centric perspective, brand equity is the net present value of a brand based on the future earnings resulting from the sales of the brand products; whereas, in line with the customer-centric perspective, customer lifetime value (CLV) is the net present value of a customer based on his/her future transactions with the company (Kumar & Reinartz, 2016).

Both perspectives could affect the firm's capacity to grow, although there is an overlap in some areas. Product-centric appears to enable companies to extend their product portfolio and acquire new customers in new markets and, on the other hand, customer-centric enables firms to retain and increase the earnings of current offerings from their customer

portfolio (Ambler et al., 2002). Hence, brand equity and customer equity (and CLV) are increasing their importance in academia and practice.

Marketing literature presents a diverse and rich variety of CLV models (Kumar & Reinartz, 2016; Zhang et al., 2015). Among these approaches, CLV models based on recency-frequency-monetary value (RFM) segmentation remain an important alternative, mostly because require few variables to predict customer value and they are easy to implement (Fader et al., 2009). Recently Zhang et al. (2015) proposed an extension to these CLV models based on RFM that includes a new variable called clumpiness that, in contexts suitable to the presence of excessive buying behaviors, improves prediction power when compared to traditional RFM estimation. Even though the extension proposed by Zhang et al. (2015) is valuable, it remains addressing only the customer perspective, a characteristic of traditional RFM models. It means that both RFM models and the extension of RFM model proposed by Zhang et al. (2015) do not take into account the product perspective for the estimation of customer value. Furthermore, given the existence of variability in recency, frequency, and monetary values among product categories, the prediction power of RFM models becomes lower.

Inspired by the challenge of solving such issues and of summarizing customer data into useful information for marketing managers, we propose a new approach to predict customer value based on RFM by product category, called RFM/P model. It consists in integrating two marketing perspectives: product and customer, combining them to provide a more complete overview of the firm future cash flow. In this model, first the customer values are estimated for each product (or product category) and then these estimations are aggregated to get the overall customer value. By using such model, there is no need to choose between product or customer perspective.

In the remaining of the paper, we first present the arguments supporting the combination of product and customer perspectives, followed by the specification of the proposed RFM/P model. The empirical validation of RFM/P was done in two companies from different industries: a financial services company and a supermarket. In the analysis we compare the proposed RFM/P with the traditional RFM model in terms of predictability of future customer value. Besides that, we also bring a novel analysis by combining product and customer perspectives that is made possible when RFM/P is implemented. Finally, the conclusion and suggestions for future research are presented.

## **2. Product and Customer Perspectives as Sources of Value**

In the last decades firms have become more customer-centric organizations, adding a customer perspective to the analysis of the company expected revenues, until then, predicted solely on expected sales of products. Although this new perspective is very relevant, the previous perspective should not be forgotten. In most cases, managers will want to make evaluations and decisions based on both perspectives: products (or brands) and customers. According to Ambler et al.

(2002): “Firms should think of brand and customer assets as two sides of the same coin. One perspective without the other is unlikely to be as effective, and the combination will most often be greater than either alone”. The expected total cash flow from products must be a good proxy for the expected total cash flow from customers, and vice-versa. Thus, the insights from performing these two analyses will probably be better than just one of them. Matching products with profitable customers, as a matrix shown in Figure 1, will allow companies to efficiently manage their marketing assets.

Figure 1 – Product and Customer Portfolio

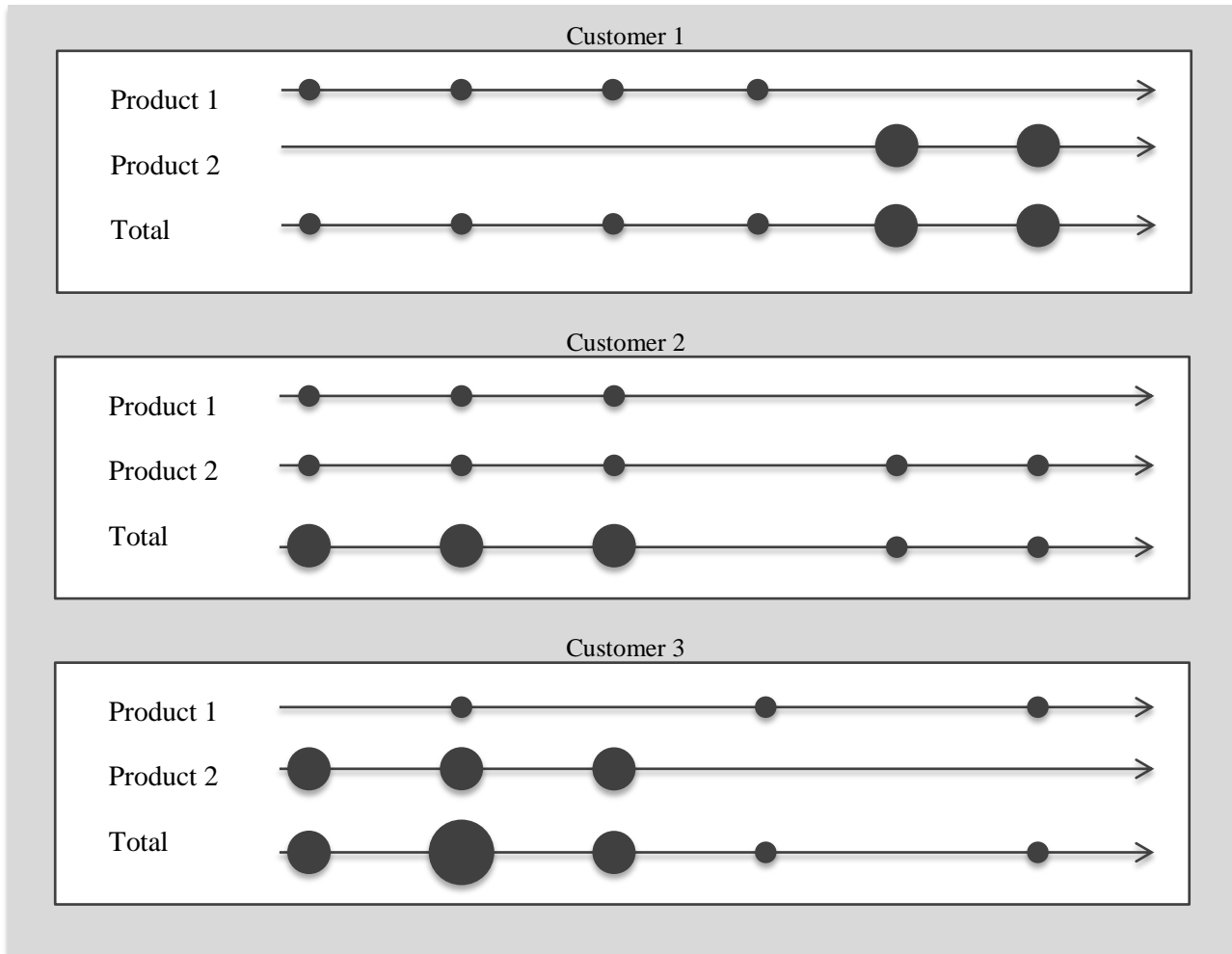
|                   | Customer 1 | Customer 2 | ... | Customer Portfolio     |
|-------------------|------------|------------|-----|------------------------|
| Product 1         |            |            |     |                        |
| Product 2         |            |            |     |                        |
| ...               |            |            |     |                        |
| Product Portfolio |            |            |     | Total Expected Revenue |

Strategies usually adopted by firms to maximize the customer equity are known as add-on selling and consist on increasing sales as a result of offering other products to their customers, more expensive (upgraded) products or more quantity of the same product (Villanueva & Hanssens, 2007). Despite this common practice by companies to increase the amount spent by customers, many CLV models do not capture it since they assume that average revenue for an individual customer is stationary, that is, does not vary over time (Villanueva & Hanssens, 2007). Our suggestion to deal with this reality is to compute the expect customer value separately by product (or product category) and then aggregate the values to estimate the CLV. The disaggregated analysis will allow considering changes in customer purchase behavior, since the model will assume a stationary average margin per product, which jointly with a probability to buy that product, can predict differences in the customer total contribution margin, depending on the expected number of purchases for each product. Furthermore, the customer value predicted by the disaggregated model will also capture some variations resulting from inter-purchase times and also recency among products. The data necessary to compute CLV, as in the traditional RFM model, is available in most companies that have customer purchase history: recency-frequency-monetary value by product (RFM/P). Although, this proposal can contemplate issues related to cross-selling, up-selling and cases in which the number of different products purchased by the customer is reduced, it still cannot deal with the situation regarding the increase in sales due to increment of quantity from the same product.

To illustrate some situations regarding changes in the average revenue for an individual customer and differences

in inter-purchase times among products, addressed by splitting the estimation of customer value by product, we will present three hypothetical examples of customer purchase history. His/her transactions are displayed in Figure 2, where the circles indicate the occurrence of purchases and their size represent the amount of contribution margin. Customer 1 made purchases in time periods 1, 2, 3, 4, 5 and 6. He started buying product 1, after a couple of periods, decided to spend more money and switch to product 2. In this case, if the purchases of each product are aggregated, probably the model will not capture the up-selling process and will underestimate the customer value. Customer 2 made transactions in time periods 1, 2, 3, 5 and 6. He/she usually bought products 1 and 2, but after a while, he/she bought only product 2. In this situation, if the purchases of each product are aggregated, probably the model will not capture the down-selling process and will overestimate the customer value. Finally, customer 3 made purchases in time periods 1, 2, 3, 4 e 6. He/she started buying products 1 and 2, but in different frequencies and monetary values. Then, the customer stops buying product 2 and keeps buying product 1 with lower frequency. Again, if the purchases of each product are aggregated, probably the model will not capture the down-selling process, mixing the product purchasing frequencies, and, consequently, overestimating the customer value.

Figure 2 – Examples of Customer Transaction Data



Therefore, computing the expected customer value separately by product and, then, aggregate the values to estimate the CLV will allow analysts to better predict customer value and identify which are the key products for the valuable customers. Thus, it enables managers to have a more complete overview of the companies future revenues. Additionally, it will be possible to evaluate the dependence and the risk associated to certain products and customers. Predicting customer value by product enables firms to find the answer for relevant questions such as: Given that the customer is going to repurchase, what are the products he/she is probably going to repurchase?

### 3. The RFM/P Model

In order to demonstrate our proposal for integrating the customer and product perspectives by computing the expected customer value in a disaggregated form represented in Figure 1, we select BG/NDB and BG/BB as representatives of CLV models based on RFM segmentation, and compare the results between the aggregated and disaggregated estimations. The general CLV formula is defined in Equation 1 (Rosset et al., 2003):

$$E(CLV) = \int_0^{\infty} E[m(t)]S(t)d(t)dt \quad (1)$$

where  $E[m(t)]$  is the expected contribution margin in period  $t$ ,  $S(t)$  is the survivor function that defines the probability of the customer to be “alive” in period  $t$  and  $d_t$  is the discount factor that reflects the present value of money in period  $t$ .

Assuming that the contribution margin for a given customer is independent of the transaction process (frequency of purchase) and stationary, it is possible rewrites the Equation (1) as follow:

$$E(CLV) = E[m] \int_0^{\infty} E[z(t)]S(t)d(t)dt \quad (2)$$

where  $E[m]$  is the expected contribution margin per transaction,  $E[z(t)]$  is the expected number of transactions in period  $t$ ,  $S(t)$  is the survivor function that defines the probability of the customer to be “alive” in period  $t$  and  $d_t$  is the discount factor that reflects the present value of money in period  $t$ .

Finally, considering that time is discrete and that our suggestion consists in split the customer value by product, the Equation (2) is modified to:

$$E(CLV) = \sum_p^P E[m]_p \sum_{t=0}^{\infty} E[z]_{pt} S_{pt} d_t \quad (3)$$

where  $E[m]_p$  is the expected contribution margin per transaction by product (or product category)  $p$ ,  $E[z]_{pt}$  is the

expected number of purchases of product  $p$  in period  $t$ ,  $S_{pt}$  is the survivor function that defines the probability of the customer buying product  $p$  in period  $t$  and  $d_t$  is the discount factor that reflects the present value of money in period  $t$ .

According to BG/NBD model, the expected number of future transactions for a customer with purchase history  $X(t)$  is (Fader et al., 2005b):

$$E(X_p(t)|r, \alpha, a, b) = \frac{a + b - 1}{a - 1} \left[ 1 - \left( \frac{\alpha}{\alpha + t} \right)^r {}_2F_1 \left( r, b; a + b - 1; \frac{t}{\alpha + t} \right) \right] \quad (4)$$

where  $r, \alpha, a, b$  are BG/NBD parameters,  $X_p(t)$  represents the purchase history  $(x, t_x, T)$  by product (or product category)  $p$ ,  $x$  is the number of transactions,  $t_x$  is the time of the last transaction (recency),  $T$  is the length of the calibration time period, and  ${}_2F_1$  is the Gaussian hypergeometric function.

Whereas, according to BG/BB model, the expected number of future transactions for the next  $n^*$  transactions opportunities by a customer with purchase history  $X(t)$  is (Fader et al., 2010):

$$E(X(n, n + n^*)| \alpha, \beta, \gamma, \delta, x, t_x, n) \quad (5)$$

$$= \frac{1}{L(\alpha, \beta, \gamma, \delta | x, t_x, n)} \frac{B(\alpha + x + 1, \beta + n - x)}{B(\alpha, \beta)} \times \left( \frac{\delta}{\gamma - 1} \right) \frac{\Gamma(\gamma + \delta)}{\Gamma(1 + \delta)}$$

$$\cdot \left\{ \frac{\Gamma(1 + \delta + n)}{\Gamma(\gamma + \delta + n)} - \frac{\Gamma(1 + \delta + n + n^*)}{\Gamma(\gamma + \delta + n + n^*)} \right\}.$$

where  $\alpha, \beta, \gamma, \delta$  are BG/BB parameters,  $X_p(t)$  represents the purchase history  $(x, t_x, n)$  by product (or product category)  $p$ ,  $x$  is the number of transactions,  $t_x$  is the transaction opportunity at which the last observed transaction occurred (recency),  $n$  is the number of transaction opportunities and  $n^*$  is the number of next transactions opportunities.

Regarding the expected contribution margin per transaction by product,  $E[m]_p$ , the simple way to compute it is the observed customer average transaction value:

$$E[m_x]_p = \frac{\sum_{i=1}^x m_{ip}}{x} \quad (6)$$

where  $m_{ip}$  is the contribution margin per transaction  $i$  by product (or product category)  $p$ ,  $i$  represents the purchases of product  $p$  made by the customer and  $x$  is the total number of transactions.

Alternatively, Fader et al. (2005a) suggest that the expected contribution margin per transaction follows a gamma-gamma distribution, resulting in a weighted average between the population mean,  $\gamma\nu/(q - 1)$ , and the customer

transaction value mean,  $m_x$ :

$$E[M|v, q, \gamma, m_x, x] = \left(\frac{q-1}{vx+q-1}\right) \frac{\gamma v}{q-1} + \left(\frac{vx}{vx+q-1}\right) m_x \quad (7)$$

where  $v, q, \gamma$  are parameters of the transaction value model,  $x$  is the number of transactions and  $m_x$  is the observed customer average transaction value. In this case, to obtain expected contribution margin per transaction considering the disaggregated approach, the estimation of the model present in Equation 7 must be done separately by product. Thus, the weighted average is obtained from the product average transaction value and customer average purchase amount of that product.

Both models, BG/NBD and BG/BB, describe a repeat-buying behavior in noncontractual settings wherein the time to “dropout” is modeled using the BG (beta-geometric mixture) timing model, similar to Pareto (exponential-gamma mixture) timing model, but it assumes that dropout occurs immediately after a purchase. The main difference between BG/NBD and BG/BB is related to the model used to estimate the repeat-buying behavior while active. The first assumes that a customer purchases “randomly” around his/her (time-invariant) mean transaction rate, characterized by the Poisson distribution, and the heterogeneity in the transaction rate across customers follows a gamma distribution. The latter assumes that the customer purchases history can be expressed as a binary string that follows a beta-Bernoulli distribution, being more adequate for companies which transactions can only occur at fixed regular intervals or specific events or when transaction data are reported in this way. Thereby, the model selection depends on the situation and the data availability.

#### 4. Empirical Application

In order to validate the proposed model, we implemented it in multiple datasets from two companies operating in different industries in Brazil. The first is a large financial services company with national operations, and the second is a medium supermarket with regional operation. The data contains, among other variables, all of their customer transactions data by product category. The analyses were conducted for four samples based on two cohorts extracted from each dataset. Cohorts 1 and 2 from the financial services company and from the supermarket comprise the customers who made their first purchase of at least one of the product categories during the first and second quarter of the calibration period respectively.

Given the need to check the predicted customer values against the real customer values to compare the performance of the aggregated estimation (traditional RFM) with that of the proposed disaggregated model (RFM/P), we restricted the estimation of the expected customer values for a period of six months. The precision of the estimation of the sum of all customer values was determined based on the percentage of the real sum of all customer values, calculated by the sum of the predicted customer values over the sum of the observed customer values. In order to check the precision of the



estimation of each customer value we used five measures: mean absolute error (MAE), median absolute error (MDAE), root mean squared error (RMSE) e Pearson Correlation. Finally, we also accounted for the ranking of real customer values versus predicted customer values through Spearman correlation.

In this section, we first present the description of each dataset used. After, we choose a customer transaction history to explain the rationale behind RFM/P, exemplifying one of the possible scenarios that lead to a better prediction precision of RFM/P. Finally, we present the results and the analysis of the estimation of the customer values for the next six months for both the financial services company and the supermarket.

#### 4.1 Datasets

**Financial Services Company.** The dataset from the financial services company contains the monthly binary transaction information (1 if the customer has made a purchase of a given product category or 0 if the customer has not made a purchase of a given product category). The contribution margin provided by each customer in a given month is the sum of the contribution margin of all the purchases made during this month for each product category. The dataset have a transaction history of 28 months.

The product categories considered for the financial services company were based on the product segmentation currently used by company. In this way, there are three product categories that are related to the type of investment made by each customer. As the company required the name of the product categories remained anonymously, we named them as products 1 to 3. It is important to highlight that product 2 has the highest average contribution per customer and product 3 has the lowest average contribution margin per customer. Besides that, the customers have more unstable purchasing behavior across the product categories, meaning that they vary in recency, frequency and monetary values among the product categories (see Appendix 1).

Once the transaction data is provided in binary information, the BG/BB model was chosen to estimate the expected number of future transactions for the next six months (Equation 5). The expected contribution margin was estimated in two ways: the observed customer average transaction value (Equation 6), and the expect contribution margin per transaction (Equation 7).

**Supermarket.** The dataset from the supermarket contains the full transaction history with every purchase made by each customer for each product category. The dataset have a transaction history of 22 months. It comprises only the customers who are part of the supermarket's loyalty program. Given this, this dataset has the particular characteristic that the customers do not vary much their purchasing behavior among the product categories (see Appendix 1). This situation contrasts with that of the financial services company and, because of it, we decided to verify the performance of the

proposed disaggregated RFM/P model in such scenario. As the gain in predictability of RFM/P comes mostly from the existence of differences in recency, frequency and monetary values for the each product category, we expected that a more stable transaction history would represent an extreme case in which RFM/P would lead to lesser gains in predictability when compared with traditional aggregated RFM models.

The product categories considered for the supermarket were also based on the product segmentation currently used by the company. In this way, there are nine product categories: grocery (food), household supplies, bakery, housewares, meat, produce, beverages, fresh food, and personal care.

Given the availability of the full transaction data for each product category, BG/NBD model was chosen to estimate the expected number of future transactions for the next six months (Equation 4). The expected contribution margin was again estimated in two ways: the observed customer average transaction value (Equation 6), and the expected contribution margin per transaction (Equation 7).

#### **4.2 Rationale behind RFM/P**

As a means to explain the rationale behind our proposed RFM/P model, we have chosen a specific customer purchasing history to clarify why it is important to take into account the customer purchasing behavior of each product category instead of using only the aggregated transaction history. Having a behavior similar to that present in Figure 2-Customer 1, the customer transaction history presented in Figure 3 is from one of the customers of the financial services company. The first three lines present the purchases of products 1, 2 and 3 made by the customer. In the fourth line, the aggregated purchasing history, summing up the three products categories, is presented. Again, the size of the circles represent the contribution margin amount of each purchase and this monetary value is also informed right above each circle. Figure 3 shows how customer behavior may differ across product category and how this may influence the precision of RFM model prediction. The customer made purchases of product 2 in 12 of the 17 first months of the calibration period and the contribution margin brought in each month is considerably higher compared to the median contribution margin considering all customers that is \$18. However, from the 18<sup>th</sup> month on, the customer stopped purchasing product 2 and started purchasing product 1 and bringing a much lower contribution margin per month. In addition to that, the customer did not transact in the last two periods.

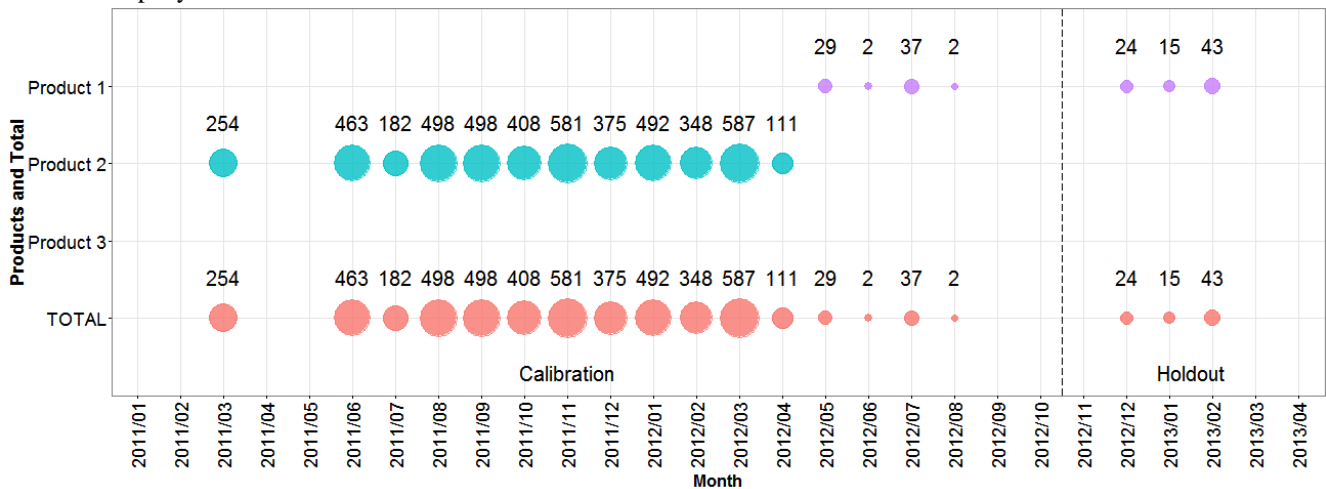
Considering the amount of months with transaction ( $x$ ), the recency value ( $t_x$ ), and the amount of transaction opportunities ( $n$ ) from Equation 5, and if we only take into account the aggregated binary transaction history of this customer, shown in the line named "TOTAL" in Figure 3, and throw out the first month with transaction, we will get  $x=15$ ,  $t_x=17$ , and  $n=19$ . Besides that, the customer average contribution margin is approximately \$307. This scenario is quite

interesting and, because of that, the estimated value of this customer for the next six months is \$421.

Now, based on the proposed disaggregated estimation (RFM/P), once we take into account the binary transaction history of this customer for each product category, shown in the lines named “Product 1”, “Product 2”, and “Product 3” in Figure 3, and throw out the first month with transaction, we will get the following values of  $x$ ,  $t_x$ , and  $n$  for each product category: product 1 ( $x=3$ ,  $t_x=3$ ,  $n=5$ ), product 2 ( $x=11$ ,  $t_x=13$ ,  $n=19$ ), and product 3 does not have any month with transaction. In terms of the customer average contribution margin by product category, the values are the following: product 1 (\$41), product 2 (\$413), and product 3 does not have any month with transaction. In this scenario, it is possible to reduce the influence of the relatively high customer average contribution margin of product 2 once its transaction history has a recency of only 13 out of 19 transactions opportunities and thus the probability that the customer will buy Product 2 again is very low. As consequence of it, the estimated value of this customer for the next six months based on the disaggregated model is \$23.

In the next six months, the real value brought by this customer was \$82. It means that the absolute prediction error of the aggregated estimation is \$339 ( $|\$421 - \$82|$ ), whereas the absolute prediction error of the disaggregated estimation is \$59 ( $|\$23 - \$82|$ ), which is much lower. From this example, it is possible to understand the rationale behind our proposed RFM/P model and why it has the potential to improve aggregated RFM estimation precision.

Figure 3: Example of aggregated (Total) and disaggregated (Products 1, 2 and 3) transaction history of a given financial services company customer



### 4.3 Expected Customer Values – Financial Services Company

In order to test the consistency of our results, the same analysis was conducted using two different sample datasets as aforementioned: cohort 1 (3705 customers) and cohort 2 (4646 customers). The precision of the predicted values of the customers from the financial services company for the next six months are presented in Table 1, for the alternative in which

the contribution margin was determined based on the customer average contribution margin (Equation 6), and in Table 2, for the alternative in which the contribution margin was determined based expected contribution margin (Equation 7).

Table 1: Evaluation of the prediction by RFM and RFM/P using BG/BB model and the average contribution margin (Equation 6) - financial services company

| Model                            | % of real sum of 6 month values | MAE       | MDAE     | RMSE        | Spearman Correlation | Pearson Correlation |
|----------------------------------|---------------------------------|-----------|----------|-------------|----------------------|---------------------|
| RFM (Aggregated) - Cohort 1      | 1.460                           | \$ 671.15 | \$ 11.10 | \$ 4,134.78 | 0.65                 | 0.66                |
| RFM/P (Disaggregated) - Cohort 1 | 1.106                           | \$ 517.28 | \$ 8.76  | \$ 3,645.65 | 0.66                 | 0.71                |
| RFM (Aggregated) - Cohort 2      | 1.291                           | \$ 874.64 | \$ 14.52 | \$ 5,454.45 | 0.69                 | 0.81                |
| RFM/P (Disaggregated) - Cohort 2 | 1.125                           | \$ 756.90 | \$ 12.79 | \$ 5,367.79 | 0.69                 | 0.83                |

Table 2: Evaluation of the prediction by RFM and RFM/P using BG/BB model and the expected contribution margin (Equation 7) - financial services company

| Model                            | % of real sum of 6 month values | MAE         | MDAE     | RMSE        | Spearman Correlation | Pearson Correlation |
|----------------------------------|---------------------------------|-------------|----------|-------------|----------------------|---------------------|
| RFM (Aggregated) - Cohort 1      | 1.771                           | \$ 986.82   | \$ 31.09 | \$ 5,918.52 | 0.63                 | 0.60                |
| RFM/P (Disaggregated) - Cohort 1 | 1.137                           | \$ 530.77   | \$ 21.71 | \$ 3,653.46 | 0.68                 | 0.71                |
| RFM (Aggregated) - Cohort 2      | 1.965                           | \$ 1,597.36 | \$ 49.25 | \$ 7,711.49 | 0.63                 | 0.70                |
| RFM/P (Disaggregated) - Cohort 2 | 1.156                           | \$ 771.75   | \$ 30.82 | \$ 5,399.55 | 0.71                 | 0.83                |

The results of Tables 1 and 2 show that when the disaggregated RFM/P model is used, almost all of the six measures of prediction accuracy were considerably improved in comparison to the results of the aggregated RFM model. It means that the proposed disaggregated RFM/P model lead to more accurate predictions of the customer values for the next six months than traditional aggregated RFM model. This is possible because, once the financial services company customers have very diversified and sometimes volatile purchasing behavior among each product category, we eliminate the bias of using the aggregated transaction history by estimating the customer values by product category. Thus, when the transaction history generates different frequency, recency, and monetary values for each product categories, RFM/P performs better.

#### 4.4 Combining Product and Customer Perspectives – Financial Services Company

Besides the potential to reach more accurate customer value estimations, the proposed RFM/P model also allows the combination of product and customer perspectives. Figures 4, 5, and 6 summarize the customer value estimations by

product category for the next six months for customers of both cohort 1 and cohort 2 using the average contribution margin (Equation 6).

In Figure 4, the concept presented in Figure 1 is applied for the product and customer portfolio of the financial services company. Even though it is possible to analyze the complete matrix considering each individual customer, given large amount of customers, in Figure 4 the customer portfolio was summarized in deciles determined by ordering the customers based on their values. The figure presented is a heatmap that shows the expected customer values by customer deciles and product categories. From this heatmap, it is possible to analyze the value of each cell and understand how the estimated values for the next six months are distributed among the intersections of product categories and customer deciles. The cell colored in dark blue demonstrates that customers from the first decile that are expected to buy product 2 have an average expected value much higher than all the other cells.

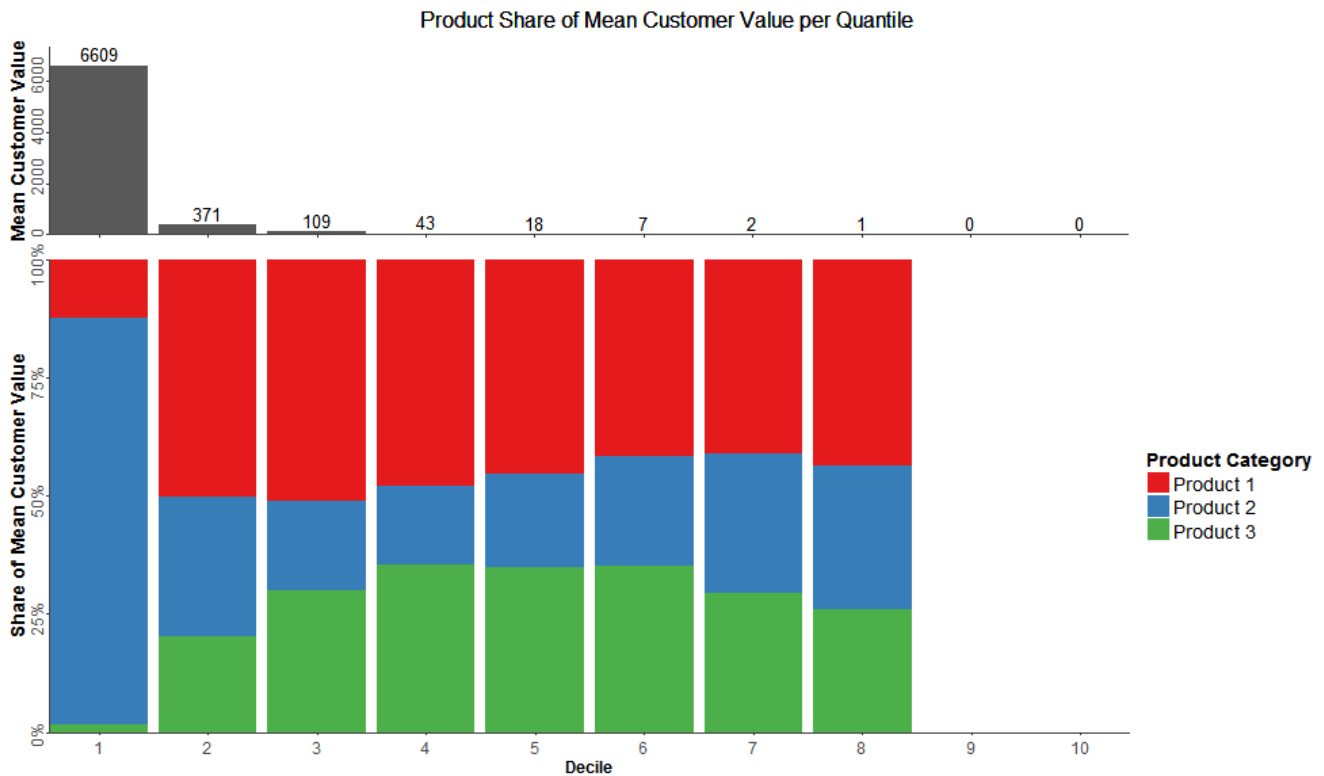
Figure 4: – Heatmap of Product and Customer value Portfolio – Financial Services Company



In Figure 5, the intersections of mean customer values by deciles and the product categories from Figure 4 are presented together with the mean overall customer value for each decile. The bar plot on the top presents the mean of the overall customer value for each decile. Underneath the top bar plot, there is a stacked plot that displays how the mean

overall customer values for each decile from the bar plot right above is distributed among the product categories. In this way, the plots from Figure 5 demonstrate that the value brought by all the customers are highly concentrated in the 10% most valuable customers (decile 1) and that, among these most valuable customers, product 2 represents almost 90% of the mean overall customer value from this decile.

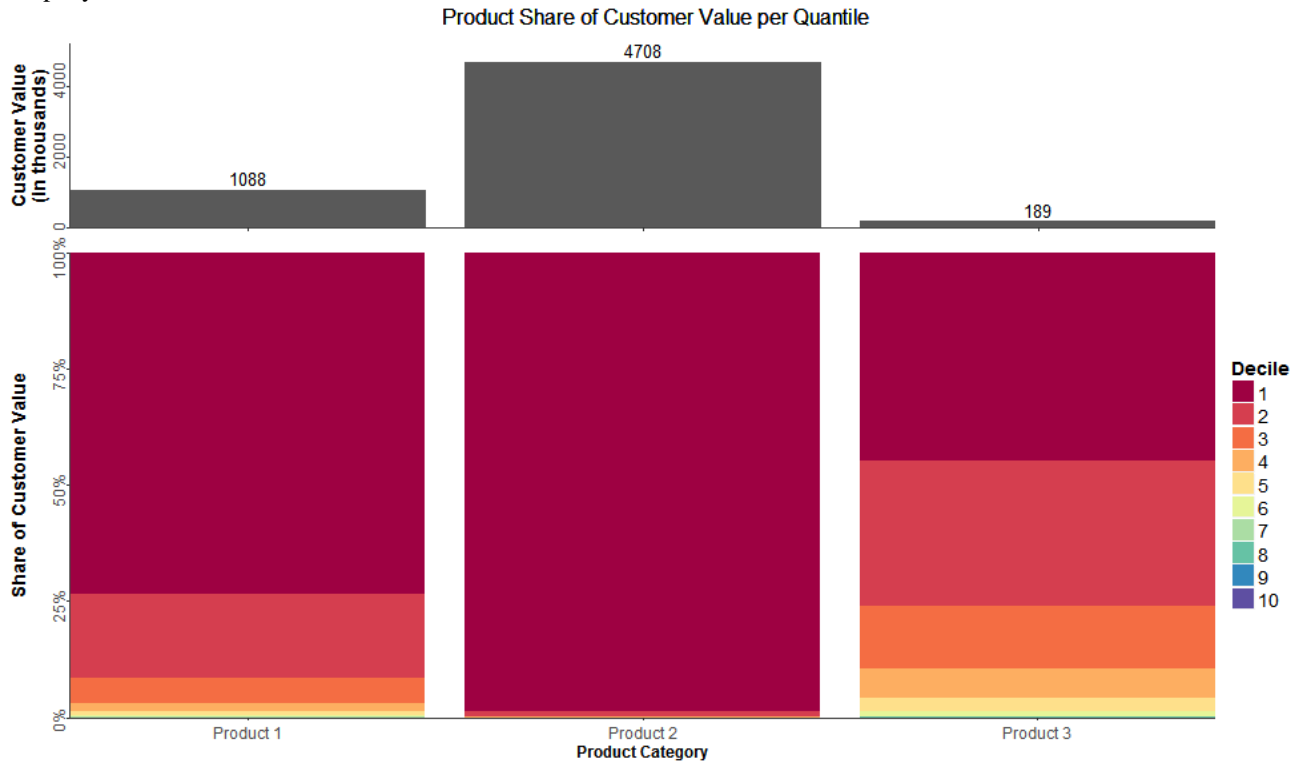
Figure 5: Product Category Share of Mean Customer Value per Decile - Financial Services Company



In Figure 6, by estimating the expected values of customers from the financial services company for the next six months, we could again take advantage of the combination of product and customer perspectives. For the sake of exploration of the possibilities brought by the use of the proposed RFM/P model, in Figure 6 we demonstrate another possible situation that also brings interesting managerial insights both for product and customer management. The bar plot at the top of Figure 6 now show the total customer value for each product category, while the stacked underneath the top bar plot displays how the total customer values for each product category from the bar plot right above are distributed among the deciles determined after ordering the customers from the most valuable to the least valuable one. Such figure demonstrates that the sum of customer values for product 2 is approximately \$ 4708000 and almost all of this total value is concentrated in the first decile. In contrast, product 3, which has the lowest sum of customer values, has its total value less

concentrated in the first decile, meaning that the difference in terms of value between the most valuable customers and the less valuable ones is lower.

Figure 6: How total customer values for each product category are distributed among the deciles - Financial Services Company



The results presented in Figures 4, 5, and 6 were possible because the customer value estimations for the next six months were calculated based on our proposed RFM/P disaggregated model. These insights provided by the disaggregated estimation of customer value indicate how the combination between product and customer perspectives brings a novel view that enables managers to improve their decision making about both customer and product management. Taking the case of the financial services company as an example, it should be noticed that not even the company has almost its entire expected value dependent on its 10% most valuable customers, but this most valuable decile has almost its entire value dependent on only one product category (product 2). As product 2 is the product category of the financial services company that has the highest cash flow volatility, future earnings are subjected to a quite risky situation.

#### 4.5 Expected Customer Values - Supermarket

In order to check the consistency of our results, the analysis was again conducted for the supermarket dataset using two different cohorts from the whole dataset: cohort 1 (125 customers) and cohort 2 (39 customers). The results of the predicted value of the customers from the supermarket for the next six months, presented in Tables 3 and 4, confirmed our

expectation about accuracy of disaggregated RFM/P model compared to the traditional aggregated RFM estimation when applied to a case in which the recency, frequency and monetary values are more stable among the product categories. The accuracy measures demonstrate that the estimation of both methods were much closer than in the case of the financial services company. The percentage of the real sum of all the customer values for the next six months and the Spearman correlation for the customer values were slightly better with the traditional aggregated RFM estimation in the case of cohort 2. All of the other measures for both cohort 1 and 2 were better with the disaggregated RFM/P estimation.

Table 3: Evaluation of the prediction by RFM and RFM/P using BG/NBD model and the average contribution margin (Equation 6) - supermarket

| Model                            | % of real sum of 6 month values | MAE       | MDAE      | RMSE        | Spearman Correlation | Pearson Correlation |
|----------------------------------|---------------------------------|-----------|-----------|-------------|----------------------|---------------------|
| RFM (Aggregated) - Cohort 1      | 0.821                           | \$ 667.23 | \$ 260.85 | \$ 1,758.55 | 0.80                 | 0.85                |
| RFM/P (Disaggregated) - Cohort 1 | 0.851                           | \$ 644.62 | \$ 233.28 | \$ 1,659.39 | 0.82                 | 0.88                |
| RFM (Aggregated) - Cohort 2      | 0.842                           | \$ 519.06 | \$ 282.16 | \$ 860.80   | 0.81                 | 0.90                |
| RFM/P (Disaggregated) - Cohort 2 | 0.834                           | \$ 486.40 | \$ 180.02 | \$ 836.24   | 0.80                 | 0.90                |

Table 4: Evaluation of the prediction by RFM and RFM/P using BG/NBD model and the expected contribution margin (Equation 7) - supermarket

| Model                            | % of real sum of 6 month values | MAE       | MDAE      | RMSE        | Spearman Correlation | Pearson Correlation |
|----------------------------------|---------------------------------|-----------|-----------|-------------|----------------------|---------------------|
| RFM (Aggregated) - Cohort 1      | 0.838                           | \$ 671.65 | \$ 254.31 | \$ 1,756.87 | 0.82                 | 0.85                |
| RFM/P (Disaggregated) - Cohort 1 | 0.857                           | \$ 644.12 | \$ 244.76 | \$ 1,663.47 | 0.83                 | 0.88                |
| RFM (Aggregated) - Cohort 2      | 0.842                           | \$ 519.06 | \$ 282.16 | \$ 860.80   | 0.81                 | 0.90                |
| RFM/P (Disaggregated) - Cohort 2 | 0.830                           | \$ 492.15 | \$ 182.41 | \$ 856.27   | 0.79                 | 0.90                |

Since the supermarket dataset contains the full transaction history, it was possible to sum all the transactions made by each customer in a given month and transform the transaction history of each customer into a discrete transaction history as a means to estimate the customer values for the next six months using BG/BB model. The results only for cohort 1 are presented in Appendix 2 and, as expected, the results are similar to those demonstrated in Tables 3 and 4 when BG/NBD model was used.

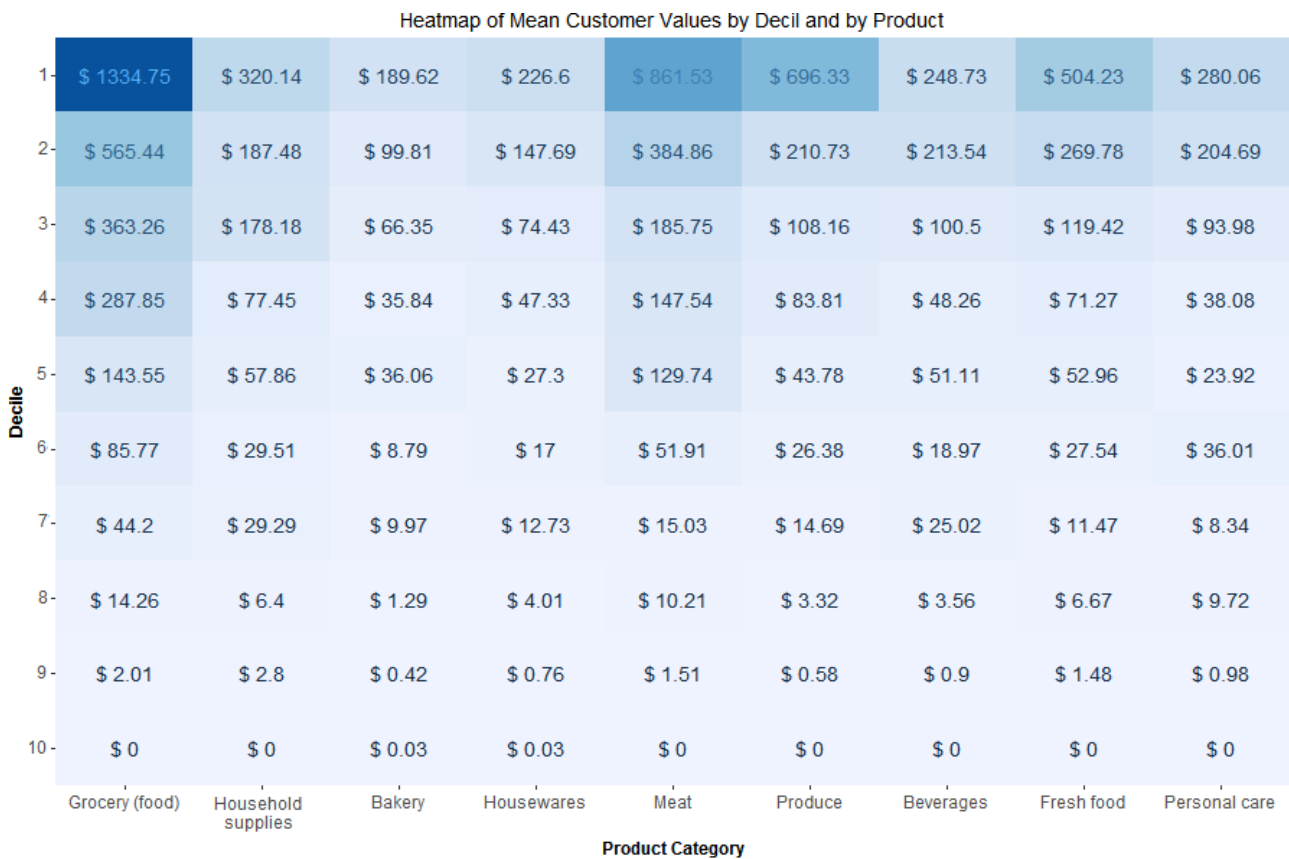
These results demonstrate that even in an extreme case in which recency, frequency and monetary values are more stable across product categories, disaggregated RFM/P model performed quite well. Even though more extensive tests in a wider variety of settings must be done, the results obtained so far indicate that the disaggregated RFM/P model might be used as a substitute for the traditional RFM models without loss of prediction accuracy.



#### 4.6 Combining Product and Customer Perspectives - Supermarket

By estimating the expected values of customers from the supermarket for the next six months, we can again take advantage of the combination of product and customer perspectives. Although the same analysis presented in Figures 5 and 6 can also be done, in Figure 7 we presented again only the heatmap of product and customer value portfolio. Exploring the heatmap, one can easily identify what are the product categories that have higher mean customer values along several deciles: grocery (food) and meat. Furthermore, by analyzing only the first decile, we note that the product categories produce and fresh food have an important participation in the overall value of the most valuable customers. Finally, this figure demonstrates how the supermarket customer values are more distributed across products categories and also across the customer value deciles. This contrasts with the financial services company that have its customer values highly concentrated on product 2 and in the first decile.

Figure 7: Heatmap of Product and Customer value Portfolio - Supermarket



## 5 Conclusion

The move toward a customer-centric management not necessarily should mean that managers may not consider important data from products that could provide good insights. The proposed RFM/P model enables executives to have a more complete overview of the firm future profits. It is an alternative to traditional RFM models that integrates two important marketing perspectives, which are usually treated separately, in the prediction of cash flows: customer and product perspectives. The split of the analysis of the customer value by product (or product category) suggested, besides bringing relevant information that contributes to a better management of marketing assets, also adds prediction power to CLV models based on RFM. The main reason for this lies in the fact that the disaggregated model can capture some customer purchase behavior changes resulting from up-selling, cross-selling or reductions in the number of different products. These add-on selling strategies are usually not contemplated by many CLV models that assume a stationary customer average contribution margin. Moreover, the disaggregated approach also includes in the estimation the differences in frequency and recency existent among products, improving the accuracy of the predicted customer value.

The results of our research demonstrate that product data can add useful information to manage marketing assets and estimate CLV more precisely. In addition, it also has the potential to reduce the sum of customer values prediction error as well as to improve the individual customer value forecast error, helping companies to better manage their customer base. Hence, there are evidences that the RFM/P model estimates CLV more accurately than traditional aggregated RFM models, performing better or at least equivalent to them. In this way, we argue in favor of using RFM/P to predict the customer value since there would be no disadvantages, only benefits in adopting the disaggregated approach.

Finally, given the proposed RFM/P model, we suggest that future researches employ efforts to extend the application of RFM/P to other companies from different industries. We also believe the same disaggregated estimation of customer value could also be tested in other models of CLV that are not related to the family of RFM models.

### Appendix 1

In Table 5, we present the average values of recency, frequency, and monetary values for the product categories of the financial services company and of the supermarket. By analyzing the values for the product categories of the financial services company, one can evidence that products 1, 2, and 3 have very different recency, frequency and monetary values. In contrast, all product categories of the supermarket have very similar average recency and frequency values. The average monetary values are also quite close across the product categories, except for grocery (food) and meat that have higher values.

Table 5: Average recency, frequency, transaction opportunities, and monetary values for the product categories of the financial services company and of the supermarket.

| Product Category           | Number of transactions (x) | Recency (t,x) | Transaction opportunities (n) | Contribution margin |
|----------------------------|----------------------------|---------------|-------------------------------|---------------------|
| Financial Services Company |                            |               |                               |                     |
| Product 1                  | 6                          | 10            | 18                            | \$ 102              |
| Product 2                  | 4                          | 6             | 16                            | \$ 2114             |
| Product 3                  | 9                          | 11            | 16                            | \$ 17               |
| Supermarket                |                            |               |                               |                     |
| Grocery (food)             | 6                          | 9             | 13                            | \$ 127              |
| Household supplies         | 5                          | 8             | 12                            | \$ 48               |
| Meat                       | 5                          | 8             | 12                            | \$ 92               |
| Beverages                  | 5                          | 8             | 12                            | \$ 37               |
| Produce                    | 5                          | 9             | 12                            | \$ 53               |
| Bakery                     | 5                          | 8             | 12                            | \$ 22               |
| Housewares                 | 5                          | 8             | 12                            | \$ 32               |
| Fresh food                 | 5                          | 8             | 13                            | \$ 48               |
| Personal care              | 5                          | 8             | 12                            | \$ 34               |

## Appendix 2

The results of the prediction accuracy measures for the estimation of the supermarket customer values for the next six months using BG/BB model are presented in Tables 6 and 7. One can notice that these results are similar to those presented in Tables 3 and 4 when BG/NBD was used.

Table 6: Evaluation of the prediction by RFM and RFM/P using BG/BB model and the average contribution margin (Equation 6) - supermarket

| Model estimated                  | % of real sum of 6 month values | MAE       | MDAE      | RMSE        | Spearman Cor CLV | Pearson Cor CLV |
|----------------------------------|---------------------------------|-----------|-----------|-------------|------------------|-----------------|
| RFM (Aggregated) - Cohort 1      | 0.838                           | \$ 575.77 | \$ 243.70 | \$ 1,596.37 | 0.80             | 0.88            |
| RFM/P (Disaggregated) - Cohort 1 | 0.822                           | \$ 571.32 | \$ 184.46 | \$ 1,573.23 | 0.81             | 0.89            |

Table 7: Evaluation of the prediction by RFM and RFM/P using BG/BB model and the expected contribution margin (Equation 7) - supermarket

| Model estimated                  | % of real sum of 6 month values | MAE       | MDAE      | RMSE        | Spearman Cor CLV | Pearson Cor CLV |
|----------------------------------|---------------------------------|-----------|-----------|-------------|------------------|-----------------|
| RFM (Aggregated) - Cohort 1      | 0.843                           | \$ 642.32 | \$ 306.50 | \$ 1,774.65 | 0.82             | 0.85            |
| RFM/P (Disaggregated) - Cohort 1 | 0.822                           | \$ 613.50 | \$ 241.78 | \$ 1,727.01 | 0.82             | 0.87            |

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